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Analyzing the Impact of Malaria Fever in Osun State Using a Time Series Approach

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Abstract

The study employs a time series approach to assess the impact of malaria fever in Osun State. Data for this research was collected from the records of the State of Osun Hospitals Management Board in Ede. Time series models were developed, and a range of tests were applied to the data, with the stationarity test being the most crucial. This test was conducted using graphical methods, correlograms, and unit root tests. The results of the stationarity test showed that the series became stationary after the first difference. Analysis using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) revealed that AIC slightly outperformed BIC in generating the best predictions. Furthermore, performance indices such as RMSE and Theil U inequality proved to be the most reliable metrics. The forecast indicates that malaria is more prevalent during the rainy season, particularly in stagnant water, and is influenced by other factors. The study recommends that the government take action to reduce malaria transmission by providing health education and launching awareness campaigns at various religious centers, including mosques, churches, and shrines, to fight this deadly disease.

Keywords: Analyzing, Impact, Malaria Fever, Osun State, Time Series Approach.

Introduction

Malaria is a prevalent parasitic disease in Africa, known for its potential to be fatal. It is a significant global health concern, particularly in developing regions such as

Sub-Saharan Africa. The disease remains one of the leading causes of death and illness, especially among young children under five years old and pregnant women (Schapira,

2004). Each year, more than 300 million people suffer from acute malaria, leading to over one million deaths. Nearly 90% of these fatalities occur in Africa, with children under five accounting for approximately two-thirds of the deaths (Ghosh et al., 2006; WHO, 2002).

Children are particularly vulnerable to malaria due to their lack of natural immunity, which makes them more likely to develop severe cases of the disease. Malaria poses a critical public health challenge in the tropical and subtropical regions of Africa, where people living in endemic areas face a heightened risk of infection (Birhanie et al., 2014). The disease is caused by the protozoan *Plasmodium* (Iwuafor et al., 2016) and is transmitted through the bite of an infected mosquito (Obimakinde and Simon-Oke, 2017). Malaria affects approximately half of the global population, with 3.3 billion people living in 106 countries at risk (Nigeria Malaria Fact Sheet, 2011).

In Nigeria alone, over 300,000 deaths occur annually due to malaria, with an estimated 100 million cases reported each year (Nigeria Malaria Fact Sheet, 2011). Despite these alarming statistics, there is a significant lack of awareness about the dangers of malaria in many developing and underdeveloped countries. This study aims to investigate malaria patterns in Nigeria, with the goal of predicting future outbreaks and offering recommendations for appropriate actions by relevant authorities. Recently, malaria has been classified as an epidemic in Africa due to its widespread prevalence, affecting a large proportion of the continent's population (Gillet et al., 2010).

Africa accounts for approximately 175 million of the 216 million global malaria cases recorded (Nigeria Malaria Fact Sheet, 2011). Countries such as Nigeria, the Democratic Republic of the Congo (DRC), Ethiopia, and Uganda are responsible for nearly half of all malaria-related deaths worldwide (Nigeria Malaria Fact Sheet, 2011). The epidemic primarily affects Sub-Saharan African nations like Nigeria, presenting a significant public health challenge that requires urgent attention. The epidemiology and symptoms of malaria fever are closely related, with the disease being transmitted specifically through the bite of female *Anopheles* mosquitoes, which thrive in areas with stagnant water, poor sanitation, and contaminated food (Odikamnoru et al., 2018).

MATHEMATICAL PRELIMINARIES

The $ARMA(p, q)$ model above can be expressed as

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) y_t = \theta_0 + (1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q) \varepsilon_t$$

where B is the backward shift operation, that is

$$B^k Y_t = Y_{t-k} \text{ for } k \text{ +ve integer}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

The Autoregressive Integrated Moving Average Process is represented using the model

