Malaria Temporal Variation and Modelling Using Time-Series in Sussundenga District, Mozambique

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Abstract

Malaria is one of the leading causes of morbidity and mortality in Mozambique with the 5th highest prevalence in the world. Sussundenga district in Manica Province has documented high *P. falciparum* incidence at the local rural health center (RHC). Sussundenga is a rural district located along the Mozambique, Zimbabwe border. *P. falciparum* transmission in this area is unique as there are differing control policies on each side of the international border. The study objective was to analyze the *P. falciparum* temporal variation and model its pattern in Sussundenga district, Mozambique. Data from weekly epidemiological bulletins (BES) were collected from 2015 to 2019, which records confirmed *P. falciparum* cases from health facilities. These data categorize confirmed cases into two age groups: under 5 years and 5-years and older. *P. falciparum* incidence and temporal variation were calculated. Temporal clusters were identified using dendrograms. A time-series analysis was carried out. For temporal modeling a Box-Jenkins method was used applying an autoregressive integrated moving average (ARIMA). Over the study period, 372,498 cases of *P. falciparum* were recorded in Sussundenga, 177,957 from under 5 years (47.5 %) and 194,541 (52.2 %) from 5 years and older. There were weekly and yearly variations in incidence overall (p < 0.001). There was a decreasing trend in cases for those under 5 years while there was a slight increase in those 5 and older. For those under 5, week 2 of the year had the highest number of cases (1170 Sd 34 ) while week 35 had the fewest (354 Sd 17.8). For those 5-years and older, cases also peak at week 2 (1295 Sd 245) with week 31 having the fewest cases (341 Sd 193.5). The findings indicate that cases are decreasing in those under 5 years and are increasing slightly in those 5 years and over. *The P. falciparum* case occurrence presents a weekly temporal pattern peaking during the wet season. Based on the temporal distribution and using ARIMA modelling, more efficient strategies that target this seasonality can be implemented to reduce the overall malaria burden in Sussundenga District, and regionally.

Background

Malaria is an ancient disease that occupies a unique place in annals of history. During millennia, the victims of the disease includes Neolithic dweller, early Chinese and Greeks, princes and paupers [1]. Globally there were 228 million malaria cases recorded in 2018, one-hundred times more than current COVID19 pandemic, with 405,000 deaths. The sub-Saharan Africa region has the highest burden of malaria cases with 93% of all malaria cases reported from this region. More than half of these cases come from only six countries namely: Nigeria (25%), Democratic Republic of Congo (12%), Uganda (5%), Cotè d’Ivoire, Mozambique, and Niger (4%) each [2].

Mozambique reported 8,921,081 malaria cases with 1114 fatalities in 2018, making it one of the leading causes of morbidity and mortality in the nation. However, little progress in malaria control has been made over the past 20 years [3]. Manica province is in the central region of Mozambique and recorded 821,775 malaria cases occupying the 4th place in the country [4].
Sussundenga district in Manica Province has documented high *P. falciparum* incidence at the local rural health centers (RHC). Sussundenga is a rural district located along the Mozambique, Zimbabwe border. *P. falciparum* transmission in this area is unique as there are differing control policies on each side of the international border.

The goal of the United Nations was to eradicate malaria globally by 2030, with a modeling study determining feasibility with dramatic increases in interventions by 2050 [5]. Very few studies on temporal trends in malaria cases have been reported in Mozambique especially using granular weekly surveillance data. The existing reports are based on monthly data that are not always suitable for local planning purposes. Understanding these underlying trends and variation is very important for planning and timing interventions at the local scale for the highest impact.

Rural Health Centers (RHCs) in Mozambique collect a large volume of time series case data from symptomatic malaria patients. Analyses of these data are retrospective and generally only detect patterns after they have happened. Using these data for mathematical modelling can explain, describe and predict malaria cases. Modelling not only can produce valid results but are inexpensive. This can be helpful for planning in malaria control and eradication efforts [6].

