

Spatio-temporal Epidemiology of Malaria Mortality in Nigeria: Why the war against poverty must be won

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Malaria is a major parasitic disease in the world including Nigeria which currently bears the brunt of the global malaria mortality burden. This paper responds to the need for all countries in the world including Nigeria to understand the geographical distribution and drivers of malaria mortality with the aim of consolidating the gains of global malaria elimination. The thrust of this paper therefore was to examine the geographical distribution, spatial clustering and determinant(s) of malaria mortality in Nigeria from 2006 to 2010. Retrospective data used in this research were obtained from published sources and were analysed with the aid of statistical and spatial analytical tools. Very noticeable state variations were observed in the pattern of malaria mortality, and strong and persistent clustering of malaria-related deaths was found in northwest Nigeria particularly Kano State due to high levels of malaria transmission. Lastly, there was a significant and differential effect of poverty on its geographical distribution; with the greatest effect felt in the north of Nigeria. In order to reduce death toll associated with the disease, the war against poverty must not only be intensified but should be mainstreamed into the national malaria control programme.

Introduction

Malaria is one of the most researched vector-borne and infectious diseases in the world because of its heavy global morbidity and mortality burden. It is caused by *Plasmodium* which is transmitted by the bite of the females *Anopheles* mosquito. In 2017, 219 million malaria cases were recorded worldwide as against 239 million in 2010 and 217 million in 2016 (WHO, 2018). Unfortunately, most of these reported cases are borne by the WHO African region (WHO 2015; 2018). In 2017, the WHO African Region accounted for 93% of all global malaria deaths. In addition, it accounted for 88% of the relatively few global malaria deaths observed in 2017 compared to 2010 (WHO 2018). Millions of people over the world do not enjoy access to malaria prevention and treatment; as a result, malaria cases and deaths are unregistered and are therefore unreported (WHO 2015), and the problem of inaccessibility to healthcare still remains a big obstacle to malaria elimination (Cibulskis *et al.*,

2016) and the realisation of the Sustainable Development Goals (SDGs).

Given the severity of this disease, WHO (2015: 5) saw the "...urgent need to accelerate progress by reducing morbidity and mortality in all countries by increasing the number of malaria free countries, territories and areas and by identifying approaches that aim to reduce transmission". Hence, the organisation declared its vision of "a world free of malaria" (WHO, 2015). Furthermore, WHO had encouraged malaria-endemic countries to define their subnational epidemiology to develop and deploy appropriate intervention (WHO, 2015). This task would obviously be hard to accomplish without spatial data on malaria incidence and prevalence. It, then, means effective malaria control strategies would require geographic and temporal distribution of malaria deaths and its determinants to successfully eradicate malaria (Adigun, 2015; Gething *et al.*, 2015; Selemani *et al.*, 2015). Assessing spatio-temporal distribution of malaria

mortality is therefore key to malaria control (Onyiri *et al.*, 2015).

Specifically, Nigeria accounted for 19% of the world's malaria mortality figures in 2017 followed by the Democratic Republic of the Congo (11%), Burkina Faso (6%), United Republic of Tanzania (5%), Sierra Leone (4%), Niger (4%) and India (4%) (WHO, 2018). Nearly 80 % of Nigerians live in high transmission areas where they are exposed to a number of *Anopheles* species namely *An. Gambiae*, *An. Funestus*, *An. Arabiensis*, *An. Mouceti*, and *An. Mili*. The major plasmodium species in the country is the *Plasmodium falciparum* (WHO, 2018). The country currently operates the National Malaria Strategy Plan (2014-2020) whose objective *inter alia* is to ensure that 80% of Nigerians take appropriate malaria preventive and treatment measures by 2020, thereby creating a malaria-free Nigeria. Furthermore, the document made some geographic observations on malaria prevention and control however its one size-fits-all approach to prevention and control is highly inappropriate for the uneven distribution of malaria transmission.

Given the foregoing, the focus of this paper was to describe and analyse spatio-temporal patterns of retrospective malaria mortality from 2006 to 2010 with a view to informing and strengthening current national malaria prevention and control programmes.

The specific questions addressed in this paper were: what is the nature of the retrospective spatial pattern of malaria mortality in Nigeria? Is there significant spatial clustering of malaria mortality and if it exists, are there significant clusters and hotspots? What is/are the major driver(s) of the geographical distribution? Does spatial nonstationarity exist in the relationship between malaria mortality and explanatory factors? Lastly, what are the policy implications of the research? The benefit of this study is twofold. First, information about where and when malaria clustering occurs in the population is essential for policymakers and planners in intervention and resource allocation (Selemani *et al.*, 2015; Ouedraogo *et al.*, 2018) and assessment of the impact of malaria control interventions (Onyiri *et al.*, 2015; Macharia *et al.*, 2018). Second, uncovering geographically variable risk factors give hints to the nature of local epidemiology of malaria and where a combination of targeted

interventions may require local implementation (Homan *et al.*, 2016).

A major constraint that we encountered in the course of writing this paper is that of current data on malaria and mortality. However, the data utilised for analysis in this study sourced from the National Bureau of Statistics (NBS) covering the period 2006-2010 is the most current published data on the subject.

Literature review

Nigeria is a malaria-endemic country. Previous studies in the country about the subject have examined the geographical distribution of malaria morbidity in Nigeria as Osayomi (2014), Onwuemele (2014), Adigun *et al.* (2015) and Onyiri *et al.* (2015) have adequately demonstrated. Like malaria morbidity, it is expected that malaria mortality would be geographically heterogeneous in Nigeria. However, much is yet to be known about the spatial distribution of malaria mortality in Nigeria. Malaria, as previously mentioned, is a vector borne common to the tropical and temperate regions of the world. Its distribution of morbidity and mortality, based on a review of existing literature, is not uniform across population and geographic space, and is thus shaped by a variety of drivers: demographic, socioeconomic, climatic, environmental, and health/vector control measures.

