Spatial distribution and sociodemographic risk factors of malaria in Nigerian children less than 5 years old

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Abstract

Malaria remains a leading cause of morbidity and mortality among children in Nigeria less than 5 years old (under-5). This study utilized nationally representative secondary data extracted from the 2015 Nigeria Malaria Indicator Survey (NMIS) to investigate the spatial variability in malaria distribution in those under-5 and to explore the influence of socioeconomic and demographic factors on malaria prevalence in this population group. To account for spatial correlation, a Spatially Generalized Linear Mixed Model (SGMM) was employed and predictive risk maps was developed using Kriging. Highly significant spatial variability in under-5 malaria distribution was observed (P<0.0001) with a higher likelihood of malaria prevalence in this group in the North-west and North-east of the country. The number of malaria infections increased with age, children aged between 49-59 months were found to be at a higher risk (Odds Ratio=4.680, 95% CI=3.674 to 5.961 at P<0.0001). After accounting for spatial correlation, we observed a strong significant association between the non-availability or non-use of mosquito bed-nets, low household socioeconomic status, low level of mother's educational attainment, family size, anaemia prevalence, rural type of residence and under-5 malaria prevalence. Faced with a high rate of under-5 mortality due to malaria in Nigeria, targeted interventions (which requires the identification of the child's location) may reduce malaria prevalence, and we conclude that socioeconomic impediments need to be confronted to reduce the burden of childhood malaria infection.

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Key words: Generalized linear mixed models; kriging; spatial variability; variogram; Nigeria-MIS; Nigeria.

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Conflict of interests: The authors declare no potential conflict of interests.

Data Availability Statement: The analyzed dataset is freely available upon request from the Measure Demographic Health Survey (DHS) websites: www.dhsprogram.com/data/dataset/Nigeria.

Ethical statement: The 2015 Nigeria Malaria Indicator survey (NMIS)-protocols were ethically cleared by the Nigeria Health Research Ethics Committee of the Federal Ministry of Health (NHREC) and the Internal Review Board of the ICF International in Calverton (USA). The study was based on a publicly available data obtained upon request through MEASURE DHS http://www.measuredhs.com and the consent to participate was not applicable, hence, an informed consent was provided by all the surveyed participants through their caregiver or parents prior to malaria test and the administration of questionnaires.

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Introduction

Malaria continues to claim more than 400,000 lives each year as confirmed by the World Health Organization (WHO); in 2017, sub-Saharan Africa accounted for 80% of all cases and 90% of mortality due to malaria, 61% of which affecting children less than 5 years old (under-5) (WHO, 2018). Nigeria is a malaria-endemic country in sub-Saharan Africa that has continuously recorded a high burden of malaria morbidity and mortality, especially in the under-5 group (WHO, 2018). Unlike many other sub-Saharan African countries, which have recorded a significant decline in malaria burden, the number of malaria cases in Nigeria increased with about 500,000 in 2017 (WHO, 2018). Although, the mortality rate decreased from about 202 deaths per 1,000 live births to 129 deaths per 1,000 live births between 2003 to 2013 in the under-5 group, statistics show that malaria accounts for approximately 30% of all deaths in this part of the population in Nigeria (Okonko *et al*., 2009; Okeke and Okeibunor, 2010; Onyiri, 2015). Resolution no. 3 of the 2030 Agenda for Sustainable Development Goals (SDGs) adopted by the United Nations (UN, 2018), concerns health, the worldwide improvement of which requires reduction of the malaria burden and its associated mortality as outlined by WHO (2019). Therefore, a better understanding of malaria distribution is of high relevance in

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Nigeria, as is investigating of the spatially influential factors that fully explain the patterns of under-5 infections.

