IMPACTS OF CLIMATE VARIABILITY ON MALARIA PREVALENCE IN RWANDAN HIGHLANDS

BY

MANIRAGABA ABIAS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREEE OF DOCTOR OF PHILOSOPHY OF ENVIRONMENTAL HEALTH IN THE SCHOOL OF ENVIRONMENTAL STUDIES, UNIVERSITY OF ELDORET, KENYA

JULY 2018

DECLARATION

This thesis is my original work and has not been submitted for any academic award in any institution; and shall not be reproduced in part or full, or in any format without prior written permission from the author and/or University of Eldoret.

---------- Date: ----------

Signature

Maniragaba Abias
SES/DPhil/03/10

Supervisors

This Thesis has been submitted with our approval as University supervisors.

---------- Date: ----------

Signature

Dr.G.M. Simiyu
Department of Biological Sciences and Health
School of Environmental Studies
University of Eldoret
P.O. Box 1125 - 30100, Eldoret

---------- Date: ----------

Signature

Dr. B.N. Mwasi
Department of Environmental Management and Monitoring
School of Environmental Studies
University of Eldoret
P.O. Box 1125 - 30100, Eldoret

---------- Date----------

Signature

Prof. N. Kato
Directorate of Research and Post Graduate Studies
University of Rwanda
P.O. Box 3286 Kigali

DEDICATION

To my lovely children **Bright** and **Ebenezer Maniragaba** and beloved wife A. **Ndacyayisenga** who had to bear my family absence, to my Mother, Sisters and Brothers for your moral support.

ABSTRACT

Fluctuations in climate variation could influence the emergence and re-emergence of vector-borne infectious diseases such as malaria in highlands. The transmission of malaria is caused by vector and arthropod that strive in area with high rainfall and they are limited by low temperatures and high altitudes. Malaria vectors for many years were found in lowlands and not found in highlands because of weather conditions. The present research sought to evaluate the possible impacts of climate variability on malaria prevalence in Rwandan highlands. Using secondary data on malaria cases from medical records in selected Health Centres of highlands and meteorological parameters data collected from meteorological stations, regression analysis was used to determine relationship between climate variability and malaria prevalence. Spatial analysis methods examined the distribution of malaria incidence in selected Districts of Rwandan highlands, Pearson Correlation determined direction and strength of the linear relationship between malaria and the meteorological parameters while time series analysis with SARMA helped to make prediction. Analysis of data for 11 years period indicated that; maximum temperature did not have high variation; it was in the range of 23 and 25^{o}C, while minimum temperature varied considerably with a range of 8.02 and 14.55, average of minimum and maximum indicated linear growth as it combines the values of maximum and minimum temperature (16.34 and 19.54^{o}C), rainfall was increasing throughout of the period of study with high variation and extreme weathers, the monthly average was between 95.62 to 156 mm. In Karongi it varied between 87.00 to 122 mm, Muhanga it was between 80.63 to 235 mm and Rubavu it was between 81.33 to 136 mm. Relative humidity was also important, its variation was not too high since the highest value of relative humidity was 72.24% and the lowest was 66.10%. Generally relative humidity was decreasing with time. With 5% level of significance, all selected climate parameters were not correlating with malaria transmission at the same level; in Karongi malaria prevalence had a strong positive correlation with: maximum temperature and rainfall, r=0.68, a moderate positive correlation with rainfall and relative humidity, r=0.5 and a strong positive correlation with average temperature and rainfall, r=0.66. In Muhanga malaria prevalence had a strong positive correlation with minimum temperature, r=0.76, while in Rubavu malaria prevalence had a weak positive correlation with maximum temperature and relative humidity, r=0.44 and a weak positive correlation with average temperature, rainfall and relative humidity r=0.33. It was predicted that in 2018 malaria prevalence in Karongi would be 879.277/1000 in Muhanga 97.69/1000 and Rubavu 3.71/1000. Results show evidence of the strong existence of relationship between climate parameters and malaria prevalence in highland areas of Rwanda. All national programs on malaria control should take into account this area of Rwandan highland, since it is highly susceptible to climate change and malaria prevalence.

TABLE OF CONTENT

LIST OF APPENDICES

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

ABBREVIATIONS AND ACRONYMS

A.fenestus: *Anopheles fenestus*

A.gambiaes s.l.: *Anopheles gambiae*

ACT: Artemisinin-based Combination Therapy

ADF: Augmented Dickey Fuller (Unit Root Test)

AQ: amodiaquine

ARI: Acute Respiratory Infections

ARMA: Autoregressive Moving Average

ARMAX: Autoregressive Moving Average with Exogenous variable

Av_max_temp: Average maximum temperature

Av_mean_Humidity: Average mean humidity

Av_mean_temp: Average mean temperature

Av_min_temp: Average minimum temperature

BC: Before Christ

CFC: Chlorofluorocarbon

CH: Community Health

CHW: Community Health Workers

CQ: Chloroquine

CQ/Kg: Doe of chloroquine per body weight

CRA: Comparative Risk Assessment

CRU: Climate Research Unit

DEM: Digital Elevation Model

DFID: Department for International Development

DHS: Demographic and Health Survey

DMS: Degree Minute Second

DRC: Democratic Republic of Congo

DTR: Diurnal Temperature Range

DW: Durbin Watson

ECM: Error Correction Model

EIP: Extrinsic Incubation Period

EIR: Entomological Inoculation Rate

ENSO: El Nino Southern Oscillation

EWS: Early Warning System

FAO: Food and Agriculture Organization of United Nation

GCM: General Circulation Model

GDP: Global Domestic Production

GEM: General Equilibrium Model

GHG: Green House Gas

GOR: Government of Rwanda

GTAP: Global Trade Analysis Project Models

HMIS: Health Management Information System

HSSP: Health Support Service Project

IAM: Integrated Assessment Model

ICCM: Integrated Community Case Management

ICF: International Coach Federation

IM: Intramuscular

IPCC: Intergovernmental Panel on Climate Change

IRS: Indoor Residual Spraying

ITCZ: Inter-Tropical Convergence Zones

ITN: insecticide-treated mosquito net

LLIN: Long Lasting Insecticidal Net

MAM: March, April and May

MAPE: Mean Absolute Percentage Error

MDG: Millennium Development Goals

MIASMA: Modelling framework for the health Impact Assessment of Man-induced Atmospheric changes

MINIRENA: Ministry of Natural Resources

MINISANTE: Ministère de la Santé

MINITERRE: Ministry of Lands, Environment, Forestry, Water and Mines

MIP: Malaria in Pregnancy

MOH: Ministry of health

MOPDD Malaria and Other Parasitic Diseases Division

NISR: National Institute of Statistics of Rwanda

NMCP: National Malaria Control Programme

P.falicipalum: Plasmodium falicipalum

P.ovale: Plasmodium ovale

P.vivax: Plasmodium vivax

P: Plasmodium

PCR: Polymerase Chain Reaction

PMI: Presidential Malaria Initiative

RBC: Red Blood Cells

RBC: Rwanda Biomedical Centre

REMA: Rwanda Environment Management Authority

RMC: Rwanda Meteorological Centre

RR: Relative Risk

RTD: Rapid Diagnostic Test

SARMA: Seasonal Autoregressive Integrated Moving Average

SDG: Sustainable Development Goal

SRW: Seasonal Random Walk

TauDEM: Terrain Analysis Using Elevation Model

Tmax: Maximum Temperature

Tmin: Minimum Temperature

WI: Wetness Index

Ukaid: United Kingdom Agency for International Development

UNEP: United Nation Environment Program

UNFCC: United Nation Framework Convention on Climate Change

UR-CMHS-SPH: University of Rwanda-College of Medical and health Sciences- School of Public Health.

VBD: Vector Borne Diseases

VMW: Village malaria workers

WHO: World Health Organisation

WMO: World Meteorological Organisation

DEFINITION OF OPERATIONAL TERMS

1. Climate: Climate is the long-term weather pattern (for at least 30 years) in an area. The climate includes general patterns and extremes of drought, rains, storms, and freezing temperatures (Philander, 2008). Climate is different from weather; Weather is the condition that prevails at a given moment and may change within days or even hours. In fact climate is what you expect and weather is what you get (McMichael *et al*., 2003).

2. Climate change: Climate change refers to a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period (typically decades or longer). *United Nations Framework Convention on Climate Change* (UNFCCC), defines climate change as "a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods."

3. Climate variability: Climate variability refers to variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all temporal and spatial scales beyond that of individual weather events (IPCC, 2001).

4. Highland regions: In Africa, the highlands are defined to be at altitude higher than 1500 m elevation above sea level or with daily mean temperatures of below 20°C (Githeko, *et al*., 2014 & Wandiga, *et al.,* 2006).

5. Incidence Rate: The incidence of disease is defined as the number of new cases of disease occurring in a population during a defined time interval. The number is useful as a measure of the risk of disease (Oleske, 2002).

6. Malaria: The word comes from mediaeval Italian words: **mal** = bad, **aria** = air.
Genus of mosquito-transmitted coccidian blood parasites. The name comes from Greek: plasmodion = small organism.
The taxonomy of parasite is: Kingdom: Protista, Phylum: Apicomplexa, Class: Sporozoasida, Order: Eucoccidiorida, Family: Plasmodiidae, Genus: *Plasmodium* (Marcus, 2009)
7. Prevalence rate: The prevalence rate, often referred to as prevalence, is the total number of cases (both new and pre-existing) in a specific period of time (Oleske, 2002):

ACKNOWLEDGMENTS

This thesis is a result of the collaboration and support of many people. In particular, I would like to thank most sincerely my supervisors, Dr. G.M. Simiyu, Prof. Njyunwa Kato Jonas and Dr. Mwasi N. Ben for their professional guidance, encouragement, availability and tireless efforts in making this work a success. I cannot forget to thank Dr. Shem Mwasi, a part time Lecturer in Department of environmental biology and health, for accepting to spare time and critic my thesis. The support I received from them was truly first rate and highly appreciated.

I am also thankful to the Management committee of University Adventist of Lay Adventists of Kigali (UNILAK) and the Government of Rwanda through Rwanda Educational Board (REB) for their financial support that enabled me to undertake my PhD studies.

I am also very grateful to the entire University of Eldoret staff, both academic and administrative without whom the strong background of this research would not have been be attained.

More gratitude goes to: staff members of Rwanda Biomedical Centre (RBC) Division of Malaria in particular Messrs C Karema, N. Umulisa, A. Kabayiza and Mr M. Habimana of Rwanda Meteorological Centre. Further gratitude is due to the Medical Director of Kabgayi Hospital, Sr. Dr. Béata Murekatete. I cannot forget the staff members of Rwanda Natural Resource Authority (RNRA) for their assistance during the data collection period.

Last but not least my appreciation goes to Messrs D. Thomson, A. Mukabutera and R. Hinda of University of Rwanda, Prof. N.I Bideri, Dr J.C Zigama, Dr. G. Habiyaremye, Dr. Kayongo's Family and Messrs S. Isange, A. Butera, C. Habyarimana, F. Mukasekuru of UNILAK for their support and encouragement.

May God bless them abundantly!

CHAPTER ONE
INTRODUCTION

1.0 General background

Malaria is both preventable and treatable disease. Yet more than 220 million cases of malaria are estimated to occur each year, and approximately 785,000 people die from the disease annually. Half of the world's population, some 3.3 billion people living in 109 countries, are at risk of malaria (Paaijmans *et al.,* 2009). Worldwide, malaria is the fifth-leading cause of death from infectious diseases (after respiratory infections, HIV/AIDS, diarrheal diseases, and tuberculosis) (WHO, 2014).

Examinations of climate, ecosystem, and health connections suggest that climate change and variability may have significant and widely ranging impacts on human health. In 1988, the Intergovernmental Panel on Climate Change (IPCC), a multidisciplinary scientific body, was established by the World Meteorological Organization and the United Nations Environment Program to advise governments on climate related issues. To understand the human health implications of weather changes, it is thus efficacious to have some discussion of the observed and projected changes in climate and the climate system (Patz *et al*., 2008).

In her speech of 23rd March 1999, Brundtland stressed the role of climate variation on human health by altering weather patterns and by disturbing life-supporting natural systems and processes. The discussions are still going on dealing with the exact causality between human behaviour and climate change. But it is well known the concern of adverse consequences of climate variability on human health.

The WHO (2015), identified the scenarios in which climate change has effect on human health, among others it was included: increasing disease transmission seasons and altered geographic ranges of disease, emergence of new diseases and re-emergence of diseases that were at one time controlled. The disease which had been almost eliminated, and is coming back, sometimes surpassing earlier recorded levels and climate depending is Malaria.

Malaria carried by mosquitoes offers an example of a parasitic disease that may return to population with global warming. Rising sea levels caused by climate change may lead to flooding, which in turn gives the *Anopheles* mosquito species more breeding grounds. Warmer average temperatures would also increase the mosquito's season. Global climate change can and will create other complex relationships between environments, human susceptibility to disease, and the transmission of infections (Marcy, 2004).

In the troposphere, where viable atmosphere is located, the lapse rate defines an important feature of the temperature distribution that decline with height above the surface in the lowest 10- 15 Km of the atmosphere represented by:

$$\Gamma \equiv -\frac{\delta T}{\delta z} \qquad (1)$$

Where T is the temperature and z is altitude and the deltas indicate a partial derivative.
The global mean tropospheric lapse rate is about 6.5^{o}C km^{-1}, but the lapse rate varies with altitude, season, and latitude. Temperature is the most widely recognized climatic variable (Hartmann, 2016).

For East African region, the research conducted by Kevin (2009), found that for every 1000-meter gain in elevation, temperatures decrease by 6^{o}C. Minimum temperature for parasite development of *Plasmodium falciparum* and *Plasmodium vivax* approximates 18^{o}C and 15^{o}C, respectively, limiting the spread of malaria at higher altitudes.

Increasing altitude also results in decreasing mosquito abundance in African highlands.
Temperature, humidity and availability of clear water bodies (standing or slow moving) are keys to mosquito bionomics. They determine the spatial (North and South longitudes; altitude; desert areas) and temporal (seasonal) limits of the disease.

Biological process models are an important component of the discussion. Biological models estimate the responsiveness and thresholds of parasites, pathogens, and vectors to temperature and precipitation (Rosenthal, 2009). Based largely on studies of vector and/or parasite development, warming and increases in humidity are predicted to open up new zones for malaria in Africa (Kazembe, 2007).

UKaid (2009) developed a new model applied on altitude for assessing the impact of climate change on malaria. The model used the product of incidence time's population size to estimate an absolute amount of malaria in Rwanda. Taking the sum for all altitudes provides a measure for expected changes in malaria, taking into account the altitudinal distribution of the population in the country.

Rwanda Environmental Management Authority (2010) in Figure 1 below shows the overall analysis and the malaria lapse rate (in green) against rural population (blue bars). The change from the 1980s (green) to present (blue line) can be compared against future projected increase in temperature (red line).

In the 2050s, as a result of climate warming (2.2ºC, the central projection), the population at risk for malaria in rural areas over 1000 meter (99% of the population) is predicted to increase by 153%. Approximately half of this predicted increase in mean temperatures has already occurred since the 1980s, and is likely to have raised the national burden of malaria in recent decades.

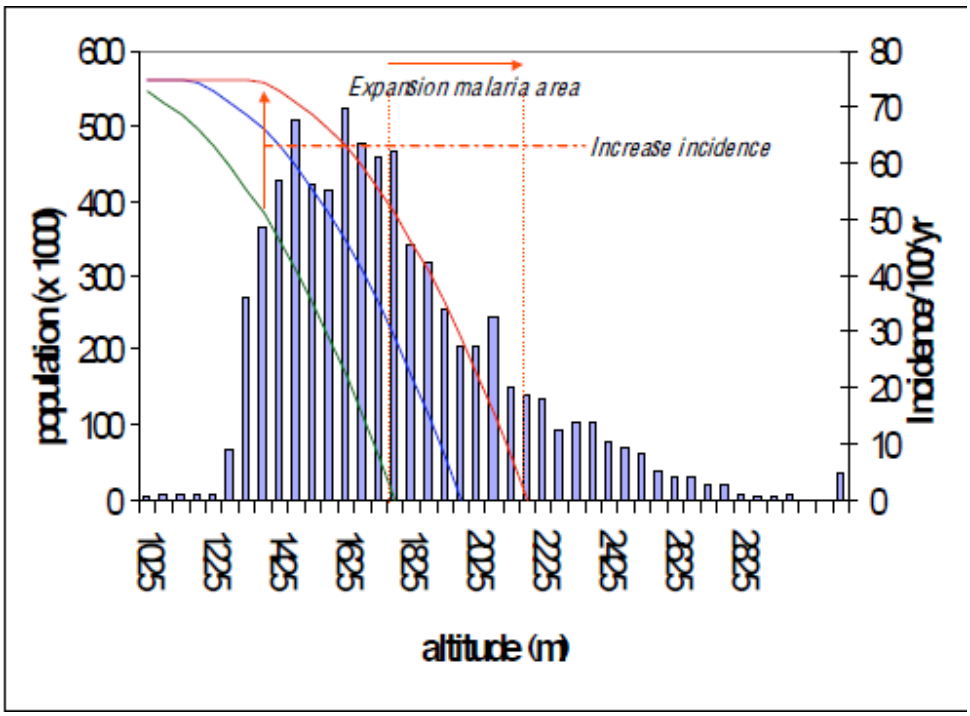


Figure 1: Malaria risk model in Rwanda

(Source: Rwanda Environmental Management Authority, 2010).

Climate is one of several important factors influencing the incidence of infectious diseases (Olivier & Hidore, 2002). Other important considerations include socio demographic influences such as human migration and transportation, drug resistance and nutrition, as well as environmental influences such as deforestation, agricultural development, water projects, and urbanization. In this era of global development and land-use changes, it is highly unlikely that climatic changes exert an isolated effect on disease; rather the effect is likely dependent on the extent to which humans cope with or counter the trends of other disease modifying influences (Walsh *et al*., 1993). Around 3.3% of the earth's surface changed from one climate category to another between 1951 and 2000 (Lafferty, 2009). This gave occasion to adaptation of several vector borne diseases.

Numerous, and in some cases conflicting, predictions have been developed regarding the frequency, severity, and duration of epidemics that may emerge. With respect to the biogeographical focus of this issue, the central question is whether pathogens and parasites that are currently restricted to lower latitudes where the world's greatest biodiversity lies move toward poles (mostly north) and upward in altitude (Chapin III *et al.*, 2012).

1.1 Problem statement

Before 2005, malaria was the leading cause of morbidity and mortality in Rwanda with periodic epidemic outbreaks in the high altitude areas (MINISANTE, 2011). Since 2000, close to 1 million cases of malaria have been recorded each year countrywide of these cases more than half are hospital visits and deaths occurring for children under age 5 (Thaxon, 2009). Malaria is also a significant health risk for pregnant women and their unborn children, particularly first-time mothers and women with HIV (NISR *et al.*, 2011).

Rwanda had made a big achievement toward malaria eradication as it was among the pillars of MDG (UNICEF, 2015), but, recently WHO Global Malaria Program (2015) reported a tripling in confirmed malaria cases (from 483 000 to 1.6 million), and a doubling in admissions (from 5306 to 11 138) between 2012 and 2014 According to preliminary analysis conducted by the MOPDD, the vast majority of this increase is among persons over five years of age (RBC, 2017). This increase in malaria case numbers in Rwanda

(according to RBC) are most likely due to resistance increase to insecticides, anti-malarial drugs, substandard LLINs and climate variability (President's Malaria Initiative, 2014).

While most of highlands of Rwanda are located in the fringes of endemic zones, where transmission is limited by rainfall or by lower temperatures, there are strong seasonal patterns and occasional major epidemics (Bizimana, 2015). In such regions, climate is a major determinant of year-to-year changes in malaria incidence. In some locations, warming trends in the past two decades might have contributed to changing the epidemiology of malaria (Paul & Dirk, 2004). But what effects will future changes in climate have on malaria in Rwandan highland?

The Intergovernmental Panel on Climate Change (IPCC, 2007) predicted an average temperature rise of 1.5–5.8 °C across the globe during the 21st century, accompanied by increased extreme and anomalous weather events including heat-waves, floods and droughts. Currently there are few if any published data that provide information on malaria status and climate change in Rwandan highland regions, partly because the science of climate and health is not well developed. The relationship of changes in vector-borne diseases attributable to climate change is therefore still unknown, which is a serious obstacle to evidence-based health policy change. Although the impacts of climate variability on vector-borne diseases can be observed, the same cannot be said of climate change because of the slow rate of change.

Regarding research priorities, there is a great need to better understand the current relationships between “multiple physical phenomenon” of weather and disease, while at the same time we must begin to consider future risk estimates required by policy makers. New discoveries from field data are particularly essential in constructing credible simulation models.

1.2 Objectives

a. General objective

To evaluate the possible impacts of climate variability on malaria prevalence in Rwandan highlands

b. Specific Objectives

1. To determine the variation of temperature, rainfall and relative humidity in Rwandan highlands for the period of 11years.
2. To determine malaria incidence in Rwandan highlands for the period of 11 years.
3. To determine the relationship between meteorological parameters and malaria incidence in Rwandan Highlands.
4. To model and predict changes in the incidence of malaria attributable to climate variation.

1.3 Hypotheses

H_x1: There is no relationship between meteorological parameters and malaria incidence in Rwandan highland.

H_x2: Climate variability does not affects the future incidence of malaria in Rwandan highlands.

1.4 Scope of study

The study was limited to climate variables (temperature, rainfall and relative humidity) and malaria clinical data analysis and established the relationship between them. Data collected and used in this research cover the period 2004 - 2014. This period of study included scale-up of anti-malarial interventions of 2005 and climate change awareness, as clearly indicated in MDG goal 6 and 7. The study was based in Rwandan highlands; in Karongi, Muhanga and Rubavu districts, where malaria incidence is limited by low temperature and altitude.

1.5 Justification of study

Climate variation impact assessment refers to research and investigations designed to find out what effect future changes in climate could have on human health and the natural world.

Climate can affect infectious disease patterns because disease agents and their vectors are clearly sensitive to climatic conditions; this study aims at examining the relationship between intra-annual climate variability and malaria transmission in highland region of Rwanda. The relationships of variability in rainfall, relative humidity and temperature to malaria transmission was to be assessed based on vulnerability monitoring, seasonal climate variability data and epidemiologic surveillance.

Scientific based knowledge on climate variations in Rwanda is limited, but it is fully recognized that the country is one of the most vulnerable nations in the world in regard to climate changes. Thus, climate change preparedness for Rwanda is essential both in a local, national and international context (Rwanda Environmental Management Authority, 2010).

It was needed to conduct further analysis, however the MOPDD attributes the increase in cases to a number of factors including the increase of total number of patients seeking health care in health facilities, increased rainfall and agricultural environmental modification, significant drop in ITN coverage (43% coverage of one ITN for every two people), mosquitoes' resistance to pyrethroid insecticide, increased number of health facilities reporting into the system, and increased availability of RDTs and ACTs among other causes (1st Rwanda Malaria Forum, 2012). It also important to note that malaria has been increasing in the eastern African region, thus it will be challenging for Rwanda to control malaria while trans-border exchanges are intense.

The highlands of Rwanda were selected because in most of highlands areas people have little or no immunity against malaria parasite, so all categories of people are affected. This is different from lowland where immunity is high among most adults and malaria is mostly confined to young children and pregnant women. As consequence, low immunity in highlands communities makes malaria an epidemic disease characterised by mortality and morbidity among children and adults. Any changes to causing factors like climate variation, effect can be observed at community level.

Therefore, in lowlands all conditions for malaria transmission are fulfilled but in the highlands, where adaptation was impossible, it needs to find out if the current variation of climate is affecting malaria development as it highly depends on climate.

1.6 Significance of study

This study has a significant impact as it shows climate and malaria relationship, different preventive measures can be implemented based on climate predictions and therefore the substantial burden of disease associated to vector borne diseases like malaria in Rwanda can be reduced.

The researcher has interest in establishing the association between climate and disease prevalence in new areas. Rwanda has high density of population what resulted to environmental degradation and declining of landholding, most of time goes hand in hand with informal settlements that increase vector borne diseases breeding sites. The study is addressing the phenomenon that is taking place in highlands where malaria is tends to increase.

Recognized as early warning indicator of climate change, mountain ecosystem became an object of chapter 13 of agenda 21, the action endorsed by the Earth Summit in 1992 and the recent Rio + 20 outcome document, “The future we want” mountain issues need to be covered by SDGs, especially the goals concerning poverty, environmental sustainability, water, energy, climate change and natural disaster. As the nick name indicate “a country of thousand hills” Rwandan ecosystem is dominated by mountain, what makes this research unique since the changes that can be recorded in Rwanda should serve as indicator of climate change effect for other regions. As Rwanda was chosen as the centre for sustainable development goals, it will be necessary to consider all opportunities attached to its ecosystem in order create and improve adequate policies and frameworks particularly at the trans-boundary level and provide incentives for investments in sustainable development.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

This chapter presents a review of the impacts of climate or global change on human health. By presenting theory on malaria development and transmission, environmental factors influencing malaria development and transmission were presented with the case of Rwandan highland region.

The chapter also examines Africa's vulnerability to climate change; it reviewed studies that analysed the relationship between climate change and malaria prevalence, methodologies used in analysing, association between climate and malaria in Rwandan highlands.

2.1 Theory relating to malaria development and transmission

2.1.1 Climate influence on malaria life cycle

Malaria transmission depends on the diverse factors that influence the vectors, parasites, human hosts, and the interactions among them (see malaria cycle indicate in appendix 3 and 4. These factors may include, among others, meteorological and environmental conditions, the innate and adapted immunity of the human hosts, the resistance of the vector species to *Plasmodium* infection, public health system, housing standards, vector control, road construction, irrigation projects, population movements and war-like conditions (Lafferty, 2009). The most apparent determinants are the meteorological and environmental parameters, such as rainfall, temperature, humidity, and vegetation (Kiang, 2009). When other parameters remain more or less constant, the meteorological and environmental conditions are indeed considered as the driving factors of malaria causes (Githeko, 2009).

According to (Pascual *et al*., 2006) Historical analyses of climate patterns coupled with biological process models provide additional explanatory power. For example, observed altitudinal increases in *falciparum* malaria in the East African highlands during the past 30

years have been associated with increasing temperatures and are consistent with models of *anopheline* mosquito vector development.

2.1.2 Malaria and environment

The Greek physician Hippocrates was the first to make a connection between the proximity of stagnant bodies of water and the occurrence of fevers in the local population (McMichael & Woodruff, 2008). The Romans also associated marshes with fever and pioneered early efforts at swamp drainage. Appropriately, the role of standing bodies of water and marshes in causing fevers was described by the Italians as "aria cattiva" (spoiled air) or "malaria" (bad air) beginning in the mid-sixteenth century, and the latter term entered the English language as "malaria" some 200 years later. Malaria was used as additional platoon for attacking enemies in early human history. During the coldest years of the little ice age 1560s – 1730s reports on malaria outbreak in the countries like England and Scotland were associating malaria with weather conditions (Lindsay & Martens, 1998).

2.1.3 Climate change and human infectious diseases

Climate changes include alternations in one or more climate variables including temperature, precipitation, wind, and sunshine (Metz, 2010). These changes may impact the survival, reproduction, or distribution of disease pathogens and hosts, as well as the availability and means of their transmission environment as Figure 2 indicates. The health effects of such impacts tend to reveal shifts in the geographic and seasonal patterns of human infectious diseases (Dziedzic, 2010).

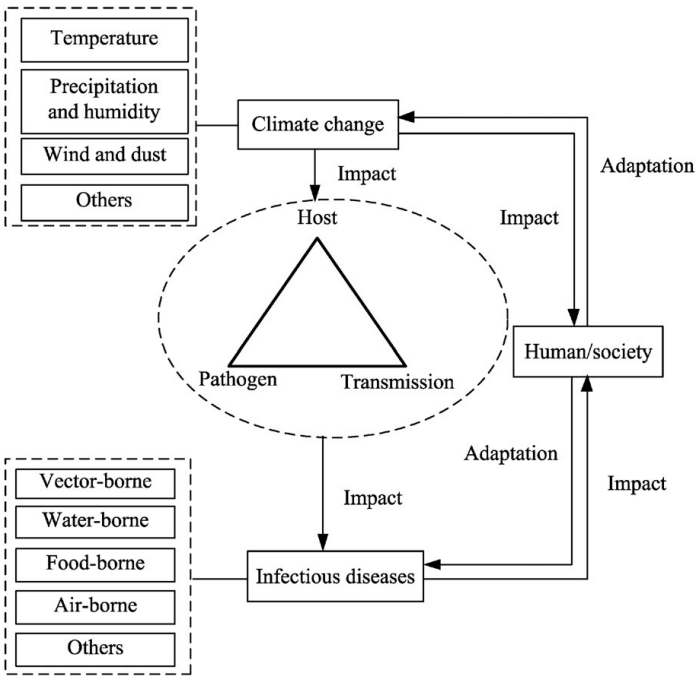


Figure 2: Climate change, human infectious diseases, and human society (Source: Oaks *et al.,* 1991).

Impact of global climate change on human infectious diseases can be examined through its impacts on the three disease components: pathogen, host, and transmission environment. Human is important and active factor during this process; he may mitigate the impact of climate change through adaptation practices.

2.1.4 Stratification of malaria zones

The concept of stratification, developed by WHO in the mid-1980s, characterized epidemiologic zones of malaria in terms of their main determinants, including climate, the location of sources of water and of mountains, vector biology, anthropology, social and economic factors (World Health Organization, 2014).

Using stratification, a country or continent could be broken down by geographic area and/or by population characteristics, and a number of epidemiologic, biologic, social, and economic factors could be identified that would govern the choice and intensity of antimalarial interventions. The scale of application of stratification varied considerably,

from the characterization of large homogeneous areas to that of very small epidemiologic units, such as a locality. With a few exceptions, however, stratification has not been widely adopted or implemented, in part because a large amount of detailed baseline information was required (Dziedzic, 2010).

Malaria transmission is seasonal and correlates with relatively predictable patterns of rainfall, although transmission may continue at lower levels during the dry season. Because of the extremely high inoculation rates, virtually all of those living in these areas become infected early in life (Aron *et al.*, 2001).

2.1.5 Highland fringe malaria

Although some malaria cases can be found at altitudes of 2,800 meters, the disease does not generally occur above 1,500 meters (Patz *et al.,* 2008). Because of fluctuations in climate and global warming, vector *anophelines* may begin to flourish at higher altitudes. The altitudes subjected to this type of malaria problem may vary greatly according to the geographic location. In particular settled populations living at higher altitude, normally free of malaria may have little or no acquired immunity to malaria and may suffer from devastating epidemics (Brian, 2009). Such situation recently occurred in the highland plateaux of Madagascar, where malaria had previously been eradicated or nearly so (Githeko *et al.*, 2000). Similar, less devastating epidemics have been seen in Papua New Guinea, in Ethiopia, and on the mountain slopes of Kenya. Even without an expansion in the range of vector *anophelines*, however, economic conditions many force nonimmune highland populations to search for work in lower highland fringe areas, where they may be exposed to intense malaria transmission (Tulu, 1996).

2.1.6 Climatic factors and malaria transmission

Climatic factors greatly influence the pattern and level of malaria transmission in Rwandan highlands region, in Africa and the world. The most important climatic factors that directly affect malaria transmission are temperature, rainfall and humidity (Chapin III *et al*., 2012). The ranges of minimum and maximum temperature greatly affect the development of the malaria parasite and its mosquito vector, which determines malaria transmission (Martens,

1999). The present geographical distribution of malaria is explained by a combination of environmental factors (especially climate) and social factors (such as disease control measures). Efforts last century to control malaria succeeded in eradicating the disease from temperate zones and much of the subtropics, but the world is now facing a resurgence of malaria, because of climate variation (Hales & Woodward, 2003).

2.1.7 Temperature and parasite development

Temperature affects the life cycle of the malaria parasite. The time required for the parasite to complete its development in the gut of the mosquito is about 10 days, but it can be shorter or longer than that depending on the temperature. As the temperature decreases, the number of days necessary to complete the development increases for a given *Plasmodium* species. *P. vivax* and *P. falciparum* have the shortest development cycles and are therefore more common than *P. ovale* and *P. malariae* (Feenstra *et al,*. 1998).

The time needed for the parasite to complete its development in the mosquito, decreases to less than 10 days as temperature increases from 21°C to 27°C, with 27°C being the optimum. The maximum temperature for parasite development is 40°C. Below 18°C, the life cycle of *P. falciparum* in the mosquito body is limited. The minimum temperatures are between 14–19°C, with *P. vivax* surviving at lower temperatures than *P. falciparum*. Malaria transmission in areas colder than 18°C can sometimes occur because *Anopheles* often live in houses, which tend to be warmer than the outside temperature (Loevinsohn, 1994), this may happen in highland area where transmission is limited by low temperature.

2.1.8 Temperature and mosquito development

Development of the mosquito larva also depends on temperature; it develops more quickly at higher temperatures. Higher temperatures also increase the number of blood meals taken and the number of eggs laid by the mosquitoes, which increases the number of mosquitoes in a given area. The minimum temperature for mosquito development is between 8–10°C;

the optimum temperature is 25–27°C, and the maximum temperature for is 40°C (Wilson, 2001).

2.1.9 Influence of altitude and temperature on malaria transmission

According to (Bizimana, 2015), altitude (elevation above sea level) is one of the most important factors that determine the pattern of malaria transmission in Rwanda. Altitude in Rwandan highlands varies from 1800 metres above the sea level to more than 3,000 metres above the sea level. Altitude influences the distribution and transmission of malaria indirectly, through its effect on temperature. As altitude increases, temperature decreases, so highlands are colder and lowlands are warmer, (Chemonics International Inc, 2003).