Malaria time series studies using weekly data are not common globally. In Asia studies in Afghanistan and India were carried out to forecast malaria using ARIMA model with monthly data [7, 8]. In Africa the Box-Jenkins modelling was used in Zambia and Ghana for malaria forecasting also using monthly data [9, 10]. In Mozambique malaria morbidity forecasting using ARIMA model were performed using weekly and, ARIMA intervention analysis for mortality monthly data in Chimoio Municipality [11, 12]. Malaria depends largely on weather and, there are great variation over the week. Weeks precipitation of 400 mm followed by 0 mm are common and average temperatures below 18°C and 24 °C in consecutive weeks are also common. These events will greatly influence the mosquito breeding and malaria infection in following weeks. Using monthly data may not captures the events and unappropriated measures taken.

The study objective is to analyze the *P. falciparum* temporal and spatial variation of malaria and model its pattern using weekly data throughout Sussundenga district, to predict the expected malaria occurrence cases in advance, for application of timely prevention and control interventions.

**Material And Methods**

2.1. Study area

Sussundenga is a district of Manica Province in Western Mozambique has a land area of 7,107 square kilometers and a population of approximately 168,000 permanent residents. Located in the center of the province it borders with Manica, Vanduzi, Gondola, and Macate Districts to the north; Mossurize District to the South, Sofala Province to the east, and the Republic of Zimbabwe to the West (Figure 1) [13]. The inhabitants of the district are mainly rural citizens, with 20% under 4 years old and less than 3 % greater than 65 years old. The majority of the population live in traditional huts (90 %) with less than 1% with
piped water, 77 % with no latrine access and less than 3% with electricity [14]. Sussundenga is administratively divided in 4 wards, Sussundenga - Sede, Dombe, Moha and Rotanda, with 15 villages. In the district there are 13 rural health centers (RHCs).

The district presents two major seasons, the rainy from November to March, and the dry season from April to October. The average rainfall is around 1200 mm. The average annual temperature is 21.2°C and the highest temperature recorded was 38.9°C in January and the lowest was 6.3°C, recorded in July [13].

2.2. Study subject

Public RCHs in Sussundenga, collect daily *P. falciparum* malaria case data that are compiled to produce the Weekly Epidemiological Bulletin (BES) and sent to the planning division of Sussundenga District. Here they are compiled to produce the District weekly epidemiologic bulletin. This surveillance system was established in 2015 and is ongoing as part of the national malaria control program (PCMN) These data were collected from 12 of the 13 RHCs, from 2015 to 2019. The 13th RHC was recently built. These reports capture positive cases using mostly rapid diagnostic tests (RDT) SD BIOLINE Malaria Ag P.f. (HRP-II) ™ and few microscopy for confirmation. The weekly surveillance data are included in additional File 1. These data categorize confirmed cases into two age groups: under 5 years and 5-years and older. For population data, the annual population projection from the National Institute of Statistics of Mozambique [15] from 2015 to 2019 was used. Before data analysis missing data were calculated using multivariate normal procedure [16]. A schematic representation of data flow and analysis is presented in Figure 2.

2.3. Data analysis

Analysis of variance (ANOVA) was performed to determine differences between weeks and years using Tukey test for mean separation. The model used was:

\[
Y_{ij} = \mu + \tau_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}
\]  

Where:

\(\mu\) is the overall mean response, \(\tau_i\) is the effect due to the \(i\)-th level of factor A (month), \(\beta_j\) is the effect due to the \(j\)-th of factor B (week) and \(\gamma_{ij}\) is the effect due to any interaction between the \(i\)-th level of A and the \(j\)-th level of B [17].

*P.falciparum* incidence per 100 person-years was calculated dividing the total number of cases by total population and then multiplied by 100 [18].

\[
\text{Incidence rate} = \frac{\text{Total number of cases}}{\text{Total population}}
\]  

The hierarchical cluster analyses followed three basic steps: a) calculate the Euclidian distances using a 1.0 cluster cutoff for the weeks, 2) link the clusters and, 3) choose a solution by selecting the right
number of clusters [19]. For the preparation of choropleth maps of the malaria incidence in Sussundenga District, data on the administrative division of the country was acquired from the Mozambique National Mapping Center (CENACARTA). The data from the administrative division were clipped and added to the incidence data of malaria for age group 0 to and 4 and over five years old categories using ArcGIS 10.7.1 (ESRI, Redlands, CA USA) [20].

