Nigeria's malaria prevalence in 2015: a geospatial, exploratory district-level approach

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Abstract

This study used data from the second Nigeria Malaria Indicator Survey (NMIS) conducted in 2015 to investigate the spatial distribution of malaria prevalence in the country and identify its associated factors. Nigeria is divided into 36 states with 109 senatorial districts, most of which are affected by malaria, a major cause of morbidity and mortality in children under five years of age. We carried out an ecological study with analysis at the senatorial district level. A malaria prevalence map was produced combining geographic information systems data from the Nigeria Malaria Indicator Survey (NMIS) of 2015 with shape files from an open data-sharing platform. Spatial autoregressive models were fitted using a set of key covariates. Malaria prevalence in children under-five was highest in Kebbi South senatorial district (70.6%). It was found that poorest wealth index ($\beta = 0.10$ (95% CI: 0.01, 0.20), $p = 0.04$), mothers having only secondary level of education ($\beta = 0.78$ (95% CI: 0.05, 1.51), $p = 0.04$) and households without mosquito bed nets ($\beta = 0.21$ (95% CI: 0.02, 0.39), $p = 0.03$) were all significantly associated with higher malaria prevalence. Moran's I (54.81, $p<0.001$) showed spatial dependence of malaria prevalence across contiguous districts and spatial autoregressive modelling demonstrated significant spill-over effect of malaria prevalence. Maps produced in this study provide a useful graphical representation of the spatial distribution of malaria prevalence based on NMIS-2015 data. Clustering of malaria prevalence in certain areas further highlights the need for sustained malaria elimination interventions across affected regions in order to break the chain of transmission.

Introduction

Malaria is a major public health problem globally, with approximately 247 million cases worldwide and close to 620,000 deaths in 2021 (World Health Organisation, 2022). According to the United Nations Children's Fund (UNICEF) (2019), 77% of all deaths occur in children under five years of age (under-5). Africa has the highest burden of this disease in the world with Nigeria contributing the highest number of malaria cases (20%) per country (WHO, 2022) as well as 20% of all deaths in children under-5 (UNICEF, 2019). The high impact of malaria in children calls for focused malaria control in this key population. Over the last decade, increased support of malaria control programmes from the Government of Nigeria and its partners has resulted in a decline in malaria prevalence based on microscopy testing in the under-5 group (National Malaria Elimination Programme, NMEP, 2016). In addition, there is better support for preventive measures like mass distribution of Insecticide-Treated Nets (ITNs), intermittent preventive therapy and Indoor Residual Spraying (IRS) (Bamiselu *et al.*, 2016; NMEP, 2016; US President's Malaria Initiative,

2022). Adequate evidence-based planning for implementation of these intervention programmes is essential for increased coverage and effectiveness.

Geospatial modelling of malaria endemicity in Nigeria has shown a declining risk from hyper- to holo-endemic transmission in 19 out of its 36 states (Snow et al., 2017) but hotspots still exist. These malaria hotspots are pockets of high incidence, which persist during low-transmission seasons and act as the driving force to spread the disease in neighbouring areas during high-transmission seasons (Bousema *et al.*, 2012). It is thus important to identify areas of potential clustering or hotspots of high malaria prevalence to target malaria intervention programmes adequately. A spatiotemporal study assessing environmental predictors of malaria using the Nigeria Malaria Indicator Survey (NMIS) of 2015 reported significant spatial autocorrelation of malaria incidence rate that was higher in the northern than in the southern geopolitical zones (Okunlola & Oyeyemi, 2019).

Studies carried out in other malaria-endemic regions have identified risk factors associated with malaria prevalence, such as family income, health seeking behaviour and age of children (Xu *et al.*, 2012), ITN usage (Atieli *et al.*, 2011), high temperatures, rainfall and proximity to water bodies (Guthmann *et al.*, 2002; Protopopoff *et al.*, 2009; Pourtois *et al.*, 2023) and type or place of residence (Koram *et al.*, 1995). A review of malaria indicator survey data in eight countries in sub-Saharan Africa (Pond, 2013) showed large prevalence disparities between rural and urban areas. In Nigeria, a study which analysed the premier NMIS report (Adigun *et al.* 2015) described factors significantly associated with malaria prevalence, such as socioeconomic status, place of residence, age and sex of the affected child (Adigun *et al.*, 2015), income and ITN usage (White *et al.*, 2011; Bassey & Izah, 2017), IRS (Shittu *et al.*, 2018),environmental factors (Oluwafemi *et al.*, 2013) and parents' educational level (Kunihya *et al.*, 2016; Shittu *et al.*, 2018). These literature-based, potential risk factors for malaria in Africa are broadly classified in the framework shown in Figure 1.

