

**MODELING THE TREND OF MALARIA REPORTED CASES IN KISUMU COUNTY,
KENYA**

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**A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENT FOR THE AWARD OF DEGREE OF MASTER OF SCIENCE IN
MEDICAL STATISTICS OF THE UNIVERSITY OF NAIROBI**

2019

DECLARATION

I certify that this research project does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any institution of higher education; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person where due reference is made in the text.

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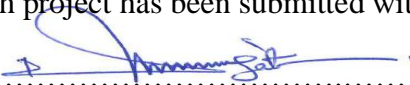
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DEDICATION

I dedicate this work to my entire family and friends for tirelessly supporting and encouraging me

During my study period.

ACKNOWLEDGEMENTS

I thank the Almighty God for his guidance through my study period, without his provisions and guidance, my participation in this program of study would have been futile. Secondly, special thanks go to my supervisors Dr. Vincent Otieno and Dr. Joseph Mung'atu for their great insight, tireless unreserved support and guidance throughout the research process. I appreciate the University of Nairobi administrators and staff at large for regular guidance on the whole research process. I also sincerely thank my friends and family for supporting, advising and encouraging me throughout the time I have worked for my project.

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ABBREVIATIONS AND ACRONYMS

ACT	Artemisinin Combined Therapy
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
DDT	Dichlorodiphenyltrichloroethane
DHIS2	District Health Information System 2
GLM	Generalized Linear Models
GOK	Government of Kenya
HIV	Human Immunodeficiency Virus
IDSR	Integrated Disease Surveillance and Response System
IRR	Incidence Rate Ratio
ITN	Insecticide-treated bed nets
KHS	Kenya Health Service
KNBS	Kenya National Bureau of Statistics
MOH	Ministry of Health
MOP	Malaria Operational Plans
NGO	Non-Governmental Organization
NMCP	National Malaria Control Program
PMI	President's Malaria Initiative
SDGS	Sustainable Development Goals
UHC	Universal Health Coverage
UN	United Nations
WHO	World Health Organization

ABSTRACT

Background: Although there has been an extensive scale up of Malaria interventions in Kenya, Malaria infections persist at unacceptably high levels in some of the regions. Even with renewed calls to eradicate the disease through increased international donor assistance and country specific government involvement, Malaria is still a cause of worry in the endemic regions.

Study objective: To determine the factors associated with the incidence of Malaria in Kisumu County over time.

Methodology: The study was a repeated cross-sectional survey involving secondary data analysis of routinely reported Malaria cases. The population of interest were patients confirmed to have Malaria by laboratory test. A sample size of 384 was randomly selected from all laboratory-confirmed Malaria cases as reported by health facilities in Kisumu County from January 2014 to December 2017. The analysis involved checking for completeness, consistency and accuracy of the data. This included descriptive, trend analysis and time series analysis (ARIMA). Negative binomial regression model was used to measure the effect of each of the selected predictor variables on incidence of Malaria and the Incidence Rate Ratio (IRR), was reported. Frequency distribution of each variable and each category for each of the categorical variables was calculated and presented using version 3.5.1 R statistical software.

Results: The overall pattern of the reported malaria cases had variations in seasons for weekly cases. Whereas, the best fitted time series model developed for predicting the number of weekly reported cases of malaria was ARIMA (2, 0, 1). Negative Binomial was essentially the best model which fit the data since the dispersion parameter given by Poisson Regression Model had been reduced from 70.292 to 1.103. Kisumu East, Seme, Nyando, Kisumu Central localities, the year

2017 and the total number of patients who underwent a laboratory confirmation test for malaria were statistically associated to the incidence of Malaria in Kisumu County over time ($P < 0.001$).

Conclusion: The findings provide better insight of environmental and socio-economic impacts malaria incidences at the same time providing an important information for the prediction of the disease. Nonetheless, there is need to encourage health professionals to regularly review and report cases of malaria in their facilities. This is because, reporting frequencies, completeness and the consistency of malaria reported cases remain extremely low.

CHAPTER ONE: INTRODUCTION

1.0 Overview

This chapter presents the study background, the area profile, problem statement and objectives of the study. It is also include the justification of the study.

1.1 Background

Malaria is among the major killer diseases within tropical regions. Sub-Saharan Africa bears its burden than any other region across the globe. The parasites are spread to humans through bites from infected anopheles mosquitoes introducing the protozoans into the human body. Even with renewed calls to eradicate the disease through increased international donor assistance and country specific government involvement, Malaria is still a cause of worry in the endemic regions.

According to the world Malaria report, Anti-Malaria programs has slowed down in many parts of the world and it is unlikely that the world will achieve targets for 2020 set by the WHO Global technical strategy in reducing Malaria incidences. A year on from this recognition, still there is no significant progress in global Malaria control (WHO 2018). Globally, malaria cases were estimated at 219 million cases having occurred in 2017 as compared to 239 million cases that occurred in 2010. Even though the cases were fewer by 20 million in 2017 than in the year 2010 worldwide, from 2015 to 2017 there was a slight upward change in trend, suggesting that progress had generally stalled(World Malaria Report,2018).

The WHO statistics of 2017 reveal that the Sub-Saharan Africa is still suffering greatly from Malaria deaths with 200 million cases comprising of 92% of the global burden. Malaria has impacted the health and economic development of sub-Saharan African countries negatively and

is considered a major impediment to sustainable development by the world's poorest regions (Gallup & Sachs, 2001).

The 2030 Agenda adopted in September 2015 by World leaders was to ensure Sustainable Development globally. The aim is to eradicate poverty, improving health, reduce inequity and address challenges related to climate change by the year 2030. In order to track progress, they created a number of Sustainable Development Goals (SDGs), each having a specific target to be realized in the next 15 years. One of the set targets is to end epidemics of neglected tropical diseases and Malaria by 2030. A set of indicators to track success on Malaria eradication is, the number of Malaria incidence experienced in a population and the number of people affected by neglected tropical diseases and are seeking interventions against these diseases (“SDG Indicators,” 2018)

To reaffirm the position of Sustainable Development Goals (SDGs) on global health priority, is the inclusion of universal health coverage (UHC)(Barasa, Nguhiu, & McIntyre, 2018).The purpose of UHC is to make sure that all citizens of a state are able to access curative, rehabilitative and preventive health services at minimum costs, thereby eliminating disparities in access to health care. This also includes; free consultation, diagnosis services for normal ailments and getting drugs for free. The Kenyan UHC model of dispensation by the current government calls for the enhancement of HIV, Tuberculosis and Malaria treatment in the country, with the aim of eradication of these diseases.

More than 70% of the entire population in Kenya is at risk of Malaria which is the major cause of ill health (KNBS, 2015). In 2017, confirmed Malaria incidences were 2,783,846 as reported by the public health facilities. The diagnosed cases contributes correspondingly to the high number

of malaria deaths in the Kenyan population, which increased from 2016 to 2017 as a result of stalled progress in Malaria prevention. With the aim of achieving the largest reduction rate in morbidity and mortality, President's Malaria Initiative (PMI) has always considered the regions of Kenya experiencing the high incidences of Malaria since 2013.

The counties of Kisumu, Vihiga, Migori, Bungoma, Homa Bay, Kakamega, Busia and Siaya all together have a projected population of about 9.6 million in 2018 bearing the highest incidence of malaria in Kenya (President's Malaria Initiative, 2018). The quarterly surveillance bulletin released in December 2016 revealed that, 73% of all confirmed Malaria cases were reported from these counties (President's Malaria Initiative, 2018). Execution of Malaria control interventions focuses on endemic areas and are usually guided by the epidemiological zones. They include, community managing the cases as they occur and intermittent preventive treatment in pregnancy (Musuva et al., 2017)

It is in the light of this discourse that the Kenyan government and other developing partners in the health sector have remained dedicated in improving the delivery of health service in various parts of the country, with high priority being placed on prevention and control measures of Malaria in endemic regions with eventual elimination. This being one of the objectives that were to be realized by 2018, together they aimed at reducing Malaria burden by two-thirds. (MOP, 2019).

1.2 Problem Statement:

Efforts to scale up prevention and control of Malaria has accomplished significant milestones in Kenya. This is an indication that elimination and ultimate eradication is conceivable. Success reports are diverse with some regions nonetheless experiencing either reversals (Cohen et al., 2012) and aggravated incidences of malaria or stagnation (Zhou et al., 2011). According to Cohen

et al., 2012, the fact that some regions in Kenya that had previously achieved substantial control of Malaria experience portents of resurgence threatens to significantly reverse. Some of the strides already made within the key performance indicators such as reduction in child mortality (Hamel, Odhacha, Roberts, & Deming, 2001).

Although there has been an extensive scale up of Malaria interventions in Kenya, its infections persist at unacceptably high levels in some of the regions. Kisumu County is one of the regions that bear the heaviest burden with regards to Malaria renaissance. President's Malaria Initiative has prioritized Kisumu as one of the most affected by the recent explosion. This is in order to refocus and facilitate modest reduction in Malaria morbidity and mortality across the affected regions. This study therefore called for a trend assessment and the corresponding factors to the prevailing Malaria statistics within Kisumu County as a part approach to the overall course. The ability to identify the factors overtime in the reported Malaria incidences is expected to be a key milestone towards the prevention discourse; precisely the control and management of the disease.

