UNIVERSITY FOR DEVELOPMENT STUDIES

MODELING THE CLIMATIC DETERMINANTS OF MALARIA CASES USING POISSON SWITCHING REGRESSION MODEL

AHMED MOHAMMED

2021

UNIVERSITY FOR DEVELOPMENT STUDIES

MODELING THE CLIMATIC DETERMINANTS OF MALARIA CASES USING POISSON SWITCHING REGRESSION MODEL

BY

AHMED MOHAMMED
(BSc. Mathematics and Statistics)

(UDS/MAS/0004/19)

Thesis Submitted to the Department of Statistics, Faculty of Mathematical Sciences, University for Development Studies in Partial Fulfillment of the Requirements for the Award of Master of Philosophy Degree in Applied Statistics

September, 2021

DECLARATION

Student

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree in this University or elsewhere:

Signature: …………………….……… Date: ……………………..

Name: ……………………………………………………………………………….

Supervisor

I hereby declare that the preparation and presentation of this thesis was supervised in accordance with the guidelines on supervision of thesis laid down by the University for Development Studies.

Signature…………………………… Date: ………………………..

Dr. Solomon Sarpong (Principal Supervisor)

Signature: …………………………. Date: ………………………..

Mr. John Abonongo (Co-Supervisor)

ABSTRACT

Malaria has become a common disease that affects the health of every household. The canker is expected to continue with its devastating effects for a long period given the absence of sufficient interventions to mitigate it. Several researches have been undertaken to investigate the pattern of malaria cases in Ghana. This study modeled the effects of climatic variables on monthly malaria cases in Wenchi Municipal using Poisson Switching Regression Model. Secondary data on malaria from January, 2013 to December, 2020 were obtained from the municipal health directorate. Rainfall, temperature and relative humidity data in the area for the same period were also obtained from the meteorological office. The data was analyzed using Poisson switching regression model. Using the climatic variables in the data collected the malaria cases were modeled in two and three different states. The three states were low, moderate and high states. The three-regime Poisson regression was preferred over the two–regime Poisson as it had better statistics (AIC, BIC and log-likelihood). The results revealed that, low malaria cases were recorded in the period between 2015 and 2016, moderate cases were between 2013 and 2014 and midyear 2020. In general terms, this study revealed positive relationship between malaria incidence and the climatic factors in low state while depicting a positive relation with rainfall and temperature during the moderate state and positive for only relative humidity in the high regime. Proactive measures spearheaded by the Ghana Health Service to sensitize the public on the need to

practice safe malaria habits to avoid malaria transmission during periods of high malaria incidence is highly recommended.

ACKNOWLEDGEMENTS

I am highly grateful to the Almighty for His Guidance throughout my studies in this school. Aside this, my acknowledgement goes to the following personalities;

First of all, my appreciation goes to my supervisor, Dr. Solomon Sarpong and co-supervisor, Mr. John Abonongo for their immense support in ensuring that, this piece of work is in compliance with the University's standards and requirement.

Moreover, I will be highly ungrateful to forget to show appreciation to the Head of Department Dr. Suleman Nasiru for his unflinching support and guidance throughout my course work and finally in undertaking this research. May Allah abundantly bless you sir.

To all my colleagues and staff of the Statistics Department, I say a big thank you.

Finally, I am indebted to my lovely wife Mrs. Alimatu Oware for her emotional support and love in achieving this mark.

DEDICATION

This piece of work is dedicated to my loving parents Mr. Baba and Mrs. Sahadatu Mohammed who have been strong pillars in pushing me to pursue this academic height.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
EIR	Entomological Inoculation Rate
GLM	Generalized Linear Model
GME	Generalized Maximum Entropy
GIS	Geographical Information System
GHS	Ghana Health Service
IRS	Indoor Residual Spraying
MDG	Millennium Development Goals
NDVI	Normalized Difference Vegetation Index
OLS	Ordinary Least Squares
PR	Parasite Ratio
TPR	Test Positivity Ratio
VAR	Vector Auto regression
WHO	World Health Organisation

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Malaria is a fatal disease caused by a parasitic plasmodium that infects a female anopheles mosquito. The anopheles mosquito in turn infects unsuspecting victims through bites. People infected with the disease exhibit high fevers with high body temperatures and flu-like illness. The bane of this disease is a huge drain on many national economies due to the fact that it causes high morbidity rate and continues to claim more than 400,000 lives every year. Most countries with high malaria burden are already identified among the needy countries making the disease maintain a vicious cycle of disease and poverty (Bereka et al., 2017).

An estimated 228 million cases of malaria occurred in 2018 worldwide, compared with a rather higher 251 million cases in 2010 and 231 million cases in 2017 (WHO, 2019). Recent reports by the World Health Organization (WHO) conceded that nineteen (19) countries in sub-Saharan Africa and India carried almost 85 percent of the global malaria burden. Six countries accounted for more than half of all malaria cases worldwide: Nigeria (25 percent), the Democratic Republic of the Congo (12 percent), Uganda (5 percent), Cote d'Ivoire, Mozambique and Niger with 4 percent each. The most vulnerable groups remain children under five years of age and pregnant women. In moderate to high transmission malaria endemic countries, malaria infection during pregnancy and the consequent placental infection are important contributors to low birth weight. Among the 38 moderate to high transmission countries in sub-Saharan Africa, the estimated 11 million pregnancies exposed to malaria infection in 2018 resulted in about 872,000 children born with low birth weight, representing 16 percent of all children with low birth weight in these countries. By sub-region, the percentage of low birth weight children due to malaria was, in line with exposure to malaria infection during pregnancy, highest in West Africa (18 percent of low birth weight children), followed by Central Africa (20 percent) and East and Southern Africa (12 percent) (WHO,2019).

The number of disability-adjusted life years, a measure of disease burden caused by malaria, was estimated worldwide to be thirty-four million in the year 2004, with thirty-one million in sub- Saharan Africa (WHO, 2004). Malaria alone costs Africa's economy more than twelve billion United States Dollars annually (Jima et al., 2010). Malaria therefore not only affects the health status of Africa's population, but also has far-reaching economic consequences impeding economic development. The impact of malaria on the population and its significance on development in the African region was recognized by the Abuja Summit in April 2000 as the first African summit of Heads of government on malaria control. The communiqué from the meeting calls, among other things, for more research on trends in incidence and prevalence of malaria, epidemic outbreaks and clinical epidemiology (Sachs, 2000). A better understanding of the distribution of malaria has been identified as a very worthwhile tool in the control of the disease (Marsh and Snow, 1997).

Malaria is hyper-endemic and remains a huge challenge on public health in Ghana. For recent years, there seem to be scaled up measures in the treatment and intervention strategies of malaria in the country. Yet, the disease still maintains its place as the leading cause of morbidity and mortality among the Ghanaian populace. According to the Ghana Health Service (GHS) report, suspected malaria cases accounted for about forty percent outpatient morbidity, thirty-five percent hospital admissions and eighteen percent of all recorded mortalities in government hospitals. Indeed, the actual number of malaria cases is probably higher than the recorded. This is because, the recorded cases did not include cases in the private health centers as well as cases being treated by self-medication by the individuals in their homes. With 3 percent of global malaria cases and deaths, Ghana is among the 15 highest burden malaria countries in the world. Ghana and Nigeria reported the highest increase in absolute case numbers (500,000 new cases) from 2017 to 2018, which represents a 5 percent increase versus 2017 levels (from 213 to 224 per 1000 of the population at risk) (WHO, 2019).

The malaria situation could be aggravated by the challenges posed by climate change. Although the impact of the climate on human health is uncertain, an increase in the incidence of malaria has been identified as a potential impact of climate change in South America and in Africa. Climatic factors that feed into the phenomenon could have a direct bearing on the number of malaria cases. A number of studies have reported association between malaria cases, rainfall and temperature. For example, a study carried out in Ethiopia by Teklehaimanot et al. (2004) revealed an association of malaria with rainfall and minimum temperature, the strength of which varied with altitude. In South Africa, variations in annual cases of malaria were shown to be related to patterns of rainfall and temperature (Craig et al., 2004). Malaria as a disease is therefore closely bound to conditions which favour the survival of the anopheles mosquito in the form of habitat and breeding sites and which favour the life cycle of the parasite in term of suitable temperatures.

Myriads of researches on malaria have been undertaken globally and in Ghana using different kinds of models to investigate the determinants of the disease. We are faced, today, with the need to predict the drift and transmission of diseases with a greater accuracy and over longer periods of time, and more often with limited empirical data (Huppert & Katriel, 2013). This study therefore models a Poisson switching regression model for the climatic determinants of malaria.

1.2 Problem Statement

Malaria remains a major public health problem for the world population. Developing countries especially sub-Saharan Africa are seriously affected by this disease. To curb this, myriads of research making use of parametric models have been carried out. These models are normally based on assumptions which often require data that are normally distributed. However, real life data are often not normally distributed and hence require manipulations to achieve the desired normal distribution assumption. Apart from using models that are based on the assumptions of normality, there is tendency to overlook the fact that, malaria cases are counts and hence cannot be modeled with continuous distributions.

Some studies have reported the relationship between climate variability and malaria caseloads. Semenza and Jonathan (2018) and Johnson et al. (2018) opined that climatic and meteorological factors have considerable impact on vector borne diseases and anopheles vector abundance and the extrinsic cycle that the parasites perform inside mosquitoes. Thus, they may affect malaria incidence and constitute the driving forces of malaria epidemics. Although climatic indices influence malaria epidemiology, the relationship between climatic variability and malaria case intensity in Ghana is not properly understood and scarcely documented. Also, the information obtained from the studies spanned over relatively shorter periods. For this reason, malaria incidence in Ghana continues to negatively affect the lives of many citizens. To avoid this, scientific studies that delve more into the epidemiology of the disease using better techniques become very imperative. Also, data on malaria cases are counts of events which require models suitable for that nature. This study therefore examines the relationship between climatic variables and malaria cases using the Poisson switching regression model.

1.3 Research Questions

1. What is the pattern of malaria incidence in the Wenchi Municipality?
2. To what extent do the months affect malaria incidence in the Wenchi Municipality?

3. Which climatic variables significantly influence malaria incidence in the locality?

1.4 General Objective

The general objective of this study is to model the effects of climatic variables on malaria incidence using Poisson Switching Regression Model.

1.5 Specific Objectives

The specific objectives of the study are;

1. To model malaria cases using Poisson Switching Regression model
2. To investigate the effects of months on malaria cases.
3. To identify the climatic factors that influence malaria cases.

1.6 Significance of the Study

Malaria is a pivotal part of health. Researchers are constantly making efforts in their research to reduce its prevalence. Malaria is a leading cause of both maternal and infant mortality in Ghana. As part of the Millennium Development Goals (MDG) of Ghana, Goals 4 and 5 seeks to reduce child mortality and improve maternal care. MDG 6 seeks to combat HIV/AIDS, malaria and other diseases. It is in the light of these that it is imperative to carry out this study to help health practitioners and the nation to adequately resource itself towards the fight to end the endemic. The findings of this research will provide empirical support for health managers' strategic decisions in several critical areas of operation, and above all, provide a reliable guide to meet hospital management in their monthly and seasonal requisition for treatment kits and other malaria protocols. This will greatly help in formulation of strategies towards curbing the prevalence and incidence of malaria.

1.7 Scope and Limitations of the Study

This research was confined to the objectives of the study. The study was not without some constraints. Some of which include time constraints and financial inadequacy since the research was solely self-sponsored. Relevant materials such as journals and articles pertaining to the research also proved difficult to come across.

1.8 Structure of the Thesis

The thesis is organised into five chapters. Chapter one contains the introduction of the research while chapter two comprises of review of related literature. Chapter three outlines the methodology employed in this research while chapter four presents the analysis and discussion of results. Chapter five is comprised of summary, conclusion and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

Countless number of researches have been undertaken on malaria using various models to elaborate on its incidence and accompanying burden on the population. This chapter discusses a review of those relevant research literatures that have been previously undertaken.