In this study, NMIS-2015 data were used to describe the spatial distribution of malaria prevalence in the under-5 group as well as identify associated preventive, individual and environmental factors that affect malaria prevalence. While others have analysed these factors at national and/or statelevels, this paper explored them at the senatorial district level for a more focused look at where malaria hotspots persist. In light of limited resources due to other competing health challenges that prevail in developing countries, our findings can contribute to the planning of targeted, more cost-effective programme interventions towards malaria elimination in Nigeria.

Materials and Methods

Study area

Nigeria is a sub-Saharan African country with a diverse tropical climate including temperatures ranging between 25°C and 40°C and annual rainfall varying between 500 and 4,000 mm. It spans a northern arid, landlocked region to southern coastal areas (Adigun *et al.*, 2015) divided into 36 states belonging to six geopolitical zones (North East, North Central, North West, South East, South West, and South) and one Federal Capital Territory (Figure 2). Administratively, each state is further sub-divided into three senatorial districts, while the Federal Capital Territory consists of only one making a total of 109 senatorial districts (Sowunmi *et al.*, 2012). Nigeria has a population of over 213 million people (World Bank, 2021), with 97% at constant risk of malaria (US President's Malaria Initiative, 2022). The constant rainfall and high humidity levels in most parts of the country make it conducive for breeding of the malaria parasite's mosquito vector *Anopheles*. Our analysis was performed based on secondary data from the NMIS-2015 aggregated by senatorial district.

Nigeria malaria indicator survey data

The NMIS-2015 data on socioeconomic, demographic, malariometric (parasitaemia and anaemia) and environmental predictors were obtained from the Demographic and Health Survey Programme's website (https://dhsprogram.com) and used for fitting the models during analysis. This (second) NMIS was a survey

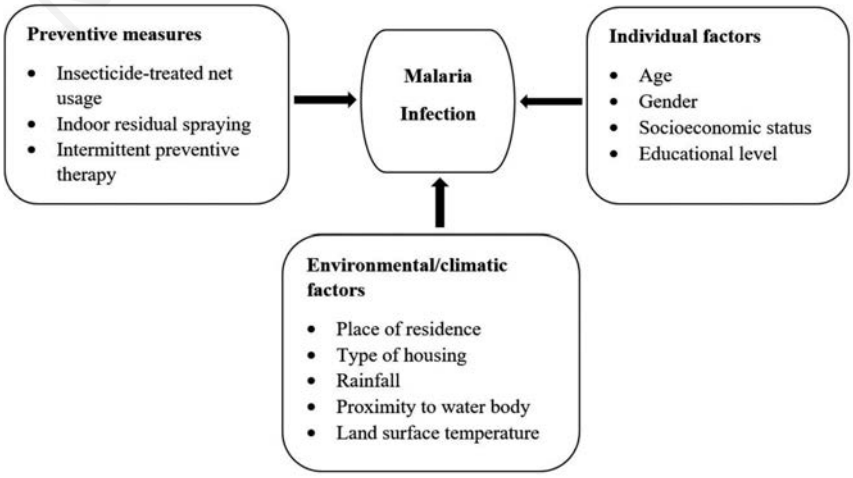

Figure 1. Conceptual framework of risk factors affecting malaria prevalence in Africa.

of over 8,000 household samples in 333 clusters between October and November 2015 based on a two-stage, random-cluster sampling method. All women aged 15 – 49 years and all children aged 6 – 59 months in selected households were eligible for inclusion in the study. Data on demographic characteristics, socioeconomic status, knowledge, management and prevention of malaria were collected from women via interviewer-administered questionnaires. Blood samples were collected from children for malariometric indices according to the NMEP (2016). Rapid field diagnosis was carried out using quality-assured test kits, while thick and thin blood films were sent to laboratories for microscopy. More detailed description of the NMIS methodology is available from the 2015 NMIS report (NMEP, 2016).

This study included results from 5,754 children under-5 (*i.e.* all children in the NMIS dataset who received final malaria parasitological test results) collected from all clusters within 104 of the 109 senatorial districts in Nigeria (data from five districts were missing). From the map in Figure 3, it can be seen that some senatorial districts lack survey cluster points, especially in the North-East and South-East regions. For the North-East region, the NMIS-2015 report states that data collection was not conducted in rural areas due to the state of insecurity at the time of the survey (NMEP, 2016). For other districts with missing data, we can only assume that these were not sampled for data collection in the main survey.