1.3. Research Questions

- i. What is the trend of reported Malaria cases among those who sought facility treatment?
- ii. What is the best fit time series model for predicting weekly reported Malaria cases in Kisumu County?
- iii. What are the factors contributing to the occurrence of Malaria cases?

1.4. Study Objective

To determine the factors associated with the incidence of Malaria in Kisumu County over time.

1.4.1 Specific Objectives

- i.** To describe the trends of reported Malaria cases among those who sought facility treatment.
- ii.** To identify the best fit time series model for predicting weekly reported Malaria cases in Kisumu County.
- iii.** To model factors associated with incidence of Malaria in Kisumu County.

1.5 Justification of the Study

Kenya recently adopted the county system of governance, where policy making, health related decisions and the distribution of resources is at the county level (GOK 2013). Efforts towards Malaria prevention, control and elimination require that resources are optimally distributed. Since Malaria data is available, there is need to analyze the existing underlying data over time in a bid to prevent Malaria incidences, especially at the epidemiological zones level. This is due to the already documented health system shortcomings of non-use of evidence in the fight for Malaria control and eradication

Malaria situation with regard to facility reported cases and distribution remains unclear within the recent past in the study area, despite the above mentioned studies in various parts of the country. Therefore, this study aimed at mapping the corresponding factors contributing to the incidence of Malaria with the trend data on Malaria cases across the region. The study will provide useful insights to program planners and policy makers in assessing progress at each level and focusing

future efforts in preventing and controlling incidences of Malaria, while providing evidence driven public health action at the same time.

1.6 Study Limitations

1. The study was facility-based using only individuals who sought facility treatment, this could be either a possible under estimation or over estimation on incidence rate of malaria in the region. This also means that, prediction of future malaria incidences and the degree to which the results could be generalized is limited.
2. The use of secondary data is limiting due to the fact that the available data are not collected to address research questions for this particular study. It is therefore, not unusual that some of the important variables were not available for the analysis.

CHAPTER TWO

LITERATURE REVIEW

2.0 Overview

In this section, works of several authors concerning concept definitions and various researches done was reviewed. Research works, empirical works and authors' opinions are looked at. Below are the focuses of the review.

2.1 Malaria

Malaria is among the most prominent diseases that has been studied and profiled as having the highest mortality rates (Sudhakar & Subramani, 2007). According to (Worrall et al., 2003), Malaria prevalence is high in the poorest continents and countries and is commonly known as the disease of the poor.

The cause of Malaria is a parasite known as plasmodium that is found in female mosquitoes. Malaria symptoms comprises of joint pains, Shivering, headache, fever, chills, nausea and vomiting. It has got four species of plasmodium that is plasmodium ovale, plasmodium falciparum, and plasmodium Malaria and plasmodium vivax. Infections related with the plasmodium falciparum has got adverse effects, as it is resistant to chloroquine and therefore it requires other treatment options. The other types of Malaria are considered not life threatening, due to the fact that individuals infected with either of them are able to recover in a months' time without being treated. Using insecticide treated nets and adoption of Artemisinin Combined Therapy (ACT) has assisted in reducing morbidity and mortality rates globally, though Malaria still poses a threat in our part of the world(Houeto, D'hoore, Ouendo, Charlier, & Deccache, 2007)

2.2 Global malaria epidemiology

WHO 2019 Malaria report projected malaria incidence to have reduced globally from 72 to 59 cases per 1000 population at risk, in the period 2010 and 2017. Despite achieved reduction by 18%, the population at risk still stands at 59 for the last 3 years. Currently populations living in Malaria endemic areas are more than 40% and the great majority are found in Sub-Saharan Africa (WHO, 2000).

2.3 Epidemiology of malaria in Kenya

Malaria has remained as the leading public health problem accounting for over 16 percent of outpatient consultations. Infection risk and Malaria transmission is largely determined by rainfall seasons, temperature and altitude, resulting to variations in incidences of Malaria by seasons and across different regions in Kenya. With 17 million living in areas of seasonal Malaria and another 14 million living in endemic areas, about 70 percent of Kenya's general population is at risk for Malaria. Plasmodium parasites infecting humans strike in different geographic regions in Kenya, from all the four species. Plasmodium falciparum, accounts for 99 percent of infections resulting to the most severe form of Malaria. However, there has been a significant progress in the fight against Malaria in the county (President's Malaria Initiative, 2018).

Kenya tailors its Malaria control efforts and has placed high priority on Malaria endemic areas in order to realize highest reduction rate. With support from other partners which includes the Global Fund and the National Malaria Control Program, there has been major progresses in reporting prevention and treatment measures of Malaria. Malaria prevalence from 2010 to 2015 has declined from 11 percent to 8% nationwide and in the endemic areas near Lake Victoria it declined from 38% to 27% , as shown by the recent household surveys conducted (Githinji et al., 2017)

2.4 Application of Time Series Analysis in Modeling Incidence of Malaria

The use of time series in the field of public health can be dated back to the 20th century when Dr. John Brownlee a public health officer, geneticist, epidemiologist and medical statistician investigated the periodicity of weekly number of deaths from infectious diseases (bronchitis, Pneumonia and influenza) in London between 1876 and 1897, using a mathematical method known as periodogram to find bronchitis or pneumonia in the absence of influenza in a period of 33 weeks (Brownlee, 1919).

Numerous Studies have taken a look at the incidences of Malaria and one of such include (Lin et al., 2009) in fitting an ARIMA model, to the explanatory variable in investigating whether non-endemic provinces of China imported Malaria was related to the falciparum Malaria in the endemic provinces. The seasonal ARIMA (1, 1, 1) and (0, 1, 1) incidence of Malaria model fit the data best of all the models tested, according to Akaike Information Criterion(AIC).

In relation to the climatic factors which leads to Malaria outbreak, (Keatinge et al., 2000) using time-series data took into account threshold temperature where mortality was lowest in estimating the heat related mortality due to climate change in Europe. According to the findings, European population was expected to have a minor increase in heat related deaths and adapting to future higher temperature's since they had adapted to average summer temperatures. They further suggested that, it is important to account for acclimatization process when assessing increased temperature's and heat waves impacts.

Future incidences of Malaria cases are often predicted from their history overtime. A time series analysis often does this and therefore this study was steered towards identifying the trends and the best fit times series model for predicting monthly reported cases of Malaria in Kisumu County over the period 2014 to 2017 using time series analysis. A suitable way of describing the incidence

of Malaria is essential in ensuring proper planning and evaluation in the implementation of programs to monitor and control the disease, especially in endemic zones.

2.5 Application of Generalized Linear Models in Modeling Incidence of Malaria

Appropriate models for count data are the Generalized Linear Models where transformations to adopt the appropriate nonlinear model, is the alternative to rescaled categories. Modeling count data is only feasible using “generalized linear models” (GLMs) where the response variable does not have to be normally distributed. The dependent variable is the random component in GLMs, which assumes a certain distribution. Different conditions could be used to model count data using Negative binomial or Poisson regression models.

GLMs has been used in several studies to model the incidence of Malaria. (Adenomon, 2014), employed Negative binomial and Poisson regression models in the study of Malaria prevalence trends in Minna, Nigeria. Prevalence of Malaria was found to be on the rise on monthly basis by 6%. Also, Malaria relationship with environmental and socioeconomic variables were examined using health production modified model in Sudan. There was a significant relationships between Malaria, water bodies and rainfall(Musa, Shohaimi, Rasidah Hashim, & Krishnarajah, 2012).

This research study was guided by the count models, based on the 3 predictors which influence incidence of malaria as reported by health facilities. The outcome variable was the number of patients testing positive for malaria. In case the assumptions of poisson regression was not met, negative binomial regression model was to be used as an alternative. The most flexible model is the negative binomial regression model and is frequently used to study count data with over dispersion(Hilbe.J.M, 2007). This knowledge is important in the advancement of malaria warning systems in Kisumu County, hence enabling effective Malaria control measures to be put in place in time.

$$\ln(\lambda) = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k$$

2.6 Conceptual Framework

Numerous factors affect the incidence of Malaria which tend to vary depending on area of residence. In some locales the transmission and incidence could be high and in some locales it could be very low depending on the different climatic and non-climatic factors favoring the incidence of disease. The climatic variables that influence the breeding of Malaria vectors are rainfall, humidity and temperature, whereas migration and urbanization are some of the non-climatic factors influencing the incidence of disease (Gubler et al., 2001). Therefore, the study examined the environmental and socio-economic factors of Malaria incidence in Kisumu County.

2.6.1 Environmental Factors

Malaria vectors tend to breed in favorable environmental conditions with high temperatures, low altitude and rainfall. Also, the presence of stagnant waters and bushes around homes favors the breeding of Malaria vectors. Whereas increased urbanization tends to reduce the rate of Anopheles breeding (Messina et al., 2011).