In the Rwandan highlands, the issue is to determine malaria transmission occurrence in relation to temperature, rainfall and relative humidity. The increased temperature allows the development of parasites to occur in the mosquitoes, and the mosquito population also increases as the temperature rises. Beyond 2,400 metres, the temperature does not go high enough to support malaria transmission and these areas were free of malaria (CHAI; E2Pi, 2011). Long time ago Rwandan highlands was free of malaria, and most of Rwandan highlands above 1,500 metres had little or no locally transmitted malaria (World Health Organization, 2014).

2.1.10 Rainfall and malaria transmission

Anopheline mosquitoes breed in water. So the right amount of rainfall is often important for them to breed. Different *anopheline* mosquitoes prefer different types of water bodies in which to breed (Bettina, 2005). In Rwanda, water collections that support vector breeding appear mainly after the rains, and therefore malaria transmission is important after the rainy season (Bizimana *et al.*, 2015).

Note that the anopheline mosquitoes that transmit malaria do not breed in foul-smelling polluted water. Too much rainfall can flush away breeding habitats temporarily, but mosquitoes start breeding as soon as the rain stops. In most cases, flushing has a bigger impact on vector breeding habitats in the highlands and hilly areas than in the lowland

plains (Goosse *et al*., 2010). Not all water collections are suitable for the mosquito life cycle. In Rwanda, rain water collections are the most important breeding ground, as the *anopheline* mosquitoes prefer to breed in fresh water collections created after the rainy season (Gahutu *et al*., 2011).

There are also places where less rainfall and drought can favour mosquito breeding and malaria transmission. Such places are usually covered by vegetation throughout the year streams and rivers often flow rapidly (Pierre-Louis *et al.*, 2010). When the rains fail or are delayed, the flow of streams is interrupted and pooling occurs along the stream. Pooling creates a favourable environment for mosquito breeding. Malaria vectors mainly breed in stagnant water collections, rarely in slightly moving waters and never in rapidly flowing rivers and streams (Bettina, 2005). In drier areas, rainfall can also affect malaria transmission indirectly through its effect on humidity. Vegetation cover increases after rainfall, which in turn increases the relative humidity of the environment (IPCC, 2002).

2.1.11 Relative humidity and malaria transmission

Expressed as a percentage; (0% humidity would mean the air is completely free of moisture and 100% humidity would mean the air is completely saturated with moisture). Relative humidity affects malaria transmission through its effect on the activity and survival of mosquitoes. Recall that mosquitoes need to live at least 8–10 days to be able to transmit malaria; this is the length of time required for the parasite to develop inside the mosquito host. If the mosquito dies before the parasite has developed, then transmission of the parasite cannot occur (Kazembe, 2007).

Mosquitoes survive better under conditions of high humidity. They also become more active when humidity rises. This is why they are more active and prefer feeding during the night – the relative humidity of the environment is higher at night. If the average monthly relative humidity is below 60%, it is believed that the life of the mosquito is so short that very little or no malaria transmission is possible (Wilson, 2001).

2.1.12 Non-climatic factors of malaria transmission

Factors that affect malaria transmission, but which are not related to the climate, are called non-climatic factors. The type of vector, the type of parasite, environmental development and urbanisation, population movement and migration, the level of immunity to malaria in the human hosts, insecticide resistance in mosquitoes, and drug resistance in parasites, all have a role in affecting the severity and incidence of malaria (HImeidan & Kweka, 2012).

2.1.12.1 Malaria vectors

Not all mosquitoes transmit malaria, only *Anopheles* mosquitoes can carry the malaria parasite. In Rwanda there are many species of *Anopheles* mosquitoes, but only four of them are known to transmit malaria parasites, and just one of them, *Anopheles arabiensis*, is responsible for more than 95% of malaria transmissions (Grasso *et al.*, 2010).

Different species of *Anopheles* mosquitoes differ in their capacity to transmit malaria. This depends on the biology and behavior of the mosquitoes. Mosquitoes in the *Anopheles gambiae* group (which includes *A. arabiensis)*, are the most efficient malaria vectors in the world. These mosquitoes are found only in Africa. In fact, the higher incidence of malaria in Africa compared to other parts of the world is mainly due the efficiency of these mosquitoes in transmitting the parasites (Schlagenhauf-Lawlor, 2001).

Mosquitoes need a blood meal to develop and reproduce. They can take their blood meal either from humans or animals. Mosquitoes that mainly feed on humans are more efficient to carry malaria than those that feed on animals (HImeidan & Kweka, 2012). One reason why mosquitoes in the *A. gambiae* group are very good vectors of malaria is that they prefer to bite humans more than animals. Mosquitoes that feed on humans and animals equally are much weaker vectors of malaria. Others feed exclusively on animals and are not malaria vectors. Therefore, the type of *Anopheles* mosquitoes and their feeding behavior influence the intensity of transmission in an area (Chua, 2011).

Mosquitoes adapted to breeding close to human settlements, and able to breed in a wide range of environments, are also better vectors of malaria than mosquitoes that breed away from human habitation. Some mosquitoes breed in small pools that are partially or completely exposed to the sun, while others prefer to breed in shaded stagnant pools. *A. gambiae* mosquitoes breed in a wide range of habitats, including small water collections such as hoof-prints, water-filled holes in rocks and trees, as well as dams, river beds and lake shores. Because *A. gambiae* vectors can breed in so many different habitats, they are responsible for much of the malaria transmission in Africa (Blanford *et al.,* 2013).

The main vector of malaria in Rwanda, *A. arabiensis*, can be found in a variety of water collections, mainly closer to human habitations. However, stagnant water collections in borrow pits, ponds, micro-dams, pools in small rivers, and streams created immediately after the rainy season, are the most important breeding habitats for this vector (DFID, 2009).

2.1.12.2 Water development projects and malaria transmission

Agricultural development, particularly with the use of irrigation, creates breeding sites for malaria mosquitoes, leading to increased malaria transmission. For instance, the use of irrigation to flood agricultural land during rice cultivation has long been associated with an increase in the number of vectors and a corresponding increase in the burden of malaria (Malakooti *et al.*,1997). Irrigated farming and rice agriculture is becoming more common in the lowlands of Rwanda with less applicable in highlands (Muhanga, 2013).

2.1.12.3 Malaria transmission, population movement and migration

Population movements have significant implications for malaria transmission. The majority of the population movements in Rwanda involve people moving from the highlands to the malaria-endemic lowlands as seasonal labourers (in capital city of Kigali). These people are often employed as daily labourers in the crop fields during the planting and harvesting seasons, when malaria transmission is at its peak (Wandiga *et al*., 2006).

Migration for the purpose of permanent settlement in a new area is also common in Rwanda and is a major factor associated with malaria transmission. Migration is often from

densely populated malaria-endemic lowlands to highlands, where the population density is low and the soil is more fertile. Major environmental transformations like deforestation, and new construction etc, take place during resettlement, enhancing the proliferation of mosquito breeding sites, and resulting in major malaria outbreaks (Brian, 2009).

2.1.12.4 Human host factors

Differences in human hosts also affect the pattern of malaria transmission and the severity of the disease. When it comes to malaria, people are either immune, or non-immune. Immune people often have a better chance of tolerating the effects of malaria and surviving the disease than non-immune people. In highly endemic areas, children under five years of age and pregnant women are the most at risk, because they have weak immunity to malaria infection. Immunity to malaria develops slowly after several infections and children need at least five years to develop their immunity. Pregnant women have less immunity to malaria due to their pregnancy (Karema *et al.*, 2012).

Certain population groups can be infected by some types of malaria parasites, but not by others. For example most Africans south of the Sahara can get infected by *falciparum* malaria, but not by *vivax* malaria. This is another reason why most of the disease and deaths due to malaria occur in Africa, because *falciparum* malaria is the deadliest form of malaria and is highly prevalent in the continent (Oaks *et al*, 1991); (Becker *et al*., 2010).

2.1.12.5 Drug resistance in malaria parasites

Drugs kill malaria parasite inside the human body. However, after repeated use of an anti-malaria medicine, the parasite can develop resistance to that particular drug or to similar medicines. As a result, the parasites inside the human body can no longer be killed and patients cannot be cured unless new drugs are developed for treatments (CHAI; E2Pi, 2011). If malaria parasites show resistance to drugs, these parasites are not cleared by treatment from infected individuals, they are easily picked up by vector mosquitoes, and transmitted to new susceptible individuals who then develop drug-resistant malaria.

Moreover, more people who are not getting cured by drug treatment means that more will die of malaria (Renate, 2009).

2.1.12.6 Interruption of control and prevention measures

Malaria is a curable disease if the parasites remain susceptible to available treatments, and it can be prevented by using several methods. However, long-term and sustained implementation of prevention and control measures is necessary to significantly reduce or eliminate the problem from a country or a specific geographic area. As a result of long-term successful interventions, a local population can lose their immunity to malaria in an area where it has been reduced to a low level for some time. Remember that repeated infections are necessary to develop immunity to malaria. Immunity gets lower or is lost if a person moves out of a malaria endemic area, or is protected from infection for several years. Therefore, if control and preventive measures are stopped before the disease is eliminated, malaria can surge back and affect more people, and affect them more severely than before (Kevin, 2009). This case was reported in Rwanda that after experiencing a large decline in malaria cases from 2005 to 2011, Rwanda is currently experiencing an increase in reported malaria cases, from a low of 200,000 malaria cases in 2011, to over 2.6 million cases reported in 2015 (President's Malaria Initiative, 2017).

2.1.12.7 Human modification to the environment

Can create larval development sites and "man-made" malaria. For example, massive logging in Gishwati forest has resulted in a proliferation in certain areas of sunlit pools of water (Aron *et al.*, 2001), an ideal habitat for *An. gambiae*. Road building and other types of infrastructure projects, as well as agriculture and irrigation, are among a number of human activities that can spread malaria and other vector-borne diseases. In some regions, human activities can have the opposite effect. For example, deforestation in Thailand has led to the disappearance of malaria in some areas (Oaks *et al.* 1991).

2.1.13 Methods for Climate Change Impact Assessment

Theory of modelling: Scientists use mathematical formulae, combined with the modelling ability of computers and available data sources, to create an understanding of how climate and weather effects work in different parts of the atmosphere. The purpose of the models is not just to understand atmospheric interactions, however, but to predict how they will work in the future. Predicting the weather will be of great benefit in helping people prepare for adverse phenomena such as the longer-term effects of drought or floods (Goosse, *et al*., 2010).

2.1.13.1 Model in epidemiology

Specific attention is drawn on the methodological aspects of each study, which is classified according to the specific problem in question, as well as the type of statistical model considered, as detailed by Grasso, *et al*. (2010).

As far as the specific problem addressed by each study is concerned, it refers to:
Primary studies, which analyze the direct effects of rising temperatures on the burden of diseases;
Secondary studies, which consider socio-economic effects of temperatures growth including Integrated Assessment Models (IAMs), General Equilibrium Models (GEMs) and Global Trade Analysis Project Models (GTAP);
Comparative Risk Assessments (CRA), which integrate climate models for projecting future climate changes and "primary studies" for estimating the effects on health.
In terms of the type of statistical model which each of the surveyed study is based on, the following broad classes emerge:

Stationary and non-stationary time series models, such as ARMAX (Auto Regressive Moving Average with exogenous variables) models, ECM (Error Correction Models), possibly with seasonal components;

Non-parametric forecasting models, such as single and double exponential smoothing, Holt-Winters methods (additive, no seasonal, multiplicative);

Panel data and spatial models

Many economic, socio-demographic, environmental and climatic variables are observed through time (t=1,...,T) and across "individuals" (i=1,...,N), where the notion of "individual" used in the present context is broad enough to embrace real individuals, households, countries, geographical areas, firms, economic sectors, etc. A variable observed through time and across individuals, *Yit*, is said to have a panel data structure (Kleinschmidt, 2001).

Tools for monitoring climate change and human health

Predicting modelling approaches are classified into several categories including (Kiang, 2009):

- Statistical based models - empirical models incorporating a range of meteorological variables have been developed to describe the climatic constraints (the bio climate envelope) for various vector-borne diseases (CLIMEX; DIMEX; GCMs);
- Process-based (mathematical) models - process-based approach is important in climate change studies as some anticipated climate conditions have never occurred before and cannot be empirically based (i.e. MIASMA);
- Landscape-based models - climate influences the habitat of pathogens and diseases vectors. There is a potential in combining climate-based models with the various environmental factors that can be measured by ground-based or remote sensing, including satellite data;

Predictive models for early warning systems (EWS)

Relevant measurements fall into the following broad classes (Paaijmans *et al.,* 2009):

- Meteorology: various meteorological factor influence heath processes. Temperature, relative humidity, rainfall and wind speed are the most important parameters;
- Health markers: one way to address the complex causality of most health outcomes is to select indicators that are highly sensitive to climate changes, but relatively insensitive to other influences. The data requirements for attributing and measuring impacts may be quite different, depending on health issue and region;

- Other explanatory factors: monitoring will need to measure not just climate and health. The principal categories of modifying factors that must be considered are the following: age structure of population at risk; underlying rate of disease; level of socio economic development and existing infrastructures (water and sanitation); environmental conditions, quality of health care; specific disease control measures.

The Linear Regression Model is one of the most frequently used statistical tools. Its purpose is to relate the values of a single variable Y to one or more other variables X_1, X_2,.. X_p, in an attempt to account for the variation in Y in terms of variation in the other variables. With only one other variable this is often referred to as simple linear regression. The usual situation is that the data available consist of n observations y_1, y_2, ..., y_n for the dependent variable Y, with corresponding values for the X variables (Bryan & Manly, 2000).

Time series models have been used extensively for predicting the evolution pattern of diseases, and more specifically to assess the relationship between environmental exposure and mortality or morbidity over long time periods. These predictions are a necessary step for quantifying the potential impact of climate on health and the related costs. In the field of climate based Early Warning Systems (EWS), which are used to predict the occurrence of epidemics of infectious diseases, Chaves and Pascual (2007) review and compare linear and non-linear models for forecasting seasonal time series of diseases. Using American coetaneous leishmaniasis, as an example, the models are evaluated based on the predictive R^2 for forecasting the data "out-of-fit". Seasonal autoregressive models that incorporate climatic covariates are found to provide the best forecasting performance.

2.2 Review of studies related to climate variability and malaria prevalence

2.2.1 Speculation on malaria ecology

The present restriction of malaria to the tropics suggests a strong effect of climate on this disease. While climate does affect malaria transmission, other factors probably enforce the current distribution. Most notable is a strong increase in per-capita gross national product with latitude. This results in both greater surveillance and increased funds for control and

treatment in temperate areas. Today, malaria endemic countries have GDPs one fifth that of low malaria prevalence countries, researchers are suggesting that economic forces particularly environmental destruction, have pushed malaria out of temperate zones. Malaria is harder to control under the climatic conditions where it is holoendemic (transmitted year-round) and malaria might depress economic development in a positive feedback loop. In other words, tropical climate might increase infectious diseases such as malaria, which then depress economic growth required for disease control (Lafferty, 2009).

The evidence of above statement is seen where malaria is a major vector-borne disease in sub-Saharan Africa and more generally, in the tropical zone (that include Rwanda) spreading from America, throughout tropical Africa up to the Asian continent. Its increase throughout the world has been attributed to the environmental changes, leading to an expansion of the geographical limits of the disease. The latter is the leading cause of morbidity and mortality, and is therefore a big threat to socioeconomic development to the poorest countries situated in that tropical zone (Blanford et al., 2013). However, most of all literatures are pointing out the importance of climate variables and ecological conditions on malaria/diseases development and transmission.

Ayanleh (2010) in the research on **"**Analysis and Prediction of the Possible Impacts of Climate Change on the Future Distribution of the Vector-borne Disease, Malaria in Panama**"** stated that ecosystem was assumed to be constant in order to facilitate the analysis and comprehension of the roles of the three other factors. From the information that obtained from the prediction based on GIS work, the first relationship to be analysed was the link between ecosystem and the population density and the link between Topography and abiotic factors: temperature/rainfall.

2.2.2 Climate and malaria

Scientific evidence suggests that malaria varies seasonally in highly endemic areas. Malaria is probably the vector-borne disease most sensitive to long-term climate change. Malaria thus provides several illustrative examples (based on historical studies) of the link between

infectious disease and climate change (Beniston, 2002), (Blanford et al., 2013), (Wanjala et al., 2011), (Shakoor et al., 2006).

Githeko et al. (2000) compared monthly climate and malaria data in highland Kakamega and found a close association between malaria transmission and monthly maximum temperature anomalies over three years of 1997–2000.
Various time series studies explore the relationship between average temperatures, mid-night temperatures, temperatures in conjunction with rainfall rates, as well as November and December temperatures on malaria. In particular, Freeman & Bradley (1996) found a significant impact of climate on malaria in Zimbabwe, the Debre Zeit sector of Ethiopia, Rwanda, and the Northwest Frontier Province in Pakistan, respectively. December temperatures coupled with humidity are used by Bouma & van der Kaay (1996) to predict incidence rates of malaria in Pakistan. Other studies consider temperature and deforestation to be associated with malaria transmission in Tanzania and Kenya (Matola *et al*., 1987), (Malakooti *et al*., 1997). According to the latter study forest clearing has been the cause for increases in malaria transmission. Patz *et al*. (2008), found out that soil moisture correlates with the human-biting rate of mosquito vectors with a two-week delay. Also soil moisture and entomological inoculation rate are related, with infective parasites taking a six-week time to develop.

It has been hypothesized that increasing temperatures could be part of the reason why malaria can now survive at higher altitudes. Many other confounding factors, however, could be causing the increase in malaria in these areas (Patz & Lindsay, 1999). The dynamics of the geographical spread of malaria are analysed by Pascual *et al*. (2006). The authors focus on the most important malaria species for humans, *Plasmodium falciparum* and *Plasmodium vivax*, whose range is limited at high altitudes by low temperatures. They investigate whether global warming could drive the geographical spread of the disease and produce an increase in incidence at higher-altitude sites. They use data for four high-altitude sites in East Africa from 1950 to 2006. A nonparametric analysis that decomposes the variability in the data into different components is performed and reveals that the dominant signal in three of the sites and the subdominant signal in the fourth one

correspond to a warming trend. To assess the biological significance of this trend, the authors drive a dynamical model for the population dynamics of the mosquito vector with the temperature time series and the corresponding detrended versions. This approach suggests that the observed temperature changes would be significantly amplified by the mosquito population dynamics with a difference in the biological response at least one order of magnitude larger than that in the environmental variable. By using parametric models they also find the existence of significant (linear) trends.

2.2.3 Diurnal Temperature Range (DTR) and malaria transmission

The standard relationships describing the effects of temperature on malaria parasite and mosquito life history derive largely from laboratory studies. These studies conducted under constant temperature conditions tend to use measures such as average monthly temperature to characterize environmental conditions. However, natural environments are highly dynamic; diurnal temperature ranges (DTRs, the difference between the minimum and maximum temperature) of 5 to >20 °C are common across many malaria transmission settings in Africa, including highland and lowland environments (Paaijmans *et al*., 2010).

2.2.4 Rainfall and malaria

Patz *et al*., (2008) studied the effect of soil moisture to determine the effects of weather on malaria transmission. Compared to raw weather data, hydrological modelling has several potential advantages for determining mosquito breeding sites. High soil moisture conditions and vector breeding habitats can remain long after rainfall events, depending on factors such as watershed, run-off and evapotranspiration. For *An. gambiae*, the soil moisture model predicted up to 45% and 56% of the variability of human biting rate and entomological inoculation rate, respectively.

2.2.5 Malaria risk in the highlands

In the research conducted by Githeko (2009) in the western region of Kenya on entomological perspective of malaria by comparing malaria risk in highland and lowland, it was found out that western Kenya is of particular interest. Since on a relatively small

spatial scale there is considerable variation in altitude, climatological conditions and land-use patterns. As a consequence, the epidemiological situation of malaria varies as well. Result showed that malaria was transmitted throughout a two-year study period in a highland area of western Kenya (at 1600 m altitude and above). Malaria prevalence was relatively low, with a two year average of 10% among school children in the age of 5 - 10 years (minimum 0% and maximum 17% prevalence). Larval habitats of *An. gambiae s.l.* were present in the highland area, although their number was rather limited compared to a lowland area 40 km to the northwest (at 1200 m altitude).

Experimental studies showed that larvae of *An. gambiae s.s.* and *An. arabiensis* did not survive the cool environmental temperatures in the highland area, whereas adults of both species (placed in cages) survived inside local houses in the same area.

The combined experimental and field observations suggested that the contribution of a locally breeding vector population to malaria transmission in the highland area was negligible. More likely, the few infections among school children were caused by infected mosquitoes that emigrated from areas where environmental conditions are more favourable.

Martens (1999) has investigated the possible changes in the distribution of malaria. Increases in temperature and rainfall would most probably allow malaria vectors to survive in areas immediately surrounding their current distribution limits. How far these areas will extend both in terms of altitude and latitude depends upon the extent of warming. The IPCC (2002) has published maps of increases in the incidence rate of malaria in Africa, for a modest warming scenario of +1°C. It is seen that the regions with the sharpest rise in the rate of infection are those which lie above 1,000 m. In these highland regions, even a modest rise in temperature may lead to a spread of the disease into hitherto disease-free regions. It is seen here that there is a quasi-exponential increase in the incidence of malaria, which is, at least in part, consecutive to changing climatic conditions for the period 1975-1990 (Beniston, 2002).

In the research conducted by Pascual *et al*., (2006) on “Malaria resurgence in the East African highlands: Temperature trends revisited”, it was found out that the incidence of

malaria in the East African highlands has increased since the end of the 1970s. The study used the same data obtained from the Climate Research Unit (CRU, Norwich, U.K.) global grid of 0.5° resolution (data set CRU TS 2.1) using the temperature data, now updated to the present from 1950 to 2002 for four high-altitude sites in East Africa; Kericho in western Kenya (latitude, 0.30 S; longitude, 35.37 E), Kabale in southwestern Uganda (1.25 S, 29.71 E), Gikongoro in southern Rwanda (2.45 S, 29.85 E), and Muhanga in northern Burundi (3.02 S, 29.83 E) where malaria has become a serious public health problem. With both nonparametric and parametric statistical analyses, the research found evidence for a significant warming trend at all sites.

Shanks *et al*., (2002) investigated whether the re-emergence of malaria in Western Kenya could be attributed to changes in meteorological conditions. The existence of trends in a continuous 30-year monthly malaria incidence dataset (1966–1995) was tested for Malaria, it was found out that malaria incidence increased significantly during the period of study (1966–1995). In contrast, climate did not indicate a significant change that could precipitate transmission of malaria. Therefore, the authors conclude that climate changes have not caused the highland malaria resurgence in Western Kenya. They suggest that two other factors may have influenced the increase in malaria hospitalizations: an increase in malaria severity indicated by an increased in fatality rate (from 1.3% in the 1960s to 6% in the 1990s) that is most likely linked to chloroquine resistance. Secondly, travel to and from the Lake Victoria region by a minority of the tea estate workers also exerts an upward influence on malaria transmission in Kericho, Kenya, since such travel increases the numbers of workers asymptomatically carrying gametocytes, which mediate disease transmission.

Lindsay & Martens (1998) consider the progressive rise in the incidence of malaria over the last decades in African highlands. The phenomenon is largely a consequence of agro forestry development, and is exacerbated by scarce health resources. Moreover, in these areas, where the pattern of malaria is unstable, the epidemic may be precipitated by relative subtle climate changes and therefore requires special monitoring. The authors used mathematical models to identify epidemic-prone regions in highlands of Africa, and to

quantify the difference expected to occur as a consequence of projected global climate change. To make estimates about the areas that are vulnerable to epidemic outbreaks of malaria, they use data and models from Geographic Information Systems (GIS) (computerized mapping systems) and Remotely Sensed (RS) imagery data from earth-orbiting satellites. Correlations among variables were found. However, the authors observe that since correlation doesn't imply causality these results are not conclusive and require further investigation. To model the dynamics in highlands malaria in relation to climate change they use an integrated system, scenario-based approach (Martens, 1999; Stern *et al.,* 2011). Evidence is found that the direct influence of climate may contribute to malaria risk. However, this effect cannot be claimed as the most important determinant of malaria transmission. The effects of temperature on mosquito development, feeding frequency, longevity and incubation period are estimated. The model is linked to baseline climatology data from 1931 to 1960 and uses integrated techniques to generate climate scenarios. Their findings suggest that it is not possible to prove that any single factor has caused the outbreaks in African highland. Projected climate changes are likely to modify the epidemics in the regions: 260–320 million more people are projected to be affected by malaria by 2080 as a consequence of new transmission zones. All of these researches were basing analysis on establishing the relationship of malaria and climate change in general while according to Hales & Woodward (2003), transmission rates vary within regions and within countries. It needs the research that focuses on Highlands region of Rwanda so that it can be differentiated from other African highland.

2.2.6 Climate and ecosystem-based malaria epidemic prediction models

According to the model developed by (Githeko, 2010), he classified the highland into three ecosystems; these being the flat bottomed valleys (U-shaped) the narrow bottomed valleys, (V) shaped and the plateau. Using the highland of western of Kenya it was concluded that "U" shaped ecosystems require mean rainfall of 150mm/month for mosquito populations to increase.

"V" shaped valleys require mean rainfall of 250-300mm/month for mosquito population to increase. The U shaped valleys have more than twice the size of breeding habitats

compared to the V shaped valley. The U shaped valley has 3 times more adult *Anopheles gambiae* females that the V shaped valley. 2.2-fold more people in the "U" shaped valley have an immune response to malaria compared to the "V" shaped valley ecosystem. This model was applied by Wanjala *et al*. (2011) and found that the V-shaped ecosystems have very low malaria prevalence and few individuals with an immune response to two major malaria antigens and they can be considered as epidemic hotspots. These populations are at higher risk of severe forms of malaria during hyper-transmission seasons. The plateau ecosystem has a similar infection and immune response to the V-shaped ecosystems. The U-shaped ecosystems are transmission hotspots. In this research time series analysis was not used for spatial malaria prediction.

2.2.7 Malaria and climate change in Rwanda

In the research conducted in the Eastern region of Rwanda on; Analysis of Anthropogenic and Regional Climate Change Impacts on Ecological and Malaria distribution in Eastern Rwanda for the period 1980-2009, (Habiyaremye (2011) reported that malaria incidence is linked to climate variability like temperature, Rainfall and relative humidity. Relationship with rainfall (r=0.672) but both humidity and temperature correlate strongly with malaria cases with r =-0.846 and r=0.988 respectively in season A.

While in season B malaria had moderate correlation with rainfall, it was in weak relationship with humidity but correlates strongly with temperature. The correlations coefficients were 0.471, 0.123 and 0.896 for rainfall, humidity and temperature respectively.

Lastly, season C rainfall moderately correlated again with malaria (r=-0.430) while both humidity and temperature were in strong relationship with malaria incidences (r=0.946 for humidity and r=0.896 for temperature).

Bizimana (2015) highlighted Climate Variability and Malaria in Rwanda: Spatial Assessment of Social Vulnerability at Different Scale Levels. It was indicated that: Malaria outbreaks in Rwanda correspond to the periods of increasing temperature mainly associated with El Niño. Generally the number of malaria cases was higher before interventions

period. In Burera highlands, a moderate association between climate variability and malaria incidence was evidenced.

The Study covered the whole country and identified qualitative social vulnerability to malaria. But quantitative analysis was not performed, despite a well done spatial analysis. It would be better to make such study relational, by integrating prediction of malaria and climate parameters over time (10 or 20 years), as well as spatial modelling so that decision makers could use the findings from this study for proper malaria control.

Several models that included Rwanda covered large part; region or continent and did not take into account small-scale anomalies that might affect distribution of malaria, such as highlands and relative anthropogenic activities. To cover this large gap made in researches, localised monthly temperature rainfall and relative humidity were used to provide climate data and analysis for malaria incidence modelling and prediction.

Most of studies on malaria prevalence in Rwanda, established direct association of climate variables with malaria without considering the life cycle and incubation period of the parasite, therefore the model established may have had errors, what was expected to be corrected in this study using e-views.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

This Chapter presents the study area, data sources and describes the methodology applied in the study. This study uses spatio-temporal, correlation, and econometric approaches (unit root tests and SARMA). The spatial method examined the distribution of malaria at the health centers level within the District, while Pearson Correlation determined the direction and strength of the linear relationship between malaria and the meteorological variables. The econometric approach was applied to (1) validate and examine the intrinsic characteristics (stationarity) of malaria cases, rainfall, and temperature; (2) test seasonal variation; 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 seasonal variation of malaria and meteorological variables using SARMA.

3.1 Study area

3.1.1 Description of Rwanda

Rwanda is a small (26,338 km^2), land-locked country in the Great Lakes region of Eastern Africa, bordered by Uganda, Burundi, the Democratic Republic of the Congo, and Tanzania. It has a population of approximately 12 million people (projection from 2012 census results), making it the most densely populated country in continental Africa. Administratively, the country is made up of 30 districts, which are divided into sectors, cells (*cellules*), and 14,953 *umudugudus* (villages of 50–100 households).

Rwanda has a complex existing climate, with wide variations across the country and with very strong seasonality (DFID, 2009). It is primarily a mountainous country, with average altitude of 900 m in south-west, 1500 to 2000 m in the south and the centre of the country, 1800 to 3000 m in the highlands of the north and the west and 3000 to 4500 m in the regions of Congo-Nile Crest and the chain of volcanoes (President's Malaria Initiative,

2014). The equatorial climate is modified by this widely varying altitude across the country. It leads to a more temperate climate than much of the rest of East Africa. Average annual temperature in Rwanda ranges between 16ºC and 20ºC though they are much lower than this in the higher mountains (MINIRENA, 2013).

In 2014 the entire population was at risk for malaria as indicated on Figure 3; the entire country was divided into malaria slide positive rate. Highlands region on map is characterised by slide positive below 5%, and it is located in Northern and Western Provinces of Rwanda.

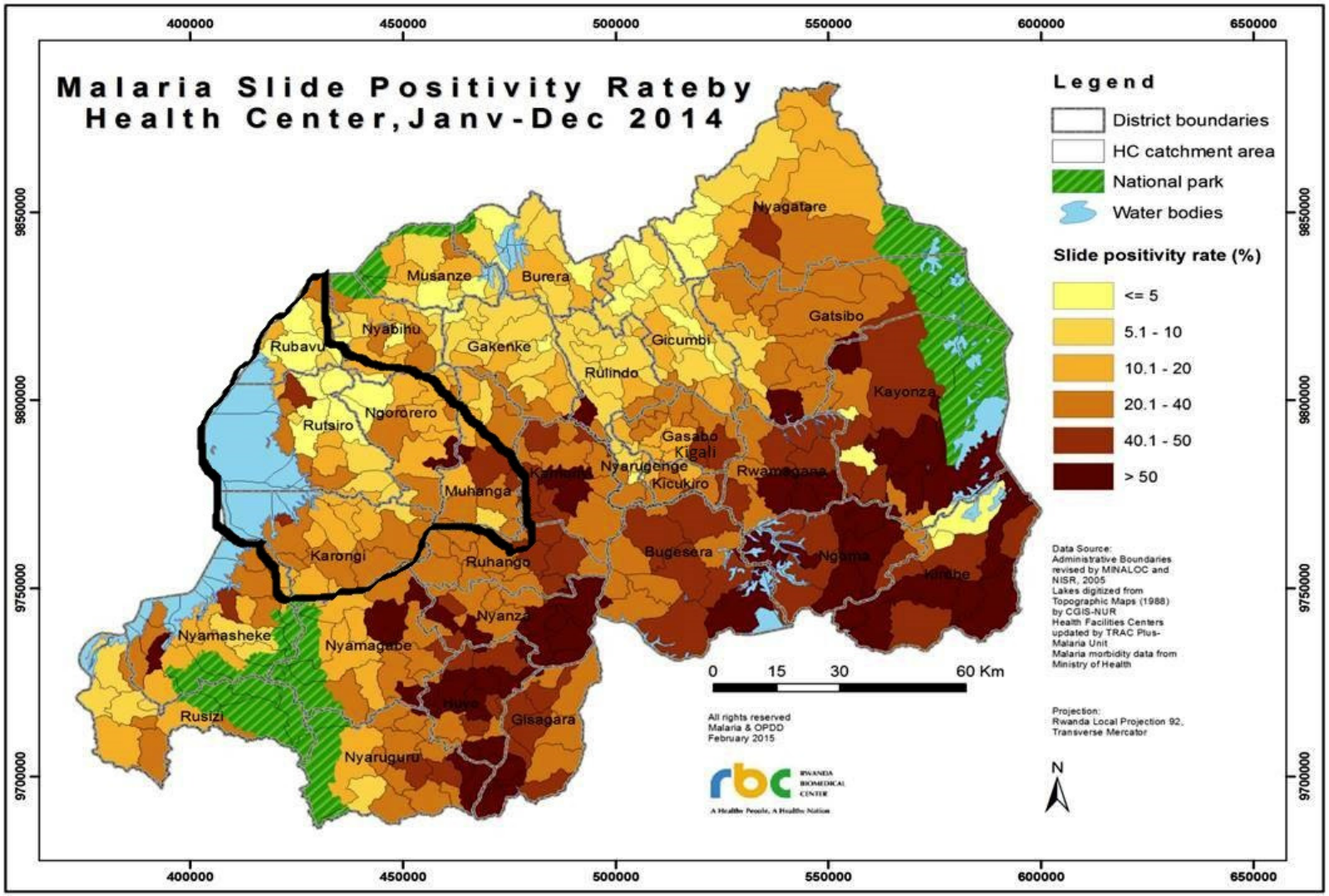


Figure 3: Topography of malaria risk according to the Districts of Rwanda

(Source: President's Malaria Initiative, 2014)

As Figure 3 indicates, the colours differentiate the areas with high malaria prevalence and areas with low malaria prevalence. Clear yellow indicates low malaria prevalence and it is located in highlands, while grey colour indicates high prevalence it is based in the lowlands of Eastern and Southern part of the country. The black line indicates the limitation of selected study area.