A large number of studies on malaria prevalence in endemic regions have focused on the spatial patterns of its distribution (Diggle *et al.,* 2002; Kazembe and Mathanga, 2016; Machault *et al.,* 2010; Ayele *et al.,* 2013; Samadoulougou *et al.,* 2014; Ferrao *et al.*, 2018; Umer *et al.*, 2018). Each of these studies provide evidence that the geographical distribution of malaria is not spatially random. Evidence of links between malaria prevalence and environmental factors such as rainfall, temperature, the Normalized Difference Vegetation Index (NDVI) as well as socioeconomic factors, such as poverty have been observed. However, many of these studies give scant attention to spatial statistical approaches that not only focus on the descriptive aspect of the geostatistical methods, but also consider the relationship between malaria and the spatial effects of factors as those mentioned. Spatial analytical methods, in which the expected values and the covariance structures of the sample data are modelled based on accurate, inferential statistics have resulted in more efficient analyses (Zimmerman and Harville, 1991; Stroup *et al.,* 1994). Furthermore, among these studies, only a few have considered analyzing data of the under-5 group (Diggle *et al*., 2002; Kreuel *et al.,* 2008; Samadoulougou *et al.,* 2014). It has been documented that sub-Saharan African countries bear the major burden of under-5 mortality associated with malaria, so it is imperative to understand the spatial pattern of malaria disease distribution and risk factors across the high-risk areas with reference to the under 5s via a nationally representative dataset. Only few studies have dealt with spatial modelling of malaria distribution in Nigeria and most of these studies have been largely based on hospital and clinical studies within communities and at the state level without much consideration of the under-5 group (Awolola *et al.,* 2007; Onwujekwe *et al*., 2009; Kalu *et al.,* 2012; Efe and Ojoh, 2013; Ebenezer *et al.,* 2014; Weli and Efe, 2015). These studies found that the main environmental and socioeconomic factors associated with malaria distribution are rainfall, NDVI, temperature and low family income. Moreover, independent analysis of malaria prevalence with respect to socioeconomic, environmental and geographical factors with national-level data has been demonstrated (Idowu *et al.,* 2009; Onwuemele, 2014; Adigun *et al.,* 2015; Akpan *et al.,* 2019; Onyiri, 2015). Their results show that day land surface temperature, NDVI and rainfall are the most important spatial predictors of malaria transmission. Further, using the first implemented 2010 Nigeria Malaria Indicator Survey (NMIS) data, Gawayan *et al.* (2014) and Adebayo *et al.* (2016) studied the comorbidity of malaria and non-malaria diseases among children in Nigeria using Bayesian geostatistical models. Their result shows a significant relationship between socioeconomic inequalities and the geographical differences in malaria distribution. Low socioeconomic status has proven to be a strong predictor of childhood deaths attributed to malaria and studies have identified family poverty as the major factor (Diggle *et al.,* 2002; Onwujekwe *et al.,* 2009; Ayele *et al*., 2013; Gayawan *et al.,* 2014; Adebayo *et al.*, 2016). These papers show that significant progress has been made in studying malaria epidemiology in Nigeria. However, evaluating the relationship between the geographical distribution of the disease and plausible risk factors across the nation remains largely unexplored, especially with regard to the under-5s. Our study therefore aimed to explore the influence of socioeconomic, demographic and geographical factors on childhood malaria prevalence that may aid future control and prevention efforts in Nigeria. Our second goal was to develop predicted risk maps for under-5 malaria in order to identify areas that should be targeted for effective public health resource allocation and intervention strategies, which is essential for the WHO Global Technical Strategy for Malaria 2016–2030 (WHO, 2019).

Materials and methods

The study data

The analysis in this paper is based on data available from the second and the most recent NMIS (2015) on malaria prevalence among children aged under 5 years in Nigeria. The survey was commissioned by the National Malaria Control Programme and implemented by the National Population Commission (NPC) together with donor agencies like Roll Back Malaria (RBM) partners. The sampling frame for the 2015 NMIS was the 2006 National Population and Housing Census (NPHC) of the Federal Republic of Nigeria, of which a total population of 140,431,790 people was recorded (NMC, 2015).

A two-stage probability sampling strategy was implemented for the data collection. At the first stage, 9 cluster Enumeration Areas (EAs) were selected from each stratum (NMC, 2015). The sample represented each state in Nigeria and the result of the sample included a total of 333 clusters across the country, 138 urban clusters and 195 clusters in rural areas. In the second stage, an equal probability sampling was adopted, where 25 houses were selected in each of the clusters. All women aged 15-49 years in each household were interviewed and, in addition, all children aged 6-59 months from the selected households were tested for malaria and anaemia via blood samples (NMC, 2015).