Different localities have different environmental conditions and development levels that in one way or another influence malaria breeding. Some sub counties are more bestowed with vegetation cover than others, stagnant water among others. This has implications on the mosquitos breeding correspondingly rendering the respective populations within the different localities susceptible to infections at varied rates. In this study, locality was measured by the different sub counties within Kisumu County.

2.6.2 Socio-economic Factors

The poor are known to have high risks of being infected with malaria frequently unlike the rich. Reason being, majority of low income earners cannot afford proper housing that offer minimum protection against mosquitoes with less ability to get effective prevention measures and malaria treatment. (Onwujekwe, Ojukwu, Ezumah, Uzochukwu, & Dike, 2006).

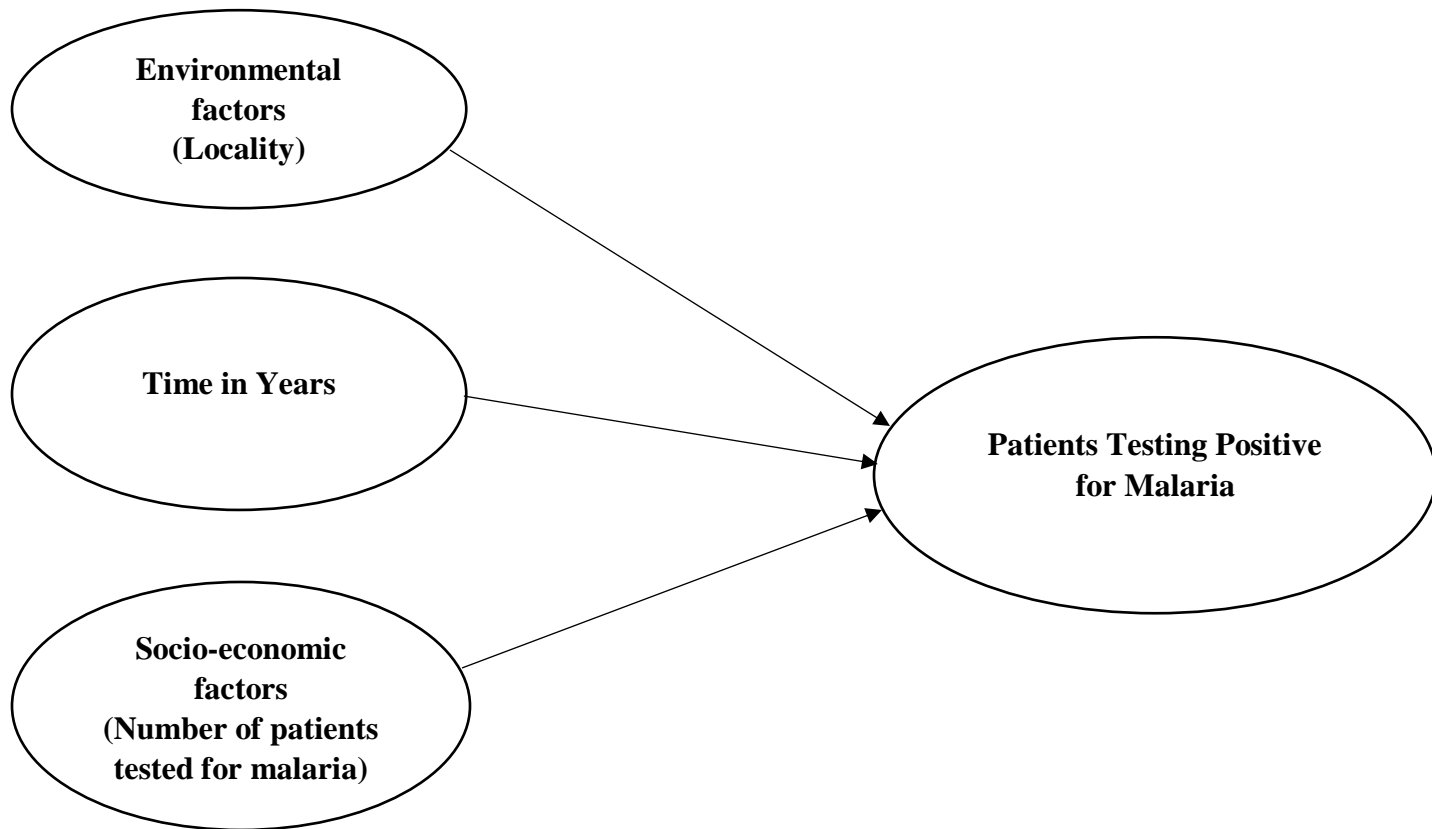
Urbanization is a recent occurrence that currently shapes the lifestyle of people including their interactions with the insect vectors. Rural setups are characterized by low developmental agricultural tracks of land while urban setups are basically built environments. Further, urban residence are characterized with class and generally sensitized populations with regards to public health. This study measured socioeconomic state of the populations by looking at the total number of patients tested for malaria at the health facilities.

The following conceptual framework was considered in this study.

Figure 1: Conceptual Framework

Independent Variables

Dependent Variable



CHAPTER THREE

METHODOLOGY

3.0 Overview

This chapter outlines the Box-Jenkins ARIMA modeling Approach Time Series and statistical applications of Malaria data to be applied in detail. While choosing the appropriate model, greater attention was given to one that incorporates information that influences the response variable notwithstanding the fact that not everything associated with the response is known.

3.1 Study Design

A repeated cross-sectional survey using routinely reported national Programme data on Malaria cases, as reported by health facilities in Kisumu County from January 2014 to December 2017.

3.2 Study Area

Kisumu County is located in the former Nyanza Province and its headquarters is Kisumu City, which is, situated approximately 370km west of the Kenyan Capital, Nairobi. According to 2009 census, Kisumu County had a population of 968,879 people and covers an area landmass of 2085.9km² and 567km² covered by water.

3.3 Study Population

The study population included individuals at risk of Malaria in Kisumu County.

Inclusion Criteria:

All patients confirmed to have Malaria by laboratory test were recruited in the study.

Exclusion Criteria:

Patients diagnosed with ailments other than Malaria were excluded.

3.4 Sample size Determination

Fischer's et al (1998) formula was used to determine the sample size for the study as follows:

$$n = \frac{Z^2 pq}{d^2}$$

Where:

n = is the desired sample size (if the target population is over 10,000)

Z = 1.96 which corresponds to 95% confidence level.

p = is proportion of patients confirmed to have Malaria by laboratory test

q = is (1-p) is proportion of patients confirmed **not** to have Malaria by laboratory test

d = Standard Error at 95% confidence limit (0.05).

Since the proportion of patients confirmed to have Malaria by laboratory test (P) was not known, it was estimated to be 50% (Mugenda & Mugenda, 2003)

Therefore

$$n = \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2}$$

n = 384 laboratory-confirmed Malaria patients

3.5 Sampling Procedure

Any patient who was referred to the laboratory by the clinical officer/nurse after presumptive diagnosis of malaria and fulfilled the criteria for inclusion was enrolled in the study.

3.6 Data Collection Methods

Secondary data of all laboratory-confirmed Malaria cases as reported by all Health Facilities was downloaded from the District Health Information System (DHIS2) using the standard application programming interface provided. The data included weekly number of malaria cases.

3.7 Description of Variables

The model fitted was:

$$g(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

Dependent Variable:

Patients testing Positive for Malaria.

Independent Variables:

The independent variables are factors contributing to the incidence of malaria cases.

These included:

- i. Locality
- ii. Time in years
- iii. Total tested

Table 3.1: Dummy table for Analysis

Variable	Definition
Dependent Variable	
Patients testing positive for malaria	Patients confirmed to have Malaria by laboratory test
Independent Variables	
Locality	Categories: (0 “Kisumu West”, 1. “Kisumu East”, 2. “Kisumu Central”, 3. “Muhoroni”, 4. “Nyando”, 5. “Seme”, 6. “Nyakach”
Time in Years	Categories: 0 “2014”, 1”2015”, 2 “2016” and 3”2017”
Total Tested	Number of patients tested for malaria at the facility

3.8 Data Analysis

The analysis involved checking for completeness, consistency and accuracy of the data. This include descriptive, trend analysis and time series analysis (ARIMA).ARIMA model was used and applied to Time Series Data of Malaria reported Cases in Kisumu County.

The influence of time in years, total number of patients tested and locality on the number of Malaria cases was evaluated. Frequency distribution of each variable and each category for each of the categorical variables was calculated and presented using version 3.5.1 R statistical software. A significant count model negative binomial regression model was used to measure the effect of each of the predictor variables on the number of Malaria cases and the Incidence Rate Ratio (IRR), was reported. The statistical significance was measured using the 95% confidence interval and P values. Missing data was addressed using single imputation method.

3.9 Data Quality assurance procedures

Data was downloaded from the DHIS2 using the standard application programming interface provided. Each facility's data was visually cross-checked subjected to range and limit tests to confirm obvious outliers or errors in transcription. All cleaning was done within a well-documented data cleaning script to facilitate review and ensure reproducibility. The cleaned data was stored in comma delimited format (csv) in a password protected computer accessible to the investigators only, with a backup maintained on a separate encrypted solid state flash drive.