$$\psi(B) X_t = \phi(B) \nabla^d X_t = \theta(B) e_t$$

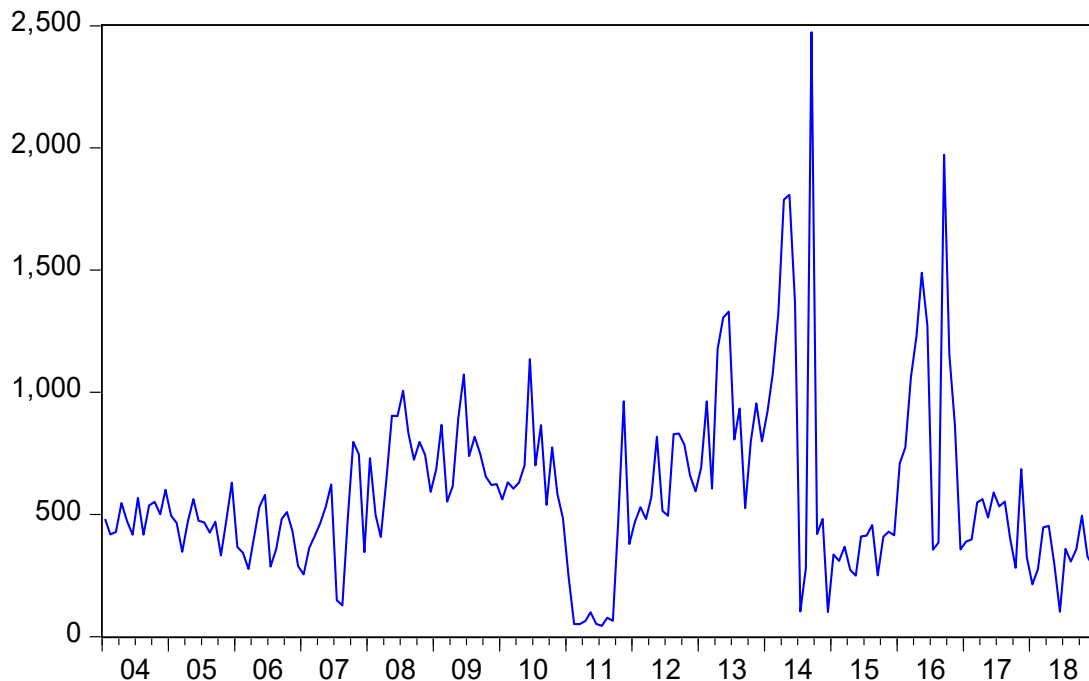
Where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 \dots - \phi_p B^p$

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 \dots - \theta_q B^q$

DATA ANALYSIS AND INTERPRETATIONS

The data for the study spans from 2004 to 2018 and was sourced from the archives of the Osun State government. It was analyzed using Econometrics-View software.

MALARIA RECORD FROM 2004-2018



Time Plot of the Raw Data

Upon visual inspection of the raw data, it appears to be stationary. However, this observation will be further confirmed through the Augmented Dickey-Fuller Test during the identification testing phase.

Unit Root Test

The unit root test is a statistical test used to assess the stationarity of the data. The decision rule for this test is as follows:

Decision Rule: Reject H_0 if $t^* > ADF$, otherwise do not reject H_0 .

H_0 : Series has unit root (data is non-stationary)

Against

H_1 : Series has no unit root (data is stationary)

UNIT ROOT TEST OF THE ORIGINAL DATA

Null Hypothesis: MALARIA_RECORD has a unit root

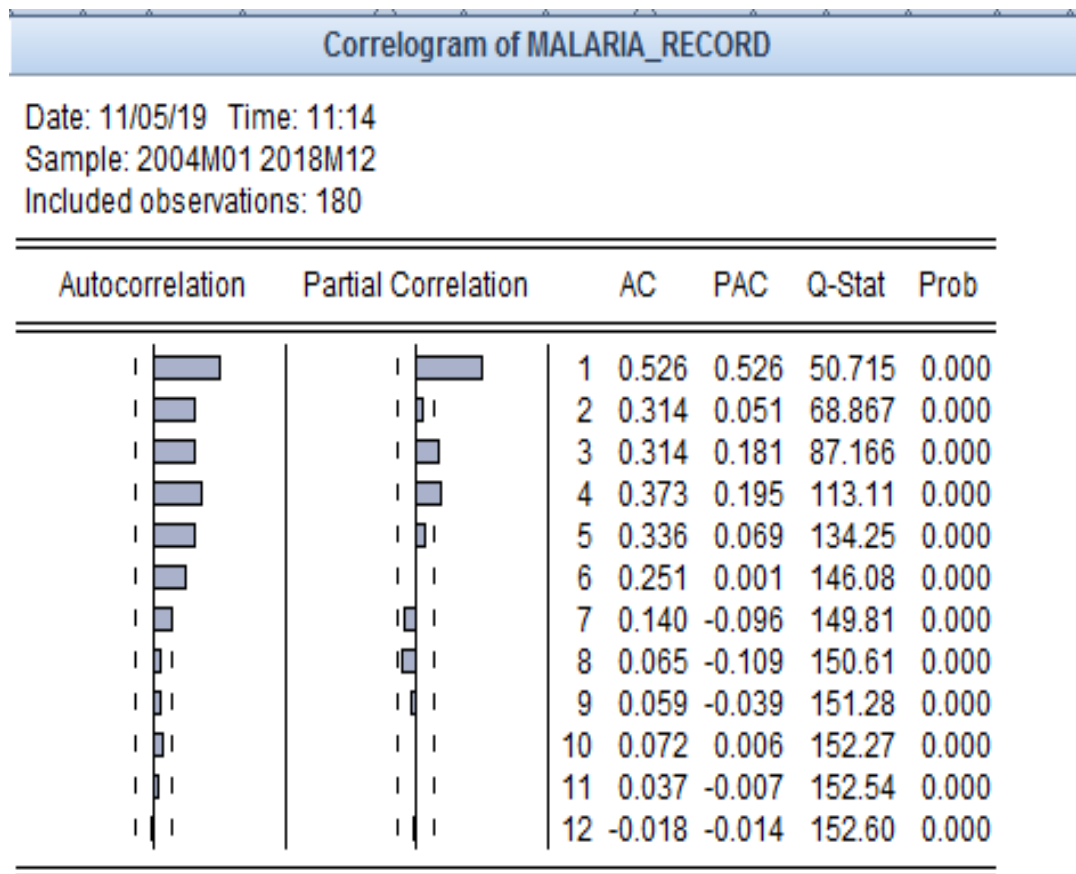
Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-7.370388	0.0000
Test critical values:		
1% level	-3.466994	
5% level	-2.877544	
10% level	-2.575381	