Moreover, the surveyed clusters were subsequently georeferenced with specific data files on geographic locations of the clusters and Global Positioning System (GPS) coordinates were recorded for the approximate centre of each of the primary sampling units (NDHS, 2016). To ensure each respondent's confidentiality, the geographical locations were randomly displaced at 2 km for urban clusters and up to 10 km for rural clusters as seen in Figures 1 and 2. The figures show the survey locations across Nigeria's 37 states, including the Federal Capital Territory (FCT) of Abuja. More details on the 2015 NMI survey may be obtained via the MEASURE DHS website (NDHS, 2016). Note that some parts of Borno State in the north-eastern region of Nigeria were not covered by the 2015 NMIS due to security concerns and therefore not included in the analysis (NMC, 2015).

The response variable

In controlling the risk of malaria and reducing the high mortality rate in endemic regions, the WHO recommends timely diagnosis and instant treatment as key strategies; hence, both microscopy and Rapid Diagnostic Tests (RDTs) are approved for malaria diagnosis in field surveys (WHO, 2015), as they were in the 2015 NMIS. Though the RDT has been mostly utilized during population surveys due to reliability, lower expense and speedy approach for early detection of the malaria parasite in human blood. In this study, the outcome of interest was based on malaria RDT survey results as a binary indicator of the presence of malaria parasites in the child's blood sample, where 1 signifies the presence of malaria and 0 the opposite. A total of 6,070 eligible children between ages 6 and 59 months that participated in the 2015 NMI survey were included in the analysis.

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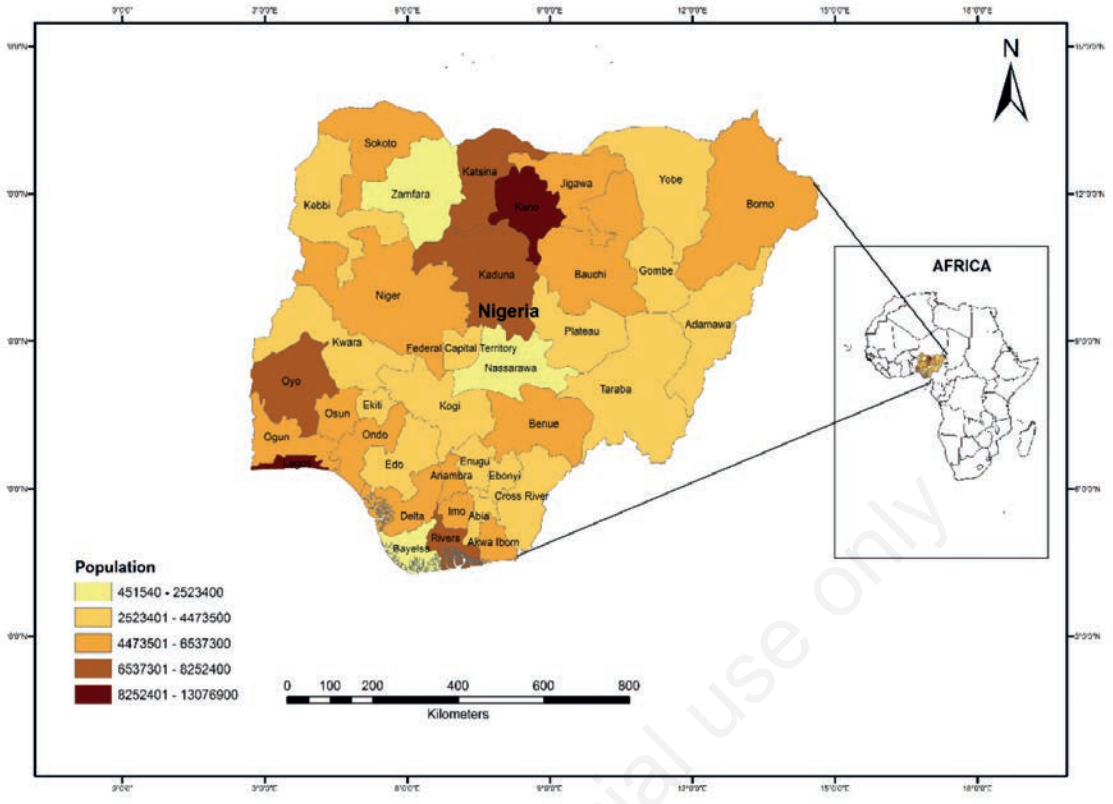

Figure 1. Map of Nigeria (the study area) based on the 2006 population census, indicating 333 clusters (37 states, including the Federal Capital Territory (FCT) under the 6 geopolitical regions).