3.1.2 Highland region of study area

Rwandan highland lies in West, North and Southern part which is one of the four categories of Rwandan relief. The study area covers 3 Districts; Karongi and Rubavu in Western province in the range of Congo-Nile divide and Muhanga district in Southern province. The study area lies in 1.505^{o} and 2.317^{o}S and 29.244^{o} and 29.813^{o}E at an altitude ranging from 1,500 to 3000 m above the sea level. Note that the districts comprise lower land relief for instance foothills, but the altitude is dominated by highland parts with altitude of 1500 m above the sea level (Figure 4).

Temperature is 16 – 21^{o}C the lowest temperature is 6^{o}C. The rainfall patterns are characterized by four seasons, a short rainy-season from September to November and a longer rain season between March to May. Between these seasons are two dry periods, a short dry period between December to February and a long dry period from June to August. Rainfall is around 1500 mm per annum in the north and northwest volcanic highland areas.

Rubavu District: It is composed by 12 administrative sectors as presented on Figure 3; Rubavu District is located in the Western Province at 152 km from Kigali. It is bordered on the east by Nyabihu District, West and North by DR Congo and South by Rutsiro District. Rubavu District has an equatorial climate with temperatures ranging between 15°C – 20° C, but at night-time temperatures can drop to 6°C especially at the vertices, the average altitude is between 1300 to 3000 m above the sea level, with average annual rainfall of 1200 to 1500 mm. The coordinates of the district are: 1.505^{o} and 1.767^{o}S and, 29.244^{o} and 29.437^{o} E (Rubavu, 2013).

Muhanga District: It is one of the eight districts comprising the Southern Province. The District covers an area of 647.7 km^{2} and, it is neighbouring the Districts of Gakenke in the

North, Kamonyi in the East, Ruhango in the South and Ngororero in the West. The coordinates of the district are: 1.73^{o} and 2.145^{o} S and, 29.614^{o} and 29.819^{o}E.

One part of Muhanga District is located in the "central plateau" of the country with topography of hills type. With high and low peaks, this part constitutes one of the best elements of the central "plateau" of the country. The other part of the District is on the high mountains of the Nil-Congo, in general the altitude has average of 1500 – 2300 m above the sea level. The District is located in an area well-watered, between 1100 mm and 1200 mm of rainfall per year, with temperature of 15 to 22^{o}C. This region enjoys a climate of four seasons of which two rainy seasons and two dry seasons: a short rainy season, which extends from October to December, a short dry season that runs from January to February, and a long rainy season from March to June and a long dry season from June to August or early September. (Muhanga, 2013).

Karongi District is one of the seven Districts in the Western Province. It is bordered by Rutsiro to the north, Ngororero and Muhanga districts to the north-east, Nyamasheke and Nyamagabe districts to the south, Ruhango district to east and it borders with the Democratic Republic of Congo and Lake Kivu to the west. Karongi is among the districts of Rwanda which has a high density, with 334 persons per square kilometre and faces high demographic growth with average annual growth rate of 1.7 %. Karongi District is divided into 13 administrative sectors, (Imirenge). The District experiences tropical climate of high altitude. It is one of Rwanda regions which have high rainfall. The amount of rainfall in the district benefits the area and It is characterized by two dry seasons covering the period from December to January and from June to mid September, and It is also characterized by two rainy seasons the long rains start in mid-September and end in December and from February to June. Karongi district is characterized by highlands area with steep features and altitude varying between 1470 to 2200 m above the sea level, temperature varies between 16 – 21^{o}C with rainfall ranging from 1100 to 1500 mm. its coordinates are 1.73^{o} and 2.145^{o}S and 29.614^{o} and 29.819^{o}E. The Figure 4 summarizes the topography of study area.

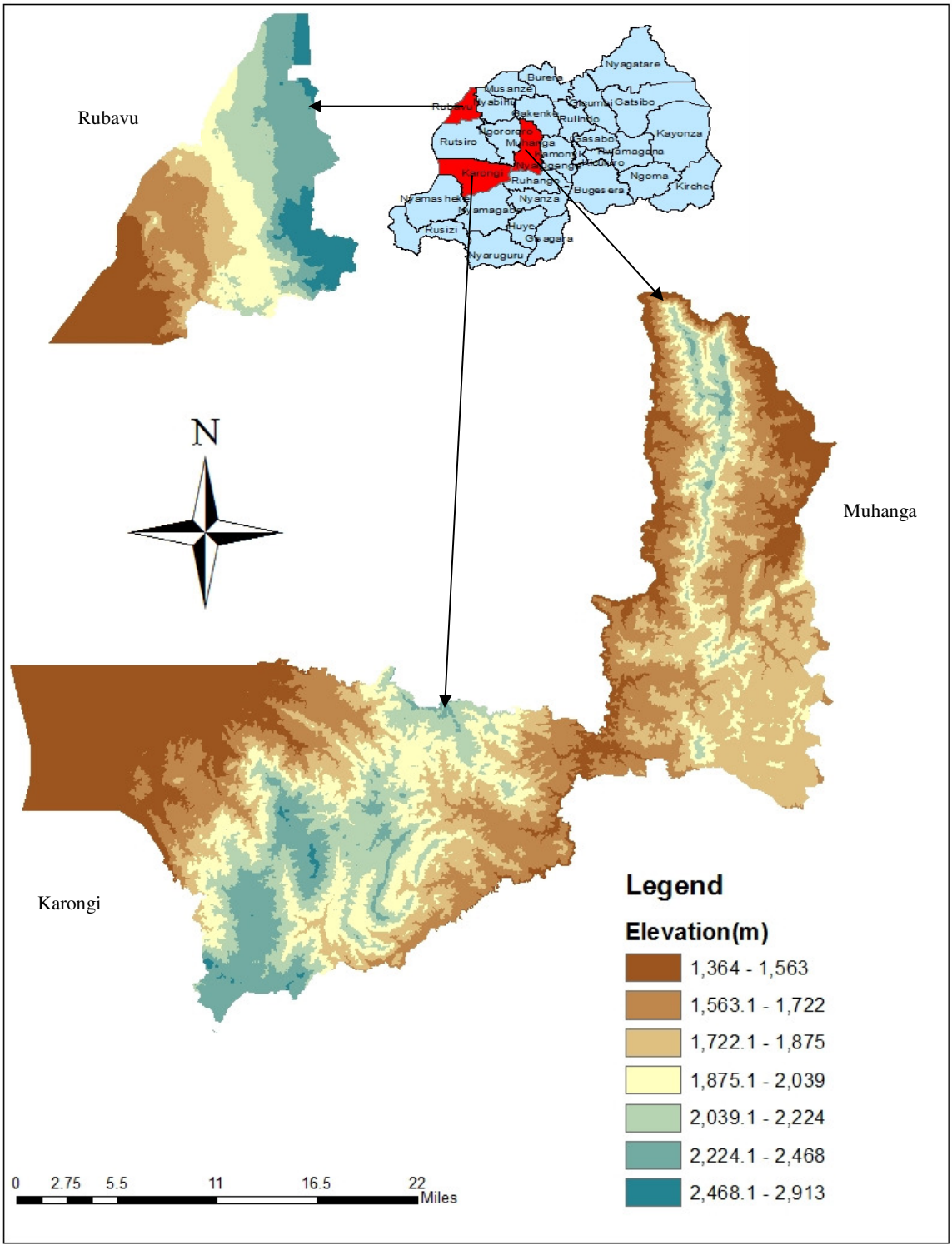


Figure 4: Topographic map of the study area (Muhanga, Karongi and Rubavu) (Source: Author, 2015)

3.2 Research Design

This study was intended to evaluate the possible impacts of climate variability on malaria prevalence in Rwandan highlands. The design of the research was developed from the theory which states that "in East African highlands every 1000 m increase in altitude is associated with a 6.5^{o}C decrease in temperature". From this theory, Rwandan highlands were used as shelter against malaria.

The study design was descriptive survey using longitudinal data (2004-2014), collected from health centres and meteorological stations selected using multistage cluster sampling of districts in highlands area of Rwanda and from district to sectors making the catchment of health centres. Data analysis used regression, correlation and model development for future prediction.

3.3 Study population

The population covered in this study are from western region of Rwandan highland in the period of 2004 to 2014, the districts of study was selected based on their location in the range of Congo-Nile divide, where altitude is more regular with less valleys. The study included health centres and malaria cases identified in the period of study over a total population of 1,117,814 equivalents to 9.3% of national total population. According to (Ministry of Health, 2012), the total health centres in this area was 81 supervised by 8 District Hospitals, distributed in five Districts of study area over total 30 Districts. Since the entire area of western highland of Rwanda could not all be covered, it was necessary to sample a small number of population.

3.4 Sampling procedure

3.4.1 Multistage cluster sampling

This sampling procedure was selected because it was not possible to compile a list of the element composing population (Cresswell, 2009), in a multistage cluster sampling researcher indentified first the groups. According to Hedt-Gauthier (2014), multistage

cluster sampling means that the sample increasingly smaller, embedded units. In this case selection of malaria cases in the period of 2004-2014, embedded in (or "clustered in") Health centres, and health centre which are clustered in districts, as indicated on Figure 5.

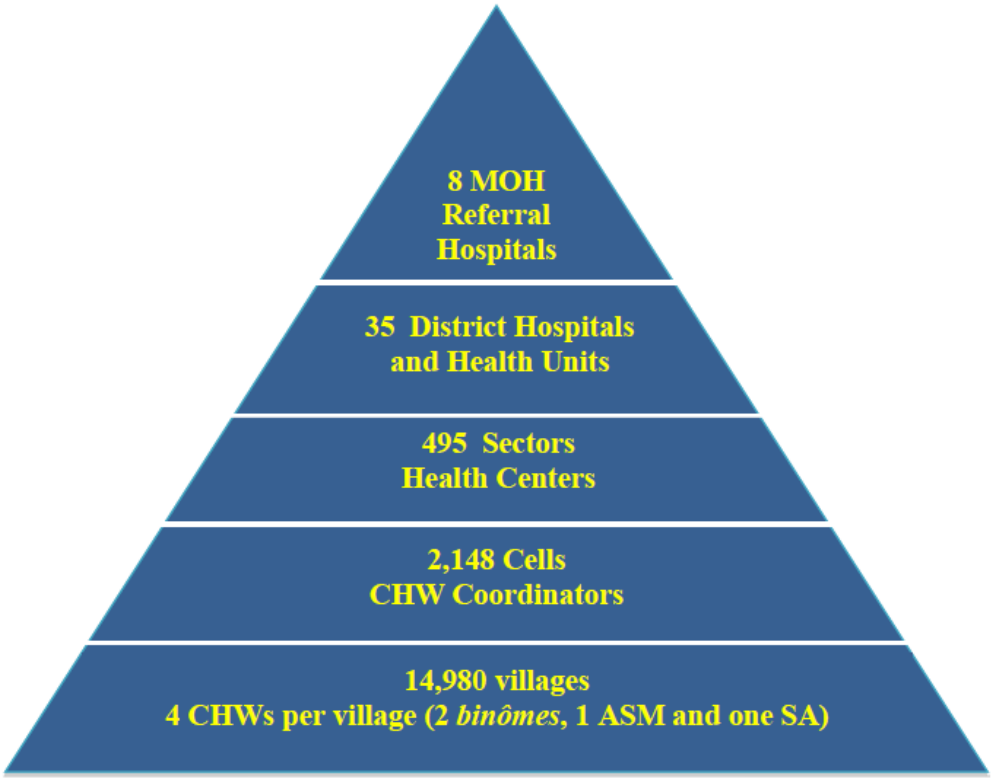


Figure 5: Rwanda health system organization indicating health centers and sectors (Source: President's Malaria Initiative, 2014)

A multistage cluster sample of malaria identified selected districts in Rwandan highland, and randomly sampled few health centres, based on conditions that health centre was operating during the period of study (2004-2014), and record of malaria has remained uniform, with the same calibration and the same precision. Only 26 health centres had enough data for the desired study period as reports in HMIS were indicating. This was consisting of a two-stage cluster sample with District as stage one, and Health centres as stage two. Study found 145,159 cases out of 693,112 average populations from 26 identified Sectors.

3.5 Data collection methods

3.5.1 Research permit and authorization

Prior to data collection, this study was examined by National Health Research Committee for approval, and then forwarded to the Ministry of Education in the Directorate of Science, Technology and research who recommended it to Rwanda National Ethic Committee for Ethical Clearance delivering. The Ethical Clearance certificate was used to sign a memorandum of understanding (MOU) with Malaria and Other Parasitic Disease Division of Rwanda Biomedical Centre (All issued documents are presented in Appendix 7). The importance of this MOU was to allow the research to be carried out in Rwanda with facilitation of different identified institutions.

3.5.2 Preliminary visit and primary data collection

The reconnaissance visit was made for locating specific health centers and meteorological stations in the study area. All health centers visited, geographical coordinate were recorded using GPS. From 2005 Rwanda reshuffled administrative entities that caused the names of health centers to change as well. Preliminary visit helped to identify the true names of health centers and their catchments which are Sectors (newly established local administrative entity). Since every sector was assigned a health center, the identification was made with reference to information given by Social Affairs officers in respective sectors.

3.5.3 Malaria cases collection

Epidemiological data used were monthly malaria cases, between October 2004 and December 2014, collected at health centre facility level in each district for routine reporting to the HMIS. Data included parasitological confirmed cases symptomatically diagnosed as malaria by trained health workers.

Data were aggregated at sector's level for all health facilities in each area as template Table presents in appendix 5. Data for 11 years were available in the three districts of study area, giving 26 units (equivalent to 26 sectors and health centres).

3.5.4 Climate data collection

Time series daily meteorological data of the period 2004–2014 composed by daily temperature, rainfall and relative humidity, were obtained from Rwanda Meteorological Agency (RMA). The parameters collected were from 3 meteorological stations located in study area; Mubuga for Karongi District, Kivumu for Rubavu District and Karambi for Muhanga District. Data were computed as mean minimum monthly temperature, mean maximum monthly temperature, average of mean maximum and minimum temperature, average monthly rainfall and average of relative humidity as indicated on template Table in appendix 5.

3.5.5 Population data generation.

Population data needed were from 2004 to 2014 and they were interpolated and extrapolated using 2002 and 2012 census with growth rates computed using National Institute of Statistics census data.

3.5.6 Spatial data collection and data analysis tools

Shape file of vector data storage format for health centres (at a scale of 1:250,000) obtained from Rwanda Biomedical Centre (RBC).

Topographic map showing different relief of Rwanda and other maps were obtained from Rwanda Natural Resource Authority (RNA),

Hand held GPS, model Unistrong G3 was used to obtain spatial coordinates,

Application Soft-wares: Microsoft Excel, STATA, E-views7 and ArcGIS 10.

3.5.7 Desk Top Study

Study combined other sources of data and information, like published and unpublished documents, research report, conference proceeding books and government publications for discussion and interpretation of results.

3.6 Data Analysis

3.6.1 Malaria prevalence rate calculation

Monthly malaria incidence was calculated for each health centre using total malaria case counts from health centres, over total annual population estimates from national census of 2002 and 2012, times 1000, or

$$\frac{Number\ of\ malaria\ cases}{Population\ in\ a\ given\ period} x1000 \quad (2)$$

According to (Kirck, 2008).

The following is the formula used to estimate population from 2004 up to 2014.

$$N_t = N_0 e^{rt} \quad (3)$$

Where N_t =size of population at time t, N_0 =size of population at time zero, e=base of natural logarithms =2.71828, r=rate of population growth, t=time elapsed.

Percentage Change = ((Most recent number-Previous number)/Previous number)* Percentage.

Table of population estimation in every sector of health centre's catchment for the period 2004-2014 and were presented on appendix1.

3.6.2 Data cleaning

Data collected from HMIS in RBC and Rwanda Meteorological Agency (RMA), were first cleaned in order to harmonize years, geographical area and data. STATA and EXCEL were used interchangeably to clean data.

The following are the steps in data cleaning using STATA:

Removal of unnecessary records like removal of missing values that was represented by "0" since there was confusion on missing value and "0" value, Generation of variables, Making average of daily records (temperature: Minimum, Maximum and mean, rainfall and relative humidity

Daily measurements were dropped to keep averages only, for better analysis months were given a numerical value (not text), month was dropped to keep months numerical only, Districts were given the names and values that match the malaria dataset, and excel was used to present data in Tables and Figures using pivot method.

On the other hand, the simple average of meteorological data and malaria cases were used to present climate variability and malaria incidence in study area, graphs and tables were applied to analyze and interpret acquired data from study area.

3.6.3 Descriptive statistics analysis

Descriptive statistics were used for organizing, summarizing, and presenting data in an informative way using tables, figures and maps. Average was computed for all variables and median to fill missing data, standard deviation to present variability of climate and malaria prevalence. Descriptive statistic was used also to make a comparison between variables of study with seasons of the year; long rain season, short rain season, long dry season and short dry season.

Data were normalised using mathematical transformations; for example, natural logarithm transformation was employed to obtain a more homogeneous variance of a series to be used in simple and multiple linear regressions and forecasting. Logarithmic transformation was used to avoid spurious prediction since data were not collected in the same units. E.g: Temperature in 'degree centigrade' and rainfall in 'mm'.

3.6.4 Inferential statistics analysis

Simple linear regression

Simple Regression Analysis was applied to establish climate parameters and malaria incidence correlation with time (2004 to 2014), and to deduce coefficient of correlation and determinant coefficient R^2. For further analysis, the study required the establishment of relationships between climate variability and malaria incidence in the highland of Rwanda.

3.6.5 Multiple Linear Regression Model

The aim is to model the dependence of malaria incidence on covariates including maximum temperature, minimum temperature, and average of minimum and maximum temperature, rainfall and relative humidity in Rwandan highlands. Assuming other factors hardly to control were held constant. Throughout this study adoption of the following notation for the variables: x_1 is temperature, x_2 is rainfall while x_3 is relative humidity.
The model is:

$$y = ß_0 + ß_1X_1 + ß_2X_2 + ß_3X_3+\varepsilon \quad (4)$$

Where ε is a random error with a mean of zero and a constant standard deviation σ. The model was estimated by finding the coefficients of the x values that make the error sum of squares as small as possible. In other words, the estimated model equation was

$$\hat{y}= b_0 + b_1x_1 + b_2x_2 + b_3x_3+\varepsilon \quad (5)$$

With y = estimation of malaria incidences

b_o was intercept

b_1, b_2 and b_3 were regression coefficients

x_1 was the independent variable temperature

x_2 was the independent variable rainfall

x_3 was the independent variable relative humidity.

Significance level used was 5%: which is the probability of rejecting null hypothesis when it is true.

The explanation power (squared correlation R^2): The R^2 measures the goodness of fit of the regression model and indicated the explanatory power of the model. The R^2 was used to measure the proportion of variations in malaria incidence that is caused by variation in climate parameters. A high R^2 represented a higher influence of climate parameter, while a low R^2 signified a weak relationship between climate variation and malaria incidence.
The following Figure 6 summarizes the strength and direction of the Pearson coefficient of correlation computed from linear regression analysis.

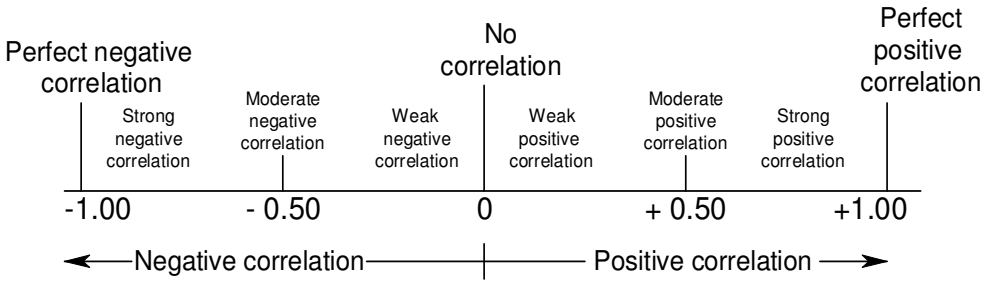


Figure 6: Measure of the strength of the linear relationship between variables (Source: Bryan & Manly, 2000)

3.6.6 Global test: Test of multiple Regression Model validity

The ability of the independent variables: X_1. X_2, X_3 to explain behaviour of the dependent variable Y can be tested. To put this in question form: can the dependent variable estimated without relying on the independent variable? The test used is referred to as the global test. Basically, it investigated whether it is possible for all independent variables to have zero net regression coefficients. To put it in another way, could the amount of explained variation, R^2, occur by chance? (Lind *et al*., 2001).

In this study, there was three independent variables, b_1, b_2 and b_3 are sample net regression coefficients, the corresponding coefficients in the population are given the symbols β_1, β_2 and β_3. Test was made to see whether the net regression coefficients in the population are zero. The null hypothesis was:

$$H_o: \beta_1 = \beta_2 = \beta_3 = 0$$

3.6.7 Seasonal time series forecasting using Seasonal Autoregressive Moving Average (SARMA)

Time series model was used; to monitor malaria situation in the study area and forecast with modeling and detection of seasonal transmission patterns in the distribution of malaria in the study area.

Forecasting methods was quantitative since the data collected on malaria incidence temperature, rainfall and relative humidity was available and could be quantified. It was assumed that the pattern of the past will continue into the future, therefore the growth rate of climatic parameters were added to the average of every month to yield future malaria predictors till 2019. In such case, forecast was developed using a time series method or a causal method. The analysis focused exclusively on quantitative forecasting method.
The E-view package used dynamic Model: The data here was fitted as

$$x_t = f(x_{t-1}, x_{t-2}, x_{t-3} \ldots). \quad (6)$$

Auto Regressive Moving Average model, where the autoregressive component is of order p and the moving average part is of order q, or ARMA (Autoregressive Integrated Moving Average) (p, q) was:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (7)$$

The following command was used in e-views

ls lnincidence c @trend @expand(@month, @dropfirst)

The command @expand(@month) creates 12 dummy variables, one for each month of the year, which are seasonal factors. Because constant has been included, it needs to exclude one of the dummy variables in order not to fall in the dummy variable trap. January was excluded, by using option @dropfirst.

Time Series Models and Forecasting used Multivariate analysis, where the observations are of multiple variables.

3.6.7.1 Validation of forecasting assumption

Assumption of predictors values was validated based on what has been published by different scholars; According to the United Nations Intergovernmental Panel on Climate Change, the 20th century has been warmed 0.8^{o}C higher than the previous ones and only the last 3 decades get 0.6^{o}C warmer than before. Average global temperatures will increase between 1.8^{o}C and 4.0^{o}C. Extremes of the hydrologic cycle (e.g, floods and droughts) are also expected to accompany global warming trends (Patz *et al*., 2008). Rwanda has experienced a temperature increase of 1.4^{o}C since 1970, higher than previous global average, and can expect an increase in temperature of up to 2.5^{o}C by the 2050s from 1970. Rainfall is highly variable in Rwanda but average annual rainfall may increase by up to 20% by the 2050s and 30% by 2080 from 1970 (Republic of Rwanda, 2011). Recent work on creating and analyzing the first global humidity dataset has shown that RH is almost constant on large spatiotemporal scales, but considerable regional structure and temporal variability remains (e.g. diurnal RH variability may be around 25%) (Lieshout *et al*., 2004).

3.6.7.2 Creation of Dummy variables

Dummy variables were used to deal with categorical independent variables in a multiple regression model. Note that when a categorical variable has *k* levels, *k* -1 dummy variables are required, for this case it is 12-1=11 dummy variables.

Using $\hat{y}$ to denote the estimated or forecasted malaria prevalence, the general form of the estimated regression equation can be:

$$\hat{y} = b_o + b_1t + b_2M_2 + b_3M_3 + b_4M_4 + b_5M_5 + b_6M_6 + b_7M_7 + b_8M_8 + b_9M_9 + b_{10}M_{10} + b_{11}M_{11} + b_{12}M_{12} \quad (8)$$

Where:

$\hat{y}$ = estimated or forecast of malaria prevalence in a period t

b_1t = time period or trend coefficient and time period.

b_2M_2 = 1 if time period t corresponds to the second month of the year; 0 otherwise

b_3M_3 = 1 if time period t corresponds to the third month of the year; 0 otherwise

b_4M_4 = 1 if time period t corresponds to the forth month of the year; 0 otherwise

b_5M_5 = 1 if time period t corresponds to the fifth month of the year; 0 otherwise

b_6M_6 = 1 if time period t corresponds to the sixth month of the year; 0 otherwise

b_7M_7 = 1 if time period t corresponds to the seventh month of the year; 0 otherwise

b_8M_8 = 1 if time period t corresponds to the eighth month of the year; 0 otherwise

b_9M_9 = 1 if time period t corresponds to the ninth month of the year; 0 otherwise

$b_{10}M_{10}$ = 1 if time period t corresponds to the tenth month of the year; 0 otherwise

$b_{11}M_{11}$ = 1 if time period t corresponds to the eleventh month of the year; 0 otherwise

$b_{12}M_{12}$ = 1 if time period t corresponds to the twelfth month of the year; 0 otherwise

3.6.7.3 Forecasting with Exogenous Variables

Using forecasting with exogenous variables issued from future climate assumption, E-Views has estimated the model over the period *2011January to 2014 December*, for malaria incidence data available and used to calculate seasonal factors, trends and different coefficients in the model.

When the forecast sample was set to the entire sample that includes actual historical data, it was possible to check for forecast accuracy. E-Views compare the forecasted (predicted) values from the model (over the period *2011January to 2014December*) to the actual data and compute the forecast evaluation table.

Deseasonalizing

Seasonal patterns were removed from time-series data for easy use by public databases. Data that has been stripped of its seasonal patterns which is referred to as *seasonally adjusted* or *deseasonalized* data, using the formula;

$$d_t = \frac{y_t}{Corresponding \quad seasonal \quad index} \quad (9)$$

Thereafter excel was used to estimate the trend line and determinant coefficient.

From malaria prevalence on the seasonal dummy variables with estimated function the equation was:

Yt = Constant + trendt + Seasonalt, after deseasonalizing the equation became Yt = Coefficient + $trend_t$ (12)

The equation of trend line on the curve y = bo +b_1x was expressed as estimated time series equation that was adjusted as:

T_t = bt +b_o. It is forecast equation (10)

The R-squared from this regression provides a better measure of fit when the time series exhibits considerable seasonality.

3.6.7.4 Model validation

Validation was done by directly comparing model results with malaria cases reported in the years not included in the model generation, for testing if model was accurate or greater than the tolerance (Committee on Mathematical Foundations of Verification, Validation, and Uncertainty Quantification, 2001).

The results of the model were computed by replacing calculated values in the model equation for estimation of malaria incidence in a given time. Malaria cases were current data reported in the years 2015 and 2016.

3.6.8 Spatial statistical analysis

Quantitative spatial analysis helped to find meaning in spatial data. Quantitative analysis method was used to reduce large data sets to smaller amounts of more meaningful information, explore data to suggest hypotheses or examine the distribution of data. Exploratory data analysis (EDA) techniques were used for this.

Quantitative methods for spatial data analysis was used in conjunction with seasonal auto regressive integrated moving average (SARMA) methods used for non-spatial data because of the distinguishing features of spatial data, in this case data were clustered; first according to the districts, second according to health centres in different sectors. Observations of spatial data are not independent, but it is assumed that features that are close together in geographical space are in some way related example: temperature, rainfall and relative humidity are interrelated. Different results could also be obtained when applying the same technique to the same distribution of data; simply by varying the spatial units used.

Quantitative spatial methods used were:

Exploratory and descriptive statistics. These helped to describe the distribution of spatial phenomena. Histogram was created to show the distribution of malaria incidence and different climate parameters.

For exploratory and descriptive statistical models, GIS tools provided attribute data; altitude, location of health centres, distances to nearest observations for input into nearest neighbour statistics or cluster analysis.

Predictive statistics. These are used to look at relationships between spatial phenomena. For example, regression analysis was used to look at the relationship between altitude and temperature, rainfall and relative humidity. In this instance, geographical data sets of altitude and malaria prevalence were overlaid in the GIS to provide histograms of paired observations that show the relationship between the dependent variable (malaria prevalence) and the independent variable (temperature, rainfall and relative humidity). Here histogram was used for regression analysis and the subsequent model used to predict the malaria prevalence for areas in the future.

Process models

Process model attempted to describe interaction of the data objects that are modelled in the representation model. The relationships were modelled using quantitative spatial analysis tools. Since there were many different types of interactions between variables of study, ArcGIS was used to provide quantitative mapping analysis. Process modelling that was used is referred to as cartographic modelling. Process model was used to describe processes, in prediction it gave malaria incidence if temperature continues to raise exponentially or if rainfall decreases.

3.7 Ethical considerations

The study involved basically accession of health data recoded by health centres and stored as database and publicly available, such as malaria cases and meteorological data in the period of study 2004-2014. They were used for the purpose of this research only, once

publication is proposed authorisation from RBC will be important as signed in the memorandum of understanding in 2015.

3.8 Limitations of study

The study on impact of climate variability on malaria incidence in Rwandan highland for the period of 2004 – 2014 was first and foremost limited by data availability; it was intended to cover the whole region of highland, this was not possible due to irregularities in malaria cases reporting at health centre's levels. Even the reported cases had some gaps that were filled using median calculation of data in the same months of the year. The period covered by this study should be extended even up to 30 years but it was not possible due to the shortage of climatic data to cover such long period.

There were limitations in future projections of variations and its impacts especially spatial projection because of digital elevation model maps shortage. Other limitations aroused due to uncertainty on how mankind will alter the climate in the future for prediction. For instance, limitation in future climate variation depends on the future socio-economic which, in turn, depends on factors such as population, economic growth, technology development, energy demand, methods of supply, and land use. Projection was based on assumption by which, all parameters that we could not control remained stable.

CHAPTER FOUR
RESULTS, ANALYSIS AND INTERPRETATION

4.0 Introduction

This research Analyzed and predicted possible impacts of climate variability on Malaria incidence in Rwandan highlands. This was to confirm whether malaria vectors for many years found in lowlands and not found in highlands, had shifted due to variation of climatic conditions.

This chapter presents the results and interpretation of analysis.

4.1 Variation of temperature, rainfall and relative humidity in Rwandan highlands for the period of 2004 - 2014.

Climatic data presented were from three district: Muhanga (data from Karambi meteorological station), Rubavu (data from Kivumu meteorological station) and Karongi (Data from Mubuga meteorological station), where altitude varies between m1496 and m3000. These data are divided into minimum, maximum, average of both temperatures minimum and maximum, rainfall and relative humidity.

Data collected indicated that, in the period of 2004 - 2014 minimum temperature varied between 8.03 and 14.56^{o}C, maximum temperature varied between 23.31 and 25.28^{o}C, average of mean temperature varied between 16.35 and 19.54^{o}C. Rainfall varied between 95.62 and 156.94 mm, while relative humidity varied between 66.10 and 72.24 % as the Table 1 gives summary of data while appendix 6, Figures 7-12 indicate variation of climate parameters.

Table 1: The values of Climatic variables over 11 years in three districts

Year	AV_MAX_TEMP (in ^{o}C)	AV_MIN_TEMP (in ^{o}C)	AV_MEAN_TEMP (in ^{o}C)	RAINFALL in mm/Month	AV_MEAN_HUM In %
2004	24.44	8.25	16.35	107.44	72.24
2005	25.28	8.03	16.66	98.92	69.72
2006	24.52	11.73	18.11	120.14	69.75
2007	23.31	13.02	18.19	98.62	71.03
2008	23.59	14.54	19.07	95.62	73.68
2009	24.09	14.34	19.19	96.48	70.35
2010	24.05	13.60	19.54	113.38	68.29
2011	23.94	12.60	18.17	124.28	70.72
2012	24.35	13.55	18.99	109.13	68.86
2013	24.40	14.56	19.49	104.49	66.10
2014	24.28	13.06	18.45	156.94	66.67
Total	24.19	12.79	18.53	111.69	69.58

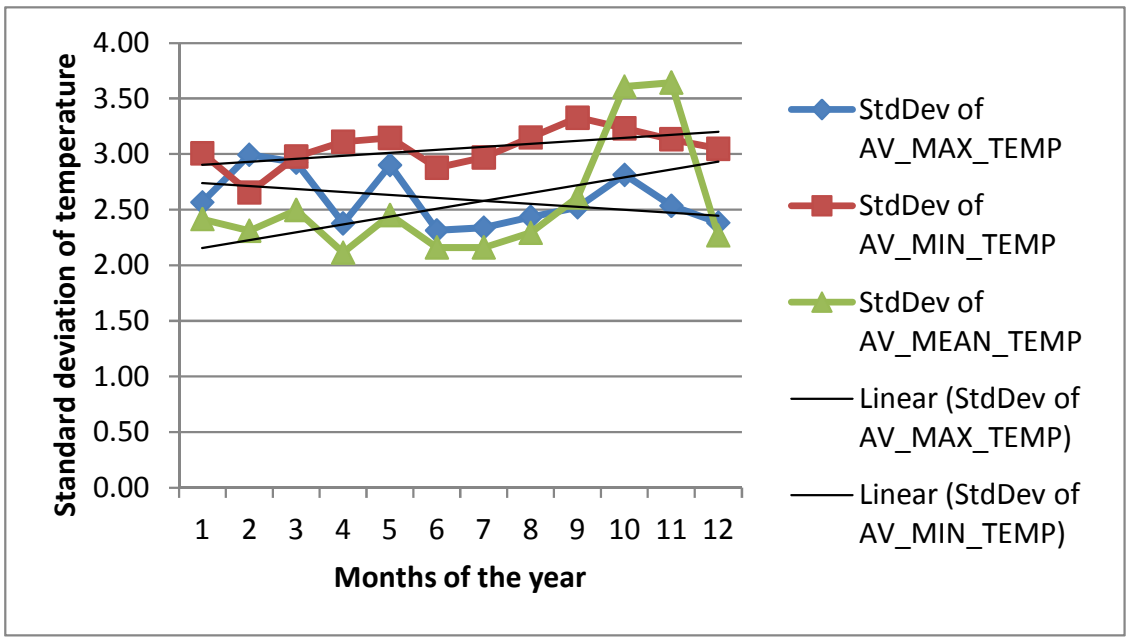


Figure 7: Standard deviation of annual temperature in 3 Districts.

