Association between Climatic Variability and Malaria Risk in Tanzania

By

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DECLARATION

This dissertation was carried out and presented for the examination for the Masters of Science in Meteorology by me Msemo Hellen Elimo at the University of Nairobi.

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If it were not of the almighty God to give me power and blessings, this work would not have been, *May the Lord be Magnified, Psalm 32:8-9*

ABSTRACT

Malaria is still a major public health problem in the United Republic of Tanzania, is the leading cause of outpatient and inpatient health service attendance and the leading cause of death in both children and adults.

This study examines the relationship between climate variability and malaria cases in some selected areas in Tanzania. This was realized through studying the trends, correlation analysis and modeling of the rainfall, maximum and minimum temperature and laboratory confirmed malaria cases time series. Data from four mainland sentinel hospitals and total malaria cases from Zanzibar Island were used to investigate this link. Climate data comprised monthly minimum and maximum temperatures and monthly rainfall for the period of 1978-2008, while laboratory confirmed malaria cases were for the period between 2000 and 2008 from hospitals near the meteorological stations. The epidemic alert threshold for each month was determined as the average monthly malaria cases in the over five (5) years plus two times the standard deviation.

The results revealed a non linear relationship exists between climatic variability and malaria cases in most hospitals i.e. Dareda, Rubya, Mpwapwa, Utete and Zanzibar. Furthermore the result showed that at extreme conditions such as higher amounts of rainfall, higher or temperatures affect malaria transmissions. However studies show that weather extremes may trigger epidemics outbreaks in particular areas, higher temperatures in combination with favorable patterns of rainfall and surface water, will prolong transmission seasons in some endemic locations. The result also pointed out weather phenomena such as La Niña and El Niño affects the mosquito population hence malaria transmissions.

Furthermore, when the Malaria epidemic transfer model when simulated using a rainfall threshold of 150 mm/ month of rain for highland areas poor results were obtained in some areas. A higher threshold of 300 mm/ month of rain when used in Zanzibar produced better result. However when climatic data were standardized and modeled better results was obtained as compared to the assigned threshold.

The study was done in only four sentinel hospitals out of 21 sentinel center, extension of the study for the remaining center is recommended. Lack of long term malaria data is the major

challenge in investigating the impact of climate variability hence climate change this need to be addressed.

The association observed between malaria cases and the climate variability is crucial for the health sector in Tanzania and other sectors that are affected directly or indirectly by weather variables. More studies need to be done so as to improve on the tools that have been established.

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ACRONYMS

ACT	:	Artemisinin Combination Therapy
AFM	:	Africa Fighting Malaria
Apr	:	April
CPC	:	Climate Prediction Center of the United States of America
Dec	:	December
ENSO	:	El Niño- Southern Oscillation
Feb	:	February
IRS	:	Indoor Residual Spraying
ITNs	:	Insecticide-Treated Bed Nets
Jan	:	January
JJA	:	June, July and August
MARA	:	Mapping Malaria Risk in Africa
Max	:	Maximum
Min	:	Minimum
Nov	:	November
Oct	:	October
RF	:	Rainfall
Sep	:	September
WHO	:	World Health Organization
MoH	:	Ministry of Health of Tanzania

CHAPTER ONE
INTRODUCTION

1.0 Background

Malaria is a major public health problem in sub-Saharan Africa (Guofa *et al.*, 2003). It is estimated that Malaria epidemic causes between 12% and 25% of estimated annual worldwide Malaria deaths including up to 50% of estimated annual mortality in persons under 15years of age (Worrall *et al.,* 2004).

Malaria is still a major public health problem in the United Republic of Tanzania, is classified as the leading cause of outpatient and inpatient health service attendance and the leading cause of death in both children and adults (Government of Tanzania 2001). Studies conducted in Tanzania shows that over 96% of Tanzania's population lives in areas of malaria risk (Roll Back Malaria 2003), and malaria is the most commonly reported health complaint in the country (Government of Tanzania, 2001). Also studies on economic burdens of malaria shows that most people spend significantly more on malaria preventive activities.

In recent times malaria epidemics have been reported to reemerge in the East African highlands but the reasons advanced for this remains controversial. Several mechanisms have been hypothesized, including increased travel from the malaria-endemic areas to the highlands, degradation of the healthcare infrastructure, anti-malarial drug resistance, local malaria transmission in the highlands as a consequence of land-use changes and global warming (Guofa *et al* 2003). Despite the common assumption that the transmission of vector-borne diseases in highland areas is constrained by temperature, in reality a number of other important factors including topographical features may play a role, and may buffer the disease system against any potential impact of climate change. The altitudinal limits of malaria transmission, for example, are in many localities far below what would be expected on the basis of temperature alone. In some cases this might be a product of insufficient rainfall, but in many instances it appears that the dominant factor is the presence or otherwise of suitable breeding sites for efficient malaria vectors (Cox *et al.* 1999).

The dynamics and distribution of malaria are strongly determined by climatic factors (Rogers *et al* 2000). However, the exact influence of climate and the likely consequences of climate change are unclear. In part, this is because transmission of the disease is determined by a suite of other socio economic, environmental and behavioral factors that can exacerbate or negate climatic influences.

Early detection and accurate forecasting of the time, place and intensity of these epidemics is important for emergency preparedness, planning and response. This may be done by using the climate variables of rainfall and temperature. However, there is need to clearly understand of the relationship between rainfall and malaria cases on one hand, and temperature and malaria cases on the other, and the relevant temperature and rainfall thresholds that enhance malaria risk.

According to Craig *et al*., (1999), the lower limit of temperature suitability is determined by the number of mosquitoes surviving the incubation period, while parasite development only ceases at 16°C, transmission below 18°C is unlikely because few adult mosquitoes survive the 56 days required for sporogony at that temperature, and because mosquito abundance is limited by long larval duration. At 22°C sporogony is completed in less than three weeks and mosquito survival is sufficiently high (15%) for the transmission cycle to be completed. The upper limit of temperature suitability is determined by vector survival, as sporogony takes less than a week. Temperatures of above 32°C have been reported to cause high vector population turnover, weak individuals and high mortality. Thermal death for mosquitoes occurs around 40–42°C and daily survival is zero at 40°C. On the other hand the relationship between mosquito abundance and rainfall is complex and best studied when temperature is not limiting. Studies have demonstrated the association between *Anopheles gambiae* species abundance and rainfall but a direct, predictable relationship does not exist (Craig et al, 1999). *Anopheles gambiae* species are seen to breed more prolifically in temporary and turbid water bodies, such as ones formed by rain while in permanent bodies predation becomes important (Charlwood *et al*. 1995). By contrast *Anopheles funestus* prefer more permanent water bodies. However, both temporary and permanent water bodies are dependent on rain. Rain is also related to humidity and saturation deficit. A cumulative precipitation of 80 mm/ month is a suitable condition for malaria transmission, the 80 mm/ month rainfall threshold have been used in various studies (Craig et al, 1999). However there is evidence that transmission can occur in areas with lesser precipitation. Certain vectors of malaria, such as *Anopheles* *funestus* are less dependent on rainfall, since they prefer to breed in more permanent habitats (van Lieshout *et al.*, 2004). Thus, simultaneous analysis on the long-term time series of meteorological and parasitological data is critically needed to demonstrate the effects of climate on malaria cases. Moreover, climate variability (short-term fluctuations around the mean climate state on a fine time scale) may be epidemiologically more relevant than the mean temperature increase (Guofa *et al.*, 2003). However in Tanzania, the association between climate variability and malaria epidemics and malaria surge in endemic areas has not been rigorously examined. This study attempts to address this issue according to the objectives highlighted in the next section.

1.1 Problem Statement

Malaria is a major public health problem in Tanzania and it is responsible for more than one-third of deaths among children under five years and for up to one-fifth of deaths among pregnant women. The relationship between malaria risk and climate variability is not well established for effective control measure.

1.2 Objective of the study

The overall objective of this study is to model the association between climate variability and Malaria Risk in some areas of Tanzania.

1.2.1 Specific Objectives

- To examine the relationship between
  - (i) Rainfall and Malaria cases and
  - (ii) Temperature and malaria cases
- To model the relevant temperature and rainfall threshold of malaria risk

1.3 Problem Justification

Malaria has been a major cause of economic loss and public health problem in many countries including Tanzania until recently. Currently health staff depends on surveillance methods in detecting epidemics this is achieved through monitoring unusual reports of malaria cases in malaria endemic areas in which weekly data on malaria cases and malaria deaths, particularly before and during the expected epidemic season are recorded, while in epidemic-prone places surveillance is done by keeping a running graph of malaria cases and update it weekly, either on squared paper or using a computer. Despite the implementation of intervention and control programs, malaria epidemic continues to cause high economic burden to many people. The use of climate information in the early warning systems may lead to a better lead time before epidemics and hence allow for timely pre-positioning of resources for control and prevention of the epidemics thus reducing the mortality rate and economic burden caused by Malaria.

1.4 Study Area

The study covered four sentinel hospitals, Rubya, Dareda, Mpwapwa and Utete in Tanzania mainland and Zanzibar in which total malaria cases data were used (Figure 1). Five climatological homogeneous zones were used in selecting representative weather stations used in this study namely Zanzibar, Dodoma, Arusha, Nyerere International Airport (NIA) and Bukoba (Figure 2).

Tanzania lies between latitudes 1–12°S and longitudes 29–40°E; the country is bounded by the great East African lakes, namely: lakes Victoria in the north, Tanganyika to the west and Nyasa to the south. To the east, lies the Indian Ocean. The country includes Africa's highest point (Mount Kilimanjaro, 5950 m above sea level) and lowest part (the floor of Lake Tanganyika, 358 m below sea level).

However, most of Tanzania, except the eastern coastline lies above 200 m above the sea level. The total rainfall amounts for stations in Tanzania vary from year-to-year as well as having large seasonal variations. The mean annual rainfall totals range from below 500 mm in the drier central areas to just over 1000 mm in the wet areas, although the coastal region including the Islands of Zanzibar and Pemba and parts of south-western Tanzania may receive over 1500 mm. Zanzibar is an autonomous state consisting of two large islands Unguja and Pemba, and several smaller islands all of which are located off the north-eastern coast of the Tanzania mainland. It is situated a few degrees south of the equator. Its tropical climate is characterized by hot humid weather, with the hottest weather generally occurring from December to March.

The mean annual temperatures vary from one location to another, for example along the Coastal areas and the Island (Unguja and Pemba), the annual maximum temperature is about 30.9^0C and the annual mean minimum Temperature is about 21.2^0C, while in central part of Tanzania which the annual mean minimum Temperature is about 21.2^{0}C, while in central part of Tanzania which is more of semi arid region the annual temperatures ranges from16.9^{0}C to 28.9^{0}C for minimum and maximum temperatures respectively, the northern part of Tanzania along the Lake Victoria basin the annual minimum temperature is about 16.8^{0}C and the annual maximum temperature is about 26.0^{0}C. In the north eastern part of Tanzania the annual temperatures range from 14.5^{0}C to 25.9^{0}C for both minimum and maximum temperatures respectively.

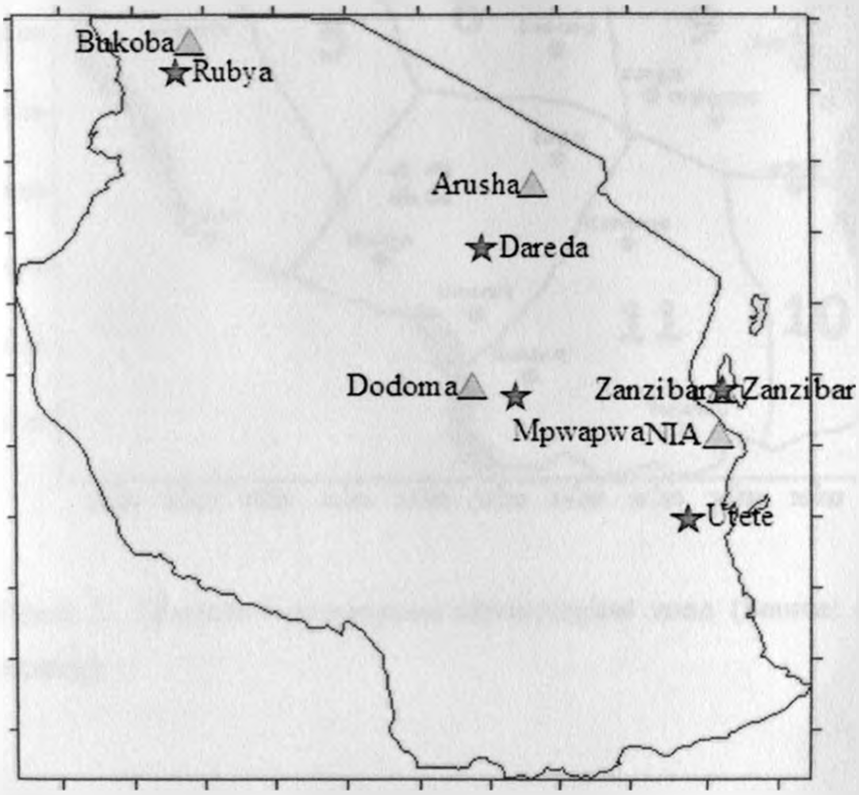

Figure 1: Sentinel hospital and representative meteorological weather stations

Source: The map was contracted using Surfer technique

Key

△ - Representative meteorological weather station

★ - Sentinel Hospital

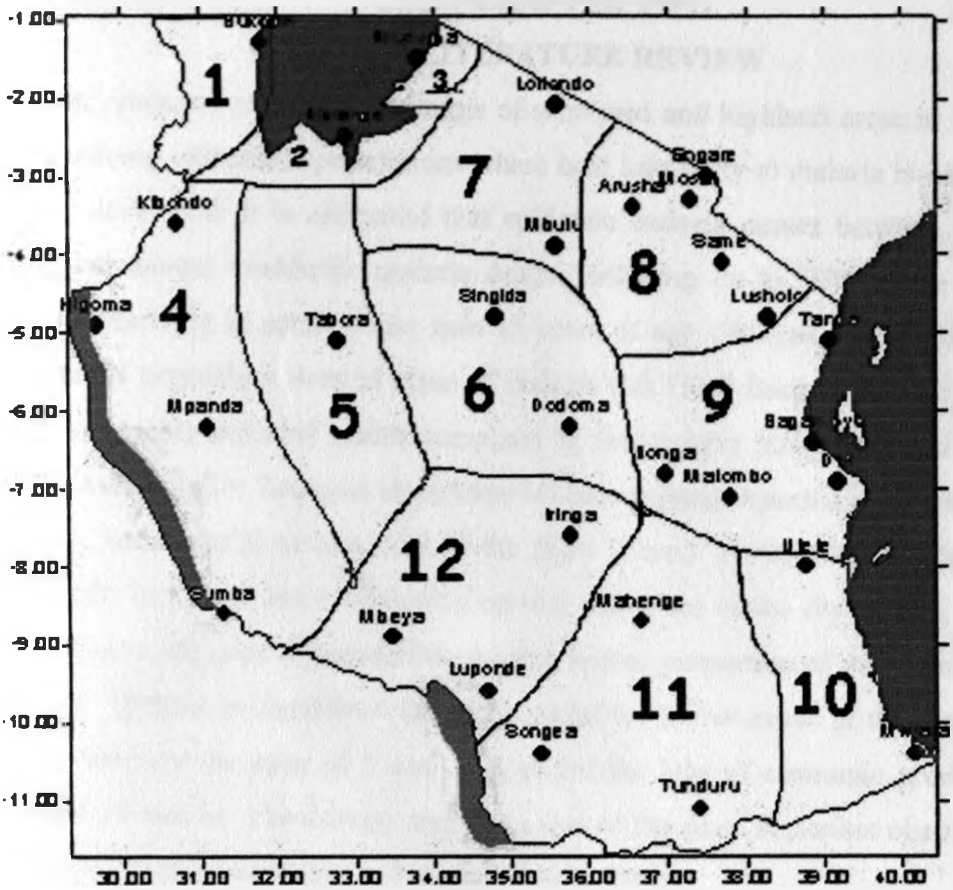

Figure 2: Tanzania homogeneous climatological zone (Source: Tanzania Meteorological Agency)

