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Spatio–Temporal Clustering of Malaria Morbidity in Nigeria (2004-2008)

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Abstract

Malaria is one of the primary causes of morbidity and mortality in the world. Many studies exist on the geographical patterns of malaria infection in different parts of the world. However, little is known on the spatial heterogeneity of malaria in Nigeria, where it is one of the principal sources of illness and death. Understanding its spatio-temporal dynamics would be helpful in the design of effective location-specific malaria prevention and control programmes. The aim of the study was to analyse the spatio-temporal patterns of malaria morbidity in Nigeria, and identify climatic, environmental and socioeconomic risk factors underlying these patterns. Data used in this study included malaria cases from year 2004 to 2008, ground elevation, forest cover, wetlands, urbanisation, poverty, temperature, rainfall, minimum temperature, maximum temperature and humidity. Spatial analytical techniques such as Global Moran's *I* and Anselin's Moran *I* were used to determine the degree of spatial clustering of malaria and detect malaria hotspots respectively for each year. Spatial distribution of malaria were mapped at the state level. There was significant clustering of malaria in 2006 and 2008. The spatio-temporal cluster analysis generally suggested the existence of a fairly stable Kano-Katsina malaria cluster in northwestern Nigeria. Urbanisation (R^2= 14.4%; $p < 0.05$), poverty (R^2= 13.9%; $p < 0.05$) and forest cover (R^2= 10.7%; $p < 0.05$) had significant contributions to malaria morbidity. In the final regression model to determine the combined effect of the four factors using the backward selection approach, urbanisation was the only dominant factor. No doubt, malaria morbidity in Nigeria varies unevenly over space and through time. Its geographical distribution is significantly influenced by the level of urbanisation, forest cover and poverty. These results suggest the urban malaria phenomenon is present in Nigeria, and has a social gradient in morbidity. The study concludes that intervention efforts should take into consideration the spatial heterogeneity of malaria transmission in order to obtain optimum outcome.

Key words: Malaria, Spatial clustering, Spatial statistics, Linear regression, Nigeria.

Introduction

The World Health Organisation (W.H.O) estimated that 3.3 billion people were at risk of malaria in 2011, with the highest risk found among the sub-Saharan Africa populations. Specifically, about 80% of cases and 90% of malaria related deaths occurred in the WHO African Region, with children under five years of age and pregnant women bearing the brunt [1]. In response to its heavy burden, malaria was listed as one of the target diseases of the Millennium Development Goals (MDGs). Despite this global intervention, the MDG 50 percent reduction in global malaria target by 2015 appears to be unattainable.

In the last decade, research has shown that malaria morbidity exhibits spatial and temporal variability, and therefore interest has increased in exploring various climatic, environmental and socioeconomic factors affecting the spatial distribution of malaria morbidity. Empirical evidence shows transmission depends on the distribution and abundance of malaria vectors, which are responsive to environmental, climatic and socioeconomic factors such as land cover, rainfall, altitude and temperature.

Considerable variations in the spatial distribution of malaria cases have been observed in Yunnan province of China [2], Thailand [3], Bangladesh [4], Iran [5], Somalia [6], Ethiopia [7], Kenya [8], northeastern Tanzania [9], Vietnam [10], Malawi [11], Mozambique [12-13], Zambia [14], and the Democratic Republic of Congo [15]. While geographical patterns of malaria

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morbidity have been previously studied in these countries, spatio-temporal patterns of this disease in Nigeria have not been well explored. Though preventable and treatable, malaria infection is highly endemic, and forms a major public health challenge in Nigeria. Malaria-related deaths comprised eleven percent of maternal mortality; it accounts for 25 percent of infant mortality, and 30 percent of under-5 mortality in Nigeria [16]. Despite some policy responses like the Abuja Declaration and Plan of Action 2000 and the 2005 Anti-Malaria policy, malaria appears to be on the increase.

This article therefore investigates the spatio-temporal pattern of malaria morbidity using state level malaria morbidity data. In detail, it seeks to describe the degree of spatial clustering, and identifies hotspots of malaria in Nigeria using geographical information system (GIS). In addition, it attempts to establish the association of a wide range of climatic, environmental and socioeconomic factors with malaria morbidity. The findings of this study would be useful for the following: (a) Understanding the underlying forces of the spatio-temporal pattern which is capable of guiding policy makers and relevant stakeholders to make evidence based policy decisions. (b) identification of disease clusters and population at most risk for appropriate malaria prevention and control, and (c) detection of consistencies or irregularities in disease clusters over time and across space.

The remaining part of this paper is divided into six sections. The next section is a description of the study context. The second section contains a conceptual framework and review of the literature on the spatial and temporal distribution and their associated risk factors. The third section describes the data sources and methodology. Section four shows the results of the study. The results are extensively discussed in the fifth section. The paper ends with the conclusion and some recommendations.

Study Context

Nigeria is located in West Africa between longitudes 3^o to 15^o east and latitudes 4^o to 14^o north. It has an area of 923,800 square kilometres and a population of over 140 million during the 2006 census. The country is divided into thirty six states and the Federal Capital Territory, and is characterized by different natural landscapes which include mangrove swamps, rainforests, guinea savanna, sudan savanna, sahel savanna and montane vegetation (found on high altitudes). Nigeria's climate is humid tropical in nature, characterized by dry and rainy seasons. The combination of ecological and climatic zones not only provides favourable breeding conditions for the malaria vector, but also affects the seasonal occurrence, intensity and length of malaria transmission [16]. Malaria transmission in the country is distinctly cyclical with a higher morbidity during the rainy season. The most common malaria vector species in Nigeria are the *Anopheles gambiae* species and the *A. funestus* group while the most prevalent species of malaria parasites in Nigeria is *Plasmodium falciparum* accounting for about 98 percent of malaria cases in Nigeria [16]. The population subgroups most affected by malaria in Nigeria are children under the age of five and pregnant women [17].