2.1 Review of Previous Studies

Climatic conditions such as rainfall, temperature have for some time now, shown to have some association on malaria incidence which cannot be over emphasized. A recent research finding established a significant association between malaria cases and the minimum temperature, relative humidity and amount of rainfall. However, no significant association between malaria cases and the maximum temperature was found (Hussien et al., 2019). This findings, according to the authors, was justified by the increasing temperature which could extinct the parasite in the vector. This is in agreement with other results in literature showing that increasing maximum temperatures hampered malaria incidence. For instance, Nkuranziza et al. (2010) opined that maximum temperature was evident to have a negative effect on malaria incidence in Burundi. This relationship was explained by the interruption of mosquito development caused by high temperature and its repressive effects (DaSilva et al., 2004).

Adu-Prah et al. (2015) in their study concluded that temperature and humidity have some association with malaria prevalence in Ghana, although annual rainfall in the model was found to be less significant. Their study however, showed evidence of rainfall as a predictor of malaria incidence in Ghana. To provide a clearer understanding of climate variability and the impacts on malaria prevalence, they examined the varying spatial and seasonal distribution in malaria prevalence over a period in Ghana. Trajectory and time series analyses were employed for temporal distribution. In addition, they conducted a Geographical Information System (GIS) based analysis of the spatial distribution of annual malaria incidence against climate variables which led to their observation of an increased national annual malaria incidence.

Krefis et al. (2011) conducted a study to investigate temporal relationship between weekly malaria incidences in young children who are less than fifteen years of age and weekly rainfall in Konongo and Agogo areas of Ghana. The findings of their research showed that, rainfall level predicted malaria incidence after a nine week time lag and after a time trail between one and two weeks. The analysis confirmed that high precipitation data directly affect malaria incidence in a highly malaria prone area which will improve early warning systems and enhance intervention system. Increasing monthly malaria incidence in China has been found to be positively correlated with monthly climatic factors as precipitation, temperature and relative humidity (Bi et al., 2003).

A lag correlation analysis that was carried out to investigate the extent of association existing between temperature, rainfall and malaria incidence revealed a rather weak correlation between malaria incidence and those climatic variables. An exception was seen with maximum temperature and an instance for rainfall. The study revealed maximum temperature as the most significant variable affecting malaria caseloads, notwithstanding the fact that other climatic factors also offer a somewhat high degree of predicting malaria disease trends. The results suggested a minimal direct or linear relationship between malaria incidence and climate variables and underscore the complex and dexterous nature of malaria transmission trends (Klutse et al., 2014).

Amekudzi et al. (2014) in a study on the impact of climate change in coastal Ghana with rainfall and temperature as primary inputs emphasized that malaria as a disease, is driven by climate change. Malaria cases are mostly recorded when rainfall reaches its peak during the months of May to July and likely to change in the future due to changes in rainfall pattern. The study predicted that malaria prevalence is expected to decrease due to increased droughts and rise in temperatures above 35°C, conditions which make breeding difficult for mosquitoes that transmit malaria.

Tay et al. (2012) investigated the relationship between climatic variables and malaria case incidence in three eco-epidemiological settings in Ghana and observed different effects of rainfall, temperature and relative humidity on the incidence of malaria in these settings. They asserted that, adequate insight of climate variability and its impact on the incidence of malaria on a micro geographic scale might come in handy in predicting malaria outbreak before its occurrence, either to strengthen control measures necessary to curb its intensity or at least to prepare adequately for treating victims. Aside climatic factors, their study also suggested other non-climatic variables including nearby water-courses, vegetation index and soil type to also impact malaria incidence and transmission. This was also supported by Kreuels et al. (2008) in their study. They also cited among other factors such as socio-economic and geographical factors.

Asare and Amekudzi (2017) investigated climate driven malaria variability in Ghana using a regional scale dynamical model. The results of their model showed that rainfall peaks of two-month time lag greatly affected malaria transmission. The findings further revealed that malaria eco-variability in terms of its intensity and duration were largely controlled by rainfall peaks.

M'Bra et al. (2018) in their study investigated the association between malaria incidence and rainfall, temperature and normalized difference vegetation index (NDVI) using negative binomial regression models. The results of their study revealed that seasonal variation in the number of malaria cases parallels the seasonality of rainfall and NDVI but however, opposed to temperature. These variations were founded on the understanding of the effects of temperature and rainfall on the life-cycle of Anopheles vector and malaria parasite transmission cycle (Craig et al., 1999). They contended that temperature levels, whether high or low, limit the activities of mosquitoes and the development of the larvae and therefore reduce the rate of transmission of the disease in the following months. This was evident and supported by Dekel et al. (2017) in their study on the identification and classification of developmental stages of the malaria parasite by the use of imaging flow cytometer.

Mbouna et al. (2019) also examined the relationship between climate and two common malaria indicators; parasite ratio (PR) and entomological inoculation rate (EIR) in Cameroon. The study made use of a comprehensive survey data for PR and different surveys for EIR that enabled the seasonality of transmission intensity to be examined. The relationships of malaria with climatic determinants were apparent in the survey data, as PR increased with temperature until a peak within twenty-two to twenty-six degree Celsius and thereafter reduced, with a peak prevalence occurring at rainfall rates of 7 mm a day. The findings of the research also affirmed the impact of population density, with PR higher in rural areas as compared to urban areas.

Additionally, Akpalu and Codjoe (2013) investigated the economic analysis of climatic variables on malaria caseloads in Ghana. They conducted their research in two folds. First, they employed the Augmented Dickey-Fuller and Granger causality tests to investigate the effect of climatic variables on malaria incidence in each district. Second, in their quest to investigate the incidence of malaria in the year 2008, they opted for the use of ordinary least square (OLS) regression and generalized maximum entropy (GME) methods. The findings of their study revealed that, malaria incidence nationwide were influenced by humidity levels and number of rainy days. Interestingly, their study suggested that, the disease was likely to have a high negative impact on middle income class compared to the high earning group. This could be controlled and avoided by intensifying formal education nationwide.

Mahama (2019) in his research using controlled interrupted time series analysis design to model the effect of indoor residual spraying (IRS) on malaria morbidity trends in some parts of Ghana revealed that monthly malaria test positivity rate (TPR) for the period of his study followed a seasonal trend with peaks between July and October each year and a decreasing trend between November of a particular year and February of the ensuing year. This observation appeared to have a positive correlation with the rainfall pattern of the savanna regions of Ghana. These regions have a single rainfall season which begins between May and June and ends between September and October each year and it is in this period the population of malaria-causing mosquito peak in the region. The study revealed an immediate decrease in malaria TPR following both cycles of IRS implementation in the Gushegu and Karaga districts compared to the districts that were used as controls.

Shimaponda-Mataa et al. (2017) in a study modeled the impact of selected climatic variables on the incidence of malaria in Zambia. They employed geoadditive semi-parametric Poisson regression model. In order to avoid effect of scale, they utilized standardized data. The use of standardized data ensured that, limitations posed by highly non-linear mechanism of temperature dependence on vector and parasites were avoided (Gething et al., 2011). The findings of the study demonstrated a strong positive correlation between malaria occurrence and precipitation as well as with minimum temperature. Aside these, other environmental factors such as landscape in urbanized areas were found to be as equally responsible for malaria incidence.

Aulia et al. (2018) employed the use of an autoregressive integrated moving average (ARIMA) time series model in their study to forecast malaria incidence with climatic factors as the predictor variables in Indonesia. The study concluded that rainfall, temperature and relative humidity are predictors and exhibited strong correlations with malaria cases in the Mandailing Natal area.

Also, Gomez-Elipe et al. (2007) conducted another study in Burundi to forecast malaria incidence using monthly reports and environmental variables through a time series ARIMA model. Their research derived a model using vegetation index and rainfall values. This was based on the assumption that these factors had a direct influence on malaria vector density within a month lag which was sufficient for a complete incubation of the mosquito larvae. The study found relationship between malaria incidence rate and rainfall and vegetation density. The study discovered that maximum temperature unlike minimum temperature was highly correlated with malaria incidence. The rationale according to their study was that, the mean minimum temperature level always exceeded the temperate level conducive to sustain the parasitic cycle in the malaria vector. Hence, the little variations observed at temperature levels higher than that level did not have a noticeable impact on the incubation period, in contrast to situation in maximum temperature.

Eikenberry and Gumel (2018) in their research to develop a mathematical model for climate change and malaria transmissions dynamics indicated malaria parasites and vectors as having temperature and rainfall-dependent life cycles. Thus, they were restrained by climate to the earth's warmer latitude and altitude ranges. Malaria incidence caseloads was found to follow altitude in countries such as Zimbabwe and Kenya and the expansion of disease into some areas, particularly the highlands of western Kenya, to an extent be inferable to warmer temperatures (Patz et al.,1996; Pascual et al., 2006).

Ankamah et al. (2018) developed a vector autoregression (VAR) model for the monthly caseloads of malaria counts and its association with some climatic variables such as rainfall, relative humidity and maximum temperature in the Kumasi Metropolis. They contended that malaria incidence was really influenced by all three factors and that the effects of the said variables on malaria incidence were highest in some specific months in the year. The model found as high as thirteen percent of malaria incidence being accounted for by maximum temperature alone.

Also, Mohammadkhani et al. (2019) did a research to assess the influence of climatic factors on malaria incidence in two provinces in Iran. The research analysis of the climatic variables and malaria cases were done on monthly basis using negative binomial regression. The results of the study revealed a significant positive correlation between average, minimum and maximum monthly temperature and malaria incidence. Rainfall and low humidity (less than 60 percent) had negative correlation with malaria incidence whiles a high relative humidity level (>60 percent) was found to correlate positively with malaria incidence. After varying the levels of the climatic variables, malaria incidence was significantly influenced. For instance, a unit percent increase in humidity caused a four percent increase in malaria in the same month and a significant six percent in the following month. They concluded that, humidity of over 60 percent and temperature were effective weather parameters in the malaria incidence rates.

Sena et al. (2015) in the study used the Spearman correlation coefficient to estimate the association between malaria and climatic variables. The study revealed the peaks of malaria caseloads in some years coincided with the peaks of rainfall, and the pattern of rainfall was relatively less fluctuating. Rainfall was negatively correlated with number of malaria cases at lags of zero and one month, but positively correlated at lags of two to four months. Mean relative humidity exhibited relatively high positive correlations at lags of three to four months. Monthly mean maximum and minimum temperatures however showed weak correlation at lags of 0 to 4 months.

Another study was conducted to quantify the association between meteorological variables and incidence of Plasmodium falciparum in areas noted with unstable malaria transmission in Ethiopia. Over a period of six to seven years, the study employed the use of morbidity data pertinent to microscopically confirmed cases from a number of localities. A model was subsequently developed which comprised of rainfall, mean minimum temperature and the vector caseloads recorded the previous month fitted with morbidity data from the localities under study. The model was seen to perform relatively better in areas with high or low incidence of the vector compared with moderate case areas. The study contended of a high association of the meteorological variables and the vector caseloads. However, maximum temperature did not appear to have any improvement in the model (Abeku et al., 2004).

Alhassan et al. (2017) also modelled trends of malaria cases in the Kassena Nankana Municipality using time series analysis. Their prior motive was to develop an adequate model for forecasting future trends of malaria in the Kasena Nankana Municipality. The study elaborated that, highest reported cases of malaria in the municipality were in the months of June to November which were as well the major rainy seasons with the highest precipitation in the study area.

Cator et al. (2013) on their part, undertook a research to develop protocols and methods for a proposed year-round longitudinal survey combining environmental monitoring alongside adult parasite and larval sampling in some weather transmission sites. The study sought to illustrate the benefits of examining the diurnal fluctuation in temperature between different potential mosquito resting habitats and likely implications for malaria transmission. They found warmer daily temperature levels within the urbanized transmission sites as compared to the rural weather stations. This was as a result of the fact that temperatures during the night were higher and thus, such differences translated to significant variation in mosquito lifespan and malaria transmission.

Furthermore, Paaijmans et al. (2009) at the end of a study provided a somewhat vivid explanation of the link between malaria incidence and climate with focus on temperature in Kenya. Their study applied thermodynamic model for insect development fitted to empirical data obtained for different but constant temperatures to establish that temperature variations can significantly alter the viability of the parasite, hence rate of malaria transmission. The study found that daily mean temperature variation greater than twenty-one degree Celsius hampered malaria parasite development compared with constant temperature whiles mean temperature fluctuation less than that degree aided its development. Conclusively, they were of the view that, research models that disregard diurnal fluctuation may over estimate malaria risk in lukewarm areas and underreport risk in cooler environments.