The population subgroups most affected by malaria are pregnant women and children under the age of five (Federal Ministry of Health, 2001; Malik *et al.*, 2006; WHO, 2012; Iyanda *et al.*, 2020). Malaria in pregnancy is a cause of maternal mortality as well as a risk factor of low birthweight and neonatal mortality. Pregnant women are vulnerable to malaria because of the vulnerable state of their immunity. On the other hand, children under the age of five accounted for about 80% of all malaria deaths in the WHO African region (WHO, 2021). This is so because they do not have acquired immunity (Tsegaye, Ayele and Birhanu, 2021)

Positive socioeconomic conditions is key to the elimination of malaria worldwide (Soussa *et al.*, 2022). In other poverty greatly hinders malaria eradication. This is because poor populations live in environments which often predispose them to malaria. When infected, they may not have the ability-to-pay for medical treatment and consequently resort to substandard treatment options which might endanger their health and

cause death. On the other hand, malaria episodes robs patients them of their productivity and daily incomes. Therefore, malaria is both the cause and effect of poverty (WHO, 2000; Worall *et al.*, 2005; Teklehaimanot and Mejia, 2008; Osayomi, 2014; Adigun *et al.*, 2015; Tusting *et al.*, 2016; Khagayi *et al.*, 2017; Byass *et al.*, 2017; Ouedraogo *et al.*, 2018). In Spain, poor socioeconomic conditions were identified to be determinants of autochthonous malaria (Souza *et al.*, 2022).

Climatic factors are one of the determinants of malaria endemicity (Ceccato *et al.*, 2005; Singh *et al.*, 2009; Adigun *et al.*, 2015; Sewe *et al.*, 2016; Nwani *et al.*, 2018; Sewe *et al.*, 2016; Adewoyin and Adeboyejo, 2017; Chen *et al.*, 2021). Temperature, for instance, is critical to the birth and development of mosquitoes and parasite. In addition, it affects cycle duration, juvenile development and its survival too (Ceccato *et al.*, 2005; Donkor *et al.*, 2021). Higher temperature influences the frequency of human blood meals and reproduction rates of mosquitoes (Hay *et al.*, 2000). In recent times, global warming trends are shaping the geographical distribution of malaria vectors (Li *et al.*, 2021). This clearly means that malaria and its vectors now exist in areas with no previous history. Therefore, its global coverage is widening on account of climate change. Evidence has shown a positive association between malaria mortality and temperature in Sweden (Chen *et al.*, 2021).

Like temperature, rainfall affects life cycle and breeding patterns of the mosquito (aa *et al.*, 2021). Malaria cases often increase with rainfall (Dev *et al.*, 2010). Rainfall provides surface water in which female anopheles can lay eggs. Even in arid regions where temperature are remarkably high, malaria morbidity occurs only when rainwater forms breeding habitats for mosquitoes (Hay *et al.*, 2000). Besides the pools formed by rainfall, different mosquito species also use irrigation canals, tire nuts, mangrove swamps, to reproduce as long as the water are still and unpolluted. Highest malaria deaths in western Yunnan of China occurs between May and October which coincides with the rainy season (Bi *et al.*, 2013). Zhou *et al.*, 2010 also showed that these climate parameters average monthly temperature and rainfall are positively related to malaria incidence in central China. In South Africa, Ngomane and de Jager (2012) noticed

that malaria transmission that always followed rainfall patterns in Mpumalanga province.

Environmental factors also play a vital role in malaria transmission and mortality. High altitude affects mosquito reproduction, malaria morbidity (Adeola *et al.*, 2016), and in turn mortality. Cooler temperature at higher altitudes does not support the mosquito survival. In other words, malaria cases and deaths would occur more often in low altitude regions for example the northern and eastern parts of South Africa (Gerritsen *et al.*, 2008). Surprisingly, malaria cases were reported in the East African highlands. It was initially suspected that climate change was responsible but was later found to be increasing anti-malaria resistance (Shanks *et al.*, 2002).

Forested areas provide a suitable environment for mosquitoes (Adigun *et al.*, 2015; Adefemi *et al.*, 2015; Beraznewa and Byker, 2017) to breed because of their favourable microclimatic conditions. Vegetation type and growth influence vector population size. It determines the presence or absence of animal/ human hosts and in turn affects the availability of blood meals (Ceccato *et al.*, 2005). In Vietnam, a significant proportion of malaria morbidity and mortality are within the central mountains ad forested areas of the country (Erhart *et al.*, 2005). In the Greater Mekong subregion of Asia, there is noticeable concentration of malaria along its international borders, which are surrounded by forest and forest fringes (DelaCollette *et al.*, 2009). In the forested and hilly area of western Yunnan where people with low income, educational status, and poor perception of malaria, the malaria burden was unusually high (Bi *et al.*, 2013).

Malaria is very common in urban areas (Mabogunje, 2007; Morse *et al.*, 2016). Imported malaria were concentrated around the main cities and conurbation of Spain (Soussa *et al.*, 2022). Hotspots of malaria mortality were found in the neighbourhoods of Ghana's capital city, Accra. It was discovered that water bodies in the city contributed to malaria mortality (Fobil *et al.*, 2012). In Nigeria, malaria is endemic to Nigerian urban centres because they "...are generally characterized by unhealthy conditions which increase the Nigerian urban population's degree of susceptibility to malaria" (Osayomi, 2014: 110).

Access to health facilities poses a great challenge to the reduction of malaria cases and deaths too. Al-Taiar *et al.* (2008) reported a positive relationship between physical accessibility and severity of malaria among Yemeni children. The severity of infection increased mild to severe with increasing driving time to the point of treatment. [Vector control](#) is central to malaria control and elimination strategies because of its significance in malaria prevention and control (WHO, 2021). Vector control methods such as Long Lasting Insecticidal Nets (LLINS), Insecticide Treated Nets (ITNs), Indoor residual Spraying (IRS) help reduce the exposure of the human population to malaria vectors and malaria incidence and mortality.

Based on the foregoing, the study therefore hypothesised that the geographical distribution of malaria is a function of demographic, socio-economic, environmental, climatic and health/vector control variables. Moreover, it is also expected that the strength and comparative importance of these drivers would, in the same vein, vary geographically.

Data and methods

The data used in this study were assembled from a variety of secondary sources listed in Table 1. These were the only available data sources at the time of the research. Retrospective data on malaria deaths at the state level in Nigeria from 2006 to 2010 (the data was most recent and available at the time of the study) were obtained from the Annual Abstract of Statistics 2012 published by the country's statistical agency, National Bureau of Statistics (NBS). Other pieces of state level information extracted from this same source include state population figures, rainfall, forest reserve area (proxy measure of vegetation cover), level of urbanisation (measured by population density) the number of health care facilities, and absolute poverty level (%). State level data on population of children under five years of age, and population of women 15 years of age above were collected from both the Annual Abstract of Statistics 2012 as well as the Priority Tables Volume IV, published by the National Population Commission (NPC).