3.10 Ethical considerations

Considering that secondary data was used, there was no interaction with human participants in this study. However, all the personal information generated from this study was treated with a lot of confidentiality. Approval to conduct the study was sought from the Ethics Research Committee at

Kenyatta National Hospital/University of Nairobi (**KNH-ERC/A/338**). Permission to use the DHIS2 data was also obtained from Health Management Information Systems (HMIS) at the Ministry of Health Kenya.

3.12 Dissemination of Research Findings

Reports on the research findings was compiled, written and presented to the Institute of Tropical and Infectious Diseases. The results will also be published in relevant journals to add knowledge on the goal of elimination of Malaria in Kenya.

CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.0 Overview

The analysis of the various models and findings are presented in this chapter. Poisson and Negative Binomial regression models as used in the modeling. Primary analysis and summary of results of the data was also presented.

4.1 Study Sample

The study included 384 reported Malaria cases in the final analysis, for the period January 2014 - December 2017. The data was obtained from the IDSR Disease Surveillance registry through the DHIS2 platform, Kenya.

4.2 Descriptive Analysis

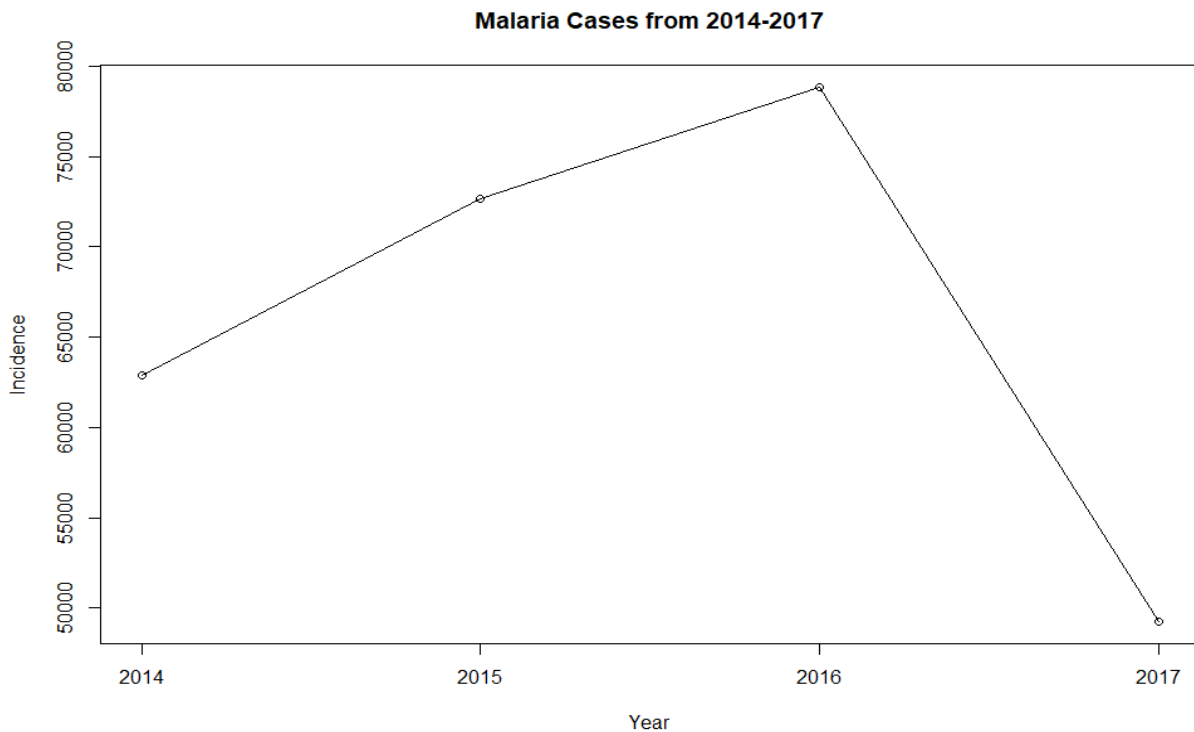


Figure 2: A line graph illustrating reported Malaria Cases from 2014-2017

With respect to time in Years, 2016 saw the highest incidence of malaria and it directly followed by the year 2015, 2014 and 2017 in that order. There was a sharp decline of cases in 2017 compared to the other years which implies that reported malaria cases are unpredictable throughout the years.

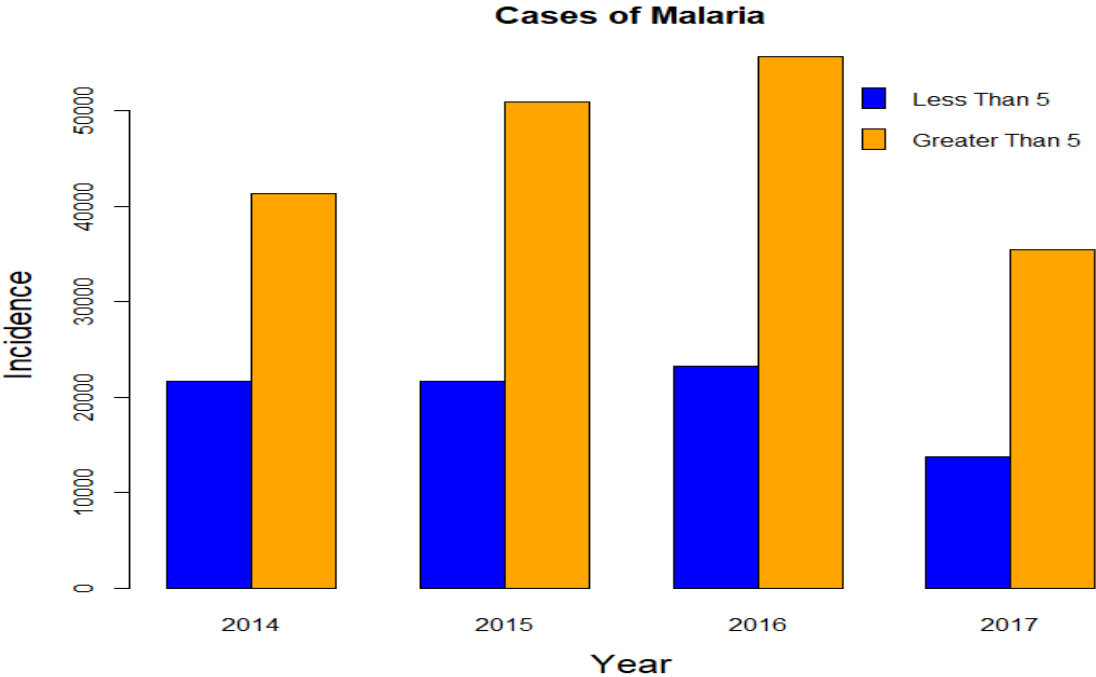


Figure 3: A bar graph illustrating the number of cases of malaria for the two age groups.

From Figure 3 above, it is evident that the highest malaria cases (incidence) struck in 2016 amongst the greater than 5 age group, followed by greater than 5 age groups in 2015 and 2014 respectively. The least cases were recorded for the less than 5 age group in 2017.

