

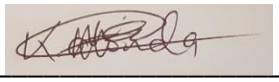
INVESTIGATING THE RELATIONSHIP BETWEEN METEOLOROGICAL VARIABLES AND MALARIA CASES IN LOWERSHIRE: CASE STUDY OF MASANDUKO AREA IN NGABU, CHIKWAWA, SOUTHERN MALAWI.

[ARNOLD MATUNDULU]
Thyolo, Malawi

Dissertation submitted to Ndata School of Climate and Earth Sciences of the Malawi University of Science and Technology in partial fulfilment of the requirements for the Bachelor of Science degree in Disaster Risk Management

July, 2021

DISSERTATION APPROVED BY:

SUPERVISOR:
Mr Vincent Katonda Signature: 

ASSESSOR:
Title, Initials, Name Signature: _____

DECLARATION

I **Arnold Matundulu** declare that this work is my own and that it has never been submitted to Ndata School of Climate and Earth Sciences or any other institution for academic purposes. All information sources used in this paper have been properly acknowledged.

Signature: 

Date: 19/06/2021

DISCLAIMER

This document describes work undertaken as part of a program of study at Ndata School of Climate and Earth Sciences of the Malawi University of Science and Technology. All views and opinions expressed therein remain the sole responsibility of the author(s) and do not necessarily represent those of the School.

COPYRIGHT STATEMENT:

This copy of the dissertation has been supplied on condition that anyone who consults it is understood to recognize that its copyright rests with its author and that no quotation from the dissertation and no information derived from it may be published without acknowledgment.

ABSTRACT

Malaria is one biological hazards that of late has been declared the major cause of deaths in Malawi annually. This makes malaria more deadly than the novel Coronavirus diseases (COVID 19). There is little understanding of the relationship between climatic variables such as temperature and rainfall on malaria, especially in rural areas. Studies on malaria have pointed out that rural residents in Malawi are more prone to mosquito bites and consequently malaria than urban areas. The objective of this study was to investigate the influence of climatic factors on the incidence of malaria in lower shire targeting the Masanduko area in TA Ngabu. Methods: Secondary data on malaria surveillance numbers (n= 136, 291) were extracted from the Chikwawa health information system for the period 2010-2020, while data on climatic variables for the same period recorded at Ngabu weather station was obtained from the meteorological department in Blantyre. MICROSOFT EXCEL version 16 was used to plot graphs for trend analysis of the climatic variables plus malaria cases before linear correlation and regression analysis in SPSS version 25 to suggest a predictor model of malaria epidemic over explanatory variable (rainfall, and temperature). Results: This study found that malaria cases are recorded throughout the year in the area. The study found no enough evidence of climate variability over the study area but the smaller increases in average min and max temperature and rainfall were associated with malaria incidence in areas around Masanduko. Maximum temperature remained the only parameter with a significant correlation coefficient in both wet and dry seasons. Maximum temperature also shows strong relation when correlated across the month with a lagged effect of one month (r-value=0.836, p value=0.003). The max temperature was used to generate a model which will be able to explain about 40% of the variation of some malaria cases in the Masanduko area for a given month being attributed to maximum temperature for the previous month. (R^2=0.405, β =758.514, 95% confidence, CI= 14683.048-55923.475). The model will make it possible to predict the number of malaria cases expected to be registered for the area in any upcoming month using current weather conditions in the previous month particularly maximum temperature thereby giving the picture of the severity of the coming outbreak to the community members, health practitioners, government officials and other NGO bodies responsible. The

predicted malaria cases would be scaled as extreme, moderate, and/or normal, and the appropriate measures planned or put in place. The study also suggests a way to test the performance of the model.

ACKNOWLEDGEMENTS

Firstly, my heartfelt appreciation goes to my parents Mr. and Mrs. Matundulu for all the financial and material support that they have been providing in my education. You people have done so much in my life and without your support; I could not have attended tertiary education. May the good Lord give you long and healthy life as He continues showering you with blessings. Another heartfelt appreciation goes to pastor Y.M. Phiri for your spiritual and emotional counseling on top of physical guidance. God Bless you.

My sincere gratitude goes to the Department of Climate Change and Meteorological Services (DCCMS) and Mr. Kachicha of Chikwawa District Health office for providing me with the data that I used in this project.
I'm also highly indebted to my supervisor Mr. V. Katonda, for direction and motivation.
Your instructions, insight, and encouragement helped me write this thesis.
Special thanks to my classmates, you people played an important role in my education and you made it a memorable experience for me.
Above all, I give thanks to God Almighty, the maker of all things; I am forever grateful for his grace and tender mercies.

TABLE OF CONTENTS

Contents *Page*

1. CHAPTER 1: INTRODUCTION 1
   1.1. Background 1
   1.2. Problem Statement 2
   1.3. Main and Specific Objectives 3
   1.4. Research Questions 3
   1.5. Significance of Study 4

2. CHAPTER 2: LITERATURE REVIEW 5
   2.1. Climate and weather interaction with disease-causing pests 5
   2.2. Literature Review based on concepts 5
   2.2.1. Influence of temperature 5
   2.2.2 Influence of rainfall 8
   2.3. Malaria epidemiology in Malawi 8
   2.4. Studies of climatic factors and malaria incidence in Africa 9

3. CHAPTER 3: METHODOLOGY 10
   3.1. Study area 10
   3.2. Research design and conceptual framework 11
   3.2.1. Type of research 11
   3.2.2. Sampling design 11
   3.2.3. Statistics design 12
   3.2.4. Operation design 12
   3.3. Materials and methods 12
   3.3.1. Data collection 12
   3.3.2. Data analysis 14

4. CHAPTER 4: RESULTS AND DISCUSSIONS 18
   4.1. Monthly variations of temperature precipitation, and malaria cases 18
   4.2. Seasonal trend Analysis for weather parameters and malaria cases 20
   4.3. Relationship between Malaria cases and weather parameters 26
   4.3.1 Correlation analysis 26
   4.3.2 Regression analysis 29
   4.4. Discussion 30

5. CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS 32
   5.1. Conclusions 32
   5.2. Recommendations 32

6. REFERENCES 33

7. APPENDICES 35

ACRONYMS/ABBREVIATIONS

DCCMS	Department of Climate Change and Meteorological Services
DHIS	District Health Information System
GDP	Gross Domestic Product
HIMS	Health Information Management System
ITNs	Insecticide-treated bed nets
Max	Maximum
Min	Minimum
MGDS	Malawi Growth and Development Strategy
RDT	Rapid diagnostic tests
SDGs	Sustainable Development Goals
SDA	Seventh-Day Adventist
SPSS	Statistical Package for Social Science
TA	Traditional Authority
WHO	World Health Organisation

LIST OF FIGURES

Figure. *Page.*

Figure 1: shows Study area map……..11

Figure 2: shows a summary of the methodology ……..17

Figure 3: shows Mean Monthly Maximum Temperature ……..18

Figure 4: shows Mean Monthly Minimum Temperature ……...19

Figure 5: shows Total Monthly Rainfall……..20

Figure 6: shows max temperature trend in wet season……..21

Figure 7: shows max temperature trend in dry season……..21

Figure 8 shows minimum temperature trend in wet season……..22

Figure 9: shows minimum temperature trend in dry season……..23

Figure 10: shows rainfall trend for wet season…..24

Figure 11: shows rainfall trend for dry season ……....24

Figure 12: shows malaria case trend in wet season ……..25

Figure 13: shows malaria case trend in dry season……..26

Table *Page*

Table 1: Shows Correlation Coefficients in wet season……27
Table 2: Shows Correlation Coefficients in dry season……..…28
Table 3: Shows Correlation Coefficients across months……..28
Table 4: Shows Correlation Coefficients across months with a lagged effect……..29

1. CHAPTER 1: GENERAL INTRODUCTION

1.1. Background

Nowadays, climate change is a very big concern and it influences the epidemiology of vector-borne diseases (Bezirtzoglou, Dekas, & Charvalos, 2011). Climate changes are changes in one or more climate variables, including temperature, relative humidity, rainfall, wind, and sunshine (Torre, 2018). A report published by NOAA and NASA confirmed that 2010 to 2019 was the hottest decade since record keeping began 140 years ago (Borunda, 2020). The analysis also revealed that 2019 was the second hottest year ever recorded and that ocean temperatures were the highest than they have ever been. These changes may affect the survival and reproduction of vectors and the transmission of vector-borne diseases. Malaria is one of the most climate-sensitive mosquito-borne diseases. Climate changes can directly affect malaria transmission by shifting the vector's geographic range and increasing the reproductive and biting rates and by shortening the Plasmodium incubation period (Wu et al., 2016).

Malaria is a life-threatening disease caused by parasites that are spread from one person to another through the bites of infected female Anopheles mosquitoes. A malaria case is confirmed by a demonstration of asexual forms (trophozoite stage) of the parasite in a thick or thin peripheral blood film or by rapid diagnostic test (RDT) in the presence of fever (Lunde et al., 2013)

The disease claims thousands of lives annually worldwide. According to the world health organization (WHO), in 2019 only there were an estimated 229 million cases of malaria worldwide with a death toll estimated at 409 thousand. Africa taking about 94 percent of the total malaria cases and deaths. Children aged under 5 years are the most vulnerable group affected by malaria such that in 2019, they accounted for 67 percent (274 000) of all malaria deaths worldwide.

Apart from climate change impact, temperature, rainfall, and relative humidity are also influenced by geographical location. Most importantly, the three metrological factors are affected by altitude. Low altitude is associated with higher temperatures

and low rainfall amounts. Relative humidity depends on the interplay between precipitation and temperature.

Correlation/regression analysis is a method of statistical evaluation that is used to study the strength of relationship between two numerically measured, variables. For many decades, researchers in many have applied it to establish possible connections between variables. This analysis technique is used in this study to investigate the level of relationship between the meteorological factors with malaria cases for at least 11 years.This will help us understand the interplay between temperature, precipitation and malaria outbreak in Masanduka area in TA Ngabu in Chikwawa district part of the low lying zone popularly known as the lower Shire.

1.2. Problem statement

Malawi lies within the tropics where there are heavy rains from November to April. During this period, it is generally hot and wet. Mosquitoes breed rampantly and malaria cases are high. Communities close to streams and stagnant waters are highly at risk of getting malaria-causing parasites from the female anopheles' mosquitoes as they breed just close to the people. Malawi Malaria Impact Evaluation Group report of 2016, indicates that malaria is highly endemic with 95 percent of the country's population at risk of infection. Malaria is responsible for 95 percent of all outpatient visits and 40 percent of hospital deaths. Much as the threat stands for the whole country, the lower shire is more at risk because the altitude of the lower shire valley is a few meters above sea level, the rising of the water table during the rainy season leads to the formation of ponds and marshes that are breeding sites for the mosquitoes. Permanent wetlands or swamps (Ndindi and Elephant marsh) characterize Nsanje and Chikwawa districts. There are large stretches of stagnant water especially during wet season and temperatures are generally above 21°C. This provides the best ground for the mosquitoes to breed, resulting in increased malarial transmission in this region. Elephant marsh covers part of TA Ngabu. Despite the area being a wetland, it is also a flood-prone area.