The ARIMA model has three values to be determined, namely “p” weeks over P period, each of 52 weeks sets in our dataset, differencing over “d” adjacent weeks or D periods, and moving averages sustained over “q” weeks or Q periods [7]. In other words, the p and q are the number of significant lags of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) plots, respectively, and d is the different order needed to remove the ordinary non-stationarity in the mean of the error terms [21, 22].

The ARIMA model using Box – Jenkins methods was performed in three principal steps:

1) Model identification tentative from the ARIMA class. 2) Estimation of parameters in the identified model. 3) Diagnostic checks.

1. Model identification tentative: in this step, graphical devices namely, autocorrelation function (ACF) and partial autocorrelation function (PACF) as guides to select one or more Autoregressive Integrated Moving Average (ARIMA) models were used.

2. Estimation of parameters in the identified model: in this step, the precise estimate of the coefficients of the model is selected, chosen from the identification step.

3. Diagnostic check: this step is used to determine if the estimated model is statically adequate. If the identified model passes the diagnostic check, the model is ready to be used for forecasting, if it fails, the model is modified through a new cycle process.

After obtaining a stationary series, a basic model can be identified. There are three basic models, AR (autoregressive), MA (moving average) and, their combination ARMA. When regular differencing is applied in conjunction with AR and MA, they are referred as ARIMA, with the “I” meaning “integrated” [10].

The model used was:

\[ y_t = \theta_0 + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q} \]  (3)

Where: \( y_t \) is the real value at the of t, \( \theta \) and \( \phi \) are the moving average and autoregressive coefficients respectively, \( p \) and \( q \) are integer numbers referencing order of the autoregressive and moving average respectively, \( \epsilon_t \) is the error, \( d \) is the differencing parameter [10].

Data were tested for stability plotting the temporal trend and tested using the Mann-Kendal method. The Bartlett test was used to assess normality, and the Dick-Fullert test was performed to determine stationarity. Seasonal differencing was applied to remove seasonal trend. Plots of auto correlation
function (ACF) and partial auto correlation functions (PACF) were created to determine the trends in the data. The lowest values of Akaike Information Criteria (AIC) and Short Bayesian Criteria (SBC) were used to assess the goodness of the fit among identified models. Ordinary least-mean squares (OLS) was used for model estimation. For diagnosis check, residual plots of ACF and PACF and Portmanteau test were used. The forecasting was performed for 52 weeks of 2016. The statistical analysis were carried out using SPSS20, Xlstat and NCSS 2020.

**Results**

3.1. Descriptive and ANOVA

Over the 260 weeks (from 2015 to 2019), 372,498 cases of *P. falciparum* were recorded in Sussundenga, 177,957 from under 5 years (47.5 %) and 194,541 (52.2 %) from 5 years and older (Figure 3). The average weekly cases for the under 5 age group was 680 (Standard deviation (Sd) = 250.1) and 748 (Sd = 320.1) for the 5 and older age group.

Year 2017 had the weeks with highest peaks in cases with 1,263 cases in the under 5 age group at week 9 and 1,797 cases in the 5 and older age group at week 5. The lowest weekly malaria cases were recorded in 2018 with 30 and 19 cases for the under 5 and five and older age groups respectively, both at week 32. On average, the under 5 age group presented the highest number of cases (1,170 sd 34) at week 2 and the fewest cases at week 35 (354 Sd 17.8). In the five and older age group malaria cases were highest at week 2 (1,295 Sd 245) and the lowest cases (341 Sd 193.5) at week 31.

Year 2019 presented the overall highest number of cases for both age groups with 41,887 and 50,326 cases in the under 5 and 5 and older groups, respectively. Year 2018 presented the least cases 27,611 and 30,777 in the under 5 and 5 and older groups, respectively.