*MacKinnon (1996) one-sided p-values.

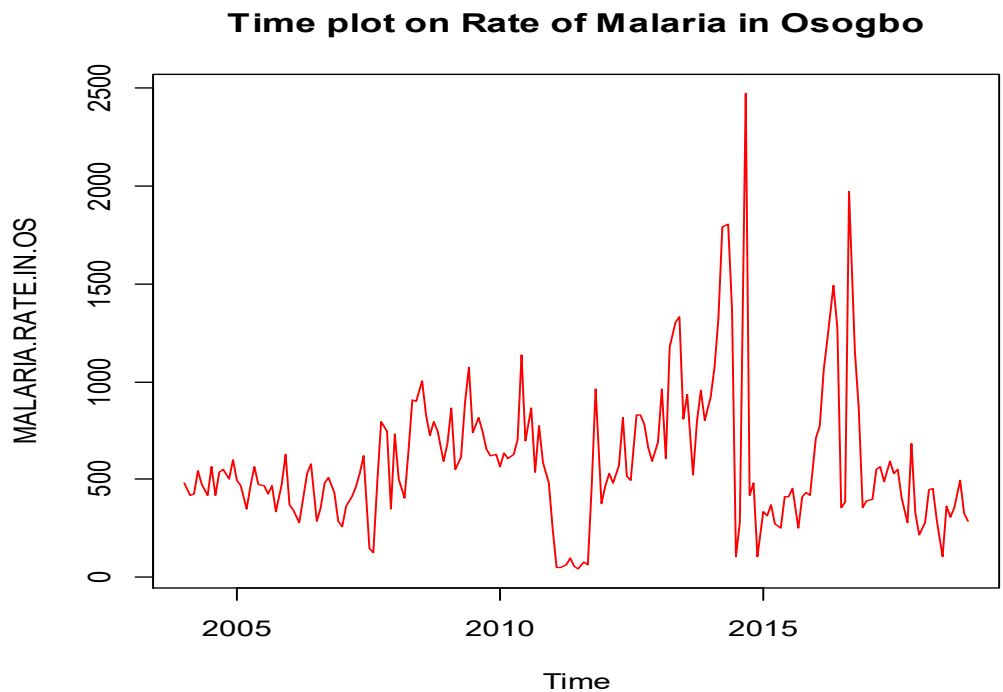
CORRELOGRAM OF THE ORIGINAL DATA



INTERPRETATION

The first output above shows the unit root test for the original data, while the graph above depicts the correlogram. From the first output, we can observe that the absolute value of the Augmented Dickey-Fuller test statistic is 7.370388, which is significantly higher than the critical value at the 5% significance level (-2.877544). Additionally, the p-value (0.0000) is

less than 0.05, indicating that the null hypothesis cannot be accepted. Therefore, we conclude that the data is stationary.