Rural area residents are more prone to mosquito bites and consequently malaria. This is according to the study by Mzilahowa et al. (2016) supported by the findings of the 2010 Demographic and Health Survey (DHS), which demonstrated that in urban areas especially Blantyre malaria positive cases were more likely to have a history of recent travel to rural areas.

However, the impacts of rainfall and temperature on malaria incidence and transmission are poorly understood in rural areas (Chigoneka, 2020). There is no research study in the lower shire that has been conducted to seek the impacts of climatic variables on malaria incidence. This study, therefore, seeks to determine the relationship between precipitation and temperature, and the prevalence of malaria cases amongst the population surrounding Masanduko area in Ngabu, which is found inside the extensive lower Shire area.

1.3. Main and Specific objectives

1.3.1. Research objectives

The main objective of the study is to determine the relationship between precipitation, and temperature with the prevalence of malaria cases in the lower shire.

1.3.2. Specific objectives

To achieve the main objective, the following specific objectives will be carried out

(1) Determining monthly variations of precipitation, temperature, and malaria cases over the study area for the past 11 years (2020-2020).
(2) Determine seasonal trends of precipitation, temperature malaria cases from 2010-2020 for the study area.
(3) Determine the relationship between the meteorological variables (rainfall and temperature) and malaria from 2010-2020.

1.4. Research Questions

After the study, the following questions will have been answered in detail.

1) What are the monthly variations of precipitation, temperature, and malaria cases for Masanduko area over the past 11 years
2) What are the seasonal trends of precipitation, temperature, and malaria cases from 2010-2020 for Masanduko Area
3) What is the relationship between meteorological variables (rainfall and temperature) and malaria cases in the said area

1.5. SIGNIFICANCE OF THE STUDY

Malaria burden affects resilience to other hazards such as floods and drought that affect the country Malawi due to climate change (DoDMA, 2015). The study of the level of association between malaria occurrence and climatic variables will aid authorities in decision making to take proper public health actions i.e. enrolling proper control programs to avoid and control a potential risk of malaria epidemics in the study area as well as the surrounding places.

The study will also help in the achievement of the recent government's announced goal to eliminate malaria, the leading cause of death in the country, by 2030. To aid this, the study has established a formula, which will help in predicting numbers of malaria cases for a particular month using meteorological and malaria data for the previous months. The application of this research's findings is in direct support of one of the five priority areas of the Malawi Growth and Development strategy MGDs, which is Health and Population Management. That also supports and promotes the third Sustainable Development Goal (SDG 3) which is ensuring healthy lives and promote the well-being of all ages.

2. CHAPTER 2: LITERATURE REVIEW

2.1. Climate and weather interaction with disease vectors.

Recently it has been observed that the demographic range of insect pests is increasing. Rising global temperatures have the potential to lengthen the season and increase the geographic range of disease-carrying insects. As temperatures, gets warm, mosquitoes and other warm-weather vectors could be able to move into higher altitudes and new regions farther from the equator. For example, in some regions of the United States of America, warming is lengthening the season for Zika-carrying mosquitoes. The increased range of insects can also be a result of international trade that can transport different organisms maybe through the sea or the airplanes for this reason the distribution range is less considered but the environmental conditions of the location and the organism survival. The change has also resulted in the extinction of other organisms due to unfavorable available weather; others adapt to the change and mutate to match the current change (Service & Building, 2008) which is common to the insects, in this case, the mosquitoes which are the subject topic in this research.

Considering temperature in a broad sense and more details on its impact on the behavioral, survival, and production dynamics of insects (Khan, Kumar, Hussain, & Kalra, 2009). Temperature can be classified into an ambient temperature that's the temperature of the surrounding air and the soil temperature, which encompasses the diurnal, annual ranges within the soils. All these temperatures are slowly being modified with climate change although the effect is minimal for soil temperatures.

2.2. Literature Review based on concepts.

2.2.1. Influence of temperature

Temperature can be defined depending on the source of it, for example, the body temperature is the optimal temperature for the metabolic processes in an organism, (Spodopter et al., 2008) the ambient or environmental temperature is the one felt by the surface of an animal's body. The temperature in general affects the

biochemical, physiological, and behavioral processes of animals (Thomas & Blanford, 2003). Biological pest control uses the concept of environmental/ambient and body temperature to match the outcome of host-parasite interaction (Thomas & Blanford, 2003). Pathogen ability to kill host depends crucially on body temperature and how this fluctuates with external environmental conditions thus a body temperature ambient temperature relationship, keep in mind that these temperatures are different in many instances (Bennett, Kukal, & R, 1999). Most insects adopt one of these thermal strategies, regulate body temperature behavior, and conform to the thermal environment (external) and certain extremes.

Shapiro, Whitehead, and Tomas (2017) outline the influence of temperature on key transmission-related traits of Indian malaria Mosquitoes, Anopheles *Stephensi*, and the malaria parasite plasmodium falciparum. These traits include mosquito biting rate, mosquito mortality rate, and the rate of Plasmodium development inside a host.

Main findings show that biting rate, adult mosquito mortality rate, plasmodium parasite development rate inside the mosquito, and finally vector competence are all temperature-sensitive.
For the overall picture of implication given by temperature, Shapiro, Whitehead, and Tomas (2017) use a standard model of relative vectorial capacity, which suggests that the overall temperature for all traits is 29°c with 12 °c and 38 °c for minimum and maximum temperatures respectively.
However, the robustness of the vectorial capacity approach is challenged by an earlier study by Mordecai et al. (2013). This study stresses that the empirical data in any vectorial capacity model as used by Shapiro in 2017 violet several model's assumptions therefore it serves as an alternative. In this regard, Modecai et al. (2013) use a model of relative force of infection that they claim captures better the observed biology of vector-parasite interaction. This model suggested that a temperature optimum for transmission being 26 °c with a minimum of 17 °c and 35 °c respectively.

2.2.1.1. Mosquito mortality rate and temperature

Most Conventional malaria transmission models assume a constant rate of mosquito adult deaths per day due to extreme heat (Paaijmans, Blanford, Chan, & Thomas, 2012). Paaijmans et al. (2012) found this trend is common from 30°c above. However, Lunde et al. (2013) have also a different view saying that this constant rate of adult mosquito deaths is true for the laboratory tests. He argues that external mosquito factors such as predation, encountering insecticides and food stress are not considered in the models. Proof of adult mosquito dying quickly when it gets warmer is shown in a field study on geographically distinct populations of female anopheles mosquitoes in Southeast Asia and Latino America (Boyd, 2010)

The truth is that the mortality rate of mosquitoes is quite well affected by other factors which are impossible to influence. Only female mosquitoes feed on the blood of warm-blooded animals more especially humans. If a mosquito finds enough victims to bite and avoids being destroyed, it can live as long as three weeks. During that time, it may lay up hundreds of eggs. This means even if more adult mosquitoes will be dying every day, more hatching will also be happening and there is a constant replacement.

2.2.1.2. Rate of plasmodium and mosquito development and temperature

Malaria parasites complete their life cycle by alternating between the human and mosquito bodies. They use the large difference in temperature exposure between humans and mosquitoes to regulate their bionomics. Malaria parasites are exposed to high temperatures in humans ranging from 37 °c to 41 °c during feverish periods in the patient. Pavithra et al. (2004) showed that the repeated exposure to extreme temperatures promoted the development of *P. falciparum* in the red blood cells.

Analysis of temperature and development rate presented in Ikemoto (2008) using a thermodynamic model showed that the estimated intrinsic optimum temperatures for the development of the malaria parasites, *Plasmodium falciparum*, and *P. vivax*, in the adult mosquito stage and that of the vector mosquito *Anopheles* are all 23-24°C.

These bugs typically stop biting humans in temperatures below 10°C. To survive the winter or to endure drought, mosquito eggs and certain types of larvae enter into diapause which is a delay of development due to a change in the environment where the pest becomes inactive.

2.2.1.3. Mosquito competency and biting rate under influence of temperature

Several studies indicate close to and below 10°c census as the temperature where the mosquitoes typically stop biting humans. Under these conditions, mosquitoes go into dormancy just to survive the winter. This maximum temperature where mosquitoes can't bite anymore is not certain. This could explain the reason why we have malaria cases throughout the year in the tropics and particularly Malawi because it is rare to explain winters with temperatures below 10°c.

2.2.2. Influence of Rainfall

The average amount of precipitation/rainfall received by an area is an important determinant of species to be found in that location even the type of plants to be grown there(Tadross et al., 2009). High precipitation affects the quality and quantity of mosquito breeding habitats causing either an increase to their population by maintaining their breeding sites or a decrease, by flushing out mosquito larvae from their breeding sites.

2.3. Malaria epidemiology in Malawi

Speaking during a televised launch of a nationwide anti-malaria initiative known as the 'Zero Malaria Starts with Me' campaign on 22 June President Lazarus Chakwera heard lamenting that statistics on malaria infection in the country are worrying. The common malaria vectors in Malawi are Anopheles gambiae, arabiensis, and anopheles funestus. These species are found throughout sub-Saharan Africa and a lot about them is known not just from studies in Malawi but from many other countries in the region. (Mzilahowa et al., 2016). There are notable differences in the

endemicity of the disease across the country, with lakeshore and low-lying areas experiencing intense and perennial malaria transmission, while upland areas are characterized by seasonal transmission coinciding with the wet season. (Mzilahowa et al., 2016). Rural area residents are more prone to mosquito bites and consequently malaria. This is according to the study by Mzilahowa et al. (2016) supported by the findings of the 2010 Demographic and Health Survey (DHS), which demonstrated that in urban areas especially Blantyre malaria positive cases were more likely to have a history of recent travel to rural areas.

2.4. Studies of climatic factors and malaria incidence in Africa

The relationship between climatic factors and malaria incidence in sub-Saharan Africa has been discovered. There is a general observation that as temperature increases in most parts of Africa, malaria incidence is projected to substantially increase (Yu et al., 2015). However, Yu et al. (2015) put it that there are other non-climatic factors such as gross domestic product (GDP) and sound malaria interventions which also alter the malaria risk landscape. This implies that sound malaria treatment interventions such as mosquito biological control could disturb mosquito cycles.

In a study in Ethiopia, lagged effects of rainfall and temperature were found to be associated with malaria epidemics (Abeku et al., 2004). Rainfall and temperature lag of two months was also found to be positively associated with malaria in South Africa (Ikeda et al., 2017). Climate was found to be the leading agent of inter-annual variation in malaria prevalence in Zimbabwe. In particular, rainfall, temperature, and water vapor were found to be important predictors of increased malaria incidence (Mabaso et al., 2006). A similar study in Mozambique found an association between malaria and relative humidity, rainfall, and temperature (Zacarias & Andersson, 2011).

3. CHAPTER 3: METHODOLOGY

3.1. Study Area

The study was conducted around Masanduko area. The place is located in Traditional authority Ngabu the largest TA in Chikwawa district southern Malawi. The area is located is at latitude 16.27 south and 34.53 east. (http//elevationmap/malawi.com). The choice of this place was because of the presence of a manned meteorological station nearby where meteorological data for this study was recorded. This weather station has been in operation since 1971 and an individual who collects data twice a day operates it. The station personnel operates from 7:30 am to 5:00 pm daily. The data is then sent to the Department of climate change and meteorological services (DCCMS) in Blantyre. Another preference for this area is the presence of Ngabu rural health center as well as Ngabu SDA health center, which are approximately 2 kilometers apart. The figure below is the map showing the study area.