Analysis of Variance (ANOVA) indicated a statistically significant difference in malaria incidence between years and weeks, for both categories, P = 0.0001), DF = 204; and Fcal = 38.863 and Fcal = 16.8374, for 0 to 4 and 5 and more years respectively.

For 0 to 4 years old, there was no difference between years 2017 and 2018 and there was difference between the other years (Table 1A). For more than five years old, there was no difference between years 2015, 2016 and 2017 and there was difference between the other years (Table 1B).

Table 1. Malaria cases mean separation between years. A. 0 to 4 years. B. Five and more years.

3.2. Temporal clusters

Figure 4 presents the weekly malaria temporal clusters for age 0 to 4 and 5 and more years old. For 0 to 4 years old, three malaria clusters were identified: cluster 1 of five weeks, from week 31 to 35, where occurs
low cases of malaria, in average 394 sd 168.9 per week. The second cluster, from weeks 20 to 47, with moderate number of cases, in average 570 sd 173.2 cases per week. Cluster 3, from week 48 to week 19, with high malaria cases, in average 855 sd 202.4 weekly.

For five and more years old, two temporal clusters were identified: cluster 1, from week 48 to 24, with high malaria cases, in average 846 sd 272.4 weekly cases and, cluster 2, from week 23 to 47, with moderate cases, in average with 516 sd 171.4 cases.

3.3. Malaria incidence spatial variation for 0 to 4 years old category

Figure 5 presents the choropleth maps of spatial distribution of malaria incidence in the last five years and the average cases in 0 to 4 years. The maps present in average a high concentration of malaria incidence in Sussundenga – Sede RHC and low concentration of malaria incidence in RHCs in Rotanda and Dombe. Moha admirette post presents a moderate concentration of malaria incidence. Overall, children 0 to 4 years in Dombe and Rotanda administrative posts presents 0.5 episodes of malaria per year while, residents of Moha administrative post presents around one-episode case of malaria per year and residents of Sussundenga-Sede presents more than one-episode case of malaria per year.

3.4. Malaria incidence spatial variation for older than five years category

Figure 6 presents the malaria spatial incidence variation from 2015 to 2019 in patients from 5 and more years old. The maps indicate a moderate concentration of malaria incidences in Sussundenga – Sede, Rotanda and Moha admirette posts and low concentration of malaria incidence in admirette posts of Dombe. On average patients in this category will experience 0.27 cases of malaria per year. Overall, one in six residents in Dombe, Rotanda and Moha administrative posts will have an episodes of malaria per year while, one in three residents of Sussundenga-Sede will experience an episode case of malaria per year.

3.5. ARIMA modelling (0 to 4 years old)

Figure 7.A presents the trends for the temporal series plot for age 0 to 4 years. There a decreasing tendency of malaria cases in ages 0 to 4 to years old confirmed by Mann-Kendal test, Sen's slope = -0.521. The series presents several peaks and fluctuations, the weekly peaks are separated by more than few weeks suggesting a seasonal pattern.

The Bartlett test indicated normality for the data, Jack Bera = 4.35, P = 0.114, DF = 2 and no transformation was needed. Dick-Fuller test indicated a non-stationarity of the mean Tau = 4.35, P = 0.114, DF = 2 and first-order differencing was applied and a stationary pattern obtained (Figure 7.B).

Figure 7 C and D presents the features of the data for autocorrelation (ACF) and Partial Autocorrelation (PACF) plot. The ACF indicates an exponential decay and PACF with a single spike at lag 1 suggesting an ARMA (2,1) for non-seasonal and ARMA (1,1) for seasonal components.
In eight experimented, the selected final model for malaria patients 0 to 4 years category was ARIMA (2,2,1) (1,1,1) and the trend equation was:

\[ X_t = 741.0547 - 0.4336641 \times (\text{Date}) \]

All the coefficients were statically significant at 0.05. Table 2A presents the goodness of the fit results.

