

On Time Domain Analysis of Malaria Morbidity in Nigeria

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Abstract That malaria contributes substantially to the poor health situation in Africa is an understatement. To help government in the continuous provision of necessary measures needful to curb increasing spread of the parasites, there is a need to build an appropriate time domain model which can be used to forecast the future rate of spread. As a result of this, ARIMA model was built for analyzing the secondary data collected on the incidence of malaria. It was discovered that the data was not stationary and stationarity was achieved through 2nd order differencing. The ACF and PACF of the differenced data suggested possible models for selection. AIC and MSE were used to select the models that really provided a best fit for the time series. From various ARIMA models generated, ARIMA (2, 2, 3) model was found to best fit the malaria data. Ljung-Box test and Shapiro-Wilk test met all necessary conditions for independence and normality. The model was used for forecast and it was observed that there is going to be a steady increase in malaria prevalence.

Keywords: autocorrelation function, partial autocorrelation function, stationarity, malaria morbidity, ARIMA

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1. Introduction

Malaria is a great burden on the African health system, as it is responsible for 20 to 40 % of outpatient visits and 10 to 15% of hospital admissions [1]. In Sub-Saharan Africa (SSA), 10.8% of all disability-adjusted life years (DALYs) were lost to malaria in 1990 causing it to ranked second after HIV/AIDS. Furthermore, while malaria contributed 2.05% to total global deaths in 2000, it was responsible for 9.0% of all deaths in Africa [2].

According to WHO (1997), the total cost of malaria to Africa was US\$1.8 billion in 1995 and US\$ 2 billion in 1997. Malaria is also a major problem in Papua New Guinea as it accounts for a high proportion of sickness and death. This is because in addition to human suffering, it also put severe stress on the health facilities and directly hinders economic growth. It has been suggested that a malaria vaccines would be best, most cost effective and safe public health measure to reduce the burden of malaria [3]. While its effect on people of all ages is quite immense, the most serious impact of malaria is on pregnant women and children because they have less immunity. When a malaria infection is not properly treated in pregnant women, it can cause anemia and also lead to miscarriages, stillbirths, underweight babies and maternal deaths. It has been one of the greatest burdens to mankind, with a mortality rate that is unmatched by any other modern disease other than tuberculosis [4] and it remains the

leading cause of death in children under five years in Africa [5].

Also, frequent cerebral malaria can lead to disabling neurological consequences. With regards to school children, malaria is a major cause of absenteeism in endemic countries. It is estimated that about 2% of children who recover from cerebral malaria suffer brain damage including epilepsy [2]. Durueke [6] carried out a research on the incidence, management and bionomic of malaria in children under 5years of age in some parts of Imo State using chi-square test for proportion, the results revealed that the incidence of malaria in the studied area was inversely proportional to the socio-economic levels and standard of living of the areas under study. Gerritsen *et al.* [7] carried out an analysis on malaria incidence in Limpopo Province South Africa from 1998 to 2007, using chi-square test of independence and time series analysis, the result showed that out of 58768 cases of malaria reported including 628 deaths, the mean incidence of malaria was 124.5 per 100, 000 person and the mean mortality rate was 1.1% per season. Also, there was a decreasing trend in the incidence over time, and the mean incidence in males was higher than in females. Ayeni [8] conducted a research on Malaria Morbidity in Akure South West, Nigeria using time series analysis. The result revealed that malaria morbidity was generally low before 2004 and that the reported cases of malaria increased from 43,533 in 2004 to about 62,121 cases in 2008. From the result also, malaria morbidity index revealed an increase of 0.005 annually between 2000 and 2008. Korenromp *et*