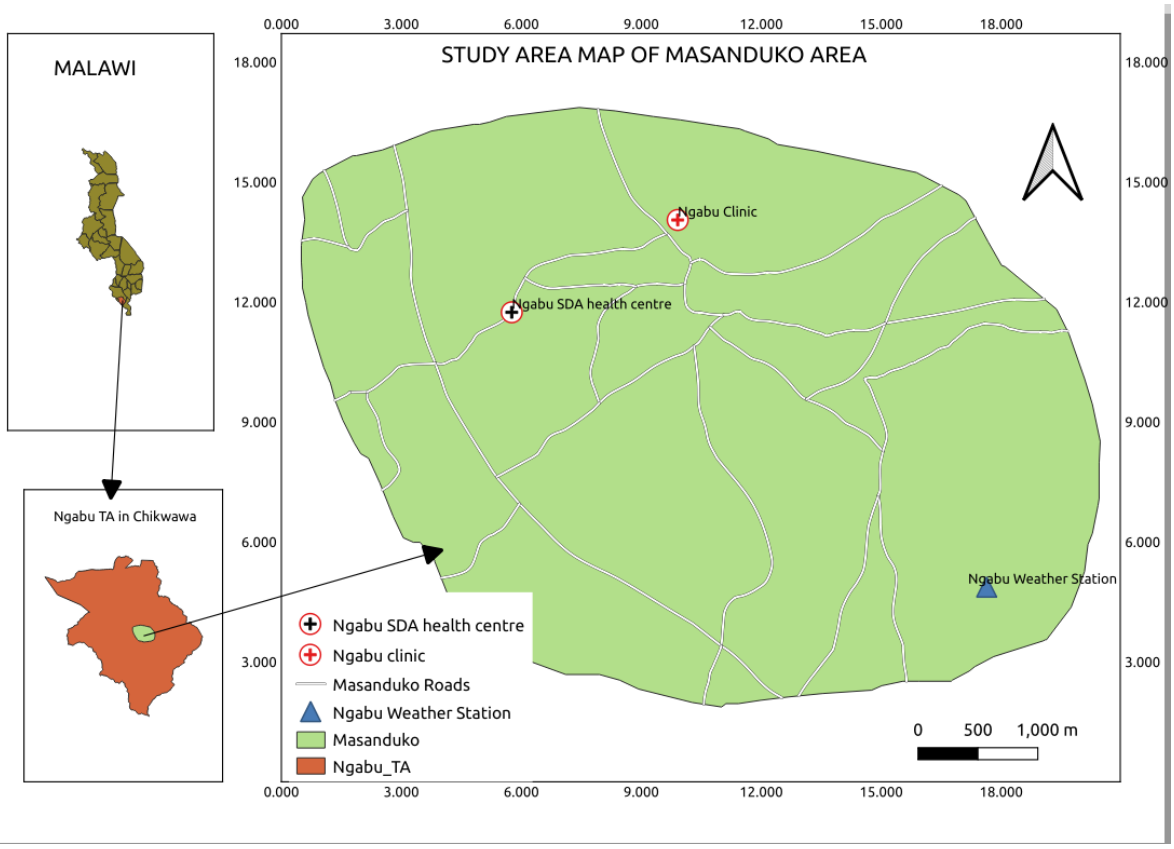


Figure: 1 is a map for Masanduko area in Ngabu showing the position of Ngabu clinic, Ngabu SDA health center as well as Ngabu weather station

3.2. Research design and conceptual framework

3.2.1. Type of research

The research will adopt the quantitative way of data analysis following a research form of a case study. The problem with a case study type of research is that the results are only applied to that area of study because the research automatically is selective in variables to be studied (Broadhurst, Holt, & Doherty, 2012). So the results cannot be generalized as the omitted variables in that area also play their role but are not of interest to the researcher hence the results most of the time are fitted there.

3.2.2. Sampling design

The study will use the convenience and purposive or pragmatism sampling design. This sampling design chooses a sample that is easiest to obtain and is known as accessibility sampling (Wojtek, 2007), in this case, the study area has a weather station and health facilities that are located within the same climatic zone but most importantly proximity to each other is no more than 2km. However, this sampling becomes a problem when it comes to biasness, as it is difficult to consider the number of malaria cases as a true representation of all people who suffered from malaria within the study duration. Some People may have not gone to the hospital or else gone to a private clinic whose data were not included in the study.

3.2.3. Statistics design

The study will use parametric and non-parametric statistical approaches. Parametric measurements are those statistical techniques that are used to answer questions that demand the establishment of a relationship between dependent and independent variables. In this case, the relationship between malaria variables and climatic or weather variables. Such approaches include regression and correlation. On the other hand, non-parametric statistical approaches include man Kendal analysis that deals with trends and U-tests to mention a few. In this study, we will employ time series analysis.

3.2.4. Operation design

The research will be done in two stages depending on the statistical approach used in that stage. Firstly the data will undergo non-parametric statistical analysis which will use time series analysis using excel 2016 to examine the trends of the variables in this study. Then the data will undergo parametric statistical analysis such as correlation and regression to see if the climatic variables are related to malaria outbreaks in the lower shire. The latter stage will be done with the aid of SPSS version 25.

3.3. Materials and Methods

3.3.1. Data collection

The type of data used in this study is secondary for both meteorological variables and malaria case data. Secondary data is time-saving and cost-efficient(Crawshaw & Chambers, 2001). The study uses two datasets as follows:

3.3.1.1. Data on Disease surveillance

Malaria data was collected from Chikwawa DHO for 11 years period (2010-2020). All malaria cases according to the Chikwawa district malaria coordinator were defined based on the diagnostic criteria and principles of management of malaria issued by the ministry of health in Malawi. Only cases confirmed from the laboratory and a critical test in local health centers in the study area were included in the study. Information of cases included age range. Data present was only grouped into under-five and above five.

With the help of the Chikwawa district malaria coordinator data recorded at Ngabu SDA and Ngabu public health centers was extracted from the Health management information system (HMIS) and was aggregated into one excel sheet. Since reliable estimates of the incidence of malaria are not available through a standard national surveillance system in Malawi (Mathanga et al., 2012), the Health Management Information System (HMIS) is the only available tool that stores such data based on passive surveillance of outpatient and inpatient malaria cases reporting to any government or mission health facility in Malawi.

Reported at district-level monthly counts of confirmed and suspected malaria cases for 132 months were collected between January 2010 and December 2020. Case data are recorded on paper forms at health facilities within a district, then aggregated monthly at the facility level. Facility data are later aggregated to the district level and then entered into an electronic database, the District Health Information System (DHIS). (Mzilahowa et al., 2016). Within the Health Management Information System (HMIS) facilities self-report. The completeness of the data reported in the HMIS has been steadily going up, now standing at over 90%. Over this period, different malaria diagnosis approaches were used(Chandramohan et al., 2002). Before 2011, there was no widespread use of rapid diagnostic tests (RDT) as the policy had not been adopted leading to a high proportion of unconfirmed malaria cases. Therefore, the clinical diagnosis of malaria was widely used before 2011 (Chandramohan et al., 2002). The use of RDT was adopted in 2011 leading to a marked improvement in the quality of the data as an increasing percentage of cases were now being confirmed (Namuyinga et al., 2017)

3.3.1.2. Meteorological data

Weather data, which incorporate the Maximum and Minimum temperatures, and rainfall, for 11 years from 2010 to 2020, was accessed from the department of climate change and meteorological services (DCCMS). The data consisted of monthly average maximum and minimum temperatures as well as monthly average rainfall.

3.3.2. Data analysis

3.3.2.1. Data preparation

The data sets were grouped into two groups namely wet (rain season) which begins in November to April. The wet or growing season range starts from one year to the following year. This implies that there are 10 wet seasons from 2010 to 2020.

The second group is the dry season. According to this study, the dry season is defined as a range of months whose monthly average rainfall during the study period ranges from 0 to 9 mm. This dry period includes months from May to October. Since these months are within the same year the dry seasons separate among years, therefore, there are 11 dry seasons from 2010 to 2020. The data was grouped in both groups

meaning that a single data set was set to be in both groups depending on the months' range. Malaria case data for both areas understudy was summed up within each month and season. Average maximum and minimum temperature were calculated for each month and season and finally, the average rainfall and total rainfall for each month and total rainfall for each season were calculated.

3.3.2.2. Time Series Analysis

The time series analysis from Microsoft excel package 2016 was used to determine the overall pattern or trends of change of weather parameters and change or trend of malaria cases separately over the study period.

The trend was calculated using Excel trend function embedded in the program. It is used to calculate a linear trend line through a given set of dependent y-values and a set of independent x-values and return values along the trend line.

Each trend was further tested to check if it was significant. The significance tells us the amount of general increase or decrease. A big increase means that the independent variables were revolving between a large range of numbers on the scale. The significance was shown using r^2 values generated by the trendline. In statistics, the coefficient of determination denoted as R^2 or r^2 is the proportion of the variance in the dependent variable that is predictable from the independent variable. R^2 is always between 0 and one and sometimes is expressed as a percentage (between 0-100%) The higher the R^2, the better the model fits data. In this, study R^2 values greater than 5 (50%) were considered significant.

3.3.2.3. Correlation Analysis

Correlation studies give a way of knowing the association prevailing between dependent variable (predictand) and independent variables (predictor). In this research, the correlation will help to understand the contribution of each climate variable to the occurrence of malaria cases in the vast lowly part of lower shire over the past 11 years. The correlation was done using SPSS statistical package employing Pearson's correlation coefficient. Pearson's correlation coefficient is the test statistics that measure the statistical relationship, or association, between two continuous variables(Samuels, 2015). It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship. It is known as the best

method of measuring the association between variables of interest because it is based on the method of covariance (Samuels, 2015).

Below is Pearson's correlation formula:

$$r = \frac{\sum xy - \frac{(\sum x)(\sum y)}{n}}{\sqrt{\left(\sum x^2 - \frac{(\sum x)^2}{n}\right)\left(\sum y^2 - \frac{(\sum y)^2}{n}\right)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where r= correlation coefficient, x= meteorological element, y= Malaria data. The coefficient r ranges from -1 to +1 where the value r = 1 means a perfect positive correlation and the value r = -1 means a perfect negative correlation (Samuels et.al, 2014). The statistical correlation coefficients denoted as r was used to assess the strength and direction of the relationship. The significance of the relationship between malaria and Climatic variables namely Maximum and Minimum temperature, and rainfall was determined using p-values that came along with the correlation coefficient. The strength of correlation significance was also indicated by t-values that were read from t-distribution tables.

The malaria cases in Ngabu and weather parameters were subjected to correlation analysis to test for their relationship separately in the wet, dry season, and whole year correlation that is to establish the type of the relationship that exists.

Schober, Boer & Schwarte (2018), consider an r-value between 1.0 and 0.9 as very strong, 0.89 to 0.7 as strong, 0.69 to 0.4 as moderate, and 0.39 to 0.1 as a weak linear correlation.