Conceptual Framework and Previous Literature

Malaria is a vector borne parasitic disease that is affected by a wide range of factors. Many studies have identified these risk factors, which can be roughly divided into environmental, climatic and socioeconomic, to be largely responsible for the spatial and temporal variability in malaria transmission. The concept of disease risk cells which indicates that variations in the interaction of environmental and social factors inform the differential in communities' exposure to disease risks. Hence, the spatial variation in the malaria morbidity in Nigeria is expected

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to be explained by climatic, environmental and socioeconomic risk factors.

Climatic Factors

Climatic factors such as rainfall, temperature and humidity are critical to mosquito breeding and malaria transmission. Areas with greater amounts of rainfall, higher temperature and high levels of humidity are expected to have higher malaria morbidity because such areas favour mosquito breeding [10, 12, 18]. Rainfall often lead to small puddles serving as mosquito breeding sites and increases humidity, which facilitate mosquito survival [18]. The birth and development of mosquitoes and the parasite are dependent on temperature. Also, higher temperature increases the number of blood meals mosquitoes take and the number of times they lay eggs. However, extreme temperature conditions do not favour reproduction. Here, it is hypothesized that rainfall, temperature and humidity are positively related to malaria morbidity.

Environmental Factors

Studies have shown that elevation has a significant negative effect on malaria morbidity [9, 11, 19]. This is because cooler temperatures at higher altitudes do not support mosquito reproduction. In line with this fact, it is expected that there would be an inverse relationship between elevation and malaria morbidity. The effect of forest cover on malaria morbidity is somewhat debatable. There are two contrasting views on its effect on malaria. The first is forest conditions strongly support the proliferation of mosquitoes. As illustrated by Stresman [20]:

> "In an area where the predominant land use is forest, temperature is generally much cooler as the result of the abundance of shade provided by trees, humidity is greater as a result of the increased ability of the vegetation and soil to retain moisture and there is a high probability that permanent breeding sites will be present along with many geological features for water to pool when there is intense precipitation. These conditions would suggest the possibility of high malaria transmission".

This view is supported by other authors [10, 18, 21]. In fact, the malaria occurrence in forested areas has been described as "forest malaria" [10]. The second view emphasizes that malaria prevalence is higher in deforested areas/forest fringes than in forested areas. Deforestation modifies environmental conditions which, in turn shortens the mosquito's development cycle [20]. Given their relatively shorter cycle, the vectors become infectious earlier than expected; and live longer to transmit malaria and increase their biting frequency [20]. It is also important to add that malaria risks are heightened when forests give way to the construction of roads, dams, irrigation facilities, buildings, artificial water bodies and fish ponds. This is achieved when these human activities alter microclimatic conditions and thereby increase the number of mosquito breeding sites. Following this, this study assumed that there is a positive relationship between forest cover and malaria morbidity.

Urbanisation is an important environmental determinant. There have been conflicting findings on the effect of urbanisation on malaria morbidity which can be broadly classified into two viewpoints- positive and negative. On one hand, the former perspective is of the view that high urbanisation levels translate to high malaria morbidity levels. In other words, malaria is widespread in urban centres. This can be explained by the nature of urban settings where poor quality housing, unpaved roads and limited access to health care facilities provide little protection against malaria [22] and the huge population of urban dwellers constitute a potential source of blood meals

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for mosquitoes, which is facilitated by the closer human–vector contact being enhanced by the proximity of breeding sites [9]. This probably accounts for the reason why some authors describe malaria in urban centres as urban malaria [9]. On the other hand, the negative viewpoint posits that the malaria burden is lighter in urban centres due to their inherent prevailing conditions which either discourage mosquito breeding or destroy mosquito territories. For example, high bet net coverage, high socioeconomic status, good housing [9], high pollution levels [23], and limited supply of clean water [24] adversely affect the birth and development of malaria vector species and eventually contribute to the low risk of malaria in urban areas. Though there are divergent standpoints on the urbanisation-malaria nexus, it was assumed in this paper that the urban areas are at greater risk of malaria.

Wetlands are suitable mosquito vector habitats because of the presence of water which provides the required moisture for mosquito breeding. Populations within such environs would be highly susceptible to malaria infection. This fact is supported by Stresman [20] and Hakre et al. [21]. It is hypothesized that wetlands contributes to malaria morbidity.

Socio-economic Factors

Poverty is an important risk factor of malaria disease. Malaria has maximum effect in many of the world's poorest countries [25], and poor and disadvantaged communities [10, 19, 26]. Besides the fact that poverty affects malaria, malaria also affects poverty. In other words, there is a reciprocal relationship between malaria and poverty. It is both the root and consequence of poverty. Poor individuals and poor households live in environments which predispose them to malaria. In addition, they do not have the money to provide good nutrition; bear the cost of medical treatment or buy medicine. Besides the financial barriers to accessibility to healthcare, they also have limited access to healthcare facilities probably because of the long distance they might have to travel to obtain medical care. In turn, malaria hampers labour productivity- a number of work days are lost and affects the little income flows and further deepens poverty in households, with greater spill-over effects. In fact, [1] puts it succinctly: "…Poverty sustains the conditions where malaria thrives, and malaria impedes economic growth and keeps communities in poverty." Given this fact, the study hypothesized that there is a direct and positive relationship between poverty and malaria morbidity. In summary, the spatial distribution of malaria in Nigeria is significantly influenced by rainfall, temperature, humidity, ground elevation, forest cover, urbanisation, wetlands and poverty