Data on socio-economic variables such as the Human Development Index (HDI) and Human Poverty Index (HPI) were retrieved from the Human Development Report (2008-2009) produced by the United Nations Development Programme (UNDP), Nigeria. Lastly, data on the vector control were obtained: insecticide-treated Net (ITN) ownership from the 2013 Nigeria Demographic and Health Survey report.

Table 1: Variables and data sources

Variable	Source
DEPENDENT VARIABLES	
Malaria Mortality (2006-2010) (Y_1)	NBS Annual Abstract of Statistics 2012
Malaria Mortality Rate per 100,000 (Y_2)	NBS Annual Abstract of Statistics 2012
INDEPENDENT VARIABLES	
DEMOGRAPHIC VARIABLES	
Population size	NBS Annual Abstract of Statistics 2012
Population Density per State	NBS Annual Abstract of Statistics 2012
Children < 5years per state	National Population Commission, Priority Table, Volume IV
Women 15 years of age and above	National Population Commission, Priority Table, Volume IV
ENVIRONMENTAL VARIABLES	
Rainfall	NBS Annual Abstract of Statistics 2012
Forest(Forest Reserve in hectares)	NBS Annual Abstract of Statistics 2012
Access to Healthcare (Number of Healthcare Centers)	NBS Annual Abstract of Statistics 2012
VECTOR CONTROL VARIABLES	
Insecticide-treated Net (ITN) Ownership (%)	Nigeria Demographic and Health Survey 2013
SOCIO-ECONOMIC VARIABLES	
Human Poverty Index	Human Development Report Nigeria 2008-2009, UNDP
Human Development Index	Human Development Report Nigeria 2008-2009, UNDP
Poverty Level (Absolute Poverty)	NBS Annual Abstract of Statistics 2012

Source: Compiled by Authors

Raw numbers and mortality rates were mapped for comparison because it might reveal “distinct geographical patterns that convey different but complementary information.” (Gething *et al.*, 2016: 2440). The malaria mortality numbers for each state from 2006 to 2010 were summed up and divided by the number of years (5) to derive the state average. The annual malaria mortality rate per 100,000 persons at each state was determined for each of the five years and the whole study period. This was arrived at by dividing the number of deaths per state by the state population multiplied by 100,000.

The following spatial analysis tools were employed to answer the earlier stated questions: Global Moran’s I, Local Moran’s I, Ordinary Least Square (OLS) regression and the Geographically Weighted Regression (GWR). Global Moran’s I was used to determine the degree of geographical clustering of malaria deaths for each calendar year and the entire study period. Moran’s I tests the null hypothesis that the spatial distribution of malaria mortality in Nigeria is random. The index value

lies between -1 (negative spatial autocorrelation) and +1 (positive spatial autocorrelation).

Local Moran’s I, an indicator of local spatial association, identifies significant clusters of malaria mortality in geographic space. The clusters of malaria mortality could be one or a combination of the following:

- a. High-High (HH) - States with high malaria mortality surrounded by States with similarly high malaria mortality.
- b. High- Low (HL) - States with high malaria mortality surrounded with States with low numbers,
- c. Low-High (LH) - States which have low malaria mortality adjacent to those with high malaria mortality
- d. Low-Low (LL) - States with low malaria mortality levels are bordered by States with similarly low malaria mortality.
- e. Not significant- No cluster.

The goal of the ordinary least squares (OLS) regression analysis was to estimate the relationship between the explanatory variables and the dependent variable, malaria mortality. Two separate regression models whose dependent variables were malaria mortality numbers (Y_1) and malaria mortality rates (Y_2) were estimated, and their independent variables include demographic, climatic, environmental, socioeconomic and vector control variables (see Table 1). The analysis assumed that relationship between the malaria mortality and the explanatory variables is constant over geographic space.

A couple of OLS diagnostic tests provide some indication of the presence of statistical conditions such as spatial non-stationarity (Koenker statistic); homoscedasticity (Studentised Breusch Pagan (BP), the absence of normality (Jarque Bera) and variable redundancy (Variance Inflation Factor (VIF)). The presence of spatial non-stationarity is confirmed if the Koenker statistic is not statistically significant. Jarque Bera is significant when residuals do not match the normality distribution. An independent variable is redundant only if its VIF value is 7.5 and above. Prior to the OLS, correlational analysis was first done to ascertain direction and strength of relationships among the variables.

GWR is a local spatial regression technique. Unlike OLS, it analyses spatially varying relationships over space. It simply detects spatial non-stationarity (i.e. a situation in which the relationship between the dependent variable and independent variable(s) is not static but varies over geographic space). The performance of the OLS and GWR models are compared based on the Akaike Information Criterion (AIC). AIC tells which of the two models is a better fit; the model with a relatively low AIC value is always considered to have stronger explanatory power and therefore, a better fit in the explanation of spatially varying relationships. A remarkable feature of this method is the map visualization of local regression coefficients, coefficient of determination and associated results. Spatial analysis and cartographic designs were possible with the help of ArcGIS 10.4.1 version.

Results

In Nigeria, a total of 286, 635 deaths were reported from 2006 to 2010. In 2006, Nigeria had 1190 deaths (24.07 /100,000) which steadily increased to 9179 (161.82/100,000) deaths in 2009 and suddenly rose to 261,543 (2066.21/ 100,000) deaths (Figure 1).