Spatial analysis and modelling

The Global Positioning System (GPS) data used were environmental covariate variables from satellite-based sources (raster layers), administrative boundary shape files and the vector layers. The latter were collected for each cluster surveyed during NMIS-2015. The environmental covariate variables (associated with each surveyed cluster but displaced up to 2 km (for urban points) and 10 km (for rural points from the actual location) by geo-masking (NMEP, 2016) shown in Table 1 were obtained from the Demographic and Health Survey Programme (https://dhsprogram.com). Additionally, administrative boundary shape files for Nigeria at the country and senatorial district levels were downloaded from the humanitarian data exchange website (https://data.humdata.org/group/nga) (United Nations Office for the Coordination of Humanitarian Affairs, 2019).

The Nigerian administrative boundary shape files were linked

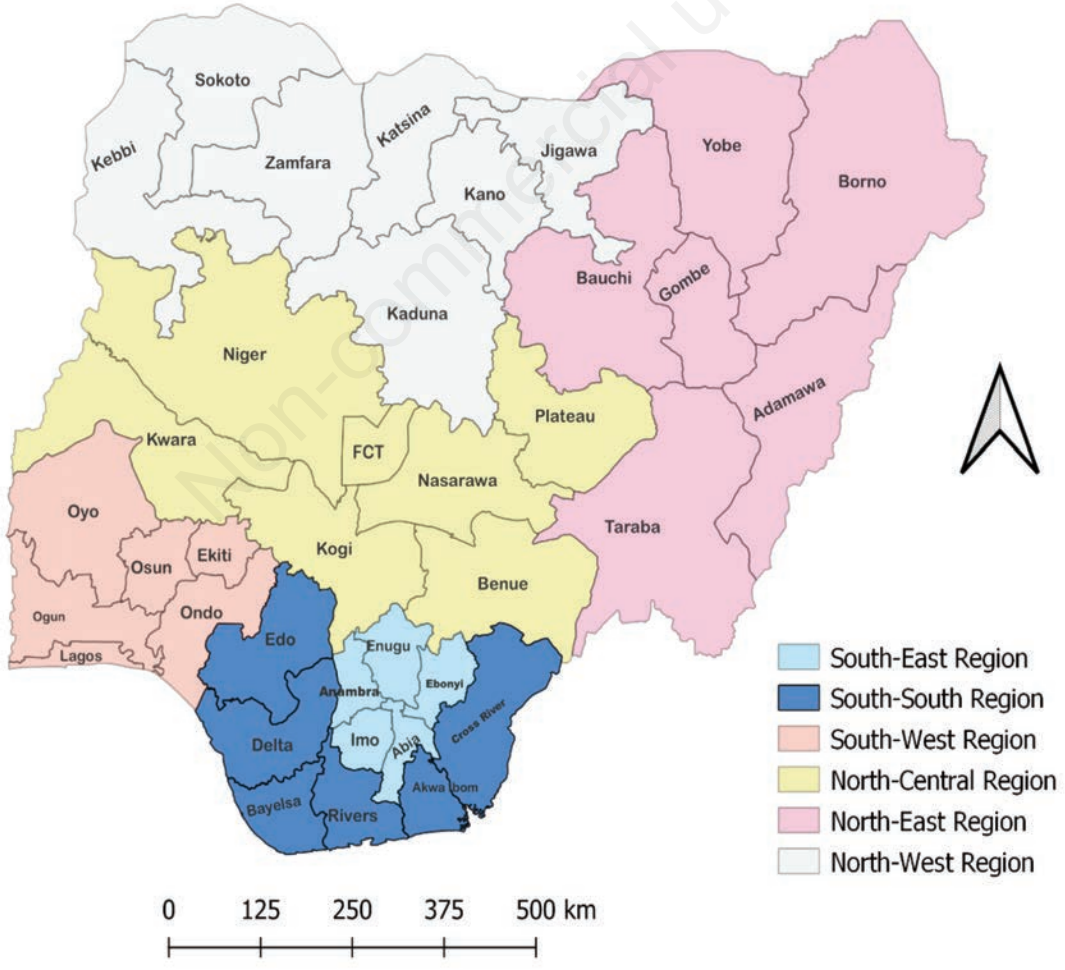

Figure 2. Map of Nigeria showing its 36 states,the Federal Capital Territory and the six geopolitical zones.

with the NMIS survey cluster coordinates in QGIS v.3.28.4 (https://docs.qgis.org) to create a joined shape file and produce the maps shown in Figures 2 and 3. This joined shape file was further merged with NMIS survey data and the environmental covariate variables using Stata v. 15.1 (Stata Corporation, College Station, TX, USA). Malaria prevalence (NMEP, 2016) based on positive thick blood smear microscopy tests (the gold standard for malaria diagnosis) was used as outcome variable. This was computed in Stata v. 15.1 by calculating the proportion of children testing positive out of all children subjected to blood smear microscopy. Malaria prevalence was described by geopolitical zones, states and senatorial districts, and areas with the highest prevalence (Table 2). A choropleth map was generated using Stata v. 15.1 for a graphical representation of malaria prevalence by senatorial districts (Figure 4). A multiple linear regression model was fitted to determine the relationship between malaria prevalence and the covariates shown

Table 1. Sources of environmental covariates data used for the Nigeria Malaria Indicator Survey 2015.