CHAPTER TWO

LITERATURE REVIEW

Malaria epidemic is a serious scourge of semi-arid and highland areas in Africa. Epidemics occur among vulnerable populations where host immunity to malaria is often nonexistent or poorly developed. It is estimated that epidemic malaria causes between 12% and 25% of estimated annual worldwide malaria deaths including up to 50% of the estimated annual malaria mortality in persons less than 15 years of age (Worrall *et al.*, 2004). Over 96% of Tanzania's population lives in areas of malaria risk (Roll Back Malaria 2003), and it is the most commonly reported health complaint in the country (Government of Tanzania 2001) studies conducted in Tanzania shows that Malaria-related expenses are significantly higher in the dry, non-malarial season than in the rainy season. Households sought treatment more frequently and from more expensive service providers in the dry season, when they have more money also poorer households spend a higher proportion of their consumption in both seasons. Malaria is considered the major cause for the decrease in the learning capacity of people between the ages of 5 and 25, and for the loss of economic productivity of those between 15 and 55. The disease represents one of the most important obstacles to economic development and investment in Tanzania (MoH, 2002).

Malaria is endemic in almost all parts of Tanzania. However the situation is not homogeneous. The variations in endemicity are conveniently classified as unstable seasonal malaria, stable malaria with seasonal variations, and stable perennial malaria. Unstable seasonal malaria occurs with a transmission period of not more than 3 months in year. In such situations, malaria may occur in epidemic if there are increased transmissions, morbidity and mortality (Mboera and Kitua, 2001). Areas with unstable malaria transmission include the highlands with altitudes up to 2000 m, temperatures up to 20^{0}C and a mean vapor pressure of 13-5 millibars. Stable malaria with seasonal variations occurs where there is seasonal intense transmission for 3 to 6 months in a year. It occurs in high altitude plains with temperature above 15^{0}C, and mean vapor pressure of 10-20 millibars. About 33% of the population in Tanzania lives in these areas (MoH, 2002). On the other hand stable perennial malaria occurs along the coast extending inland as far as 240 km. Areas along Lake Nyasa and Victoria experience a similar endemicity. In Tanzania malaria is mainly transmitted by

Anopheles gambiae, Anopheles arabiensis and Anopheles funestus, Anopheles rivolurum and *Anopheles marshallii* have also been identified as a vector of malaria in north-eastern Tanzania (Mboera e*t al.,* 2007). Other malaria vectors such as *Anopheles arabiensis* are known to be present in semi arid areas.

Malaria is unstable and fluctuates in intensity both spatially and temporally, thus resources for control have to be spread in time and space to be prepared for outbreaks, which have occurred in the past despite very aggressive and effective Malaria control operation (Gunawardena, 1998). Having a forecasting system in place will contribute to a more focused approach for control, and have a positive impact on the resource allocation for malaria control over space and time (Briët, *et al*., 2008). While many factors play a role in the spatial and temporal distribution of malaria, climate variability (both spatial variation of the long term seasonal mean of weather variables and temporal aberrations from the long term seasonal mean) has been shown to be important in explaining its occurrence (Bouma *et al.*, 1996, Githeko *et al* 2000, Hoek *et al.*, 1997) and is considered a major determinant (Grover-Kopec *et al.,* 2006). Temperature, rainfall, and humidity affect breeding and survival of certain species of anopheles mosquitoes that carry the malaria parasite, as well as development of malaria parasites within vector mosquitoes, thereby creating a link between weather and malaria. Rainfall anomalies are widely considered to be a major driver of inter-annual variability of malaria incidence in the semi-arid areas of Africa and are therefore included by the Roll Back Malaria Technical Support Network for Epidemic Prevention and Control as one of the key indicators for the development of malaria early warning systems (WHO, 2002). The goal of Roll Back Malaria is to halve the burden of malaria by 2010.

Analysis of time-series malaria and climate data have been conducted over the last century in many parts of the world, and have indicated that rainfall excess (or occasionally drought) is correlated with changes in malaria incidence in certain eco-epidemiologic settings,(Connor, 1999) apparently as a result of its impact on the population dynamics of the *Anopheles species* mosquito vector (Koenraadt *et al.,* 2004). While there are well-recognized causal relationships between rainfall and malaria transmission (creation of breeding sites favors larger numbers of juvenile, and therefore adult, mosquitoes; increased humidity favors vector survival) the relationship is often non-linear with excessive rainfall sometimes even resulting in less malaria than expected (Lindsay *et al*., 2000). There are a number of explanations for this nonlinearity (Najera *et al*., 1998). The most widely cited studies shows that excessive rainfall may wash out breeding sites, but other possible factors may be important, such as increased host protection in the light of changes in risk perception, density-dependent vector-host interaction, and possible reductions in temperature, which may result from high evapo-transpiration following a deluge. A converse process has also been observed in some humid areas where drought has increased malaria transmission because it results in pooling of rivers and the creation of breeding sites. In general, however, the perceived wisdom is that in the warm semi-arid lowland areas in Africa, rainfall excess is an important predictor of epidemics (WHO, 2002). Malaria early-warning systems based on vulnerability assessment and rainfall variability were used in India in the early part of the 20th century. It is only in recent years, however, that there has been a concerted effort to develop such systems for epidemic prone areas in Africa. (Hay *et al*, 2001; Thomson *et al.*, 2001, WHO, 2001, Goddard *et al.*, 2002).

At present, there are no practical tools for temporal prediction of the occurrence of malaria based on observed rainfall or weather forecasts in Tanzania. For Africa, such tools have been developed (Teklehaimanot *et al*., 2004) and applied. Recent work (Thomson *et al*., 2006; Myers e*t al.*, 2000) focuses on malaria early warning systems, in which flags are raised when epidemics are expected. It is difficult to define, especially in Tanzania, at what level malaria incidence is thought to be normal, as the malaria time series show strong long-term fluctuations and it is, therefore, difficult to set thresholds. In general, disease forecasting is most useful to health services when it predicts case numbers two to six months ahead, allowing tactical responses to be made when disease risk is predicted to increase (or decrease) (Goddard *et al*., 2002). For this reason this work will avoids the problem of setting epidemic thresholds, and focuses on forecasting malaria cases. Malaria case numbers are influenced by factors intrinsic to malaria such as infectivity, immunity and susceptibility of vectors and humans, and extrinsic, environmental factors such as rainfall. There are number of possible models for malaria prediction from biological to statistical models. In biological process models, typically consisting of sets of equations, prediction can be done with details of all pathways, parameters and variables believed to be important for the dynamics of the disease (Goddard *et al*., 2002). In statistical models, temporal or spatial autoregressive terms account for the fact that case numbers depend on past or nearby case numbers through (sometimes cyclical) intrinsic processes, as well as for (unobserved) extrinsic auto correlated factors or factors with fading effects. This study is limited to some statistical models that are robust enough but relatively easily implemented (and /or that have been used successfully elsewhere in malaria forecasting studies.

CHAPTER THREE

DATA AND METHODS

3.0 Introduction

This chapter describes the data used and the methods of analysis. The methods used to achieve the objectives of the study include time series analysis and epidemic alert detection model.

3.1 Data

The data used in the study include monthly laboratory confirmed malaria cases and climate data that includes monthly rainfall values and monthly maximum and minimum monthly air temperature respectively

3.1.1 Climate Data

Climate data which comprises of monthly rainfall and monthly maximum and minimum air temperature were collected from five representative meteorological weather stations namely, Arusha, Nyerere International Airport (NIA), Dodoma, Zanzibar and Bukoba. The Meteorological data were available from 1978 to 2008, covered a period of 30 years. The 30 years were used so as to have a sufficient data base period for climatology. The data were obtained from Tanzania Meteorological Agency

3.1.2 Malaria Cases Data

Malaria cases data comprises of laboratory confirmed (i.e. blood sample that tested positive with malaria parasite) monthly malaria cases obtained from National Malaria Control Project (NMCP) in Tanzania, they were available for a period of 9 years from 2000 to 2008 from five hospitals: - Rubya, Dareda, Zanzibar, Utete and Mpwapwa, only five hospitals were singled out due to the consistence in the data series.

3.1.2 Data Quality Control

The data were subjected to quality control procedure with the aim of identifying outliers in the time series. The consistency of the data was also checked by comparing the data records amongst themselves and with that of neighboring stations. Examples of the possible errors and inconsistencies that may be found in the data records includes:-

- Daily maximum or minimum temperatures are unrealistically high or low.
- Inconsistence in the rainfall figures e.g. negative values or very high values

3.2 Methods of Analysis

This section outlines the procedures used to generate results of the study. The data were subjected to quality control and homogenization procedures. Time series analyses were applied to investigate the trends in the data series. Correlation analysis was done to investigate the association between malaria cases and climatic variable. Epidemics detection method was also done to identify epidemic alert threshold in highland areas and epidemic surges in malaria endemic areas.

3.2.1 Missing Data

There were no missing data procedures done in this study, since the data sets given were complete.

3.2.2 Homogeneity test

The data were then passed through homogeneity test. Reliable climatological time series are essential for the analysis of climate trends, climate variability and for the detection of anthropogenic climate change (Vincent, 1998). Therefore before any series can be used in climate studies it should be homogeneous. A homogeneous climate time series is defined as one where variations are caused only by variations in weather and climate (Sneyers, 1990). Inhomogeneities in stations data records data records are often caused by changes in observation routines, among which stations are station relocations, changes in measuring techniques and observing practices, differences in formulae for mean calculation. These can lead to misinterpretations of the climate of a region.

A range of techniques for the identification and adjustment of various inconsistencies in climatological data sets have been developed (Alexanderson *et al.*, 1997; Vincent, 1998; Vincent *et al.*, 2002). Most of these techniques are based on relative homogeneity that involves the comparison of a candidate series with a reference series and patterns are identified in the relationships between the series (Vincent, 2002).

The homogenization techniques are usually based on maximum likelihood approaches, regression models termed as Bayesian procedures, visual techniques to identify major inhomogeneities in a time series and station history reports. However the latter two techniques have some shortcomings, first on (of the latter two) is not sufficient for local scale studies as corrections are intended to be general adjustments only, and the second involves review of the station history files which is a tedious process besides that frequently these reports do not provide sufficient information for the proper identification all non climatic changes (Vincent, 1998). In this study cumulative single mass curve analysis was used to study the homogeneity in the rainfall and temperatures data series.

The cumulative mass curve technique involves accumulating monthly records for these stations and plotting these values against time for each of the station. The test has been used in various studies (Ocholla *et al.*, 2006). Cumulative mass curve analysis involves two methods, the cumulative single mass curve analysis and the cumulative double mass curve analysis. Cumulative single mass curve analysis employs the plot of cumulative records of a time series against time, whereas the cumulative double mass curve analysis employs the plot of a time series of the deviation of a station's accumulated value from the average accumulation of the group against time. In both methods straight line would indicate a homogeneous record whilst heterogeneity would be indicated by significant deviation of some of the plot from the straight line.

3.2.2 Time series Analysis

Time series analysis was used to study the effect of climate on malaria cases in some areas in Tanzania. Time series is made up of four components which are (a) trend, (b) seasonal change, (c) cyclic changes and (d) random fluctuations.

There are two main goals of time series analysis: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described. Once the pattern is established, it can be interpreted and integrated with other data. In this study trend in both malaria data and climatic variables was investigated.

3.2.3 Correlation Analysis

The index or statistic most commonly used to indicate the strength of the association between two variables is the correlation coefficient r. Just as the mean and variance give a useful summary description of one distribution, the correlation coefficient gives useful summary description of association between a two distributions. Pearson's product moment correlation coefficient r can take values from +1 to -1 by which means it indicates how close to linearity the associations (Roger *et al.*, 1996). Person's correlation (r) was used to investigate the association between malaria cases and the climatic variables

$$r = \frac{\sum(X_i-\bar{X})(Y_i-\bar{Y})}{(n-1)S_X S_Y} \quad \ldots\ldots (1)$$

Where

$\sum X_i$ and $\sum Y_i$ are the sum over all the n measure of X and Y respectively

r is the Pearson's correlations index

S_x and S_y are standard deviation of X and Y variable respectively

3.3 Early Malaria Epidemic Prediction Model

This sub section illustrates the following processes model construction, identification of malaria cases, rainfall and temperature anomaly. It also gives out the description of the Early Malaria Prediction Model.

3.3.1 Model Construction

The modeling procedure involves analyzing historical malaria and climate data. This is referred to as retrospective data analysis.