3.3.2.4. Regression Analysis

The Regression analysis was done to obtain an equation that predicts the effect of weather parameters on the future occurrence of malaria cases around the Masanduko area. Forward regression technique was used with the aid of SPSS version 25. Equation 2 will be used to predict the Number of malaria cases using weather parameters that are significantly correlated with it. The regression equation is given as

$$y = a + B_1X_1 + B_2X_2 + \cdots + B_nX_n + \mathcal{E} \ldots\ldots\ldots\ldots (2)$$

Where a = Y-intercept

B_1 through B_n = regression coefficient

X_1 through X_n = independent variables (weather parameter)

E = error

The model performance will be tested using the model performance difference between the predicted and the observed malaria cases in a month, which is given as

$$\text{Model performance} = \frac{\text{Predicted malaria cases - Recorded malaria cases}}{\text{Recorded malaria cases}} \times 100 \quad \ldots\ldots (3)$$

This implies that the bigger the percentage the higher the efficiency of the model.

The figure below summarizes the methodology:

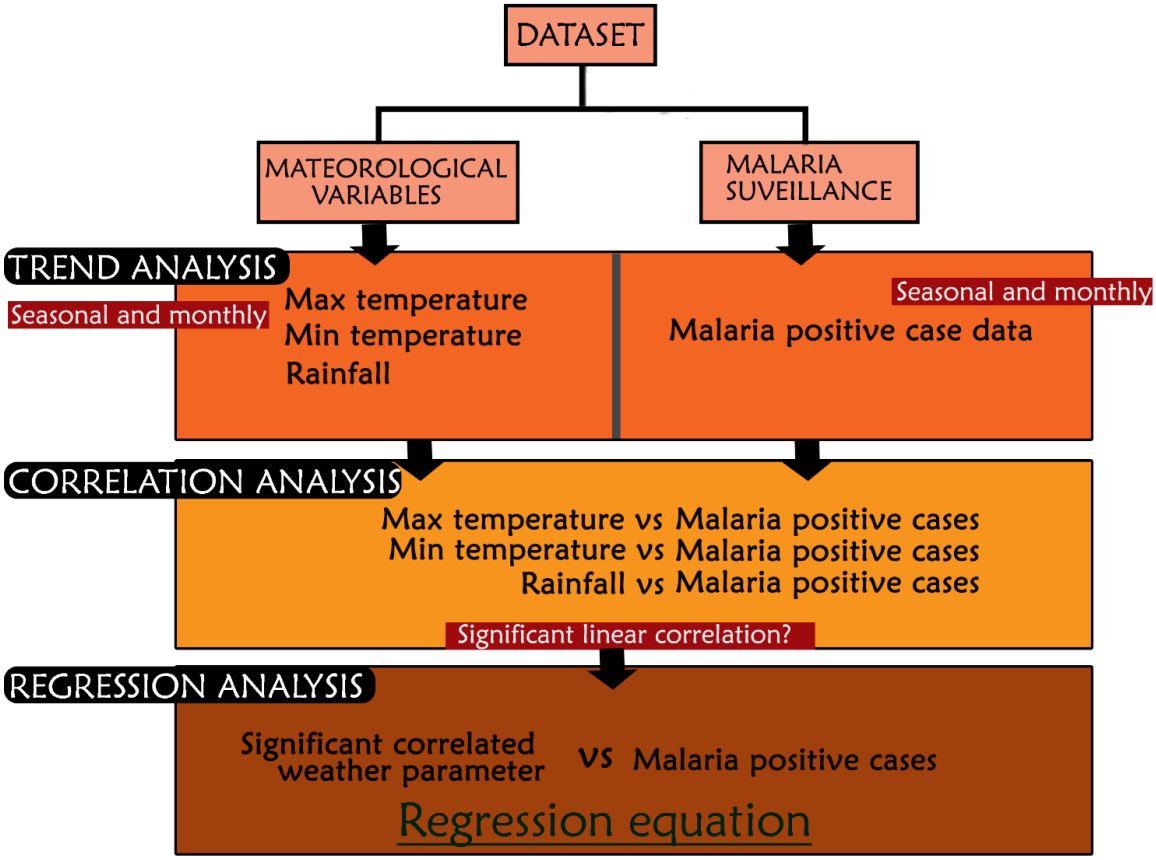


Figure 2 shows the summary of the methodology

4.0. CHAPTER 4: RESULTS AND DISCUSSIONS

4.1. Monthly variations of temperature, precipitation, and malaria cases.

4.1.1. Variations of Average monthly Maximum Temperature versus malaria cases in Masanduko, Ngabu

The average highest maximum temperature values were observed in October and November, Other extreme peaks above 30°c were observed in December, January, and April May, August, and September. The lowest average max temperature was 28.0°c observed in July.

The histogram of malaria cases shows a decreasing trend of malaria from January through December with the highest number of malaria cases observed in February and the lowest total cases recorded in December.
Figure 2 below presents the summary.

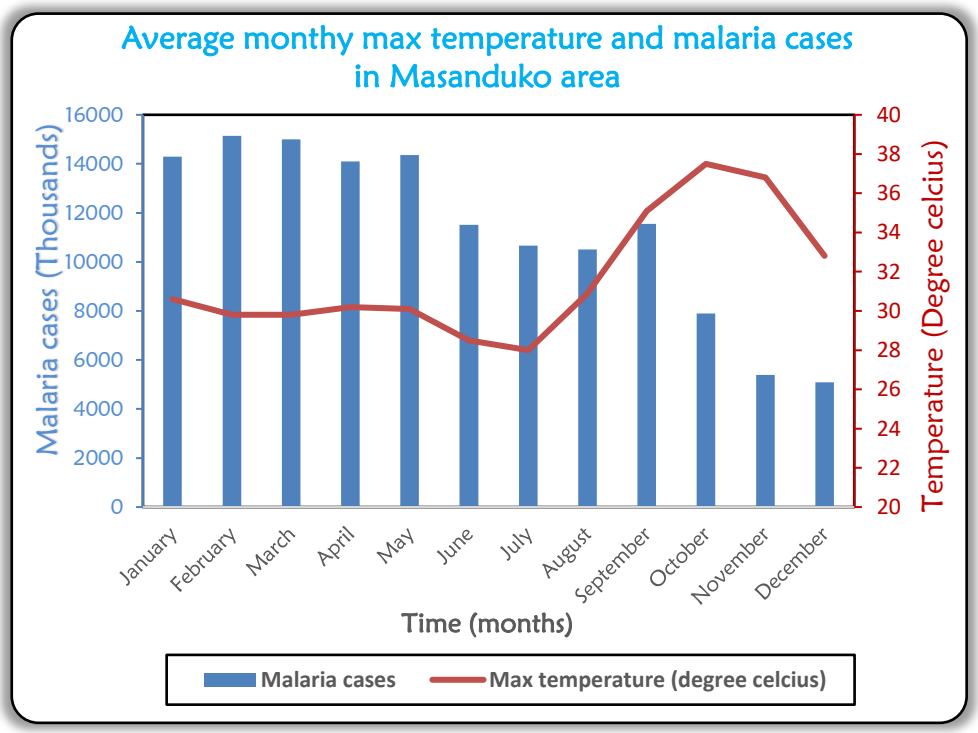


Figure: 3 shows the Mean Monthly Maximum Temperature versus malaria cases for Masanduko area, Ngabu.

4.1.2. Average Monthly Variation of Minimum Temperature versus malaria cases in Masanduko, Ngabu

The highest minimum temperature was observed in November but on average the highest minimum temperatures were observed in the growing season with minimum temperatures more than 19.^{0}c and the lowest was observed in July.

The highest number of malaria cases was observed to be in January and the lowest in December.

The following figure gives the summary.

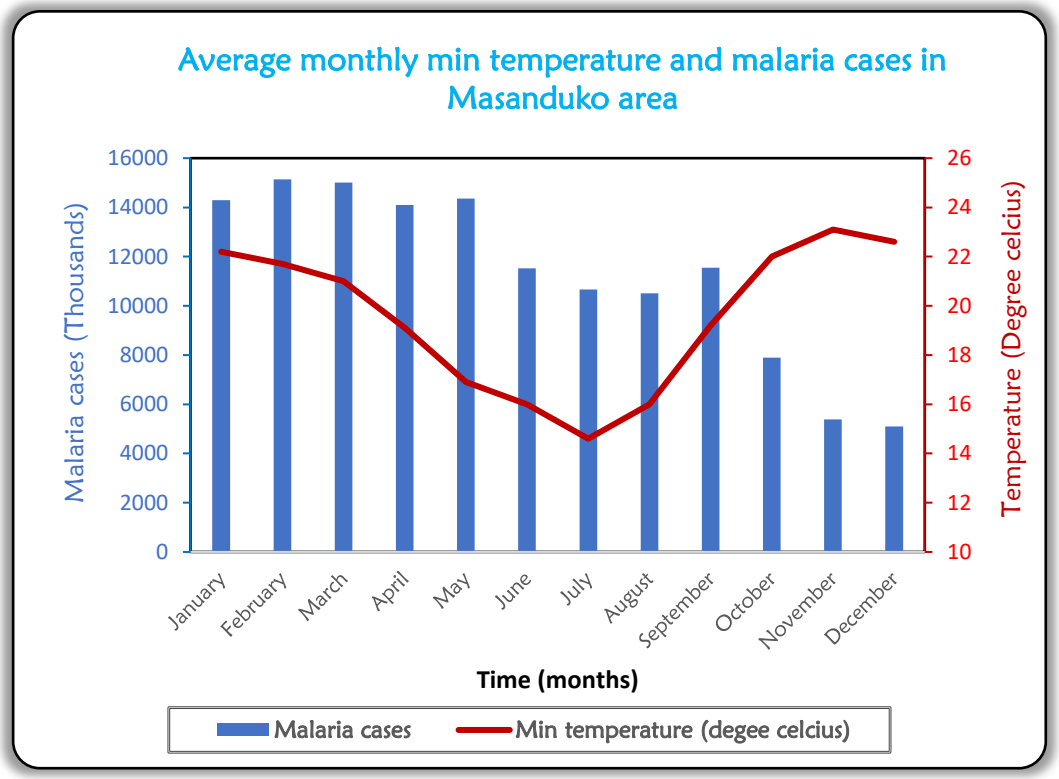


Figure 4: shows Mean Monthly Min Temperature versus monthly cases for Masanduko area.

4.1.3. Total and average Monthly Rainfall versus total monthly malaria cases in Masanduko area, Ngabu

The rainfall plot shows a steady decrease in rainfall from January to April. The months considered the dry season in this study has average monthly rainfall amounts ranging from 0 to 9 mm. Total rainfall and average rainfall share the same axis.

On the other hand, the histogram of malaria cases shows a decreasing trend of malaria from January through December with the highest number of malaria cases observed in February and the lowest total cases recorded in December.

The following figure presents the summary.