al. [9] carried out a study titled “Forecasting Malaria Incidence based on monthly case reports and Environmental Factors in karuzi Burudi, from 1997 to 2003”. Using time series analysis, the result revealed that the exploration of the incidence of malaria, precipitation, temperature and vegetation for 1997 to 2003 showed no clear trend, and suggests a seasonal dependency in the series with a 6-month period for the incidence and a 12-month period for rainfall, temperature and vegetation. Opara [10] carried out a study titled “The effects of malaria during pregnancy on infant mortality in Abia State Nigeria between 1993 and 1999”. Using chi-square test for independence, the result showed that malaria during pregnancy increased neonatal mortality by lowering birth weight. Adebola and Okereke [11] conducted a study titled “Increasing Burden of Childhood Severe Malaria in a Nigerian Tertiary Hospital: Implication for control, between January 2000 and December 2005”. Using logistic Regression, the result showed that severe Malaria constituted an important cause of hospital admission among Nigerian children especially those aged below 5years. The result also revealed that there was significant increase in the proportion of cases of severe malaria from 2000 to 2005. In a parasitology laboratory, malaria was found to be the major killer among pediatric illness and death in Kinshasa [12]. Baird *et al.* [13] conducted a research on the seasonal malaria attack rates in infants and young children in northern Ghana from 1996 to 1997. Using fisher’s exact test and chi-square test of independence, the results showed that the mean parasitemia count at the time of reinfection in the dry season roughly equaled that in the wet season. Among authors who have equally worked on malaria incidence with sufficient contributions are Wilson [14]; Reed *et al.* [15]; Gurein *et al.* [16]; Pattanayak *et al.* [17]; Lindsay *et al.* [18]; Nchinda [19]; Sulaimon [20]; Wiwanitkit [21];

Thus, the burden of malaria is a challenge to human development and despite the devastating effects of the disease, the importance of a malaria-free environment in promoting economic development and poverty reduction has not been fully appreciated in Nigeria. This challenge should therefore be faced with resolve since good health is not only a basic human need but also a fundamental human right and a prerequisite for economic growth [22].

Perhaps the impact of malaria has not been demonstrated in sufficient quantitative terms that might convince politicians, policy makers, program managers and development partners to devote the needed attention and resources to combating this dreadful disease in the country. It has however becomes necessary to develop a stochastic model that will help in predicting the prevalence of this disease in future and assist the Government in formulating policies that will help in curbing this deadly disease among communities in south western part of Nigeria.

2. Materials and Methods

The population of this study shall be based on the monthly malaria cases recorded in Ogun State Hospital, Ilaro between January 2003 and December 2015 respectively.

The general notation of ARIMA model is ARIMA (p, d, q) , where “ p ” is the order of Autoregressive Component, “ d ” is the order of differencing used and “ q ” is the order of Moving average components in the model. The Autoregressive and Moving Average Component are described below and the concept of differencing is described in the next section.

Depending on the above definition, the ARIMA models can be classified into

2.1. Autoregressive (AR) Models.

When the value of the current output y_t depends solely on p prior outputs and the current input (random shock) etc, the Box-Jenkins model takes the form of

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + e_t \quad (1)$$

Or

$$\Phi(B)y_t = e_t \quad (2)$$

and is called an Autoregressive Model of order p , denoted by AR(p) or ARIMA $(p, 0, 0)$.

2.2. Moving Average (MA) Models.

When the current output y_t depends solely on the current input and q prior inputs, the Box-Jenkins Model takes the form of

$$y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (3)$$

Or

$$y_t = \Theta(B)e_t \quad (4)$$

and is called a Moving Average of order q , denoted by MA(q) or ARIMA $(0, 0, q)$.

2.3. Mixed Autoregressive and Moving Average (ARMA)

When the current output y_t depends on both the AR and MA process, the Box-Jenkins model, takes the form of equation (1) and is called an Autoregressive and Moving Average Model, denoted by ARMA(p, q) or ARIMA (p, d, q) when stationary has been achieved through differencing. Stationary is achieved using

$$w_t = \nabla y_t = y_t - y_{t-1}. \quad (5)$$

It can be shown that $y_t - y_{t-1} = (1 - B)y_t$ for a difference of order one.

A difference of order two implies that the first order differenced series is differenced again resulting in

$$\begin{aligned} k_t &= w_t - w_{t-1} = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\ &= y_t - 2y_{t-1} + y_{t-2}. \end{aligned} \quad (6)$$

The result again is a new time series k_t , having two less observations than the original series y_t .

This can be generated to d^{th} order differencing, where d is the order of differencing required to achieve mean stationarity. Thus, the general ARIMA model is given as

$$y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \tag{7}$$

The one-step ahead forecast for time t+1 is given by:

$$y_t = \phi_1 y_t + \phi_2 y_{t-1} + \dots + \phi_p y_{t-p+1} + e_{t+1} - \theta_1 e_t - \theta_2 e_{t-1} - \dots - \theta_q e_{t-q+1} \tag{8}$$

Except e_{t+1} the random shock at time $t + 1$, all other parameters are known.

All the identified parameters shall be estimated using the method of maximum likelihood.