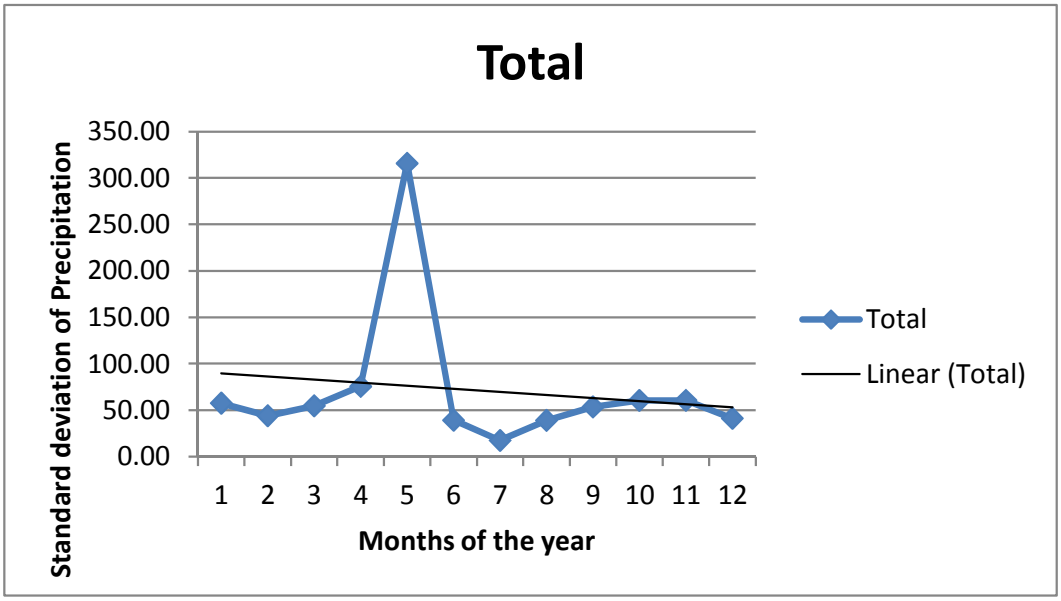


Figure 8: standard deviation of annual precipitation in 3 Districts

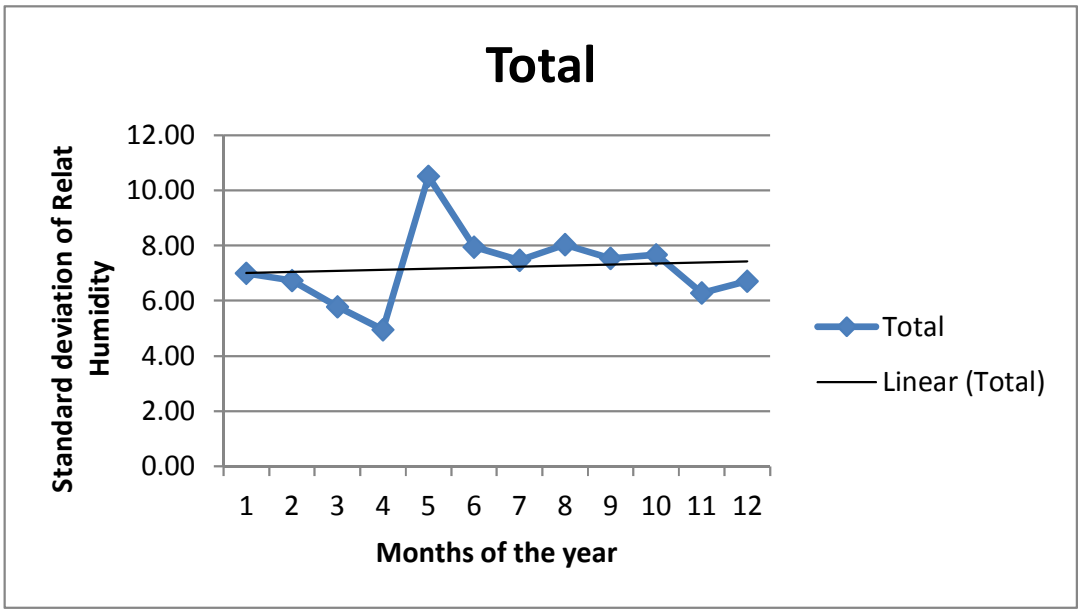


Figure 9: Standard deviation of annual relative humidity in 3 Districts

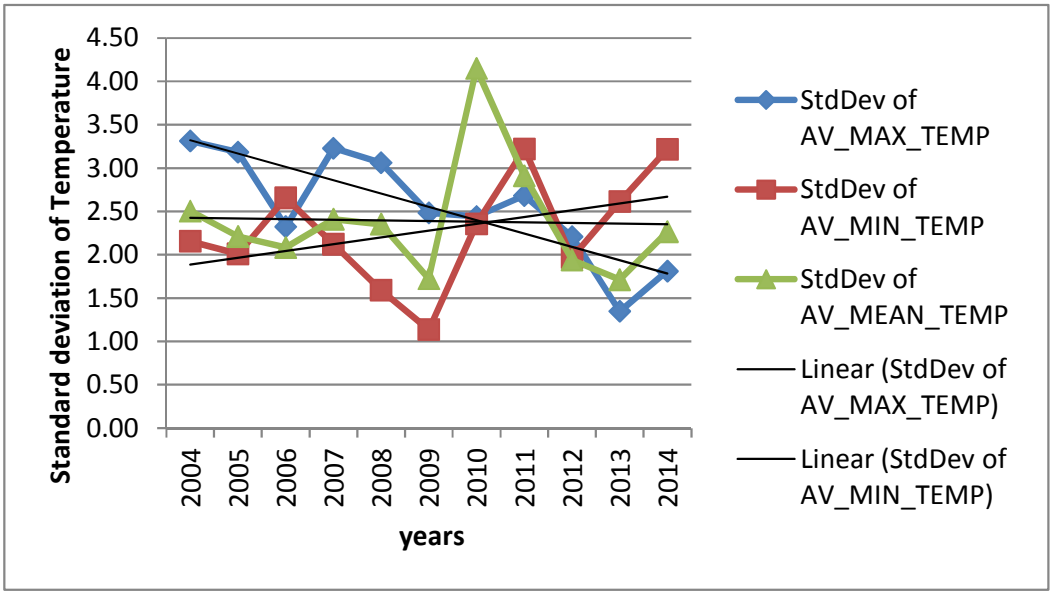


Figure 10: Variation of temperature for a period of 11 years in 3 Districts

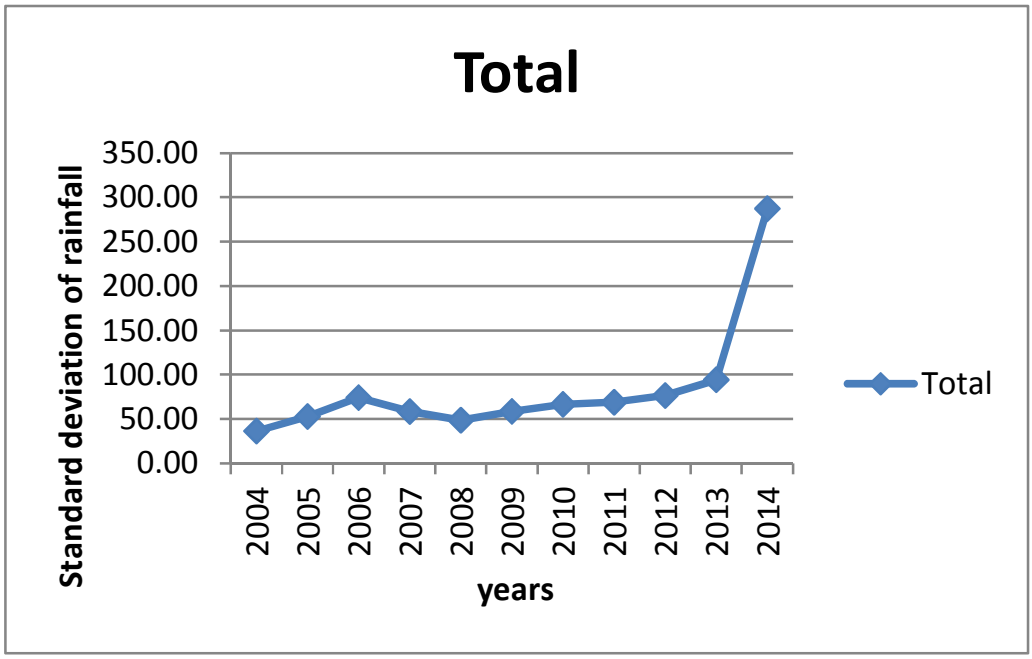


Figure 11: Variation of rainfall for a period of 11 years in 3 Districts

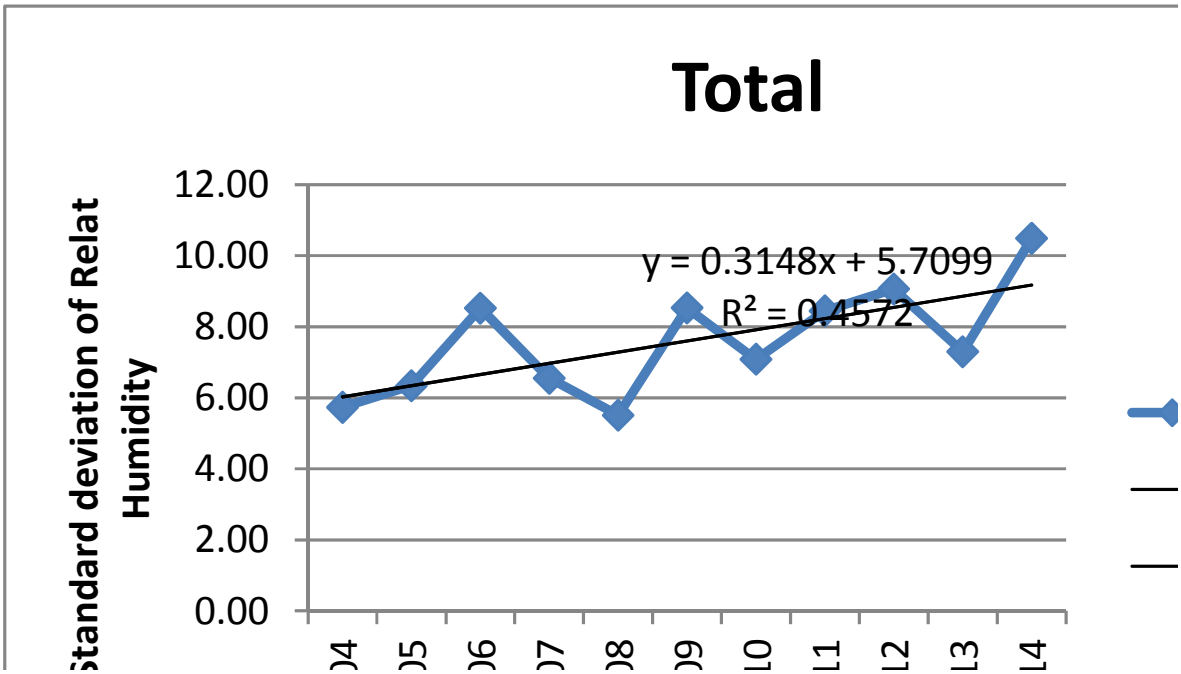


Figure 12: Variation of relative humidity for a period of 11 years in 3 Districts

As Table 1 indicated, maximum temperature did not vary significantly in the period of 2004-2014, it went from 23.31°C in 2007 to 25 °C in 2005, while minimum temperature varied between 8.02 °C in 2005 to 14.55 °C in 2013, average of minimum and maximum temperatures stood at 19.54 °C in 2010 and 16.34 °C in 2004. Rainfall had important variation because since 2011 the value was above 100mm; it was even 156.93mm in 2014. The lowest value of rainfall was in 2010 with 92.36mm. Relative humidity indicated reduction during the period of study; it went from 72.23% in 2004 to 68.29% in 2010.

4.2 Malaria incidence in Rwandan highlands for the period 2004 - 2014.

The second objective of the study was to determine malaria incidence in Rwandan highlands for the period 2004-2014. To achieve this objective, data collected from respective health were analysed and presented on Table 2

Table 2: Malaria incidence in study area for the period 2004 – 2014.

Year	Karongi	growth rate%	Muhanga	growth rate %	Rubavu	growth rate%	Grand Total
2004	8.62		28.02		3.43		14.15
2005	9.37	8.7	20.29	-27	3.92	14	11.78
2006	11.47	22	22.60	11	4.91	25	13.64
2007	5.40	-52	6.64	-70	2.75	-44	5.10
2008	3.53	-34	4.25	-35	1.96	-28	3.35
2009	4.84	37	6.34	49	2.17	10	4.63
2010	1.18	-75	3.80	-40	1.16	-46	2.12
2011	0.07	-94	1.77	-53	0.05	-95	0.68
2012	0.33	371.4	1.93	9	0.12	140	0.85
2013	1.64	397	6.53	238	0.14	16.6	2.98
2014	5.04	207	11.61	77	0.45	221	6.12
Grand Total	4.39		9.05		1.80		5.35

The Table 2 indicated that Muhanga had the highest incidence 28/1000 in 2004 but later came to 1.77/1000 in 2011. The second in malaria incidence was Karongi where the highest incidence was in 2006 with value of 11.47/1000, which reduced to 0.07/1000 in 2011. Rubavu had the lowest incidence among the three districts since the highest value of incidence was observed in 2006 at 4.91/1000 and the lowest value of incidence was observed in 2011 and it was 0.05/1000. The growth rate indicated the presence of malaria in Rubavu but at the lowest level.

4.2.1 Malaria variation in Study area

In study area, malaria incidence indicated variation similar to national variation Figure 31, what has been observed in study area is that; the altitude is inversely proportional to

malaria incidence; this gives an opportunity to classify the districts of study area according to their malaria incidence as follow: Muhanga, Karongi, and then Rubavu. The Figure 13 presented variation of malaria in different districts over the period 2004-2014.

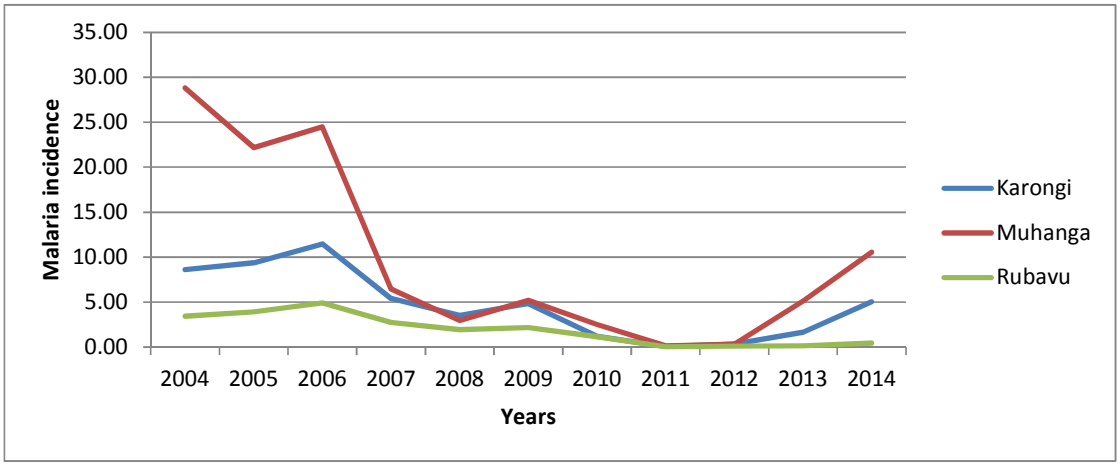


Figure 13: **Variation of malaria incidence in study area**

4.3 Relationship between climate parameters and malaria prevalence in Rwandan highlands for the period 2004-2014.

The third objective of this study was to establish the relationship between climate parameters (temperature, rainfall and relative humidity) and malaria prevalence. Data were collected in three districts and presented in Table 3.

Table 3: Average malaria incidence, temperature, rainfall and relative humidity for 2004-2014

Year	Malaria incidence	Max temp in ^{o}C	Min Temp in ^{o}C	Mean temp in ^{o}C	Av of Rainfall	Rel Hum
2004	14.44	24.44	8.24	16.34	107.44	72.23
2005	12.46	25.27	8.02	16.65	98.91	69.72
2006	14.31	24.51	11.72	18.10	120.13	69.74
2007	5.03	23.31	13.02	18.18	98.62	71.02
2008	2.88	23.58	14.54	19.07	95.61	73.67
2009	4.22	24.08	14.34	19.19	96.47	70.35
2010	1.65	24.05	13.60	19.54	113.38	68.29
2011	0.08	23.94	12.60	18.16	124.60	70.71
2012	0.26	24.35	13.55	18.99	109.12	68.86
2013	2.47	24.40	14.55	19.48	104.49	66.09
2014	5.73	24.28	13.05	18.44	156.93	66.66
Grand Total	5.14	24.18	12.78	18.53	108.11	69.58

Table 3 indicated that malaria incidence varied between 12/1000 and 14/1000 between 2004 and 2006, after it reduced sensibly to 5/1000 in 2007, since then the lowest value stood in 2011 at 0.08/1000. There was a linear increase from 2011 and following years as Table 3 gives the detail on this variation.

4.3.1 Seasonal variation of malaria incidence

Rwanda annual weather is divided into four seasons; long dry season from June to mid-September, Short rain season in mid-September, October, and November, Short dry season in December to February, Long rain season March, April and May (MAM). These seasons affect malaria distribution in the country.

Malaria transmission occurs year-round with two peaks (May-June and November-December) in Rwanda, following distinct rainy seasons (MINISANTE, 2011). Figure 14 presented malaria prevalence according to different seasons of the year from 2004 to 2014.

Muhanga always presented high annual malaria prevalence than others, secondly comes Karongi and lastly Rubavu. But the growth rate was higher in Karongi.

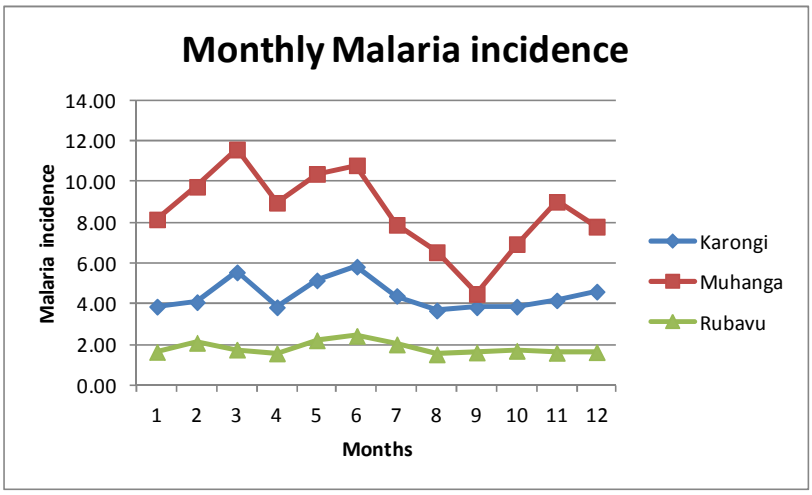


Figure 14: Monthly malaria incidence in study area for 11 years.

From the Figure 14, the month of March showed important peaks of transmission in Karongi and Muhanga, while in Rubavu additional peak was observed in February. In December, except Karongi other curves were different. Annual May/June's peaks of transmission remained throughout the area of study.

4.3.2 Malaria trend variation according to the seasons of the year

Long rain Season

Long rain season is extended over March, April and May, expressed moderate malaria incidence, this season is among the wet seasons of Rwandan climate. In the period of study, 2006 had the highest incidence in the three districts starting from Muhanga, Karongi then Rubavu. Growth rate indicated Karongi with 78.81%, Rubavu 21%, then Muhanga 15%. For malaria incidence Muhanga continued to lead the series but growth rate was less than Muhanga's. The variation of malaria incidence in the long rain season for the period 2004-2014 is presented on Figure 15.

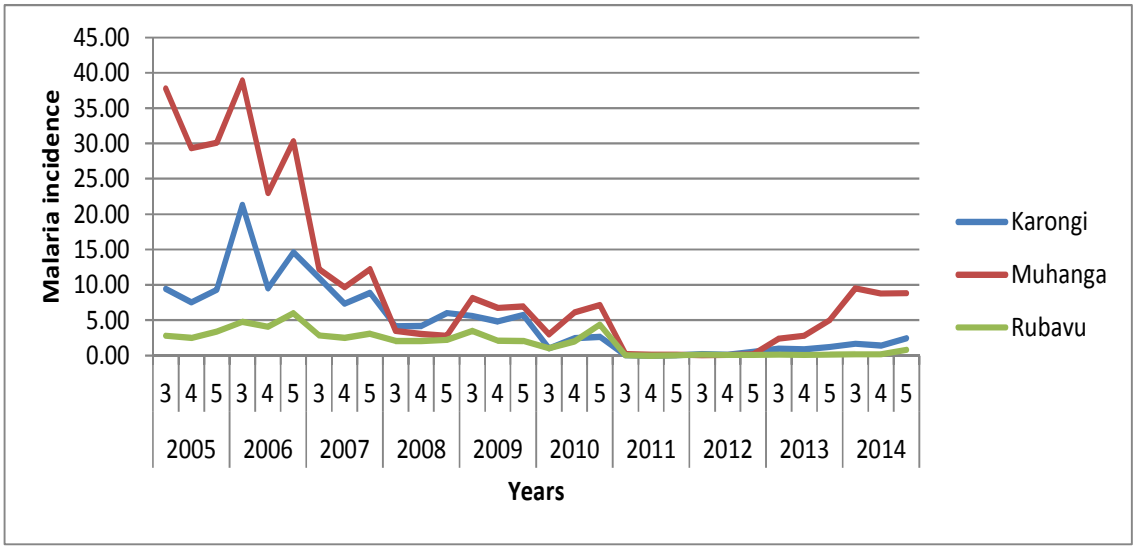


Figure 15: **Long rain season malaria incidence for the period 2004-2014**

Generally the average monthly rainfall in the area of study was around 150.22mm (with maximum of 289.96 mm in 2014 and minimum of 81.73 mm in 2009). For the districts; Muhanga had average of 198.34mm (with maximum of 685.77mm in 2014 and minimum of 75.33mm in 2009), Karongi had average of 123.85mm (with maximum of 197mm in 2013 and minimum of 83.00mm in 2009), and Rubavu had average of 122.25mm with (with maximum of 194.67mm in 2012 and minimum of 70.5mm in 2014). Due to heavy

rain that is expected in this season, toward the end, malaria transmission became important. The average of seasonal malaria prevalence was 5.97/1000.

In Rubavu, rainy seasons was not favourable for malaria transmission except in 2006 and 2010 where temperature arrived at 17.05°C and 17.18°C respectively, these values corresponded to the increase in incidence as shown on the Figure 15. Otherwise during the rainy season in Rubavu malaria incidence was not very important as compared to other districts.

Long dry Season

It covers the month of June to mid-September; the average of malaria incidence was 4.79/1000. Muhanga in this season remained with highest malaria prevalence than other remaining two districts of study, as Figure 16 presents.

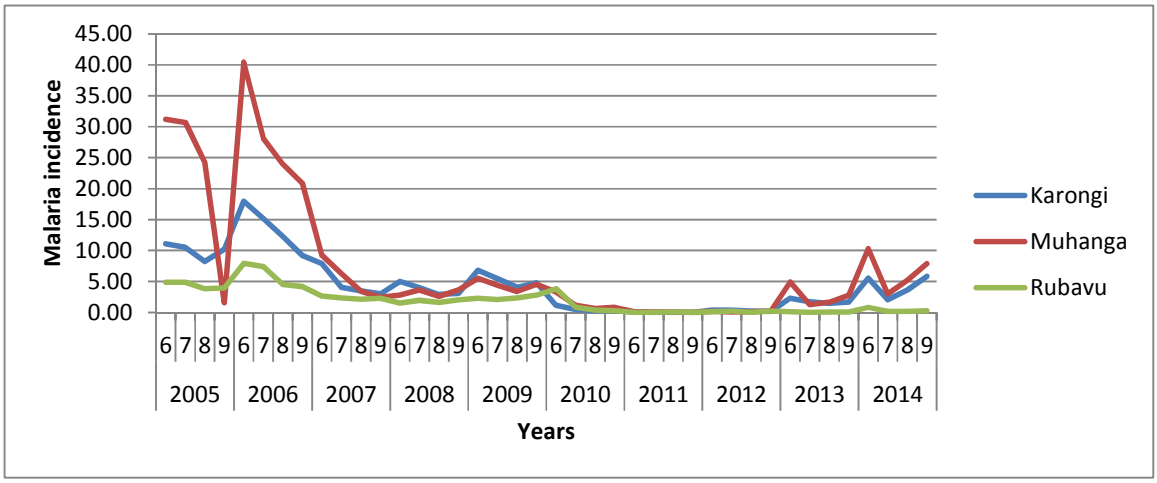


Figure 16: Long dry season malaria incidence for the period 2004-2014

Generally the quantity of average rainfall was 67.02mm with maximum of 95.86mm in 2011 and minimum of 43.68mm in 2009, values that are below the required quantity of rain for seasonal malaria transmission, but this period comes after long rain season that leaves behind breading sites for mosquitoes. The peak of malaria transmission on Figure 16, are on the month of June where transmission is high because this month comes after May of

the long rain season. Rubavu had the lowest malaria prevalence in this season but with highest quantity of rainfall.

Long dry season had average temperature of 18.47°C with 20°C in Karongi, 19.19°C in Muhanga and 15.56°C in Rubavu. The temperature was in the threshold of malaria transmission.

Relative humidity was 64.91% with 57.05% in Muhanga, 67.43% and 71.78% in Karongi and Rubavu, all of these values were in the range of malaria transmission.

Short rain Season

This season starts from mid-September to November. It was characterized by low malaria incidence and trended to increase at the end of season in November as Figure 17 presents. Muhanga came with the highest level of malaria transmission especially in 2004, 2006 and after 2012 where the incidence values were above 12/1000. For Karongi, in the short rain season 2005 showed special increase of incidences that was above Muhanga's, and increase was higher after 2012 for Muhanga and Karongi.

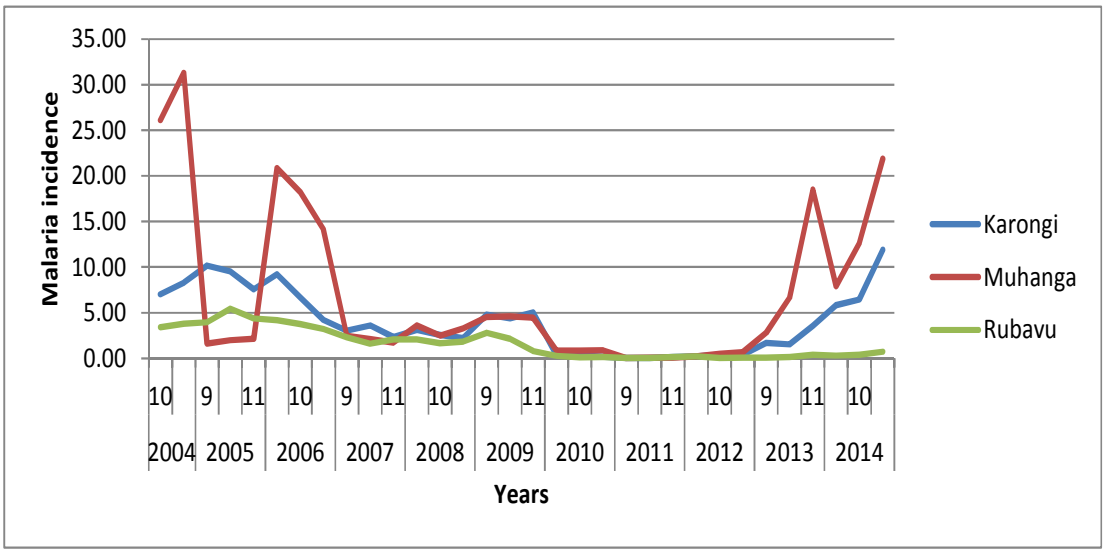


Figure 17: Short rain season malaria incidence for the period 2004-2014

The month of November is in the triad of short rain season, the month that was reported by MINISANTE (2011) for having high peak of malaria incidence with June. November comes after September and October the months in which rain is less intense compared to long rain season. In the period of study, the average of rainfall in this season was 128.73mm with maximum of 174.48mm in 2011 and minimum of 92.44mm in 2004.

Average temperature was 19.91°C during this season with 19.73°C in Karongi, 20.61°C in Muhanga and 15.66°C in Rubavu, the latter had the lowest malaria incidence that was corresponding to low value of temperature. Relative humidity was very high, with 69.78% of average, 62.68% in Muhanga, 72.29% in Karongi and 75.67% in Rubavu.

Short Dry Season

The season covers the month of December, January and February, it is a short dry season but rain is very important. Average malaria incidence was 5.08/1000 and the highest incidence was in Muhanga 8.53/1000, Karongi had 4.19/1000 and Rubavu 1.77/1000 as the Figure 18 gives detail.

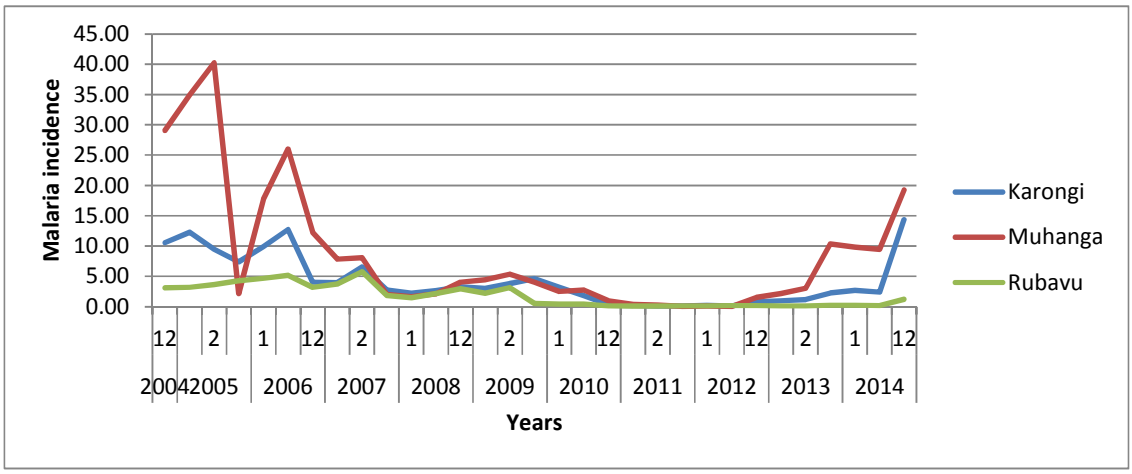


Figure 18: Short dry season malaria incidence for the period 2004-2014

From the Figure 18 rainfall indicated high variability that was between 69.70mm in 2012 and 149.56mm in 2009; Karongi had average rainfall of 129.69mm, while Muhanga and Rubavu had 119.4mm and 119.08mm respectively.

As compared to other seasons of the year, the short dry season showed important difference of malaria incidence and the peak of malaria incidence in February.

Temperature during the short dry season was in the minimum requirement of malaria life cycle to be completed except Rubavu; Karongi had average of 19.65^{o}C, Muhanga 19.76 ^{o}C and Rubavu 15.23^{o}C.

Relative humidity during the short dry season was at the average of 71.60%; with 73.87% in Karongi, 64.44% in Muhanga and 77.89% in Rubavu.

4.3.3 Multiple linear regression analysis of malaria incidence on climate variables

Multiple linear regression analysis was done using E-views7; results for respective districts are presented in Tables 4, 5 and 6. Note that temperature was presented in its 3 levels; Maximum temperature, Minimum temperature and mean temperature for each district. The tables were differentiated using letters a, b and c.