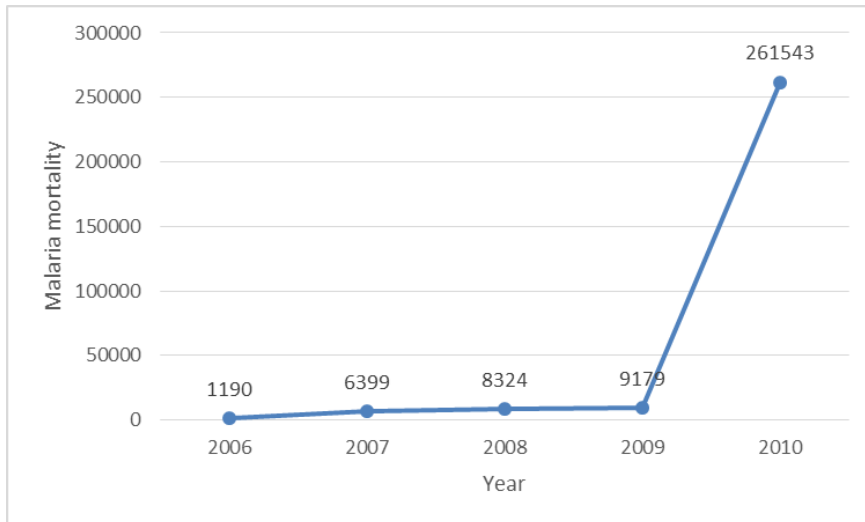


Figure I: Malaria mortality from 2006 to 2010

Spatio-temporal distribution of malaria mortality in Nigeria

Spatial temporal distribution of malaria mortality numbers

In 2006, the largest number of malaria deaths were recorded in Ondo (147), Kebbi (122) and Sokoto (109) states while Taraba (0) Enugu (1), Abia (3) and Nasarawa (4) had the lowest number of deaths arising from malaria (Figure 2). The distribution in 2007 is remarkably different from that of 2006. Katsina (2,175), Taraba (608), Yobe (466) reported the largest figures in the country. In contrast, Ebonyi (0), Plateau (0), Akwa Ibom (1) had the lowest prevalence. In 2008, Katsina (3,014) again

led other states on the death toll list while Sokoto (0), Akwa Ibom (2) and Ekiti (4) states reported the lowest. In 2009, Kano (1,897) suddenly emerged with the largest number of deaths followed by Katsina (1,681) and Anambra (771). The lowest numbers were found in Rivers (2) and the Federal Capital Territory (3). With respect to 2010, Kano (259, 921) still maintained the lead in malaria mortality while very few cases were observed in Akwa Ibom (2) and Ogun (2) states. For the 2006-2010 period, Kano state (52,413) stood out in the spatial distribution.

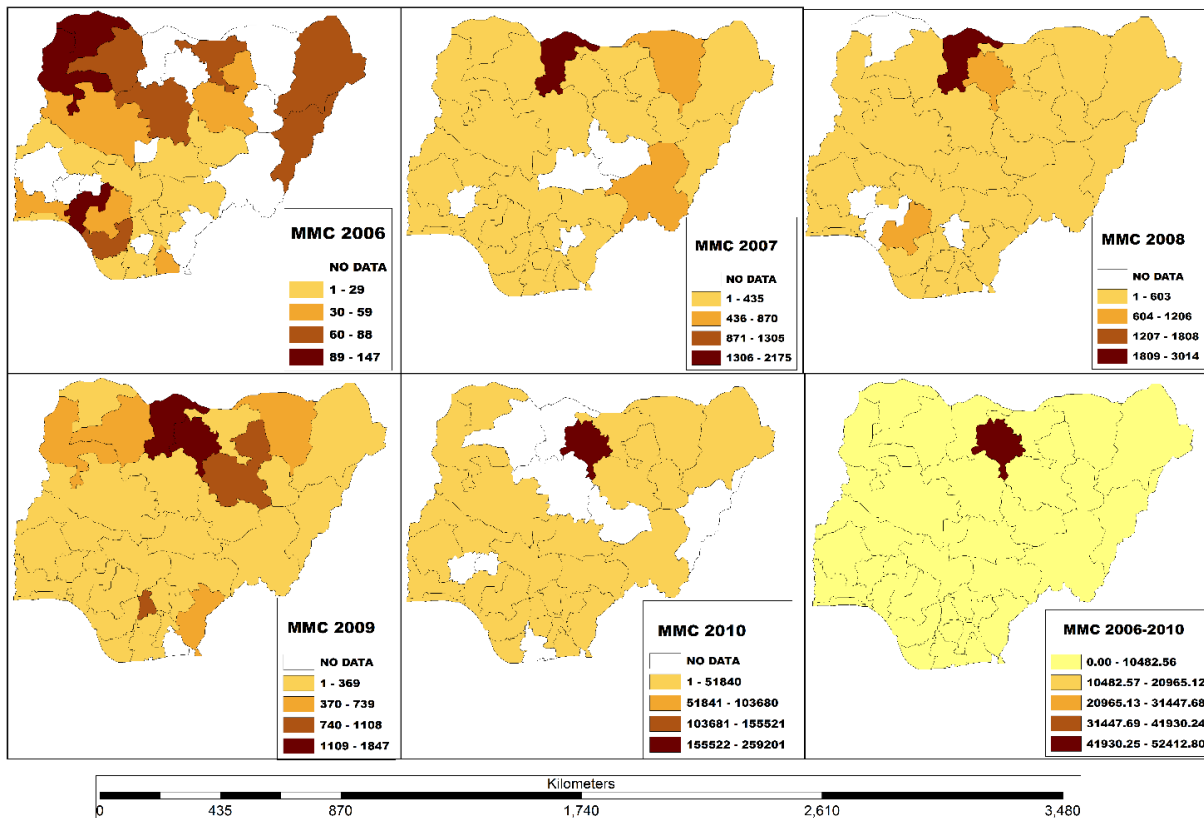


Figure 2: Spatio-temporal distribution of malaria mortality in Nigeria from 2006 to 2010

Spatio-temporal distribution of malaria mortality rate

In 2006, Ondo (3.12/100,000), Kebbi (2.75/100,000) and Sokoto (2.15/100,000) were the states with the highest mortality rates while the rest of the country reported relatively low rates. In 2007, the spatial pattern changed. The highest mortality

rates were found in the northern part of the country particularly Katsina (27.4/100,000), Taraba (19.29/100,000), and Yobe (14.65/100,000) while low mortality persisted in other parts of the country. In 2008, Katsina (37.9/100,000) still had the highest mortality levels, followed by Edo (27.28/100,000) and Yobe (13.93/100,000) states. Again, Katsina

(21.18/100,000) remained the state with the highest mortality rate in the country in 2009 while the whole southern Nigeria generally reported low rates with exception of Anambra (13.45/100,000) and Cross River (12.56/100,000) states. In 2010 and 2006-2010 study period, Kano state recorded an unusually high mortality rate in the country (2015.95/100,000 and 407.64/100,000) respectively (Figure 3).