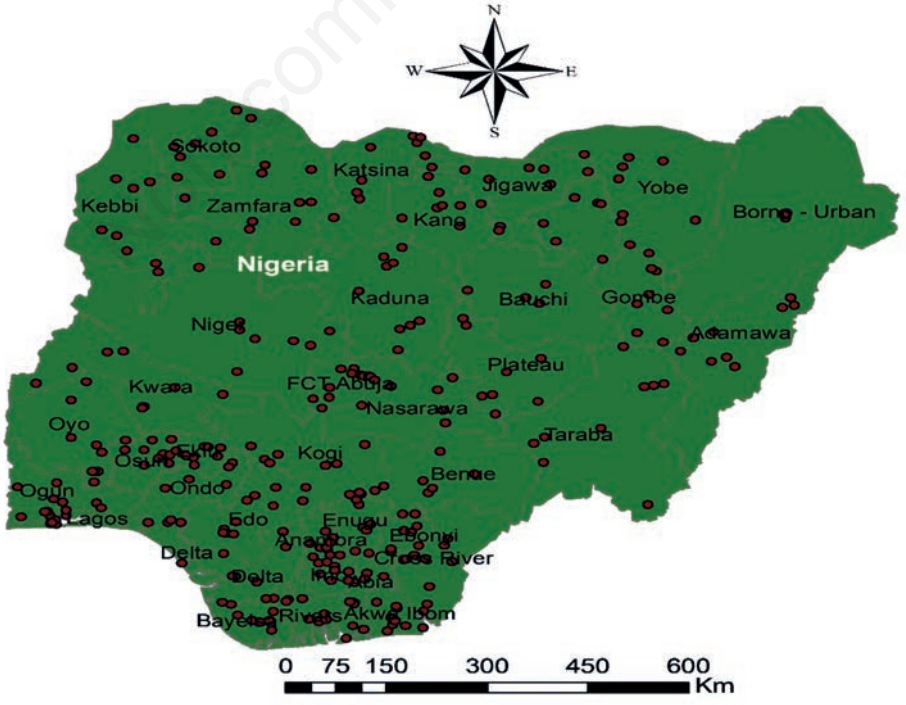

Figure 2. Map of Nigeria showing surveyed locations of under-5 malaria prevalence including the 7,745 households selected from 333 clusters randomly displaced 2 km for urban clusters and 10 km for rural clusters for confidentiality reasons.

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The explanatory variables

The explanatory variables were the selected baseline socioeconomic, demographic and geographic variables obtained at the household and individual levels from the 2015 NMIS. These variables were selected after a comprehensive literature review (Diggle *et al.,* 2002; Gayawan *et al.,* 2014; Samadoulougou *et al.,* 2014; Adigun *et al*., 2015; Adebayo *et al.,* 2016). However, the household wealth index, which is described as an indicator of the household's economic status categorized as (poorest, poorer, middle-range, richer and richest) were generated using Principal Component Analysis (PCA) from NMIS. The PCA value is estimated based on household's ownership of consumer goods, household dwelling characteristics, source of drinking water, sanitation facilities such as type of toilet facilities in the household, material for household construction and other factors related to individual household's socioeconomic status. Therefore, the variables above were not included independently in the present analysis, but predictor variables previously identified as influential factors in malaria disease risk from prior studies were. They included sex, age in months, anaemic status, mother's educational level, age and sex of the head of the household, type of place of residence, household wealth index, use of mosquito indoor residual spray in the past twelve months, use of Long-Lasting Insecticidal Nets (LLINs) during sleep and number of household members. Moreover, the states and regions were considered as the geographic variables linked with the Cartesian coordinates (longitude & latitude) and employed as spatial random components for the purpose of locating the malaria observations in space as seen in the variable descriptions (Table 1).