Upon the fitting of the above discussed model, diagnostic checks shall be carried out to ensure normalcy using the following validity checks

- Residual Analysis
- Shapiro – Wilk Test of Normality
- The Ljung-Box Test - A portmanteau test according to Box and Pierce (1970) proposed statistic:

$$Q = n \left(\hat{p}_1^2 + \hat{p}_2^2 + \dots + \hat{p}_k^2 \right) = n \sum_{k=1}^n \hat{p}_k^2 \tag{9}$$

Thus, a general “portmanteau” test would reject the ARIMA (p, d, q) model if the observed value of Q exceeds an appropriate critical value in a Chi-Square distribution with $k - p - q$ degrees of freedom.

• **The Akaike Information Criterion (AIC)**

The AIC is defined as

$$AIC = -2l / T + 2K / T \tag{10}$$

Where l is the log likelihood computed as:

$$I = -\frac{T}{2} \left\{ 1 + \log_e(2\pi) + \log_e \left(\frac{\hat{e}'\hat{e}}{T} \right) \right\} \tag{11}$$

3. Results

3.1. Checking for Stationarity and Determination of The Appropriate Arima Order

On checking for stationarity and determination of the appropriate arima order, the following graphs and tables were derived

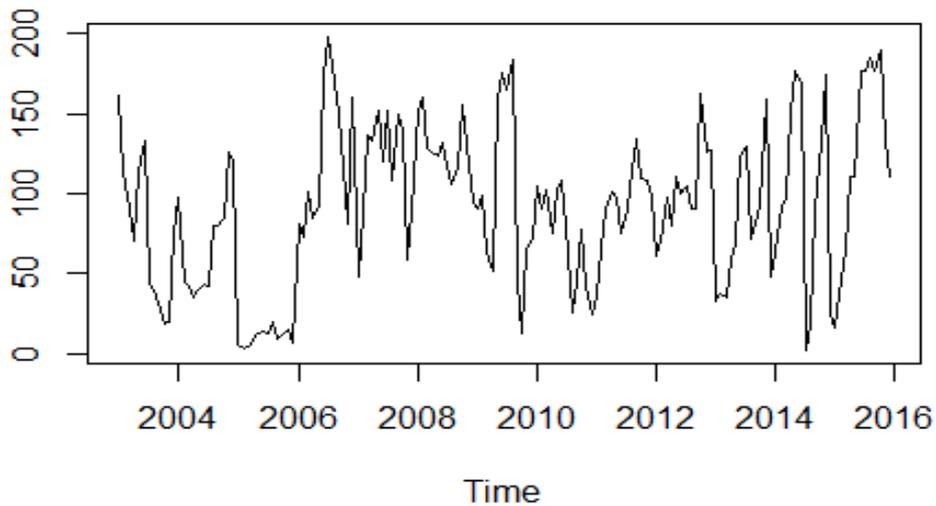


Figure 1. Time series plot of malaria data

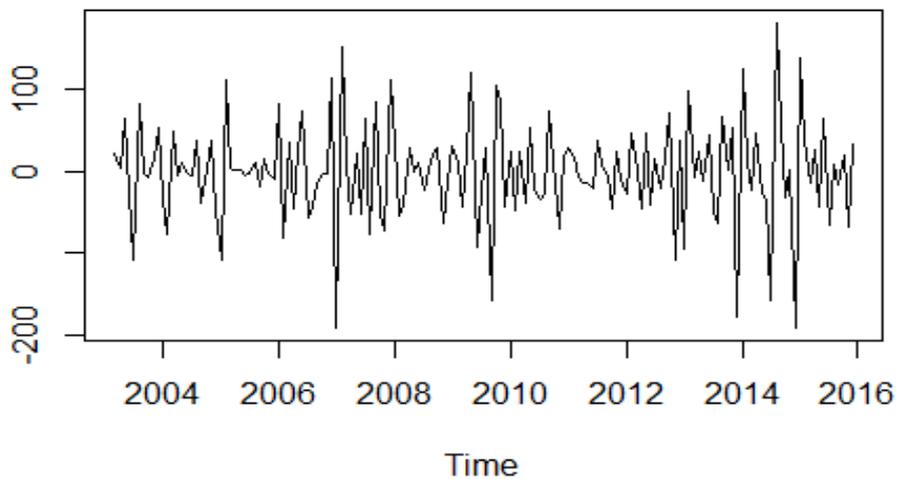


Figure 2. Plot of 2nd differenced malaria data.