Sewe (2017) in his study in three areas in Kenya sought to point out the need for the use of malaria surveillance and climate data for policy making by assessing the relationship between climate changes and malaria mortality and by building malaria admission forecasting models. The research modeled lagged correlation of rainfall and temperature with malaria mortality, malaria admission forecasting models for one to three months lead times were developed using general additive models. The relationship between sensing variables, land surface, normalized difference vegetation index (NDVI) and rainfall were explored by using distributed lag non-linear models. The study found those factors to be correlated with malaria mortality at varying degrees. Mean temperature of 9 weeks lag was found to be significant with a higher risk for mean temperature above 25 Degrees Celsius. Weekly rainfall levels of excess 120mm resulted in increased mortality risk. The effect of precipitation was consistent in the areas under study. NDVI below 0.4 resulted in increased risk of malaria mortality. For precipitation values below 20mm at week five resulted in a delayed lag effect and in the malaria admission forecasting modeling, the boosted regression models proved to be a better predictor.

Moreover, Kotepui and Kotepui (2018) in a study to assess the impact of weekly climatic variables on weekly malaria incidence in Thailand used Spearman's rank correlation in their analysis. The results of their study found correlation between rainfall, mean temperature, relative humidity and malaria incidence. The impact of these climatic variables was frequent in specific provinces in the country.

Devi and Jauhari (2006) in a research assessed the association between climatic variables and malaria incidence in Dehradun using Pearson's correlation analysis. The correlation coefficient depicted higher positive correlation between monthly malaria incidence and monthly minimum temperature, mean temperature and rainfall with a one-month lag effect. The association with rainfall was however found to be greater in comparison to temperature. They also noted that due to the nature of biological processes and the degree to which the parasite depends on such physical factors as altitude, temperature, surface water, vegetation and humidity, the time lag between rainfall and malaria was region dependent.

Yao et al. (2018) in a study assessed the factors influencing the vulnerability of households in Bole District to malaria and its accompanying economic consequences on the households. Multiple linear regression model was used to analyse the factors and to examine the relationship between these determinant and malaria incidence in the households. Their study revealed that malaria incidence was affected positively by rainfall and temperature. They further concluded the direct and indirect malaria treatment cost had negative impact on household budget.

Mattah et al. (2020) conducted a study to understand the behaviour of climate variables and how they affect the breeding of mosquitoes in the urban coastal towns of Accra and Takoradi Metropolitan Areas. The study used explanatory research design with techniques to outline the impact of the climatic variables such as rainfall and surface temperature on the population of larvae of female Anopheles mosquito. They concluded that rainfall significantly affect malaria cases in the two areas. The study also predicted an increase in monthly rainfall in these areas and a shift in pattern of rainfall which will in turn shift mosquito breeding from seasonal to perennial and hence increased malaria incidence in the cities.

Another study was carried to investigate the impact of climate variability on malaria incidence in the Kumasi Metropolis in Ashanti Region of Ghana. The findings of the study found all factors responsible for malaria transmission to be ideal during the periods of dry spells between rainfalls. During this period, malaria incidence was high prevalent. The study also revealed other factors such as environmental and socio-economic factors to be responsible for increasing malaria incidence in the metropolis (Wihibeturo, 2014).

Mba and Aboh (2006) carried out a research into the prevalence and management of malaria in Ghana taking Volta Region as a case study. The study concluded that, the nature of the region was somewhat favorable for the breeding of mosquitoes and that the prevalence of malaria was more visible in some subpopulation in the area. It further revealed that constituents in areas with two rainy seasons were the highest hit by the menace since the malaria parasites flourished in rainfall prone seasons.

Rejeki et al. (2018) in a study sought to establish a relationship between weather factors and malaria cases in endemic areas in Indonesia using three count data regression models namely, Poisson model, quasi-Poisson and negative binomial models. The study employed ecological time series using monthly data. The independent variables were the weather factors while the dependent variable was the positive malaria cases. The negative binomial regression model was considered as the best among the three. The study further revealed that humidity at lag 2, precipitation at lags 3 and 12 and previous malaria cases at lag 12 had a significant correlation with malaria cases.

Another study was undertaken with the objective of identifying the environmental factors that are linked with clinical malaria among non-immune travellers in Ivory Coast. The data was analysed in a random effect mixed Poisson regression model taking into account the sampling design. The study revealed that, malaria was significantly associated with the cumulative time spent in areas having NDVI in excess of 0.35 and a mean temperature greater than 27 degree Celsius (Texier et al., 2013).

2.2 Poisson Switching Regression Model

Malaria cases are counts and hence best be modeled using a discrete distribution such as Poisson regression models**.** Switching regression models form a suitable model class for regression problems with unobserved heterogeneity. A basic issue encountered in applications of switching regression models is choosing the number of states of the switching regime.

Hambuckers et al. (2018) undertook a study to model the behaviour of random sums over time which is particularly useful in explaining the dynamics of operational losses. However, time-varying dependence structures made it a difficult task. In order to tackle these issues, they formulated a new Markov-switching generalized additive compound process combining Poisson and generalized Pareto distributions. In the end, they were able analyse a staggering dataset of 819 losses incurred at an Italian bank through fraud. The findings of their study discovered an improved method of estimating total loss distribution over time relative to standard alternatives.

In a research work conducted by Kan and Fu (1997), a more detailed application of Poisson switching regression model was employed. The study intended analyzing the groceries shopping behavior of housewives in Taiwan. Initially the research data was modeled with the negative binomial distribution. However, results obtained were not satisfactory in a way that parameter estimates were mostly imprecisely estimated, while their signs were similar to their Poisson counterparts. The unsatisfactory results with the use of the negative binomial model was explained by the fact while the negative binomial specification allow for only over dispersion but not under dispersion, the Poisson model was a limiting case when the conditional mean of the dependent variable is equal to its variance. Housewives' shopping frequency was modeled as a Poisson processes using a Poisson switching regression model which allowed shopping behavior of working and nonworking housewives to be different parametrically. A significant finding of their study was that, nonworking housewives' response to an increase in their shadow price of time was stronger, though negatively, than that for working housewives. This was as a result of the positive income effect of the shadow price for working housewives on household production input demands. The Poisson switching regression model was supported by a likelihood-ratio test with parameter equality restriction for working and nonworking housewives being imposed.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

In this chapter, the study defined and gave a vivid description of count data models with focus on Poisson regression in the analysis and modeling of malaria incidence. The researcher began by describing the study area, source of data and the data description. A comprehensive elaboration of the analysis plan was thoroughly discussed.

3.1 Study Area

The study area of this research was the Wenchi Municipal in the Bono Region of Ghana. The Wenchi Municipality has an estimated total population of one hundred and two thousand, one hundred and seventy five (102,175) with a total land size of three thousand four hundred and ninety four square kilometres (3494sqkm). The inhabitants of this area are mainly into animal and crop farming. The region lies in both the Guinea Savannah and moist-semi-deciduous vegetation zones of Ghana. The rainy season of the area occurs between April and October and a short dry period in August with average rainfall of about 1140-1270mm. The municipality is flanked by the Tain River, Subin and Black Volta which are dammed to support dry season farming. The dry season occurs between November and February (Ministry of Food and Agriculture, n.d.).

3.2 Data and Source

The research employed the use of secondary data on malaria cases from the health information management department of the Municipal Health Directorate. Data was also taken from the weather forecast station in the area. These data span for the period from January, 2013 to December, 2020. The data was analysed using R and Stata statistical softwares.

3.3 Poisson Distribution

The Poisson distribution is applied to data sets that satisfy the following conditions:

1. when the observation events are countable and events occur independently.
2. when the average frequency of occurrence for the time period in question is known and
3. the events are countable and occur in a fixed time interval.

Mathematically, the probability of events following a Poisson distribution can be expressed as

$$f(q \text{ events in fix time}) = \frac{\lambda^{q} e^{-\lambda}}{q!}, \quad q = 0,1,2,\ldots \tag{3.1}$$

where q is the number of times an event occurs in an interval, λ is the average number of events in a given interval. The mean and variance of a Poisson random variable are the same and related as

$$E(q) = Var(q) = \lambda \tag{3.2}$$

Thus, the number of observed occurrences fluctuates about its mean λ with a standard deviation given by the equation $\sigma = \sqrt{\lambda}$ .The variance as a function of q is the probability mass function. The Poisson distribution is deduced as a limiting case of the binomial distribution. This can be applied to system of models with large number of possible events, each of which rarely occurs.

According to Nelder and Wedderburn (1972), the Poisson distribution belongs to the exponential family. Taking logs of the Poisson function gives

$$\log f(q_i) = q_i \log(\lambda_i) - \lambda_i - \log(q_i) \tag{3.3}$$

It can be noted from the coefficient of q_i that the canonical parameter is $\theta_i = \log(\lambda_i)$. This implies that log value serves as the canonical link. Hence, the inverse link function is obtained by solving for λ_i as;

$$\lambda i = e^{\theta i} \tag{3.4}$$

and that we can rewrite the above as

$$b(\theta_i) = e^{\theta i} \tag{3.5}$$

The last term in equation (3.3) is a function of q_i only, so we identify

$$c(q, \varphi_i) = \log(q_i!) \tag{3.6}$$

We can take $a_i(\varphi)$ and $\varphi = 1$, just as in the binomial case. Differentiating the cumulated function $b(\theta_i)$, this gives,

$$\lambda_i = b(\theta_i) = e^{\theta_i} \tag{3.7}$$

3.4 Generalized Linear Models (GLM)

Nelder and Wedderburn (1972) first introduced the concept of generalized linear models (GLM). GLMs provided a unified framework to study various regression models, rather than a separate study for each individual regression. Generalized linear models (GLM) are extensions of classical linear models. Some of which are linear regression models, analysis of variance (ANOVA) models, logistic regression models, Poisson regression models, log-linear models, and many more other models. The above models share a number of unique properties, such as a common method for parameter estimation and linearity. A generalized linear model consists of the following components:

1. A random component, specifying the conditional distribution of the response variable Q_i, given the explanatory variables.
2. A linear function of the covariates, called the linear predictor.

3.5 The Exponential Family

Generalized linear models are used to model data that follow distributions in the exponential family with probability density function

$$f\left(q;\theta,\varphi\right)=\exp\left\{\frac{q\theta-b\theta}{a\left(\varphi\right)}+c\left(q;\varphi\right)\right. \text{ or}$$
$$\log f\left(q;\theta,\varphi\right)=\frac{y\theta-b\theta}{a\left(\varphi\right)}+c\left(q;\varphi\right) \tag{3.8}$$

Where φ is a dispersion parameter and $a\left(\varphi\right)$, $b\left(\varphi\right)$ are known functions.

From the exponential family distribution, the conditional expectation and variance of Q is a function of the mean λ together with the dispersion parameter φ. This is given by

$$E\left(Q_i\right)=\lambda_i=b^{'}\left(\theta\right) \text{ and}$$
$$\operatorname{var}\left(Q\right)=\sigma_i^2=b^{''}\left(\theta\right)a\left(\varphi\right) \tag{3.9}$$

where $b^{'}\left(\theta\right)$ and $b^{''}\left(\theta\right)$ are the first and second derivatives of a known function $b\left(\theta\right)$ in the exponential family. For some distributions, the dispersion parameter is usually fixed to 1.

Differentiating with regards to equation(3.7), the conditional variance becomes,

$$\operatorname{var}(Q)=a_i(\varphi)b''(\theta)=e^{\theta i}=\lambda_i \tag{3.10}$$

This implies, the mean and variance are equal.

3.6 Poisson Regression

Poisson regression analysis technique is employed when modeling response variable that depicts count data (Cameron and Heckman, 1998). Several modifications of the Poisson regression model have been propounded which take into consideration the problem of over-dispersion in actual data. These problems arise mainly as a result of presence of autocorrelation and spatial clusters in the data (Cameron and Trivedi, 1998). Moreover, Poisson regressions have been employed in various fields of research, from health, management, finance and other diverse fields.