Data	Source (derived dataset)	Period	Dataset cell size
Enhanced vegetation index (EVI)	Moderate resolution Imaging Spectroradiometer (MODIS) https://modis.gsfc.nasa.gov/data/dataprod/mod13.php	2015	~5x5 km
Land surface temperature (LST)	Moderate resolution Imaging Spectroradiometer (MODIS) https://modis.gsfc.nasa.gov/data/dataprod/mod11.php	2015	~6x6 km
Proximity to water bodies	Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG) http://www.soest.hawaii.edu/pwessel/gshhg/	2017	Not applicable
Rainfall	Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) https://www.chc.ucsb.edu/data/chirps	2015	~5x5 km

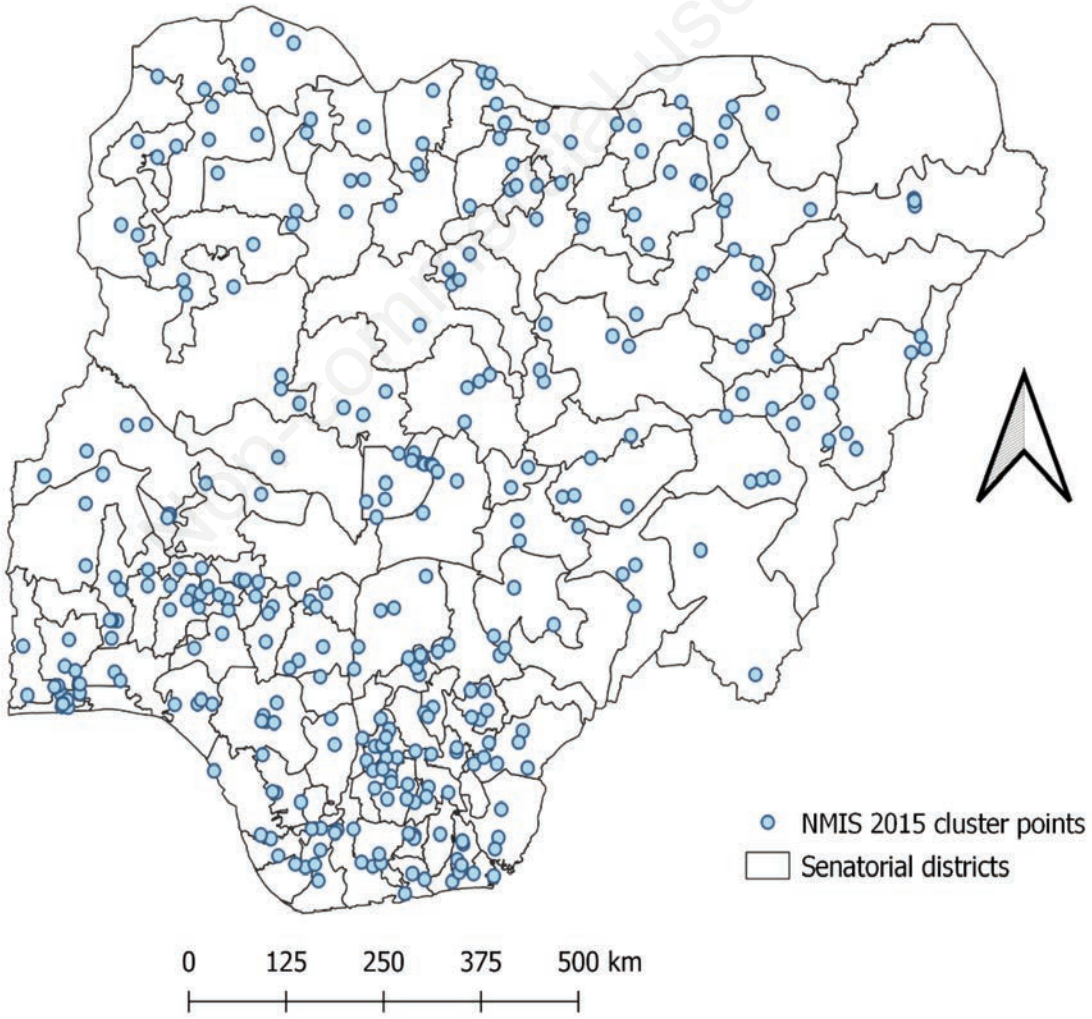

Figure 3. Senatorial districts in Nigeria with 2015 Nigeria Malaria Indicator Survey cluster points.