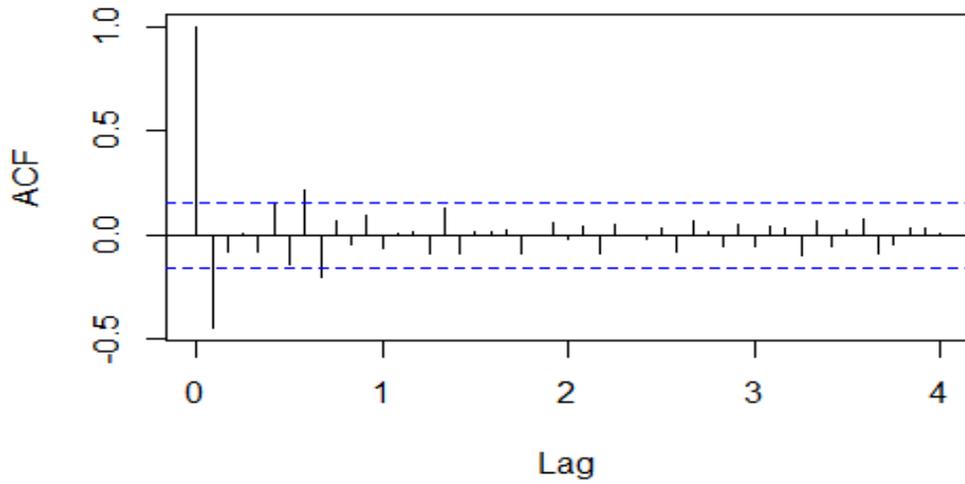


Figure 3. ACF plot of 2nd differenced malaria data

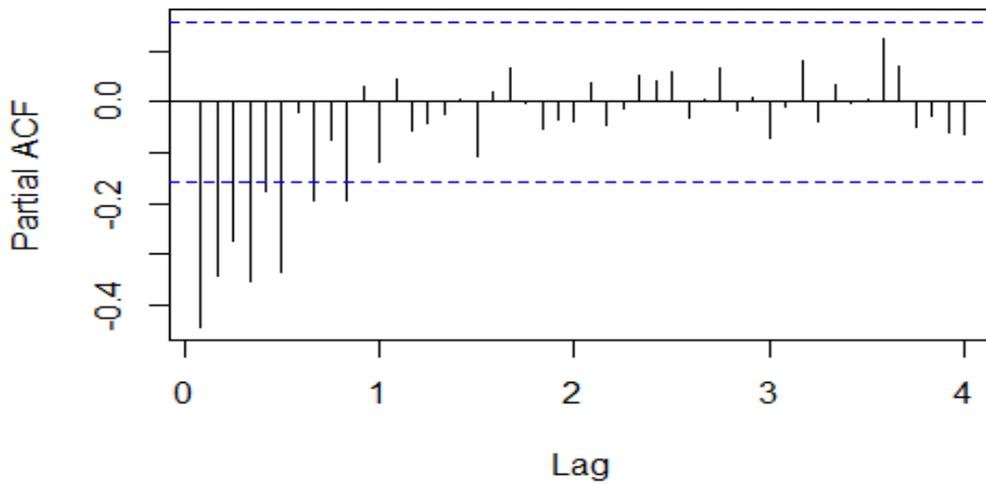


Figure 4. PACF plot of 2nd differenced malaria data

Table 1. Possible ARIMA Models for Malaria Series

Model	AIC	BIC	LOG LIKELIHOOD	MSE (σ^2)
(1, 2, 2)	1578.69	1590.840	- 785.35	1485
(1, 2, 1)	1596.53	1605.640	- 795.26	1731
(2, 2, 2)	1578.82	1594.008	- 784.41	1457
(3, 2, 1)	1587.07	1602.254	- 788.53	1576
(3, 2, 2)	1578.79	1597.012	- 783.4	1453
* (2, 2, 3)	1571.03	1589.249	- 779.51	1367 *
(1, 2, 3)	1582.59	1597.779	- 786.3	1516
(3, 2, 3)	1572.47	1593.731	- 779.24	1365
(4, 2, 3)	1571.91	1596.204	- 777.95	1351
(4, 2, 4)	1570.32	1597.652	- 776.16	1316

Model specification for the best fit ARIMA order in Table 1 is given as:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3}. \quad (12)$$

Substituting the values of the parameters, we have

$$y_t = -0.2503y_{t-1} + 0.4299y_{t-2} + e_t + 0.9515e_{t-1} + 0.9487e_{t-2} - 0.9002e_{t-3} \quad (13)$$

3.2. Diagnostic Check on ARIMA (2, 2, 3) Model

The Shapiro-Wilk test of normality gives a test statistic of $W = 0.93379$, with a P-value of 0.0000012 which indicates that the residuals are normally distributed at 1%, 5% and 10% significance levels.