3.3.1.1 Malaria data: Identification of malaria case anomaly

The long term mean of the cases was first calculated. By subtracting the mean from the number of cases in each month, the monthly case anomaly was then obtained. The monthly case anomaly is better presented as a percent departure from the long term mean. This is given by:-

$$PD = \left(\frac{X-\overline{X}}{\overline{X}}\right) * 100 \quad \text{...} (2)$$

Where, PD is the percent departure from the long term mean

X is the observed time series value

$\overline{X}$ is the long term mean

3.3.1.2 Rainfall anomaly

In many lowland areas where drainage is poor the minimum mean monthly rainfall that allows the mosquito population to increase is 150 mm/ month. Rainfall below this threshold has no effect on mosquito populations and therefore no effects on malaria. In well drained highlands the threshold rainfall for mosquito population increase is not usually well known, however a threshold of 250-300 mm/ month is assumed (Githeko, 2009). In order to determine malaria trends in time the logical statement is established to identify the signal. The logical conditions/ categories of rainfall amounts filter and identify positive rainfall signals and convert it into categorical data and effectively remove "noise" from the data. On the other hand the amount of monthly rainfall that was associated with past malaria epidemic can be determined graphically. The logic equation can be as follows

=IF(J31<200,0,IF(J31<251,1,IF(J31<301,2,IF(J31<351,3,4))))................................(3)

Thus

If rainfall < 200mm = 0

If rainfall < 250mm = 1

If rainfall < 301mm = 2

If rainfall < 351mm = 3

If rainfall > 351mm = 4

3.3.1.3 Calculation of temperature anomalies

Temperature anomaly is obtained from long term monthly data for maximum and minimum temperature. Thirty (30) years of data is required in obtaining the climatological value. This data is referred to as the climatology of the site under investigation. To obtain the anomalies climatology data was subtracted from monthly data of the years of interest. After obtaining the anomalies the data was filtered using a logical formula designed to remove the noise (the formulation of this logic equation follows the same argument as in equation one above only that the rainfall is replaced with total filtered temperature anomaly) and to remain with extreme cases so as to determine the climate variability of the given area and its influence on the malaria transmission.

3.3.1.4 The Model

The model is a simple formula that combines rainfall and temperature anomalies in a specific way to calculate the risk of a malaria epidemic, the first sign of a risk is seen in anomalous temperatures before a rainy season. Normally the peak of the temperature anomaly occurs two months before the rainfall threshold is exceeded. For example take January temperature anomaly and combine it with March rainfall anomaly. This will give a forecast for June of the same year. Some times temperature anomalies are observed but rainfall is below the threshold level. The model returns a zero risk. For example if the temperature anomaly is +3 and the rainfall level is zero the $3 \times 0 = 0$. This removes the false epidemic signal.

Then the model is constructed using the following equation.

$$ER = \left(\frac{T_i x R_{i+2}}{T_m x R_m}\right) * 100 \quad \text{...} (4)$$

Where T_i is the i_{th} filtered total temperature anomaly,

R_{i+2} is the lag two filtered rainfall

T_m and R_m are the maximum filtered temperature and rainfall anomaly observed respectively. ER is the epidemic risk predicted in percentage.

3.3.1.5 Model construction using standardized data

In this case climatic variable data are standardized while the malaria cases data remains untransformed. The anomalies are then calculated, filtered and then simulated into the model to determine the epidemic risk. The standardization is done using the equation five below

$$SV = \frac{X - \overline{X}}{SD} \quad \text{..} \quad (5)$$

Where

SV is standardized value

SD is the standard deviation

X is the time series value

$\overline{X}$ is the long term mean

3.4.2 Epidemic detection

There is no globally or regionally applicable definition of malaria epidemics. Epidemic thresholds are established according to local epidemiological settings. This requires surveillance system, laboratory procedures, data analysis, timely reporting and notification, there are two thresholds that are valuable for the prevention and control of malaria epidemics

- an alert threshold for early warning and
- an epidemic threshold for early detection.

In this study epidemic detection was based on the method proposed by Cullen *et al.*, 1984 which employ the use of mean and standard deviation (MeanSD). Specificity of the MeanSD method for threshold calculation is high compared with other existing methods i.e. C-SUM and quartile methods for seasonal diseases such as Malaria. The C-SUM is the mean calculated over the combined previous, current and following month's data for the past 5 years. The method can be refined by adding a 95% confidence interval (1.96 SD). On the other hand quartile method involves the use of an alert when current cases exceed the upper 3rd quartile or the upper normal limit, determined from 5 years of retrospective monthly case data. The MeanSD is based on the assumption that the number of cases in time approximates a normal distribution. The epidemic alert threshold for each month was determined as the average monthly malaria cases in the past five (5) years plus two times the standard deviation. Equation 4 illustrate,

$$E = \overline{X} + 2SD \qquad (6)$$

Where, E is the epidemic value,

$\overline{X}$ is the long term mean and SD is the standard deviation

According to Guofa *et al.*, 2003, Cullen's method for epidemic detection based on untransformed monthly malaria outpatient numbers is a sensitive method. The epidemic incidences of the five sentinel hospital with their corresponding period were identified.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

The chapter presents and discusses results found in the study. Homogeneity of the data is discussed, followed by trend and correlation analysis, epidemic detection and the model results.

4.1 Results from Data Quality Control

4.1.1 Single Mass curve

Figure 2 shows the results of single mass curve when applied to Arusha monthly rainfall series. The plot shows nearly a straight curve which means homogeneity on the tested series. All weather data in all representative weather stations were found to be homogeneous.

However quality control could not be applied to malaria cases data due to their nature. Their quality control would involve going back to the respective hospitals and verify on the methods used in data collection. This was not possible due time limitations of the duration of the project.

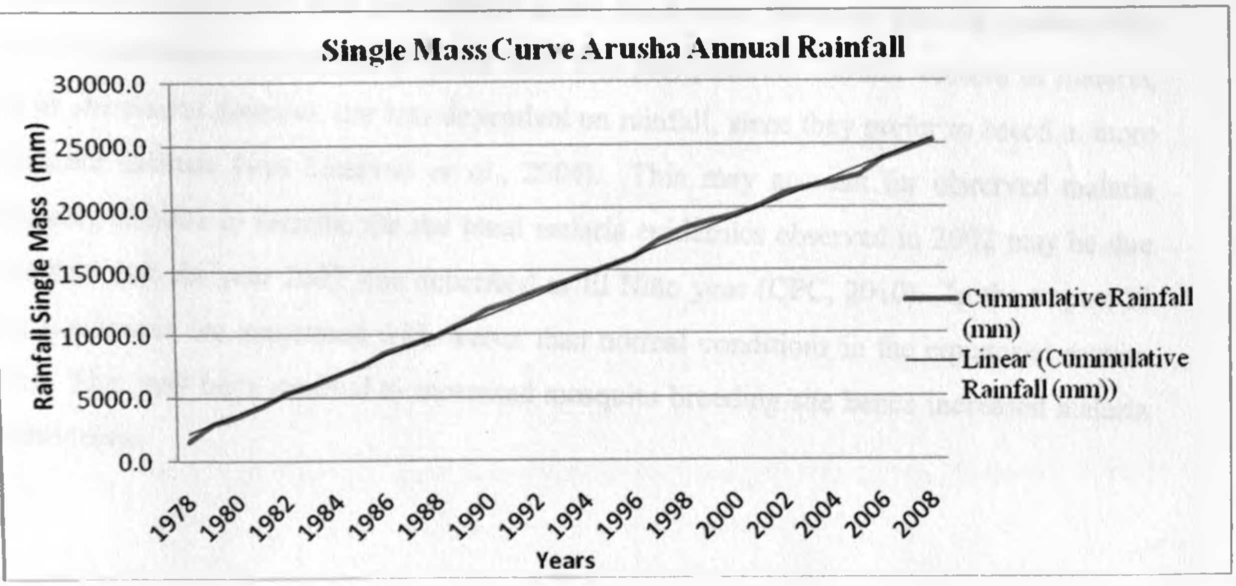

Figure 3: Single Mass Curve homogeneity test for monthly rainfall series of Arusha weather station

4.3 Epidemic detection

Epidemic alert threshold for each month was determined as the average monthly malaria cases in the past five (5) years plus two times the standard deviation. The base year was from 2000 to 2004 from the data set of 2000 to 2008. Table 1 shows an example of results of mean plus two standard deviations done in this study.

Table 1: Mean plus two standard deviations in Dareda

2000-2004	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean+ 2SD	**375**	**401**	**384**	**512**	**510**	**336**	**223**	**195**	**259**	**221**	**275**	**216**

In Dareda hospital Epidemics were observed in September and October 2002 and in March and April 2001 figure 4 explains. This was realized when the graph of mean plus two standard deviations was plotted in the same graph with malaria cases observed in 2001 and 2002. According to Climate Prediction Centre (CPC, 2010), the year 2001 was under the influence of La Niña conditions especially in the month of January and February, La Niña conditions are associated with low rainfall to dry conditions. However there is evidence that malaria transmission can occur in areas with less precipitation. Certain vectors of malaria, such as *Anopheles funestus*, are less dependent on rainfall, since they prefer to breed in more permanent habitats (van Lieshout *et al.*, 2004). This may account for observed malaria epidemics of 2001 in Dareda. On the hand malaria epidemics observed in 2002 may be due to the fact that the year 2002 was described as El Niño year (CPC, 2010). In the tropics El Niño conditions are associated with wetter than normal conditions in the equatorial eastern Africa. This may have resulted to increased mosquito breeding site hence increased malaria transmissions.

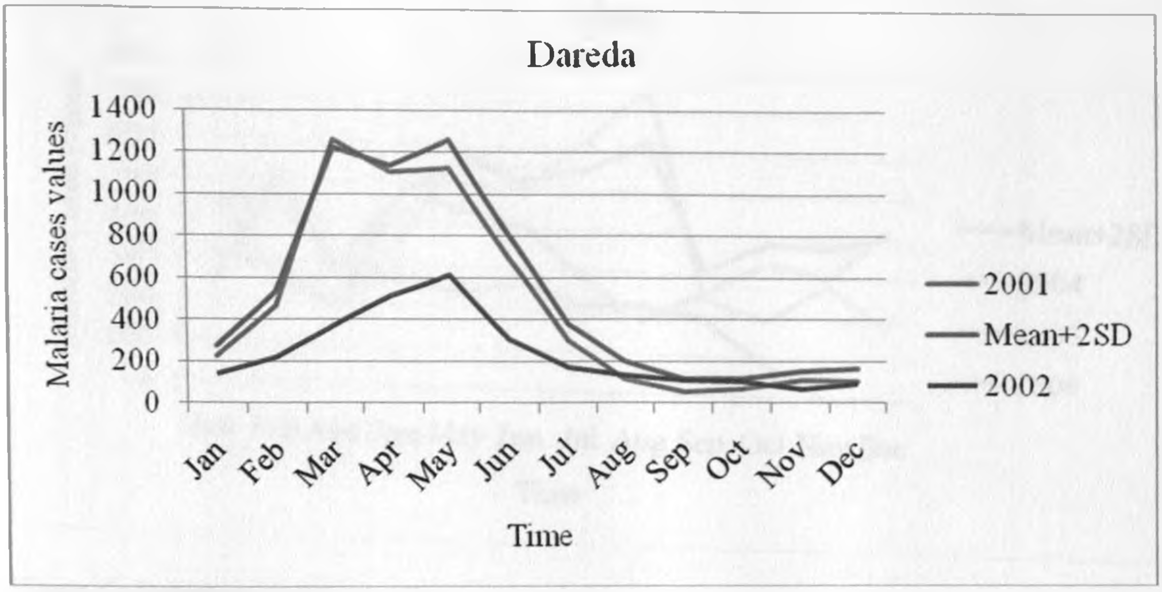

Figure 4: Epidemic in Dareda

Utete is in low land area in which rainfall plays a major factor in malaria transmission. Epidemics in Utete hospital were identified in February 2006, December 2004, May and August 2005, figure 5 clarify. The observed epidemics may be due to rainfalls rather than other climatic variables such as temperatures. Epidemics observed in 2006 may be associated with warm conditions which were observed in this year, these conditions resulted in normal to above normal rainfall, in Utete for example rainfall records from September to December shows that rainfall total was 573.5 mm, according to van Lieshout et al., 2004 a minimum level of monthly rainfall of 80 mm for at least four consecutive months (concurrently with the window of suitable temperature) is essential for seasonal malaria transmission. The value of 80 mm per month was also described by the MARA project (Mapping Malaria Risk in Africa) as a prerequisite rainfall condition for endemic malaria (Craig *et al.*, 1999; MARA, 1998). On the other hand malaria epidemics observed in 2004 and 2005 may have been attributed to El Niño conditions observed in May, June, July (MJJ) season in 2004 to December, January, February (DJF) season in 2005 which resulted to normal to above normal rainfall in many parts of the eastern equatorial Africa.

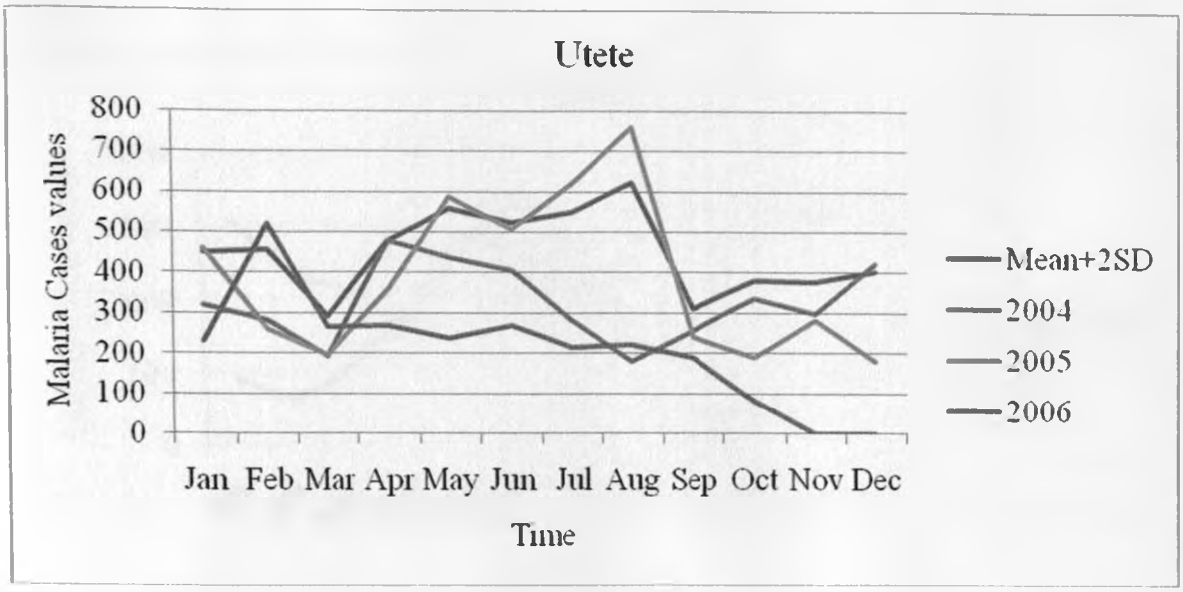

Figure 5: Epidemic in Utete

In Rubya epidemics were detected in April and May 2006 figure 6 explains. The 2006 epidemics were due to El Niño conditions which resulted in normal to slightly above normal rainfall. Rainfall plays an important role in malaria epidemiology, mosquitoes breed in standing water (usually freshwater pools or marshes) and therefore mosquito abundance is affected by rainfall and the availability of surface water (van Lieshout et al., 2004). Rainfall also affects relative humidity and hence the longevity of the adult mosquito, this results to epidemics which affect a large number of populations of a given area.