in Table 3. Based on our conceptual framework (Figure 1), covariates put into the model for each child were age, sex, place of residence, household wealth index, mother's highest educational level, proportion of children under-5 who slept under an ITN the night before the survey, household IRS in the past 12 months before the survey, amount of rainfall, Enhanced Vegetation Index (EVI), Land Surface Temperature (LST) and proximity to permanent water bodies. The equation for the model was:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \quad \text{Eq. 1}$$

where y is the outcome variable; β_0 the intercept; x the covariates (from 1 to the nth number); β the coefficients of the variables (from 1 to the nth number); and ε the error term.

Next, we tested for spatial autocorrelation of the malaria cases using Moran's *I,* a correlation coefficient with values ranging from -1 to +1 used to detect spatial distribution. A zero score shows random distribution of values with no correlation between neighbouring values, positive scores indicate clustering of areas of similar values and negative scores that neighbours are dispersed, i.e. they have dissimilar values (Pfeiffer et al., 2008). To calculate Moran's *I*, a spatial weighting matrix, *W*, was created in Stata v. 15.1 that puts a greater positive weight on contiguous, neighbouring districts and less weight on distant districts. The equation is as follows:

$$I = \frac{N}{S_0} \Sigma_i \Sigma_j W_{ij} \frac{(x_i - \bar{x})(x_j - \bar{x})}{\Sigma_i (x_i - \bar{x})^2} \quad \text{Eq. 2}$$

where N is the number of districts; W_{ij} the spatial weight between districts i and j; S_0 the aggregate of all the spatial weights; x_i and x_j the observations for districts i and j; and the mean $\bar{x}$ (Tsai & Perng, 2011). The spatial autoregressive models were fitted to assess the source of spatial autocorrelation, *i.e.* whether or not the outcome in one district had been affected by outcomes, covariates or spatially autoregressive errors from neighbouring districts. Three models were fitted with spatial lags of malaria prevalence, its significant covariates and autoregressive errors, respectively, using the gener-