For diagnostic check, the residual ACF and PACF plot (Figure 5 F and G) both indicate that all the terms are within to the confidence intervals implying that the residuals are “White noise”. The Portmanteau test of the residuals also indicated the model adequacy., Portmanteau = 13.35, P = 0.42, DF = 13.

Using equation 1 the malaria cases for 0 to 4 years patients were forecasted for year 2016 (Table 3). Figure 5 E presents the predicted trends and intervals (90 ad 95 %).

3.6. ARIMA modelling (Five and more years old)

Figure 8.A presents the trends for the temporal series plot for five and older years. There is an increasing tendency of malaria cases in five and more years old patients confirmed by Mann-Kendal test, Sen’s slope = 0.100. The series presents several peaks and fluctuations, the weekly peaks are separated by more than few weeks suggesting a cyclical pattern.

The Bartlett test indicated normality for the data, Jack Bera = 17.17, P = 0.1011, DF = 2. Dick-Fuller test indicated a non-stationarity of the mean, Tau = -3.96, P = 0.118, DF = 2, and first-order differencing was applied and a stationary pattern obtained (Figure 8.B).

Figure 8 C and D presents the features of the data for autocorrelation (ACF) and Partial Autocorrelation (PACF) plot. The ACF indicates an exponential decay and PACF with a single spike at lag 1.

In eight experimented, the selected final model for malaria patients with five and more years was ARIMA (2,2,1) (1,1,1) and the trend equation was:

\[ X_t = (715.3047) + (0.2524547) \times (\text{Date}) \]

All the coefficients were statically significant at 0.05. Table 2.B, presents the goodness of the fit results for age category five and more years.

For diagnostic check, the residual ACF and PACF plot (Figure 7 F and G) both indicate that all the terms are interior to the confidence limit implying that the residual are “white noise”. The Portmanteau test of the residuals also indicated the model adequacy to lag 16, Portmanteau = 13.29, P = 0.4253, DF = 13.

Using equation 1 the malaria cases for 0 to 4 years patients were forecasted for year 2016 (Table 3). Figure 5 E presents the predicted trends and intervals (90 ad 95 %).

Discussion
Malaria occurrence varies between weeks and years is Sussundenga. This pattern was also reported in Chimoio, Mozambique and other regions in the world [23, 28, 29]. This study identified three malaria clusters of malaria occurrence for under five age categories. One with the highest number of cases occurring from week 48 to week 19 coinciding with the rainy season and hot weather. Another cluster from week 31 to 35 with the lowest number of cases, coinciding with a dry and hot period when there is low humidity. The last cluster from weeks 20 to 47, with moderate number of cases coinciding with a dry and cold season. For age category over five years old, only two cluster where identified, one from week 48 to 24, with high malaria cases, coinciding with the rainy season and another cluster from week 23 to 47 coinciding with the dry period. Similar pattern was reported in Chimoio and Maputo [23,26]. Similar pattern was reported in Senegal 23 % of malaria positive cases were reported during rainy season and 9 % during dry season.[30]. Seasonal differences in bloodstream infectious diseases was also reported in central Europe [31].

The malaria incidence in this study was 91.3 per 100 for under five patients and 27.3 per 100 in over five categories. Nigeria reported 27% of parasitemia in children [2]. In Chimoio an average of 20.5 per 100 persons malaria incidence was reported, in Manica Province 43 per 100 persons and 33 per 100 persons in Beira [23,31,32]. The World Health Organization reported an positivity testing of 30 % for Mozambique [2].

This study finds a spatial variation of malaria cases between administrative wards. Similar results were reported in Mozambique [23, 28, 32] in Africa [33, 34] and other parts of the World [35, 36]. This study finds a decreasing tendency of malaria cases for age category 0 to 4 years. The reduction of malaria cases in children can be attributed to the mother’s attentiveness, at the first sign of fever they take their children to the health unit. The decreasing pattern in this category was also reported by the World Health Organization for Mozambique [3]. In Tanzania the peak prevalence shifted from children 5 to 9 years to those aged 10 to 19 years [35]. Decreasing cases in this age range and shift to higher ages with clinical malaria may be an indicator of effective malaria control.