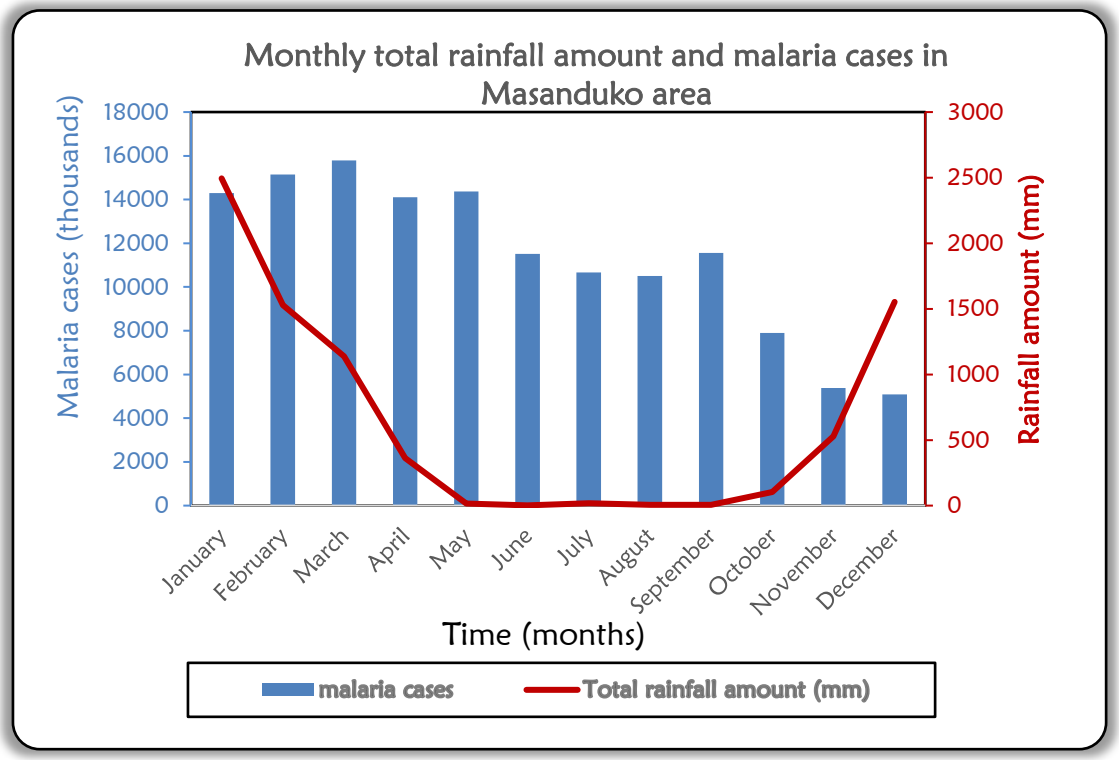


Figure: 5 shows average monthly and total monthly rainfall versus malaria cases for Masanduko area, Ngabu

4.2. Seasonal trend Analysis for weather parameters and malaria cases

4.2.1. Seasonal trend Analysis for Maximum temperature for Masanduko area

The highest maximum temperature in the wet season was in 2015/16 and 2012 registered the highest max temperature in the dry season.

However, when tested for significance, the trends in both wet and dry seasons do not show any significance. For the wet season (r^2=0.008,) and dry season (r^2=0.0091), The following figures 5 and 6 give the trends of Maximum temperature in wet and dry seasons respectively.

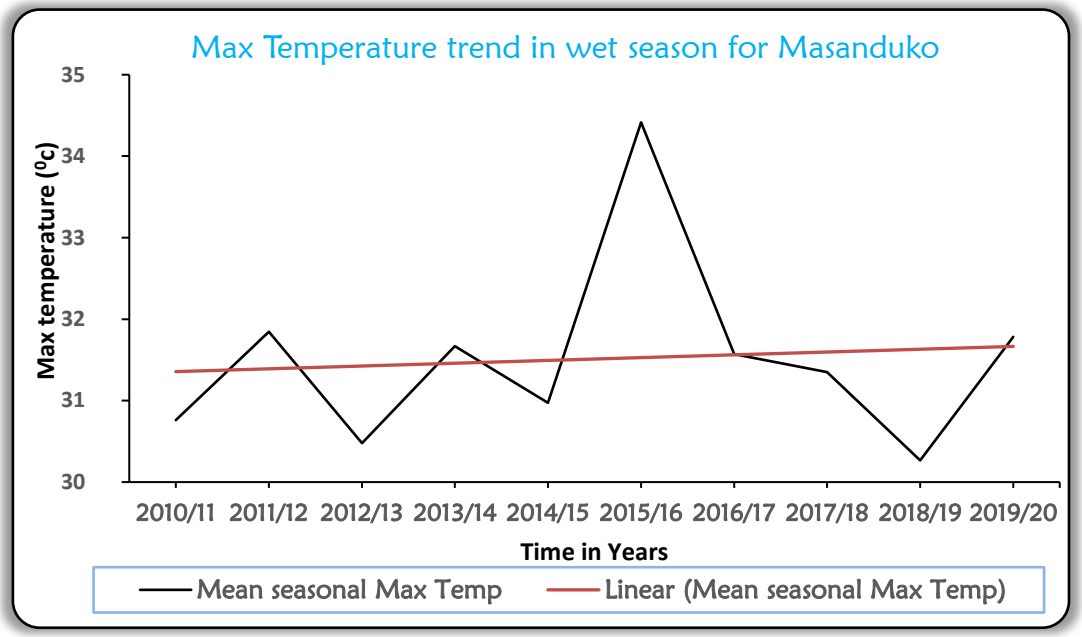


Figure: 6 shows max temperature trend in wet season in Ngabu

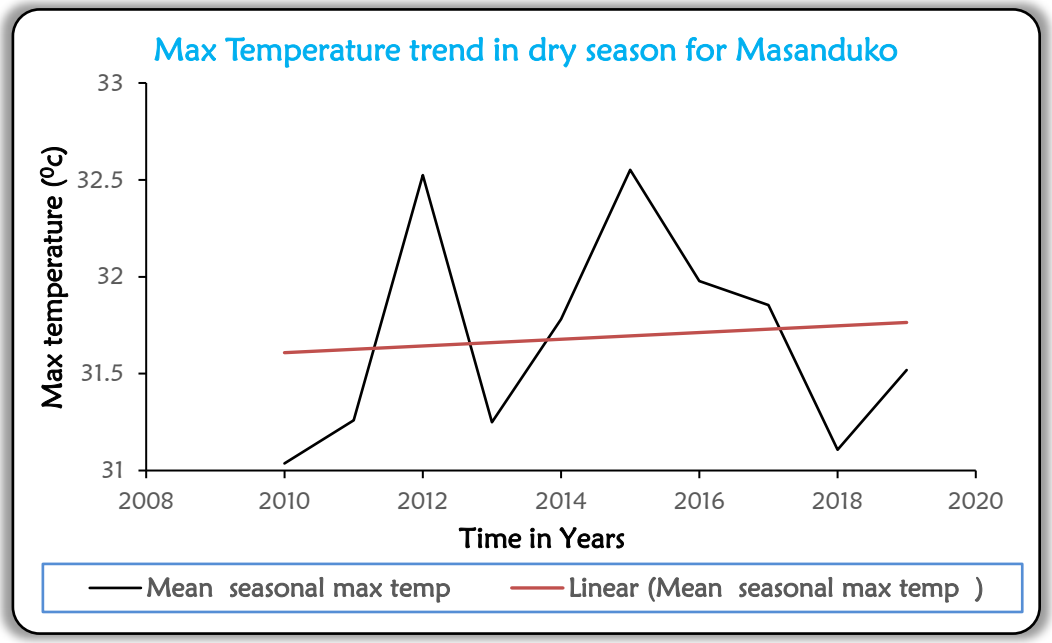


Figure: 7 shows max temperature trend in dry season in Masanduko

4.2.2. Trend Analysis for Minimum temperature in Masanduko

Just like for maximum temperature, the trends analysis of minimum temperature, in general, showed an increase but not a significant trend in both dry and wet seasons. The minimum temperature was lowest in 2012/13 during the growing season and was lowest in 2013 during the dry season.

Results for the significance test are as follows: Wet season (r^2=0.07,) and dry season (r^2=0.0091).

The trends are summarised with the aid of the following figures 7 and 8 in the wet and dry season respectively.

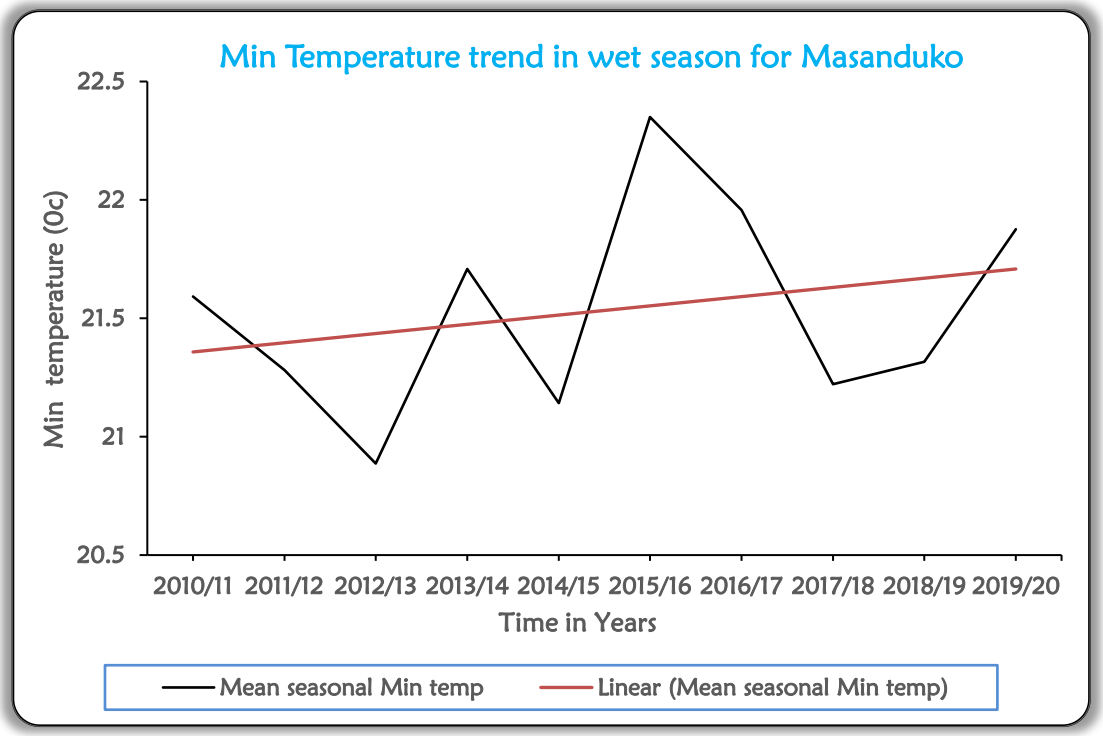


Figure: 8 shows the minimum temperature trend in wet season in Ngabu

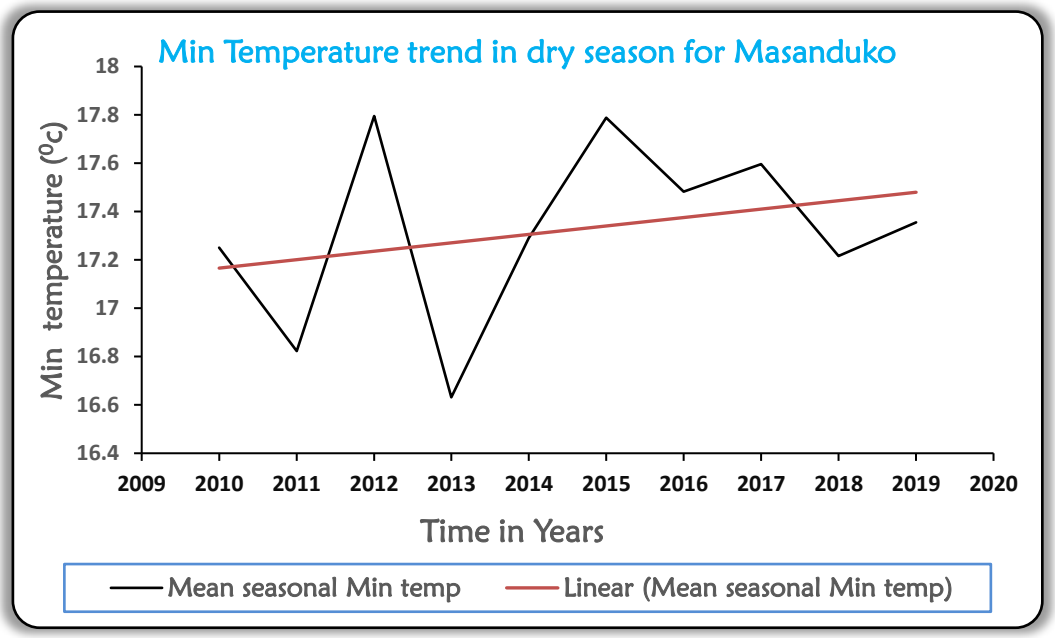


Figure: 9 shows the minimum temperature trend in dry season in Ngabu

4.2.3. Trend Analysis for rainfall in Ngabu

The time series analysis of rainfall was done in the dry and wet seasons separately. The overall trend in the wet season shows a slight increase in rainfall from year to year in wet seasons. The analysis also shows an overall decreasing trend of rainfall in the dry season.