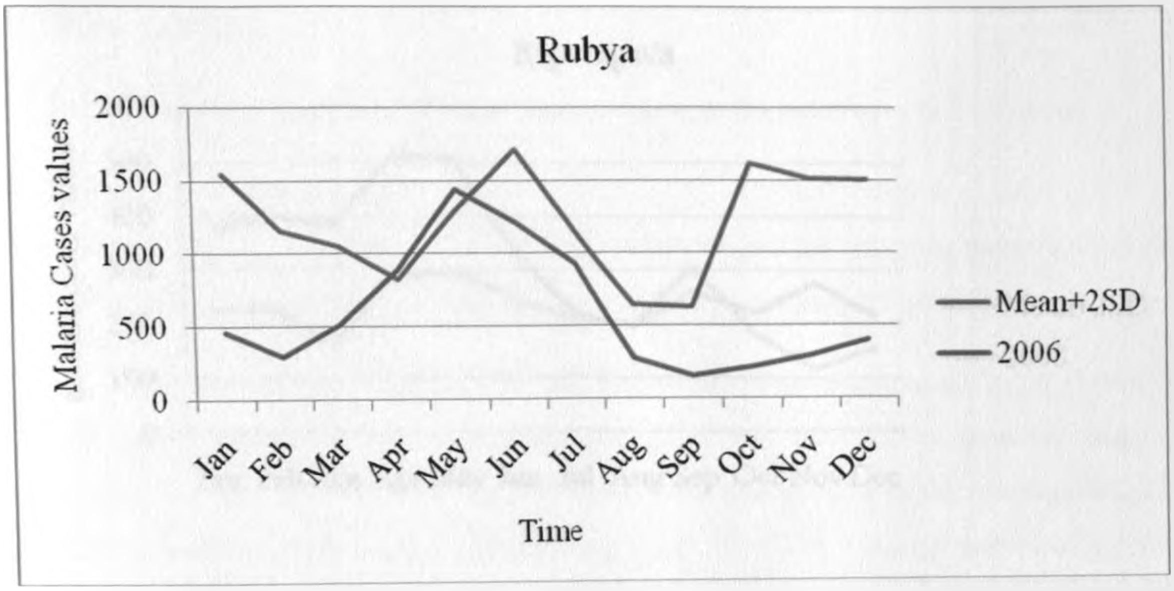

Figure 6: Epidemic in Rubya

On the other hand in Mpwapwa hospital epidemics were observed in August and September 2008. Figure 7 shows the observed epidemics. Despite of the fact that Mpwapwa is semi arid region of Tanzania which features single rainfall season mainly that of long rains of March to May (MAM), malaria epidemics do occur outside this season, this may be attributed to other factors such as environmental factors which encompass increased anophelism due to human activities. Some studies explains that abnormal increases in anophelines populations and the establishment of vectors outside their zone of distribution are due to natural factors but are also often due to human activity (man-made malaria), (Onori and Grab., 1980).

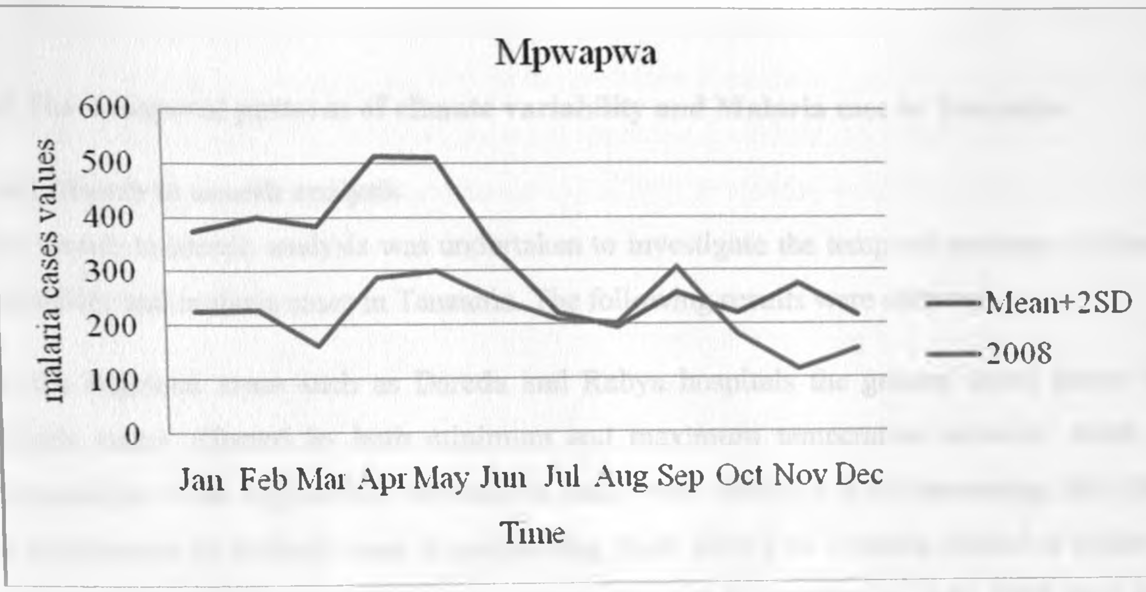

Figure 7: Mpwapwa epidemics

However there were no epidemics detected from 2000 to 2008 in Zanzibar figure 8 explains, this might be due to the method used for epidemic detection was of higher threshold or may be due to the on going malaria intervention programs, a lesser threshold would have produced better results. Trend analysis on malaria cases shows a decreased trend. Although the result shows no epidemics in the Island but many past studies shows that the Island community has suffered a lot from malaria epidemics.

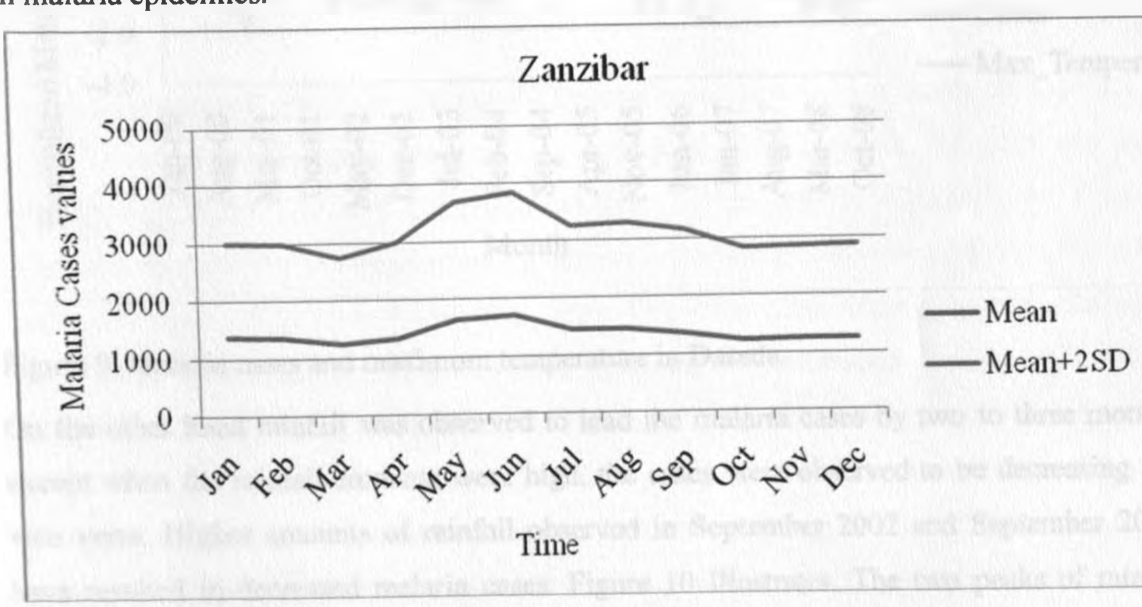

Figure 8: Epidemic in Zanzibar

4.4 The Temporal patterns of climate variability and Malaria case in Tanzania

4.4.1 Month to month analysis

The month to month analysis was undertaken to investigate the temporal patterns of climate variability and malaria cases in Tanzania. The following results were obtained

In the highland areas such as Dareda and Rubya hospitals the general trend shows that malaria cases affected by both minimum and maximum temperature however when the temperatures were high or low the malaria cases were observed to be decreasing, this effect of temperature to malaria cases is manifesting itself after 2 to 3 month period of higher or low temperature, for example higher temperature peak observed in July 2002 may have contributed to the low cases observed in September 2002, figure 9 illustrates.

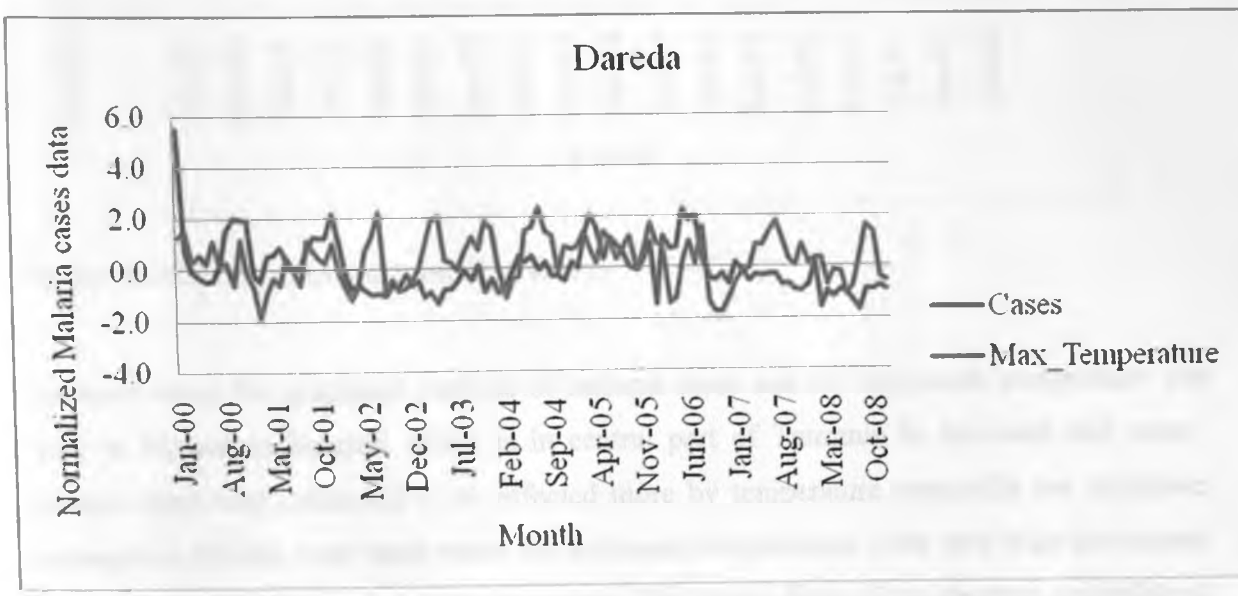

Figure 9: Malaria cases and maximum temperature in Dareda

On the other hand rainfall was observed to lead the malaria cases by two to three months, except when the rainfall amounts were high, the cases were observed to be decreasing and vice versa. Higher amounts of rainfall observed in September 2002 and September 2006, have resulted in decreased malaria cases. Figure 10 illustrates. The two peaks of rainfall observed in September 2002 and 2006 respectively may have been excess in such away that destroyed the mosquito habitats thus resulted to reduced malaria cases. However some studies argues that weather extreme may trigger epidemics in particular areas, for example higher temperatures, in combination with conducive patterns of rainfall and surface water, will prolong transmission seasons in some endemic locations. In other locations, climate variability will decrease transmission via reductions in rainfall or temperatures that are too high for transmission.