Material and Methods

Data Sources

The number of state level reported malaria cases from 2004 to 2008 was provided by the National Bureau of Statistics, Nigeria. Missing values were imputed by averaging the values from the adjacent states. The average values of malaria cases were calculated for each state by dividing the total number of malaria cases from 2004 to 2008 by 5. Annual values for rainfall, minimum temperature, maximum temperature, humidity were used as climatic variables influencing malaria morbidity, and obtained from the Annual Abstract of Statistics 2009 published by the National Bureau of Statistics. Missing values were also observed for some states and were interpolated. Environmental factors comprise forest cover, ground elevation, wetland and urbanisation. For forest cover, the area extent of forest reserves in each state served as a surrogate. These values were retrieved from the Annual Abstract of Statistics 2009. Ground elevation represented by the percentage of state area that is covered by highlands, and percentage of state that is wetland are based on data generated by [27]'s spatial analysis of flood plains from SPOT Satellite elevation data. The degree of urbanisation per state is represented by a proxy measure, population density (i.e the ratio of state‘s population to its area in square kilometres). Due to the lack of data on the percent of state population that is urban in Nigeria, this proxy measure is the only available information that can be used in this study. It is assumed that the higher state averages would represent higher levels of urbanisation and vice versa. Population of the thirty six states and Federal Capital Territory was based on the 2006 Population census conducted by the National Population Commission. The use of the 2006 figures stood on the assumption that the country's population had remained static. Poverty was represented by the poverty density index. In this study, the index was expressed as the proportion of number of poor households in each state to the land area of the given state. The number of poor households in each state was obtained by multiplying the poverty incidence rate (often expressed in percentage) of each state by the state's population size. Subsequently, the number of poor households per state was divided by the total land area per state to give the poverty index (number of poor households per square kilometre). Conceptualization and computation have been described elsewhere [28].

Methods

The analysis was in three phases. The first phase was to determine the degree of spatial clustering of malaria, using Global Moran's *I*. The second was to identify the location of spatial clusters with the aid of the Local Moran's *I* statistic, and the last explored the possible association of malaria with selected risk factors, using the linear regression method.

Global Moran's I Statistic

It is used as a measure of spatial auto-correlation. It tests for the existence of random spatial patterns in any given phenomena. If the result indicates otherwise, there is an evidence of spatial autocorrelation. In particular, spatial autocorrelation measures the nature and strength of interdependence between data. Positive spatial autocorrelation occurs where similar values tend to occupy adjacent locations whereas negative auto-correlation implies that high values tend to be located next to low ones. On the other hand, if the spatial arrangement is completely random, then this implies the absence of spatial autocorrelation. Moran's *I* ranges approximately from +1 (for positive spatial autocorrelation) to -1 (negative auto-correlation) and its expected value in the absence of autocorrelation approximates zero. However, an inadequacy of the Global Moran's I is its inability to indicate where the significant clusters of a given phenomenon are located and nature of the localized cluster (whether negative or positive). In order to make up for this inadequacy of the Global Moran's I, the Anselin Local Moran's *I* was engaged.

Anselin Local Moran's I

It belongs to the family of local indicators of spatial association (LISA). Like other LISA tools, it points out where a given pheno-menon forms clusters in space. Specifically, LISA measures whether the morbidity rate for each state is closer to the values of its neighbours. In that way, it discerns similarity and dissimilarity among the spatial units in question. This statistics generates five cate-gories of local spatial patterns—High-High indicates clustering of high values of malaria incidence (positive autocorrelation); low-high indicates that low values are next to high values of malaria incidence (negative spatial autocorrelation); low-low indicates clustering of low values of malaria incidence (positive spatial autocorrelation); high-low indicates high values are proximate to low values of morbidity incidence (negative spatial auto-correlation), and not significant indicates the absence of spatial auto-correlation. Mapping and analyses were done using ArcGIS Version 9.3.

Statistical Analysis

The effect of climatic, environmental and socioeconomic factors on the spatial distribution of malaria rates were explored using the simple linear regression. First, the dependent variable, average number of malaria cases went through logarithmic transformation so as to fulfill the principle of normality. Second, the individual effect of each risk factor was explored separately, and then all the significant factors were included in the final multiple regression model. The choice of linear regression model was driven by the need to determine the individual and collective contribution of the independent variables to the variation in the dependent variable.

Results

Nigeria had a total number of 17,861,155 malaria cases for the five years of observation. The highest reported malaria morbidity occurred in 2007 (4, 948, 838), followed by 2006 (3, 547, 830) and 2004 (3, 247, 241) as depicted in Figure 1.