Findings in this study indicated that the under five patients have more malaria cases than the age group five and more year old. Similar results were reported in Chimoio [23], in South Africa under five patients reported malaria positivity and in Zimbabwe 90 % of malaria cases were from age group five and more years old [26, 27].

Both qualitative and quantitative bioinformatics models are advocated for forecasting and public health promotion [40]. An agent-based model validated real data of malaria incidence collected in Chimoio, Mozambique [41]. In recent years an increase usage of time series techniques is observed giving better results [42].

The ARIMA (2,2,1) (1,1,1) 52 models in this study provide the best possible approach to forecast malaria cases per week over the years for different age categories. The goodness of the fit was 68.15% for under five malaria patients and 73.2 % for over five-year-old patients. Very few ARIMA studies were carried out using weekly data. In Chimoio a similar study indicated and ARIMA (2,1,0) (2,1,1) model with the
goodness of fit of 72.5 % [12]. Similar studies were carried out in Ghana, Afghanistan, India, Ghana, Zambia, South Africa and Senegal and Nigeria using monthly data with comparable results [7,8, 9, 10, 26, 29].

The ARIMA model of this study is robust and inexpensive and can predict the expected number of malaria cases in advance. This can lead to timely prevention and control planning measures such as awareness campaign, correct time and place to spray and, elimination of vector breeding places. As a result, malaria reduction can occur saving lives and improving livelihood of the Sussundenga inhabitants.

5. Limitations of the study

This study result may be over or under estimated since generally there are underreported cases, especially from places with absence of health center and, some cases patients may be diagnosed more than once a year, self-medication and use of traditional healers [23]. The missing data were 13 %. Missing data proportion is directly related to the quality of statistical inference although, there is no established cutoff regarding an acceptable percentage of missing data set for valid statistical inferences [44].

Conclusion

The findings indicate that cases are decreasing in those under 5 years and are increasing slightly in those 5 years and over. *The P. falciparum* case occurrence presents a weekly temporal and spatial pattern peaking during the wet season. Based on the temporal distribution and modelling using ARIMA, more efficient strategies that target this seasonality can be implemented to reduce the overall malaria burden in Sussundenga District, and regionally. The model can be used to test other infectious diseases and other models should be tested.

Declarations

Ethics of approval and consent to participate

This study is part of the Malaria Risk, Prevention, and Health Seeking Behaviors in Sussundenga, Mozambique Project. All participants, or the guardians provided informed written assent and consent prior to participation. To carry out the study approval from the institutional Review (IRB) committee from the University of Minnesota and, from Comissão Nacional de Bioética em Saúde (CNBS) from the Ministry of Health of Mozambique, approval number 560/CNBS/19.

Consent for publication

N/A

Availability of data and materials
Data are available as additional file 1.

**Competing interests**

The authors declare that they have no any competing interests

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**Authors contributions**

JLF contributed in supervising the data collection process, writing the manuscript and statistical analysis, DE contributed in English revision, AN contributed in field data collection, RM contributed in Mapping, AT contributed in data collection, KS contributed in critical manuscript revision data collection and VM contributed in blood collection RDT test.

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Tables

Table 1. Malaria cases mean separation between years. A. 0 to 4 years. B. Five and more years.

| Year | 2015 | 2016 | 2017 | 2018 | 2019 |
|------|------|------|------|------|------|
| Weeks | 52   | 52   | 52   | 52   | 52   |
| Mean  | 737⁻ | 700ᵇ | 648ᶜ | 531ᶜ | 806ᵈ |
| Sd    | 246  | 194  | 236  | 228  | 252  |

| Year | 2015 | 2016 | 2017 | 2018 | 2019 |
|------|------|------|------|------|------|
| Weeks | 52   | 52   | 52   | 52   | 52   |
| Mean  | 687ᵃ | 760ᵃ | 735ᵃ | 592ᵇ | 968ᶜ |
| Sd    | 270  | 247  | 276  | 289  | 374  |