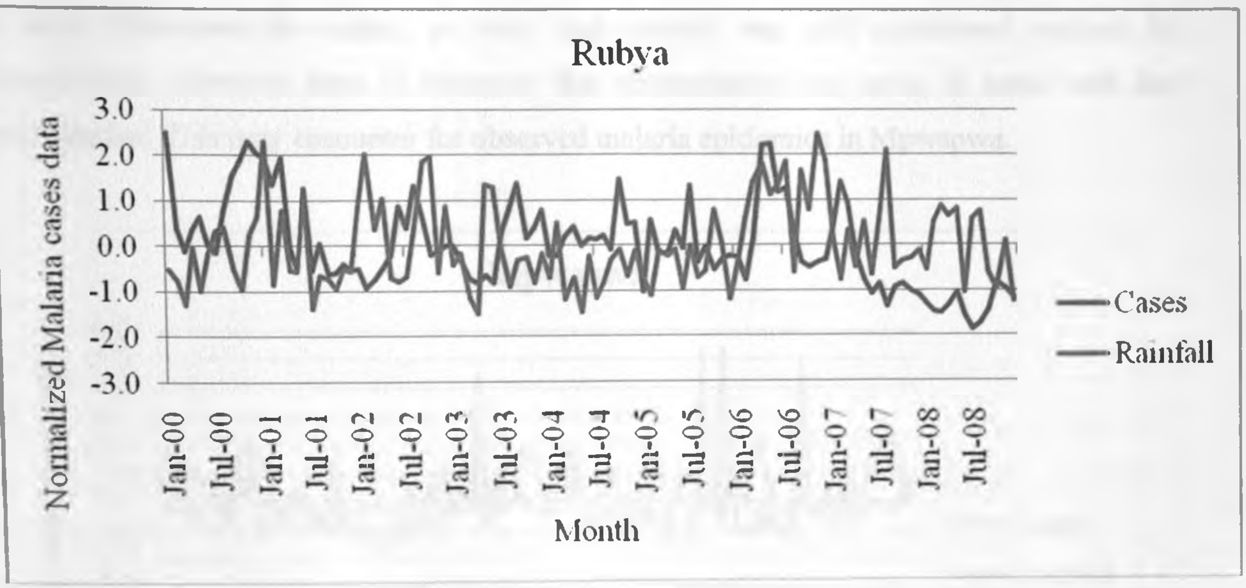

Figure 10: Malaria cases and rainfall in Rubya

However when the graphical analysis of malaria cases and the maximum temperature was done in Mpwapwa hospital which is in central part of Tanzania in the semi arid sector, malaria cases were observed to be affected more by temperature especially the maximum temperature. On the other hand when the minimum temperatures were very high the malaria cases are observed to be low and vice versa. The lower limit of temperature suitability is determined by the number of mosquitoes surviving the incubation period, while parasite development only ceases at 16°C, transmission below 18°C is unlikely because few adult mosquitoes survive the 56 days required for sporogony at that temperature, and because mosquito abundance is limited by long larval duration, (Craig *et al.*, 1999), this may have attributed to the observed trend since the average minimum temperature for this areas is 16.9^{0}C which is below the required temperature for malaria transmission to occur.

The analysis further depicted that rainfall was leading the malaria cases, except for extreme conditions when the rainfall was very high the malaria cases were decreasing, rainfall peaks observed in September 2006 and August 2007, may have contributed to the low malaria cases observed in figure 11. Extreme conditions such as floods or drought which oftenly occur in semi arid areas affect mosquito abundance hence transmissions, although it is known that flooding often causes destruction of breeding sites and a temporary reduction of vectors, it never eliminates the vector, so very high rainfall was still considered optimal for transmission. However there is evidence that transmission can occur in areas with less precipitation. This may encounter for observed malaria epidemics in Mpwapwa.

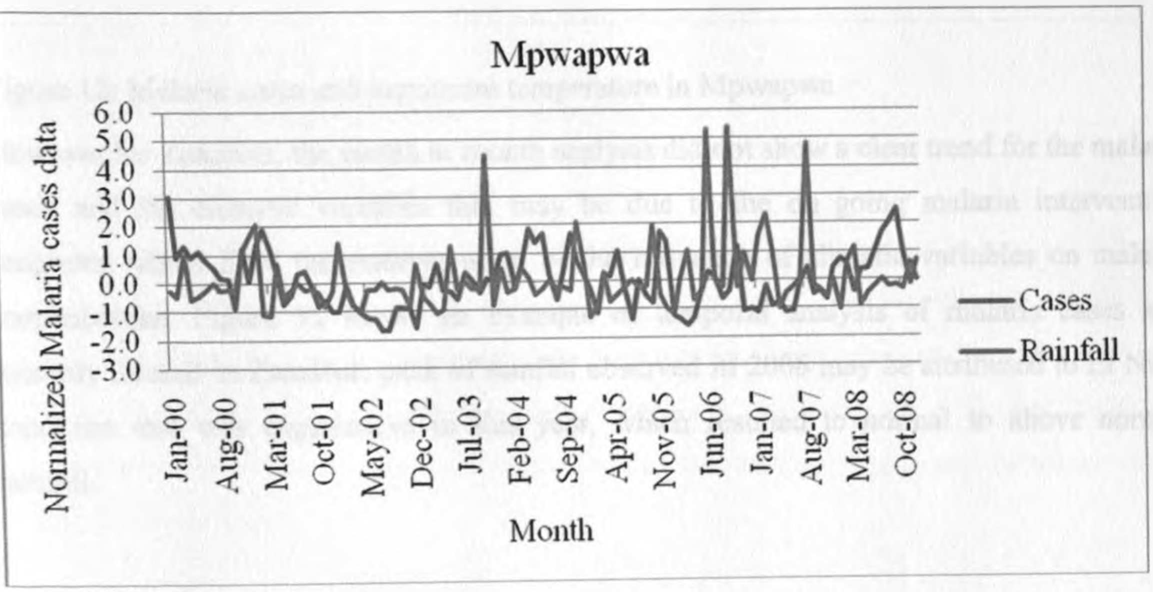

Figure 11: Malaria cases and rainfall in Mpwapwa

Further more when the analysis was done in Utete hospital which is along the coast strip and is classified as malaria endemic area, malaria surges were observed, figure 12 shows the temporal analysis between maximum temperature and malaria cases, this graph shows malaria surges in some years. Most of coastal areas temperature is not a limiting factor however other climatic factors such as rainfall and non climatic factor contributes to the malaria surges that are being observed.

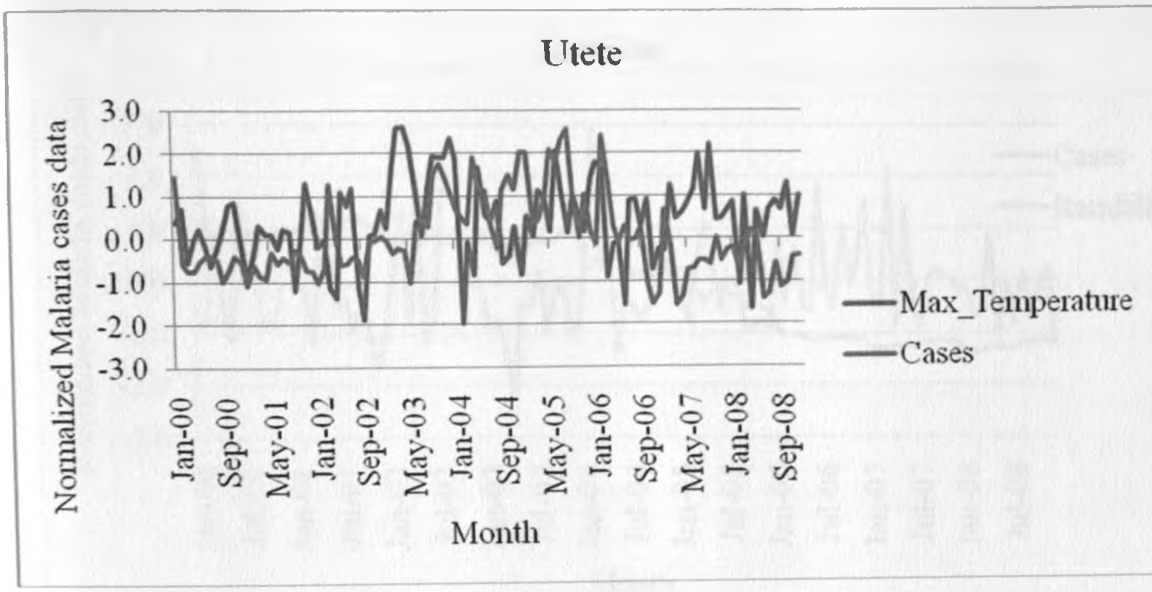

Figure 12: Malaria cases and maximum temperature in Mpwapwa

However for Zanzibar, the month to month analysis did not show a clear trend for the malaria cases and the climatic variables this may be due to the on going malaria intervention programs which limit the understanding of the influence of climatic variables on malaria transmissions. Figure 13 shows an example of temporal analysis of malaria cases and monthly rainfall in Zanzibar, peak of rainfall observed in 2006 may be attributed to El Niño condition that was experienced in this year, which resulted to normal to above normal rainfall.

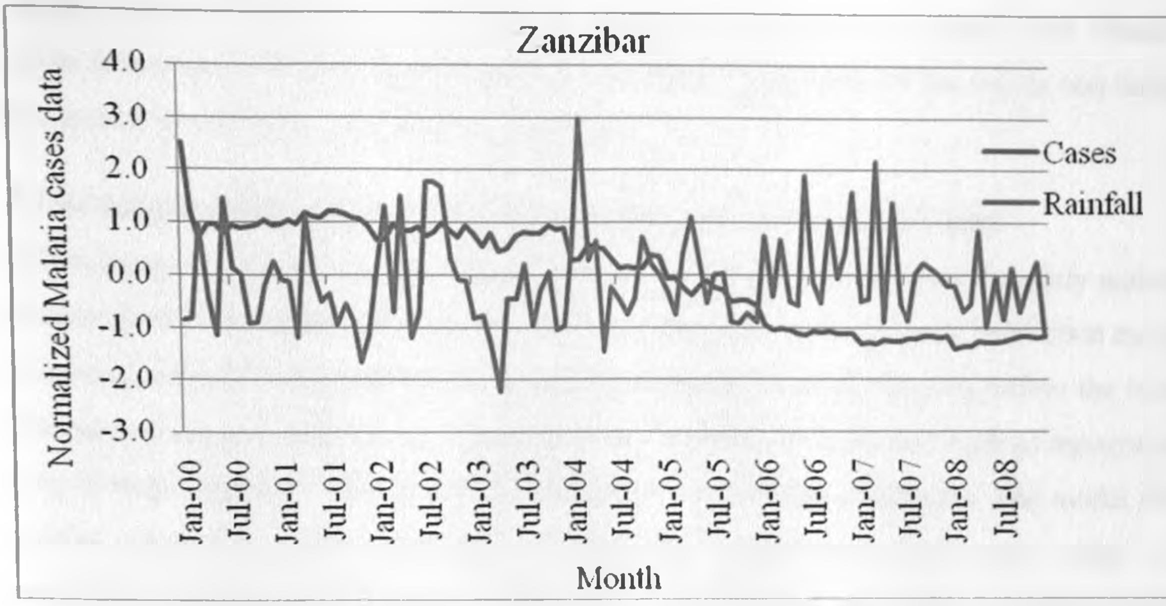

Figure 13: Malaria cases and rainfall in Zanzibar

4.4.2 Results of Correlation Analysis

Correlation analysis was done to investigate the association between maximum temperature and malaria cases, minimum temperature and malaria cases and rainfall and malaria cases, maximum temperature was highly correlated with malaria cases in Zanzibar, Mpwapwa and Utete, poor correlation was observed between malaria cases and other climatic variables in all sentinel sites, table 2 below explains. This shows that the association between climatic variable is non linear.

Table 2: Correlation analysis results

			Temperature	
Hospital		**Rainfall/Malaria cases**	**Max/Malaria cases**	Min/ malaria cases
Zanzibar	***r***	-0.11	1.00	0.14
Mpwapwa	***r***	0.28	0.57	1.62
Dareda	***r***	0.23	1.19	1.22
Utete	***r***	-0.33	\.93	2.70
Rubya	***r***	0.13	-0.23	∞

In both correlation analysis and temporal analysis between malaria cases and climatic variable done results reveals that the relationship which exists between the two is non linear, thus a model was done to unveil this association.

4.5 The relationship between climate variable and the malaria Cases

The link between climate variable and malaria cases was established using the early malaria epidemic prediction model. This model is a climate based malaria epidemic prediction model which was designed to use meteorological data starting at about six months before the onset of the rains (long and short rains). The model may be affected by factors such as topography and hydrology. However, the model can be adjusted to fit local conditions. The model first identifies anomalies in the maximum and minimum temperature which occur about 2-3 months before the on set of the rains. The model then identifies anomalies in rainfall which allows extensive breeding of mosquitoes. The risk of a malaria epidemic is calculated from the total temperature anomaly and the rainfall anomaly. The first risk of an epidemic is identified in the temperature anomaly. This relationship between climate variable and malaria cases was investigated using early malaria epidemic prediction model the following results were obtained

4.5.1 Malaria Cases Anomaly

The long term mean of the cases was first calculated so as to determine the malaria cases trend in time. The mean was subtracted from the number of cases in each month; the monthly case anomaly was obtained. The monthly case anomaly is better presented as a percent departure from the long term mean. This procedure was employed in all hospitals under investigation. Table 3 below shows only part of results from Dareda which comprises of part of the data from 2004-2005. In the example below the long term mean were 153 cases/ month. In April 2004 the percent departure was calculated as follows:

$$PD = \left(\frac{390-153}{153}\right) * 100 = 155.5\%$$

Table 3: Malaria Cases Anomaly in Dareda

Year	Cases	Mean	Departure	% Departure
Jan-04	83	153	-69.65	-45.63
Feb-04	132	153	-20.65	-13.53
Mar-04	257	153	104.35	68.36
Apr-04	390	153	237.35	155.48
May-04	424	153	271.35	177.76
Jun-04	372	153	219.35	143.69
Jul-04	119	153	-33.65	-22.05
Aug-04	102	153	-50.65	-33.18
Sep-04	42	153	-110.65	-72.49
Oct-04	39	153	-113.65	-74.45
Nov-04	61	153	-91.65	-60.04
Dec-04	72	153	-80.65	-52.83
Jan-05	105	153	-47.65	-31.22
Feb-05	280	153	127.35	83.42
Mar-05	502	153	349.35	228.85
Apr-05	496	153	343.35	224.92
May-05	440	153	287.35	188.24
Jun-05	493	153	340.35	222.96
Jul-05	246	153	93.35	61.15
Aug-05	140	153	-12.65	-8.29
Sep-05	83	153	-69.65	-45.63
Oct-05	54	153	-98.65	-64.63
Nov-05	41	153	-111.65	-73.14
Dec-05	90	153	-62.65	-41.04

4.5.2 Rainfall anomaly

A threshold of 150 mm/ month was used to determine the rainfall amount associated with past malaria cases. However the model requires different thresholds for one area to another, for example for a well drained area a higher threshold of 250 -300 mm/ month is required. Table 4 below shows part of the results obtained in Dareda using a threshold 150 mm/ month. The logical statement in equation 7 was used to identify the signal. The logic filters, identifies positive rainfall signals and converts it into categorical data and effectively removes "noise" from the data. The above procedure was done in all other remaining sites.