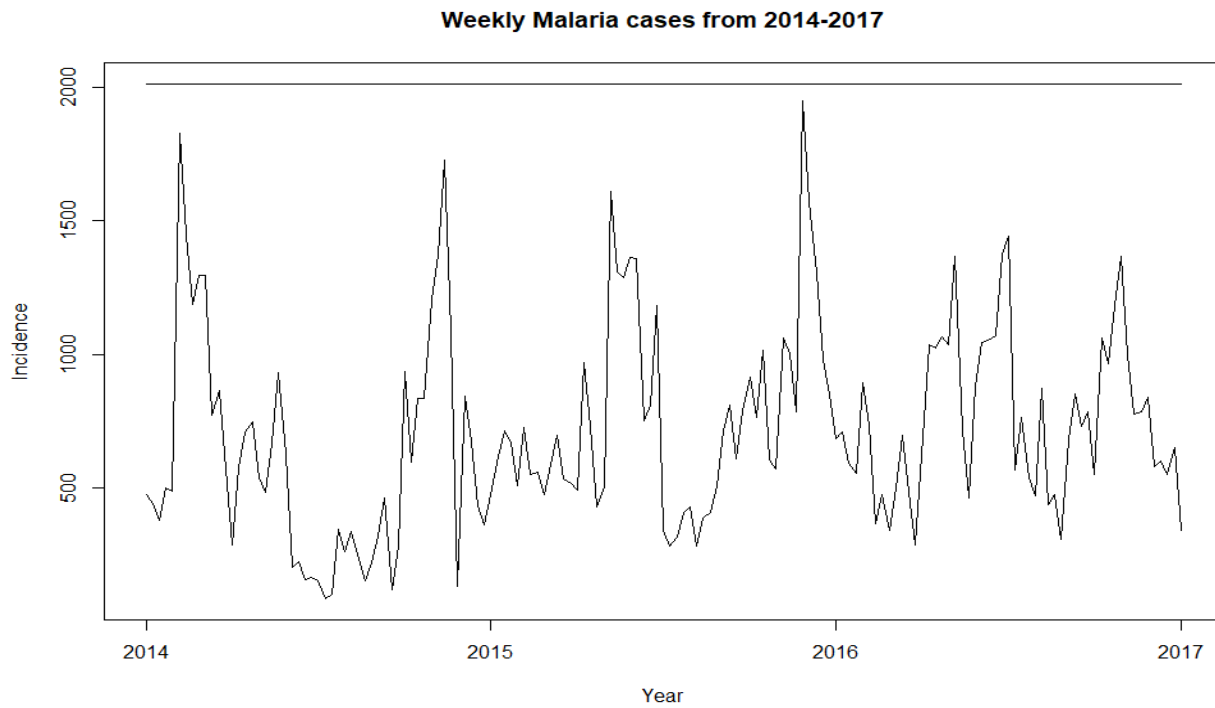


Figure 4: Trend in Weekly reported Malaria cases

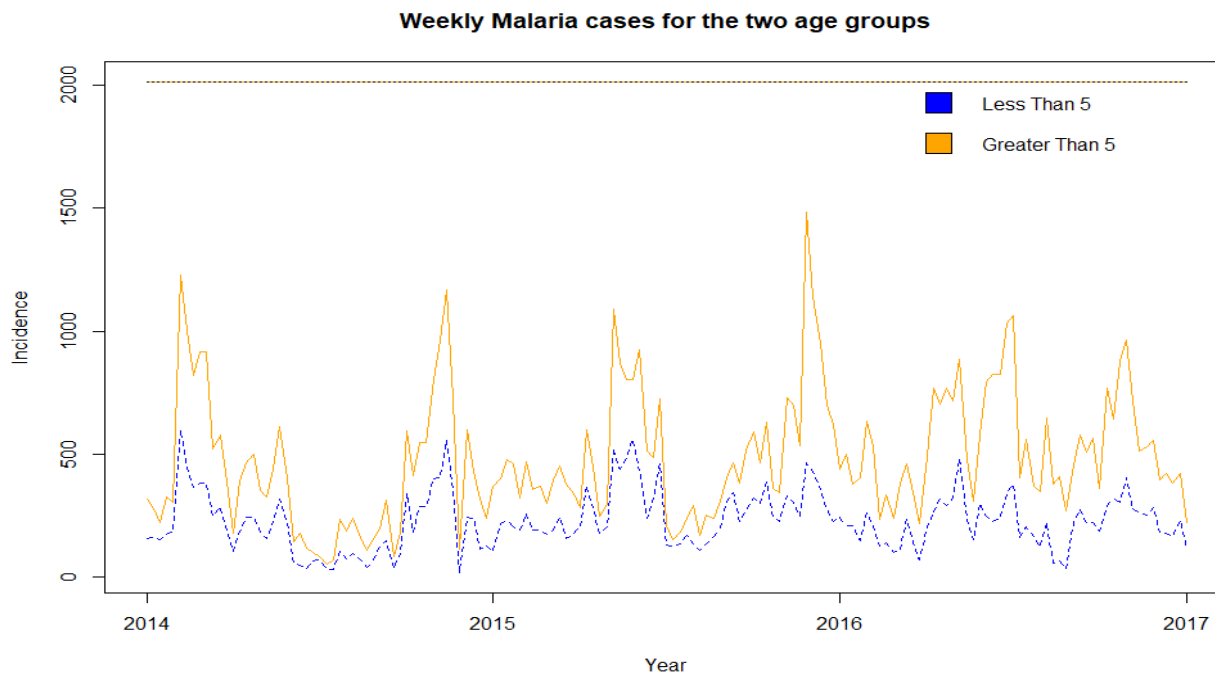


Figure 5: Trend in Weekly reported Malaria cases for under 5 and Greater than 5 years

From Figures 4 and 5, weekly Malaria incidences and weekly Malaria incidences between under 5 and greater than 5 from 2014 to 2017 were explored, which showed an upward trend and suggested a seasonal dependency in the series. Both series exhibited number of peaks a part from small scale fluctuations. From Figure 4, the significant peaks in the weekly malaria incidences series seem to be separated by weeks showing a seasonal pattern as the peak of malaria incidences follow a similar pattern with an interval of few weeks between the peaks. However both series exhibit seasonality which is evident from the strong yearly cycles. The highest peak across the time period was in 2016 while the lowest was observed in 2017 for both series.

Decomposition of additive time series

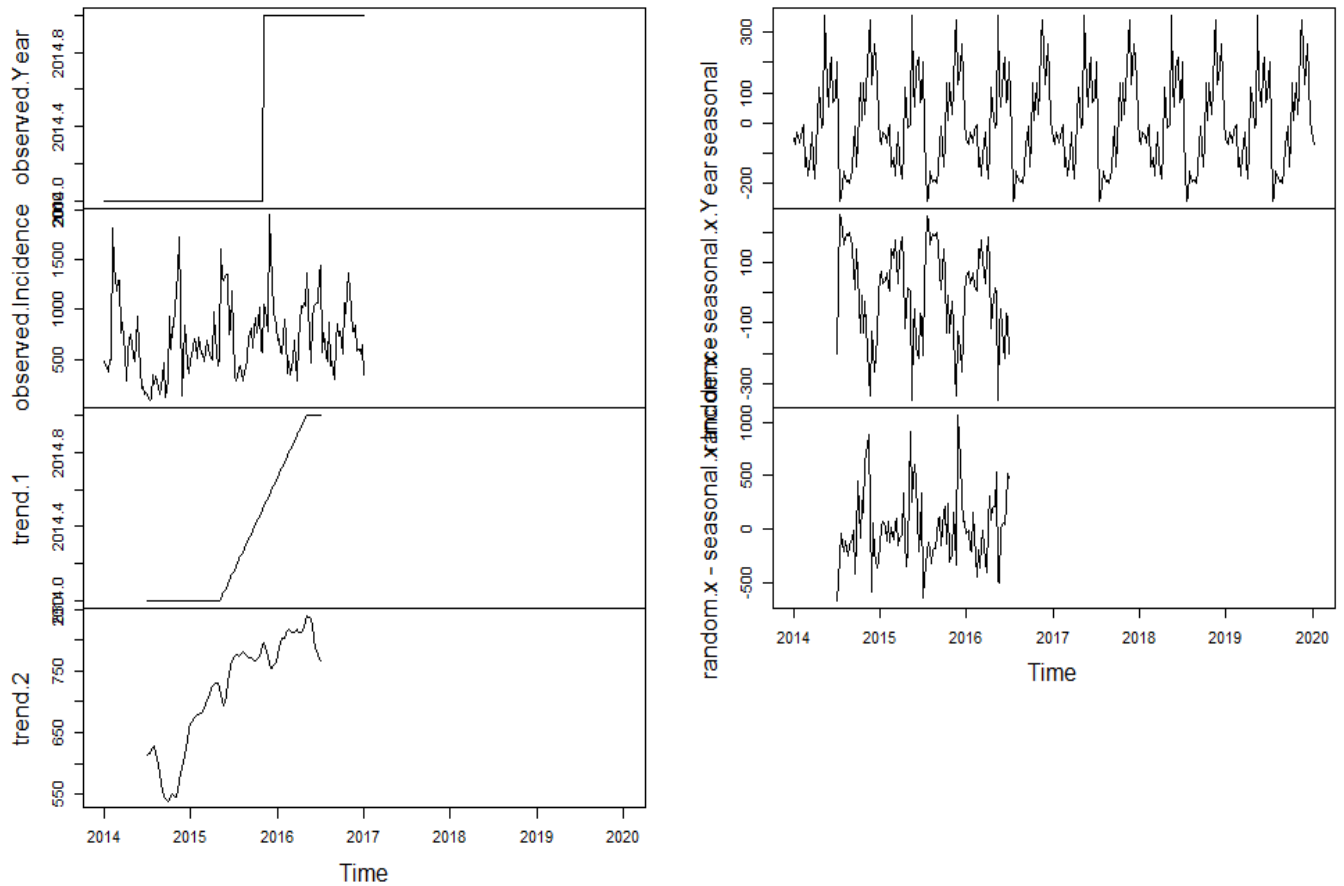


Figure 6: Decomposition of reported Malaria cases

Generally, the time series data exhibits trend, seasonal, and random components. From Figure 6 above, it is evident that the incidence of Malaria series have trend, seasonal and random components. The upward trend is clearly evident with the series exhibiting number of peaks a part from small scale fluctuations.

4.3 Model Identification

The procedure for model building involved ascertaining the order of the AR and MA components. This was guided by the ACF and PACF plots based on the Box-Jenkins approach.