ᵃ,ᵇ,ᶜ different letters indicate difference between years

Table 2. Parameter and goodness of fit estimation and measures. A. 0 to 4 years. B. Five and more years

A
| Parameter | Coefficient | SE  | AIC    | SBC    |
|-----------|-------------|-----|--------|--------|
| AR(1)     | 0.6182404   | 0.064 | 1959.42 | 1971.57 |
| AR(2)     | 0.2397399   | 0.063 |        |        |
| MA(1)     | 0.0478899   | 0.178 |        |        |
| $R^2$     | 68.15       |      |        |        |
| RMS       | 140.4589    |      |        |        |

**B**

| Parameter | Coefficient | SE  | AIC    | SBC    |
|-----------|-------------|-----|--------|--------|
| AR(1)     | 0.701       | 0.065 | 1997.84 | 2009.98 |
| AR(2)     | 0.189       | 0.063 |        |        |
| MA(1)     | 0.999       | 0.186 |        |        |
| $R^2$     | 73.2        |      |        |        |
| RMS       | 140.4589    |      |        |        |

$AR_1$ and $MA_j$ are the $i$th order of autocorrelation (ACF) and Partial autocorrelation (PACF) respectively.

AIC Alkaline Information Criterion, SBC Schwartz Bayesian Criterion $R^2$, Determination coefficient, RMA, root mean square.

Table 3. Malaria cases forecast for 0 to 4 years patients were forecasted for year 2016
| Weeks | Forecast | LL 95% | UL 95% | Weeks | Forecast | LL 95% | UL 95% |
|-------|----------|--------|--------|-------|----------|--------|--------|
| 1     | 644.5    | 327.5  | 961.4  | 27    | 616.6    | 148.4  | 1084.8 |
| 2     | 622.8    | 266.3  | 979.2  | 28    | 616.2    | 147.9  | 1084.4 |
| 3     | 628.1    | 245.7  | 1010.5 | 29    | 615.7    | 147.4  | 1084.0 |
| 4     | 626.1    | 223.9  | 1028.3 | 30    | 615.3    | 147.0  | 1083.6 |
| 5     | 626.1    | 209.1  | 1043.2 | 31    | 614.9    | 146.5  | 1083.2 |
| 6     | 625.6    | 197.2  | 1054   | 32    | 614.4    | 146.0  | 1082.8 |
| 7     | 625.2    | 188    | 1062.4 | 33    | 614.0    | 145.6  | 1082.4 |
| 8     | 624.8    | 180.8  | 1068.7 | 34    | 613.6    | 145.2  | 1082.0 |
| 9     | 624.3    | 175.1  | 1073.6 | 35    | 613.1    | 144.7  | 1081.5 |
| 10    | 623.9    | 170.5  | 1077.3 | 36    | 612.7    | 144.3  | 1081.1 |
| 11    | 623.5    | 166.9  | 1080.1 | 37    | 612.3    | 143.8  | 1080.7 |
| 12    | 623.1    | 163.9  | 1082.2 | 38    | 611.8    | 143.4  | 1080.3 |
| 13    | 622.6    | 161.5  | 1083.7 | 39    | 611.4    | 142.9  | 1079.8 |
| 14    | 622.2    | 159.5  | 1084.9 | 40    | 611.0    | 142.5  | 1079.4 |
| 15    | 621.8    | 157.9  | 1085.7 | 41    | 610.5    | 142.1  | 1079.0 |
| 16    | 621.3    | 156.5  | 1086.2 | 42    | 610.1    | 141.6  | 1078.5 |
| 17    | 620.9    | 155.3  | 1086.5 | 43    | 609.7    | 141.2  | 1078.1 |
| 18    | 620.5    | 154.3  | 1086.7 | 44    | 609.2    | 140.8  | 1077.7 |
| 19    | 620.0    | 153.3  | 1086.7 | 45    | 608.8    | 140.3  | 1077.2 |
| 20    | 619.6    | 152.5  | 1086.7 | 46    | 608.4    | 139.9  | 1076.8 |
| 21    | 619.2    | 151.8  | 1086.5 | 47    | 607.9    | 139.5  | 1076.4 |
| 22    | 618.7    | 151.2  | 1086.3 | 48    | 607.5    | 139.0  | 1075.9 |
| 23    | 618.3    | 150.5  | 1086.1 | 49    | 607.1    | 138.6  | 1075.5 |
| 24    | 617.9    | 150.0  | 1085.8 | 50    | 606.6    | 138.2  | 1075.1 |
| 25    | 617.5    | 149.4  | 1085.5 | 51    | 606.2    | 137.7  | 1074.6 |
| 26    | 617.0    | 148.9  | 1085.1 | 52    | 605.8    | 137.3  | 1074.2 |