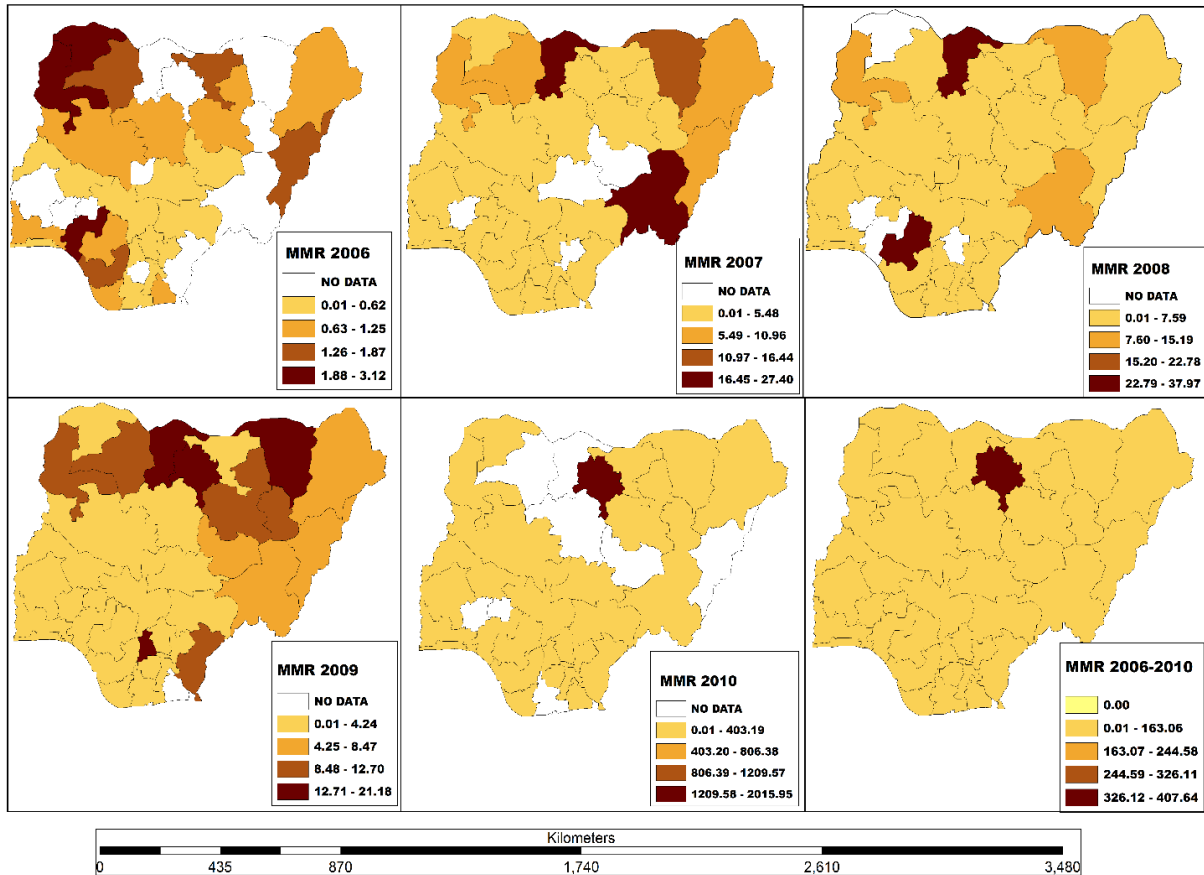


Figure 3: Spatio-temporal pattern of malaria mortality rates in Nigeria from 2006 to 2010

Geographic clustering of malaria mortality in Nigeria

The results of the global Moran’s I are set out in Table 2. With respect to malaria mortality numbers, year 2007 and 2009 exhibited a significant positive autocorrelation. In relation to malaria mortality rates, there was significant positive autocorrelation

in 2006 only. It can be inferred from these results that there was distance decay effect in the occurrence of malaria mortality in Nigeria such that neighbouring states had similar mortality rates than distant states.

Table 2: Geographic clustering of malaria mortality in Nigeria (2006-2010)

Year	Malaria mortality numbers				Malaria mortality rates			
	I	z	p value	Pattern	I	z	p value	Pattern
2006	0.152551	1.867557	0.061824	SC	0.186762	2.245195	0.024756	C
2007	0.109251	2.275492	0.022876	C	0.100563	1.499985	0.133618	R
2008	0.027892	0.894880	0.370851	R	-0.019577	0.100954	0.919587	R
2009	0.179460	2.373495	0.017621	C	0.134805	1.682608	0.092451	SC
2010	-0.019173	0.388964	0.697303	R	-0.019143	0.390146	0.696428	R
2006-2010	-0.008457	0.861109	0.389178	R	-0.003808	1.031118	0.302485	R

Key: SC: Somewhat clustered; C: Clustered; R: Random. p values (<0.05) in bold print

Hotspot analysis of malaria mortality in Nigeria

Hotspots of Malaria mortality numbers

Significant clustering of HH malaria mortality was noticed in the northwestern corner of the country specifically in Kebbi (I= 8.035422) and Sokoto (I=6.831675) in 2006. In 2009, Kano

(I=13.066027) and Katsina (I=11.415116) formed a HH cluster while Jigawa (I=-5.061158) surfaced as a LH cluster. For the 2006-2010 period, Kano (I=-3.008266) was a HL cluster (Figure 4 and Table 3).