Based on a sample $q_1, q_2, ..., q_n$ we can write $E(q_i) = \lambda$ and write the Poisson regression as

$$q_i = E(q_i) + \varepsilon_i, \; i = 1, ..., n \tag{3.11}$$

where ε_i's are the error terms.

A link function g can be defined and it relates the mean of the study variable to a linear predictor as

$$\begin{aligned} g(\lambda_i) &= \eta_i \\ &= \beta_0 + \beta_1 x_1 + ... + \beta_q x_q \\ &= x_i' \beta \end{aligned} \tag{3.12}$$

and

$$\begin{aligned} \lambda_i &= g^{-1}(\eta_i) \\ &= g^{-1}(x_i' \beta) \end{aligned}$$

The identity link function is given by $g(\lambda_i) = \lambda_i = x_i' \beta$.

The log-link function is given by

$$g(\lambda_i) = \ln(\lambda_i) = x_i' \beta$$

3.6.1 Exposure (Offset)

Poisson regression model is best suitable for rate data, where rate is a ratio of count of events to some occurrence of that of exposure. It is given by

$$\log\left(E\left(Y \mid x\right)\right) = \log\left(\text{exposure}\right) + \theta' x \qquad (3.13)$$

$$\Rightarrow \log\left(E\left(Y \mid x\right)\right) - \log(\text{exposure}) = \theta' x$$
$$\Rightarrow \log\left(\frac{E(Y \mid x)}{\text{exposure}}\right) = \theta' x \qquad (3.14)$$

For Poisson regression, the exposure estimate is normally to constrained to 1.

3.6.2 Model Specification

The Poisson model is written as;

$$P(Q_i = q_i) = \frac{e^{-\lambda}\lambda^{q_i}}{q_i\,!},\ q_i = 0,1,\ldots \qquad (3.15)$$

The log-linear specification is the commonly used formulation of the Poisson regression model. It is given by

$$\log\,(\lambda_i) = x_i^{'}\beta \qquad (3.16)$$

From equation(3.15), the expected number of events for a given time is represented as:

$$\lambda_i = E\left(q_i \mid x_i\right) = e^{x_i\theta} \qquad (3.17)$$

Thus,

$$dE(q_i \mid x_i) = \beta e^{x_i\beta} = \beta_i\lambda_i \quad (3.18)$$

The major Poisson model assumption is given by

$$E(Q_i \mid x_i) = \lambda_i = e^{x_i\beta} = \operatorname{var}(Q_i \mid x_i) \quad (3.19)$$

Thus, there is over-dispersion in the model if $\operatorname{var}(Q_i \mid x_i) > E(Q_i \mid x_i)$ and under-dispersion is said to occur if $\operatorname{var}(Q_i \mid x_i) < E(Q_i \mid x_i)$.

3.7 Poisson Switching Regression Model

A switching regression model is used to classify unobservable states in a time series. It is also used to estimate the transition probabilities for these unobservable states.

Given a random sample $I = \{1,...,n\}$. Consider the jth individual. Conditional on a vector of explanatory variables p_i, an endogenous dummy d_i and a random term ς_i, the dependent count variable z_i which follows a Poisson distribution

$$f(z_i \mid \varsigma_i) = \frac{\exp\{-\exp(p_i^{'}\beta + \phi d_i + \varsigma_i)\}\{\exp(p_i^{'}\beta + \phi d_i + \varsigma_i)\}^{z_i}}{z_i!}$$

(3.20)

The random term ς_i is interpreted as a variable which summarizes the omitted and unobserved variables or simply a measurement error. Given a vector of explanatory variables y_i, d_i is characterized by an index process

$$d_i = \begin{cases} 1 & if \ y_i'\alpha + \upsilon_i > 0 \\ 0 & otherwise \end{cases}$$

Let w_i represent all exogenous variables, and suppose that ς_i and υ_i are jointly normal with zero and covariance matrix $\Sigma = \begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$

Conditional on ς_i, d_i and z_i are dependent. Hence, then joint conditional probability density function of z_i and d_i given w_i can be written as

$$f(z_i, d_i \mid w_i) = (1-d_i) f(z_i \mid d_i = 0, w_i, \varsigma_i)\Pr(d_i = 0 \mid w_i, \varsigma_i)\} f(\varsigma_i) d\varsigma_i$$
$$\int_{-\infty}^{\infty} \{d_i f(z_i \mid d_i = 1, w_i, \varsigma_i)\Pr(d_i = 1 \mid w_i, \varsigma_i) + (1-d_i) f(z_i \mid d_i = 0, w_i, \varsigma_i)$$
$$\Pr(d_i = 0 \mid w_i, \varsigma_i)\} f(\varsigma_i) d\varsigma_i$$

where $f(\varsigma_i)$ denotes the probability density function for the random term ς_i.

Consider a change of variable $\kappa_i = \dfrac{\varsigma_i}{\sigma\sqrt{2}}$

Exploiting the fact that $f(z_i, d_i \mid w_i)$ is normal with zero mean and variance σ^2, the joint conditional probability density function of z_i and d_i, given w_i may be re-expressed as

$$f(z_i, d_i \mid w_i) = \int_{-\infty}^{\infty} \begin{cases} [f(z_i \mid d_i, w_i, \sigma\kappa_i\sqrt{2})\{d_i\Phi_i^*(\sigma\kappa_i\sqrt{2}) + \\ (1-d_i)\Phi_i^*(-\sigma\kappa_i\sqrt{2})\}]\exp(-\kappa_i^2) d\kappa_i \end{cases} \quad (3.21)$$

where $\Phi_i^*(-\sigma\kappa_i\sqrt{2}) = \Phi\left(\dfrac{y_i' + \rho\kappa_i\sqrt{2}}{\sqrt{1-\rho^2}}\right)$.

the log likelihood is given by

$$\log L = \sum_{i=1}^{n} \ln\{ f\left(z_i, d_i \mid w_i\right)\} \qquad (3.22)$$

The model is identified through functional form. Hence vectors p_i and y_i may contain the same elements. Note that mean and variance of the count variable are

$$\mu_i = E[z_i \mid d_i, w_i] \text{ and}$$
$$\mathrm{Var}\left(z_i \mid d_i, w_i\right) = \mu_i + k\mu_i^2$$

where $k = \exp\left(2\sigma^2\right) - \exp\left(\sigma^2\right)$

This implies that, the model exhibits over-dispersion as σ is by definition positive. The log-likelihood function is maximized using the Newton-Raphson algorithm. Usual hypothesis tests are valid on the basis of likelihood ratio and Wald statistics.

3.8 Model Selection Criteria

Normally, there is the tendency of two or more different models which are competing for fitting a particular regression. Due to this, it will be prudent to use robust model selection criteria to select the most adequate model. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the log-likelihood were employed as measures of goodness of fit in the selection of the best fit model. A model is ranked best among other models if it has the lowest

AIC and BIC values and the highest log-likelihood values compared to the models.

3.8.1 Akaike Information Criterion (AIC)

The AIC is one method of selecting a model that adequately describes a given data from a set of rival models. The preferred model minimizes the Kullback-Leibler distance between the model and the truth. The information criterion tries to find a best model that explains a given data using a minimum of parameters. Mathematically,

$$\text{AIC}=2k + n\log\left(\frac{RSS}{n}\right) \tag{3.23}$$

where

k is the number of parameters in the model

n is the number of observation in the data set

RSS is the residual sum of squares in the estimated model

A second order of information criterion, Akaike information Criterion corrected (AICc) takes into account sample size by adjusting the relative penalty for model complexity with small data sets. Mathematically, it is given by

$$\text{AICc} = AIC + 2k\left(\frac{k+1}{n-k-1}\right) \tag{3.24}$$

The letters have the same meaning as in equation(3.23).

3.8.2 Bayesian Information Criterion (BIC)

The BIC like the AIC is intended to provide a degree of the weight of evidence that favours one model among other models. The criterion was developed by Schwartz (1998) to serve as an asymptotic approximation to a transformation of the Bayesian posterior probability of a competitor model. Mathematically,

$$\mathrm{BIC} = \log\left(\sigma_s^2\right) + \frac{k}{n}\log\left(n\right) \tag{3.25}$$

where σ_s^2 is the error variance.

3.9 Residual Analysis

The Poisson regression is a non-normal regression. Therefore, its residuals are not in any way normally distributed and the variances are not constant. The model was assessed based on quantile residual plots and the autocorrelation function plots of the residuals. The quantile residuals eliminate the pattern in discrete data by making an addition of the smallest amount of randomization necessary on cumulative probability scale. The quantile residuals are obtained by inverting the distribution function of the dependent variable.

Mathematically, let $pi = \lim y \uparrow yi\ F\left(y;\hat{\mu},\hat{\Phi}\right)$ and $qi = F\left(y;\hat{\mu},\hat{\Phi}\right)$ .where F is the cumulative function of the probability density function $f\left(y;\mu,\Phi\right)$ then the randomized quantile residuals for y_i is $rs, r = \Theta^{-1}\left(vi\right)$ with v_i being the uniform random variable on$(pi, qi]$. The randomized quantile residuals are normally distributed discounting the variability in $\hat{\mu}$ and $\hat{\Phi}$ (Dunn and Smyth, 1996).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.0 Introduction

This chapter presents the results generated from the data analysis and its discussions. The chapter is categorized into preliminary analysis and further analysis.

4.1 Preliminary Analysis

This section presents the descriptive statistics of the data on the malaria cases and the climatic variables obtained in the Wenchi Municipal. Table 4.1 shows the descriptive statistics of the malaria cases and the climatic variables. Preliminary analysis of the malaria cases data showed as high as 5377 cases reported and a minimum value of 1257 cases with an average of approximately 2877 cases during the years under review. The highest and lowest rainfall recorded were respectively 368.04mm and 0mm with an average recorded rainfall of 98mm. A 0mm recorded rainfall means no rain at all or a trace value was recorded. The mean temperature and humidity levels during the years under review were approximately 27℃ and 87% respectively. The minimum and maximum temperature levels were 23.6℃ and 28℃ respectively. The lowest humidity level recorded was 49% whiles the highest level observed was 94%.

Table 4.1: Descriptive Statistics of Malaria Cases and the Climatic Variables

Variable	Mean	Std. Dev	Minimum	Maximum
Malaria	2876.55	992.80	1257.00	5377.00
Rainfall	98.03	76.14	0.00	368.40
Temperature	27.08	1.36	23.60	30.10
Humidity	87.02	11.62	49.00	96.00

A closer observation of the incidence of malaria cases in the municipality revealed that, the lowest malaria cases was recorded in the month of February with a value of 1257 malaria cases. Also, on the average, February recorded the least mean monthly cases of 1801. Table 4.2 clearly depicts the month of July as having the highest reported malaria cases of 5377 based on the month by month analysis of the cases. Interestingly, the month of November recorded the highest cases in terms of the minimum monthly reported cases of 3918. The same month also recorded the second highest recorded value of 5169 in terms of maximum monthly malaria cases trailing the month of July as shown in Table 4.2. Hence, the highest mean monthly malaria incidence was recorded in the month of November. This was echoed in the works of Nonvignon et al. (2016) and Darkoh et al. (2017). Darkoh et al. (2017) in their study revealed that, the month of November recorded 21% more malaria cases than other months, attributed to the fact that, malaria cases were high due to higher rainfall recorded in the preceding months.

Table 4.2: Monthly Descriptive Statistics of Malaria Cases

Month	Mean	Std. Dev.	Minimum	Maximum
January	2160.50	600.38	1511.00	3243.00
February	1801.25	578.62	1257.00	2976.00
March	1945.88	743.54	1369.00	3450.00
April	2372.00	656.97	1514.00	3312.00
May	2963.50	650.34	1981.00	3901.00
June	3468.38	677.46	2369.00	4739.00
July	3263.25	1104.56	1993.00	5377.00
August	3282.75	1008.93	1935.00	4636.00
September	2920.50	531.96	2055.00	3407.00
October	3651.38	1062.60	2259.00	5063.00
November	3917.75	959.87	2700.00	5169.00
December	2771.50	589.10	1957.00	3584.00

An investigation into the month by month summaries of rainfall in the Municipality during the years under study is shown in Table 4.3. It was evident that, the month of September has the highest mean rainfall of 183.41mm recorded for the period while the lowest mean of 7.84mm was recorded in December. The minimum rainfall levels were recorded in the months of December, January and February. These months could be seen from Table 4.3 as having the least rainfall levels in comparison to the rest of the months in respect of the maximum rainfall levels for the months. The month of September recorded the highest rainfall of 368.4mm as can be seen in Table 4.3. Generally speaking, the Wenchi Municipality experience rainfall all year round with the exception of the months that were mentioned to record no rainfall.