On the other hand figure 14 shows the effective rain signal that may have been associated with malaria epidemics in Dareda

=IF(Q2<150,1,IF(Q2<201,2,IF(Q2<251,3,4)))--- (7)

Thus

If rainfall < 150 mm = 1

If rainfall < 200mm = 2

If rainfall < 251mm = 3

If rainfall < 301mm = 4

Table 4: Rainfall Anomaly in Dareda (2000-Jun 2001)

Year	Rainfall (mm)	Rainfall filter
Jan-00	28.2	1
Feb-00	26.7	1
Mar-00	44.6	1
Apr-00	143.8	1
May-00	30.1	1
Jun-00	10.5	1
Jul-00	3.8	1
Aug-00	15.8	1
Sep-00	4.0	1
Oct-00	0.0	1
Nov-00	102.6	1
Dec-00	120.7	1
Jan-01	225.1	3
Feb-01	23.5	1
Mar-01	178.9	2
Apr-01	108.5	1
May-01	47.7	1
Jun-01	16.9	1

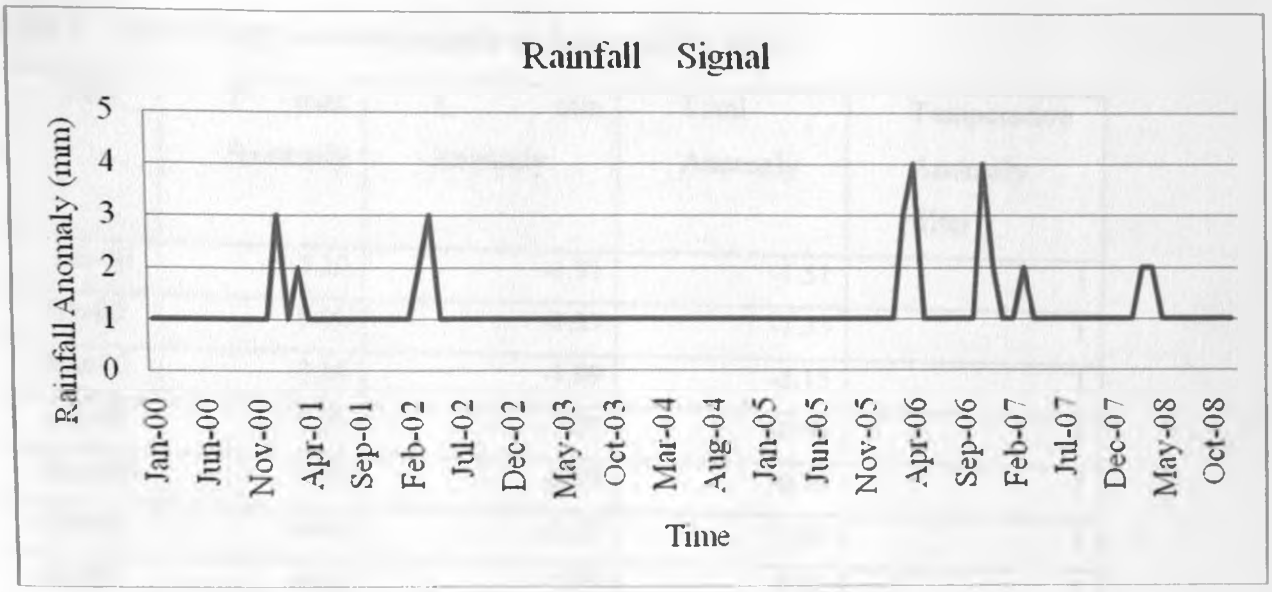

Figure 14 Effective rain signal in Dareda

4.5.3 Calculation of Temperature anomalies

The temperature anomalies for this model was calculated after determining the climatology value, 30 years of data from 1978-2008 was used to obtain this value. The climatology data was then subtracted from the maximum and minimum temperature. Total temperature anomaly from the maximum and minimum temperature was obtained by adding the two anomalies. Then the epidemic signal from the anomalies was obtained using logical statement. The above procedure was done in all sites, table 5 below shows part of results of temperature anomaly calculated in Rubya. The logical statement used is shown in equation 8 below. However for malaria epidemics to occur these temperature signals must be followed by heavy rainfall. Mosquito breeding sites become unsuitable for mosquito breeding a few weeks after the rains due to growth of vegetation. In some cases the weather signal may be present but most of the habitat is unsuitable for mosquito breeding.

=IF(H2<2,1,IF(H2<3,2,IF(H2<4,3,5)))... (8)

Table 5: Temperature anomaly signals in Rubya (2000-2001)

Year	T max Anomaly	T min Anomaly	Total Anomaly	Temperature Anomaly filter
Jan-00	0.20	-1.71	-1.51	1
Feb-00	-0.06	-1.27	-1.33	1
Mar-00	-0.16	-1.99	-2.15	1
Apr-00	0.27	-1.21	-0.94	1
May-00	0.29	-0.59	-0.30	1
Jun-00	0.02	-1.11	-1.09	1
Jul-00	-0.02	-0.79	-0.82	1
Aug-00	-0.28	-0.45	-0.73	1
Sep-00	-0.63	-0.38	-1.00	1
Oct-00	0.00	-0.77	-0.76	1
Nov-00	-0.35	-0.71	-1.06	1
Dec-00	-0.65	-0.20	-0.85	1
Jan-01	-0.95	0.33	-0.61	1
Feb-01	-0.12	0.34	0.22	1
Mar-01	-0.24	0.25	0.01	1
Apr-01	0.13	0.61	0.74	1
May-01	-0.12	0.75	0.62	1
Jun-01	-0.63	0.19	-0.44	1
Jul-01	-0.53	0.07	-0.46	1
Aug-01	0.48	-0.35	0.13	1
Sep-01	0.25	-0.32	-0.08	1
Oct-01	-0.10	-0.30	-0.40	1
Nov-01	0.53	-0.69	-0.16	1
Dec-01	0.37	-0.05	0.32	1

4.5.4 Epidemic risk

The model for predicting malaria epidemics were constructed after determining the percentage of departure of the malaria cases, rainfall anomaly and total temperature anomaly. The epidemic risk was calculated for each month using equation 4. Table 6 shows an example of part of the results obtained after construction of the model and determine the malaria epidemic risk. The epidemic risk was determined in all the sites under investigations. Then the climatic variable data were standardized and simulated in the model; the standardization was done so as to come up with automatic way of simulating the threshold without making up assumptions or choosing them arbitrary. The results of both standardized values and arbitrary assumed threshold are discussed below in details

Table 6: Data set of temperature and rainfall anomalies, malaria cases percent departure from the long term mean and the model output in Rubya (2000-June 2001)

Year	% Departure of Malaria Cases	Total Temp anomaly filtered	Rainfall filtered	Model
Jan-00	97	1	1	-
Feb-00	38	1	1	-
Mar-00	-4	1	1	12.5
Apr-00	2	1	2	25
May-00	70	1	3	37.5
Jun-00	60	1	1	12.5
Jul-00	15	1	1	12.5
Aug-00	-27	1	1	12.5
Sep-00	-7	1	1	12.5
Oct-00	157	1	1	12.5
Nov-00	177	1	3	37.5
Dec-00	157	1	3	37.5
Jan-01	174	1	2	25
Feb-01	99	1	3	37.5
Mar-01	114	1	1	12.5
Apr-01	-17	1	3	37.5
May-01	-31	1	3	37.5
Jun-01	165	1	1	12.5

Dareda

The model shows good results, for example model signal of epidemic in January 2001 was able to predict the march 2001 malaria cases, the February 2005 signal were much stronger than the cases observed in April 2005 and this may be due to other non climatic factors or the threshold used which may need to be revised, malaria cases were observed to be decreasing while the model was sensing increasing signal, this is shown in figure 15, this might be due to intervention program which are carried out by the National Malaria Control Project (NMPC) in Dareda. However when both rainfall and temperature data were standardized and filtered using two standardized units for temperature anomaly and one standardized value range for rainfall, a better prediction was obtained. The logical statement in equation 7(a) and 7(b) were used to filter the standardized temperature and rainfall data respectively. Figure 16, shows the results using standardized values.

=IF (L2<-2, 1, IF (L2<0, 2, IF (L2<2, 3, 4))) ....7(a)

=IF (C2<1, 1, IF (C2<2, 2, IF (C2<3, 3, 4)))..7(b)

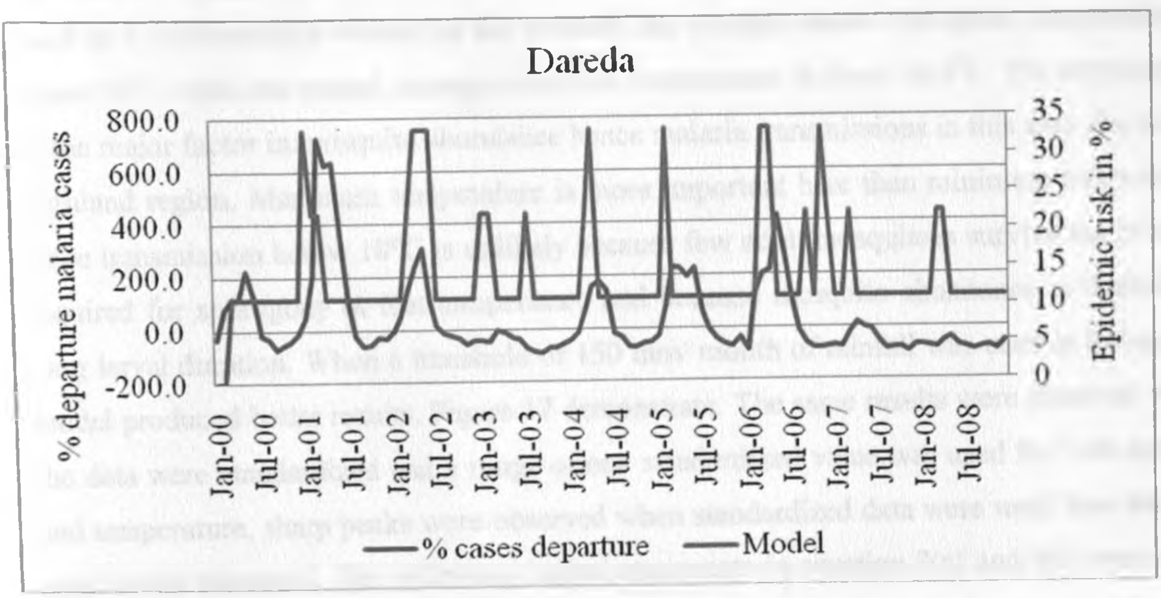

Figure 15: results using 150 mm/ month rainfall threshold in Dareda

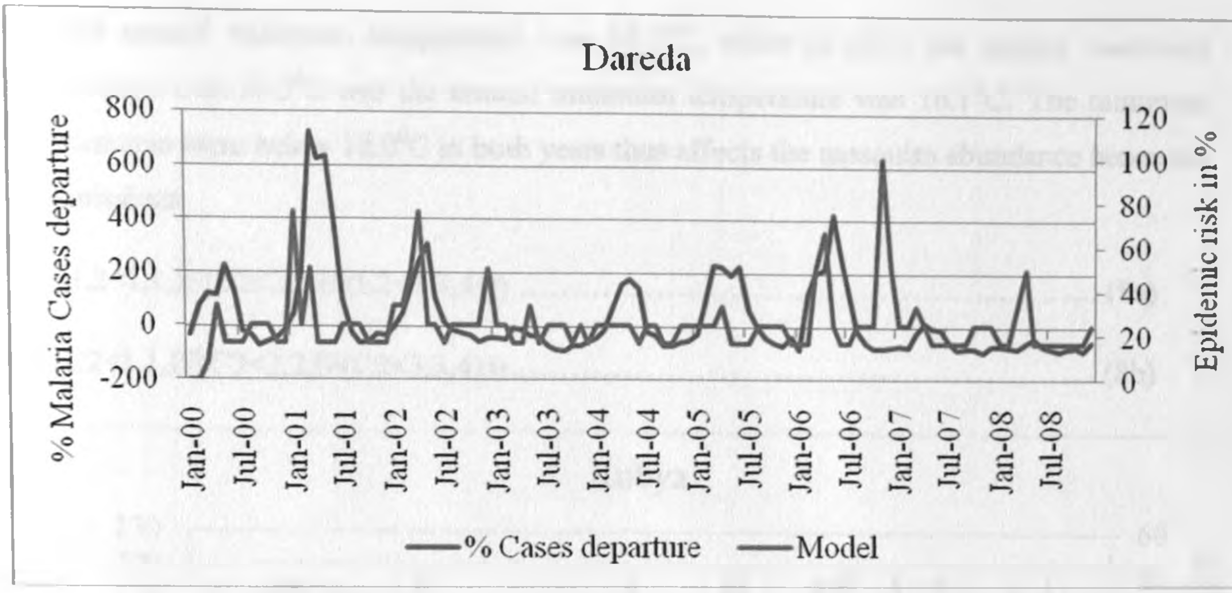

Figure 16: Epidemic risk in Dareda using standardized value

Rubya

Rubya hospital is in Kagera region in the western part of Tanzania, the climate of the area is affected by Congo air mass and the Lake Victoria effect. Bukoba Meteorological station was used as a representative station for the hospital; the average annual maximum temperature is about 26^0C while the annual average minimum temperature is about 16.8^0C. The temperature is the major factor in mosquito abundance hence malaria transmissions in this area since is in highland region. Maximum temperature is more important here than minimum temperature since transmission below 18°C is unlikely because few adult mosquitoes survive the 56 days required for sporogony at that temperature and because mosquito abundance is limited by long larval duration. When a threshold of 150 mm/ month of rainfall was used in Rubya the model produced better results. Figure 17 demonstrate. The same results were observed when the data were standardized and a range of one standardized value was used for both rainfall and temperature, sharp peaks were observed when standardized data were used than the 150 mm/ month threshold. The following logical statements in equation 8(a) and 8(b) were used to filter rainfall and temperature respectively. However the second method of using standardized value produced much stronger signal, however the model predicts less cases in the year 2000 and 2003 this may be due to the reason that these two years were dry compared to the others years under investigations, with annual total rainfall amount of 1202.9 mm and 1253.9 mm of rainfall respectively, also the annul maximum temperature in 2000 was 25.8^0C and the annual minimum temperature was 16.1⁰C, while in 2003 the annual maximum temperature was 26.3⁰C and the annual minimum temperature was 16.1⁰C. The minimum temperatures were below 18.0⁰C in both years thus affects the mosquito abundance hence the transmissions.