Table 4: **Multiple linear regression analysis of malaria incidence on temperature, rainfall and relative humidity for Karongi District**

Table 4 (a) Maximum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	148.1823	9.272569	15.98071	0.0000
MAXIM TEMPER	-50.35173	4.077830	-12.34768	0.0000
RAINFALL	0.124108	0.024334	5.100125	0.0000
RELAT HUMIDITY	2.747544	1.939688	1.416488	0.1574
R(-1)	0.341178	0.045852	7.440885	0.0000

R-squared	0.472403	Mean dependent var	-1.864316
Adjusted R-squared	0.467437	S.D. dependent var	2.888298
F-statistic	95.13461	Durbin-Watson stat	1.326191
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on maximum temperature, rainfall and relative humidity was:

Malaria incidence = 148.18 - 50.35*maximum temperature + 0.12*rainfall + 2.74* relative humidity + 0.34

The final model after removing the relative humidity, whose significance was higher than 5%, regression was: $\hat{y} = 146.63 – 46.23x_1 + 0.132x_2 + 0.345$

Table 4(b) Minimum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	55.35760	15.15730	3.652206	0.0003
MINIM TEMPER	1.125088	4.384307	0.256617	0.7976
RAINFALL	0.183503	0.027870	6.584274	0.0000
RELAT HUMIDITY	-14.22760	1.636390	-8.694500	0.0000
R(-1)	0.397211	0.053585	7.412717	0.0000

R-squared	0.283243	Mean dependent var	-1.864316
Adjusted R-squared	0.276497	S.D. dependent var	2.888298
F-statistic	41.98704	Durbin-Watson stat	1.096756
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on minimum temperature, rainfall and relative humidity was:

Malaria incidence = 55.35 + 1.12*minimum temperature + 0.18*rainfall - 14.22*relative humidity + 0.39

The final model after removing minimum temperature, whose significance was higher that 5%, regression was:

$\hat{y} = 58.83 + 0.18x_2 - 14.33x_3 + 0.39.$

Table 4(c) Mean temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	226.6965	15.99753	14.17072	0.0000
AVERAGE TEMPER	-73.43792	6.500737	-11.29686	0.0000
RAINFALL	0.146310	0.024608	5.945658	0.0000
RELAT HUMIDITY	-2.167054	1.758357	-1.232431	0.2185
R(-1)	0.416646	0.046653	8.930746	0.0000

R-squared	0.448682	Mean dependent var	-1.864316
Adjusted R-squared	0.443493	S.D. dependent var	2.888298
F-statistic	86.46983	Durbin-Watson stat	1.228338
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on mean temperature, rainfall and relative humidity was:

Malaria incidence = 226.69 - 73.43*mean temperature + 0.14*rainfall - 2.16*relative humidity + 0.41

The final model after removing relative humidity, whose significance was higher that 5%, regression was:

$\hat{y} = 232.69 – 78.34x_1 + 0.14x_2 + 0.41$.

Table 5: Multiple linear regression analysis of malaria incidence on temperature, rainfall and relative humidity for Muhanga District

Table 5(a) Maximum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.187325	4.222494	0.754844	0.4508
MAXIM TEMPER	-1.606847	2.032223	-0.790685	0.4296
RAINFALL	-0.008309	0.032484	-0.255781	0.7982
RELAT HUMIDITY	0.362632	1.056112	0.343365	0.7315
R(-1)	0.774762	0.031416	24.66108	0.0000

R-squared	0.594019	Mean dependent var	-0.563948
Adjusted R-squared	0.590198	S.D. dependent var	3.040058
F-statistic	155.4621	Durbin-Watson stat	1.432114
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on maximum temperature, rainfall and relative humidity was:

Malaria incidence = 3.18 - 1.6 maximum temperature - 0.0083 rainfall + 0.36 relative humidity + 0.77.

From the Table 7 (a), model was not possible at 5%.

Table 5(b) Minimum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.44862	6.409638	-2.098187	0.0365
MINIM TEMPER	4.109401	1.706971	2.407424	0.0165
RAINFALL	-0.038849	0.032724	-1.187153	0.2358
RELAT HUMIDITY	0.502929	0.735419	0.683868	0.4944
R(-1)	0.767722	0.031377	24.46768	0.0000

R-squared	0.598892	Mean dependent var	-0.563948
Adjusted R-squared	0.595117	S.D. dependent var	3.040058
F-statistic	158.6414	Durbin-Watson stat	1.429760
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on minimum temperature, rainfall and relative humidity was:

Malaria incidence = -13.44 + 4.10 minimum temperature - 0.038 rainfall + 0.5 relative humidity + 0.76.

Final model after removing rainfall and relative humidity whose significances were higher that 5% regression was:

$\hat{y} = -8.33 + 2.91x_1 + 0.76$

Table 5(c) Mean temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 432
Included observations: 430 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.326030	2.854176	0.114229	0.9091
AVERAGE TEMPER	0.490824	1.812029	0.270870	0.7866
RAINFALL	0.010272	0.031689	0.324135	0.7460
RELAT HUMIDITY	-0.583810	1.277080	-0.457144	0.6478
R(-1)	0.776168	0.031400	24.71840	0.0000

R-squared	0.593492	Mean dependent var	-0.563948
Adjusted R-squared	0.589667	S.D. dependent var	3.040058
F-statistic	155.1228	Durbin-Watson stat	1.439832
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence on mean temperature, rainfall and relative humidity was:

Malaria incidence = 0.32 + 0.49 mean temperature + 0.01 rainfall - 0.58 relative humidity+ 0.77

Model was not possible at 5%

The observation was the same as observed for maximum temperature in Muhanga.

Table 6: **Multiple linear regression analysis of malaria incidence on temperature, rainfall and relative humidity for Rubavu District**

Table 6(a) Maximum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 336
Included observations: 334 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-50.60351	9.945617	-5.088021	0.0000
MAXIM TEMPER	10.13012	1.242413	8.153586	0.0000
RAINFALL	0.056552	0.058770	0.962268	0.3366
RELAT HUMIDITY	3.741345	1.973696	1.895604	0.0589
R(-1)	0.208647	0.054232	3.847286	0.0001
R-squared	0.203098	Mean dependent var		-2.976366
Adjusted R-squared	0.193409	S.D. dependent var		2.092225
F-statistic	20.96214	Durbin-Watson stat		1.558641
Prob(F-statistic)	0.000000			

Regression equation for predicting malaria incidence on maximum temperature, rainfall and relative humidity was:

Malaria incidence = -50.60 + 10.13 maximum temperature - 0.056 rainfall + 3.74 relative humidity + 0.20.

Final model after removing rainfall whose significance was higher that 5% regression was:

$\hat{y} = -52.31 + 9.99\ x_1 + 4.3x_3 + 0.20$.

Table 6(b) Minimum temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 336
Included observations: 334 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.659321	9.256434	-0.935492	0.3502
MINIM TEMPER	0.550255	0.365113	1.507081	0.1327
RAINFALL	-0.007121	0.064065	-0.111151	0.9116
RELAT HUMIDITY	1.033770	2.132006	0.484881	0.6281
R(-1)	0.222571	0.059226	3.758017	0.0002

R-squared	0.048636	Mean dependent var	-2.976366
Adjusted R-squared	0.037069	S.D. dependent var	2.092225
F-statistic	4.204781	Durbin-Watson stat	1.269019
Prob(F-statistic)	0.002468		

Regression equation for predicting malaria incidence with minimum temperature, rainfall and relative humidity was:

Malaria incidence = -8.65 + 0.55 minimum temperature - 0.007 rainfall + 1.03 relative humidity + 0.22

Model equation was not possible at 5% level of significance.

Table 6(c) Mean temperature

Dependent Variable: MALARIA INCIDENCE
Sample (adjusted): 3 336
Included observations: 334 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-31.73941	9.758652	-3.252438	0.0013
AVERAGE TEMPER	3.757880	0.791362	4.748623	0.0000
RAINFALL	-0.003972	0.001697	-2.341219	0.0198
RELAT HUMIDITY	4.357348	2.136332	2.039640	0.0422
R(-1)	0.208062	0.057198	3.637574	0.0003

R-squared	0.117838	Mean dependent var	-2.976366
Adjusted R-squared	0.107113	S.D. dependent var	2.092225
F-statistic	10.98685	Durbin-Watson stat or DW	1.407632
Prob(F-statistic)	0.000000		

Regression equation for predicting malaria incidence with mean temperature, rainfall and relative humidity was:

Malaria incidence = -31.73 + 3.75mean temperature - 0.004rainfall + 4.35 relative humidity + 0.21

Final regression model at 5% was:

$\hat{y}$= -31.73 + 3.75x_1 – 0.004x_2 + 4.35x_3+ 0.21

Table 7: Summary of multiple linear regressions and test of hypothesis

	Temperature	*Regression equation*	*R-square*	*Corelation coefficient*	*Valid parameters at 5%*	*Model equation*
Karongi	**Max Temp**	$\hat{y}=148.18-50.35x_1+0.12x_2+2.74x_3+0.34$	0.47	0.68	Max Temp, Prec	$\hat{y}=146.63-46.23x_1+0.132x_2+0.345$
	Mini Temp	$\hat{y}=55.35+1.12x_1+0.18x_2-14.22x_3+0.39$	0.28	0.5	Prec, Relat hum	$\hat{y}=58.83+0.18x_2-14.33x_3+0.39$
	Aver Temp	$\hat{y}=226.69-73.43x_1+0.14x_2-2.16x_3+0.41$	0.44	0.66	Av temp, prec	$\hat{y}=232.69-78.34x_1+0.14x_2+0.41$
Muhanga	**Max Temp**	$\hat{y}=3.18-1.6x_1-0.0083x_2+0.36x_3+0.77$	0.59	0.76	None	Absent
	Mini Temp	$\hat{y}=-13.44+4.10x_1-0.038x_2+0.5x_3+0.76$	0.59	0.76	Minimum temp	$\hat{y}=-8.33+2.91x_1+0.76$
	Aver Temp	$\hat{y}=0.32+0.49x_1+0.01x_2-0.58x_3+0.77$	0.59	0.76	none	Absent
Rubavu	**Max Temp**	$\hat{y}=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20$	0.2	0.44	Max Temp, Rel Hum	$\hat{y}=-52.31+9.99x_1+4.3x_3+0.20$
	Mini Temp	$\hat{y}=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20$	0.04	0.2	None	Absent
	Aver Temp	$\hat{y}=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20$	0.11	0.33	Av temp, prec, hum	$\hat{y}=-31+3.75x_1-0.004x_2+4.35x_3+0.21$

Verification of hypothesis

H_o: $b_1 = b_2 = b_3 = 0$

The alternative hypothesis is

H_1: $b_1 \neq b_2 \neq b_3 \neq 0$, not all the b_s are zero and excluding mutually. (There is an influence of temperature, rainfall, relative humidity on malaria incidence in Rwandan highland.) Regression coefficients are b_1, b_2, b_3 ($\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3$ are valid).

From the Table 7, regression equation indicated the values of b_s different from 0, what validate alternative hypothesis and rejection of null hypothesis at 5%.

4.4 Time series analysis and forecasting changes in the incidence of malaria attributable to climate variation

E-Views offers a powerful and easy-to-use forecasting tool that allowed obtaining forecasts from estimated models.

The accuracy of the forecasts depends on the model used to produce the forecasts: E-Views simply handle the mechanics of producing the forecasts.

The forecast involved the level of malaria prevalence for the period from *2011January (the period malaria had linear increase) to 2019December*.

To accomplish this task, first it needs to specify and estimate a model. Malaria incidence was modelled as a linear function of a time trend and seasonal factors.

The results were presented in Tables 8, 9. 10.

4.4.1 Forecast analysis of malaria incidence

A forecast for malaria incidence based on the model produced was performed as shown in Figures 19 up to 27, for respective locations indicated.

Note that, E-Views show the series of equation over the forecast sample, together with 2 standard error bands.

Tables and Figures indicating the values of estimated coefficients, seasonal factors and trend or slope with forecasted output till 2019 are presented. On figures time is on the horizontal axis and the series values are shown on the vertical axis.

Table 8: Estimation output of equation forecasted with exogenous variables for Karongi

Dependent Variable: LNINCIDENCE
Sample (adjusted): 2011M01 2014M12
Included observations: 48 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.734554	0.310615	-8.803676	0.0000
@TREND	0.122549	0.006232	19.66356	0.0000
@MONTH=2	-0.402290	0.409674	-0.981976	0.3329
@MONTH=3	-0.722418	0.409817	-1.762785	0.0867
@MONTH=4	-1.479973	0.410053	-3.609219	0.0010
@MONTH=5	-0.719702	0.410385	-1.753724	0.0882
@MONTH=6	-0.357940	0.410811	-0.871303	0.3895
@MONTH=7	-1.140800	0.411330	-2.773441	0.0088
@MONTH=8	-0.988319	0.411944	-2.399162	0.0219
@MONTH=9	-1.072737	0.412650	-2.599628	0.0136
@MONTH=10	-1.299761	0.413449	-3.143700	0.0034
@MONTH=11	-0.515080	0.414341	-1.243132	0.2221
@MONTH=12	-0.488837	0.415324	-1.177001	0.2471

R-squared	0.923546	Mean dependent var	-0.620314
Adjusted R-squared	0.897334	S.D. dependent var	1.807962
F-statistic	35.23275	Durbin-Watson stat	1.082692
Prob(F-statistic)	0.000000		

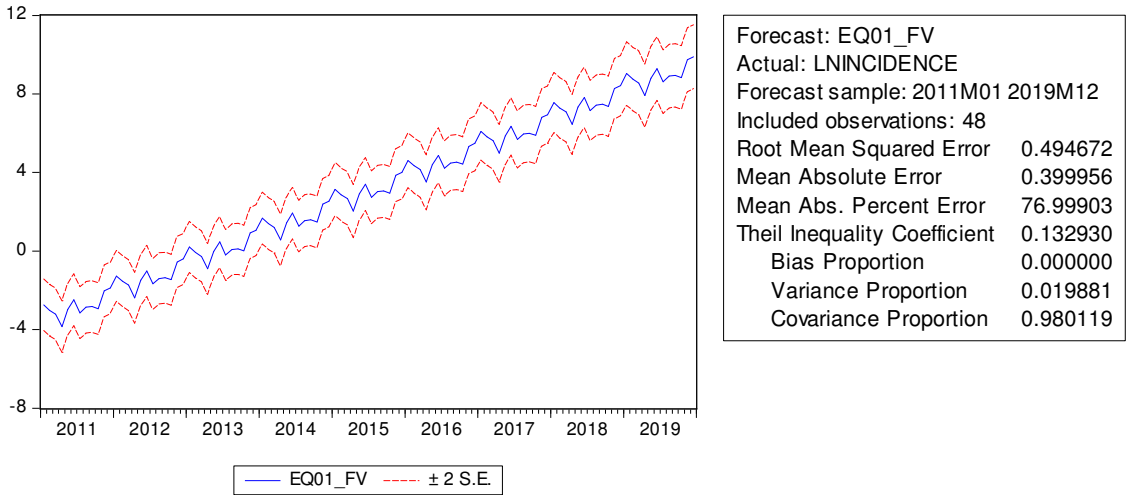


Figure 19: **Forecast Output with Forecast Evaluation table for Karongi**

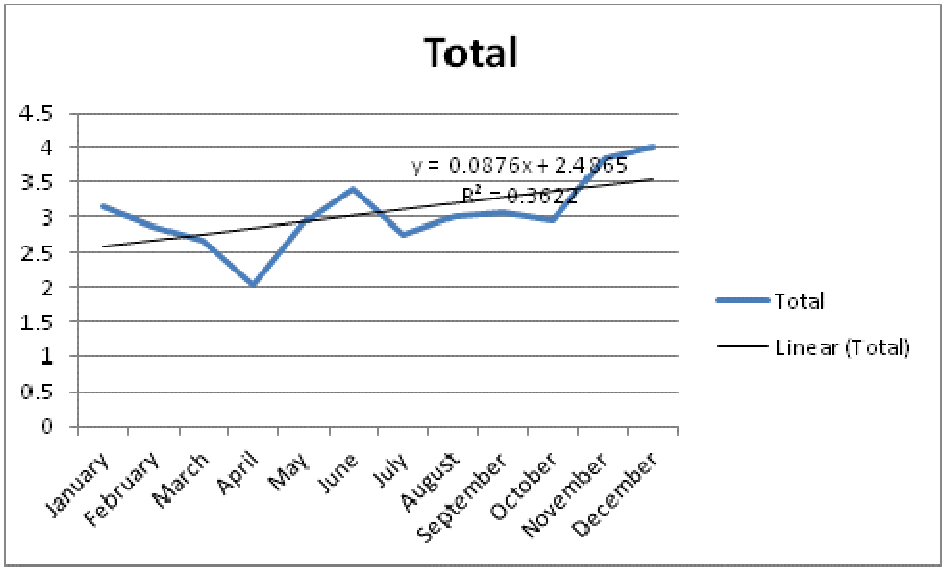


Figure 20: Annual seasonal trend of malaria incidence in Karongi

Figures 19 and 20 are presenting the results of time series analysis and forecast; generally in Karongi malaria prediction keeps malaria peaks in June and November as well as additional peak in January.

Using the formula, estimation of incidence for month four of 2015 can be:

$\hat{y} = -2.73 + b_1t + b_20 + b_30 + b_41 + b_50 + b_60 + b_70 + b_80 + b_90 + b_{10}0 + b_{11}0 + b_{12}0$

$\hat{y} = -2.73 + 0.122t + b4*M_4$

For example forecasting of April 2015

$\hat{y} = -2.734 + 0.122*51 - 1.4799*1$

$\hat{y} = 2.035$

Table 9: Estimation output of equation forecasted with exogenous variables for Muhanga

Dependent Variable: LNINCIDENCE
Sample (adjusted): 2011M01 2014M12
Included observations: 48 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.248568	0.198501	1.252225	0.2188
@TREND	0.053985	0.003983	13.55467	0.0000
@MONTH=2	-0.016241	0.261806	-0.062036	0.9509
@MONTH=3	-0.111481	0.261897	-0.425670	0.6730
@MONTH=4	-0.166526	0.262048	-0.635481	0.5292
@MONTH=5	-0.105430	0.262260	-0.402006	0.6901
@MONTH=6	-0.129081	0.262532	-0.491677	0.6260
@MONTH=7	-0.630689	0.262864	-2.399298	0.0219
@MONTH=8	-0.554493	0.263256	-2.106291	0.0424
@MONTH=9	-0.446659	0.263707	-1.693770	0.0992
@MONTH=10	-0.210008	0.264218	-0.794827	0.4321
@MONTH=11	0.091435	0.264788	0.345314	0.7319
@MONTH=12	-0.048811	0.265416	-0.183904	0.8552

R-squared	0.855481	Mean dependent var	1.323224
Adjusted R-squared	0.805931	S.D. dependent var	0.840362
F-statistic	17.26521	Durbin-Watson stat	0.460573
Prob(F-statistic)	0.000000		

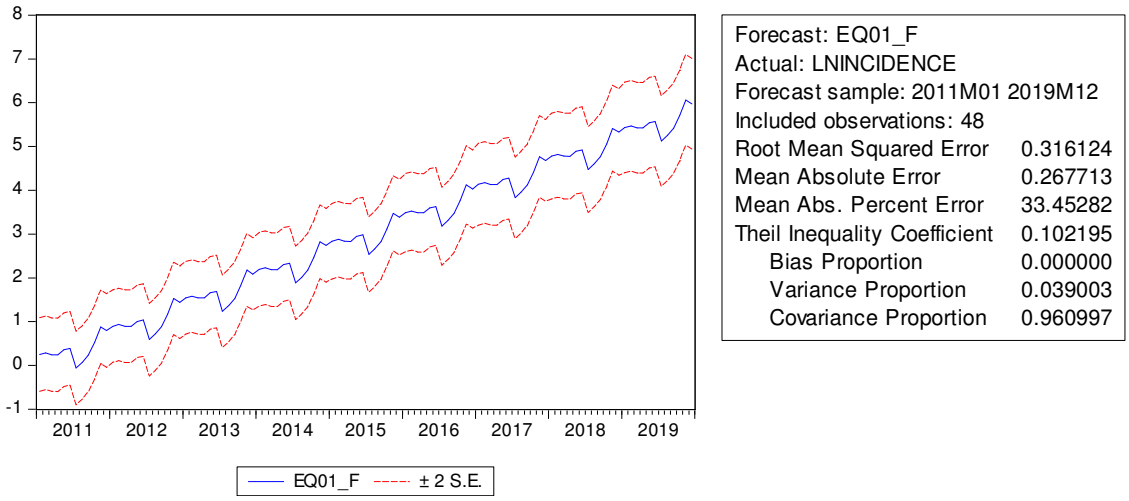


Figure 21: Forecast Output with Forecast Evaluation table for Muhanga

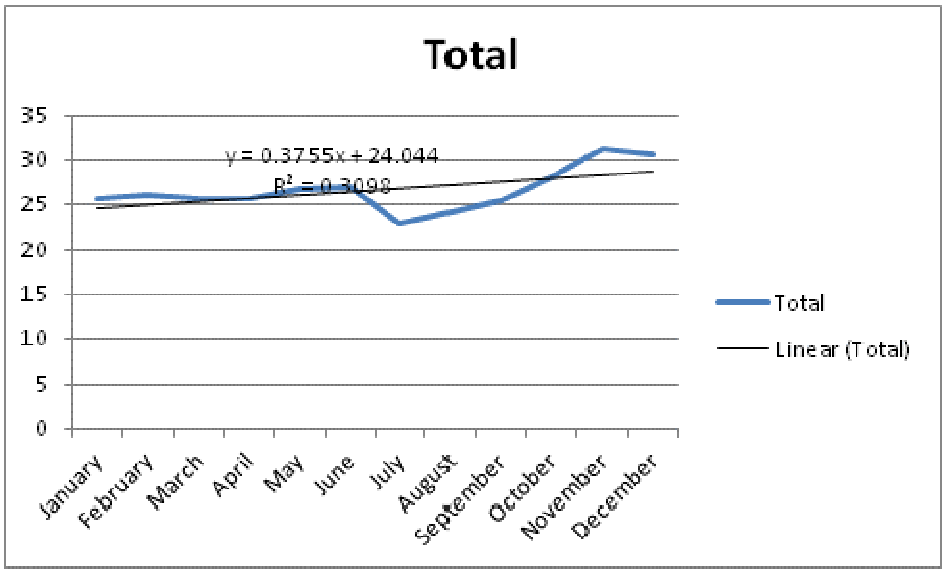


Figure 22: Seasonal trend of malaria incidence in Muhanga

Figures 21 and 22 are presenting the results of time series analysis and forecast; generally in Muhanga malaria prediction keeps malaria peaks in June and November and small increase in February.

Using the formula, estimation of incidence for month two of 2015 can be:

$\hat{y} = 0.25 + b_1t + b_21 + b_30 + b_40 + b_50 + b_60 + 0 + b_80 + b_90 + b_{10}0 + b_{11}0 + b_{12}0$

$\hat{y} = 0.25 + 0.054x_1 + b_2 * M_2$

For example forecasting of February 2015

$\hat{y} = 0.25 + 0.054 * 49 - 0.016 * 1$

$\hat{y} = 2.88$

Table 10: Estimation output of equation forecasted with exogenous variables for Rubavu

Dependent Variable: LNINCIDENCE
Sample (adjusted): 2011M01 2014M12
Included observations: 48 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.909484	0.357693	-8.134018	0.0000
@TREND	0.057954	0.007177	8.075062	0.0000
@MONTH=2	-0.198354	0.471767	-0.420450	0.6767
@MONTH=3	-0.697521	0.471930	-1.478016	0.1483
@MONTH=4	-1.196515	0.472203	-2.533900	0.0159
@MONTH=5	-0.677244	0.472585	-1.433064	0.1607
@MONTH=6	-0.359719	0.473075	-0.760385	0.4521
@MONTH=7	-0.959759	0.473673	-2.026203	0.0504
@MONTH=8	-1.199507	0.474380	-2.528580	0.0161
@MONTH=9	-0.834707	0.475193	-1.756563	0.0877
@MONTH=10	-1.208581	0.476114	-2.538428	0.0157
@MONTH=11	-0.278682	0.477140	-0.584067	0.5629
@MONTH=12	-0.011652	0.478273	-0.024362	0.9807

R-squared	0.714742	Mean dependent var	-2.182760
Adjusted R-squared	0.616940	S.D. dependent var	1.077850
F-statistic	7.308011	Durbin-Watson stat	1.442486
Prob(F-statistic)	0.000002		

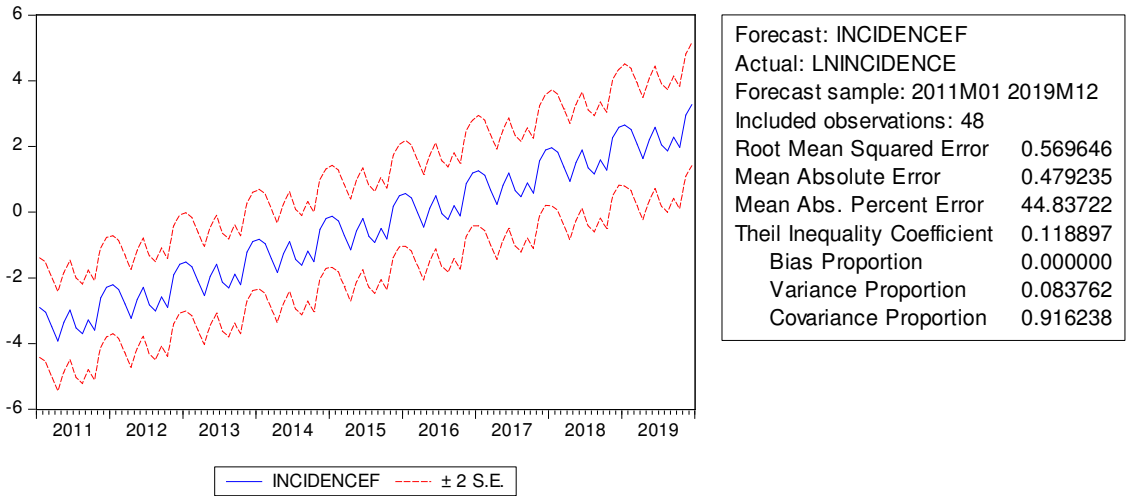


Figure 23: Forecast Output with Forecast Evaluation table for Rubavu

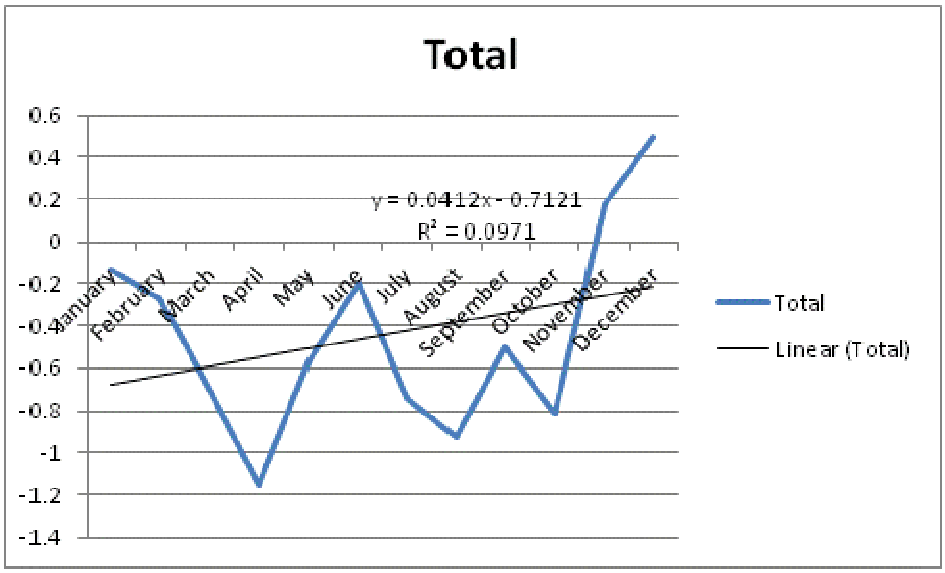


Figure 24: Seasonal trend of malaria incidence in Rubavu

Figures 22 and 24 are presenting the results of time series analysis and forecast; generally in Rubavu malaria prediction keeps malaria peaks in January, June and December.

For example third month of 2015

$\hat{y} = -2.909 + b_1t + b_20 + b_31 + b_40 + b_50 + b_60 + 0 + b_80 + b_90 + b_{10}0 + b_{11}0 + b_{12}0$

$\hat{y} = -2.909 + 0.057x_1 + b_3*M_3$

For example forecasted of March 2015

$\hat{y} = -2.909+0.057*50 – 0.697*1$

$\hat{y} = - 0.707$

4.4.2 Use of deseasonalized Time Series to Identify Trend

Using least square and seasonal trend, regression was a straight line as Figures 25, 26 and 27 indicate, pattern in the historical data or time series and then extrapolate the pattern into the future using linear trend regression. To identify this trend, linear trend equation was fitted to the deseasonalized time series using excel sheet. The only difference is that the deseasonalized data were fitted instead of the original data.

Deseasonalised time series are presented in the following figures according to the districts:

Karongi

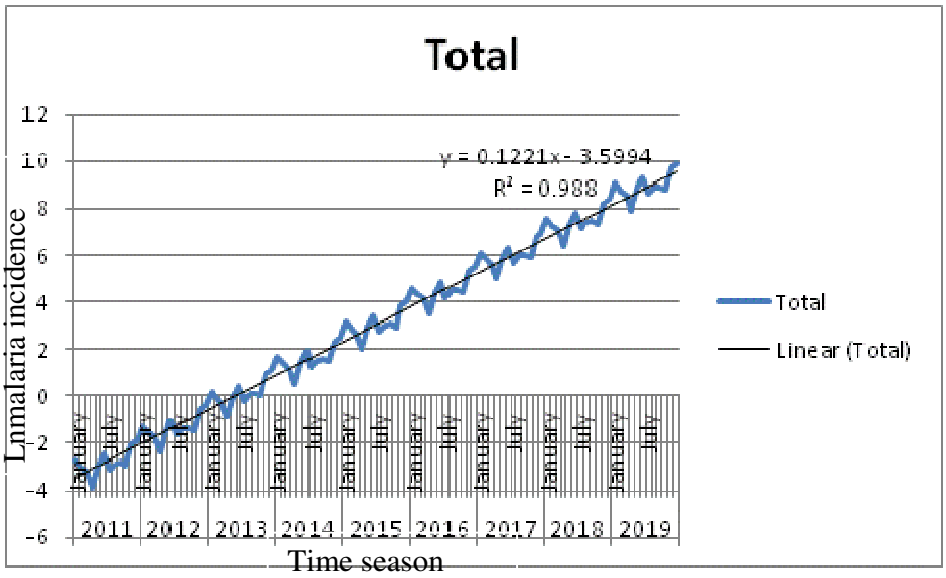


Figure 25: Least square presentation with seasonal trend of malaria incidence in Karongi

The Figure 25 indicates the least squared values plot of malaria over the year, with estimate equation; $\hat{y} = 0.1221x – 3.5994$ with R^2 =0.988 or 98% of time dependence. Adjusted equation is; $T_t = 0.1221t – 3.5994$.

Muhanga

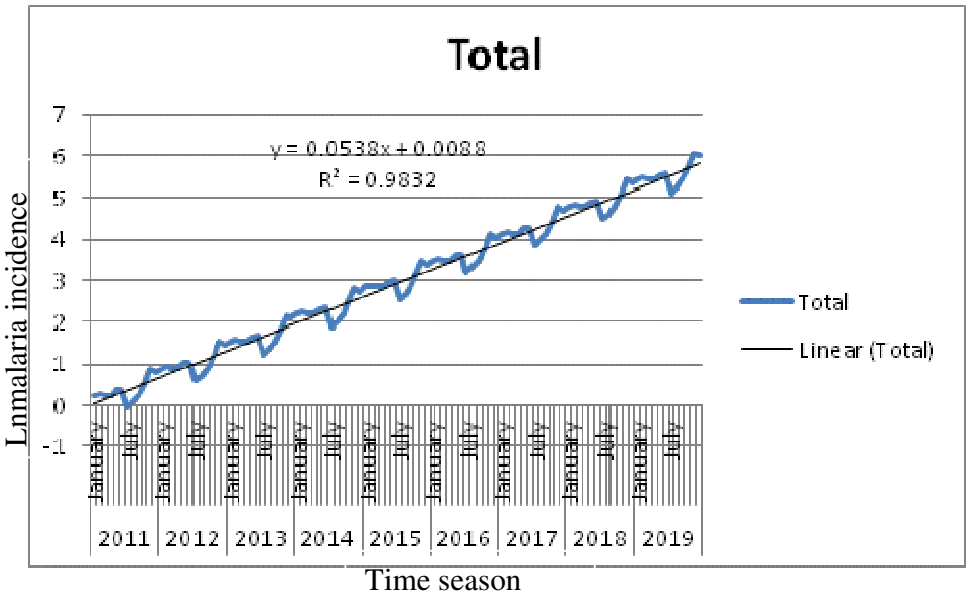


Figure 26: Least square presentation with seasonal trend of malaria incidence in Muhanga

The Figure 26 indicates the least squared values plot of malaria over the year, with estimate equation; $\hat{y} = 0.0538x + 0.0088$ with $R^2 = 0.9832$ or 98.3% of time dependence. Adjusted equation is; $T_t = 0.0538t + 0.0088$.

Rubavu

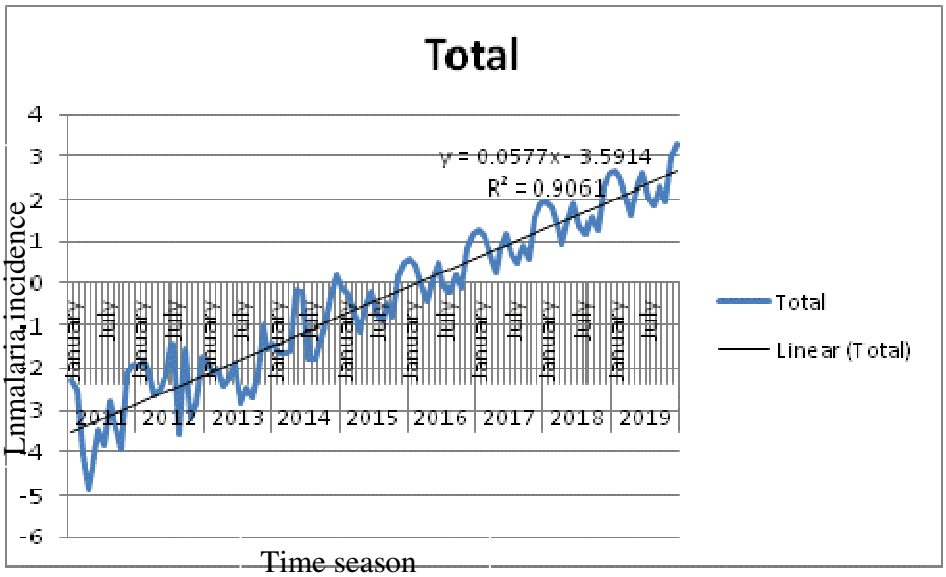


Figure 27: Least square presentation with seasonal trend of malaria incidence in Rubavu

The Figure 27 indicates the least squared values plot of malaria over the year, with estimate equation; $\hat{y} = \hat{y} = 0.0577x - 3.591$ with $R^2 = 0.906$, or 90.6% of time dependence. Adjusted equation is; $T_t = 0.0577t - 3.591$.