Table 4.3: Monthly Descriptive Statistics of Rainfall Recorded

Month	Mean	Std. Dev.	Minimum	Maximum
January	10.09	15.56	0.00	34.90
February	26.70	17.15	0.00	59.90
March	86.14	34.58	58.00	143.10
April	135.71	48.16	85.50	217.60
May	150.93	52.52	81.40	215.20
June	152.57	54.46	79.00	232.80
July	111.41	37.73	54.30	171.60
August	109.75	79.08	19.10	236.80
September	183.41	85.68	89.10	368.40
October	156.11	64.46	63.50	244.80
November	45.73	39.87	7.10	109.40
December	7.84	11.67	0.00	31.00

Table 4.4 presents the monthly descriptive statistics of the temperature levels in the municipality during the period under consideration. Generally, the mean monthly temperature in the area was seen not to differ so much, the highest mean temperature of 29.3℃ was recorded in January and lowest mean of 25.4℃ in the month of August. The maximum and minimum temperature levels of 30.1℃ and 23.6℃ were recorded in February and March respectively.

Table 4.4: Monthly Descriptive Statistics of Temperature

Month	Mean	Std. Dev.	Minimum	Maximum
January	27.48	0.61	26.60	28.50
February	29.30	0.54	28.50	30.10
March	28.25	1.98	23.60	29.70
April	28.23	0.38	27.70	28.90
May	27.39	0.39	26.80	28.10
June	26.23	0.27	25.80	26.50
July	25.60	0.42	25.00	26.50
August	25.41	0.78	24.50	27.10
September	25.94	0.61	25.20	27.20
October	26.52	0.48	25.90	27.50
November	27.35	0.55	26.50	28.10
December	27.23	0.91	25.70	28.90

A minimum humidity level of 49% and the lowest mean monthly humidity level of 62.3% were both recorded in the month of January as shown in Table 4.5. The maximum humidity levels of 96% were recorded in several months as shown in Table 4.5.

Table 4.5: Monthly Descriptive Statistics of Humidity

Month	Mean	Std. Dev.	Minimum	Maximum
January	62.25	11.52	49.00	84.00
February	72.75	10.74	54.00	83.00
March	86.12	2.64	81.00	90.00
April	90.50	1.41	89.00	92.00
May	92.12	3.00	85.00	94.00
June	94.00	0.53	93.00	95.00
July	94.25	1.28	92.00	96.00
August	93.62	0.74	93.00	95.00
September	94.75	0.71	94.00	96.00
October	94.62	1.69	91.00	96.00
November	92.62	1.77	89.00	95.00
December	76.62	10.95	52.00	86.00

In order to investigate the effect of the month on malaria cases, the negative binomial regression was fitted in order to cater for overdispersion. Table 4.6 presents the effect estimates of the months on the incidence rate of malaria cases with reference to the month of April together with their coefficients, standard error, *z*-scores and *p*-values. Given the *p*-values in Table 4.6, the months of February, June, July, August, October and November were significant in value compared to the month of April although, their significance is of not much concern. Moreover, while holding other months constant, malaria incidence was expected to decrease by a factor of 0.91, 0.76 and 0.82 respectively for January, February and March compared to the month of April. However, from the month of May, the incidence rate for malaria cases was expected to increase till the end of the year. For instance, while keeping other months constant, the month of November was expected to have 1.65 times greater malaria incidence rate compared to April incidence rate. This finding was as a result of high rainfall recorded from the month of April through to the end of the year. Darkoh et al. (2017) from their study revealed that, malaria incidence rate was normally high during high rainfall periods.

Table 4.6: Analysis of Monthly Effect on Malaria Incidence Rate

Malaria	Coefficient	Std. Error	*z*-value	P>|*z*|	IRR
January	-0.93	0.12	-0.73	0.47	0.91
February	-0.28	0.10	-2.15	0.03	0.76
March	-0.20	0.10	-1.55	0.12	0.82
May	0.22	0.16	1.74	0.08	1.25
June	0.37	0.19	2.98	0.00	1.46
July	0.32	0.18	2.50	0.01	1.38
August	0.32	0.18	2.55	0.01	1.38
September	0.21	0.16	1.63	0.10	1.23
October	0.43	0.20	3.38	0.00	1.54
November	0.50	0.21	3.93	0.00	1.65
December	0.16	0.15	1.22	0.22	1.17

The time series plot in Figure 4.1 shows the behaviour of malaria incidence and the climatic variables. The malaria plot exhibited a seasonal effect as well as the plots of rainfall, temperature and humidity. Considering the temperature plot critically, it was noted that, temperature peaks were normally at the beginning of the year in contrast to the rainfall and humidity peaks around the same time. Malaria incidence was observed to drop around the beginning of each year.

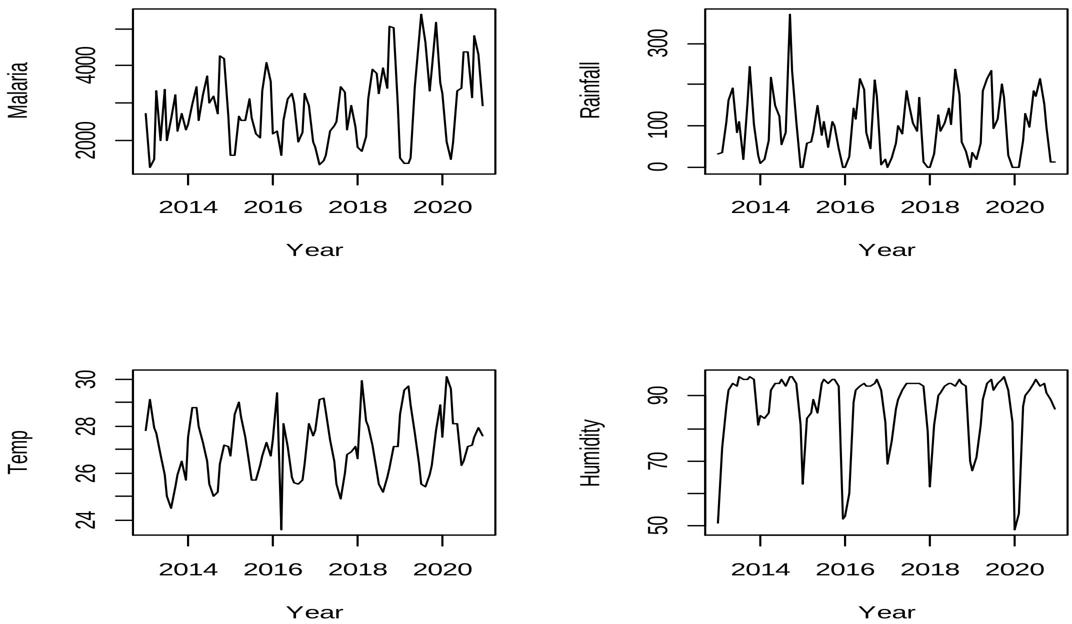

Figure 4.1: Time Series Plots of Malaria Cases and Climatic Variables

4.2 Further Analysis

From Table 4.7, the Poisson regression estimate attained a value of 8.62 when the independent climatic variables were evaluated at zero. The coefficients of rainfall and temperature were negative values except for humidity which recorded a positive coefficient. This means that, for a unit increase in rainfall level, malaria incidence dropped by approximately 0.02%. A study by Hundessa et al. (2017) found that increasing rainfall had a decreasing effect on Plasmodium vivax, hence a decrease in malaria transmission rates which supports the results of this study. This decreasing effect may be possibly due to excessive rainfall hampering mosquito population due to strong downpour which may destroy mosquito breeding grounds.

Also, for a unit increase in temperature level, malaria cases dropped by 5.5%. The *p*-values obtained showed all have significant probabilities compared to a significance level of 0.05. A null deviance value of 32368 was recorded indicating the absence of the predictor variables whiles a 26677 value for residual deviation on 92 degrees of freedom which was as a result of the inclusion of the predictor variables. The estimated Poisson regression model is given by:

$$\text{(Malaria)= } \exp[8.62+(-2.11e^{-4})\text{Rainfall}+(\text{-}5.52e^{-2})\text{Temp}+(9.74e^{-3})\text{humidity}].$$

The positive coefficient of humidity in Table 4.7 was an indication that, a unit increase in humidity had a positive multiplicative effect on malaria count. This was supported in studies by Pampana (1969) and Yamana and Eltahir (2013) which revealed that relative humidity impacted the activity and survival of mosquitoes. Yamana and Eltahir (2013) in their study reported that, mean monthly relative humidity of less than 60% caused a shortened lifespan of malaria vector thereby resulting in low malaria transmission, and a mean of less than 10% was lethal to the lifespan of the vector. Yang and Wang (2013) in their study also revealed that relative humidity was positively associated with malaria incidence rates from the same month.

Table 4.7: Poisson Regression Model

Coefficients	Estimate	Std. Error	*z* value	Pr(> |*z*|)
(Intercept)	8.62 e00	5.38 e-02	160.33	< 2.00e-16
Rainfall	-2.11 e-04	3.10 e-05	-6.79	1.10 e-11
Temperature	-5.52 e-02	1.62 e-03	-34.21	< 2.00e-16
Humidity	9.74 e-03	2.37 e-04	41.02	< 2.00e-16

The ratio of the residual deviance to its degrees of freedom resulted in a value greater than one (1) which suggested an over dispersion in the model which is in violation of assumption of equal mean and variance (equi-dispersion) of a Poisson regression. For this reason, a Poisson Switching Regression was modeled to cater for the over-dispersion in the model. Two-regimes and three-regimes Poisson Switching were fitted in order to be able to compare their suitability for the model.

4.3 Poisson Switching Regression

The model was set to switch in two–state transitions and the results are in Table 4.8. Each of the covariates is shown to be statistically significant in both regimes having equal probabilities. From Table 4.8, both regimes showed negative estimates for rainfall and temperature. Apparently, malaria cases cannot be said to be increasing through all the two states it went through. The effects rate of the two regimes is higher in regime 2, hence, that state would probably represent high state while regime 1 represents low state.

Table 4.8: Two-State Poisson Switching Regression

Regime	Variable	Estimate	Std. Error	*t*-value	Pr(> |*t*|)
Regime 1	Intercept(S)	7.96	0.09	89.84	<2.20e-16
	Rainfall(S)	-0.01	0.01	-17.00	<2.20e-16
	Temperature(S)	-0.07	0.00	-31.09	<2.20e-16
	Humidity (S)	0.02	0.00	41.40	<2.20e-16
Regime 2	Intercept(S)	10.37	0.08	123.80	<2.20e-16
	Rainfall(S)	-0.01	0.00	-98.45	<2.20e-16
	Temperature(S)	-0.11	0.01	-40.21	<2.20e-16
	Humidity (S)	0.01	0.01	41.67	<2.20e-16

The estimated two-regime Poisson regression model is given by:

$$\log(\text{Malaria}) = \begin{cases} 7.96 + & (-0.01)\text{Rainfall} + & (-0.07)\text{Temp} + & (0.02)\text{humidity} \\ 10.36 + & (-0.01)\text{Rainfall} + & (-0.11)\text{Temp} + & (0.01)\text{humidity} \end{cases}.$$

Table 4.9 shows the probabilities of transition from one state to another. From Table 4.9, the probability that malaria incidence remains in the same low regime given that it was previously in the low state is 75% whilst 73% chance it remains in a high regime given it was previously in the high state which depicts pretty stable states. This means the underlying states or regimes rarely change over a monthly period.