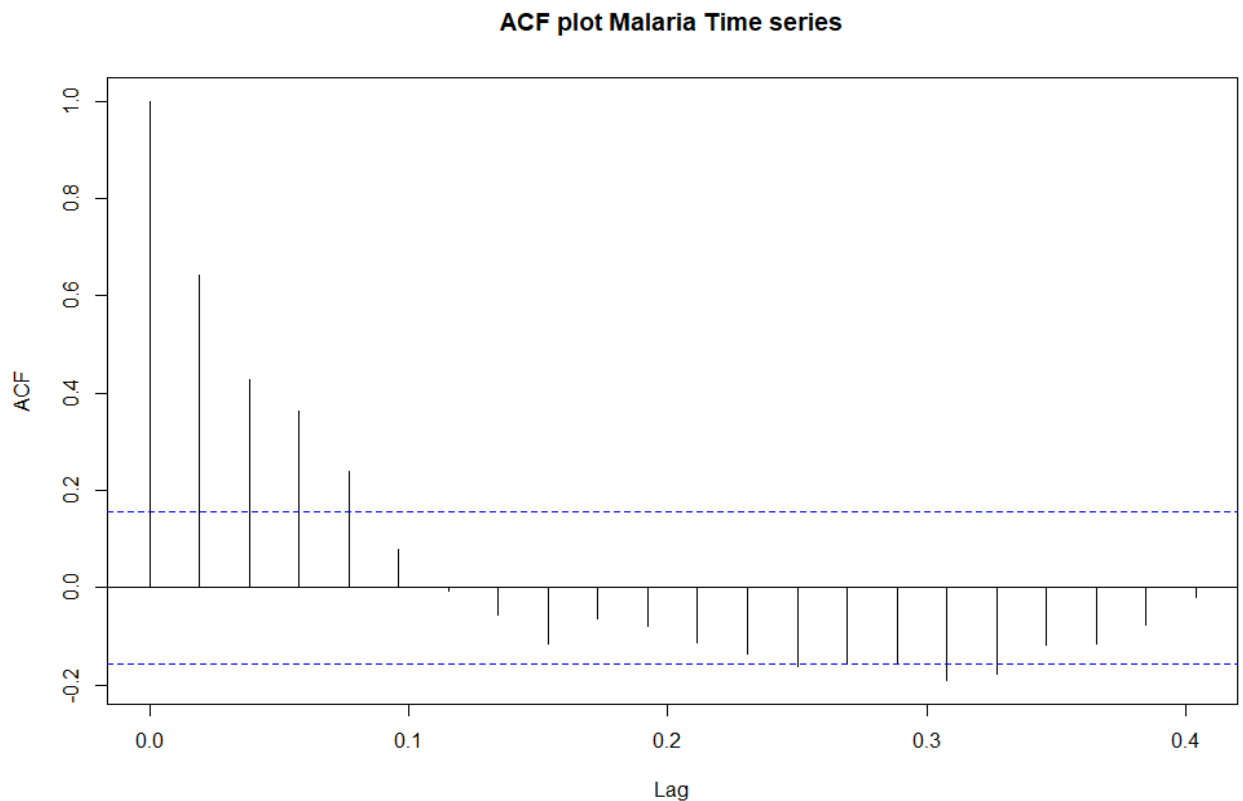


Figure 7: The Autocorrelation Function of reported Malaria cases

The autocorrelation function in Figure 7 of Malaria reported cases from 2014 to 2017 at 95% confidence level spikes significantly at lag 1, 2, 3 and 4. After lag 4 it cuts off, implying that the

moving average component of the ARIMA model of order 4(MA= 4) would be needed to describe this data set.

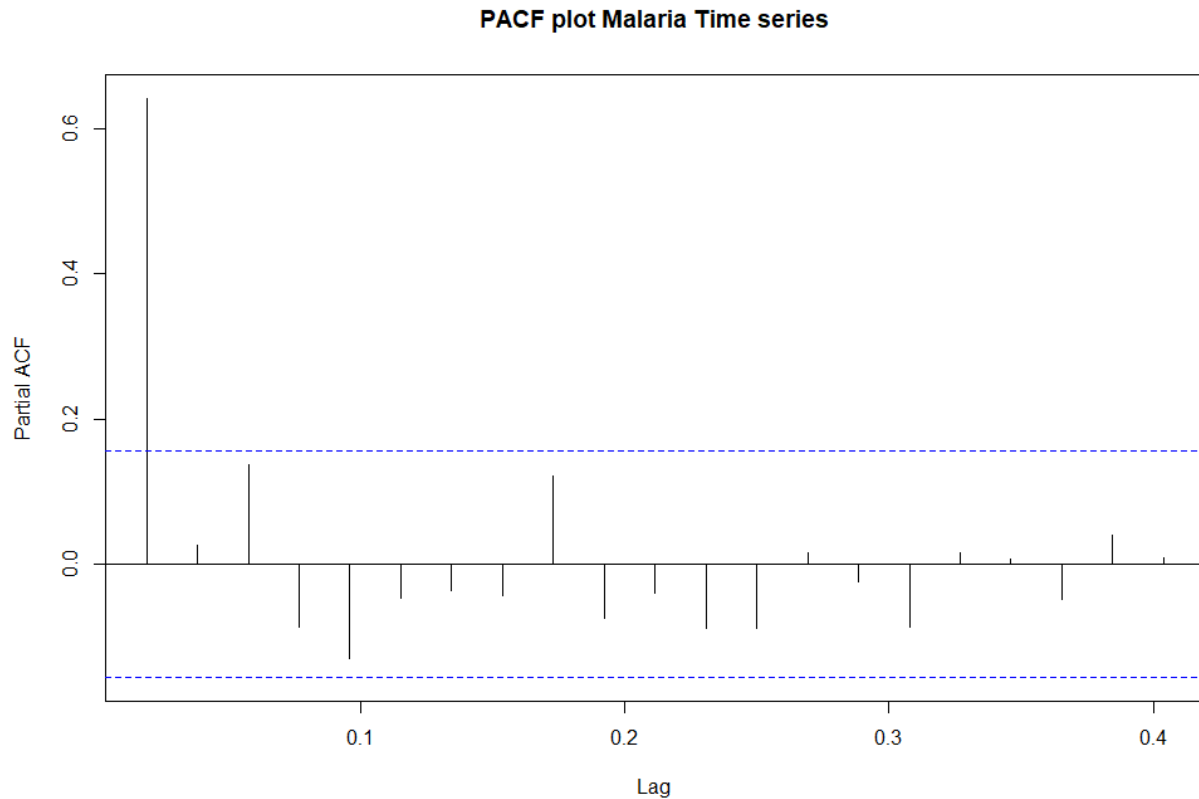


Figure 8: The Partial Autocorrelation Function of reported Malaria cases

The partial autocorrelation function in Figure 8 at 95% confidence level significantly spikes at lag 1 and then quickly cut off, implying that the autoregressive component of the ARIMA model is of order 1(A_R=1).

The ACF and PACF plots in Figures 7 and 8 respectively suggest that $q = 4$ and $p = 1$ would be needed in describing this data set as coming from a moving average and autoregressive process in that order.

Table 4.1: Testing for Stationarity

Tests	Statistics	df	P-Value
Augmented Dicker Fuller Test	-4.7214	Lag = 5	0.01

A constant mean, constant variance and a constant autocorrelation structure signifies a stationary series. The test for stationarity using Augmented Dicker Fuller Test as shown in Table 4.4 depicts that the time series is stationary with a significant p-value of 0.01.

4.2 ARIMA Model Estimations

Several ARIMA models were constructed as follows:

Table 4.2: Model Estimations.

Model	AIC
ARIMA (1, 0, 4)	5585.055
ARIMA (2, 0, 3)	5583.113
ARIMA (3, 0, 2)	5583.516
ARIMA (3, 0, 3)	5585.377
ARIMA (2, 0, 1)	5581.917

In comparing the AIC values of the five likely ARIMA models, it can be deduced that model ARIMA (2, 0, 1) is the best model for the data since it has the lowest AIC value of 5581.917. The smaller the AIC the better, as it indicates stronger evidence for one model over the other in terms of model comparison.

4.3 Diagnostic Analysis

Table 4.3: Test for normality.