It also comes out that rainfall was highest in 2018/19 for the wet season and 2011 for the dry season.

The trends in both seasons were found to be insignificant. For wet season (r^2=0.1447) dry season (r^2=0.0091)

The following figures 9 and 10 present the trends of rainfall in the wet and dry seasons respectively.

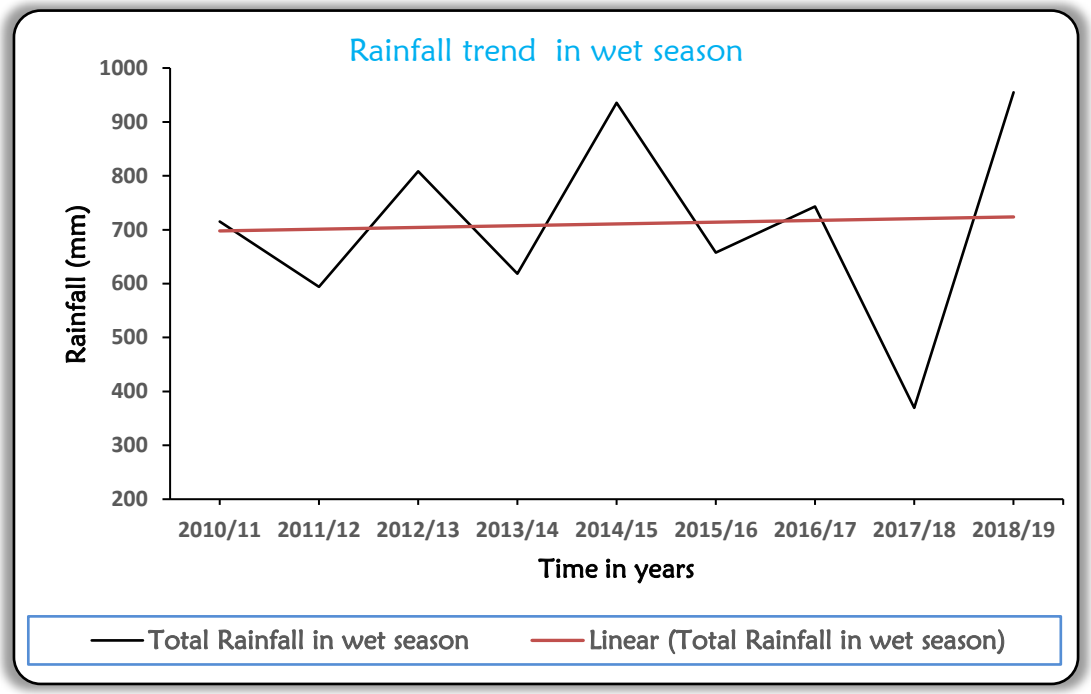


Figure: 10 shows rainfall trend for wet season in Ngabu

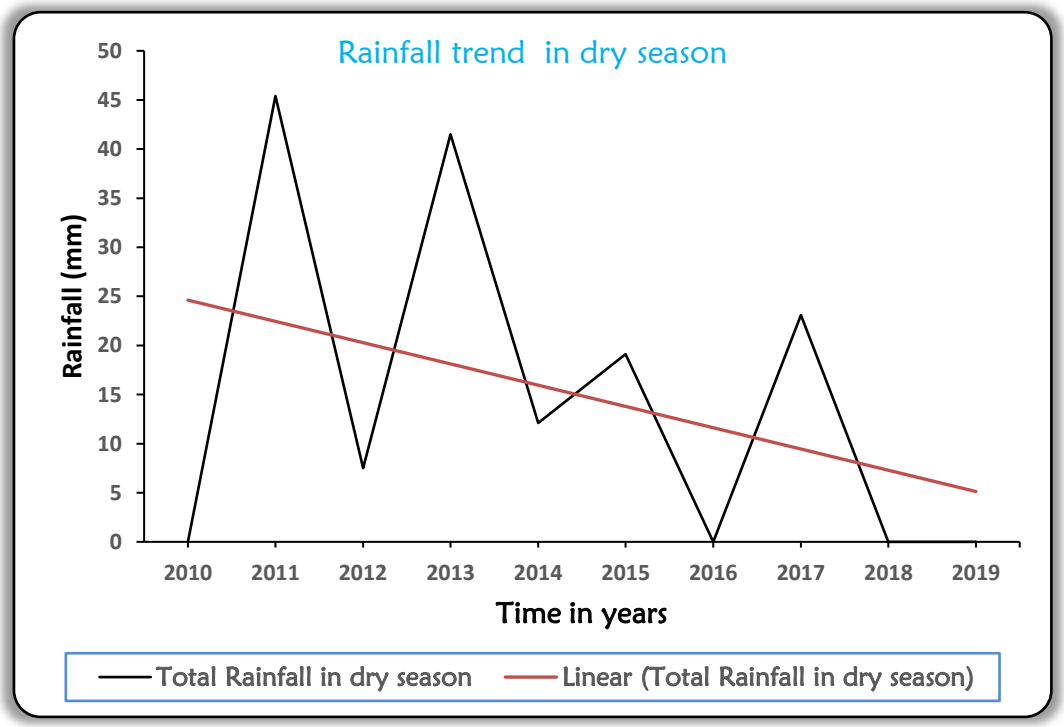


Figure: 11 shows rainfall trend for dry season in Masanduko

4.2.4. seasonal Trend Analysis for Malaria cases in Masanduko

Trend analysis of malaria showed a decreasing trend in the wet season as opposed to the dry season. The recorded cases were highest in 2014/15 seconded by 2010/11

growing season. During the dry season, the highest record was in 2015 seconded by 2016.

For the malaria cases recorded in the past 11 years, the changes do not as well meet the level to be considered as significant. For wet season (r^2= 0.2715) and dry season (r^2=0.0128)

The following figures 12 and 13 present the trends of malaria cases in the wet/growing and dry season respectively.

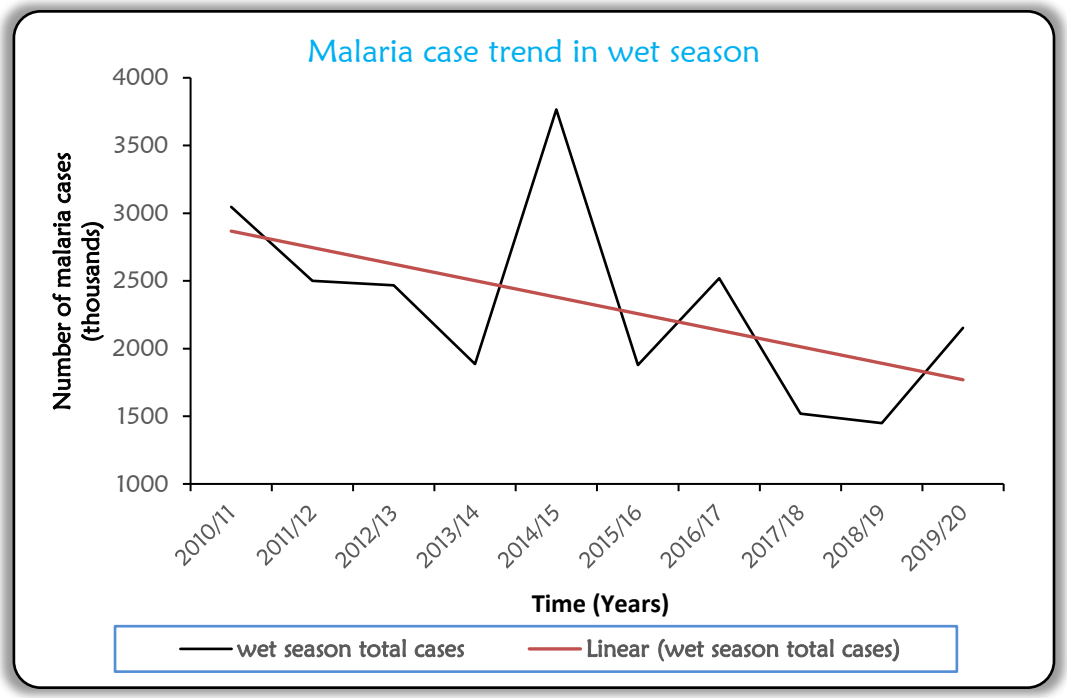


Figure: 12 shows the malaria case trend in wet season in Ngabu

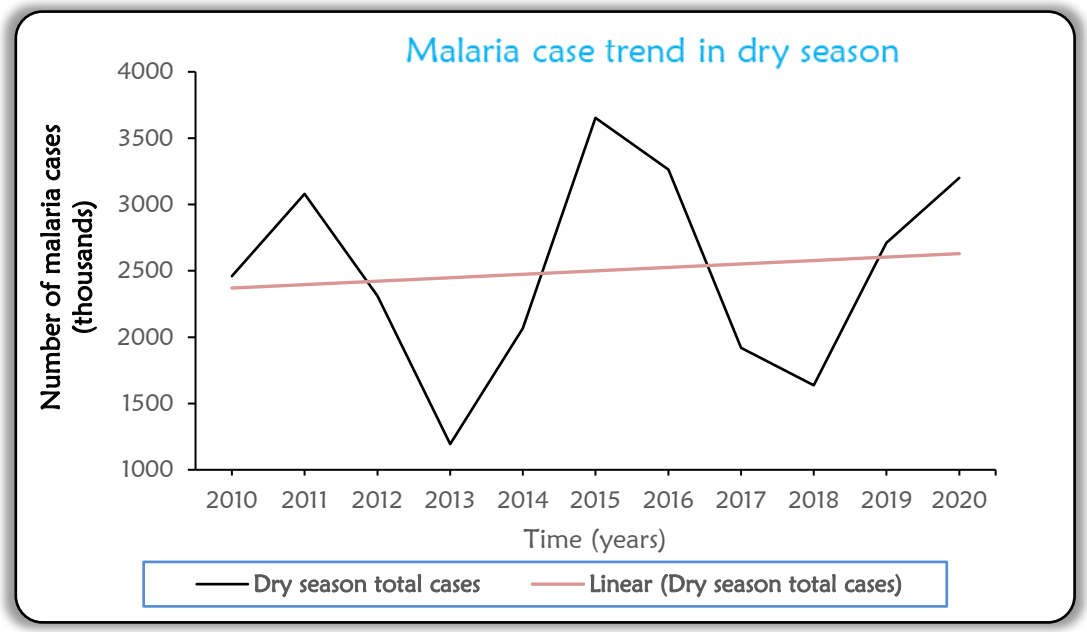


Figure: 13 shows the malaria case trend in the dry season in Masanduko

4.3. Relationship between Malaria cases and weather parameters

4.3.1. Correlation analysis

Presented in this section are the r values supported by p-values and t values. P-value tells whether any r value is significant or not. In this study, a significant r value is expected to have a p-value less than $\alpha=0.05$.