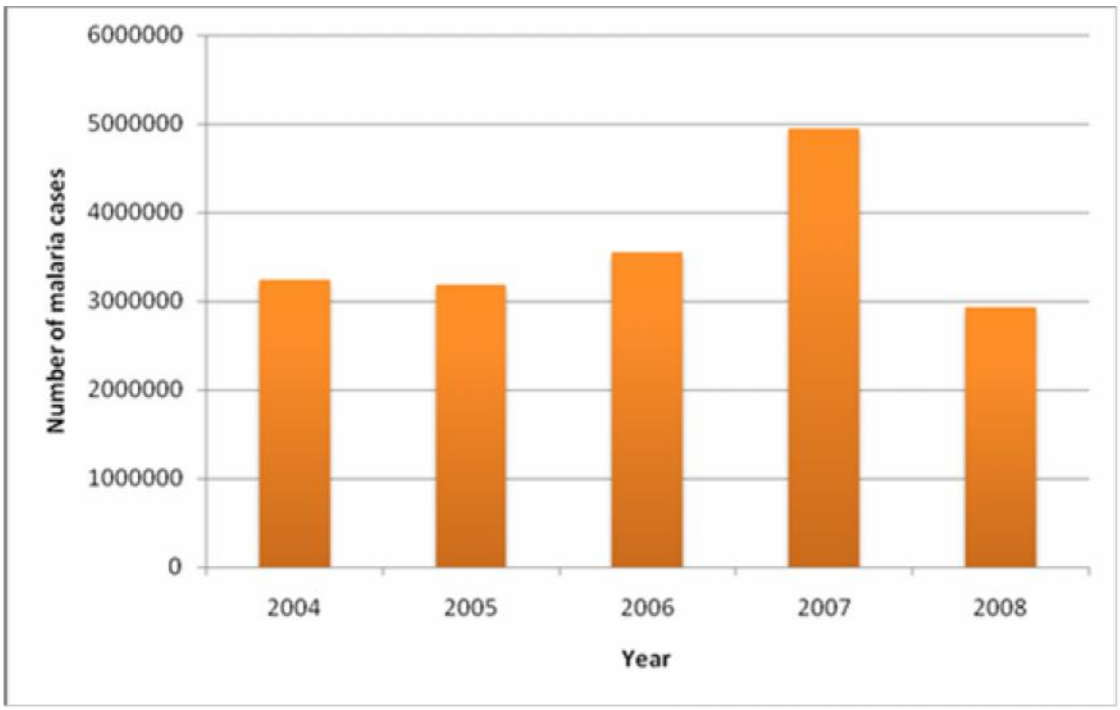

Fig. 1: Annual distribution of malaria cases.

Spatio-temporal Patterns

The spatial distribution of malaria morbidity in Nigeria from 2004 to 2008 is shown in Figures 2 to 6. Generally, malaria morbidity varied substantially across the states in Nigeria.

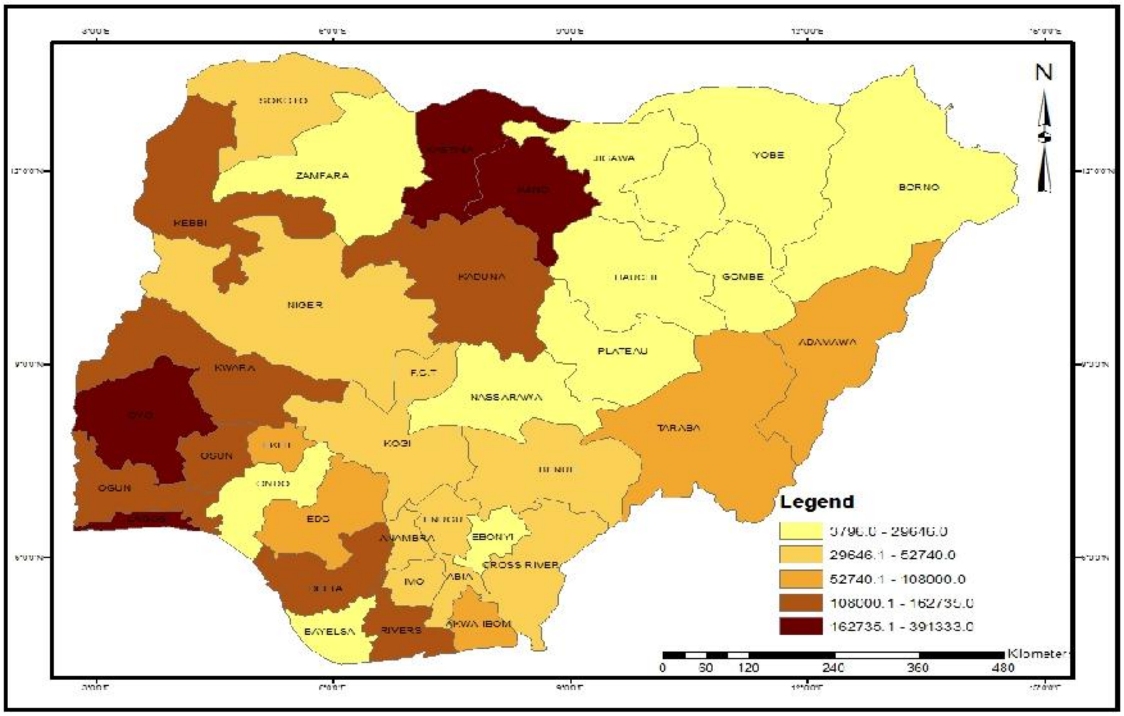

Fig. 2: Spatial distribution of malaria in 2004.