Shapiro-Wilk normality test
data: model5\$resid
W = 0.94476, p-value = 9.009e-11

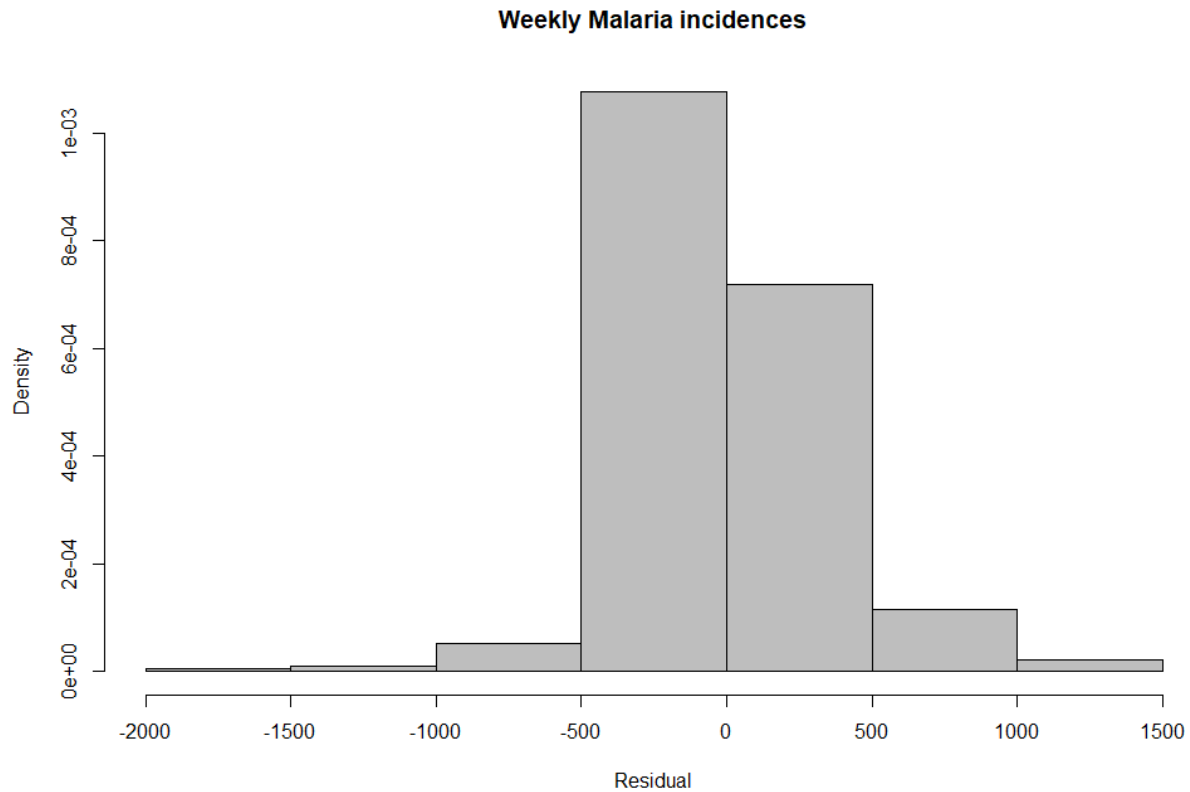


Figure 9: Histogram of the Residuals for ARIMA (2, 0, 1) Model

The diagnostic analyses using Shapiro-Wilk normality test of residuals and the normal probability plot of the residuals as shown in Table 4.5 and Figure 9 show that the residuals of the selected model has a zero mean and a constant variance. Shapiro-Wilk normality test results (p-value = <

0.0001), depicts that the residuals are normally distributed. Consequently, it can be inferred that the true mean of the residuals is approximately equal to zero and there is a constant variance among residuals of the selected model. Hence, all the model assumptions have been satisfied by the selected model. Because the ARIMA (2, 0, 1) satisfies all the necessary assumptions, it can be concluded that the model provides an adequate representation of the data.

4.4 Modeling Incidence of Malaria Cases

Table 4.4: Parameter Estimates of the Poisson Model

Covariate	Coefficients	Estimates	Standard errors	z values	pr(> z)
	Intercept	5.589	0.007	813.061	< 0.001
Locality	Kisumu West (Ref)				
	Nyakach	-0.121	0.008	-15.52	< 0.001
	Kisumu East	-0.612	0.007	-85.078	< 0.001
	Muhoroni	-0.031	0.008	-4.537	< 0.001
	Seme	0.247	0.007	35.972	< 0.001
	Nyando	0.224	0.007	33.985	< 0.001
	Kisumu Central	-0.492	0.013	-38.913	< 0.001
Time in Years	2014 (Ref)				
	2015	-0.083	0.006	-14.86	< 0.001
	2016	-0.074	0.006	-13.12	< 0.001
	2017	-0.224	0.006	-35.807	< 0.001
Total tested for malaria	Total Tested	0.001	0.000	271.587	< 0.001

Significance level <0.05

The fitted Poisson model residual deviance was given as 26219 on 373 degrees of freedom. To verify the fit of the fitted model, the value of the residual deviance 26219 on 373 degrees of

freedom was considered as observed in Table 4.6. $\frac{26219}{373} = 70.292$, a dispersion parameter of

70.292 is an indication that the data is over-dispersed as the value is far greater than 1. This implies that the model is not fit because the mean and variance of the response variable are not equal. If the mean and variance were equal, the residual deviance should be approximately equal to the degrees of freedom.

In this case, the assumption of mean equal to variance of the Poisson random variable was violated and so, a negative binomial regression model was deemed suitable and practical as they cater for over-dispersion. Also, they allow the likelihood ratio and other standard maximum likelihood tests to be applied. The fitted Poisson model had an AIC value of 29318 and a null deviance of 115777 on 383 degrees of freedom. Table 4.5 represents parameter estimates after validating the Poisson model using negative binomial regression model since the assumptions of poisson model was not met.

Table 4.5: Negative Binomial Model Parameter Estimates

Covariate	Coefficients	Estimates	Standard errors	z values	pr(> z)
	Intercept	5.185	0.085	61.076	< 0.001
Locality	Kisumu West (Ref)				
	Nyakach	-0.116	0.091	-1.268	0.205
	Kisumu East	-0.461	0.092	-4.991	< 0.001
	Muhoroni	-0.083	0.087	-0.956	0.339
	Seme	0.336	0.088	3.814	0.000
	Nyando	0.300	0.088	3.396	0.001
	Kisumu Central	-0.375	0.124	-3.024	0.002
Time in Years	2014 (Ref)				
	2015	-0.102	0.072	-1.428	0.153
	2016	-0.092	0.072	-1.272	0.204
	2017	-0.308	0.072	-4.274	< 0.001
Total tested for malaria	Total Tested	0.001	0.000	27.633	< 0.001

Significance level <0.05

The AIC of this model is 5345.2, a deviance of 411.59 on 373 degrees of freedom also following the chi-square distribution $D \sim \chi^2_{(n-p)}$ degrees of freedom. The dispersion parameter was found to be 1.103. Negative Binomial was essentially the best model which fit the data since the dispersion parameter given by Poisson Regression Model had been reduced from 70.292 to 1.103, an indication that the assumptions of poisson regression was not met.

$$\ln(\text{Incidence}) = 5.185 - 0.116\text{Nyakach} - 0.461\text{KisumuEast} - 0.083\text{Muhoroni} + 0.336\text{Seme} + 0.300\text{Nyando} - 0.375\text{KisumuCentral} - 0.102\text{Year2015} - 0.092\text{Year2016} - 0.308\text{Year2017} + 0.001\text{TotalTested}$$

Table 4.6 below shows the goodness of fit results, which clearly indicates that negative binomial regression model is a better fit for the incidence of Malaria compared to the Poisson model. To begin with, the ratios of deviance and Pearson chi-square to degree of freedom $\frac{D}{DF} \sim \chi^2_{(n-p)}$ for the Poisson model are far greater than 1, which is an indication of over-dispersion and thus Poisson is not adequate for modeling such data.

Subsequently, $\frac{D}{DF} \sim \chi^2_{(n-p)}$ negative binomial model ratios are both close to one which exhibits a good fit to the data. Additionally, Pearson chi-square, the lower deviance, and the larger log likelihood values of negative binomial are against those of Poisson. Together all of them share a similar conclusion of favoring the negative binomial model.

Table 4.6 Assessment Criteria for Poisson and Negative Binomial Models

Assessment Parameter	Poisson Regression model	Negative Binomial Regression Model
AIC	29318	5345.2
Residual Deviance	26219	411.59
Degrees of Freedom	373	373
Dispersion parameter	70.292	1.103

From the Table 4.5, Adjusting for Kisumu East, Muhoroni, Seme, Nyando, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Nyakach is $e^{-0.116(0.890)}$ 11% less than those in Kisumu West Sub-County.

Adjusting for Nyakach, Muhoroni, Seme, Nyando, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Kisumu East is $e-0.461(0.630)$ 37% less than those in Kisumu West Sub-County.

Adjusting for Kisumu East ,Nyakach, Seme, Nyando, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Muhoroni is $e-0.083(0.920)$ 8% less than those in Kisumu West Sub-County.

Adjusting for Muhoroni Kisumu East ,Nyakach, Nyando, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Seme is $e0.336(1.399)$ 40% more than those in Kisumu West Sub-County.

Adjusting for Seme, Muhoroni Kisumu East ,Nyakach, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Nyando is $e0.300(1.349)$ 35% more than those in Kisumu West Sub-County.

Adjusting for Nyando, Seme, Muhoroni Kisumu East ,Nyakach, Years 2015,2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in Kisumu Central is $e-0.375(0.687)$ 31% less than those in Kisumu West Sub-County.

Adjusting for Kisumu Central, Nyando, Seme, Muhoroni Kisumu East ,Nyakach, Years 2016,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in the year 2015 is $e-0.102(0.903)$ 10% less than the year 2014.

Adjusting for Kisumu Central, Nyando, Seme, Muhoroni Kisumu East ,Nyakach, Years 2015,2017 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in the year 2016 is $e^{-0.092(0.912)}$ 9% less than the year 2014.

Adjusting for Kisumu Central, Nyando, Seme, Muhoroni Kisumu East ,Nyakach, Years 2015,2016 and the Total number of patients Tested for Malaria ,the average number of reported Malaria cases in the year 2017 is $e^{-0.308(0.734)}$ 27% less than the year 2014.

Adjusting for Kisumu Central, Nyando, Seme, Muhoroni Kisumu East ,Nyakach, Years 2015,2016 and 2017 ,the average number of reported Malaria cases $e^{0.001(1.001)}$ increases by 0.08% for every increase in the number of patients Tested for Malaria.