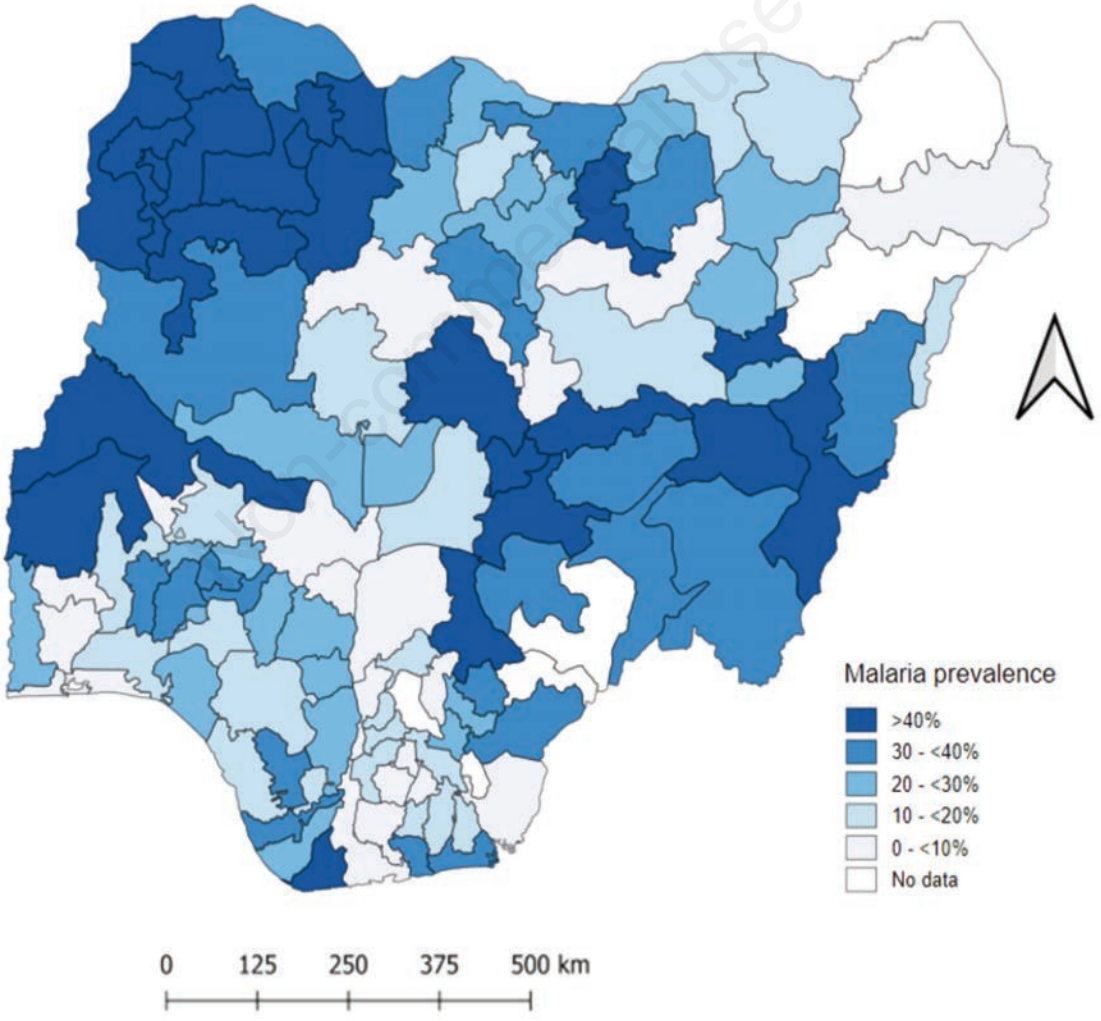

Figure 4. Distribution of malaria prevalence observed among children aged under five years across the 109 senatorial districts based on the 2015Nigeria Malaria Indicator Survey.

alized spatial two-stage least-squares (GS2SLS) estimator (https://www.stata.com), as it is robust and does not require the spatial lag to be normally distributed. The equations for the models were:

$$\text{Model 1: } y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 W_y + \varepsilon \quad \text{Eq. 3a}$$

$$\text{Model 2: } y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 W x_1 + \beta_5 W x_2 + \beta_6 W x_3 + \varepsilon \quad \text{Eq. 3b}$$

$$\text{Model 3: } y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + (I - \rho W)^{-1}\varepsilon \quad \text{Eq. 3c}$$

where y is the outcome variable; β_0 the intercept; β the variable coefficients; W_y is the lag of the outcome variable; $Wx_{1,2,3}$ the lags of the independent variables; and $(I-\rho W)^{-1}\varepsilon$ spatially autoregressive errors.

These procedures were chosen to investigate the manner of spatial dependency that could arise from the dependent variable, independent variables or from the residuals. The spatial lag is a matrix multiplication of the spatial weight matrix W with a variable (Hoffman & Kedron, 2023) that expresses the spatial dependence among districts by replacing the value of a variable in one district with a spatially weighted average of its neighbours' values (which assesses the possibility of one variable causing a similar effect in neighbouring areas).

A post-estimation test, *estat impact* in Stata v. 15.1, was used to estimate the magnitude of the direct, indirect, and total impacts of malaria and the significant covariates on malaria prevalence in the same district and neighbouring districts. The impact test describes the change in the values of the outcome variable per incremental change of the covariate averaged across all the observed spatial units (senatorial districts). The statistical significance level was set at $\alpha = 0.05$ for all tests. To assess constraints on statistical parameters based on the weighted distance between the unrestricted estimate and its hypothesized value under the null hypothesis, we applied the Wald test (Fahrmeir *et al.*, 2013).

Results

The average age of the children investigated was 30 months and their mean malaria prevalence by positive thick blood smear results was 25%. The districts with the highest prevalence were found in the North West and some North Central zones. Kebbi South senatorial district showed the overall highest prevalence (70%) as outlined in Table 2.

From the multiple linear regression model, there was strong evidence to show that the poorest wealth index (β = 0.10 (95% CI: 0.01, 0.20), $p = 0.04$), mother having secondary level of only education (β = 0.78 (95% CI: 0.05, 1.51), $p = 0.04$) and no ITN ownership (β = 0.21 (95% CI: 0.02, 0.39), $p = 0.03$) were all associated with malaria prevalence at the 5% significance level (Table 3). The coefficients show that the higher the proportion of households with poorest wealth index (mother having secondary level of education only and not using ITN when sleeping), the higher the malaria prevalence in that district. IRS, rainfall, EVI, mean LST and proximity to water bodies were not found to be significantly associated with malaria prevalence.

A positive statistically significant ($p<0.001$) Moran's I of 54.81 was observed. Spatial autoregressive models fitting spatial lags of malaria prevalence, its residuals and significant covariates, respectively, were statistically significant at the 5% level of significance (Table 4). The estimated coefficient on the spatial lag of malaria prevalence was 0.85 (95% CI: 0.55, 1.14, $p<0.001$). Posterior estimates of the parameters of the model with the spatial lag on malaria prevalence showed some evidence of direct effects of households with the poorest wealth index on malaria prevalence in the same district (rho = 0.03 (95% CI: 0.00, 0.05), $p = 0.026$). The indirect effects of the covariates were not statistically significant in all post-estimation tests (Table 5).