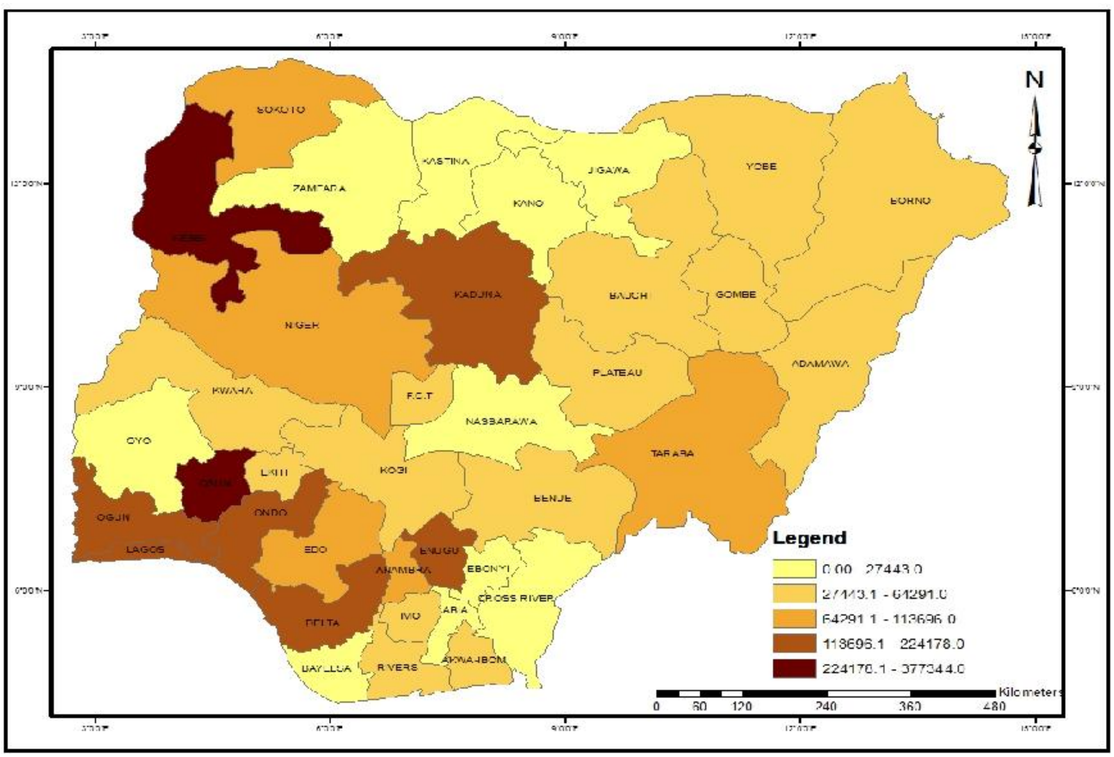

Fig. 3: Spatial distribution of malaria in Nigeria in 2005.

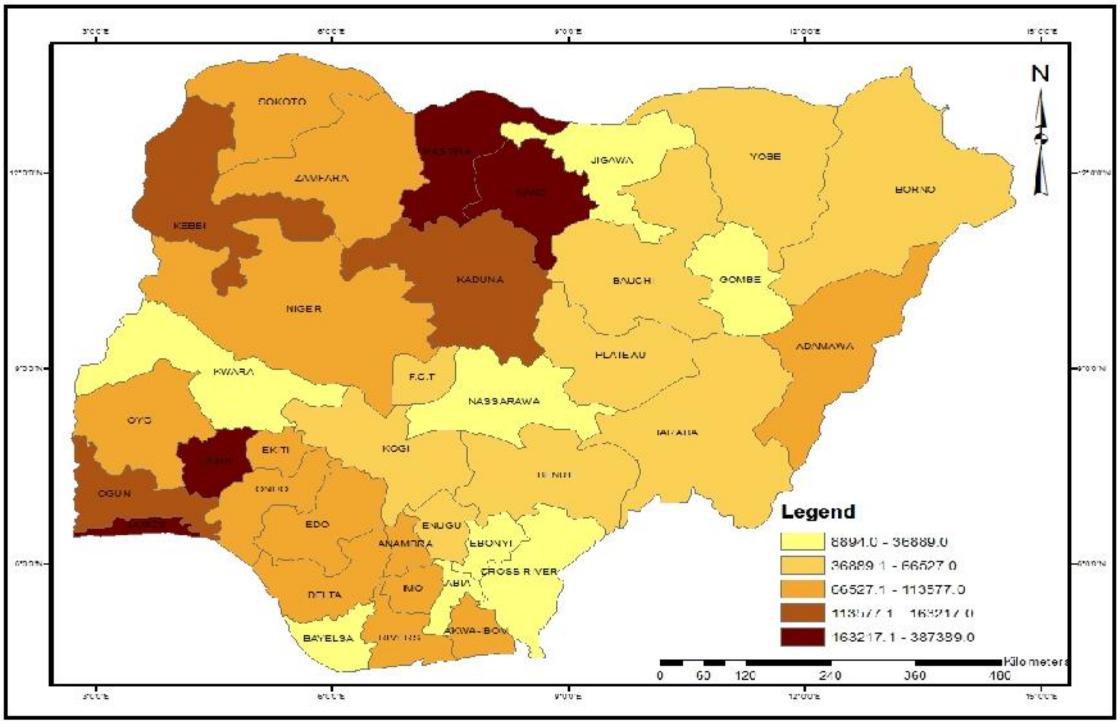

Fig. 4: Spatial distribution of malaria in Nigeria in 2006.