Statistical modelling

Many epidemiological datasets are non-Gaussian, with spatially correlated observations. A critical assumption of various statistical modelling methods is independence of observations (Nelder and Wedderburn, 1972). However, in the case of spatially correlated data, the assumption of independence is usually unrealistic for standard regression models, *i.e*. spatially correlated observations fail to satisfy the critical assumption of independence central to such models due to the fact that observations in each geographical unit usually depends on the outcome in the neighbouring units, since proximate observations are correlated in space (Stroup, 2012). If a standard regression model fits such spatial data, the model residuals are without doubt independent among the observational units, and as such the critical assumption of the independence is violated resulting in unbiased estimates and invalid inferential conclusions (Stroup, 2012). For the geo-referenced data obtained for this study, a logistic regression model as a special case of the Generalized Linear Mixed Models (GLMMs) that include all variables of interest generated spatially auto-correlated residuals (Moran's I=0.233, P<0.0001), (Cressie, 1992). The outcomes of Moran's I calculations provide a strong indication whether or not spatial autocorrelation needs to be accounted for. Therefore, the GLMM framework, which combines the Generalized Linear Models (GLMs) with the Linear Mixed Models (LMMs), (Laird and Ware, 1982; Nelder and Wedderburn, 1972; McCulloch and Searle, 2001), present a model that allows spatial random effects in addition to usual fixed effects in modelling non-Gaussian malaria prevalence data with correlations. Here, we employed the GLMM framework to fit the under-5 malaria prevalence data using the logit link function as follows:

$$g(\mu) = \log\left(\mu / 1-\mu\right)$$

unlike standard regression models, GLMM inference accounts for spatial correlation (McCulloch and Searle, 2001; Nelder and Wedderburn, 1972; Stroup, 2012). The GLMM which allows the integration of the spatial correlation model through the G-side covariance structure of the GLMM is given as:

$$\mu = E(Y \mid U = u) = \phi(X'\beta + \varphi' u)$$

where β is a dimensional vector of fixed-effect parameters, the dimensional vector of covariates and $\phi(.) = g^{-1}(.)$ the inverse link function. Specifically, we obtained a suitable spherical spatial covariance structure:

$$\delta^2\left[1-\left(\frac{3d_{ij}}{2\rho}\right)+\left(\frac{d_{ij}^{3}}{2\rho^{3}}\right)\right]1(\rho d_{ij} \le \rho)$$

via the PROC variograms procedure that adequately accounted for the spatial variability in our data as specified below.

Table 1. Socioeconomic, geographic and demographic variables analyzed for association with under-5 malaria prevalence in Nigeria.

Factor	Description
Region	North central, North-east, North-west, South-east, South, South-west
Residence	Dichotomous variable: rural* or urban
Anaemia	Dichotomous variable: yes or no*
Child slept under LLIN*	Dichotomous variable: yes or no*
Household sprayed	Dichotomous variable: yes or no*
Child's sex	Dichotomous variable: yes or no*
Sex of household-head	Dichotomous variable: yes or no*
Child's age in months	Continuous variable: minimum=6, maximum =59
Age of household-head	Continuous variable: minimum=15, maximum =98
Family size	Continuous variable: minimum=2, maximum=1344
Mother's educational level	Categorical variable: no education*, primary, secondary, higher education
Household wealth index	Categorical variable: poorest*, poorer, middle-range, richest, richer

*Long-lasting insecticidal net; **Reference variable (see Table 4).

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Let y_{ij} denote the binary response corresponding to the j^{th} child's malaria outcome at the spatial location S_i, i = 1, ..., -i take values of 1 for positive malaria outcome and 0 otherwise. Let x_{ij} represent the vector of associated covariates observed at the spatial location S_i. Within the GLMM framework, we assume that the response variable, y_{ij}, has a probability of belonging to the exponential family. Considering S_i to be a spatial location within the geographical domain D, we defined the fundamental geostatistical tool as follows:

$$\phi(d) = \frac{1}{2} E\left[y_{ij}(s_i) - y_{ij}(s_{-i})\right]^2$$

where $\phi(d)$ denotes the semi-variogram, d a spatial distance, s_i and s_{-i} two spatial locations with d-distance apart and $y_{ij}(s_i)$ & $y_{ij}(s_{-i})$ the under-5 malaria observations at the spatial locations s_i and s_{-i}, respectively. We take account of the spatial dependency of the data by integrating an appropriate spatial covariance model obtained via the semi-variogram model into the G-side covariance structure of the GLMM (Gotway and Stroup, 1997; Stroup, 2012). This was achieved by assuming that the response variable y_{ij}, conditioned on the realization of a random effect vector u_i, is conditionally independent for any spatial location S_i with conditional expectation:

$$E[y_{ij}(S_i) \mid u_i] = \pi_{ij}(S_i)$$

Thus, the linear predictor which includes the spatially correlated random effect can be represented as Spatially Generalized Linear Mixed Models (S-GLMM) in the form of

$$g(\pi_{ij}) = \eta_{ij} = X_{ij}\beta + Z_{ij}u_i(S_i)$$

where, the random term u_i defines the spatial distribution of the malaria observation, $u_i \sim N(0,\Sigma_u)$ with the spatial spherical function

Table 2. Socio-demographic characteristics of under-5 malaria prevalence in Nigeria based on 2015- NMIS.