=IF (L2<1,1,IF(L2<2,2,IF(L2<3,3,4))) .... (8a)

=IF(C2<1,1,IF(C2<2,2,IF(C2<3,3,4))).. (8b)

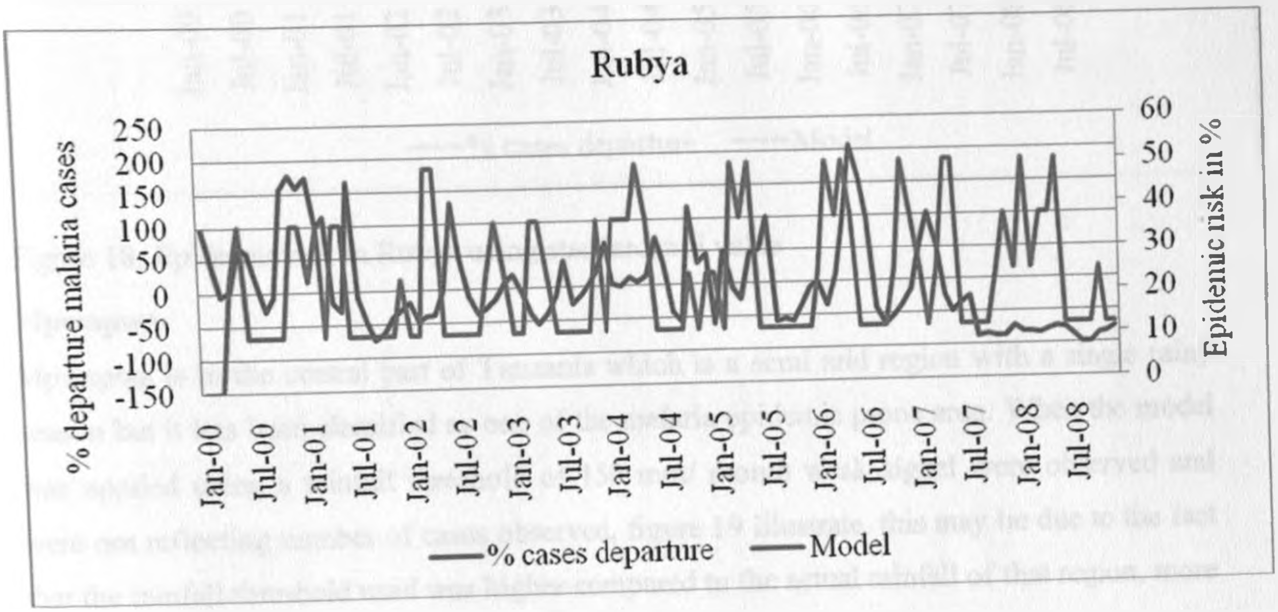

Figure 17: A 150 mm/ month rainfall threshold results in Rubya

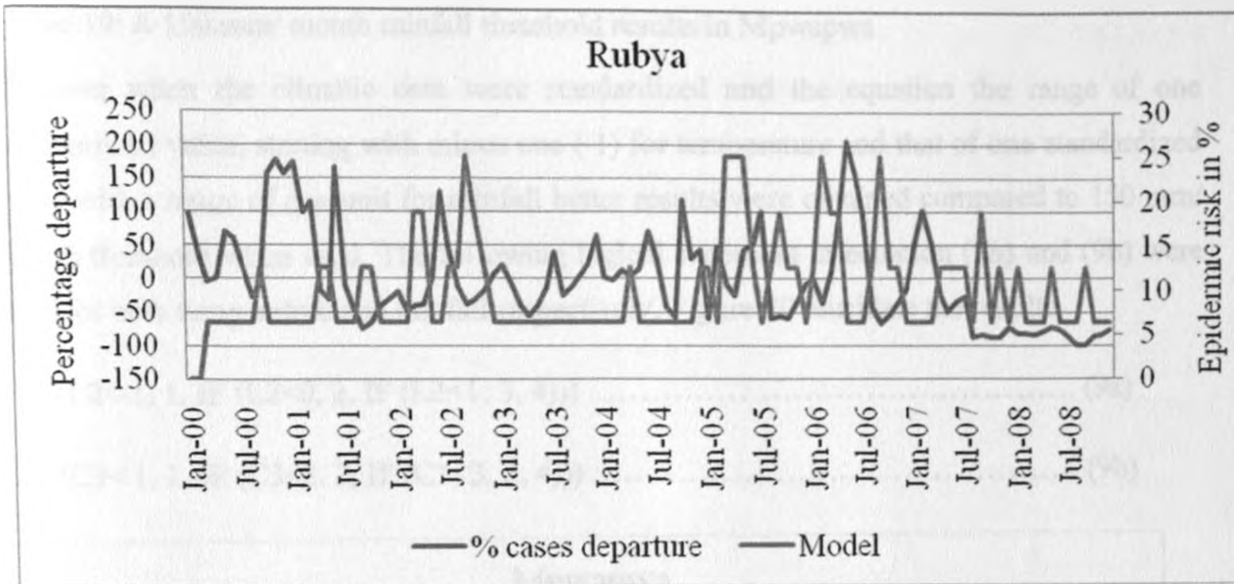

Figure 18: Epidemic risk in Rubya using standardized value

Mpwapwa

Mpwapwa is in the central part of Tanzania which is a semi arid region with a single rainy season but it has been classified as one of the malaria epidemic prone area. When the model was applied using a rainfall threshold of 150 mm/ month weak signal were observed and were not reflecting number of cases observed, figure 19 illustrate, this may be due to the fact that the rainfall threshold used was higher compared to the actual rainfall of that region, more refining of the threshold would modify the result.

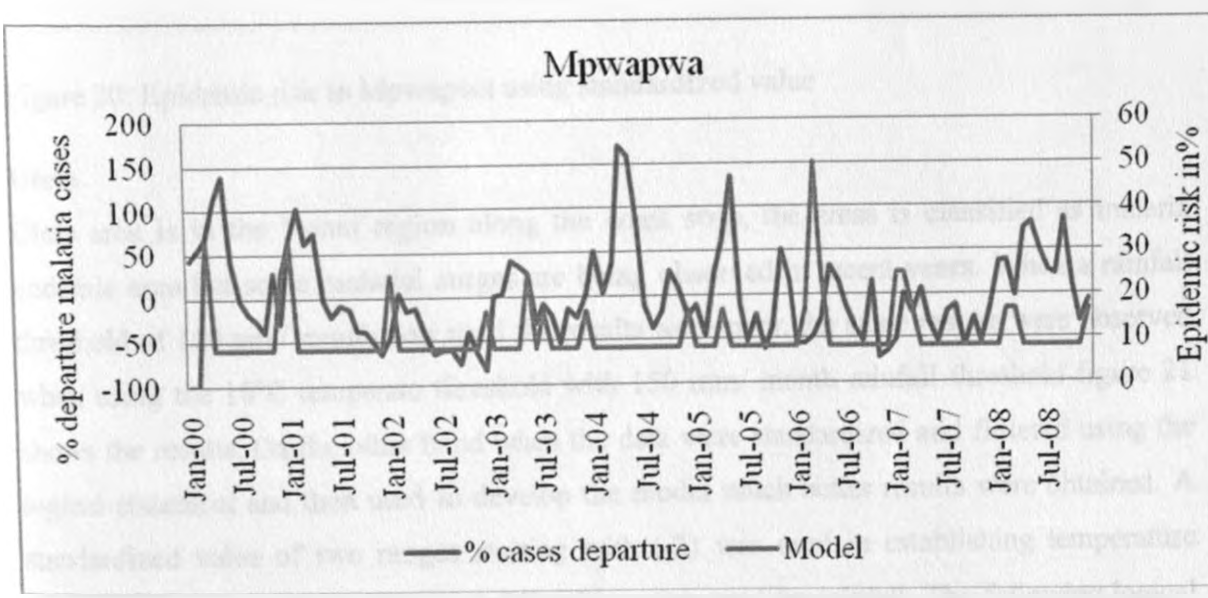

Figure 19: A 150 mm/ month rainfall threshold results in Mpwapwa

However when the climatic data were standardized and the equation the range of one standardized value, starting with minus one (-1) for temperature and that of one standardized value with a range of one unit for rainfall better results were obtained compared to 150 mm/ month threshold when used. The following logical statement in equation (9a) and (9b) were used for both temperature and rainfall respectively. Figure 20 elucidate the results

=IF (L2<-1, 1, IF (L2<0, 2, IF (L2<1, 3, 4))) .... (9a)

=IF (C3< 1, 1, IF (C3<2, 2, IF (C3<3, 3, 4))) .... (9b)

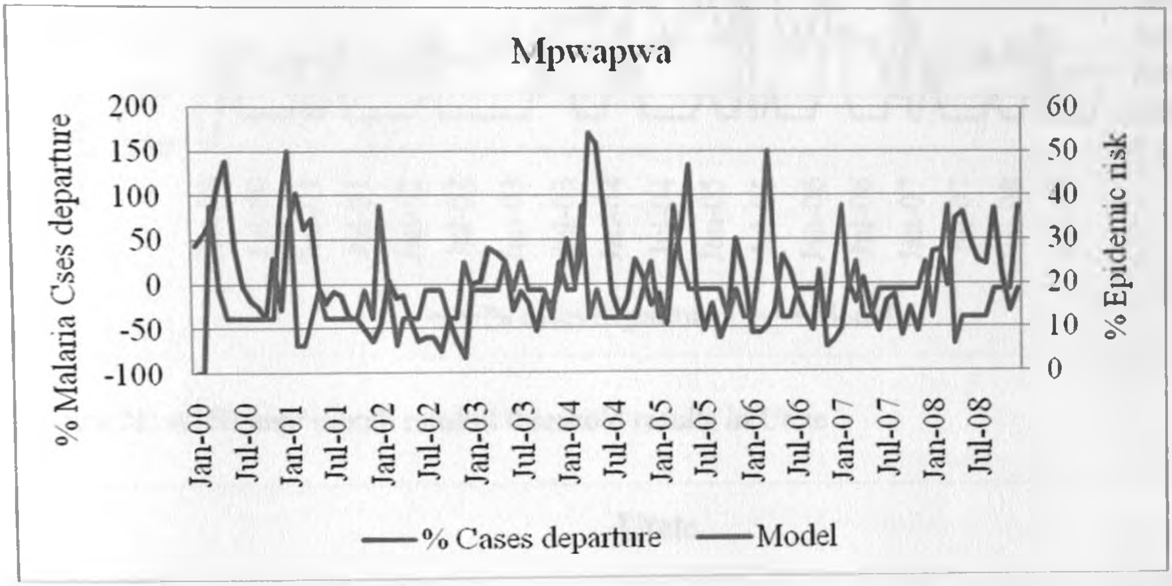

Figure 20: Epidemic risk in Mpwapwa using standardized value

Utete

Utete area is in the Pwani region along the coast strip, the areas is classified as malaria endemic area but some malarial surges are being observed in recent years. When a rainfall threshold of 150 mm/ month was used the results were poor, the same results were observed when using the 18°C temperate threshold with 150 mm/ month rainfall threshold figure 21 shows the results. On the other hand when the data were standardized and flittered using the logical statement and then used to develop the model much better results were obtained. A standardized value of two ranges starting with (-2) was used in establishing temperature threshold and a one standardized rainfall values were used for rainfall. The following logical statement in equation (10a) and (10b) was used to filter temperature and rainfall respectively. Figure 22 below shows the results when standardized values were used.

=IF (L2<-2, 1, IF (L2<0, 2, IF (L2<2, 3, 4))) .... (10a)

=IF (C4<1, 1, IF (C4<2, 2, IF (C4<3, 3, 4))) .... (10b)