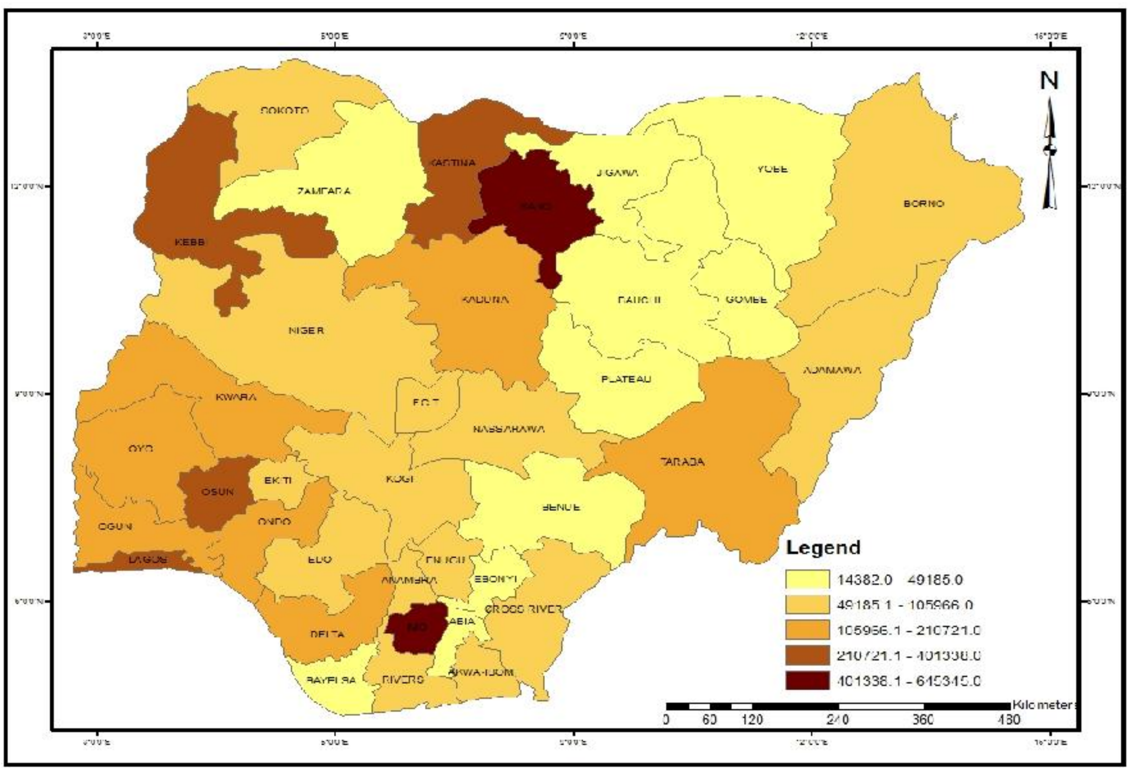

Fig. 5: Spatial distribution of malaria in Nigeria in 2007.

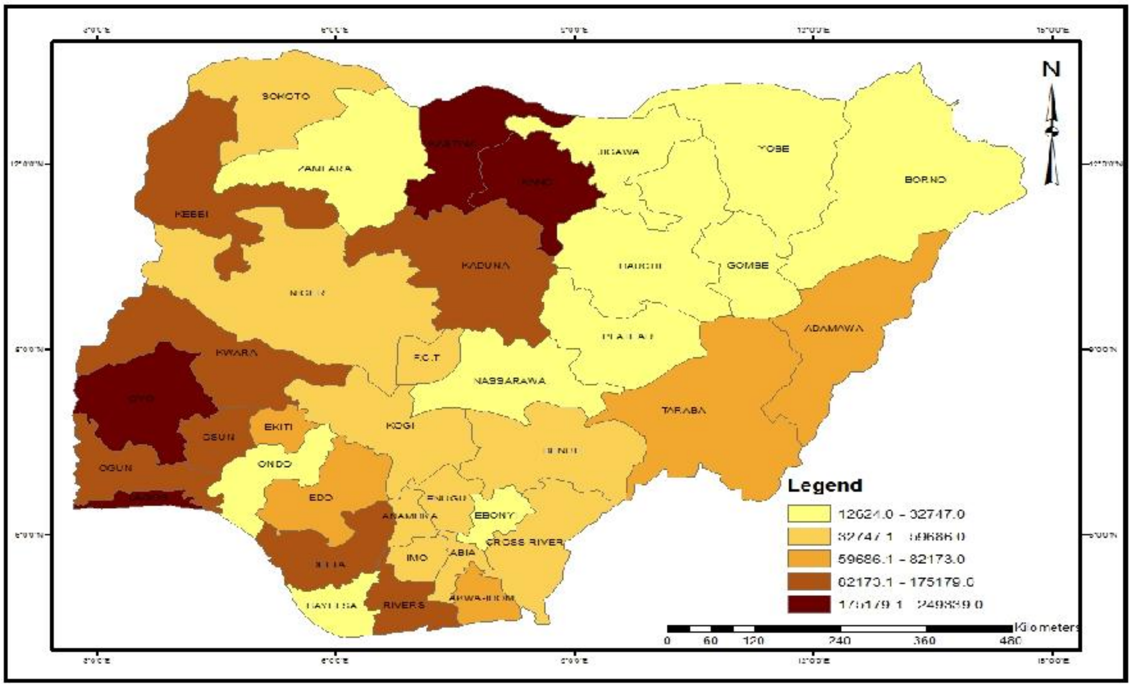

Fig. 6: Spatial distribution of malaria in Nigeria in 2008.

Figure 2 shows that malaria morbidity was most pronounced in the highly urbanized states of Kano and Katsina states (in the Northwest), Oyo and Lagos states (in the southwest). In contrast, most of the states in the Northeast and some in the north Central had some of the lowest morbidity levels. In 2005, the largest number of cases were seen in Osun and Kebbi states while most of the low morbidity cases were mainly concentrated in the northern states as shown in Figure 3. In 2006, the Kano-Katsina malaria cluster and Lagos re-emerged. Osun remained constant while majority of the northern states still had the lowest morbidity. In 2007, only Kano and Imo states had the largest numbers whereas the rest of the country had relatively lower numbers. The spatial pattern in 2008 is similar to that of 2004 with the greater number of cases in Kano, Katsina, Oyo and Lagos clusters and the lower numbers still persistent in most of the northeastern region in Figure 6.

Figures 2 to 6 and Table 1 show the degree of spatial clustering of malaria in Nigeria during the study period. There was evidence of significant positive spatial autocorrelation for malaria in 2006 and 2008. The clustering of the highest malaria morbidity in Nigeria was stronger in year 2008 (Moran's I = 0.196499, $p < 0.05$) than in 2006 (Moran's I =0.195435, $p < 0.05$). In the other years, Moran's I results suggested randomness in the spatial pattern for 2004, 2005 and 2007.