Discussion

In accordance with the NMIS-2015 report (NMEP, 2016), we found the highest prevalence of malaria in children under-5 in Kebbi South senatorial district of Kebbi State. The higher malaria incidence and risk found in the northern region than the southern region of Nigeria is in keeping with reports from previous studies analysing NMIS data (Adigun *et al.*, 2015; Okunlola & Oyeyemi, 2019). We showed that low socioeconomic status, *i.e.* having a poor household wealth index, is a significant predictor for malaria prevalence, something that has previously been reported with special reference to the level of household- or family income in other studies (Xu *et al.*, 2012; Adigun *et al.*, 2015; Dawaki *et al.*, 2016). The NMIS-2015 report described the North West region as having the highest proportion of sampled households in the lowest wealth quintile and the lowest proportions of households in the middle, richer and richest quintiles. Considering that our regression model showed that the poorest wealth quintile was significantly associated with higher malaria prevalence, this might explain why some

Table 2. Senatorial districts with the highest malaria prevalence.

Zone	State	Senatorial district	Malaria prevalence (%)
North West	Kebbi	Kebbi South	70.6
		Kebbi North	68.1
North East	Gombe	Gombe Central	68.0
North West	Zamfara	Zamfara Central	66.1
	Sokoto	Sokoto South	62.5
	Zamfara	Zamfara West	62.4
North East	Taraba	Taraba North	54.7
North West	Zamfara	Zamfara North	54.4
North Central	Plateau	Plateau Central	54.0
	Benue	Benue South	52.1

senatorial districts in the North West region also had very high malaria prevalence. Similarly, our finding that households, where mothers with secondary education as the highest level of education, were associated with increased malaria prevalence is in keeping with other studies done in northern Nigeria were a higher percentage of children with malaria were shown to have parents/guardians with low educational levels (Kunihya *et al.*, 2016; Shittu *et al.*, 2018). Since the NMIS-2015 reported that knowledge of malaria and fever management increases with educational level (NMEP, 2016), it can be expected that mothers with inadequate knowledge of malaria prevention and management would have children being prone to the disease. For the intervention programmes, we wish to stress that senatorial districts with households without ownership of ITNs had significantly higher

Table 3. Predictors of malaria prevalence in children under-five in Nigeria from the Malaria Indicator Survey 2015.

Factor	Level	Estimate (95% CI)	p
Age of child (months)	NA	0.51 (-0.70, 1.70)	0.40
Place of residence	Urban	0.15 (-0.28, 0.58)	0.49
	Rural	0.16 (-0.26, 0.0)	0.45
Household wealth index	Poorest	0.10 (0.01, 0.20)	0.04*
	Poorer	-0.64 (-0.01, 0.17)	0.07
	Middle	-0.01 (-0.11, 0.11)	0.10
	Richer	Omitted	
	Richest	-0.08 (-0.17, 0.02)	0.12
Indoor residual spraying	No	-0.18 (-0.62, 0.26)	0.42
	Yes	-0.26 (-0.86, 0.34)	0.39
Insecticide treated net usage	No ITN	0.21 (0.02, 0.39)	0.03*
	ITN not used	0.14 (-0.03, 0.32)	0.10
	All children u-5 slept under ITN	-0.11 (-0.06, 0.28)	0.20
	Some children u-5 slept under net	-0.07 (-0.13, 0.28)	0.47
Mother's educational level	None	0.23 (-0.41, 0.88)	0.48
	Primary	0.22 (-0.53, 0.97)	0.56
	Secondary	0.78 (0.05, 1.51)	0.04*
	Higher than secondary	-0.33 (-0.78, 1.45)	0.55
Rainfall	NA	-0.01 (-0.02, 0.01)	0.41
EVI	NA	-0.01 (-0.01, 0.01)	0.77
LST	NA	0.82 (-3.02, 4.66)	0.67
Water bodyproximity	NA	-0.01 (-0.01, 0.01)	0.58

*EVI, enhanced vegetation index; LST, land surface temperature; ITN, insecticide-treated nets; NA, not applicable; *Significant at α, 0.05*

Table 4. Model parameters for spatial modelling.

Model	Spatial lag	Wald	p
1	Malaria prevalence	9.66	0.002*
2	Covariates (mother's level of education, household wealth index, ITN ownership)	10.89	0.012*
3	Residuals	39.49	<0.00*

*ITN, insecticide-treated nets; *Significant at α, 0.05.*

Table 5. Post estimation test of model with spatial lag on malaria prevalence.