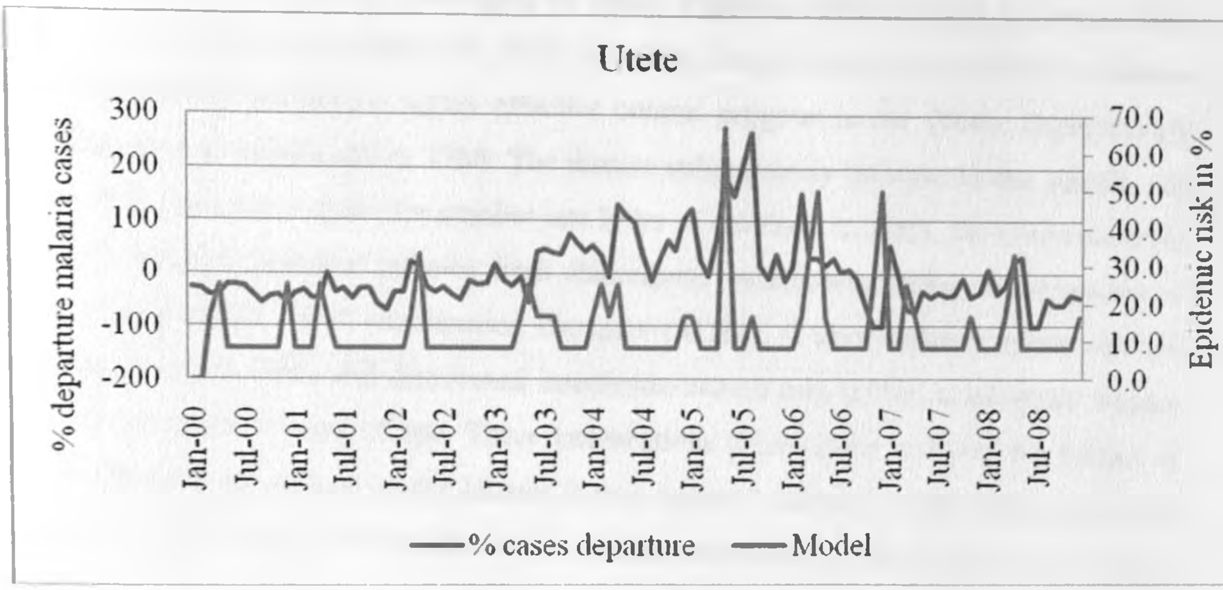

Figure 21: A150 mm/ month rainfall threshold results in Utete

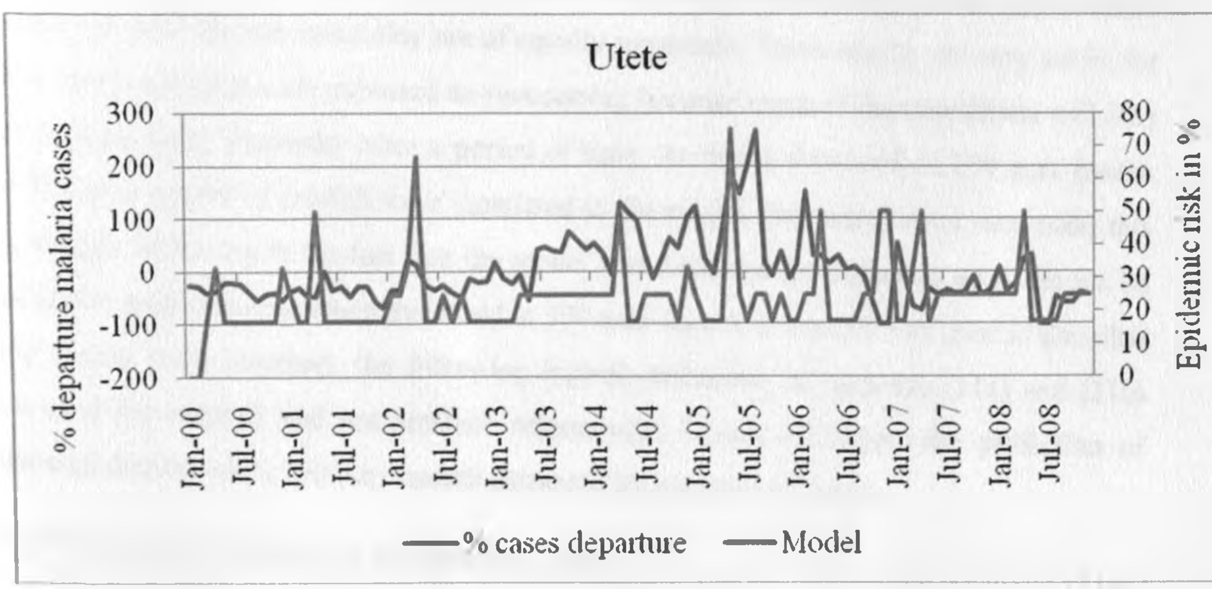

Figure 22: Epidemic risk in Utete using standardized value

Zanzibar

Zanzibar is a well drained area which requires a lot of rain to cause suitable habitats for mosquito breeding, temperature here is not a limiting factor since the area is having relatively high temperature with annual maximum mean of 30.6°c and annual mean minimum temperate of about 24°C which are good temperate for maintaining mosquito population if there is good breeding sites. According to Africa Fighting Malaria report of March 2008 under the motto keeping malaria out of the Zanzibar, Zanzibar has a long history of malaria control and benefited from a highly effective control program in the 1960s. Unfortunately this program was abandoned in 1968. The disease subsequently returned to the islands, and by the 1980s was once again the number one killer of children. In 2003, the Government of Zanzibar changed treatment policies from chloroquine, which was failing in 60 percent of cases, to artemisinin-based combination therapies (ACTs). It also initiated indoor residual spraying programs (IRS) and distributed insecticide-treated nets (ITNs) to pregnant women and children under 5 years of age. These interventions dramatically reduced the burden of malaria. Parasite prevalence on the islands is now below 1 percent (AFM, 2008). It is now considered to be malaria free area the recent data on malaria status shows one cases reported yearly.

Though Zanzibar has been declared as malaria free, clear understanding of the link between malaria risk and climate variability are of equally important. These results are very useful for future since epidemics are expected to reoccurring because most of the population will lose their malaria body immunity after a period of time. At first a threshold of 150 mm/ month and 250 mm/ month of rainfall were simulated to the model, the output were very poor, this was thought to be due to the fact that the model was designed for highlands so it can not be used in low land areas but when threshold of 300 mm/ month of rainfall was used in Zanzibar better results were obtained, the following logical statements in equation (11a) and (11b) were used for rainfall and temperature respectively. Figure 23 shows the prediction of malaria prediction when 350 mm/ month threshold for rainfall was used.

=IF (B3<300, 1, IF (B3<351, 2, IF (B3<401, 3,4))) .... (11a)

=IF(H4<2,1,IF(H4<3,2,IF(H4<4,3,4))) .... (11b)

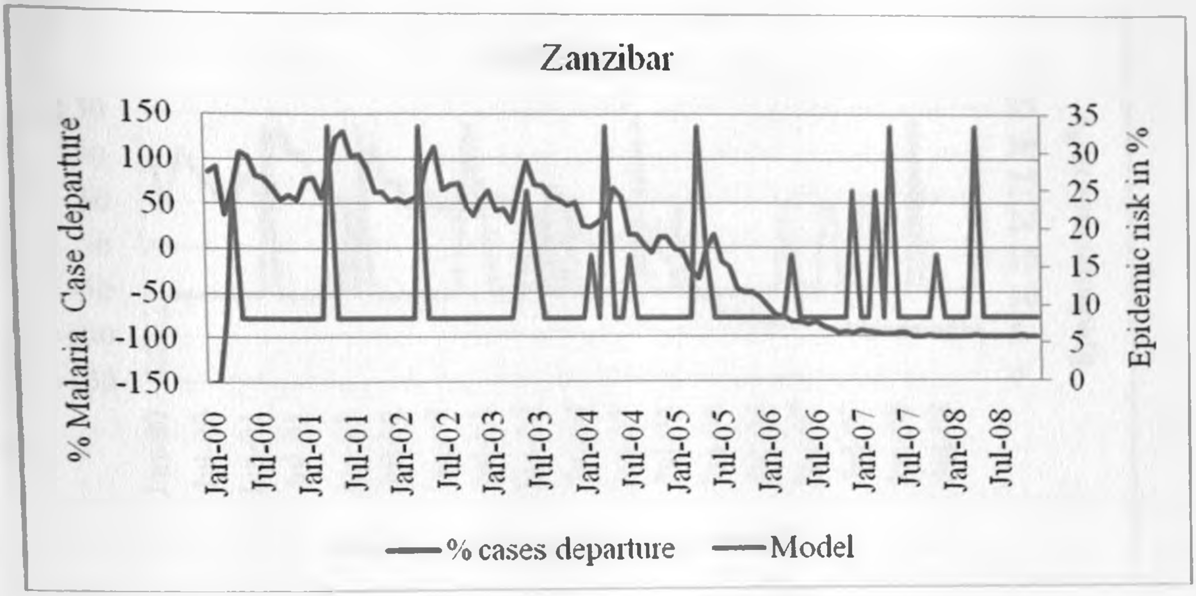

Figure 23: A 300 mm/ month rainfall threshold results in Zanzibar

However when the rainfall and temperature data were standardized and filtered using one standardized value range for total temperature anomaly and two standardized value for rainfall a better prediction were obtained. The following logic statement in equation (11c) and (11d) was used to filter the standardized rainfall data and temperature respectively. This give much better argument than assuming the rainfall threshold since data can be treated easily regardless of the amount of rainfall, figure 24 shows the result when standardized values were used.

=IF (C2<2,1,IF(C2<3,2,IF(C2<4,3,4))) .... (11c)

=IF(L2<1,1,IF(L2<2,2,IF(L2<3,3,4))) .... (11d)

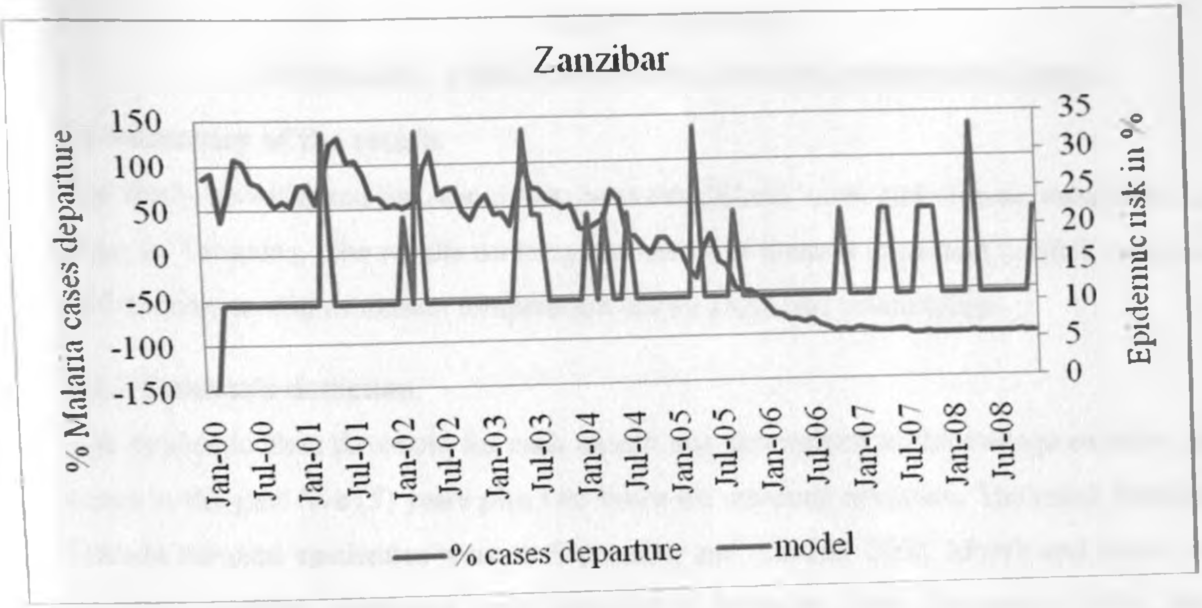

Figure 24: Epidemic risk in Zanzibar using standardized value

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATION

5.1 Summary of the results

The study investigated the association between malaria cases and climate variability in some areas in Tanzania. The results on temporal trends of malaria cases and rainfall, malaria cases and maximum and minimum temperature shows a non line relationship.

5.1.2 Epidemic detection

The epidemic alert threshold for each month was determined as the average monthly malaria cases in the past five (5) years plus two times the standard deviation. The result shows that in Dareda hospital epidemics were in September and October 2002, March and April in 2001. In Utete hospital epidemics were detected in February 2006, December 2004, May and August in the year 2005. In Rubya hospital epidemics were identified in April and May 2006. In Mpwapwa hospital epidemics were observed in August and September 2008. There were no epidemics detected in Zanzibar however some significant malaria cases were detected.

5.1.3 Temporal analysis

The month to month analysis was undertaken to investigate the temporal patterns of climate variability and malaria cases in Tanzania. The following results were obtained

The results revealed there is 2 to 3 months lag between climatic variable and malaria cases in most hospitals i.e. Dareda, Rubya, Mpwapwa, Utete and Zanzibar, this reveal that the existing relationship is not direct rather non linear one. Furthermore the result showed that at extreme conditions such as flood, high or low temperature cause reduction in malaria cases however did not stop the malaria transmission. However studies show that weather extremes may trigger epidemics in particular areas, for example higher temperatures, in combination with favorable patterns of rainfall and surface water, will prolong transmission seasons in some endemic locations. In other locations, climate variability decreases transmission via reductions in rainfall or temperatures that are too high for transmission.

The result also pointed out weather phenomena such as La Niña and El Niño play an important role in malaria transmissions, for example the El Niña condition occurred in 2002 and 2006 influenced rainfall in most part of Tanzania which resulted to increased malaria cases. However there is evidence that transmission can occur in areas with less precipitation. Certain vectors of malaria, such as *An. funestus*, are less dependent on rainfall, since they prefer to breed in more permanent habitats (van Lieshout M. *et al.*, 2004). This scenario was observed in Dareda and Mpwapwa hospital respectively.

5.1.4 Correlation Analysis

The correction analysis revealed that there is poor association between Malaria cases and the climatic variables, this shows that a non linear relationship exists between the variables.

5.1.4 Early Malaria epidemics Prediction Model

The model outputs demonstrated that reported malaria cases can be predicted in 2-3 month early before, however suitable outputs were obtained when the standardized data were used as compared to rainfall threshold of 150 mm, 250 mm-300mm of rainfall. The use of standardized values make use of extreme climate values thus the using standardized value the effect of climate variability will be well compared and examined. When the values were standardized, filtered and simulated into the model better prediction were realized in both areas under investigation, for example in Utete which is an endemic area and is along the coastal line where both maximum and minimum temperature are relatively high compared to the highlands. The model was designed be used in highlands where malaria epidemics have been observed to reoccurring, when the model was tested in coastal areas as well as Mpwapwa in central part of Tanzania which features a semi arid climatic condition the results obtained were poor, however the same model produced good output after simulating standardized climate data.

5.2 Conclusions

The results revealed a non linear relationship exists between malaria cases and climatic variables that are rainfall, maximum and minimum temperatures. The finding of this study have established that climate variables mainly rainfall, maximum and minimum temperature when standardized, filtered and simulated in the early malaria epidemic prediction model better results are obtained as compared to the use of arbitrary rainfall and temperature threshold, Furthermore using of standardized values eliminates the limitations of application of the model since it can be used not only in highlands but also in coastal and semi arid areas. On the other hand the use of standardized values helps in capturing extreme cases which are associated with climate variability, this provides crucial information on malaria outbreaks furthermore this early information is vital for intervention programs in different areas, this will reduce the number of people who die each year due to malaria infections and also reduces the indirect effect of malaria to social economic activities. Though some areas such Zanzibar has been declared as malaria free, clear understanding of the link between malaria risk and climate variability are of equally important. These results are very useful for future since epidemics are expected to reoccurring because most of the population will lose their malaria body immunity after a period of time.

The association observed between malaria cases and the climate variability is a crucial for the health sector in Tanzania and other sector that are affected directly or indirectly by weather variables. The model can be easily used by both health and meteorological sector. More studies are needed so as to improve on the tools that have been established

5.3 Recommendation

In this study the association between malaria cases and climate variability was investigated using confirmed malaria cases data from four sentinel hospital of Tanzania mainland out of 21 sentinel districts and total confirmed malaria cases from Zanzibar were also used. Therefore extension of the study for the remaining districts is recommended.

The current malaria data sets are available in many parts of Tanzania need to be improved, emphasis should be on keeping good records which will assist on getting enough data for research hence improve on the findings, lack of long term malaria data is the major challenge in investigating the impact of climate variability hence climate change.

The use of standardized malaria cases data in this investigation have shown better results, thus this study recommends the use of standardized malaria data since they enable the model to fitted in any environment

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