4.4.3 Validation of the model (results)

Reported malaria cases data were published by the Ministry of Health, Rwanda Biomedical Centre (2017) and President's Malaria Initiatives (2017), they indicated that between 2012 and 2016, Rwanda had over an 8-fold increase in reported malaria cases.

A triple in confirmed malaria cases (from 483 000 to 1.6 million), and a doubling in admissions (from 5306 to 11 138) between 2012 and 2014, were reported. The number of malaria cases increased from 2,473,387 in 2015 to 4,669,687 in 2016, with an annual incidence of 203.44 per 1,000 in 2015 and 404.88 per 1,000 in 2016. The summary of these data after calculation as Anderson, Sweeney, & Williams, (2008) indicated, were presented in Table 11.

Table 11: **Comparison of physical and modeled data**

Years	Physical measurement data				Modelled data		
	Cases	**incidence**	**ln**	**Growth fold**	**Incidence**	**Ln**	**Growth fold**
2012	483,000	45.83750822	3.8251		0.85	-0.1625	
2013					2.98	1.0919	
2014	1,600,000	145.4545455	4.9798	1.30189	6.12	1.8115	1.6590
2015	2,473,387	203	5.3132	1.066938		1.9	1.0488
2016	4,669,687	404.88	6.0035	1.129938		2.8333	1.4912

For harmonisation of data, malaria incidence was calculated for this available data, and normalised using natural logarithm then compared to data obtained by model as the Table 11 indicates.

The results indicated error of 1.6 % of data modelled as compared to reported data. Modelled data were 98.4% (ration of physical measurement/modelled data) in 2015. For the results of 2016 difference was a bit high, modelled data was more than reported data, 31.9% higher.

4.4.4 Spatial prediction of malaria incidence in study area

Figure 28 presents the results of quantitative spatial analysis; map indicated that the distributions of malaria incidence were inversely proportional to the altitude.

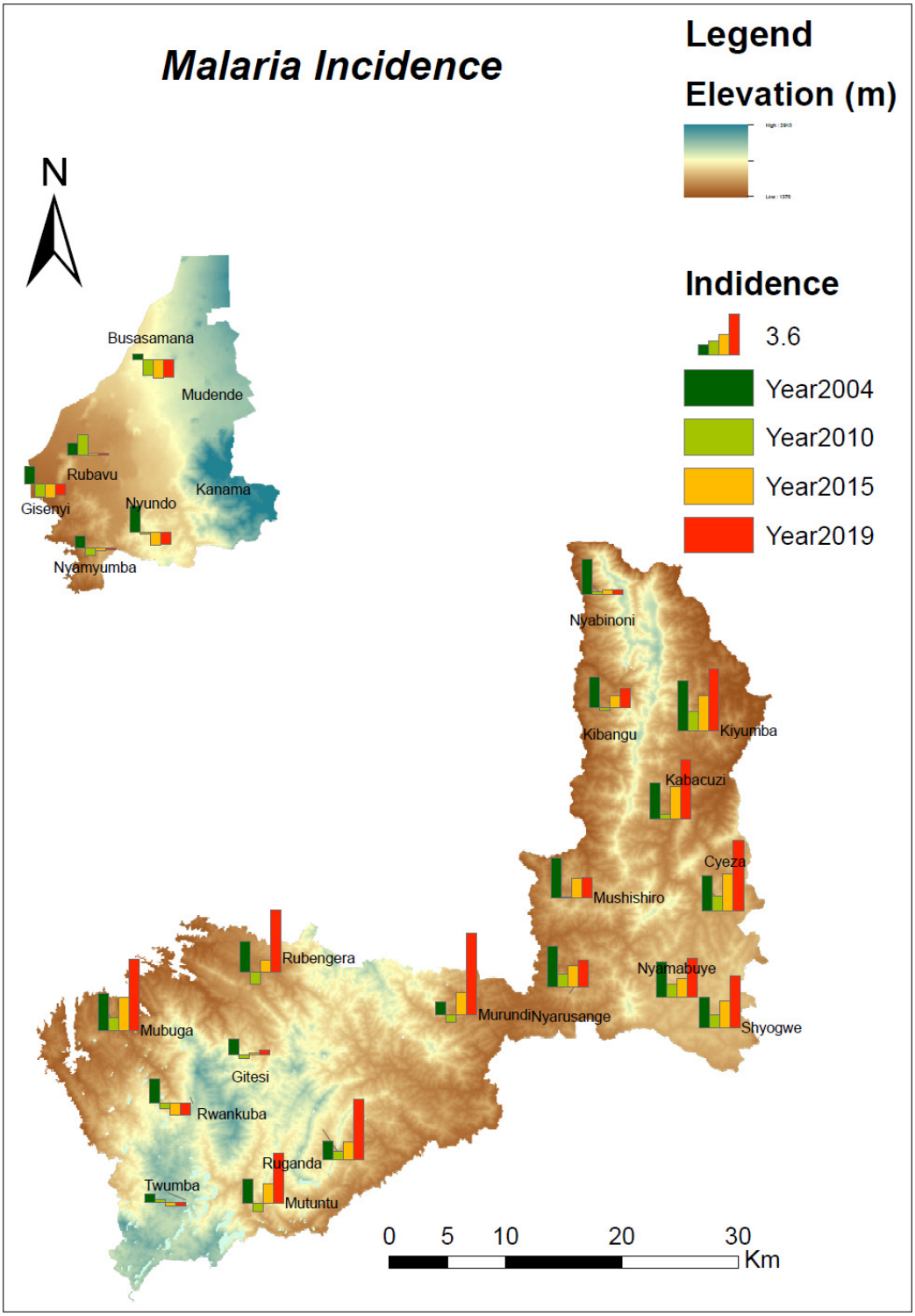


Figure 28: Spatial quantitative prediction of malaria incidence in different period 2004, 2010, 2015, 2019.

Data presented on the map were malaria incidence at the sector levels. In general, the map indicated linear progression of malaria since 2011; projection indicated unusual incidence of malaria with predicted climatic conditions in highland zones of Rwanda. Generally low altitude will continue to have high incidence, example: Kabacuzi, Murundi, Ruganda and high altitude will have low malaria incidence, example: Busasamana, Rwankuba, Nyabinoni.

4.4.5 Spatial and temporal of malaria transmission

The study area was represented by three districts that were formerly considered as malaria free zones. With climate variation, data have indicated that malaria has started to invade this new area as epidemic. Analysis used rainfall, temperature and relative humidity for prediction. With time, malaria may be common in the highland areas as breeding sites will be available. Figure 28 presents the analysed cases of possible malaria transmission in study area.

Table 12: Time series model summary

District	Model equation	Correlat coef (ρ)	R-square	Durbin Watson	Time series equation
Karongi	$\hat{y}$=-2.73+0.122x_1+b_x*M	0.95	0.92	1.08<2	T=0.122t-3.6; R^2=0.98
Muhanga	$\hat{y}$=0.25+0.054x_1+b_x*M	0.89	0.80	0.46<2	T=0.54t+0.008; R^2=0.98
Rubavu	$\hat{y}$= -2.909+0.057x_1+b_x*M	0.94	0.71	1.4<2	T=0.057t-3.59; R^2=0.90

Hypothesis was tested against null and alternative hypotheses where by:

H_o= ρ=0 Climate variability does not affect the future incidence of malaria in Rwandan highlands.

H_1= ρ≠0 Climate variability affect the future incidence of malaria in Rwandan highlands.

Table 12 has shown the value of ρ higher than 0, what indicates strong influence of climate variability on future malaria incidence in Rwandan highlands. Null hypothesis was rejected for three districts, while alternative one was valid.

CHAPTER FIVE
DISCUSSION OF RESULTS

5.0 Introduction

The first objective of this study was to determine the variation of temperature, rainfall and relative humidity in Rwandan highlands for the period of 11years. Data collected indicated high spatial and time variation of climate parameters; generally, maximum temperature ranged between 23 and 25^{o}C with lower variations, while minimum temperature ranged between 8.02 and 14.55^{o}C with considerable variations, average of minimum (16.34^{o}C) and maximum (19.54^{o}C) indicated linear growth.

Rwandan climate reflect important increase of temperature, which is linear as expressed on Figure 29, where temperature indicated long term variation, the basis from which climate change is confirmed in Rwanda. Even though Rwanda is entirely situated within the equatorial zone, it enjoys a moderate tropical climate due to its high altitude, and temperatures average of 20°C (REMA, 2001).

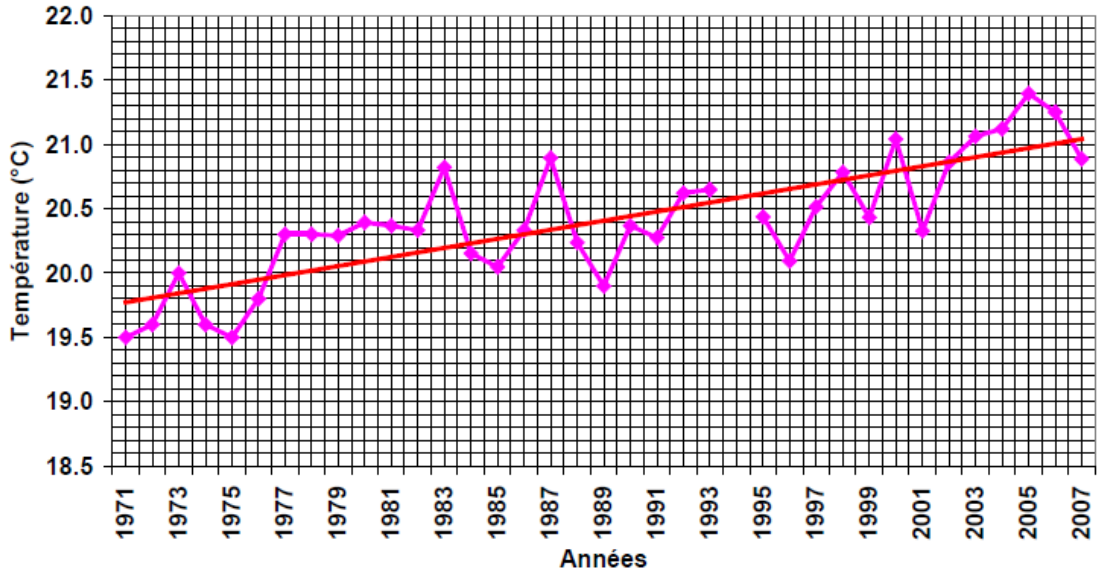


Figure 29: Long term average annual temperatures Rwanda (1971 – 2007)
(SOURCE: REMA, 2012).

In high altitude regions of Rwanda, temperature varies between 15°C and 17°C which is on an increase (REMA, 2012). The volcanic region has lower temperatures which can plunge to as low as 0°C in some areas. In the intermediary altitude zones, temperatures vary between 19°C to 29°C with an average rainfall of about 1 000 mm per year. Rainfall here is however less regular, leading to frequent dry spells (DFID, 2009).

The study has shown the difference in temperature values as compared to national temperature, in Karongi the average temperature ranged between 16.75 to 20.86^{o}C, for Muhanga, ranged between 18.25 to 20.02^{o}C and Rubavu ranged between 12.75 to 18.55^{o}C. Compared to the temperature provided by REMA, there is an increase of temperature in the study area, except in Rubavu, but the trend was positive.

The study showed the increase of rainfall, the monthly average ranged between 95.62 to 156 mm. In Karongi it varied between 87.00 to 122 mm, Muhanga varied between 80.63 to 235 mm and Rubavu varied between 81.33 to 136 mm. Rainfall in Rubavu was high, it is an area where during long period of rainfall floods become challenge for crops production, communication by roads and sometimes loss of life and properties was recorded(Chemonics International Inc, 2003) see Plate 1. Muhanga had the highest quantity of rainfall in 2014 with 235.22 mm. Compared to the national rainfall trend of Figure 30; the peak of rain was in 2011 while in the study areas the peak was in 2013.

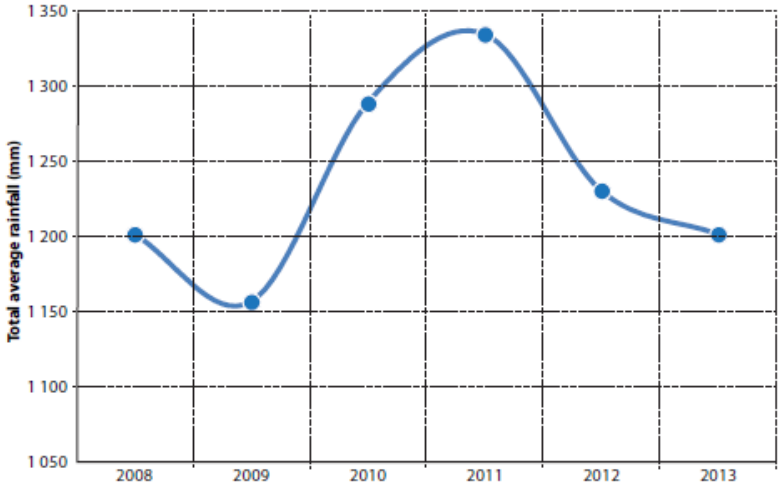


Figure 30: National rainfall trend in 2008-2013

(Source: REMA, 2015)

The figure 30 indicates positive variation of rainfall at national level. In 2009, low rainfall was recorded as compared to normal annual mean rainfall of 1200 mm per year. In 2011, extremely high rainfall was recorded which indicated high variation of rainfall. The same variation was observed in the study area as indicated on the Figure 11, but significant increase was in 2013 onward. This increase was indicated in IPCC report where indicated that Burundi and Rwanda could experience increased rainfall intensity during both rainy seasons by the 2050s, Rwanda's average annual rainfall may increase by up to 20 % level from 1970. Severe extreme weathers are some example of this rainfall increase, as seen on Plate 1 with flash floods in Rubavu in 2011 where the rainfall was 140 mm (see appendix 6).

Plate 1: Flash flood in Rubavu in 2011
(Source: Chemonics International Inc, 2003)

Relative humidity was also significant, its variation was not too high since the highest value of relative humidity was 72.24% and the lowest was 66.10%. Generally relative humidity was decreasing with time. Relative humidity with temperature and rainfall are major component of climate. Under enhanced greenhouse gases there is increase of temperature and wind which reduce humidity during the day if global warming persists (Philander, 2008). The reduction of relative humidity was correlating with the reduction of forest cover as Mavrakis & Papavasileiou (2013) indicated; shift in land use, in many cases occurring arbitrarily with no previous planning affect relative humidity in negative way. Changes resulting from human activities were observed in highland of Rwanda, what was one of the causes of relative humidity reduction. Plate 2 gave the example of the whole forest cleared for charcoal burning in Karongi.

Plate 2: Charcoal burning in Karongi
(Source: REMA, 2012)

In all districts of the study area, relative humidity was reducing; Karongi varied between 68.01-74.96%, Muhanga varied between 56.99-69.09% while Rubavu varied between 73.19 – 76.21% Generally the fluctuation of climate variables were quite different from what was normally expected, according to Chemonics International Inc, (2003) average temperature should not go beyond 16-17^{o}C while annual rainfall should be 1300-2000 mm or 108-166 mm per month, relative humidity 70% 95%. Table 1 indicated that temperature and rainfall rose while relative humidity reduced significantly.

The second objective was to determine malaria incidence in Rwandan highlands for the period of 11 years. Malaria incidence indicated high variation that divided data into two categories; since 2004 significant reduction of malaria incidence was observed that arrived at almost null in 2011; (14.44/1000 in 2004 to 0.08/1000 in 2011). From 2011 there was increase of malaria cases till 2014 (0.008/1000 to 5.73/1000) and onward as reported by (President's Malaria Initiative, 2017)

The reduction of malaria incidence in 2004-2011, was due to the fully alignment with the United State Government's vision of ending preventable child and maternal deaths and ending extreme poverty. The program started in 2005 with the goal of working with PMI-supported countries and partners to decrease malaria morbidity toward the long-term goal of elimination (1st Rwanda Malaria Forum, 2012). It was reported by World Health Organization (2014) that between 2000 and 2013, malaria admission rates decreased by more than 75% in Eritrea, Rwanda and in Zanzibar, in the United Republic of Tanzania (McMichael & Woodruff, 2008). Comparing national prevalence of malaria presented on Figure 31 and study area data on Figure 13, there was some similarities in variation but differences in reported cases.

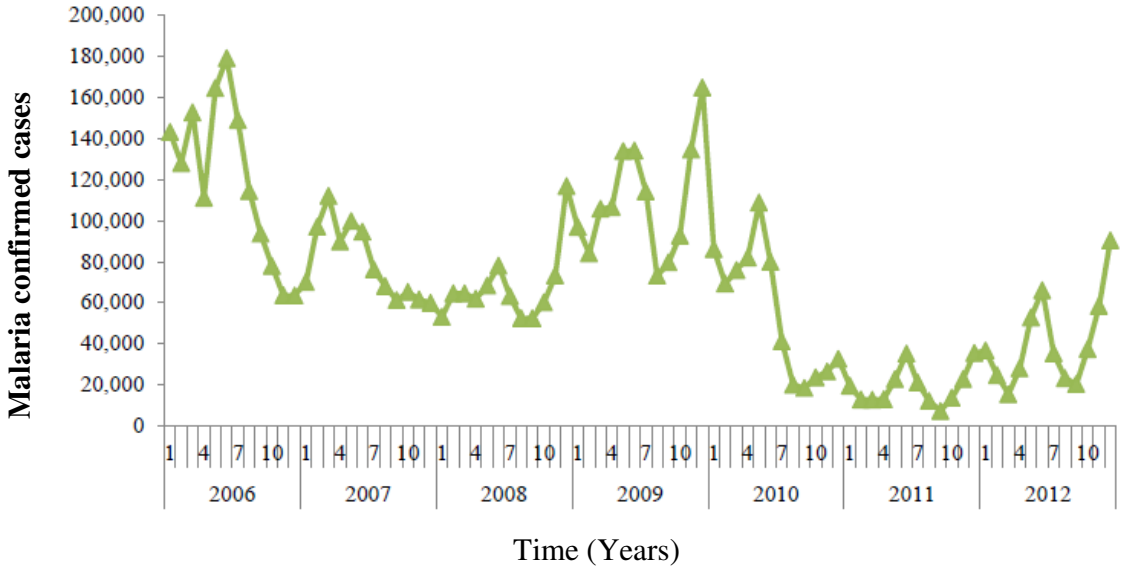


Figure 31 : Rwanda Out-Patient Department Malaria Cases (presumed and confirmed), 2006–2012

(Source: MINISANTE, 2013)

The same pattern was observed on Figure 13 where before 2006 there was still a high level of out-patients and reduction after 2006 till 2009. In late 2009 and early 2010, there was a slight increase of malaria which was due to lack of LLIN durability and subsequent loss of impact according to President's Malaria Initiative (2014) that reduced again in the late of 2010. The year 2013 was characterised by high increase of malaria incidence and onward.

In Rwanda, Malaria had two distinct periods as data indicated, the first period was 2006 – 2010 where malaria was being controlled, in some areas zero case could be recorded except 2009 where control had a problem of LLIN delay, and the second period 2011 - 2014, where malaria increased exponentially, the reason for this increase was many, as Minister of health confirmed, but climate change was among them (Gahima, 2015). Ministry of Health (2013), reported significant increase of uncomplicated malaria cases from 478,162 in 2012 to 938,384 cases in 2013 what put malaria on the second position of morbidity in 2013, while WHO Global Malaria Program (2015) reported tripling of malaria cases till 2015.

5.1 Relationship of climate variables and malaria prevalence in Rwandan highlands.

Data analysis and interpretation revealed that incidences of malaria was influenced by the seasons. According to Greek physician Hippocrates (about 400 BC) epidemics are related to seasonal weather changes, he wrote that physicians should have "due regard to the seasons of the year, and the diseases which they produce, and to the states of the wind peculiar to each country and the qualities of its waters" (McMichael *et al*., 2003)

Malaria transmission occurs year-round with two distinct peaks (May-June, November-December) in the endemic zones following distinct rainy seasons (MINISANTE, 2011). In addition to climate and altitude as determined in this study, other factors that influence malaria in the country were discussed by (Biziman*, et al*., 2015), included high human concentration (e.g., boarding schools in proximity to marshlands) for example in Muhanga and Karongi; population movement (especially from areas of low to high malaria transmission) for example in Rubavu; irrigation schemes (especially in the eastern and southern parts of the country) for example in Muhanga; and cross-border movement of people (especially in the western, eastern and southeastern parts of the country) for example in Rubavu, a busy town near Goma-Congo.

Although the country's figure shows malaria transmission peaks in May/June and November/December each year, Figure 14, indicated slight difference where March shows another important peak of transmission in Karongi and Muhanga, while in Rubavu another peak was observed in February. December shows a decrease instead of showing a peak. May/June's transmission peak remains throughout the area of study.

Since geographical and seasonal distributions of many infectious diseases are linked to climate, the possibility of using climate parameters as predictive indicators in disease EWS has long been a focus of interest (Kuhn *et al.,* 2005). The geographical distribution and population dynamics of insect vectors are closely related to patterns of temperature, rainfall and humidity.

5.2 Seasonal variation of Malaria

Seasonal analysis of malaria incidence indicated how climate variation influenced the variation of malaria prevalence in Rwandan highlands. It was confirmed that rainfall plays an important role in the creation of breeding sites for vectors as it can flush away the mosquitoes' breeding sites (Wilson, 2001). Though relative humidity and temperature play an important role in the survival and longevity of the mosquito vector, it is rainfall that regulates the development rate of both mosquito and parasite to complete lifecycle (The different variation of climate parameters are on appendix 6). When relative humidity drops below 50% to 60%, it is believed that malaria transmission cannot occur because of the reduced lifespan of mosquitoes (Mohammed *et al*., 2012, Eldridge, 2009). The mean relative humidity throughout the year was between 63.28% and 73.87%, which means relative humidity is not a limiting factor for malaria transmission in the highlands of Rwanda.

The findings of this study support the result of (Craig *et al.,* 1999) and (McMichael *et al.,* 2003), that transmission of malaria varies with weather, which affect the ability of the main carrier of malaria parasite, *Anopheline* mosquitoes to survive. Tropical temperate areas including Rwanda have the best combination of adequate rainfall, temperature and humidity allowing breeding and survival of *Anopheline* mosquitoes.

Also, the results of this study are in conformity with the findings of IPCC (2001) that malaria transmission is associated with changes in temperature, rainfall, humidity as well as the level of immunity of community in highland area. Very high temperatures are lethal for the parasite as it is for lower temperature. In areas where the annual mean temperature, is close to tolerance limit of the parasite, a small temperature increase would be lethal for the parasite. IPCC noted that at low temperature, a small increase in temperature can greatly increase the risk of malaria; this was observed in Rubavu where temperature slightly increased in the period of study.

5.3 Discussion of multiple linear regression analysis of malaria incidence against climate variables

A multiple linear regression was done to predict malaria incidence based on temperature (maximum, minimum and average of temperature), rainfall and relative humidity. The model was produced for future prediction.

Karongi

Regression analysis of malaria incidence and maximum temperature, rainfall and relative humidity showed a significant result with *F-statistic* = 95.134, $p < 0.001$, and Adjusted R squared = 0.47 or 47%. As shown in Table 4 (a), except relative humidity, other predictors had significant zero-order correlation with malaria incidence at 5% significance level. Relative humidity did not have a significant partial effect in the full model but maximum temperature and rainfall had significant partial effects. Relative humidity functioned as a suppressor variable. When other predictors were ignored, maximum temperature was negatively correlating with malaria incidence.

Climatic values showed that maximum temperature provided suitable conditions for malaria development; the maximum temperature ranged between 24.26^{o}C and 26.76^{o}C, which are the optimum conditions for malaria development. Rainfall was above the minimum requirement for malaria development; 80mm except in 2011 that was 67.7mm. Relative humidity showed gradual decrease but remained in the range of favourable conditions for malaria development above 60% and below 100%.

The regression coefficient of maximum temperature was negative, which means high temperature value became a limiting factor for malaria transmission (Anderson *et al.,* 2008). As temperature approaches 31^{o}C transmission becomes impossible. Hence we would expect an inverse relationship with high temperature. With the range of malaria development, for each increase of a degree on maximum temperature, it is expected that malaria prevalence will decrease by 46.23 when rainfall is held constant, while for rainfall each additional mm of rainfall increases malaria transmission by 0.132 factor when maximum temperature remain constant.

Regression analysis using minimum temperature, rainfall and relative humidity yielded a significant equation with *F-statistic* = 41.98, $p < 0.001$, adjusted R squared = 0.27 or 27%. As shown in Table 4 (b) except minimum temperature, other predictors had significant zero-order correlation with malaria incidence at 5% significance level. Minimum temperature did not have a significant partial effect in the full model but rainfall and relative humidity had significant partial effects. When other predictors were ignored, relative humidity was negatively correlating with malaria incidence.

Climatic values showed that minimum temperature was below the requirement range for malaria development; its value was 14^{o}C and 15^{o}C, because minimum temperature for malaria development is 16^{o}C and 17^{o}C. Minimum temperature was not a good malaria development predictor. Rainfall and relative humidity remain suitable for malaria prediction.

The intercept value was 58.83 which is the prevalence of malaria when predictors, relative humidity and rainfall are absent. This value represents other factors, except those mentioned predictors, that can increase malaria prevalence. Regression coefficient for rainfall is positive, which shows that in Karongi rainfall is still at low level to be limiting factor for malaria development since it varied between 111.5mm and 122.4mm. Observation showed the values above 80 mm of 4 preceding months of malaria peak and the trend of rainfall was positive with time. It means for each mm of the rainfall increases, is expected to increase malaria prevalence by 0.18 factors, if relative humidity remains constant. Hence it is expect a positive relationship of malaria prevalence with rainfall.

The variable relative humidity shows inverse relationship: the more is the relative humidity the less is the prevalence of malaria. Since malaria development is limited by the values below 50% and near 100%, the values of rainfall in Karongi varied between 68 and 75%. So far the negative sign for this coefficient is justified. For each additional percent of relative humidity it is expected to decline malaria by 14.33 factors when rainfall is held constant. Observation showed a decline of relative humidity which means that the area is at the risk of malaria transmission. Despite the omission of minimum temperature from the model according to Githeko & Ndegwa (2001), it

was found that in western Kenya (the area similar to Rwandan highlands), nighttimes temperatures inside village houses, where mosquitoes spend most of the time resting, are generally two to three degrees warmer than outdoor ambient temperatures. This temperature can approach favourable conditions for malaria development once indoor temperature is considered.

Regression analysis using mean temperature, rainfall and relative humidity showed a significant equation with *F-statistic* = 86.46, $p < 0.001$, adjusted $R^2 = 0.44$ or 44%. As shown in Table 4.c, except relative humidity, other predictors had significant zero-order correlation with malaria incidence at 5% significance level. Relative humidity did not have a significant partial effect in the full model, but mean temperature and rainfall had significant partial effects. Relative humidity functioned as a suppressor variable. When other predictors were ignored, mean temperature was negatively correlating with malaria incidence.

Mean temperature which resulted from average between maximum and minimum temperature, provided suitable conditions for malaria development; its value varied between 19.5^{o}C and 20.26^{o}C, the range of minimum conditions for malaria vector and parasite development. Rainfall remained in the prediction system while relative humidity was concealed by average of minimum temperature and maximum temperature from the prediction.

The intercept value of 232.69 is the response of malaria prevalence when other predictors (mean temperature and rainfall) are equal to zero. It is the point where regression equation crosses the Y-axis. The regression coefficient for mean temperature is negative. Hence it is expected to have inverse relationship for each degree the mean temperature increases; it is expected that malaria prevalence will decrease by a factor of 78.34. Minimum temperature could not predict malaria prevalence in Karongi. The combination of minimum and maximum temperature was contributing negatively to malaria prevalence if relative humidity was deleted from the model. This simply means temperature values showed favourable conditions for malaria transmission, between 19.5 and 20.2^{o}C.

Rainfall showed positive relationship with malaria development. Each additional mm of rain fall was expected to increase prevalence of malaria by factor of 0.14 factors, if mean temperature was held constant.

Muhanga

Regression analysis using maximum temperature, rainfall and relative humidity yielded a significant result with *F-statistic* = 155.46, $p < .001$, and adjusted R squared = 0.59 or 59%. As shown in Table 5 (a), all predictors did not have significant effect in the full model at 5% significance level. When the other predictors were ignored, maximum temperature and rainfall were negatively correlated with malaria incidence.

Maximum temperature between 25.6^{o}C and 27.26^{o}C in Muhanga provided optimum conditions for malaria development. Rainfall was unstable; Muhanga is on the border of malaria endemic zone where intense activities for malaria control take place (Hakizimana *et al*., 2014). Muhanga indicated the highest value of rainfall among other Districts of study in 2014 when it was 235.21mm. Given that a large part of Muhanga is located in the plateau, according to Philander (2008) the amount of rainfall decreases with altitude as well as moisture content. This can be seen by comparing rainfall within the plains and within the central parts of the vast plateau. In other years rainfall average was above 80mm while relative humidity was between 58.53% and 61.8%, relatively low but was still in the range of malaria development.

Muhanga is in the moderate-high malaria transmission regions, the highest risk of death from malaria is observed in infants and young children, whilst semi-immune adults remain susceptible to asymptomatic parasitaemia, but protected against clinical disease (Maestre & Carmona-Fonseca, 2014). Here data used was a combination of all possible cases in Muhanga as applied by (Yu et al., 2013).

Analysis of data indicated extreme weather in 2014 where rainfall stood at 235.22 mm with total average of 143.72mm, which swept away breeding mosquitoes. Malaria in that period was not significant (Anaxos, 2008). But in Muhanga and other districts of southern and western provinces, malaria incidence remained relatively high during malaria post intervention period (Karema *et al*., 2012), but negatively correlating with heavy rainfall.

Regression analysis results using minimum temperature, rainfall and relative humidity yielded a significant equation with *F-statistic* = 158.64, $p < 0.001$, and adjusted R squared = 0.58 or 58%.

It was observed that only prediction with minimum temperature was possible at 5% significant level. As shown in Table 5 (b), other predictors did not have significant effect on the full model at 5% significance level. When other predictors were ignored, rainfall was negatively correlating with malaria incidence.

Significant reduction of minimum temperature remained above the threshold for *Anopheles gambiae* mosquito vector (the main mosquito species found in the East African highlands) whose biological activity is between 8^{o}C to 10^{o}C (Dekens *et al.,* 2013), This value of minimum temperature stood between 14.6.6^{o}C and 15.2^{o}C. While the minimum temperature threshold for transmission of the *Plasmodium falciparum* parasite (the main parasite species found in the East African highlands) is 16^{o}C to 19^{o}C, temperature is lower at night than day time. According to Githeko (2010), due to the influence of diurnal maximum temperature (27^{o}C), maturity of malaria parasite may take almost 8 days only which is less than its lifespan of 23-days average of Anopheles *gambiae mosquitoes.*

The intercept was -8.33 the value of malaria prevalence when minimum temperature was absent. This value represents other factors, except the stated predictors, that can decrease malaria prevalence. Regression coefficient with minimum temperature was positive, which shows that in Muhanga minimum temperature was still at a low level to be a limiting factor for malaria development since it varied between 14.15^{o}C and 15.04^{o}C, compared to the minimum temperature for malaria parasite development which ranged between 14^{o} and 19^{o}C (Deressa *et al*., 2005). This range gives limited conditions for malaria transmission. It means that each additional degree of minimum temperature is expected to increase malaria prevalence by factor of 2.91. Hence we would expect a positive relationship of malaria prevalence with minimum temperature in Muhanga.

Regression analysis using mean temperature, rainfall and relative humidity yielded, a significant equation with *F-statistic* = 155.12, $p < .001$. R^2 = 0.59 or 59%. As shown in Table 5(c) all predictors did not have a significant effect on a full model at 5% significance level. When other predictors were ignored, relative humidity was negatively correlating with malaria incidence.

The mean temperature fell within the minimum conditions of malaria transmission (19.2^{o}C and 20^{o}C) but again malaria transmission depended on season and altitude. Githeko & Ndegwa (2001) argued that *"if the mean annual temperature is superior, or equal, to 18^{o}C; anomalies superior or equal to 3^{o}C would be expected to precipitate malaria outbreaks as long as the mean monthly rainfall is greater than 150 mm."* Here mean temperature was higher than 18^{o}C, long term anomalies was higher than 3^{o}C but rainfall was below 150 mm, so malaria outbreak was expected despite the absence of significant effect in the full model at 5% significance level.

Rubavu

Regression analysis using maximum temperature, rainfall and relative humidity showed a significant result with *F-statistic* = 20.96, $p < 0.001$, adjusted R squared = 0.19 or 19%. As shown in Table 8(a), except rainfall, other predictors had significant zero-order correlation with malaria incidence at 5% significance level. Rainfall did not have a significant partial effect in the full model but maximum temperature and relative humidity did have significant partial effects.

The increase of maximum temperature in Rubavu between 2011- 2014 with 4 units, exposed this area to high risk of malaria. Compared with malaria parasite and parasite survivorship, maximum temperature was higher than 18^{o}C, this implied that parasite development was too fast despite the low prevalence of malaria on Figure 13. The model showed that rainfall was a limiting factor for malaria prediction since it showed no significance level; but remained in the range of malaria transmission because it was between 81.33 mm in 2013 and 140.33 mm in 2011. Relative humidity was also in the range of malaria transmission; 78.65% and 73.19%, simply there was reduction of relative humidity that expected to increase transmission rate. Rubavu is in highest altitudes of the country; but according to Lindsay & Martens (1998) the highlands area are unstable for malaria pattern, because of the low and flucturating levels of transmission experienced by local community. Many of these community have no or less immunity.