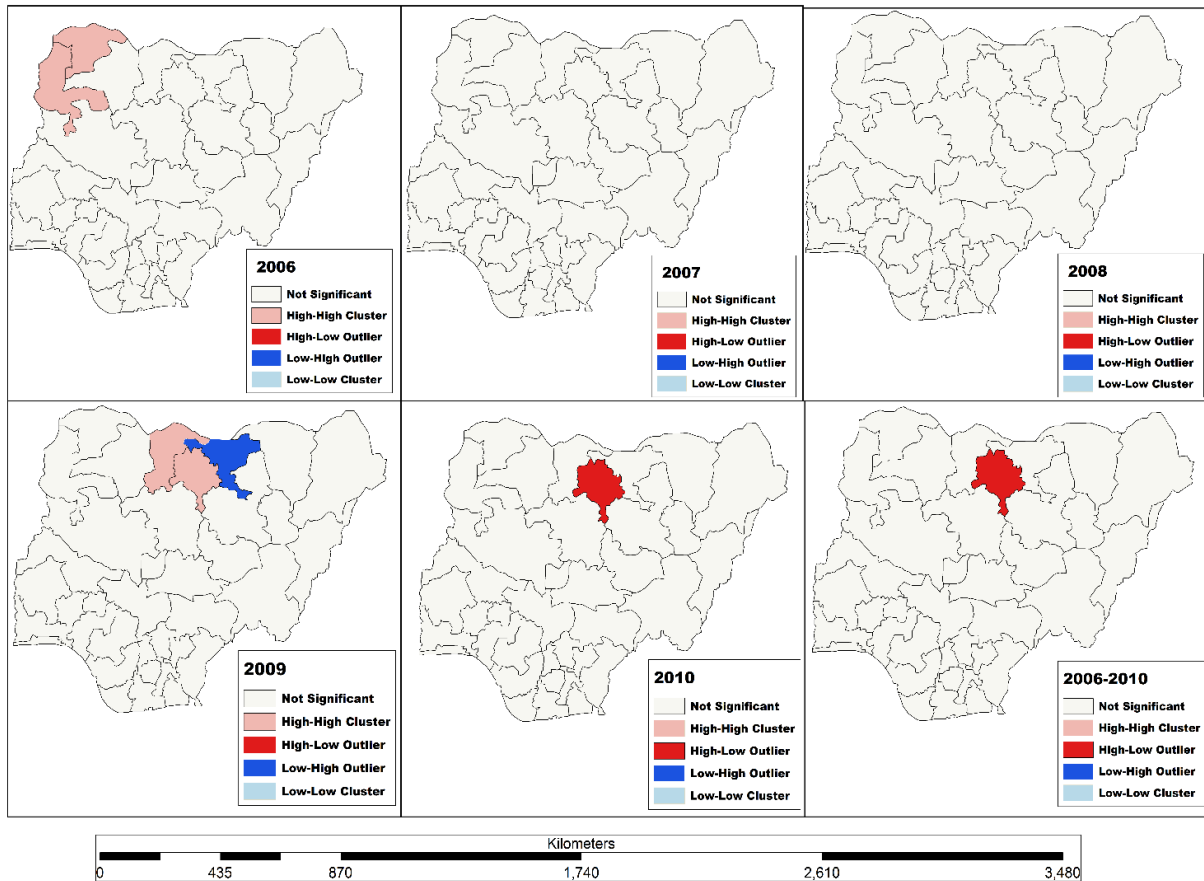


Figure 4: Hotspots of malaria mortality numbers from 2006 to 2010

Table 3: Hotspots of malaria mortality from 2006 to 2010

Year	State	I	z	p	Remark
2006	Kebbi	8.035422	4.995147	0.000001	HH
	Sokoto	6.831675	5.118837	0.00	HH
2009	Katsina	11.415116	6.789271	0.00	HH
	Jigawa	-5.061158	-2.915716	0.08549	LH
	Kano	13.066027	7.761703	0.00	HH
2010	Kano	-3.870653	-4.818402	0.000001	HL
2006-2010	Kano	-3.008266	-3.699556	0.000216	HL

Hotspots of malaria mortality rates

In 2006, there were three HH clusters in northeast Nigeria comprising Kebbi (I=8.998199), Sokoto (I=7.317823) and Zamfara (I=5.731466) states. No

clusters were found in 2007, 2008 and 2009. Kano was a HL cluster in 2010 (I=-3.871507) and 2006-2010 (I=-2.670995) (Figure 5 and Table 4).

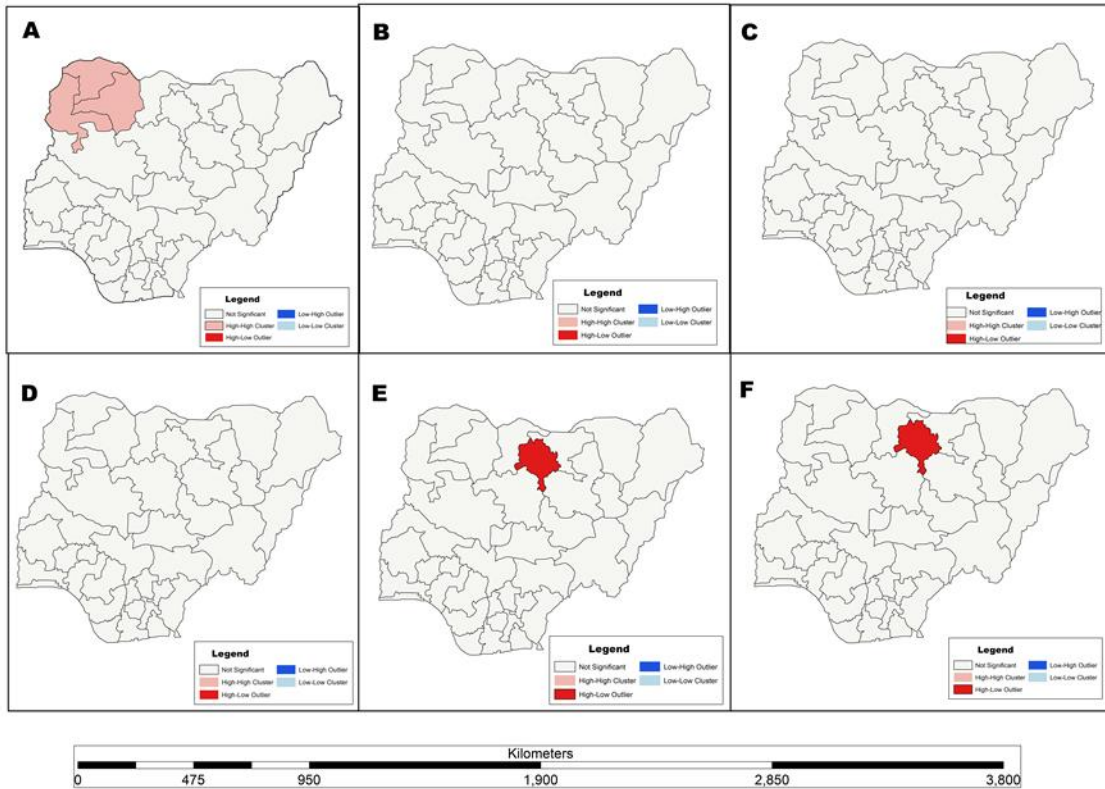


Figure 5: Hotspots of malaria mortality rates from 2006 to 2010

Table 4: Hotspots of malaria mortality rates from 2006 to 2010

Year	State	Index	z	p	Remark
2006	Sokoto	7.317823	5.533855	0.000	HH
	Kebbi	8.998199	5.640343	0.000	HH
	Zamfara	5.731466	2.904283	0.003681	HH
2010	Kano	-3.871507	-4.819	0.000001	HL
2006-2010	Kano	-2.670995	-3.27889	0.001204	HL

Association between malaria mortality and risk factors

Correlational analysis showed that poverty ($r=0.661$; $p<0.05$), women population at least 15 years of age ($r=0.427$; $p<0.05$) and children under the age of 5 ($r=0.65$; $p<0.05$) were significantly associated with malaria mortality numbers. Malaria mortality rates, on the other hand, had no significant association with any of the explanatory variables. A regression model, therefore, could not be estimated for malaria mortality rates.