Table 1: Summary of Global Moran's *I* results

Year	Index	Z score	P value	Remark
2004	0.171821	1.945798	>0.05	Random
2005	-0.041597	-0.141387	>0.05	Random
2006	0.195435	2.184612	< 0.05	Clustered
2007	0.034454	0.611932	> 0.05	Random
2008	0.196499	2.106861	< 0.05	Clustered

Table 2 lists all the states with statistically significant autocorrelation ($p < 0.05$). In 2004, there was no evidence of local spatial autocorrelation. In 2005, Katsina and Zamfara states were negatively auto correlated. On one hand, Katsina with an index of -0.986517 indicates the state had large number of malaria cases but was surrounded by states with lower numbers. On the other hand, Zamfara with its small number of cases is bounded by states with high malaria morbidity. In 2006, Kano and Katsina were positively auto correlated. This means they were not only high burden states but were surrounded by states with large numbers of malaria cases. Jigawa was negatively auto correlated. Imo was the only malaria cluster detected in 2007, showing a negative autocorrelation. In 2008, three states showed positive correlations, with Kano state showing the highest index followed by Katsina and Oyo. Overall, malaria is locally persistent in Kano and Katsina.

Table 2: Results of Local Spatial Analysis

Year	State	Index value	Z score	P value	Remark
2004	-	-	-	-	-
2005	**Katsina**	-0.986517	-2.123425	< 0.05	High-Low
	Zamfara	-1.59097	-2.838043	< 0.05	Low-High
2006	**Jigawa**	-1.118013	-2.43831	< 0.05	Low-High
	Kano	1.521421	3.460731	< 0.05	High-High
	Katsina	1.440932	3.28084	< 0.05	High-High
2007	**Imo**	-1.753886	-3.33963	< 0.05	High-Low
2008	**Kano**	1.279047	2.821116	< 0.05	High-High
	Katsina	1.172958	2.591963	< 0.05	High-High
	Oyo	1.17586	2.219479	< 0.05	High-High

Associations with Climatic, Environmental and Socio-economic Factors

Table 3 presents the results of the linear regression between malaria in the 36 states and the Federal Capital Territory of Nigeria and the separate indicators. In this model, the variables were entered consecutively to explore their effects separately. Dependent variables were log transformed. Table 3 shows the results of the bivariate regression models. None of the climatic factors were statistically significant ($p > 0.05$). Besides, all except humidity had negative beta coefficients. Only two environmental factors: urbanisation and forest cover were significant at the 0.05 significance level. On one hand, urbanisation was found to be positive and accounted for 14.4 percent in the observed variance in malaria morbidity. On the other hand, forest cover had a negative sign, and explained 10.7 percent of the total variation in malaria. The only socioeconomic factor, poverty was significantly and positively related to malaria morbidity with a coefficient of determination of 13.9 percent. Thus, only urbanisation, forest cover and poverty showed a significant individual effect on malaria morbidity.

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Table 3: Summary of Results for the full Regression Model

Variable	Beta coefficient	Significance level	Coefficient of determination
Climatic			
Minimum temperature	-0.024	0.888	0.001
Maximum temperature	-0.026	0.879	0.001
Rainfall	-0.033	0.847	0.001
Humidity	0.072	0.671	0.005
Environmental			
Urbanisation	**0.379**	**0.021**	**0.144**
Elevation	0.013	0.940	0.000
Forest cover	**-0.327**	**0.048**	**0.107**
Wetlands	0.059	0.728	0.004
Socioeconomic			
Poverty	**0.373**	**0.023**	**0.139**

Note: Significant factors in bold print

To determine the joint contribution of these three factors to malaria, a multivariable regression was estimated. The outcome indicated that the combined effect of the three on malaria morbidity was not significant. A preliminary correlation analysis of the independent variables showed there was a problem of multicollinearity. Correlation coefficient which exceeded 0.8, (which is the evidence of severe multicollinearity) [29] was noticed in the association between urbanisation and poverty ($r = 0.996$; $p = 0.00$). Therefore, the study instead adopted the backward elimination approach. This technique eliminates independent variables with little effect on the dependent variable. In operational terms, independent variables with the smallest influence would be the first to be removed; and goes on till the model is left with the most significant variable(s). The final model with the three significant factors showed that only urbanisation had a significant impact on malaria morbidity (R^2 = 14.4 %; p = 0.021) (See Table 4).

Table 4: Summary of Results for Backward Regression Model

Variable	Beta coefficient	Significance level
Full model		
Urbanisation	0.992	0.574
Forest cover	-0.204	0.258
Poverty	-0.708	0.689
$\mathbf{R^2}$	0.179	
Backward model		
Urbanisation	0.379	0.021
$\mathbf{R^2}$	0.144	

Discussion and Conclusion

There are striking variations in the geographic distribution of malaria in Nigeria. It evidently follows a space-time pattern in Nigeria. There was clustering of malaria morbidity in 2006 and 2008, with a higher degree of clustering in the latter. The local spatial patterns from 2004 to 2008 indicated that malaria seemed to be locally persistent in Kano and Katsina states. The Kano-Katsina malaria cluster is found in the most urbanized region of northern Nigeria. This high risk malaria cluster certainly points to the presence of favourable conditions for malaria transmission in these areas. Associations of risk factors with malaria morbidity were

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strongest for the positive relationships with urbanisation followed by poverty, and negative association with forest cover. The interpretation of this finding is that malaria morbidity are higher in urban areas; in areas with little or no forest cover, and among poor households.