Table 4.9: Transition Probabilities

	Current state		
	State	**Low**	**High**
Previous State	**Low**	0.75	0.25
	High	0.27	0.73

Further, a three-regime Poisson regression model was fitted for comparison to the earlier two-regime Poisson regression model in Table 4.8. A close observation of Table 4.10 revealed the covariates having negligible standard error values with probabilities all statistically significant. The estimates of the rainfall and temperature covariates were both positive whiles that of humidity was seen to be negative for regime 1. The positive estimates mean that malaria incidence did increase multiplicatively with increasing values of rainfall and temperature but was seen to decrease with a unit increase in humidity levels. In the second regime, the estimates of rainfall and temperature covariates were rather negative whiles positive for humidity. All covariates have significant estimates. In the third regime, the model recorded positive estimates for all covariates which were all significant statistically. Malaria incidence therefore, was said to increase in this state.

Table 4.10: Three-State Poisson Switching Regression

Regime	Variable	Estimate	Std. Error	*t*-value	Pr(> |*t*|)
Regime 1	Intercept(S)	6.88	0.06	106.17	<2.00e-16
	Rainfall(S)	0.01	0.00	45.32	<2.00e-16
	Temperature(S)	0.04	0.01	19.77	<2.00e-16
	Humidity (S)	-0.01	0.00	-2.67	0.01
Regime 2	Intercept(S)	11.06	0.15	73.34	<2.20e-16
	Rainfall(S)	-0.01	0.01	-55.00	<2.20e-16
	Temperature(S)	-0.24	0.01	-61.97	<2.20e-16
	Humidity (S)	0.05	0.01	64.71	<2.20e-16
Regime 3	Intercept(S)	5.33	0.08	63.71	<2.20e-16
	Rainfall(S)	0.01	0.01	8.00	1.33e-15
	Temperature(S)	0.07	0.01	28.00	<2.20e-16
	Humidity (S)	0.01	0.01	13.25	<2.20e-16

The estimated three-regime Poisson regression model is given by

$$\log(\text{Malaria}) = \begin{cases} 6.88 + & (0.01)rain + & (0.04)temp + & (-0.01)humidity \\ 11.06 + & (-0.01)rain + & (-0.24)temp + & (0.05)humidity \\ 5.33 + & (0.01)rain + & (0.07)temp + & (0.07)humidity \end{cases}.$$

Regime 2 in Table 4.10 showed a high effect among the three regimes followed by regime 1 and the regime 3 being the least effect rate. Therefore, regime 2 was classified as high state, regime 1 being moderate and regime 3 as the low state of malaria incidence. The transition probabilities of the three states are shown in Table 4.11. The probability of malaria incidence to remain in a state given it was initially in that state is seen to be a little higher in all states. That is, malaria incidence was approximately 48% likely to remain in a low regime given it was previously in that state (regime 3) than it would transition to a moderate state (regime 1) and a high incidence state (regime 2). Again, there was a 32% likelihood that incidence of malaria would remain moderate if it was previously in that moderate state over a monthly period. From Table 4.11, there was a probability of 47% that malaria cases would remain high once it was high over a month's period. It was noted from Table 4.11 that, it was highest the probability of a low state to be retained if it was previously low compared to other states in the transitions.

Table 4.11: Transition Probabilities

		Current State		
		Low	**Moderate**	**High**
Previous State	**Low**	0.48	0.36	0.16
	Moderate	0.26	0.32	0.42
	High	0.18	0.35	0.47

As evident in Table 4.12, the model was switched into different regime transitions to assess which may be best suitable for the research. A two-state and a three-state Poisson regressions were fitted, each of which generated Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and loglikelihood values respectively. From Table 4.12, the three-regime transitions would be preferable due to the fact that it tends to produce better AIC, BIC and loglikelihood values. In comparing AIC and BIC values, the best model is that which produces the smallest AIC and also the best produces the largest Loglik values.

Table 4.12: Comparing Regimes

Model	AIC	BIC	Loglik
2 Regimes	8633.17	8690.20	-4308.59
3 Regimes	4965.80	5051.35	-2470.90

4.4 Model Diagnostics

Figure 4.2 shows for each regime, their smoothed and filtered probabilities. The smoothed probabilities of each regime reduced or eliminated very high frequencies of the spectral components of each regime. The low probability frequencies were unaffected by the smooth filtering.

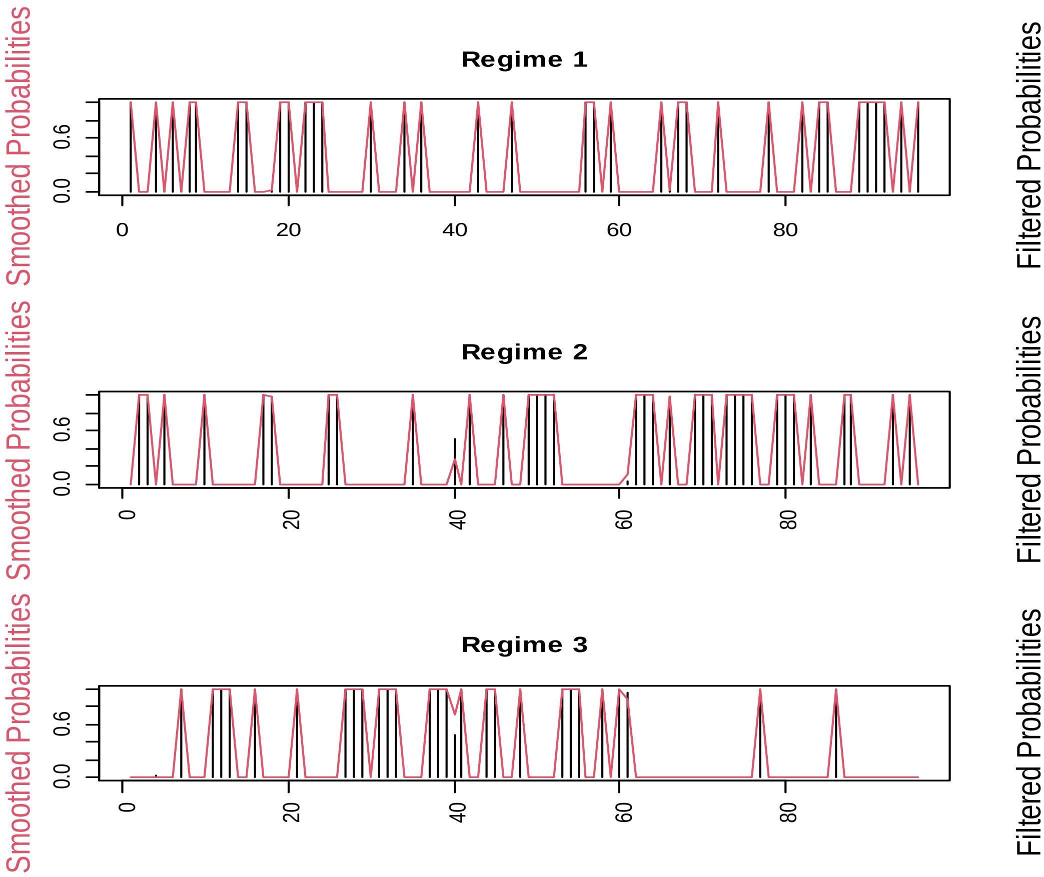

Figure 4.2: Filtered and Smoothed Probabilities for 3 Regime Poisson Switching Model

The plot in Figure 4.3 is a Pearson residual plot of the three regime Poisson regression model with the conditional residuals. The residuals depicts a classical nature of randomness, not autocorrelated but does not perfectly fit the normal distribution. However for generalized linear model (GLM) validation, normality of the Pearson residuals is not a critical criterion.

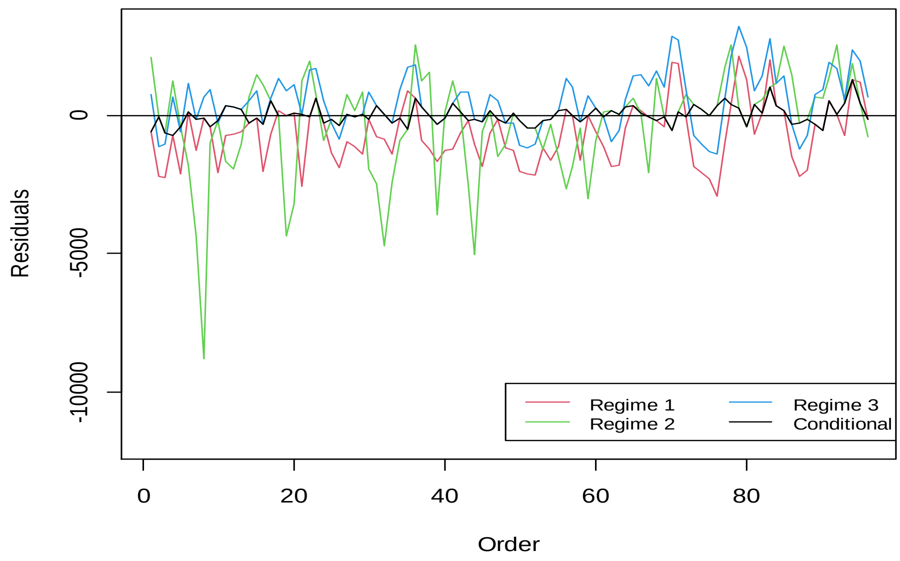

Figure 4.3: Residuals from the Poisson Switching Model

The quantile-quantile plot in Figure 4.4 showed the observed distribution of the sample increasing at the same rate as the theoretical quantiles except for some few outliers which can be seen at the extreme top of the plot. Hence the residuals are said to be approximately normally distributed.

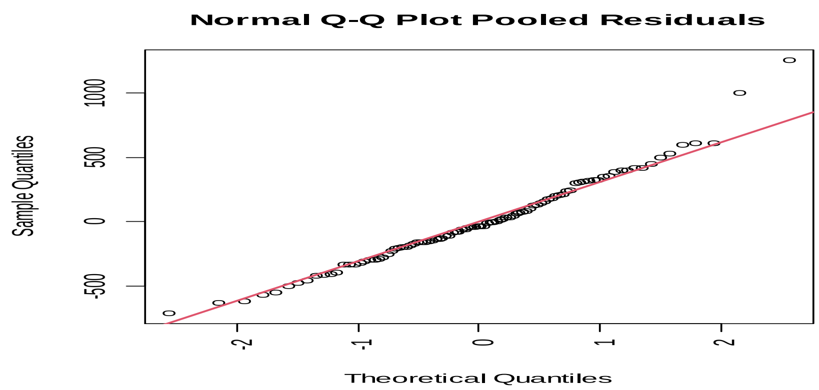

Figure 4.4: Normal Probability Plot of Residuals from Poisson Switching Model

Figure 4.5 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the model residuals. The ACF of the residuals at lags 0 and 1 showed significant spikes which indicate the presence of minor autocorrelation, with the PACF showing significant spike at the same lag. The ACF of the square residuals on the other hand exhibited significant spikes at lags 0 and 11, with the PACF showing significant spikes at lags 11 and 13. These indicate minor autocorrelation effects. The ACF show a sharp decay at lag 0 for both residuals and square residuals, an indication of stationary residuals pointing a good model fit. Generally, for a minimum number of residuals whose ACF are significant at their lags, then the residuals are said to be random in nature.