With regard to the OLS regression analysis of malaria mortality numbers, each of the three variables was thus included in the model to

determine its individual effect on the dependent variable. All except poverty were insignificant. The summary of the OLS results with poverty as an explanatory variable is presented in Table 5. Poverty is positively related to malaria mortality, and also contributes 44 % of the variation in malaria mortality numbers with an F-value of 21.1156 ($p<0.05$) and AIC of 759.871. However, the presence of spatial non-stationarity in the relationship was confirmed by the Koenker statistic of 20.692674 ($p <0.05$). The Jarque Berra statistic was significant ($JB=163.468165$; $p<0.05$) indicating no normal distribution of residuals.

Table 5: Summary of OLS results

Variable	Coefficient	Std. error	t-test	p value	Robust_SE	Robust_t	Robust_pr	VIF
Intercept	-10455.607607	2544.097666	-4.109751	0.00026	6031.870756	-1733394	0.091828	-
Poverty	4459.532946	856.406091	5.207264	0.000008	2549.587660	1.749119	0.089036	-
	AICc	Multiple R²	Adj R²	Joint F	Joint Wald	Koenker (BP)	Jarque Bera:	
	759.871227	0.436534	0.420435	27.115602 ($p=0.000$)	3.059418 $p:0.082$	20.692674; ($p=0.000$)	163.468165; ($p=0.000$)	

Following the OLS analysis, the GWR analysis was performed to confirm earlier observation. The result further confirmed the presence of spatial non-stationarity. There is a spatially varying relationship between malaria mortality numbers and poverty. Going by the results in Table 6, GWR

model (AIC: 755.972410) is relatively lower and therefore more robust than the OLS model (AIC: 759.871227), thus making it a better fit in the explanation of the geographically variable relationship between malaria mortality and poverty.

Table 5: GWR results

Diagnostics		
R ²	Adj R ²	AIC
0.5704	0.5056	755.97241032114891

The GWR model explains 14% to 57% of the variance in the spatial distribution of malaria mortality. Figure 6 reveals striking variations in the local R^2 . There is a north-south divide in the level of explanation. The highest local R^2 values were located in the northernmost part of the country particularly Zamfara, Sokoto, Kano, Kaduna,

Jigawa, Bauchi, Gombe, Borno, Yobe and Katsina states. As one move southwards, the level of explanation grows weaker. Figure 7 shows the varying influence of poverty on malaria mortality. The degree of positive relationship is at its strongest in the extreme north and diminishes southwards.