The finding about the positive relationship between malaria and urbanisation is in agreement with the positive effect school of thought. In Nigeria, malaria has been described as the "greatest environmental hazard" in many urban centres [30]. The low socioeconomic residential areas of most Nigerian cities are generally characterized by unhealthy conditions which increase the Nigerian urban population's degree of susceptibility to malaria. It is commonplace to see sewage flow from outdoor bathrooms and toilets onto the streets; drainage channels filled with stagnant and filthy water, and large heaps of refuse line the major highways and neighbourhood streets. All these unsanitary surroundings, with the appropriate microclimatic conditions, create malaria mosquito habitats. Subsequently, these vectors breed, feed and infect the numerous urban residents with malaria parasites. This finding is confirmed by Patz et al. [19] study in Amanse west district, Ghana where high malaria rates were prevalent in the district's capital. From the foregoing, it is clear that malaria is highly endemic in Nigerian urban centres

In this study it was found that morbidity was lower in areas with little or no forest cover which does not confirm studies from Vietnam, Mozambique and Ghana. Large forest cover significantly reduced the rate of malaria morbidity, which goes in line with the view that malaria prevalence is higher in deforested areas. On one hand, a possible explanation for this observation could be that Nigeria, in recent times, has witnessed an increasing rate of uncontrolled urbanisation, agricultural and road transport development, which in turn have cleared large areas of the country's natural forests, thereby facilitating closer human and malaria vector contact. On the other hand, areas with little or no forest cover are at increased risk of malaria infection, with increase in temperature. The increased temperature, in turn, increases the biting frequency rates of mosquitoes and accelerates the reproduction cycle of the malaria vector [20]. This goes contrary to [18]'s observation where it was found that disease prevalence was seen to be very high in the forest and forest fringes as compared to plains or non-forested areas in Amanse west district, Ghana, and [10]'s study which revealed a positive association between malaria parasites such as *plasmodium falciparum* and *plasmodium vivax* and percentage of forest cover of Vietnamese districts.

In this study, malaria was shown to be a disease of poverty. Malaria afflicts urban population in Nigeria particularly the poor households. This reflects a social gradient in the health status of Nigerians. The concept of social gradient in health status illustrates that people with higher socioeconomic status enjoy better health. In other words, those in the low socioeconomic strata of the society suffer worse health outcomes because of their limited access to societal resources. It therefore follows that poor households in Nigeria are highly susceptible to malaria basically due to the poor living conditions and low income which unfortunately do not confer protection against malaria. This in fact receives support from [31]'s observation that "…65% of Nigerian population live in poverty and poverty is a major factor in malaria prevention and treatment".

It is pertinent to note a few major strengths of this study. This is probably the first nationwide study of malaria morbidity in Nigeria with the aid of geospatial techniques. With these approaches, it was possible to show that malaria varies geographically; and the existence of a fairly consistent Kano-Katsina malaria hotspot in the northwestern part of Nigeria. However, there are a number of limitations of this study that are also worth noting. First, as at the time the study was being conducted, information on the state

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level distribution of insecticide treated nets (ITNs) and long lasting insect nets (LLINs) was not available. Therefore, the influence of ITNS and LLINs could not be examined. Second, there are likely to be limitations (such as overestimations, underreporting of cases) in the original data sources as it is common with data sources in developing countries like Nigeria. It is important to bear in mind that the degree of efficiency of malaria reporting system (i.e. regular monitoring and proper recording of malaria cases) may differ from state to state. For instance, states with an efficient reporting mechanism would tend to have higher malaria incidence than others with sub-standard systems. This may, partly, explain why some states have continually high or low malaria morbidity, as the case may be. Third, the interpretation of the association of the risk factors with malaria morbidity could lead to the faulty assumption that the significant risk factors of malaria are spatially homogenous (i.e uniform over space), which is absolutely unrealistic. This assumption is popularly referred to as the ecological fallacy. Based on the findings of this study, it is suggested that the following steps be taken:

- Government should intensify health education campaigns on the prevention and control of malaria.
- Environmental sanitation should be regularly enforced at the different administrative levels in the country in order to keep healthy and malaria free environment.
- Government needs to strengthen its poverty alleviation efforts not only to reduce the numbers of those who live below the poverty but also to improve their health status.
- Government should increase the distribution of ITNs and LLINs in the country so as to reduce the susceptible population as much as possible.
- Government should sustain, if operational, free malaria treatment to the most susceptible population groups: children under the age of five and pregnant women.
- Future research should be directed at a micro spatial analysis of malaria morbidity in the states particularly in the Kano-Katsina malaria cluster. It is believed that such an analysis would uncover unique geographical patterns which were not evident in the first place and further shed light into the processes that determine the spatial pattern of malaria transmission.
- The relationship between malaria, forest cover, urbanisation and poverty in Nigeria requires further investigation so as to fully comprehend the 'chemistry' of malaria transmission in Nigeria.
- GIS technology with particular emphasis on spatial statistical techniques should be integrated into the malaria surveillance system. This would provide information on the location and strength of malaria hotspots in the country.
- Further investigation on space-time analysis to determine whether malaria has become more localized or wide-spread in transmission in subsequent years.

The study of spatio-temporal clustering of malaria morbidity in Nigeria is an important step towards a comprehensive understanding of the spatio-temporal patterns of malaria and the underlying mechanisms. Based on the findings, future research and health interventions should give critical attention to the significant malaria clusters and the 'urban malaria phenomenon'. From a public policy perspective, this paper recommends that responses to malaria must take into account the spatial variation in malaria morbidity, with more attention to the most affected states and regular malaria surveillance with the aid of G.I.S. technology. These proposals may be of considerable interest to policy makers, health agencies and other stakeholders in Nigeria.

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