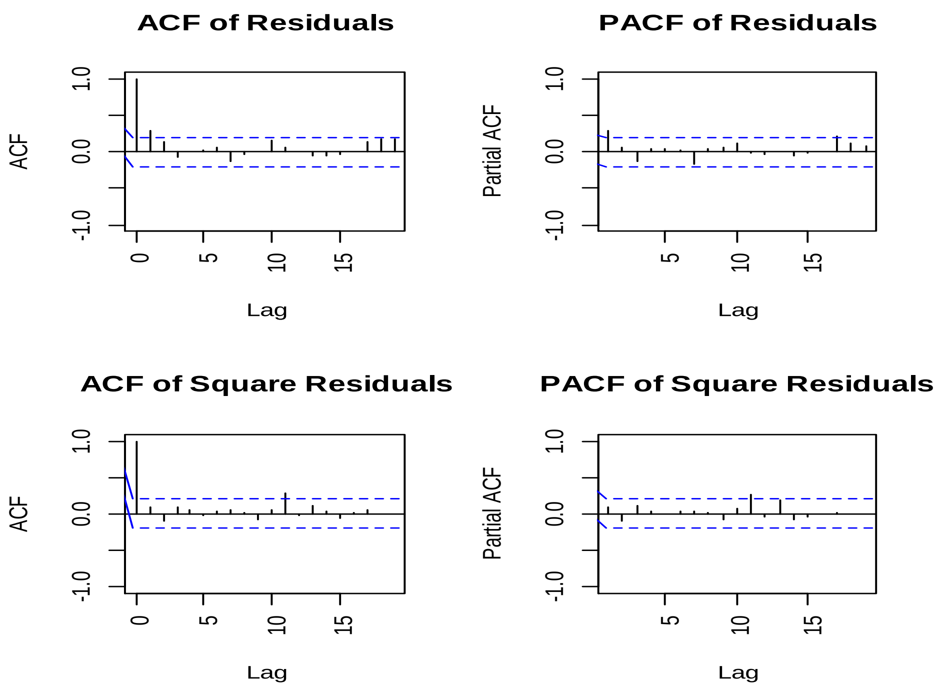

Figure 4.5: Autocorrelation Function of Residuals from Poisson Switching Model

The plots in Figure 4.6 shows the observations of the response variables and the regimes they are associated with together with their smoothed probabilities. The observations associated to regime 1 lie mostly at the extreme ends of the distribution. For regime 2, the observations equally were found to lie at the tail ends with few observations at the center. The observations associated with regime 3 lie at the center of the plot. When the states were separated, the uncertainties of the observations in the regimes are reduced. From Figure 4.6, it was noted that observations from 2015 to 2016 were associated to the low regime while observations associated to the moderate regime lie around the end of 2013 to the end of 2014. Few monthly observations in this regime were recorded mid-2020. The high regime observations from Figure 4.6 span mostly from 2017 to 2019.

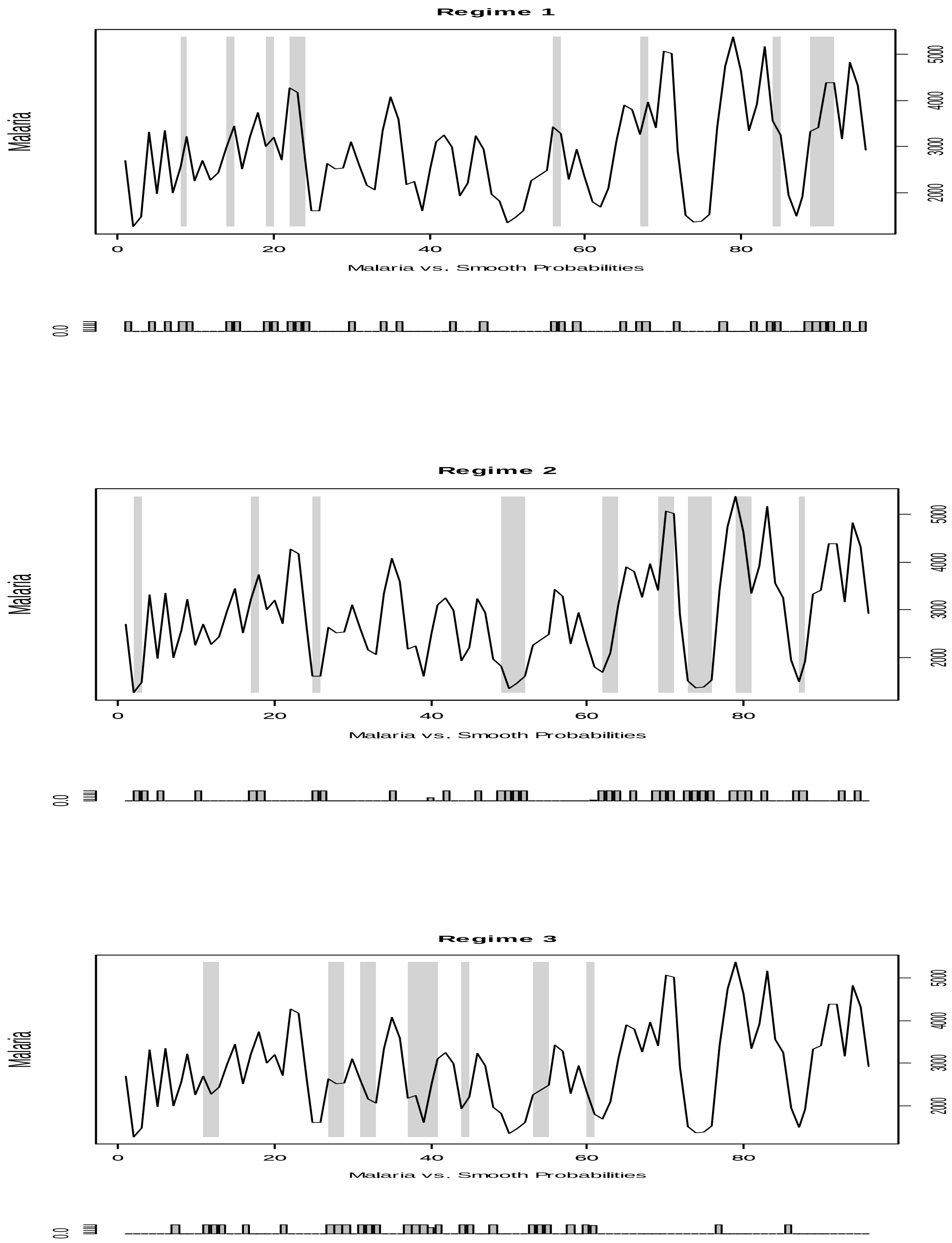

Figure 4.6: Response Variables Indicating Observations Associated with their Regimes

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

This chapter presents the summary, conclusion and recommendations of the study.

5.1 Summary

In this research, malaria cases and climate variables spanning from January, 2013 to December, 2020 were studied. In order to meet the objective of this study, Poisson regression analysis was used to analyze the data. First, preliminary analysis of the monthly data on malaria cases and climatic factors were analyzed using descriptive statistics. This revealed that malaria cases were prevalent throughout the year. However, malaria cases became more rampant in number after the first three months in each year through to the end of the year. The effect of the month was clearly seen in the increasing number of malaria incidence rate as the first three months clearly indicated a decrease in the number of malaria cases compared to other months of the year. Rainfall and humidity levels after the first three months were equally seen to record a rise in value or maintain steadily levels. The effect of November showed the highest multiplicative effect on the incidence rate of malaria.

Further analysis carried in this research showed an over-dispersion in the data. Poisson regression model fit for the model was therefore problematic due to violation of equi-dispersion assumption which needed to be corrected. Two-regime Poisson Switching and a three-regime Poisson Switching models were modeled and compared based on the Akaike and Bayesian Information Criteria and their log-likelihood. A model was better fit compared to another if it possesses the least AIC and BIC. The model with a higher likelihood was preferred. The three regime Poisson Switching Regression was therefore best fit for the study. Model diagnostics to assess the distribution of the residuals of the selected three-regime Poisson regime switching regression model was also carried out to provide more understanding of the fitness or otherwise of the model.

5.2 Conclusions

The following were conclusions drawn from the study.

First, the Poisson regression analysis employed in this study revealed that, the assumption of the equal mean and variance in the distribution was not possible. This was a confirmation that real life data and count data on diseases which are normally analysed by the Poisson distribution do not normally follow that assumption. Poisson switching regression method was introduced in order to mitigate this anomaly. A two–regime Poisson Switching was first modeled to fit the data. A three-regime Poisson model was further fitted in order to allow for comparison of the two different regimes. An analysis of the monthly effects on malaria incidence showed that, malaria cases rose after the first three months in each year and declined in the first quarter of the year. Implementation of malaria interventions within the first quarter of the year in the area would improve their efficacy in reducing mosquito breeding from the start of the malaria season, prior to increasing malaria incidence and transmission. The estimated two-regime Poisson regression model revealed malaria to have a negative relation with both rainfall and temperature while having a positive relation with relative humidity in both states.

Furthermore, a three-regime Poisson regression model estimated revealed that, malaria incidence was likely to increase in regime 1 for a unit increase in rainfall and temperature but a reverse for a unit increase in relative humidity levels as opposed to regime 2. For regime 3, it was estimated that, all the climatic variables had positive effects on malaria incidence. In comparing the different two-regime and three-regime Poisson regression models, the three-regime exhibited a higher degree in terms of its ability to explain the data. Further analysis of the residuals of the fitted model showed the conformity of the residual assumptions of normality and randomness.

5.3 Recommendations

Relying on the outcome of this study, the following were recommendations made,

1. The study results revealed certain 'high malaria incidence months' in the area. It is therefore recommended that, proactive campaign and measures spearheaded by Ghana Health Service (GHS) to sensitize the public on the need to practice safe malaria habits to avoid the rapid transmission of the disease during these periods. The use of treated mosquito nets, frequent indoor spraying as well as clearing of

bushes and desilting of nearby choked drains must be encouraged all year round.

2. Government of Ghana should expand the National Malaria Control Programme to household level and make the National Health Insurance Scheme more efficient to serve the masses.

3. Further scientific studies making use of advanced and better methodology into the behavior and spread of the disease that will in turn be geared towards the elimination of the pandemic is highly encouraged.

REFERENCES

Abeku, T. A., De Vlas, S. J., Borsboom, G. J. J. M., Tadege, A., Gebreyesus, Y., Gebreyohannes, H., & Habbema, J. D. F. (2004). Effects of meteorological factors on epidemic malaria in Ethiopia: a statistical modelling approach based on theoretical reasoning. *Parasitology*, *128*(Pt 6), 585-593.

Adu-Prah, S., & Tetteh, E. K. (2015). Spatiotemporal analysis of climate variability impacts on malaria prevalence in Ghana. *Applied Geography*, *60*, 266-273.

Akpalu, W., & Codjoe, S. N. A. (2013). Economic analysis of climate variability impact on malaria prevalence: the case of Ghana. *Sustainability*, *5*(10), 4362-4378.

Alhassan, E. A., Isaac, A. M., & Emmanuel, A. (2017). Time series analysis of malaria cases in Kasena Nankana Municipality. *International Journal of Statistics and Applications*, *7*(22), 43-56.

Amekudzi, L. K., Codjoe, S. N. A., Sah, N. A., & Appiah, M. (2014). *The impact of climate change on malaria in coastal Ghana*. International Development Research Centre.

Ankamah, S., Nokoe, K. S., & Iddrisu, W. A. (2018). Modelling trends of climatic variability and malaria in Ghana using vector autoregression. *Malaria research and treatment*, *2018*.

Asare, E. O., & Amekudzi, L. K. (2017). Assessing climate driven malaria variability in Ghana using a regional scale dynamical model. *Climate*, *5*(1), 20.

Aulia, D., Ayu, F., & Matondang, A. (2018). Analysis of forecasting malaria case with climatic factors as predictor in Mandailing Natal Regency: a time series study. In *IOP Conference Series: Materials Science and Engineering* (Vol. 300, No. 1, p. 012035).

Bereka, S. G., Habtewold, F. G., & Nebi, T. D. (2017). Under-five mortality of children and its determinants in Ethiopian Somali regional state, Eastern Ethiopia. *Health Science Journal*, *11*(3), 1.

Bi, P., Tong, S., Donald, K., Parton, K. A., & Ni, J. (2003). Climatic variables and transmission of malaria: a 12-year data analysis in Shuchen County, China. *Public health reports*, *118*(1), 65.

Boateng, A. (2012). *Modeling the occurrence and incidence of malaria cases: a case study at Obuasi Government Hospital* (Doctoral dissertation).

Cameron, A.C. and Trivedi, P.K. (1998). Regression analysis of count data, Cambridge.

Cameron, S. V., & Heckman, J. J. (1998). Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males. *Journal of Political economy*, *106*(2), 262-333.

Cator, L. J., Thomas, S., Paaijmans, K. P., Ravishankaran, S., Justin, J. A., Mathai, M. T., & Eapen, A. (2013). Characterizing microclimate in urban malaria transmission settings: a case study from Chennai, India. *Malaria journal*, *12*(1), 1-10.