Table 4. Malaria cases forecast for five and older patients were forecasted for year 2016
| Weeks | Forecast | LL 95%  | UL 95%  | Weeks | Forecast | LL 95%  | UL 95%  |
|-------|----------|---------|---------|-------|----------|---------|---------|
| 1     | 821.2    | 432.1   | 1210.3  | 27    | 790.1    | 174.5   | 1405.8  |
| 2     | 812.4    | 370.2   | 1254.7  | 28    | 790.2    | 174.3   | 1406.0  |
| 3     | 810.7    | 331.2   | 1290.3  | 29    | 790.2    | 174.2   | 1406.1  |
| 4     | 807.9    | 299.8   | 1316.3  | 30    | 790.3    | 174.2   | 1406.3  |
| 5     | 805.6    | 275.5   | 1335.8  | 31    | 790.3    | 174.2   | 1406.5  |
| 6     | 803.6    | 256.2   | 1350.9  | 32    | 790.4    | 174.2   | 1406.6  |
| 7     | 801.7    | 240.7   | 1362.7  | 33    | 790.5    | 174.3   | 1406.8  |
| 8     | 800.1    | 228.3   | 1371.9  | 34    | 790.7    | 174.4   | 1407.0  |
| 9     | 798.7    | 218.2   | 1379.1  | 35    | 790.8    | 174.5   | 1407.2  |
| 10    | 797.4    | 210.0   | 1384.8  | 36    | 791      | 174.6   | 1407.3  |
| 11    | 796.3    | 203.3   | 1389.2  | 37    | 791.1    | 174.7   | 1407.5  |
| 12    | 795.3    | 197.8   | 1392.7  | 38    | 791.3    | 174.9   | 1407.7  |
| 13    | 794.4    | 193.3   | 1395.5  | 39    | 791.5    | 175.0   | 1407.9  |
| 14    | 793.7    | 189.7   | 1397.7  | 40    | 791.7    | 175.2   | 1408.1  |
| 15    | 793      | 186.6   | 1399.4  | 41    | 791.8    | 175.4   | 1408.3  |
| 16    | 792.4    | 184.2   | 1400.7  | 42    | 792      | 175.6   | 1408.5  |
| 17    | 792      | 182.1   | 1401.8  | 43    | 792.2    | 175.8   | 1408.7  |
| 18    | 791.5    | 180.5   | 1402.6  | 44    | 792.5    | 176.0   | 1408.9  |
| 19    | 791.2    | 179.1   | 1403.3  | 45    | 792.7    | 176.2   | 1409.1  |
| 20    | 790.9    | 178.0   | 1403.9  | 46    | 792.9    | 176.4   | 1409.4  |
| 21    | 790.7    | 177.1   | 1404.3  | 47    | 793.1    | 176.6   | 1409.6  |
| 22    | 790.5    | 176.3   | 1404.6  | 48    | 793.3    | 176.8   | 1409.8  |
| 23    | 790.4    | 175.8   | 1404.9  | 49    | 793.6    | 177.1   | 1410.0  |
| 24    | 790.3    | 175.3   | 1405.2  | 50    | 793.8    | 177.3   | 1410.3  |
| 25    | 790.2    | 174.9   | 1405.4  | 51    | 794      | 177.5   | 1410.5  |
| 26    | 790.1    | 174.7   | 1405.6  | 52    | 794.2    | 177.8   | 1410.7  |