The t value/score is a ratio between the difference between two groups and the difference within the groups. The smaller the t score, the more similarity there is between the groups. The larger the t score, the more difference there is between the groups, and the higher the chances that the results are repeatable and do not happen by chance.

Tables 1, 2, 3, and 4 show the correlation coefficients (r values), the P-value, and the tabulated t-value of a significant level of 95% ($\alpha=0.05$) for the wet and dry season, across months and month with a lagged effect.

4.3.1.1. Correlation in the wet season

	Pearson coefficient (r)	P value	t-tabulated	Remarks
Max temp in wet season	**0.414**	0.033	2.201	Significant
Min temp in wet season	**0.24**	0.82	2.201	Not Significant
Rainfall in wet season	**0.218**	0.230	2.201	Not significant

Table 1: Showing Correlation Coefficients in the wet season

4.3.1.2. Correlation in the dry season

	Pearson coefficient (r)	P value	t-tabulated	Remarks
Max temp in dry season	**0.659**	0.030	2.201	Significant
Min temp in dry season	**-0.438**	0.205	2.201	Not significant
Rainfall in dry season	**-0.131**	0.719	2.201	Not significant

Table 2: Showing Correlation Coefficients in the dry season

The tables above in general show the weather parameters and the occurrence of malaria, in general, there exists relationships. In the wet season Maximum temperature, minimum temperature, and rainfall are positively correlated with malaria positive case abundance as are ideal conditions for the occurrence of the disease but the existing relationship is only significant for maximum temperature. In the dry season, there is a negative correlation between weather parameters like Minimum temperature, and

rainfall, and malaria cases. As is the case with the wet season, only maximum temperature shows a positive and significant correlation with malaria cases even though the strength is very little.

4.3.1.3. Correlation Across months

Correlation across months means malaria case data for all years were summed according to months and correlated against weather parameters for each month.

	Pearson coefficient (r)	P value	t-tabulated	Remarks
Max temp each month	**0.636**	0.026	2.201	Significant
Min temp each months	**0.249**	0.249	2.201	Not Significant
Rainfall each months	**-0.215**	-0.503	2.201	Not significant

Table 3: Showing Correlation Coefficients across months

Correlation of the three weather parameters (monthly averages) with monthly malaria case totals indicated a positive but not significant correlation for minimum temperature, negative and not significant correlation for maximum temperature. The maximum temperature was an exception as it indicated and positive, significant, and moderate strength correlation.

4.3.1.4. Correlation Across months with a lag of one month

The scenario in the table below indicates a correlation that was was run between malaria cases observed in a certain month with weather parameters but for the previous month. The idea was to check if one weather parameter for a given month could have an influence on the number of malaria cases for the next month.

	Pearson coefficient (r)	P-value	t-tabulated	Remarks
Max_temp_one month_lag	**0.836**	0.003	2.201	Significant
Min_temp _one_month_lag	**-0.131**	0.701	2.201	Not Significant
Rainfall_one_month_lag	**-0.559**	0.74	2.201	Not Significant

Table 4: Showing Correlation Coefficients across months but with a month lag.

The results indicate a significant, strong, and positive correlation between temperature and malaria and a weak negative as well as an insignificant correlation between minimum temperature and malaria cases. There is a moderate negative and insignificant correlation between rainfall and malaria cases.

4.3.2. Regression analysis

The maximum temperature remained the only factor that had a positive correlation, which was significant with malaria cases in both wet and dry seasons. The correlation of malaria cases observed in one month with temperature from the previous month also indicated a positive and significant relationship. Regression analysis was therefore conducted for the monthly mean maximum temperature and monthly total malaria cases to come up with an equation that can help predict the numbers of malaria cases for the upcoming month using observed mean temperature for a particular month. The obtained equation has a coefficient of determination of $R^2 = 0.405$ which implies that about 40% of the variation of some malaria cases in Masanduko area for a given month can be explained using maximum temperature for the previous month. For instance, the temperature in January will describe variations of malaria cases in February. The following formula was generated.

$$\textit{Malaria cases in one month} = 35303.262 - 758.514\textit{Max temperature in previous month} \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

4.4. Discussions

In the period between 2010 and 2020 climate over Ngabu has not changed significantly. This is evident from the discussed trends of the climatic variables like Maximum temperature, minimum temperature, and rainfall. Maximum temperature for instance has been fluctuating between 30^{0}c to 34^{0}c in the wet season and 31^{0}c to 32^{0}c in the dry season. The minimum temperature fluctuates between 20^{0}c to 22^{0}c in the wet season and between 16^{0}c and 18^{0}c in the dry season. According to world weather online, the annual average temperatures for Ngabu are 32^{0}c for max temperature and 20^{0}c for minimum temperature. Rainfall variations are between 300mm to 900mm in the wet season and 0 to 45mm in the dry season. The variations observed could be considered as normal as we may not have the same figures each year. All the parameters have an r^2 value of less than 50% a factor that also confirms the insignificance of the decreasing or increasing trends.

To some extent, the variations in the climatic variables can help explain the variability of malaria cases in the study area through correlation analysis. Other climatic variables like Maximum and Minimum temperatures increases at the same time the malaria cases are also increasing in both dry and growing seasons with one exception that malaria cases seem to be decreasing during the wet season. The rainfall trend in the dry season is decreasing since 2010. This trend in the dry season means the area is becoming drier.

In this study maximum temperature shows a moderate to a strong significant positive relationship with malaria cases in both wet and dry seasons separately and when correlated across months. From the graphing of monthly variations of max temperature and malaria cases, it indicates that Ngabu's average maximum temperature is higher throughout the year (ranging from 28^{0}c to 38^{o}c). Malaria cases are extremely high from January to May. During this time, temperatures deviate from 29^{o}c to 31^{o}c. The finding of this study agrees with what Shapiro, Whitehead, and Tomas (2017) suggest that the optimum temperature for mosquito activities for all traits is between 29^{o}c to 38^{o}c. The ranges that were proposed by Lunde et al. (2013) suggested that a temperature optimum for transmission being 26 ^{o}c with a minimum of 17 ^{o}c and 35 ^{o}c respectively which are also in line with what the study found. One other study in Malawi by Kazembe et al. (2006) found the optimum

temperature for mosquito transmission is between 27°c to 32°c, which is again agreeing with our research findings.

Part of this research is to predict a malaria outbreak for the next one or several months. This is very much helpful, as it will aid in proper preparation that will see authorities employ appropriate controlling measures at right time. So far, it is now possible to do the predicting part by using the prevailing maximum temperature in a particular month. The predicted Malaria cases could be scaled as extreme, moderate, and/or normal and the appropriate measures planned or put in place.

5.0. CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusion

From this study, there is no enough evidence of changing climate over the study area. Fluctuations of weather parameters herein; minimum/maximum temperature and rainfall are not significant. This can be attributed to the short duration of the study. The world meteorological organization recommends at least 30 years of observation to declare climate variability. There are great relationships between malaria cases with climate variables over Masanduko, however, the only relation between maximum temperature and malaria cases in both seasons poses a significant relationship. As such, this weather parameter can be used to develop a weather-based malaria prediction model for the area with a lead-time of a month. A malaria early warning system, based on well-organized malaria surveillance and routinely collected weather parameters data is an important tool for forecasting the endemicity of malaria for the Masanduko area, allowing authorities to act quickly with appropriate measures.

5.2. Recommendations

Since the data used in this research was for 11 years only, I recommend that future studies should incorporate long data (at least for 30 years and above).

I also recommend that further studies be carried out to determine the influence of other non-climatic factors affect the severity and incidence of malaria transmission. These factors include type of vectors and parasites, environmental developments and urbanization, population movement and migration, the level of immunity in the human hosts, insecticide resistance in mosquitoes, and drug resistance in plasmodium which is all silent in this study.

The study was spatially confined to a smaller area. The study can be scaled out to a using more than one DCCMS stations and data from more hospitals to cover a larger spatial area for a broader understanding of the relationship between malaria cases and weather parameters.

The study failed to cover more than 11 years because malaria data before 2010 was poorly reported from the Ngabu SDA and Ngabu rural health centres. As such there were large gaps in the Health Management system.

REFERENCES

Abeku, T. A., De Vlas, S. J., Borsboom, G. J. J. M., Tadege, A., Gebreyesus, Y., Gebreyohannes, H., Alamirew, D., Seifu, A., Nagelkerke, N. J. D., & Habbema, J. D. F. (2004). Effects of meteorological factors on epidemic malaria in Ethiopia: A statistical modelling approach based on theoretical reasoning. *Parasitology*, *128*(6), 585–593. https://doi.org/10.1017/S0031182004005013

Berthe, S., Harvey, S. A., Lynch, M., Koenker, H., Jumbe, V., Kaunda-Khangamwa, B., & Mathanga, D. P. (2019). Poverty and food security: Drivers of insecticide-treated mosquito net misuse in Malawi. *Malaria Journal*, *18*(1), 1–11. https://doi.org/10.1186/s12936-019-2952-2

Chandramohan, D., Jaffar, S., & Greenwood, B. (2002). Use of clinical algorithms for diagnosing malaria. *Tropical Medicine and International Health*, *7*(1), 45–52. https://doi.org/10.1046/j.1365-3156.2002.00827.x

Crawshaw, J., & Chambers, J. (2001). *A concise course in advanced level statistics: with worked examples*. 708.

DoDMA. (2015). *Malawi Hazards and Vulnerability Atlas*.

Ikeda, T., Behera, S. K., Morioka, Y., Minakawa, N., Hashizume, M., Tsuzuki, A., Maharaj, R., & Kruger, P. (2017). Seasonally lagged effects of climatic factors on malaria incidence in South Africa. *Scientific Reports*, *7*(1), 1–9. https://doi.org/10.1038/s41598-017-02680-6

Lunde, T. M., Bayoh, M. N., & Lindtjørn, B. (2013). How malaria models relate temperature to malaria transmission. *Parasites and Vectors*, *6*(1). https://doi.org/10.1186/1756-3305-6-20

Mabaso, M. L. H., Vounatsou, P., Midzi, S., Da Silva, J., & Smith, T. (2006). Spatio-temporal analysis of the role of climate in inter-annual variation of malaria incidence in Zimbabwe. *International Journal of Health Geographics*, *5*, 1–9. https://doi.org/10.1186/1476-072X-5-20

Mathanga, D. P., Walker, E. D., Wilson, M. L., Ali, D., Taylor, T. E., & Laufer, M. K.