Characteristic	Category	No.	%
Geographical region	North central	1,138	18.7
	North-east	826	13.6
	North-west	1,958	32.3
	South-east	577	8.5
	South	672	11.1
	South-west	959	15.8
Type of place of residence	Rural	4,033	66.4
	Urban	2,037	33.6
Child's sex	Male	3,079	50.7
Child's age in months	6-24 months	721	11.9
	13-24 months	1,283	21.1
	25-36 months	1,309	21.6
	37-48 months	1,417	23.3
	49-59 months	1,341	22.1
Anaemia	No	1,917	31.6
	Yes	4,150	68.4
Mother's educational level	No education	2,423	39.9
	Primary	948	15.6
	Secondary	1,568	25.8
	Higher	412	6.8
Household wealth index	Poorest	1,244	20.5
	Poorer	1,407	23.2
	Middle-range	1,175	19.4
	Richer	1,115	18.4
	Richest	1,129	18.6
Child slept under LLIN*	No	3,457	57
	Yes	2,613	43
Result of malaria RDT**	Negative	3,334	54.9
	Positive	2,736	45.1

*Long-lasting insecticidal net; **Rapid diagnostic test.

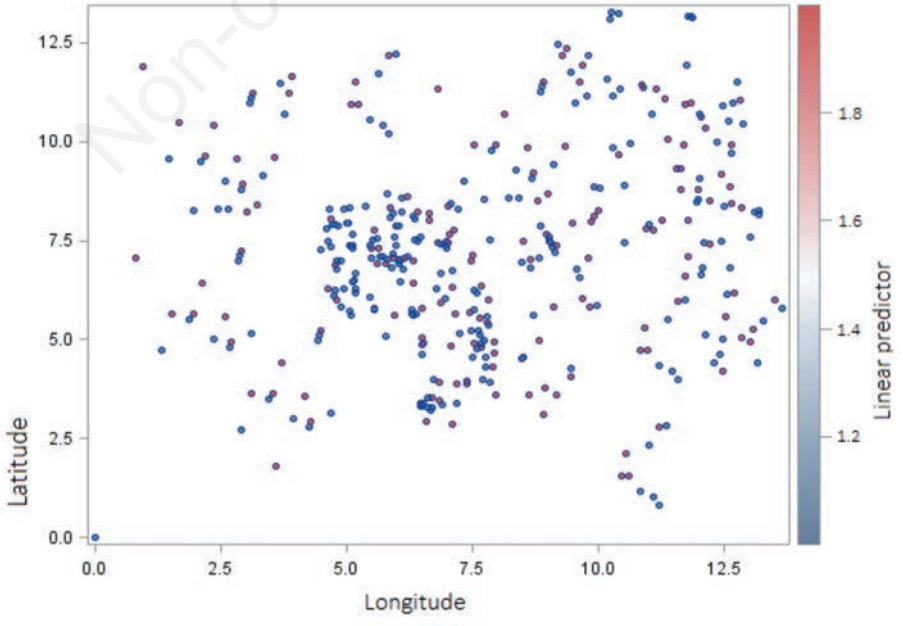

Figure 3. Scatter plot of under-5 malaria prevalence. Blue dots represent negative malaria test outcomes and red dots represent positive outcomes.

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of the distances specified by two geographic coordinates (longitude and latitude) and $g(.)$ the link function that relates the binary response to the linear predictors.

The predicted values from the model were mapped to obtain risk maps for the under-5 malaria infections at the national level. This was achieved by generating the fitted values of the response variable predicted by the S-GLMM fitted to the data, on which we applied ordinary Kriging to infer values at unobserved locations in the proximity of the data points; hence, a spherical semi-variogram model obtained via the Proc Variogram procedure was found suitable for the Kriging (Cressie, 1992). This approach enabled us to model and map the risk of under-5 malaria to identify critical hotspots of malaria clusters. The spatial analysis was carried out using ArcGIS, version 10.6.1 (ESRI, Redlands, CA, USA) and the statistical analysis was implemented using SAS statistical software, version 9.4 (SAS Institute Inc., Cary, NC, USA). The significance level in our analysis was P=0.05.