4.6.1 Significance of the Predictors:

Kisumu East Sub-county is statistically associated with the incidence of Malaria while adjusting for Nyakach, Muhoroni, Seme, Nyando, Kisumu Central, Years 2015, 2016, 2017 and the Total number of patients Tested for Malaria (p-value = < 0.001)

Seme Sub-county is statistically associated with the incidence of Malaria while adjusting for Kisumu East, Nyakach, Muhoroni, Nyando, Kisumu Central, Years 2015, 2016, 2017 and the Total number of patients Tested for Malaria (p-value = 0.001)

Nyando Sub-county is statistically associated with the incidence of Malaria while adjusting for Kisumu East, Nyakach, Muhoroni ,Seme, Kisumu Central, Years 2015,2016,2017 and the Total number of patients Tested for Malaria (p-value = 0.001)

Kisumu Central Sub-county is statistically associated with the incidence of Malaria while adjusting for Kisumu East, Nyakach, Muhoroni, Nyando, Seme, Years 2015,2016, 2017 and the Total number of patients Tested for Malaria (p-value = 0.002)

Controlling for all other covariates, Nyakach and Muhoroni localities do not show any significant association with the incidence of malaria in Kisumu County (p-value = 0.205, 0.339) respectively.

The Year 2017 is statistically associated with the incidence of Malaria while adjusting for Kisumu East, Nyakach, Muhoroni, Nyando, Seme, Kisumu Central, Years 2015,2016 and the Total number of patients Tested for Malaria (p-value = < 0.001)

Controlling for all other covariates, the years 2015, 2016 do not show any significant association with the incidence of malaria in Kisumu County (p-value = 0.153, 0.201) respectively.

The Total number of patients Tested is statistically associated with the incidence of Malaria while adjusting for Kisumu East, Nyakach, Muhoroni, Nyando, Seme, Kisumu Central, Years 2015,2016 and 2017 (p-value = < 0.001)

CHAPTER FIVE

DISCUSSION

5.0 Overview

This chapter delves into the significance and applicability of the study findings. It focuses on expounding and assessing what was found, showing how it relates to the research questions and literature review.

5.1 Discussion

5.1.1 Trend Analysis

Preliminary and further analysis in this study, investigated the change in the yearly trends of Malaria incidence in Kisumu County from 2014 to 2017 to determine if there is any increase or decrease in Malaria reported cases. A trend analysis was applied to the weekly Malaria reported cases and the appropriate ARIMA model fitted. The yearly cases have exhibited a continuous increasing trend except in 2017, where there was a decrease. The recorded yearly malaria cases for this study were also cyclical, for instance, the year 2016 had a shoot up in cases over the years 2014 and 2015 whilst the year 2017 had a decline over all the years.

This increase may be due to improve reporting system by health facilities over time, non-usage of mosquito nets by the residents and low socioeconomic status of the population. This fluctuating incidence recorded yearly could also be attached to the people not being careful about the illness or inconsistencies by the health care authorities in the management of the illness. Whereas, the decreasing trend in 2017 could be due to an increase in the use of mosquito nets, general improvement in the malaria awareness by the population of Kisumu owed to the intensive campaigns in malaria education by several organizations. Climatic changes could have also attributed to this (Anokye, Acheampong, Owusu, & Isaac Obeng, 2018).

The overall pattern of the reported malaria cases as reported by this study had variations in seasons. Weekly cases towards midyear recorded the highest number of cases whereas, the first weeks of the year recorded the lowest number of cases. This could be as a result of heavy rainfall experienced in the months of April, May, June and July which is usually the rainfall season in Kisumu and the temperature associated with rainfall seasons.

This confirms (Craig, Snow, & le Sueur, 1999), (Zhou, Minakawa, Githeko, & Yan, 2004) who revealed that that climate is a major factor in explaining the incidence of malaria. According to (Zhou et al., 2004), the incidence of malaria is influenced by rainfall since Mosquitoes need stagnant water for a complete life cycle. At the same time, (Mabaso, Craig, Ross, & Smith, 2007) also discovered that rainfall seasonality as well as minimum temperature are related to the number of Plasmodium falciparum infective bites got by an individual annually or during a season.

The best fitted time series model developed for predicting the number of weekly reported cases of malaria was ARIMA (2, 0, 1). This suggests that ARIMA (2, 0, 1) can be utilized as a forecasting model to predict the future values of a series. ARIMA works best when data exhibits a constant pattern over time with a minimum amount of outliers (Labys, 2006). Researchers can use this model to forecast malaria reported cases (Nobre, Monteiro, Telles, & Williamson, 2001). Nonetheless, incorporation of current data should be updated from time to time.

5.1.2 Significance of predictor variables on malaria incidences

Accordingly, the study investigated the association between time in years, locality and total number of patients tested for malaria in Kisumu using weekly malaria data from 2014 to 2017.

The study results revealed that, residing in Kisumu East, Seme, Nyando and Kisumu Central sub-counties were statistically associated to the incidence of malaria as compared to residing in Kisumu

West sub-county. Whereas residing in Muhoroni and Nyakach sub- counties were not statistically associated with the incidence of malaria as compared to residing in Kisumu West sub-county. The different localities have demonstrated inequalities in malaria incidence mainly due to variations in access to health services, urbanization and wealth distribution. This is similar to findings by (Galactionova, Smith, de Savigny, & Penny, 2017) in which they identified regional inequalities in the coverage of malaria interventions because of the inequality of the wealth distribution within and across many countries.

Many studies have also established that there is less access to services in the rural areas compared to the urban areas leading to less reported malaria cases from the rural sub-counties. This makes this variable a useful determinant of malaria incidence since some localities are more urban than rural and vice versa.

Generally, fluctuation in malaria incidences is evident through the last four years. The year 2017 was statistically associated to the incidence of malaria as compared to the year 2014. Whereas 2015 and 2016 were not statistically associated with the incidence of malaria as compared to the year 2014. Several factors may be accountable the changes seasonally, for example climatic changes, environmental and ecologic factors, social and economic factors for instance change in health care infrastructure. Accessibility of health facilities and drug resistance also have an influence on incidence of malaria. Although different malaria control activities were present in each year, such as activities to decrease incidence of malaria, insecticide indoor spraying, distribution of ITNs, massive malaria control campaigns and distribution of ITNs the prevalence is still constant. This is similar to findings by (Alemu, Muluye, Mihret, Adugna, & Gebeyaw, 2012).

There was a significant association between the total number of patients tested for malaria and the incidence of malaria. Though urban areas have normally been at lower risk of malaria, unpredictable and unplanned population growth has been a key determinants in causing urban or peri-urban transmission increasingly problematic. This could explain the high malaria incidence in 2016. This finding is consistent to a study carried out by (Knudsen & Slooff, 1992).

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.0 Overview

This chapter presents conclusions from the research and recommendations

6.1 Conclusions

6.1.1 Trends Analysis

The objective of this research was to determine the factors associated with the incidence of Malaria in Kisumu County over time, given the locality where the patients sought health facility intervention, Time in years and the total number of patients who were tested for malaria. The study utilized weekly malaria reported cases data from IDSR Disease Surveillance registry, for the period January 2014 to December 2017 in Kisumu County. Reported malaria cases confirmed by laboratory test was used in the analysis and modeling.

A seasonal pattern was observed in the malaria incidences in Kisumu County. ARIMA (2, 0, 1) model was found to be the best fit statistical model to predict malaria incidences in Kisumu County. The results found from this study offer useful information for policy makers to be able to effectively implement timely and effective malaria preventive and control measures.

6.1.2 Significance of predictor variables on malaria incidences

In selecting which model fitted the malaria reported cases better, goodness of fit model assessment criteria were used by exhausting both Poisson and negative binomial models. Negative binomial model was found to fit the data better than the Poisson model, based on the results. In modeling the incidence of malaria, the analysis produced AIC values (29318), deviance (26219) for the Poisson model and a dispersion parameter of 70.29 showing an over-dispersion in the data leading to a violation of one of its main assumption of the equality of mean and variance parameters.

The results obtained suggested that Kisumu East, Seme, Nyando, Kisumu Central localities, the year 2017 and the total number of patients who underwent a laboratory confirmation test for malaria were significant factors for incidence of Malaria in Kisumu County over time. Whereas, Nyakach, Muhoroni localities, the years 2015 and 2016 were not significant factors for malaria incidences. The findings provide better insight of environmental and socio-economic effects on malaria and provide important information for malaria prediction. Nonetheless, there is need for additional studies to consider which other factors influence the incidence of malaria notwithstanding environmental and socio-economic factors. Likewise, health professionals practicing in Kisumu County should be encouraged to regularly review and report cases of malaria in their facilities. This is because, reporting frequencies, completeness and the consistency of malaria reported cases remain extremely low and importantly was poorer in localities where malaria is endemic.

6.2 Recommendations

The following recommendations were made on the basis of the research findings.

- In view of the findings above, there is need for the county health department to ensure that malaria cases are reported as required by health facilities and their respective reporting tools are available.
- Future studies should focus on what factors influence reporting of malaria cases by health facilities even with the availability of reporting tools and lengthier data set should be used.

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