Craig, M. H., Kleinschmidt, I., Nawn, J. B., Le Sueur, D., & Sharp, B. L. (2004). Exploring 30 years of malaria case data in KwaZulu-Natal, South Africa: part I. The impact of climatic factors. *Tropical Medicine & International Health*, *9*(12), 1247-1257.

Craig, M. H., Snow, R. W., & Le Sueur, D. (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology today*, *15*(3), 105-111.

Danuor, S. K., Tay, S. C. K., Annor, T., Forkuo, E. K., Bosompem, K. M., & Antwi, V. (2010). The impact of climate variability on malaria incidence and prevalence in the forest zone of Ghana–A case study at two (2) hospitals located within the Kumasi Metropolitan area of the Ashanti

Region of Ghana. In *2nd International Conference: Climate, Sustainability and Development in Semi-arid Regions* (pp. 16-20).

Darkoh, E. L., Larbi, J. A., & Lawer, E. A. (2017). A weather-based prediction model of malaria prevalence in Amenfi West District, Ghana. *Malaria research and treatment*, *2017*.

DaSilva, J., Garanganga, B., Teveredzi, V., Marx, S. M., Mason, S. J., & Connor, S. J. (2004). Improving epidemic malaria planning, preparedness and response in Southern Africa. *Malaria Journal*, *3*(1), 37.

Dekel, E., Rivkin, A., Heidenreich, M., Nadav, Y., Ofir-Birin, Y., Porat, Z., & Regev-Rudzki, N. (2017). Identification and classification of the malaria parasite blood developmental stages, using imaging flow cytometry. *Methods*, *112*, 157-166.

Devi, N. P., & Jauhari, R. K. (2006). Relationship between Anopheles fluviatilis & A. stephensi (Diptera: Culicidae) catches & the prevalence of malaria cases at Kalsi area in Dehradun district (Uttaranchal). *Indian Journal of Medical Research*, *123*(2), 151.

Dunn, P. K., & Smyth, G. K. (1996). Randomized quantile residuals. *Journal of Computational and Graphical Statistics*, *5*(3), 236-244.

Eikenberry, S. E., & Gumel, A. B. (2018). Mathematical modeling of climate change and malaria transmission dynamics: a historical review. *Journal of mathematical biology*, *77*(4), 857-933.

Gething, P. W., Van Boeckel, T. P., Smith, D. L., Guerra, C. A., Patil, A. P., Snow, R. W., & Hay, S. I. (2011). Modelling the global constraints of temperature on transmission of Plasmodium falciparum and P. vivax. *Parasites & vectors*, *4*(1), 1-11.

Gomez-Elipe, A., Otero, A., Van Herp, M., & Aguirre-Jaime, A. (2007). Forecasting malaria incidence based on monthly case reports and environmental factors in Karuzi, Burundi, 1997–2003. *Malaria Journal*, *6*(1), 129.

Hambuckers, J., Kneib, T., Langrock, R., & Silbersdorff, A. (2018). A Markov-switching generalized additive model for compound Poisson processes, with applications to operational loss models. *Quantitative Finance*, *18*(10), 1679-1698.

Hundessa, S., Williams, G., Li, S., Guo, J., Zhang, W., & Guo, Y. (2017). The weekly associations between climatic factors and Plasmodium vivax and Plasmodium falciparum malaria in China, 2005–2014. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, *111*(5), 211-219.

Huppert, A., & Katriel, G. (2013). Mathematical modelling and prediction in infectious disease epidemiology. *Clinical microbiology and infection*, *19*(11), 999-1005.

Hussien, H. H. (2019). Malaria's association with climatic variables and an epidemic early warning system using historical data from Gezira State, Sudan. *Heliyon*, *5*(3), e01375.

Jima, D., Getachew, A., Bilak, H., Steketee, R. W., Emerson, P. M., Graves, P. M., & Hwang, J. (2010). Malaria indicator survey 2007, Ethiopia: coverage and use of major malaria prevention and control interventions. *Malaria journal*, *9*(1), 1-12.

Johnson, N., Fernández de Marco, M., Giovannini, A., Ippoliti, C., Danzetta, M. L., Svartz, G., ... & Moutailler, S. (2018). Emerging mosquito-borne threats and the response from European and Eastern Mediterranean countries. *International journal of environmental research and public health*, *15*(12), 2775.

Kan, K., & Fu, T. T. (1997). Analysis of Housewives' Grocery Shopping Behavior in Taiwan: An Application of the Poisson Switching Regression. *Journal of Agricultural and Applied Economics*, *29*(2), 397-407.

Klutse, N. A. B., Aboagye-Antwi, F., Owusu, K., & Ntiamoa-Baidu, Y. (2014). Assessment of patterns of climate variables and malaria cases in two ecological zones of Ghana. *Open Journal of Ecology*, *4*(12), 764.

Kotepui, M., & Kotepui, K. U. (2018). Impact of weekly climatic variables on weekly malaria incidence throughout Thailand: a country-based six-year retrospective study. *Journal of environmental and public health*, *2018*.

Krefis, A. C., Schwarz, N. G., Krüger, A., Fobil, J., Nkrumah, B., Acquah, S., & May, J. (2011). Modeling the relationship between precipitation and malaria incidence in children from a holoendemic area in Ghana. *The American journal of tropical medicine and hygiene*, *84*(2), 285-291.

Kreuels, B., Kobbe, R., Adjei, S., Kreuzberg, C., von Reden, C., Bäter, K., & May, J. (2008). Spatial variation of malaria incidence in young children from a geographically homogeneous area with high endemicity. *The Journal of infectious diseases*, *197*(1), 85-93.

Li, T., Yang, Z., & Wang, M. (2013). Temperature, relative humidity and sunshine may be the effective predictors for occurrence of malaria in Guangzhou, southern China, 2006–2012. *Parasites & vectors*, *6*(1), 1-4.

M'Bra, R. K., Kone, B., Soro, D. P., N'krumah, R. T., Soro, N., Ndione, J. A., & Schindler, C. (2018). Impact of climate variability on the transmission risk of malaria in northern Côte d'Ivoire. *Plos one*, *13*(6), e0182304.

Mahama, R. R. (2019). *Evaluation of the Effect of Indoor Residual Spraying on Malaria Morbidity Trends the Gusheigu and Karaga Districts of Northern Region, Ghana* (Doctoral dissertation, University of Ghana).

Marsh, K., & Snow, R. W. (1997). Host—parasite interaction and morbidity in malaria endemic areas. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *352*(1359), 1385-1394.

Mattah, P. A. D., Futagbi, G., Amekudzi, L. K., & Mattah, M. M. (2020). Climate variations, urban solid waste management and possible implications for Anopheles mosquito breeding in selected cities of coastal Ghana. *West African Journal of Applied Ecology*, *28*(1), 21-34.

Mba, C. J., & Aboh, I. K. (2006). Prevalence and management of malaria in Ghana: a case study of Volta region.

Mbouna, A. D., Tompkins, A. M., Lenouo, A., Asare, E. O., Yamba, E. I., & Tchawoua, C. (2019). Modelled and observed mean and seasonal relationships between climate, population density and malaria indicators in Cameroon. *Malaria Journal*, *18*(1), 359.

Ministry of Food and Agriculture (n. d.). *District Directorates.* Retrieved on May 20, 2021 from http://mofa.gov.gh/site/directorates/district-directorates/brong-ahafo-region/171-wenchi-municipal.

Miranda, A. (2004). FIML estimation of an endogenous switching model for count data. *The Stata Journal*, *4*(1), 40-49.

Nelder, J. A., & Wedderburn, R. W. (1972). Generalized linear models. *Journal of the Royal Statistical Society: Series A (General)*, *135*(3), 370-384.

Ngwa, G. A., & Shu, W. S. (1999). Amathematical model for endemic with variable human and mosquito populations.

Nonvignon, J., Aryeetey, G. C., Issah, S., Ansah, P., Malm, K. L., Ofosu, W. & Aikins, M. (2016). Cost-effectiveness of seasonal malaria chemoprevention in Upper West region of Ghana. *Malaria journal*, *15*(1), 1-13.

Paaijmans, K. P., Read, A. F., & Thomas, M. B. (2009). Understanding the link between malaria risk and climate. *Proceedings of the National Academy of Sciences*, *106*(33), 13844-13849.

Pampana, E. (1969). A textbook of malaria eradication. *A textbook of malaria eradication. 2nd edition.*

Pobbi, M. A. (2012). *A three-state Markov Chain Model of plasmodium falciparum parasitemia transmission in Ghana* (Doctoral dissertation).

Rejeki, D. S. S., Nurhayati, N., Budi, A. J. I., Murhandarwati, E. E. H., & Kusnanto, H. (2018). A time series analysis: weather factors, human migration and malaria cases in endemic area of Purworejo, Indonesia, 2005–2014. *Iranian journal of public health*, *47*(4), 499.

Sachs, J. (2000). Economic analyses indicate the burden of malaria is great. *The African Summit on Roll Back Malaria, Abuja*, 27-35.

Semenza, J. C., & Suk, J. E. (2018). Vector-borne diseases and climate change: a European perspective. *FEMS microbiology letters*, *365*(2), fnx244.

Sena, L., Deressa, W., & Ali, A. (2015). Correlation of climate variability and malaria: a retrospective comparative study, Southwest Ethiopia. *Ethiopian journal of health sciences*, *25*(2), 129-138.

Sewe, M. O. (2017). *Towards Climate Based Early Warning and Response Systems for Malaria* (Doctoral dissertation, Umeå universitet).

Shimaponda-Mataa, N. M., Tembo-Mwase, E., Gebreslasie, M., Achia, T. N., & Mukaratirwa, S. (2017). Modelling the influence of temperature and rainfall on malaria incidence in four endemic provinces of Zambia using semiparametric Poisson regression. *Acta tropica*, *166*, 81-91.

Snow, M. J., de Winter, D., Buckingham, R., Campbell, J., & Wagner, J. (1996). New techniques for extreme conditions: high temperature reverse osmosis and nanofiltration. *Desalination*, *105*(1-2), 57-61.

Tay, S. C. K., Danuor, S. K., Mensah, D. C., Acheampong, G., Abruquah, H. H., Morse, A., ... & Hassan, H. A. (2012). Climate variability and malaria incidence in peri-urban, urban and rural communities around Kumasi, Ghana: a case study at three health facilities; Emena, Atonsu and Akropong. *International Journal of Parasitology Research*, *4*(2), 83.

Teklehaimanot, H. D., Lipsitch, M., Teklehaimanot, A., & Schwartz, J. (2004). Weather-based prediction of Plasmodium falciparum malaria in epidemic-prone regions of Ethiopia I. Patterns of lagged weather effects reflect biological mechanisms. *Malaria journal*, *3*(1), 41.

Texier, G., Machault, V., Barragti, M., Boutin, J. P., & Rogier, C. (2013). Environmental determinant of malaria cases among travellers. *Malaria Journal*, *12*(1), 1-11.

Thomson, M. C., Ukawuba, I., Hershey, C. L., Bennett, A., Ceccato, P., Lyon, B., & Dinku, T. (2017). Using rainfall and temperature data in the evaluation of national malaria control programs in Africa. *The American journal of tropical medicine and hygiene*, *97*(3_Suppl), 32-45.

Wihibeturo, B. A. (2014). *Effect of seasonal variability on the incidence and transmission patterns of malaria in Urban, Peri-urban and Rural Communities around Kumasi, Ghana* (Doctoral dissertation).

World Health Organization (WHO, 2019). World malaria report 2019. Report No.: ISBN 978-92-4-156572-1.

Yamana, T. K., & Eltahir, E. A. (2013). Incorporating the effects of humidity in a mechanistic model of Anopheles gambiae mosquito population dynamics in the Sahel region of Africa. *Parasites & vectors*, *6*(1), 1-10.

Yao, K. M. A., Obeng, F., Ntajal, J., Tounou, A. K., & Kone, B. (2018). Vulnerability of farming communities to malaria in the Bole district, Ghana. *Parasite epidemiology and control*, *3*(4), e00073.