The Ljung-Box test statistic examines the null hypothesis of independence in the residuals of the Malaria series with

a Chi-squared value of 26.262 and a P-value of 0.9955 which lead to the acceptance of null hypothesis that all the autocorrelation functions are zero and this shows that ARIMA (2, 2, 3) is sufficient in modeling the incidence of malaria in Nigeria.

4. Discussion

From Figure 1 above, the series indicates non-stationarity, with both upward and downward movements. However, in order to achieve stationarity, the series was subject to second order differencing as shown in Figure 2. The ACF and PACF of the differenced series were then carried out as reflected in Figure 3 and Figure 4 to check for stationarity. These lead to a significant spike at lag 1 and dies off up to lag 48 for ACF and decay slowly in the PACF up to lag 8. The stationarity of the series is further

confirmed by performing the Augmented Dickey Fuller Test with ADF value of -14.794 and p value of 0.000 up to lag 48. Since the P-value is less than 0.05, we therefore fail to accept H_0 and hence conclude that the series is stationary in its mean and variance. This test brings to reality the fitting of a suitable ARIMA model. With few iterations on this model building strategy, a suitable ARIMA model of order (2, 2, 3) was derived for the series based on its lowest AIC, BIC and MSE values compared to others.

Forecasting From ARIMA (2, 2, 3)

Based on the set objectives of this research, forecasting was done using the fitted ARIMA model for five years forecast from 2017 to 2021. A close look at figure 5 indicates that there is going to be a slow and steady rise in the incidence of malaria in Southwestern part of Nigeria but this steady rise is observed to take long time before it can reach its peaked values.

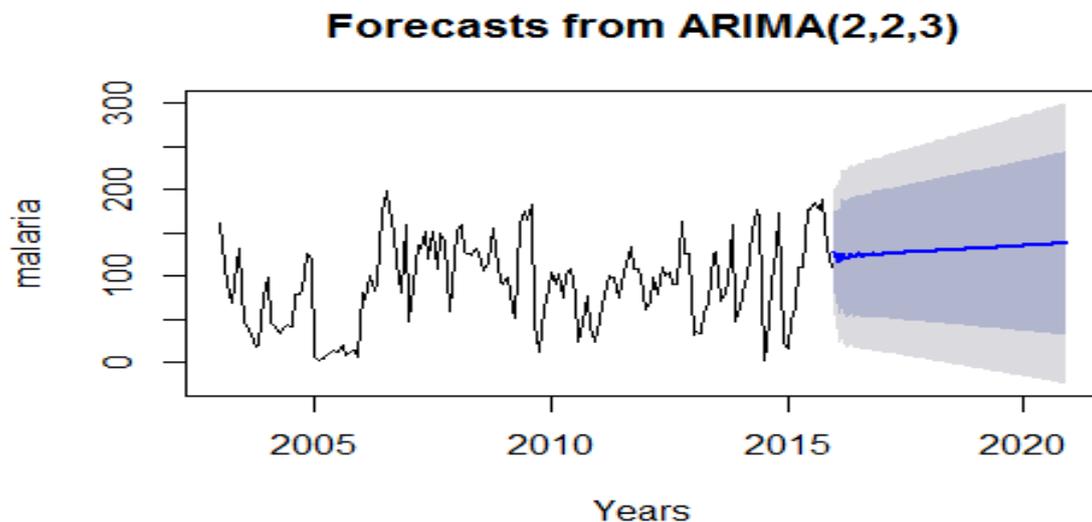


Figure 5. 5 years forecast from the fitted ARIMA model (2, 2, 3)

5. Conclusion

Having used necessary and suitable methods in line with the set goals of this research, there is no doubt that the main purpose has been fully realized.

Therefore, based on the results obtained by the empirical analysis of the data collected, the following conclusions are therefore arrived at:

- That ARIMA model (2, 3, 2) is the most appropriate fit for the incidence of Malaria in Nigeria.
- Based on the forecast findings which shows that there would be a steady rise in malaria incidence, it is advisable that clean environments should be encouraged among the citizens while Nigerian government should improve on her various health policies especially those that have to do with malaria eradication.