Impact	Estimate (95% CI)	*p*
Direct		
Households with poorest wealth index	0.03 (0.00, 0.05)	0.026*
Mother's educational level (secondary)	-0.17 (-0.39, 0.04)	0.111
No insecticide treated net usage	0.03 (-0.03, 0.09)	0.376
Indirect		
Households with poorest wealth index	0.02 (-0.00, 0.05)	0.111
Mother's educational level (secondary)	-0.13 (-0.32, 0.06)	0.165
No insecticide treated net usage	0.02 (-0.03, 0.08)	0.416
Total		
Households with poorest wealth index	0.05 (0.01, 0.09)	0.026*
Mother's educational level (secondary)	-0.31 (-0.67, 0.06)	0.097
No insecticide treated net usage	0.05 (-0.06, 0.16)	0.379

**Significant at α, 0.05.*

malaria prevalence. Although ITN usage for children under-5 increased from 16% in 2013 to 52% in 2018, it dropped again to 41% in 2021 and is still overall far from the national target of 80% (NMEP, 2020; 2022). The North Central zone was found to have the second lowest percentage of household ownership of at least one ITN (NMEP, 2016). Again, this may contribute to the clustering of high malaria cases in the country's northern region.

Moran's *I* for spatial dependence was positive and statistically significant suggesting that malaria prevalence in Nigeria is spatially dependent, with the areas of high prevalence close together. This confirms the particular high prevalence rates in the North West region displayed in Figure 4. Clustering of malaria cases has been demonstrated in previous studies and helps to identify areas of hotspots for malaria transmission (Adigun *et al.*, 2015; Okunlola & Oyeyemi, 2019). In the North West region (Kebbi North, Kebbi South, Sokoto South, Zamfara North, Zamfara Central and Zamfara West senatorial districts) had the highest malaria prevalence, while this was the case in Benue South, Plateau Central, Taraba North and Gombe Central senatorial districts of the North Central/North East regions. With reference to Figure 2, cross-border transmission of the disease from one district to the other seems likely as it can be seen that these districts and their states share boundaries.

The positive correlation between the malaria prevalence in one district and the malaria prevalence in a neighbouring district suggests a global spill-over effect. This means that a change in malaria prevalence in one district can potentially affect that in other, contiguous districts, with the possibility of a "neighbours-of-neighbours" continuation similar to a chain reaction. Our post-estimation test also showed evidence of a positive, direct impact of household poverty on malaria prevalence. Although the effect was small, it indicates the possibility of the more households there are in the poorest wealth index in a senatorial district, the higher the risk of malaria prevalence in that district. However, an indirect effect of these factors on malaria prevalence was not statistically significant, which might suggest that a change in either the mother's level of education, the household wealth index or the level of ITN ownership in one senatorial district has no spill-over effect on malaria prevalence in other districts. Nevertheless, since these factors are significantly associated with malaria prevalence and that this fact can have a spill-over effect on neighbouring districts, it can be argued that sustained, effective interventions in every district should ultimately break the chain of transmission.

It is important to target the clusters of high prevalence as they may persist as malaria hotspots, even though the overall national transmission is reduced. ITNs are said to be the cheapest and most effective long-term malaria control intervention. Efforts should therefore be made to increase ITN ownership and use this to meet the national targets for both indicators. Policies and initiatives aimed at boosting the socioeconomic status of families should also be beneficial towards the elimination of malaria as the poorest wealth index was found to be a significant predictor. Malaria intervention programmes should strengthen communication on malaria knowledge and management as well as target caregivers with low educational levels. The Government of Nigeria and its partners should make well informed, public health decisions on where to focus limited resources as this study has shown that if malaria prevalence is tackled in one district, it will have a spill-over effect of reducing prevalence in neighbouring districts.

Limitations

The use of secondary data limited the present study as the clustered regions of high transmission could not be further explored. However, the identification of malaria hotspots and spill-over effects are important for Nigeria to show improvement towards malaria elimination before 2030. Also, the results cannot be generalized outside of Nigeria since the NMIS-2015 was a cross-sectional study. Regardless, the findings with respect to the predictors of malaria prevalence in the study population, i.e. children under-5, should be useful in other malaria-endemic nations as they are the highest at-risk group for malaria morbidity and mortality.

Conclusions

Malaria remains a major public health concern in Nigeria as prevalence is still high in young children. The regional variation seems to follow the pattern of ITN usage, educational level and household wealth index which were seen to be significant malaria predictors. The clustering of malaria prevalence is an indication that transmission has not been interrupted, so the control interventions are either insufficient or not being implemented in households as prescribed. More research is recommended to investigate the reasons for higher malaria prevalence and clustering in the identified senatorial districts.

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