The intercept was -52.31 which the prevalence of malaria is when predictors; maximum temperature and relative humidity are absent, this value represents other factors, except those predictors mentioned, and that can have impact on malaria prevalence.

Each additional degree on the maximum temperature in Rubavu, was expected to increase malaria prevalence about 9.99 factors, holding other variables constant. The same is the increase of each percentage of relative humidity that causes the prevalence of malaria to increase by factor of 4.3 while holding maximum temperature constant.

Minimum temperature was too low to facilitate malaria transmission as Table 6 (b) indicated. No temperature reached the threshold of either parasite or vector development. The range was between 7.56^{o}C in 2011 and 13.94^{o}C in 2013. With the value, malaria transmission was not possible. The same was observed for combination with rainfall and relative humidity. Model equation was not possible at 5% significance level.

Minimum temperature gave unfavourable conditions for malaria development in Rubavu, when combined with rainfall and relative humidity. Spatial variation of malaria incidences was observed in Rubavu; as altitude increases, malaria prevalence decreases.

Regression analyisis using mean temperature, rainfall and relative humidity gave significant equation with *F-statistic* = 10.98, p <0 .001, and adjusted R squared = 0.10 or 10%. As shown in Table 8(c), all predictor had a significant zero-order correlation with malaria incidence at 5% significance level and had significant partial effect in the full model, but rainfall was negatively correlating with malaria incidence, while other predictors were positively correlating with malaria incidence.

Mean temperature gave a good result for malaria incidence prediction in Rubavu. Combination of temperature (minimum 13.16^{o}C and maximum 18.13^{o}C) created minimum conditions for malaria and parasite development, as R^2 value indicated. Malaria in Rubavu was not high but trend was showing that it was at high risk of malaria in the future.

This is the only case where the model showed inclusion of all predictors. Rubavu is the indicator of climate variability and malaria adaptation in Rwandan highland. The predictive model indicated that while holding all predictors as equal to zero, the value of malaria prevalence would be -31.73/1000 it meant other factors, except temperature, rainfall and relative humidity, reduced malaria prevalence.

The influence of temperature, rainfall and relative humidity on malaria incidence in Rwandan highland was tested using regression analysis according to the following hypothesis:

H_o: $b_1 = b_2 = b_3 = 0$ (There was no influence of temperature, rainfall and relative humidity on malaria incidence in Rwandan highland.) regression coefficients are 0 ($\hat{y} = b_o$).
The alternative hypothesis was:
H_1: $b_1 \neq b_2 \neq b_3 \neq 0$, not all the b_s are zero. (There is an influence of temperature, rainfall, relative humidity on malaria incidence in Rwandan highland.) Regression coefficients are b_1, b_2, b_3 ($\hat{y}= b_0 + b_1x_1 + b_2x_2 + b_3x_3$ are valid).
From the Table 7, observation of regression equation indicated the values of b_s different from 0, so null hypothesis is rejected and alternative hypothesis is retained at 5% significance level.

5.4 Predicting malaria epidemics

Like in Kenya as predicted by Githeko and Ndekwa (2001), epidemic malaria in the Rwandan highlands is caused by *Plasmodium falciparum* species and transmitted by *Anopheles gambiae s.s.* and *Anopheles funestus* mosquitoes as confirmed by Ministry of Health (2013).

Malaria epidemic in western Rwanda generally occurs in areas at altitudes of between 1500-2500 meters above sea level, where the annual mean daily temperature varies between 16-21°C as Figure 32 indicates. Topographically, these areas consist of river valleys, hills, and plateaus. The epidemics normally occur in June and November following the long rains and a short outbreak in March following the irregularity of rainfall occurred in January and February.

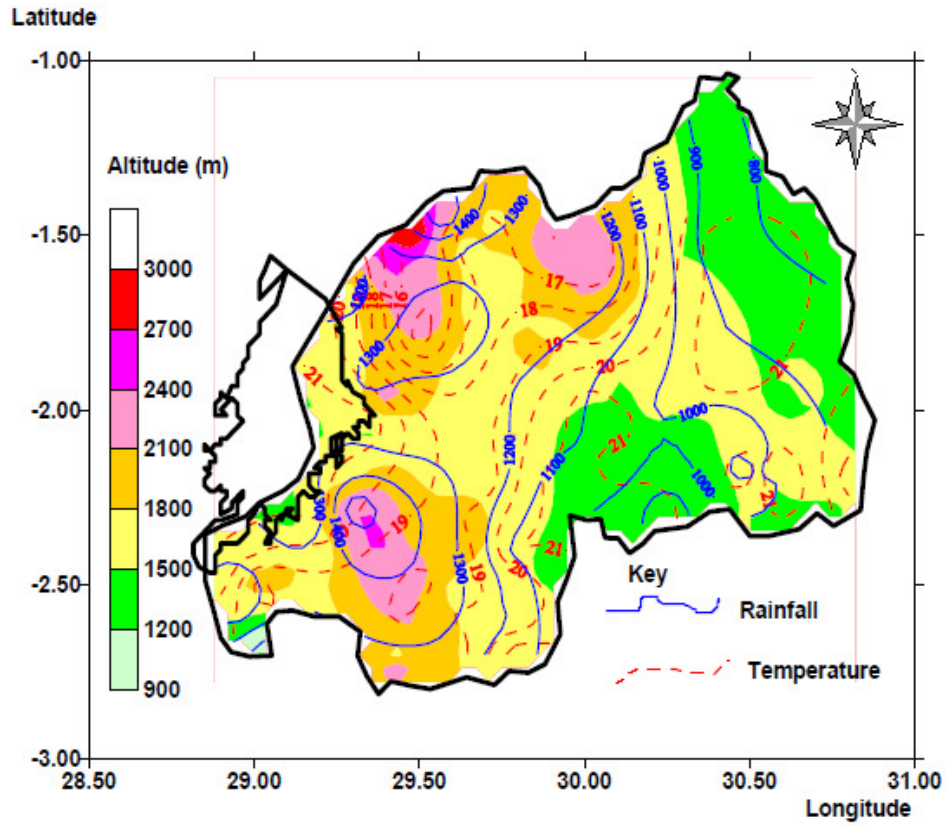


Figure 32: Elevation and climate elements

5.5 Time series analysis and forecasting changes in the incidence of malaria attributable to climate variation

The last objective of this study was to develop a model that predicts changes in the incidence of malaria attributable to climate variation. Malaria exhibits seasonal variation, and peaks are expected after periods of rainfall. The life cycle of a mosquito last maximum 30 day corresponding to one month, in the model this month is a lag period, because malaria does not come immediately after the rain, it requires time to complete the cycle. Time series analysis was based on data recorded over time, seasonal indices were calculated for every month as equation (8) indicate. The model generated is susceptible to indicate how much the people from highland areas are at the risk of having malaria.

Time series plot on Figures 19 and 20 indicated malaria seasonal incidence which is higher in the months of January, June and November-December of each year and decrease in the months of April, July and October in Karongi. For Muhanga, the Figures 21 and 22 indicated malaria seasonal incidence which is higher in the months of, June and November of each year and decrease in the months of April and July, while in Rubavu Figures 23 and 24 indicated malaria seasonal incidence which is higher in the months of January, May-June, August-September and November-December of each year and decrease in the months of March-April, and September-October. Thus, a seasonal pattern exists for malaria transmission. But the time series also had an upward linear trend that was accounted for in order to develop accurate forecasts of monthly malaria transmission as Tables 8, 9 and 10 indicated.

The usefulness of forecasting method in predicting the number of disease incidence is important. It explains the development of a system that can predict the future number of disease occurrences. Fluctuation analysis of forecasting result can be used to support the making of policy by the stakeholder. This study analysed and presented the use of Seasonal Autoregressive Moving Average (SARMA) method for developing a forecasting model that is able to support and provide prediction number of malaria incidence in community.

The model generated was validated using published data for it accuracy. Modelled results in 2016 have some uncertainties because as RBC (2017) indicated, there was a campaign all over the country for malaria control; distribution of LLIN was enhanced with IRS in malaria endemic districts, so malaria cases started reducing. The results of modelling on Figures 19, 21 and 23 indicated seasonal variation similar to what has been published by MINISANTE (2013), Karema *et al.,* (2012) and Bizimana, Twarabamenye, & Kienberger, (2015), model also indicated two annual malaria peaks; in June and November. Based on these evidences the model was validated.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.0 Introduction

This study involved the analysis of the impacts of climate variability on malaria prevalence in Rwandan highlands. Data collected from 3 selected districts of highlands were used

- to determine the variation of temperature, rainfall and relative humidity in Rwandan highlands for the period of 11years,
- to determine malaria incidence in Rwandan highlands for the period of 11 years,
- determine the relationship between meteorological parameters and malaria incidence in Rwandan highlands and
- to model and predict changes in the incidence of malaria attributable to climate variation.

Secondary data collected from the health centres (malaria cases) and meteorological data (temperature, rainfall and relative humidity), in the districts of Karongi, Muhanga and Rubavu, were analysed using correlation coefficient, multiple linear regression analysis, finally the model was generated and validated using published data in the predicted years. Finally the conclusion and recommendation were drawn from the results of the study:

Maximum temperature did not have high variation; it was in the range of 23 and 25^{o}C, while minimum temperature varied considerably with a range of 8.02 and 14.55, average of minimum and maximum indicated linear growth as it combines the values of maximum and minimum temperature (16.34 and 19.54^{o}C).

Rainfall was increasing throughout the period of study with high variation and extreme weathers; the monthly average was between 95.62 to 156 mm. In Karongi it varied between 87.00 to 122 mm, Muhanga varied between 80.63 to 235 mm and Rubavu varied between 81.33 to 136 mm. Relative humidity was also important, its variation was not too high since the highest value of relative humidity was 72.24% and the lowest was 66.10%. Generally relative humidity was decreasing with time.

Malaria incidence indicated high variation data collected were indicating two different periods; from 2004 important reduction of malaria incidence was observed that arrived at almost null in

2011; (14.44/1000 in 2004 to 0.08/1000 in 2011). From 2011 there was increase of malaria cases till 2014 (0.008/1000 to 5.73/1000) and onward.

Literature review and theories indicated different thresholds for malaria development and transmission, which allowed quantifying the risk of highland areas of Rwanda to malaria incidences. It was showed that minimum temperature remained above the threshold for *Anopheles gambiae* mosquito vector (the main mosquito species found in the East African highlands) for its biological activity (8^oC to 10^oC). The minimum temperature in study area was between 8.03^oC to 14.55^oC. While the threshold of minimum temperature for transmission of the *Plasmodium falciparum* parasite (the main parasite species found in the East African highlands) was 16^oC to 19^oC.

Regression analysis using malaria prevalence as dependent variable, with lag period of 1 month, and climate parameters as independent variable (maximum, minimum and average temperature, rainfall and relative humidity), showed that all predictors had different impacts at 5% of significance level. All the selected climate parameters were not correlating with malaria transmission at the same level; in Karongi malaria prevalence had a strong positive correlation with: maximum temperature and rainfall, r=0.68, a moderate positive correlation with rainfall and relative humidity, r=0.5 and a strong positive correlation with average temperature and rainfall, r=0.66. In Muhanga malaria prevalence had a positive strong correlation with minimum temperature r=0.76, while in Rubavu malaria prevalence had a weak positive correlation with maximum temperature and relative humidity, r=0.44 and a weak positive correlation with average temperature, rainfall and relative humidity r=0.33. Regression equation indicated the values of coefficient b_s different from 0, what validate alternative hypothesis and rejection of null hypothesis at 5%.

Results of prediction indicated the value of ρ higher than 0, what means climate variability has influence on future malaria incidence in Rwandan highlands. Null hypothesis was rejected for three districts, while alternative one is valid.

Analysis of results indicated that Karongi is expected to have high malaria incidence in the future due to climate variability followed by Muhanga, and Rubavu as confirmed by the results of analysis.

6.1 Recommendations

After carrying out this study some recommendations were formulated, specifically for the benefits to the government of Rwanda and population at large.

Temperature, important factor of climate has varied in highlands of Rwanda in the period of study; with important variation of minimum temperature and less for maximum. Monitoring and investigation on the causes are needed for proper mitigation measures as this variation may change many climatic conditions.

Highlands of Rwanda were the regions with moderate rainfall, but it has become unstable with high variability. In some periods rainfall is rare in others rainfall is high and causes disasters like floods. Therefore, climatic data should be used for the benefits of local population like in prediction of rain or dry seasons for better preparation.

Relative humidity is decreasing in the highland areas of Rwanda; it is expected to reduce productivity and increase of adaptation of new species including diseases.

Meteorological variables are among the factors that precipitate malaria epidemic; rainfall provides the breeding sites for mosquitoes, and higher temperature and relative humidity increase mosquito survival and parasite development.

Malaria is invading new areas including highlands that used to be shelters against malaria, but the altitude above 2600 m above the sea level, Malaria is still rare and its adaptation is still impossible.

The Rwandan highlands are fragile ecosystems under pressure from rising population, deforestation, and increase farming. The upland communities do not access easily to health services and the services they benefit are patchy, control of malaria may be difficult. It needs a distinct initiative to define epidemic-prone area and use the finding from this research to develop solutions to protect vulnerable communities of highlands of Rwanda from this growing problem.

In prediction using climate variability, it is highly commendable to use seasonal input so that effort can put where it is needed: Example preparation of medication and other malaria control measures just after rain season because it is the time when malaria can be on high rise

Facilitation and motivation of more research on communicable diseases in relation to climate change especially in the highlands of Rwanda is needed, as climate change is shifting diseases' ecology.

It is recommended to include the region of highlands in the program of malaria control like LLIN and IRS in the next malaria control program, because malaria with temperature resistant vectors are expected in this region.

For the entire country of Rwanda, people should sleep each night under an insecticide-treated bed net for self protection of mosquito bites.

Malaria resurgence in Rwanda is at the unusual speed in endemic areas, as it is invading new areas of Rwanda. It is recommended to combine control with environmental cleaning like reducing the possible water retaining area (breeding sites), reduction of poorly planned exploitation of natural resources of highland (illegal logging, mining activities,…), reduction of bush, living together for proper infrastructure (proper physical plan), good housing especially eliminating mosquitoes in house during the night.

6.2 Future research

Research similar to this one is needed, focusing on other predictors not covered in this research like; land use change and land cover, socio-economic development of people living in the

highlands of Rwanda in combination with effort made to reduce malaria in the period 2005-2011 and what is needed to fully control malaria.

Comparative study that cover the entire country to compare malaria prevalence and global climate change in lower-land and highland of Rwanda

Research on the linkages between climate and infectious diseases must be strengthened. In most cases, these linkages are poorly understood and research to understand the causal relationship is not well understood. This can best be accomplished with investigations that utilize a variety of analytical methods (including analysis of observational data, experimental manipulation studies, and computational modelling), that examine the consistency of climate/disease relationships in different societal contexts and across a variety of temporal and spatial scales.

Research on climate and infectious disease linkages inherently requires interdisciplinary collaboration. Studies that consider the disease host, the disease agent, the environment, and society as an interactive system will require more interdisciplinary collaboration among climate modellers, meteorologists, ecologists, social scientists, and a wide array of medical and public health professionals.

There is a need for a better understanding of the global forces such as global heating and extreme weather events with diseases (e,g Eli Niño) and their impact on increase and/or transmission of malaria.

REFERENCES

1st Rwanda Malaria Forum. (2012). *Towards Malaria Pre-Elimination: How to sustain achievements and Get to zero Malaria deaths in Rwanda.* Kigali: nmcprwanda.

Anaxos, I. (Ed.). (2008). *U_X_L Encyclopaedia of Weather and Natural Disasters.* Detroit: Thomson Gale.

Anderson, D. R., Sweeney, D. J., & Williams, A. T. (2008). *Statistics for business and Economics IIe.* Mason: South-Western Cengage Learning.

Aron, J. L., Shiff, C. J., & Buck, A. A. (2001). Malaria and Global Ecosystem Change. In J. L. Aron, & J. A. Patz (Eds.), *Ecosystem change and public health : a global perspective* (pp. 353-373). Baltimore: The Johns Hopkins University Press.

Ayanleh, D. A. (2010). *An analysis and prediction of the possible impacts of climate change on the future distribution of the vector-borne disease Malaria in Panama.* Clayton: CATHALAC.

Becker, N., Petric, D., Zgomba, M., Boase, C., Dahl, C., Madon, M., et al. (2010). *Mosquitoes and their Control* (Second ed.). New York: Springer.

Beniston, M. (2002). Climatic change: possible impacts on human health. *Climatic change and human health , 132*, 332–337.

Bettina, M. (2005). Extreme Weather Events and Health:An Ancient New Story. In W. Kirch, B. Menne, & R. Bertollini, *Extreme Weather Events and Public Health Responses.* Berlin: Springer.

Bizimana, J. P. (2015). *Climate Variability and Malaria in Rwanda: Spatial Assessment of Social Vulnerability at Different Scale Levels.* Huye: University of Rwanda.

Bizimana, J. P., Twarabamenye, E., & Kienberger, S. (2015). Assessing the social vulnerability to malaria in Rwanda. *Malaria Journal , 12* (2).

Blanford, J. I., Blanford, S., Crane, R. G., Mann, M. E., Paaijmans, K. P., Schreiber, K. V., et al. (2013). Implications of temperature variation for malaria parasite development across Africa. *Scientific Report , 3* (1300).

Bouma, M., Dye, C., & van der Kaay, H. (1996). Falciparum malaria and climate change in the North West Frontier Province of Pakistan. *American Journal of Tropical Medicine and Hygiene , 55*, 131-137.

Brian, H. (2009). *Raview of aconomic impacts of climate change in Kenya Rwanda and Burundi.* Kigali: Ecosystem Chapter.

Brundtland, H. (1999). Speech on World Meteorological Day. *Climate change and Helath.* Geneva: Commission on climate Change and Development.

Bryan, F. J., & Manly, B. F. (2000). *Statistics for Environmental Sciences.* Boca Raton: Chapman and Hall/CRC.

CHAI; E2Pi. (2011). *Maintaining the Gains in Malaria Control.* California: ALMA.

Chapin III, F. S., Matson, P. A., & Mooney, H. A. (2012). *Principles of Terrestrial Ecosystem Ecology.* New York: Springer-Verlag.

Chaves, L., & Pascual, M. (2007). Comparing models for early warning systems of neglected tropical diseases. *PLoS Neglected Tropical Diseases* , 1, 1-6, doi:10.1371/journal.pntd.0000033.

Chemonics International Inc. (2003). *Rwanda Environmental threat and opportunities asssessment.* Kigali: REMA.

Chua, T. H. (2011). Modelling the effcts of Temperature change on the extrinsic incubation period and reproductive number of Plasmodium faliciparum in Malasiya. *Tropical Biomedecine , 29* (1), 121-128.

Commission of the European Communities. (2009). *Adapting to climate change: Towards a European framework for action.* Brussels: European Union.

Committee on Climate, Ecosystems, Infectious Disease and human health and others. (2001). *Under the Weather: Climate, Ecosystem and Infectious Disease.* Washington D.C: National Academy Press.

Committee on Mathematical Foundations of Verification, Validation, and Uncertainty Quantification. (2001). *Assessing the Reliability of Complex Models: Mathematical and Statistical Foundations of Verification, Validation, and Uncertainty Quantification.* Washington DC: The National Academies Press.

Craig, M. H., Snow, R. W., & Sueur, D. (1999). A Climate-based Distribution Model of Malaria Transmission. In *Sub-Saharan Africa Parasitology Today* (Vol. 15 No 3).

Cresswell, J. W. (2009). *Research Design: Quantitative, Qualitative and mixed Methods Approaches* . London: SAGE.

Dekens, J., Jo-Ellen, P., Zamudio-Trigo, A. N., & Echeverria, D. (2013). *Climate Risk Management for Malaria Control in Kenya the Case of the Western Highlands.* New York: UNDP.

Deressa, W., Olana, D., & Chibsa, S. (2005). Community participation in malaria epidemic control in highland area of southern Oromia, Ethiopia. *Ethiopian Journal Dev. , 19* (1).

DFID. (2009). *Economics of Climate Change in Rwanda* . Oxford: Stockholm Environment Institute.

Dziedzic, N. (Ed.). (2010). *Malaria: Perspectives on diseases and disorders.* Detroit: Gale.

Eldridge, F. E. (2009). Mosquitoes. In V. H. Resh, & R. T. Carde (Eds.), *Encyclopaedia of Insects* (p. 658). Oxford: Elsevier.

Feenstra, J. F., Burton, I., Smith, J. B., & Tol, R. S. (1998). *Handbook on Methods for Climate Change Impact Assessment and Adaptation Strategies.* Amsterdam: United Nations Environment Programme (Vrije Universiteit).

Freeman, T., & Bradley, M. (1996). Temperature is predictive of severe malaria years in Zimbabwe. *Transactions of the Royal Society of Tropical Medicine and Hygiene , 90* (232).

Gahutu, J.-B., Steininger, C., Shyirambere, C., Zeile, I., & Cwinya-Ay, N. (2011). Prevalence and risk factors of malaria among children in southern highland Rwanda. *Malaria Journal , 10* (134), 1-12.

Githeko, A. K. (2010). *Model For Early Prediction of Malaria Epidemics in East African Highlands.* Nairobi: Kenya Medical Research Institute.

Githeko, A. K., Lindsay, S. W., Confalonieri, U. E., & Patz, J. A. (2000). *Climate change and vector borne diseases: A regional analysis Belletin of the World Health Organisation.*

Githeko, A. K., Ogallo, L., Lemnge, M., Okia, M., & Ototo, E. (2014). Development and validation of climate and ecosystem-based early epidemic prediction models in East Africa. *Malaria journal , 13* (239).

Githeko, A. (2009). Malaria and climate change. *Commonwealth Health Ministers' Update* , 40-43.

Githeko, A., & Ndegwa, W. (2001). Predicting malaria epidemics in the Kenyan highlands using climate data: a tool for decision makers. *Global Change and Human Health , 2* (1), 54-63.

Goosse, H., Barriat, P. Y., Lefebvre, W., Loutre, M. F., & Zunz, V. (2010). *Introduction to climate dynamics and climate modelling.* Retrieved April 13, 2012, from Fonds de Dévelopment Pédagogique of the Université Catholique de Louvain: http://www.climate.be/textbook

Grasso, M., Manera, M., Chiabai, A., & Markandya, A. (2010). *The Health Effects of Climate Change: A Survey of Recent Quantitative Research* (BC3 Working Paper Series 2010-16 ed.). Bilbao: Basque Centre for Climate Change.

Habiyaremye, G. (2011). *Analysis of Enthropogenic and Regional Climate Change Impacts on Ecological and Malaria Distribution in Eastern Rwanda.* China University of Geo sciences. Wuhan: School of Environmental Studies.

Hales, S., & Woodward, A. (2003). Climate Change will increase demand on malaria control. *The Lancet* , 1792.

Hartmann, D. L. (2016). *Global Physical Climatology* (2nd ed.). Amsterdam: Elsevier.

Hedt-Gauthier, B. (2014). *Population Survey Analysis.* eLearning Support.

HImeidan, Y. E., & Kweka, E. J. (2012). Malaria in East African Highlands during the past 30 years:. *Impact of Environmental changes , 3*, 315.

IPCC. (2002). *Climate Change 2001 Third Assessment Report* (Vol. Volume I). Cambridge: UK Cambridge University Press.

IPCC. (2007). *Climate Change 2007: Impacts, Adaptation and Vulnerability. Summary for policy makers.* Cambridge: Cambridge Univesity Press.

IPCC. (2002). *Climate Change and Biodiversity.* Cambridge: Cambridge Univesity Press.

IPCC. (2001). *Working group I Third Assessment Report.* Cambridge: Cambridge Univesity Press.

Karema, C., Aregawi, M. W., Rukundo, A., Kabayiza, A., Mulindahabi, M., Fall, I. S., et al. (2012). Trends in malaria cases, hospital admission and deaths following scale-up of antimalaria intervention, 2000-2010 Rwanda. *Malaria Journal , 11*, 236.

Karongi District. (2011). *Baseline Environmental Survey.* Karongi: Rema.

Karongi District. (2013). *District Development Plan (2013-2018).* Karongi: Government of Rwanda.

Kazembe, L. N. (2007). Spatial modelling and risk factors of malaria incidence in northern Malawi. *Acta Tropica , 102*, 126–137.

Kevin, L. D. (2009). The ecology of climate change and infectious diseases. *Ecology , 90* (4), 888-900.

Kiang, R. (2009). *Malaria Modelling and surveillance: Benchmark Report.* London: NASA Goddard Space Flight Center.

Kirck, W. (2008). *Encyclopedia of Public Health.* Fieldlestr: Spring.

Kleinschmidt, I. (2001). *Spatial statistical analysis, modelling and mapping of malaria in Africa.* Durban: Universität Basel.

Kuhn, K., Campbell-Lendrum, D., Haines, A., & Cox, J. (2005). *Using climate to predict infectious disease epidemics.* Geneva: World Health Organisation.

Lafferty, K. D. (2009). The ecology of climate change and infectious diseases. *Ecology , 90* (4), 888–900.

Lieshout, M., Kovats, R. S., Livermore, M. T., & Martens, P. (2004). Climate Change and malaria: Analysis of the SRES climate and Socio-economic scenarios: Global Environmental Change. *Elsevier , 14*, 87-99.

Lind, D. A., Marchal, W. G., & Mason, R. D. (2001). *Statistical Techniques in Business and Economics* (11 ed.). Boston: McGrsw-Hill.

Lindsay, S., & Martens, W. (1998). Malaria in the African highlands: past, present and future. *Bulletin of the World Health Organization , 76*, 33–45.

Loevinsohn, M. (1994). Climatic warming and increased malaria incidence in Rwanda. *The Lancet , 343*, 714-718.

Maestre, A., & Carmona-Fonseca, J. (2014). Immune response during gestational malaria: A review of the current knoeledge and future trend of research. *Journal of Infectious Diseases in Developing Countries , 8* (4), 391-402.

Malakooti, M., Biomndo, K., & Shanks, G. (1997). Reemergence of epidemic highland malaria in the highlands of western Kenya. *Emerging Infectious Diseases , 4*, 671-676.

Marcus, B. (2009). *Deadly Diseases and Epidemics: Malaria* (Second ed.). New York: Infobase Publishing.

Marcy, E. (2004). *Socio-Economic Impacts Asssociated with Climate change health impacts.* Toronto: Health Canada.

Martens, P. (1999). Climate change and future populations at risk of Malaria. *Global Environmental Change , 9*, 89-107.

Matola, Y., White, G., & Magayuka, S. (1987). The changed pattern of malaria endemicity and transmission at Amano in the eastern Usambara mountains, north-eastern Tanzania. *Journal of Tropical Medicine and Hygiene , 90*, 127-34.

Mavrakis, A., & Papavasileiou, H. (2013). Relative humidity and land use changes in an environmentally stressed area (Thriasio Plain – Greece). *Procedia Technology , 8*, 471-476.

McMichael, A. J., & Woodruff, R. E. (2008). Climate and infectiuos diseases. In K. H. Mayer, & H. Pizer (Eds.), *The Social Ecology of Infectious Diseases* (pp. 378-407). London: Elsevier.

McMichael, A. J., Campbell-Lendrum, D., Corvalán, C., Ebi, K., Githeko, A., Scheraga, J., et al. (Eds.). (2003). *Climate change and human health: risks and responses.* Geneva: WHO.

Metz, B. (2010). *Controlling Climate Change.* New York: Cambridge Univesity Press.

MINIRENA. (2006). *National Adapatation Programmes of Action to Climate change in Rwanda.* Kigali: Republic of Rwanda.

MINIRENA. (2013). *Rwanda Second National Communication under the UNFCCC.* Kigali: Republic of Rwanda.

MINISANTE. (2011). *Data Varidation and Verification: Procedure Manual.* Kigali: Republic of Rwanda.

MINISANTE. (2013). *Rwanda Annual health statistics booklet 2013.* Kigali: Rwanda.

MINISANTE. (2012). *Rwanda Health Statistics Booklet.* Kigali: Republic of Rwanda.

MINISANTE. (2011). *Rwanda Malaria Program Performance Review.* Kigali: Republic of Rwanda.

Mohammed, I. M., Shamarina, S., Nor, R. H., & Isthrinayagy, K. (2012). A climate distribution model of malaria transmission in Sudan. *Geospatial Health , 7* (1), 27-36.

Muhanga. (2013). *District Development Plan (2013-2018).* Muhanga: Government of Rwanda.

National Institute of Statistics of Rwanda (NISR) [Rwanda], Ministry of Health (MOH) [Rwanda], and ICF International. (2011). *Rwanda Demographic and Health Survey 2010.* Calverton, Maryland, USA: NISR, MOH, and ICF International.

National Institute of Statistics of Rwanda. (2012). *2012 Population and Housing Census.* Kigali: Republic of Rwanda.

Oaks, S. C., Mitchell, V. S., & Pearson, G. W. (1991). *Malaria: Obstacles and Opportunities.* Washington DC: National Academy Press.

Oleske, D. M. (2002). *Epidemiology and the delivery of health care services: Methodology and application* (Second ed.). New York: Kluwer.

Olivier, J. E., & Hidore, J. J. (2002). *Climatology: An atmospheric Science* (Second Edition ed.). New Jersey: Prentice Hall.

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. (D. L. Denlinger, Ed.) *Ecology , 107* (34), 15135-15139.

Pascual, M., Ahumada, J. A., Chaves, L. F., Rodo, X., & Bouma, M. (2006). Malaria resurgence in the East African highlands: Temperature trends revisited. (B. H. Singer, Ed.) *Ecology , 103* (15), 5829–5834.

Patz, J. A., Sarah, O. H., Uejio, C. K., & Gibbs, H. K. (2008). Disease Emergence from Global Climate and Land Use Change. *Madical the Clinics , 92*, 1473–1491.

Paul, O., & Dirk, W. (2004). Climate change meets habitat fragmention linking landscape and biogeographical scale levels in research and conservation. *Biological conservation* , 117, 285-297.

Philander, S. G. (Ed.). (2008). *Encyclopaedia of global Warming and Climate Change* (Vol. 1 and 2). Los Angeles: Sage.

Pierre-Louis, A.-M., Qamruddin, J., Espinosa, I., & Challa, S. (2010). *The Malaria Control Success Story.*

President's Malaria Initiative. (2014). *Malaria Operational Plan Fy 2014.* New York: USAID.

President's Malaria Initiative. (2017). *Malaria Operational Plan Fy 2017.* New York: USAID.

REMA. (2010). *Assessment of operational framework related to climate change in Rwanda.* Kigali: Government of Rwanda.

REMA. (2001). *Atlas of Rwanda's Changing Environment. Implications for climate change Resilience.* Kigali: Republic of Rwanda.

REMA. (2012). *Rwanda State of Environment and Outlook.* Kigal: Republic Of Rwanda.

REMA. (2015). *State of the Emvironment and Outlook Report.* Kigali: Government of Rwanda.

Renate, L. (2009). *Global Climate Chage and Malaria Transmission (Masters Thesis).* Oslo: Oslo Univesity College.

Republic of Rwanda. (2011). *Green Growth and Climate Resilience.* Kigali: Republic of Rwanda.

Rosenthal, J. (2009). Climate Change and the Geographic Distribution of Infectious Diseases. *EcoHealth , 6*, 489-495.

Rubavu. (2013). *District Development Plan (2013-2018).* Rubavu: Government of Rwanda.

Rwanda Biomedical Centre. (2017). *Malaria Bulletin.* Kigali: Rwanda Biomedical Center.

Schlagenhauf-Lawlor, P. (2001). *Travellers' Malaria.* Zurich: BC Decker.

Shakoor, H., Armstrong, B., Baccini, M., Biggeri, A., Bisanti, L., Russo, A., et al. (2006). Impact of high temperature on mortality: is there an added heat wave effect? *Epidemiology , 17* (6), 632-638.

Shanks, G., Hay, S., Stern, D.I., Biomdo, K., & Snow, R. (2002). Meteorologic influences on Plasmodium falciparum malaria in the highland tea estates of Kericho, Western Kenya. *Emerging Infectious Diseases , 8*, 1-10.

Stern, D. I., Gething, P. W., Kabaria, C. W., Temperley, W. H., & Noor, A. M. (2011). Temperature and Malaria Trends in Highland East Africa. *Plos One , 6* (9), 245-254.

Tulu, A. (1996). Determinants of Malaria Transmission in the Highlands of Ethiopia. The Impact of Global Warming on Morbidity and Mortality Ascribed to Malaria. *London School of Hygiene and Tropical Medicine .*

UKaid. (2009). *Economic of climate change in Rwanda.* Oxford: Stockholm Environment institute.

UNICEF. (2015). *Achieving the malaria MDG target: reversing the incidence of malaria 2000-2015.* Geneva: WHO.

Van Belle, G., Lloyd, F. D., Heagerty, P. J., & Lumley, T. (2002). *Biostatistics: A Methodology for the Health Sciences* (2 ed.). Washington: John Wiley & Sons,.

Walsh, J., Molyneux, D., & Birley, M. (1993). Deforestation: Effects on vector-borne disease. *Parasitology , 106*, 555-575.

Wandiga, S. O., Opondo, M., Olago, D., Githeko, A., Githui, F., Marshall, M., et al. (2006). *Vulnerability to climate induced highland malaria in East Africa.* Washington: AIACC.

Wanjala, C. L., Waitumbi, J., Zhou, G., & Githeko, A. K. (2011). Identification of malaria transmission and epidemic hotspots in the western Kenya highlands: its application to malaria epidemic prediction. *BioMed , 4* (81).