(2012). Malaria control in Malawi: Current status and directions for the future. *Acta Tropica*, *121*(3), 212–217. https://doi.org/10.1016/j.actatropica.2011.06.017

Mzilahowa, T., Luka-Banda, M., Uzalili, V., Mathanga, D. P., Campbell, C. H., Mukaka, M., & Gimnig, J. E. (2016). Risk factors for Anopheles mosquitoes in rural and urban areas of Blantyre District, southern Malawi. *Malawi Medical Journal*, *28*(4), 151–158. https://doi.org/10.4314/mmj.v28i4.2

Namuyinga, R. J., Mwandama, D., Moyo, D., Gumbo, A., Troell, P., Kobayashi, M., Shah, M., Bauleni, A., Eng, J. Vanden, Rowe, A. K., Mathanga, D. P., & Steinhardt, L. C. (2017). Health worker adherence to malaria treatment guidelines at outpatient health facilities in southern Malawi following implementation of universal access to diagnostic testing. *Malaria Journal*, *16*(1), 1–14. https://doi.org/10.1186/s12936-017-1693-3

National Malaria Control Programme-NMCP/Malawi ICF International. (2015). Malawi Malaria Indicator Survey 2014. *Rockville, Maryland, USA: NMCP/ Malawi and ICF International*, 124. http://www.dhsprogram.com

Samuels, P. (2015). (2015). Pearson Correlation. *statstutor Community Project*, *April 2014*.

Yu, W., Mengersen, K., Dale, P., Ye, X., Guo, Y., Turner, L., Wang, X., Bi, Y., McBride, W. J. H., MacKenzie, J. S., & Tong, S. (2015). Projecting Future Transmission of Malaria Under Climate Change Scenarios: Challenges and Research Needs. *Critical Reviews in Environmental Science and Technology*, *45*(7), 777–811. https://doi.org/10.1080/10643389.2013.852392

Zacarias, O. P., & Andersson, M. (2011). Spatial and temporal patterns of malaria incidence in Mozambique. *Malaria Journal*, *10*(1), 189. https://doi.org/10.1186/1475-2875-10-189

APPENDICES

Appendix A: Data used for correlation

A1: Data used in the wet season.

YEAR	Max temp in the wet season	Min temp in the wet season	Rainfall in the wet season	Malaria cases in the wet season
2010	30.76000000	21.59166667	715.00	3046
2011	31.84500000	21.28166667	593.90	2499
2012	30.47666667	20.88666667	808.50	2468
2013	31.66833333	21.70833333	618.50	1886
2014	30.97166667	21.14166667	935.40	3766
2015	34.41500000	22.35000000	657.63	1879
2016	31.57166667	21.95666667	743.30	2519
2017	31.34833333	21.22166667	369.50	1519
2018	30.26666667	21.31666667	954.90	1449
2019	31.78233333	21.87550000	693.80	2152

A2: Data used in the dry season.

YEAR	Max temp in the dry season	Min temp in the dry season	Rainfall in the dry season	Malaria cases in dry
2010	31.03666667	17.25000000	0	2460
2011	31.26000000	16.82333333	45.4	3079
2012	32.52500000	17.79500000	7.5	2311
2013	31.25000000	16.63166667	41.5	1194
2014	31.78166667	17.29000000	12.1	2067
2015	32.55166667	17.78833333	19.1	3653
2016	31.97833333	17.48166667	0	3264
2017	31.85333333	17.59666667	23.1	1919
2018	31.10666667	17.21666667	0	1637
2019	31.51833333	17.35500000 .0	0	2710

A2: Data for correlation across months

Month	Max temp	Min temp	Rainfall	Malaria cases
January	30.6	22.2	226.8	15548
February	29.8	21.7	139.0	14600
March	29.8	21.0	103.4	15163
April	30.2	19.1	40.8	14119
May	30.1	16.9	1.4	14157
June	28.5	16.0	0.2	11614
July	28.0	14.6	1.5	10675
August	30.9	16.0	0.5	10491
September	35.1	19.2	0.6	11413
October	37.5	22.0	9.4	7894
November	36.8	23.1	48.0	5085
December	32.8	22.6	141.2	4569

APPENDIX B: Correlation tables

B1: Correlations in the wet season

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

		Max temp in wet season(oc)	Min temp in wet season(oc)	Rain fall in wet season (mm)	Malaria cases in wet season
Max temp in wet season(oc)	Pearson coefficient	1	.773**	-.383	.414*
	Sig.(2-tailed)		.009	.274	.033
	N	10	10	10	10
Min temp in wet season(oc)	Pearson coefficient	.773**	1	-.174	.24*
	Sig.(2-tailed)	.009		.628	.082
	N	10	10	10	10
Rain fall in wet season (mm)	Pearson coefficient	-.383	-.174	1	-.218
	Sig. (2-tailed)	.274	.628		.230
	N	10	10	10	10
Malaria cases in wet season	Pearson coefficient	-.214	-.224	.418	1
	Sig.(2-tailed)	.553	.533	.230	
	N	10	10	10	10

B2: Correlations in the dry season

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

		Max temp in dry season(oc)	Min temp in dry season(oc)	Rain fall in dry season (mm)	Malaria cases in dry season
Max temp in dry season(oc)	Pearson coefficient	1	.803**	-.112	.659*
	Sig. (2-tailed)		.005	.757	.030
	N	10	10	10	10
Min temp in dry season(oc)	Pearson coefficient	.803**	1	-.563	.438
	Sig.(2-tailed)	.005		.090	.205
	N	10	10	10	10
Rainfall in dry season (mm)	Pearson coefficient	-.112	-.563	1	-.131
	Sig. (2-tailed)	.757	.090		.719
	N	10	10	10	10
Malaria cases in dry season	Pearson coefficient	.459	.459	-.131	1
	Sig.(2-tailed)	.183	.183	.719	
	N	10	10	10	10

B2: Correlations across months

*. Correlation is significant at the 0.05 level (2-tailed).

		Max temp each month (oc)	Min temp each month (oc)	Rainfall each month (mm)	Malaria cases each month
Max temp each month (oc)	Pearson coefficient	1	.596*	-.116	.636*
	Sig.(2-tailed)		.041	.720	.026
	N	12	12	12	12
Min temp each month (oc)	Pearson coefficient	.596*	1	.663*	-.249
	Sig.(2-tailed)	.041		.019	.434
	N	12	12	12	12
Rainfall each month (mm)	Pearson coefficient	-.116	.663*	1	.215
	Sig.(2-tailed)	.720	.019		.503
	N	12	12	12	12
Malaria cases each month	Pearson coefficient	.636*	.249	.215	1
	Sig.(2-tailed)	.026	.434	.503	
	N	12	12	12	12

Correlations across months with one month lag

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

		Max_temp_one_month_lag (oc)	Min_temp_one_month_lag (oc)	Rainfall_one_month_lag (mm)	Malaria cases each month
Max_temp_one_month_lag (oc)	Pearson coefficient	1	.595	-.165	.809*
	Sig.(2-tailed)		.053	.628	.003
	N	11	11	11	11
Min_temp_one_month_lag (oc)	Pearson coefficient	.595	1	-.621*	-.131
	Sig.(2-tailed)	.053		.041	.701
	N	11	11	11	11
Rainfall_one_month_lag (mm)	Pearson coefficient	-.165	.628**	1	.559
	Sig.(2-tailed)	.628	.041		.074
	N	11	11	11	10
Malaria cases each month	Pearson coefficient	.808*	-.131	-.559	1
	Sig.(2-tailed)	.003	.701	.074	
	N	11	11	11	10

APPENDIX C: Regression Table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
	(Constant)	35303.262	9254.456		3.815	.003	14683.048	55923.475
	Max temperature	-758.514	290.841	.636	-2.608	.026	-1406.548	-110.480

a. Dependent Variable: Total malaria cases

APPENDIX D: t-Distribution Table

	Confidence intervals	80%	90%	95%	98%	99%
	One tail, α	0.10	0.05	0.025	0.01	0.005
d.f.	Two tails, α	0.20	0.10	0.05	0.02	0.01
1		3.078	6.314	12.706	31.821	63.657
2		1.886	2.920	4.303	6.965	9.925
3		1.638	2.353	3.182	4.541	5.841
4		1.533	2.132	2.776	3.747	4.604
5		1.476	2.015	2.571	3.365	4.032
6		1.440	1.943	2.447	3.143	3.707
7		1.415	1.895	2.365	2.998	3.499
8		1.397	1.860	2.306	2.896	3.355
9		1.383	1.833	2.262	2.821	3.250
10		1.372	1.812	2.228	2.764	3.169
11		1.363	1.796	2.201	2.718	3.106
12		1.356	1.782	2.179	2.681	3.055
13		1.350	1.771	2.160	2.650	3.012
14		1.345	1.761	2.145	2.624	2.977
15		1.341	1.753	2.131	2.602	2.947
16		1.337	1.746	2.120	2.583	2.921
17		1.333	1.740	2.110	2.567	2.898
18		1.330	1.734	2.101	2.552	2.878
19		1.328	1.729	2.093	2.539	2.861
20		1.325	1.725	2.086	2.528	2.845
21		1.323	1.721	2.080	2.518	2.831
22		1.321	1.717	2.074	2.508	2.819
23		1.319	1.714	2.069	2.500	2.807
24		1.318	1.711	2.064	2.492	2.797
25		1.316	1.708	2.060	2.485	2.787
26		1.315	1.706	2.056	2.479	2.779
27		1.314	1.703	2.052	2.473	2.771
28		1.313	1.701	2.048	2.467	2.763
29		1.311	1.699	2.045	2.462	2.756
30		1.310	1.697	2.042	2.457	2.750
32		1.309	1.694	2.037	2.449	2.738
34		1.307	1.691	2.032	2.441	2.728
36		1.306	1.688	2.028	2.434	2.719
38		1.304	1.686	2.024	2.429	2.712
40		1.303	1.684	2.021	2.423	2.704
45		1.301	1.679	2.014	2.412	2.690
50		1.299	1.676	2.009	2.403	2.678
55		1.297	1.673	2.004	2.396	2.668
60		1.296	1.671	2.000	2.390	2.660
65		1.295	1.669	1.997	2.385	2.654
70		1.294	1.667	1.994	2.381	2.648
75		1.293	1.665	1.992	2.377	2.643
80		1.292	1.664	1.990	2.374	2.639
90		1.291	1.662	1.987	2.368	2.632
100		1.290	1.660	1.984	2.364	2.626
500		1.283	1.648	1.965	2.334	2.586
1000		1.282	1.646	1.962	2.330	2.581
$(z)\ \infty$		1.282[a]	1.645[b]	1.960	2.326[c]	2.576[d]

[a]This value has been rounded to 1.28 in the textbook.
[b]This value has been rounded to 1.65 in the textbook.
[c]This value has been rounded to 2.33 in the textbook.
[d]This value has been rounded to 2.58 in the textbook.

Source: Adapted from W. H. Beyer, *Handbook of Tables for Probability and Statistics*, 2nd ed., CRC Press, Boca Raton, Fla., 1986. Reprinted with permission.