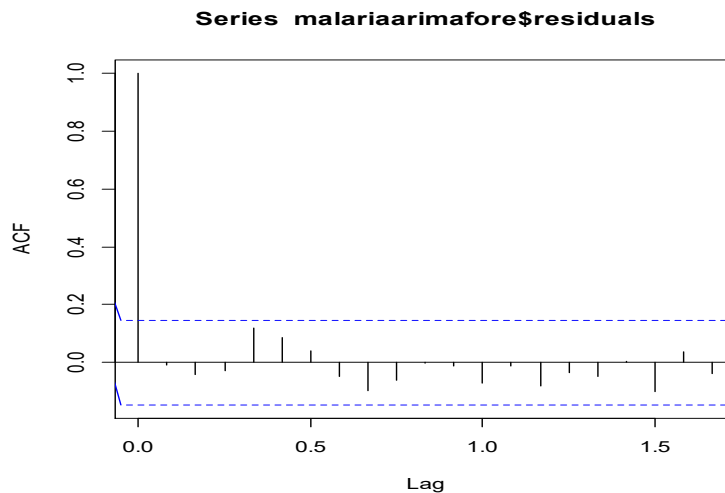
The time plot above indicates that the time series can be described using an additive model, as the random fluctuations in the data remain relatively consistent in size over time. It also shows that in 2014, there was a high rate of malaria diagnoses, while the number of diagnosed patients decreased as the years progressed. Additionally, the time plot reveals the presence of both seasonal and random variations.

ARIMA FORECAST

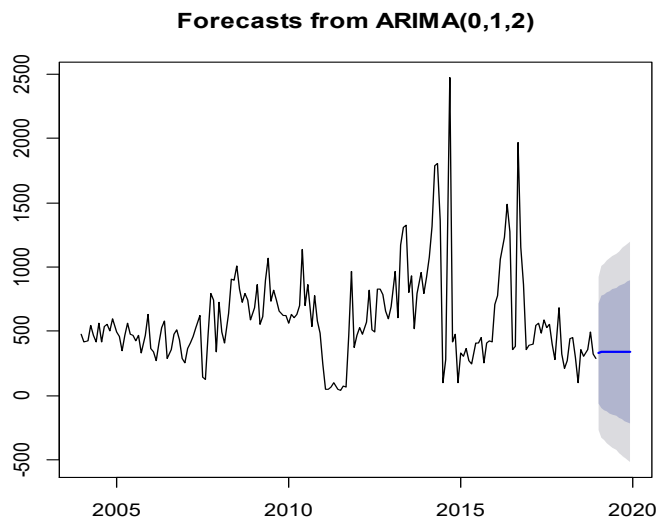
	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	2019	329.4411	-58.722	717.6042	-264.203	923.0854
Feb	2019	340.6386	-95.4397	776.717	-326.286	1007.563
Mar	2019	340.6386	-109.154	790.4312	-347.26	1028.537
Apr	2019	340.6386	-122.462	803.7396	-367.613	1048.89
May	2019	340.6386	-135.399	816.676	-387.398	1068.675
Jun	2019	340.6386	-147.993	829.27	-406.659	1087.936
Jul	2019	340.6386	-160.27	841.5475	-425.435	1106.713
Aug	2019	340.6386	-172.254	853.5312	-443.763	1125.04
Sep	2019	340.6386	-183.964	865.2412	-461.672	1142.949
Oct	2019	340.6386	-195.418	876.6955	-479.19	1160.467
Nov	2019	340.6386	-206.633	887.9101	-496.341	1177.618
Dec	2019	340.6386	-217.622	898.8994	-513.148	1194.425

Interpretation

The Lo 80 and Lo 95 represent the 80% and 95% prediction intervals for the forecast, respectively. Based on the forecast above, it appears that the rate at which patients will be diagnosed or treated for malaria will remain minimal, provided that necessary precautions are implemented.



The ARMA(3,0) model has three parameters, the ARMA(0,2) model has two parameters, and the ARMA(p,q) model has at least two parameters. Therefore, based on the principle of parsimony, both the ARMA(0,2) and ARMA(p,q) models are equally valid candidate models.



Interpretation

Above time plot show that malaria rates is non-stationary. It implies that the malaria rates data are unstable [i.e. fluctuating or moving up and down significantly from 2004 to 2020].

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

SUMMARY

This study followed a structured series of procedures and applied the necessary statistical analyses to evaluate the data. The analysis confirmed that one of the project's objectives, predicting trends, was successfully achieved. The optimal trend line was determined using the least squares method, and the resulting straight-line fit indicated an upward trend in malaria cases, as reported by the State of Osun Hospitals Management Board at State Hospital Ede. The moving average graph revealed fluctuations in the mortality rate due to malaria. Beyond seasonal variations, malaria continues to be a significant public health challenge, with its severity varying, particularly during the rainy season, due to factors like abundant vegetation and stagnant water.