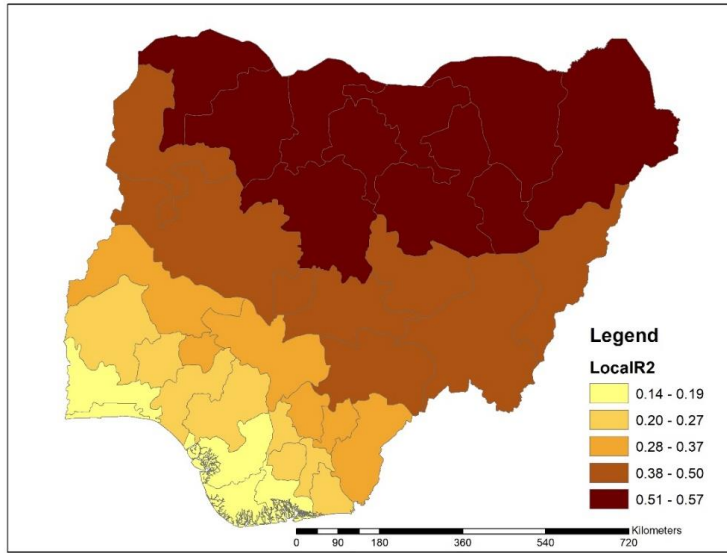


Figure 6: Local R^2

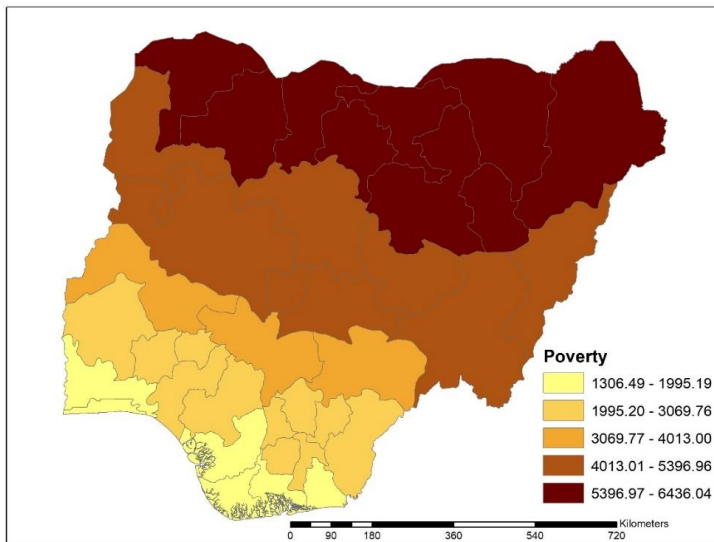


Figure 7: Poverty

Discussion

Some key findings have emerged from this research. First, the sudden spike in the number of deaths related to malaria in 2010 is very worrisome. It is probable that there was an improvement in the malaria reporting system across the country at the time which accounted for the leap in the number of deaths. Second, the 2006-2010 period witnessed striking changes in the spatial patterns of malaria mortality in Nigeria. State variations in malaria mortality could be accounted by the spatial mismatch between malaria risk and malaria intervention coverage (Adigun *et al.*, 2015), and inconsistencies in malaria reporting systems across states (Osayomi, 2014) and poor knowledge and cultural interpretations of malaria (Anyanwu *et al.*, 2017) despite the high level of public awareness. There was a significant and strong clustering of malaria mortality in northwest Nigeria, specifically Sokoto, Zamfara, Kano and Kebbi, which incidentally is the most urbanised region in the north. The presence of the significant cluster is an indication of subterranean forces driving malaria mortality. Kano, for instance, is endemic to malaria; it had over 3 million cases of confirmed malaria from 2010 to 2013 (Yakudima and Adamu, 2017). Moreover, it has a malaria prevalence rate of 40.6% prevalence among children under the age of 10 (Farouk, 2017) and has consistently surfaced as malaria morbidity hotspot for some years (Osayomi, 2014). The high incidence of malaria there has been attributed to the presence of numerous water supply and irrigation schemes which have become mosquito breeding sites (Farouk, 2017). This brings to mind Druetz *et al.*'s (2014) study of local clusters of malaria transmission in a district of Burkina Faso, where it was found that recurrent malaria hotspots were due to proximity to stagnant water bodies and artisanal dams. The question still remains: why Kano is a malaria mortality hotspot? A possible explanation could be the insecticide resistance developed by some mosquito species in Kano State. Habibu *et al.* (2017) discovered, following an experimental study, that the *An. gambiae* in Kano State had grown strong resistance to insecticides such as DDT, permethrin but showed weak resistance to bediocab. Like Kano, western Yunnan of China is a persistent malaria cluster due to high antimalarial drug resistance (Bi *et al.*, 2013). Garo Hill district

of India is known for persistent malaria transmission because of poor vector control among other factors (Dev *et al.*, 2010). There could be other reasons for the hotspot in Kano that might not be easily identifiable and as such, there is a need for further research in this regard.

The spatial analysis revealed the spatially varying influence of poverty on the geographical distribution of malaria mortality. Its greatest effect is seen in the borderline area in the north. As it is well known, malaria is an infectious disease of poverty. Nigeria unfortunately was recently labelled the “world’s poverty capital”; despite the strong economic growth it enjoys. Extreme poverty rate stands at 46.7 % (i.e. 86.9 million people) (World Poverty Report, 2019). The country has had a long history of several anti-poverty policies, which for one reason or the other achieved total failure or at best, limited success. Consequently, poverty remains persistent not only due to policy failure but also to jobless growth and a non-pro-poor growth and corruption (Khan and Cheri, 2016). Extreme poverty rate in the north is higher than the national average. Its high level of poverty, as Khan and Cheri (2016: 63) have explained, “... is much due to the high level of inefficient exploration and utilization of resources, corruption, patrimonialism, culture of dependence on the breadwinner (therefore instilling laziness) and lack of vibrant manufacturing economic sector that can absorb employable jobless youth”.

There is no single explanation as to how poverty might have induced malaria mortality but there are some pathways through poverty might have amplified the malaria mortality burden in Nigeria, which, at the same time, are not mutually exclusive. The “culture of self-medication” or lack of pharmaceutical interventions is a prominent one. In Nigeria, the first port of call for a malaria infected person is very often the drug vendor/chemist, who has little or no pharmaceutical training (Anyanwu *et al.*, 2017) because of the relative ease of access in terms of physical distance and finance. The lack of health insurance and funds to run malaria diagnosis coerce many to use monotherapies (such as artesunate, and sulfadoxine-pyrimethamine which are inexpensive and less effective than artemisinin-based combination therapy (ACT) in malaria treatment) (Etiaba *et al.*, 2015; Anyanwu *et al.*, 2017),

presumptive treatment, drug mixing which often leads to treatment failure. Counterfeit anti-malaria drugs are often purchased by the poor because they are cheaper and easy to afford (Anyanwu *et al.*, 2017). Due to the lack of health insurance, use of household savings, cutting down expenses and borrowing from others are some of the coping mechanisms in malaria treatment in Nigeria (Etiaba *et al.*, 2015) and has, in some circumstances, entrenched poverty in affected families. Poor households are the most vulnerable because they live in mosquito friendly housing and can't take chemoprevention; use an ITN, pay for effective treatment or for transportation to receive medical care (Osayomi, 2014; Johnson *et al.*, 2015; WHO, 2015; Nkegbe *et al.*, 2017, Ouedraogo *et al.*, 2018). The finding on the nexus between poverty and malaria mortality agrees with Mechior and Neto (2016), Fobil *et al.* (2011, 2012), Khagayi *et al.* (2017), Sachs and Malaney (2002); Nkegbe *et al.*, (2017); Ren, (2019). They all attest to the fact that the poorest households and poorest countries are most affected by malaria (Cibulskis *et al.*, 2016, Ren, 2019).

The study has a few limitations which need to be emphasised. First, data on malaria deaths were neither reported nor available for some states of the country for specific years, and at finer geographic scales for the whole country. If they were available, a clearer understanding of the retrospective spatial pattern would have been possible. At the same time, a note of caution needs to be issued on the official figures. Over or under-reporting cannot be ruled out as it is commonly associated with official statistics in developing countries. Second, it was hard to examine the relative contribution of some critical factors to malaria mortality such as temperature, wetlands, health seeking behaviour, poor case management, anti-malaria drug provision, anti-malaria drug resistance due to the paucity of data at the time of the study, incompleteness of data and their unquantifiable nature. Regardless of all these, the study successfully applied the methods of spatio-temporal analysis to the study of malaria mortality, which is a pioneer attempt, to the best of the knowledge of the authors.

Conclusion

This is probably the first report on the geographical distribution of malaria mortality in Nigeria which has provided great insights into its spatial patterns

and relationships and their implications for malaria control. The identification of these significant clusters would help health policy to focus on local malaria control approaches for the elimination of malaria deaths. No doubt, the spatio-temporal analysis of malaria deaths will give some direction in which health policy should take in the future. It would be easy and quick to call up the standard WHO malaria interventions- increased coverage of ITNs, improved malaria treatment (ACT), and indoor residual spraying – for the prevention of malaria deaths. As some have recently noted in western Kenya and Burkina Faso (Kapesa *et al.*, 2018; Diboulo, 2016), it is possible some interventions in malaria control are successful in some areas and fail in others. This clearly questions the efficacy of these recommended measures in some settings and queries the commonly used one-size-fits-all approach to disease control, which is very deficient in many respects. This in fact, reinforces WHO (2015: 8) view that "...the risk of malaria varies significantly within a country or area, the same strategy is not necessarily appropriate for all settings within a country". Therefore, it is about time Nigeria looked inward and searched for local and culturally appropriate interventions for application. The research findings have given a strong justification for poverty eradication for malaria control in Nigeria to be successful. It is apparent that malaria control should not only be restricted to vector control and biomedical approaches but must include poverty alleviation with strong political commitment from government. Therefore, the war against poverty in Nigeria is a *sine qua non* for a malaria free Nigeria by 2030.

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