WHO Global Malaria Program. (2015). *World Report 2015.* Geneva: WHO.

WHO. (2014). *World Malaria Report.* Geneva: Word health organization.

Wilson, M. L. (2001). Ecology and Infectious Disease. In *Ecosystem change and public health: a global perspective* (pp. 283-319). Baltimore: The John Hopkins University Press.

Yaffee, R. A., & McGee, M. (1999). *Introduction to Time Series Analysis and Forecasting: with Applications of SAS and SPSS.* San Diego: Academic Press, INC.

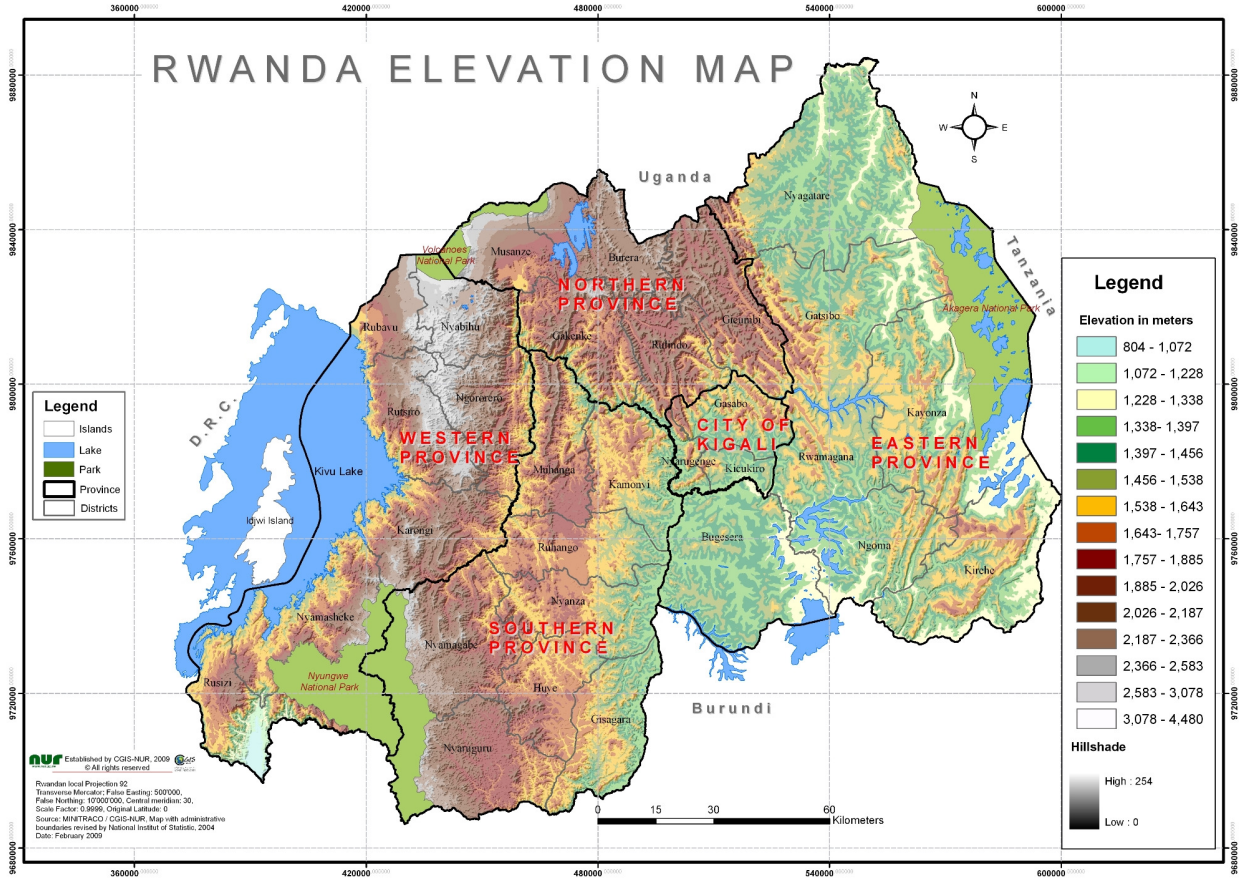
Yu, W., Mengrsen, K., Dale, P., Ye, X., Guo, Y., Tuner, L., et al. (2013). Projecting Future Transmission of Malaria Under Climate Change Scenarios: Challenges and Research Needs. *Critical reviews in Environmental Science and Technology* .

APPENDICES

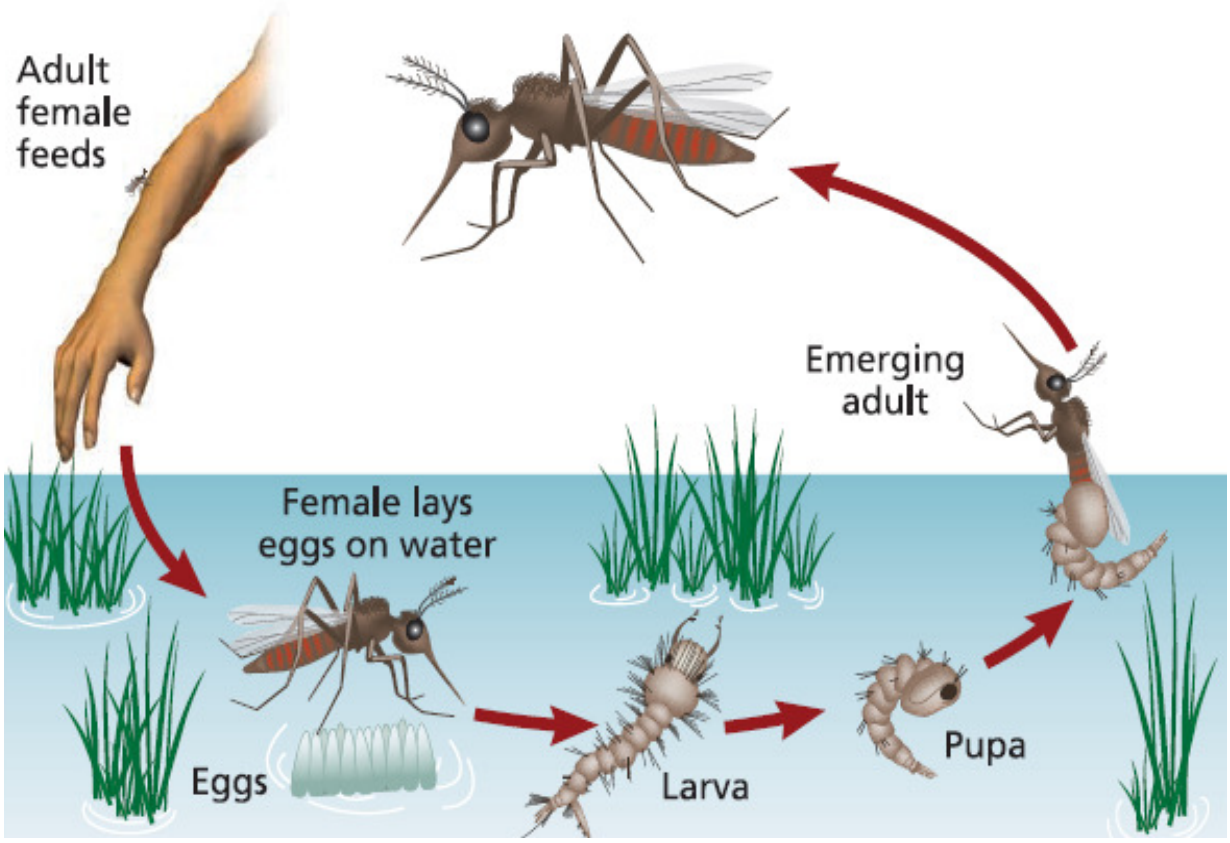
Appendix I: Population estimation of health centre's catchment in study area.

Sector	District	Health_center	Year_2004	Year_2005	Year_2006	Year_2007	Year_2008	Year_2009	Year_2010	Year_2011	Year_2012	Year_2013	Year_2014
CYEZA	Muhanga	Kivumu	28653.00	28823.00	28993.00	29163.00	29333.00	29503.00	29673.00	29843.00	30161.00	30330.88	30500.76
KABACUZI	Muhanga	Buramba	24423.61	24568.41	24713.22	24858.02	25002.82	25147.63	25292.43	25437.24	25496.00	25640.80	25785.61
KIBANGU	Muhanga	Gitega	19491.70	19569.04	19646.39	19723.74	19801.09	19878.44	19955.78	20033.13	20164.00	20241.35	20318.70
KIYUMBA	Muhanga	Nyabikenke	24900.58	24462.37	24024.16	23585.96	23147.75	22709.54	22271.33	21833.12	21733.00	21294.79	20856.58
MUSHISHIRO	Muhanga	Mushishiro	20246.41	20266.62	20286.82	20307.03	20327.24	20347.44	20367.65	20387.85	20421.00	20441.21	20461.41
NYABINONI	Muhanga	Nyabinini	17546.76	17458.14	17369.52	17280.90	17192.28	17103.66	17015.04	16926.42	16894.00	16805.38	16716.76
NYAMABUYE	Muhanga	Kabgayi	35940.96	36893.94	37846.92	38799.90	39752.88	40705.86	41658.84	42611.82	44831.00	45783.98	46736.96
NYARUSANGE	Muhanga	Nyarusange	23474.18	23749.26	24024.35	24299.44	24574.53	24849.62	25124.70	25399.79	25795.00	26070.09	26345.18
RONGI	Muhanga	Birehe+Rutake	20615.37	21253.56	21891.75	22529.94	23168.12	23806.31	24444.50	25082.68	26802.00	27440.19	28078.37
SHYOGWE	Muhanga	Gitarama+shyo	36552.47	37356.21	38159.94	38963.68	39767.41	40571.15	41374.88	42178.62	43786.00	44589.74	45393.47
GITESI	Karongi	Kirambo	20940.55	21381.83	21823.10	22264.38	22705.66	23146.93	23588.21	24029.48	24833.00	25274.28	25715.55
GISHARI	Karongi	Birambo	21231.77	21059.15	20886.54	20713.92	20541.30	20368.69	20196.07	20023.46	19915.00	19742.38	19569.77
MUBUGA	Karongi	Mubuga+Karor	16828.42	17025.62	17222.83	17420.04	17617.25	17814.46	18011.66	18208.87	18520.00	18717.21	18914.42
MURUNDI	Karongi	Munzanga	21791.32	22270.48	22749.64	23228.80	23707.95	24187.11	24666.27	25145.43	26114.00	26593.16	27072.32
MUTUNTU	Karongi	Mukungu	21054.22	21280.83	21507.44	21734.06	21960.67	22187.28	22413.89	22640.50	23054.00	23280.61	23507.22
RUBENGERA	Karongi	Rubengera	23428.28	24355.92	25283.56	26211.20	27138.83	28066.47	28994.11	29921.75	33005.00	33932.64	34860.28
RUGANDA	Karongi	Bihugu	15048.92	15324.39	15599.85	15875.31	16150.77	16426.23	16701.70	16977.16	17539.00	17814.46	18089.92
RWANKUBA	Karongi	Kiziba Camp	34870.64	35245.96	35621.28	35996.60	36371.92	36747.24	37122.56	37497.88	37905.00	38280.32	38655.64
TWUMBA	Karongi	Gisovu	22491.14	22754.70	23018.27	23281.84	23545.41	23808.98	24072.54	24336.11	24718.00	24981.57	25245.14
BUSASAMANA	Rubavu	Busasamana	22420.47	23308.21	24195.94	25083.68	25971.41	26859.15	27746.88	28634.62	31404.00	32291.74	33179.47
GISENYI	Rubavu	Gacuba II	24354.49	26451.23	28547.98	30644.72	32741.46	34838.21	36934.95	39031.70	41128.00	43224.74	45321.49
KANAMA	Rubavu	Karambo	20922.28	21732.93	22543.57	23354.21	24164.85	24975.49	25786.14	26596.78	29224.00	30034.64	30845.28
MUDENDE	Rubavu	Mudende	17483.40	18278.10	19072.80	19867.50	20662.20	21456.90	22251.60	23046.30	26000.00	26794.70	27589.40
NYAMYUMBA	Rubavu	Kigufi	29301.14	30208.21	31115.28	32022.36	32929.43	33836.50	34743.57	35650.64	37917.00	38824.07	39731.14
NYUNDO	Rubavu	Nyundo	20005.33	20963.99	21922.66	22881.32	23839.98	24798.65	25757.31	26715.98	30438.00	31396.66	32355.33
RUBAVU	Rubavu	Murara	49299.64	48218.96	47138.28	46057.60	44976.91	43896.23	42815.55	41734.87	41681.00	40600.32	39519.64

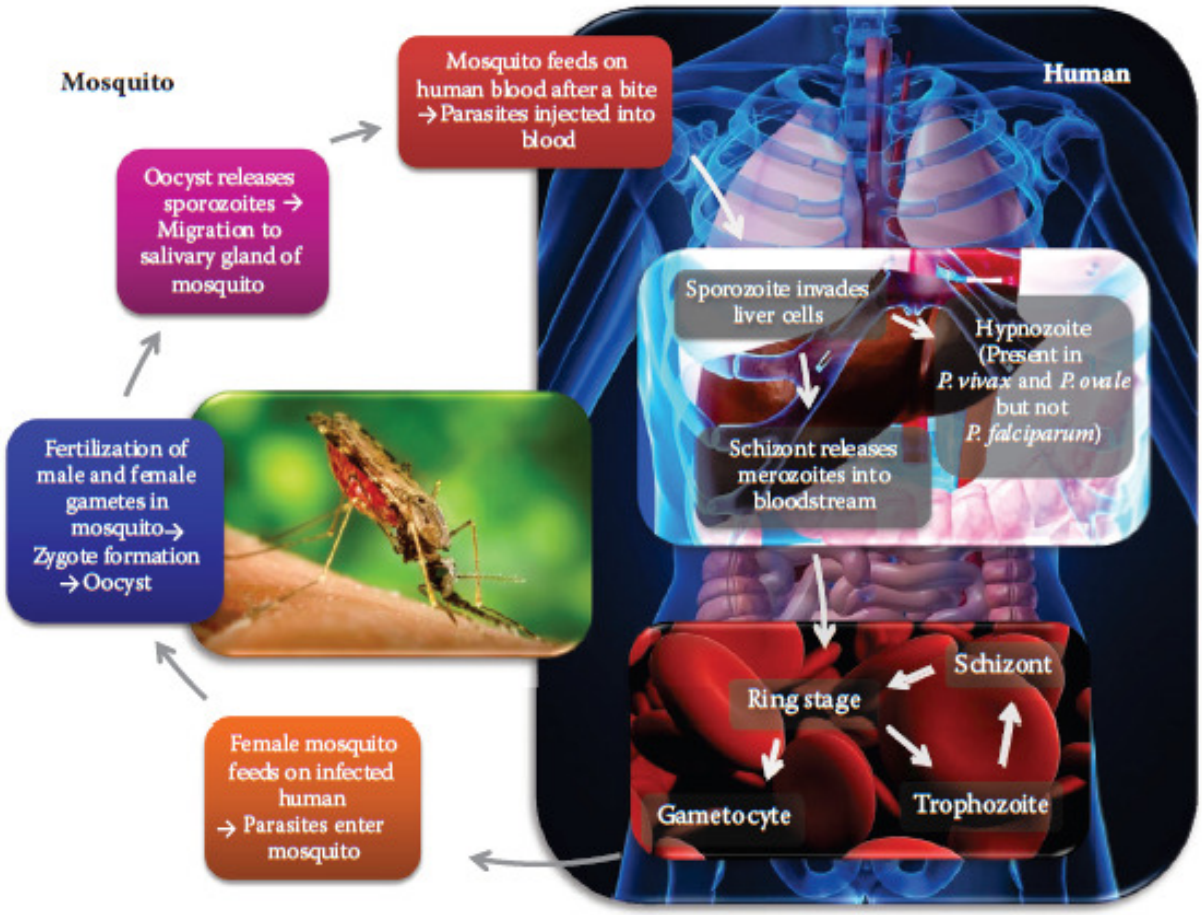
Appendix II: Topographic map of Rwanda



Appendix III: Mosquito vector cycle



Appendix IV: Parasite life cycle



Appendix V: Template of data presentation

Template of data collected from health centers

Year	Months	Health Centres				
		Hc_1	**Hc_2**	**Hc_3**	**……**	**Hc_{26}**
2004	Month1	cases	cases	Cases	Cases	cases
	Month2					
	….					
	Month12					
2005	Month1					
	Month2					
	….					
	Month12					
2006	Month1					
	Month2					
	….					
	Month12					
2007	Month1					
	Month2					
	….					
	Month12					
…						
2014	Month1					
	Month2					
	….					
	Month12					

Template of climate data collected from meteorological stations

Years	Months	Climate parameters				
		MaxTemper	MinimTemper	MeanTemper	Rainfall	RelativeHum
2004	January	a^{o}C	b^{o}C	c^{o}C	Xmm	y%
	….					
	Decemb					
2005	January					
	….					
	Decemb					
….	January					
	….					
	Decemb					
…	January					
	….					
	Decemb					
2014	January					
	….					
	Decemb					

Appendix VI: Data used in analysis, malaria incidence, temperature, rainfall and relative humidity in different district of study area

Karongi District

year	Average of Incidence	Average of AV_MAX_TEMP	Average of AV_MIN_TEMP	Average of AV_MEAN_TEMP	Average of Rainfall	Average of AV_MEAN_HUM
2004	8.62	26.13	7.38	16.75	95.00	70.36
2005	9.37	26.76	8.49	17.63	87.00	71.36
2006	11.47	25.82	13.96	19.89	123.67	69.78
2007	5.40	25.52	14.43	19.91	114.50	72.09
2008	3.53	25.35	16.37	20.86	103.00	74.96
2009	4.84	25.73	15.58	20.64	102.08	74.58
2010	1.18	25.42	15.19	20.24	118.21	71.01
2011	0.07	25.91	14.61	20.21	111.25	75.06
2012	0.33	25.63	14.90	20.26	102.50	74.25
2013	1.64	24.33	15.03	19.67	111.58	68.01
2014	5.04	24.26	14.82	19.54	122.42	69.47
Grand Total	4.39	25.49	14.17	19.81	109.26	72.02

Muhanga District

year	Average of Incidence	Average of AV_MAX_TEMP	Average of AV_MIN_TEMP	Average of AV_MEAN_TEMP	Average of Rainfall	Average of AV_MEAN_HUM
2004	28.82	26.71	10.77	18.74	97.67	69.09
2005	22.19	27.56	8.93	18.25	98.00	63.71
2006	24.49	25.74	10.97	18.32	113.79	64.70
2007	6.44	24.98	13.66	19.30	80.63	65.09
2008	2.97	25.21	13.98	19.93	83.92	68.09
2009	5.21	25.40	14.23	19.76	86.19	63.21
2010	2.51	25.62	14.19	21.98	102.17	61.68
2011	0.13	25.18	14.45	19.68	124.83	61.82
2012	0.31	25.67	14.15	19.95	99.42	58.54
2013	5.14	25.62	14.43	20.02	115.42	58.67
2014	10.54	24.64	15.04	19.22	235.22	56.99
Grand Total	8.50	25.59	13.34	19.62	113.56	62.42

Rubavu District

year	Average of Incidence	Average of AV_MAX_TEMP	Average of AV_MIN_TEMP	Average of AV_MEAN_TEMP	Average of PRECIPITATION	Average of AV_MEAN_HUM
2004	3.43	19.37	6.13	12.75	136.00	78.70
2005	3.92	20.43	6.28	13.37	115.42	75.34
2006	4.91	21.27	9.83	15.55	123.75	76.19
2007	2.75	18.32	10.39	14.53	101.33	77.30
2008	1.96	19.24	12.91	15.68	101.17	79.21
2009	2.17	20.29	12.90	16.59	102.50	74.10
2010	1.16	20.26	10.81	15.52	121.58	73.30
2011	0.05	19.82	7.64	13.59	140.33	76.58
2012	0.12	21.01	11.05	16.13	130.13	75.20
2013	0.14	22.94	14.11	18.55	81.33	73.19
2014	0.45	23.85	8.25	16.05	100.67	75.51
Grand Total	1.80	20.71	10.31	15.49	112.41	75.67

Appendix VII: Administrative documents

MANIRAGABA ABIAS
PhD. Student
University of Eldoret, Kenya
School of Environmental Studies
Department of Environmental Health and Biology
E-mail: abiasrw@gmail.com
Tel: +250783782303/+250706783901

RWANDA BIOMEDICAL CENTER
Received by.....
Date 3/12/2013
Ref .....
Oriented to .....

N° 5473
du 4/12/2013
DG

Kigali 2nd December 2013

Director General of Rwanda Biomedical Centre (RBC)
Rwanda-Kigali

Dear Sir,

RE: APPLICATION FOR MALARIA DATA ACQUISITION

It is with honour that I come to you applying for malaria epidemiological data acquisition from RBC which is under your responsibility.

Indeed, I am a PhD student in the University of Eldoret in Kenya, School of Environmental Studies, Department of Environmental Health and Biology, Environmental Health Division, I am conducting the research for final step of my studies, the title of my thesis is "*Analysis of the impacts of climate change on malaria prevalence in Rwandan highlands*" I would like you to assist me to access the data on malaria in highland regions of Muhanga, Ngororero, Rutsiro, Karongi and Rubavu, so that I can achieve well my objectives, the data can be for the period between 1983-2012. I am here in Rwanda for research and available at any time that you can need me for assistance and further information. On this application I enclosed research permit from school, abstract of my research proposal and student card.

Waiting for your favourable response to my request, I thank you.

Maniragaba Abias

CC: Head of Malaria unit RBC

MANIRAGABA ABIAS
PhD. Student
University of Eldoret, Kenya
School of Environmental Studies
Department of Environmental Health and Biology
E-mail: abiasrw@gmail.com
Tel: +250783782303/+254706783901

Kigali 25th June 2014

Minister of Health

Dear Madam,

RE: APPLICATION FOR MALARIA DATA ACQUISITION

It is with honour that I come to you applying for malaria incidence data in the districts of Muhanga, Ngororero, Karongi, Rutsiro and Rubavu for the period of 1997 up to 2013.

Indeed, I am a PhD student in University of Eldoret in Kenya, School of Environmental Studies, Department of Environmental Health and Biology, Environmental Health Division, I am conducting the research for final step of my studies, the title of my thesis is "*Analysis of the impacts of climate change on malaria prevalence in Rwandan highlands*" I would like you to assist me to access the data on malaria in the mentioned districts, so that I can achieve well my objectives. I am here in Rwanda for research and available at any time that you can need me for assistance and further information. On this application I enclosed Scientific Review Approval Notice from National Health Research Committee (NHRC)

Waiting for your favourable response to my request, I thank you.

Maniragaba Abias

Republic of Rwanda

RWANDA BIOMEDICAL CENTER

A Healthy People. A Wealthy Nation

P.O. Box 84 KIGALI

National Health Research Committee
Ref: NHRC/2014/PROT/0166

To: **Abias MANIRAGABA**
Principal Investigator

Scientific Review Approval Notice

Dear Abias MANIRAGABA,

With reference to your request for approval of the Research Protocol entitled; << **Analysis of the impacts of climate change on malaria prevalence in Rwandan highlands**>>, We are pleased to inform you that, following a thorough review and critical analysis of your proposal (**Ref: NHRC/2014/PROT/0166** dated 12th May 2014), your Research Protocol has been approved by National Health Research Committee.

However,

1) Changes amendments on approach and methodology must be submitted to the NHRC for review and approval to validate the changes.
2) A submission of quarterly progress report is mandatory
3) Submission to NHRC of final results before publication is mandatory
4) Failure to fulfill the above requirements will result in termination of study

Once again National Health Research Committee appreciates your interest in research and requests you to submit this proposal to the National Ethics Committee or IRB and then share a copy of the approval letter.

Your final approval reference number is **NHRC/2014/PROT/0166**

Yours Sincerely,

Dr. Jean de Dieu Ngirabega
Vice-Chairperson of NHRC

Signature:.....

Date:..... 12/05/2014

Dr. Parfait UWARIRAYE
Chairperson of NHRC

Signature:.....

Date:..... 12/05/14

REPUBLIC OF RWANDA

Kigali, ...18/07/2024.....
N°.....7790...../12.00/2014

MINISTRY OF EDUCATION
P.O.BOX 622 KIGALI

The Head of Rwanda National Ethics Committee
Kigali.

Attn. Prof. Justin Wane

Dear Sir/Madam,

RE: Research Project proposal for Review

I wish to introduce **Mr. MANIRAGABA Abias** to you; he is seeking for a permit to carry out research in Rwanda. Project titled: **"Impacts of Climate Change on Malaria prevalence in Rwanda highlands".** As is required by the research regulations, his project proposal requires to be reviewed by the ethics committee. It is in this regard that I am requesting that his project be reviewed among others on your review schedule.

I take this opportunity to thank you for your continued collaboration

Yours sincerely,

MINISTRY OF EDUCATION
GASINGIRWA Marie Christine
Rwanda

Dr. Marie Christine Gasingirwa
Director General,
Science Technology and Research
Ministry of Education

Cc.

- Hon. Minister of Education
- Hon. Minister of State in charge of Primary and Secondary Education
- Hon. Minister of State in charge of TVET
- Permanent Secretary, Ministry of Education

REPUBLIC OF RWANDA/REPUBLIQUE DU RWANDA

NATIONAL ETHICS COMMITTEE / COMITE NATIONAL D'ETHIQUE
Telephone: (250) 2 55 10 78 84
E-mail: info@rnecrwanda.org
Web site: www.rnecrwanda.org
Ministry of Health
P.O. Box. 84
Kigali, Rwanda.
FWA Assurance No. 00001973
IRB 00001497 of IORG0001100

October 14, 2014
No. 329/RNEC/2014

Abias MANIRAGABA
Principal Investigator
(A student)

Your Project title **"IMPACTS OF CLIMATE CHANGE ON MALARIA PREVALENCE IN RWANDAN HIGHLANDS"** has been evaluated by the Rwanda National Ethics committee.

		Involved in the decision		
			No (Reason)	
Name	Institute	Yes	Absent	Withdrawn from the proceeding
Dr.Jean-Baptiste MAZARATI	Biomedical Services (BIOS)	X		
Prof. Eugène RUTEMBESA	National University of Rwanda	X		
Dr.Laetitia NYIRAZINYOYE	National University of Rwanda(school of public Health)	X		
Prof.Alexandre LYAMBABAJE	National University of Rwanda		X	
Ms.Françoise UWINGABIYE	Lawyer at Musanze	X		
Dr. Egide KAYITARE	National University of Rwanda	X		
Sr.Domitilla MUKANTABANA	Kabgayi Nursing and Midwife school	X		

Mr. David K. TUMUSIIME	Kigali Health institute	X		
Dr. Lisine TUYISENGE	Kigali Teaching Hospital	X		
Dr. Claude MUVUNYI	Biomedical Services (BIOS)		X	

After reviewing your protocol during the RNEC meeting of 13 September 2014 where quorum was met, and revisions made on the advice of the RNEC submitted on 14 October 2014, **Approval has been granted to your study.**

Please note that approval of the protocol and consent form is valid for **12 months**.
You are responsible for fulfilling the following requirements:

1. Changes, amendments, and addenda to the protocol or consent form must be submitted to the committee for review and approval, prior to activation of the changes.
2. Only approved consent forms are to be used in the enrollment of participants
3. All consent forms signed by subjects should be retained on file. The RNEC may conduct audits of all study records, and consent documentation may be part of such audits.
4. A continuing review application must be submitted to the RNEC in a timely fashion and before expiry of this approval.
5. Failure to submit a continuing review application will result in termination of the study.
6. Notify the Rwanda National Ethics committee once the study is finished.

Sincerely,

R.N.E.C

Dr. Jean- Baptiste MAZARATI
Chairperson, Rwanda National Ethics Committee.

Date of Approval: October 14, 2014
Expiration date: October 13, 2015

C.C.
- Hon. Minister of Health.
- The Permanent Secretary, Ministry of Health.

MANIRAGABA ABIAS
PhD. Student
University of Eldoret, Kenya
School of Environmental Studies
Department of Environmental Health and Biology
E-mail: abiasrw@gmail.com
Tel: +250783782303/+254706783901

Kigali 14th April 2016

Deputy Director General Land and Mapping
Rwanda Natural Resource Authority
P.O. Box 433 Kigali, Rwanda

Dear Sir,

RE: APPLICATION FOR DIGITAL ELEVATION MAPS AND SHAPEFILES

It is with honour that I come to you applying for Digital elevation model maps and shapefiles for Muhanga, Karongi and Rubavu.

Indeed, I am a PhD student in the University of Eldoret in Kenya, School of Environmental Studies, Department of Environmental Health and Biology, Environmental Health Division, I am conducting research for final step of my studies, the title of my thesis is "*Impacts of climate change on malaria prevalence in Rwandan highlands*" I would like you to assist me to access on DEM and shapefiles of Karongi Muhanga and Rubavu.
The requested maps may contain;

- Topographic parameters
- Hydrologic network
- Land use and land cover
- Population distribution

The maps may contain as well different data for at least three different periods between 2004-2014 for malaria and climate change mapping and spatial modelling.

I am here in Rwanda for research and available at any time for further information. On this application I enclosed; Ethical clearance approval, Research permit from University, MOU signed between me and RBC as well as the abstract of my research.

Waiting for your favourable response to my request, I thank you.

Maniragaba Abias

RWANDA
BIOMEDICAL
CENTER

A Healthy People. A Wealthy Nation

IHDPC/Malaria &other Parasitic Diseases Division

DATA SHARING AND PUBLICATION AGREEMENT

Between

Malaria and Other Parasitic Diseases Division of Rwanda Biomedical Centre, (Hereinafter " Mal&OPD Division-RBC") represented by Dr Corine KAREMA

And

Mr Maniragaba Abias, PhD Candidate from University of Eldoret, School of Environmental Studies Department of Biology and Health, hereinafter referred to as the User

1. **Data under this agreement**

The data covered under this Data Sharing Agreement are: ***"malaria cases at health centre level for the period of 2001-2013; health centre shapefiles for Muhanga, Karongi and Rubavu districts health Centres catchment areas, data on mosquito nets distributed in Muhanga ,Karongi and Rubavu districts*** and all other relevant information collected on Malaria in Rwanda by from the period of 2001 to 2013.

2. **Period of Agreement**

The period of this Agreement shall be in effect from January 2015 until December 2015, or until terminated in writing by both parties to this agreement.

3. **Intended Use of Data**

In collaboration with the Malaria&OPD Division-RBC, the researcher is aiming at "documenting the past of malaria outbreaks and its relationships with climate change in Rwandan Highlands; investigating the environmental and socio-economic factors of vulnerability to malaria; and establish correlation between climate change in Rwandan highlands and malaria prevalence.

4. **Constraints on Use of Data**

Data provided by or any data collected on behalf of the mentioned division are the property of Mal& OPD Division-RBC and shall not be shared with third parties without the written permission of. Customer data shall not be sold or used, internally or externally, for any purpose not directly related to the scope of work defined in this agreement without the written permission of Malaria & OPD Division-RBC. No scientific publication of any sort or public presentation through national and international conferences, based on the data in regard to this agreement will be made by the user without informing the Mal& OPD Division-RBC.

5. **Data Security**

The user shall employ best practices, both technically and procedurally, to protect the data from unauthorized physical and electronic access.

6. **Data Elements**

Data shared with the user shall be limited to the data elements specifically defined and authorized by Mal& OPD Division-RBC. If the user wishes to collect additional data under the scope of the work, the user will

9

request permission in writing to Mal& OPD Division- RBC. Under no circumstances shall the user collect any information classified as Sensitive or Confidential without the express written approval of Mal& OPD Division-RBC. During the above mentioned period appropriate access to data will be provided to the user.

7. Data property

Data remains under responsibility of and shall not be released partly or totally or shared with third parties without the written permission of the Mal&OPD Division-RBC.

8. **Confidentiality**

Both parties agree to maintain confidentiality and privacy safeguards that were originally created as part of the agreement, including the protection from disclosure statutes under which this data were gathered. In this respect, in the any case, the User agrees to not release any information about specific identifiable subjects to anyone.

9. **Authorship**

For any publication based on the above data under the scope of this specific agreement, the User shall acknowledge the data sources and all people involved in this exercise will be cited in any publication.
People involved in the collection of these specific data are, Monique Murindahabi, Alphonse Rukundo, Noella Umulisa and Corine Karema.
Furthermore, the priority should be given to researchers from Mal&OPD Division-RBC for co-authorship selection for of any publication based on the above mentioned data. She/he will have the responsibility to go through the draft prior to the submission for publication as PhD supervisors will.

After completion of his PhD Research, the User and Mal& OPD Division-RBC should initiate further research projects in collaboration where Malaria and Other Parasitic Diseases are concerned.

10. Termination of Services

In the event that the Data Sharing Agreement is terminated in writing by one of the signatories of this agreement, the access will be closed for the user and the User will protect the acquired data from unauthorised people.

11. Authorization of Data Sharing

By the signatures of the duly authorized representatives below, and the User agree to all of the provisions of this Data Sharing Agreement.

For the User	**For Malaria and Other Parasitic Diseases Division Rwanda Biomedical Center**
Name: **Mr Abias Maniragaba**	Name: **Dr Corine KAREMA**
Title: **PhD Student**	Title: **Head of Malaria and OPD Division-RBC**
Telephone: **+250 783782303**	Telephone: **+250788303915**
Email: abiasrw@gmail.com	Email: ckarema@gmail.com
Signature: _____	Signature: _____
Date: 05/01/2015	Date: 13.01.2015

HEAD OF MALARIA & OTHER PARASITIC DISEASES DIVISION RWANDA BIOMEDICAL CENTER