CONCLUSION

The analysis shows that malaria is a prevalent disease that frequently affects individuals, with contributing factors including stress, diet, body type, insect bites, and other factors. It is widespread at State Hospital Ede, where the infection rate continues to increase each month. It is essential for the government to prioritize funding for the healthcare sector and implement the proposed measures.

RECOMMENDATIONS

While the analysis predicts a future rise in malaria cases, this can be mitigated by taking the following actions:

1. The government should invest in sufficient healthcare infrastructure.
2. Public awareness campaigns should promote proper diet and malaria prevention methods.
3. Health education initiatives should focus on the causes of malaria, helping to raise awareness among the general public.
4. Adequate treatment should be provided to those affected by malaria.
5. Insecticide-treated nets should be distributed to the public to help control mosquito populations and prevent the spread of the disease.

REFERENCES

- Adeboye, N.O., & Ezekiel, I.D. (2018). On Time Domain Analysis of Malaria Morbidity in Nigeria. *American Journal of Applied Mathematics and Statistics*, 6(4), 170 – 175.
- Akawu, C., Ikusemoran, M., & Ballah, A. (2018). Analysis of Spatial Patterns of Malaria Prevalence in Borno State, Nigeria. *Academic Research International*, 9(2), 24 – 37.
- Anokye, R., Acheampong, E., Owusu, I., & Obeng, E. (2018). Time Series Analysis of Malaria in Kumasi: Using ARIMA Models to Forecast Future Incidence. *Cogent Social Sciences*, 4, 1 – 13.
- Birhanie, M., Tessema, B., Ferede, G., Endris, M., & Enawgaw, B. (2014). Malaria, Typhoid Fever, and Their Coinfection among Febrile Patients at a Rural Health Center in Northwest Ethiopia: A Cross-Sectional Study. *Advances in Medicine*.
- Gbosh F, Cox J, Balkan S, Tamrat A, Priotto G, et al. (2006) Malaria Epidemics and Interventions, Kenya, Burundi, Southern Sudan, and Ethiopia, 1999–2004. *Emerging Infectious Diseases*. CDC. Volume 12.

- Gillet, P., Mukadi, P., Vernelen, K., Van Esbroeck, M., Muyembe, J.-J., Bruggeman, C., & Jacobs, J. (2010). External quality assessment on the use of malaria rapid diagnostic tests in a non-endemic setting. *Malaria Journal*, 9(1), 359. <https://doi.org/10.1186/1475-2875-9-359>
- Iwuafor, A. A., Egwuatu, C. C., Nnachi, A. U., Ita, I. O., Ogban, G. I., Akujobi, C. N., & Egwuatu, T. O. (2016). Malaria Parasitaemia and the use of insecticide-treated nets (INTs) for malaria control amongst under-5-year-old children in Calabar, Nigeria. *BMC Infectious Diseases*, 16(1), 151.
- Nigeria Malaria Fact Sheet (2011). Nigeria Malaria Fact Sheet. United States Embassy in Nigeria. <http://nigeria.usembassy.gov>
- Obimakinde, E.T., & Simon-Oke, I.A. (2017). The Prevalence of Malaria Infection Among Patients Attending the Health Centre of the Federal University of Technology, Akure, Nigeria. *International Journal of Tropical Disease & Health*, 27(4), 1 – 7.
- Odikamnor, O. O., Ikeh, I. M., Okoh, F. N., Ebiriekwe, S. C., Nnadozie, I. A., Nkwuda, J. O., & Asobie, G. C. (2018). Incidence of Malaria/Typhoid Co-infection among Adult Population in Unwana Community, Afikpo North Local Government Area, Ebonyi State, Southeastern Nigeria. *African Journal of Infectious Diseases*, 12(1), 33–38.
- Ozofor, N.M., & Onos, C.N. (2017). Statistical Analysis of Reported Cases of Malaria in Parklane Specialist Hospital in Enugu Urban for the Period of 2009 – 2015. *Research Journal of Mathematics*, 4(3), 1 – 10.
- Schapria, C.C. (2004). Incidence of Concerrent Malaria and Typhoid Fever Infections in Febrile Patients in Jos, Plateau State Nigeria. *International Journal of Scientific & Technology Research*, 3(4), 157 – 161.
- Sekubia, A.C., & Mensah, E.K. (2019). Analysis of Typhoid Fever Surveillance Data, Cape Coast Metropolis, 2016. *Acta Scientific Medical Sciences*, 3(2), 2 – 8.
- World Health Organization. (2018). Health System. Retrieved March 27, 2019.