References

- [1] World Health Organization (1999). World Health Report, 1999; *making a Difference*. <http://www.who.int/whr/1999/>.
- [2] WHO/UNICEF, (2003). Africa Malaria Report. WHO/CDS/MAL/2003. 1093.2003. Geneva.
- [3] Reeder J.C. (2001). Towards a Malaria Vaccine for Papua New Guinea. PNG Med J, 44, 17-23.
- [4] Sudhakar, P., and Subramani, P., (2007). "Literature Review: Insights into Formulating a Protective Malaria Medicine, Journal of Young Investigators", Volume 16, Issue 1.
- [5] Houeto, D., D'Hoore, W., Ouendo, E. M., Charlie, D. and Deccache, A., (2007). "Malaria control among children under five in sub-Saharan Africa: the role of empowerment and parents' participation besides the clinical strategies".
- [6] Durueke A.P. (2005). *A Research on the incidence, management and bionomic of Malaria in Children under 5years of age*, in parts of Isiala Mbanjo L.G.A., Imo State, Nigeria. Unpublished research work.
- [7] Gerritsen, A.; Kruger P; Van der Leo, M. and Grobusch, M. (2008). 'Malaria incidence in Limpopo Province, South Africa, 1998-2007', *Malaria Journal*. 7(1). <http://www.malariajournal>.
- [8] Ayeni, A. O. (2011). Malaria Morbidity in Akure, Southwest Nigeria: *A Temporal observation in Climate Change scenario*. Trends Applied Sci. (Res. 6): 488-494.
- [9] Korenromp, E and Kiniboro. B. (2007). Forecasting Malaria incidence estimates at Burundi Country Level for the year 1997 to 2003 draft report. http://www.W.H.O.Int/malaria/publications/atoz/incidence_estimation2.
- [10] Opara K.R, (2001) "The effects of malaria during pregnancy on infant mortality in Abia State Nigeria Between 1993 and 1999". An unpublished B.Sc. Project submitted to the department of Statistics. Abia State University, Uturu, Abia State.
- [11] Adebola P. A. and Okereke R.W. (2007). *Increasing Burden of childhood severe Malaria in Nigeria Tertiary Hospital from 2000 to 2005: An unpublished research work*.

- [12] Coene, J. (1991). Prospects for Malaria Control in Urban and Rural Kinshasa. *Ann. Soc. Belg. Med. Trop.*, 71 (1). 103-112.
- [13] Baird, J. K.; Owusu Agyei S; Utz G.C.; Koram, K; Barcus M.J.; Jones, T.R.; Fryauff, D.F. Binka, F.N.; Hoffman, S.L.; Nkruma, F.N. (2002). *Seasonal Malaria attack rates in infants and young children in Northern Ghana*. Naval Medical Research center, Silver Spring, Maryland, USA.
- [14] Wilson, M.L., (2001). "Ecology and Infectious Disease." In *Ecosystem Change and Public Health*. The Johns Hopkins University Press: Baltimore, MD: 285-291.
- [15] Reed, S.D., Laxminarayan, R., Black, D.J., and Sullivan, S.D., (2002). "Economic issues and antibiotic resistance in the community." *The Annals of Pharmacotherapy*, 36(1): 148-54.
- [16] Guerin, P. J., Olliaro, P., Nosten, F., Druilhe, P., Laxminarayan, R., Binka, F., Kilama, W.L., Ford, Guerrero, V. M., (2003). "Análisis estadístico de series de tiempo económicas", Segunda edición, México.
- [17] Pattanayak, S.K., Mercer D.E., Sills, E. and Yang, J. C. (2003). "Taking Stock of the Agroforestry Adoption Studies", *Agroforestry Systems* 57 (3): 173-186.
- [18] Lindsay W. S and Birley M., (2004). "Rural Development and Malaria Control in Sub- Sahara Africa", *EcoHealth*, Springer New York, Volume 1 Number 2. pp 129-137.
- [19] Nchinda, T.C. (2005). "Malaria: A Reemerging Disease in Africa", World Health Organization, Geneva.
- [20] Sulaiman, S., (2007). How is climate change shifting Africa's malaria map? <http://www.scidev.net.com>. Accessed on Friday, 9 October 2009.
- [21] Wiwanitkit V. (2006). Hellenic Society of Haematology, "Correlation between Prevalence of Malaria and Altitude, a Case Study in a Rural Endemic area of Thailand", *HAEMA* 2006; 9(1). pp 56-58.
- [22] Streeten P. (1981). *First thing first; meeting basic human needs in developing countries*. The World Bank. Washington.