Results

Table 2 presents the sociodemographic characteristics of children and household variables included in the study. A total of 6,070 children aged 6 to 59 months who were tested for malaria by RDT was included in this study. The mean (±SD) age of children was 4.2 (±1.5) months, the majority of whom were males (3,079 - 50.7%). The number of female children was 2,999 (49.3%). Regarding age, there were 721 children between 6-12 months (11.9%), 1,283 between 13-24 months (21.1%), 1,309 between 25-36 months (21.6%), 1,417 between 37-48 months (23.3%) and 1,341 between 49-59 months (22.1%). Most of these children lived in rural areas 4,033 (66.4%) with only a small number of them in urban areas 2,037 (33.6%). The number of under-5s with illiterate mothers was proportionally greater 2,423 (39.9%) as compared to mothers with primary education: 948 (15.6%), secondary education: 1,568 (25.8%) and higher-level education: 412 (6.8%). According to the household socioeconomic status, 1,244 (20.5%) of the children resided in the poorest households, while 1,407 (23.2%), 1,175 (19.4%), 1,115 (18.4%) and 1,129 (18.6) of them resided in the poorer, middle-range, richer and richest households, respectively. Furthermore, malaria infection was observed in 2,736 (45.1%) of the under-5s and the percentage of the children who slept under LLINs prior to the survey was 2,613 (43.0%).

Table 3 presents the goodness-of-fit results of three spatial covariance structures investigated, including the exponential spatial covariance structure SP (EXP), the Gaussian spatial covariance structure SP (GAU) and the spherical spatial covariance structure SP (SPH), (Kincaid, 2005). The spatial covariance estimates via the empirical semi-variogram model were computed using the PROC VARIOGRAM procedure in SAS (Kincaid, 2005). The results show that the SP (SPH) had the smallest Akaike Information Criterion (AIC), the smallest Akaike Information Criterion Corrected (AICC), the smallest Bayesian Information Criterion (BIC) and the smallest Res Log Likelihood, and that it thus fitted the data best. SP (SPH) was subsequently employed in our analysis (Zimmerman and Harville, 1991; Kincaid, 2005; Stroup, 2012). As shown in Table 3, the spatial random effect cluster, which characterizes the spatial variability, was significant. In the diagnosis of the residual of the S-GLMM, a random distribution was observed with no residual structure not accounted for by the model, thus indicating a good model fit to the data. Figure 3 presents the spatial scatter plot of the observed malaria data, providing values of measured variables in the form of different coloured markers for positive and negative outcomes. The plot suggests that the under-5 malaria cases were unevenly spread around the observed locations, with evidence that the spatial distribution of high values and low values with respect to malaria prevalence presented a more spatially clustered data. Thus, the distribution of malaria was not an indication of uniform distribution, rather, an indication of random spread of malaria outcome (Verly *et al.,* 2013; Keranen and Kolvoord, 2017). Hotspots of under-5 malaria infection in Nigeria were localized predominantly in the North-west and North-east regions as seen in Figure 4. From the predicted risk map, it was observed that only the South-East region had a lower likelihood of under-5 malaria. Figure 5 presents the spatial variation of under-5 malaria prevalence within the 36 states, including the Federal Capital Territory (FCT) of Abuja. The map

Table 3. Comparative fit statistics and covariance parameter estimates for the G-side spherical spatial model.

Model-fit criteria	SP(SPH)[a]	SP(EXP)[b]	SP(GAU)[c]
-2 Res Log Likelihood	5,662.11	5,668.90	5,938.35
AIC[d]	5,776.11	5,782.90	6,052.35
AICC[e]	5,777.39	5,784.18	6,053.62
BIC[f]	5,991.96	5,998.75	6,268.20
Covariance parameter estimates for SP(SPH)[a]			
Effect	**Estimate**	**SD**	**P-value**
SP(SPH)[a]	2.7156	0.1368	<0.0001
Variance	0.1086	0.0175	<0.0001
Residual	0.1627	0.0033	<0.0001

[a]spherical spatial covariance structure; bexponential spatial covariance structure; cGaussian spatial covariance structure; [d]Akaike Information Criterion (smaller is better); [e]Akaike Information Criterion Corrected (smaller is better); [f]Bayesian Information Criterion (smaller is better).

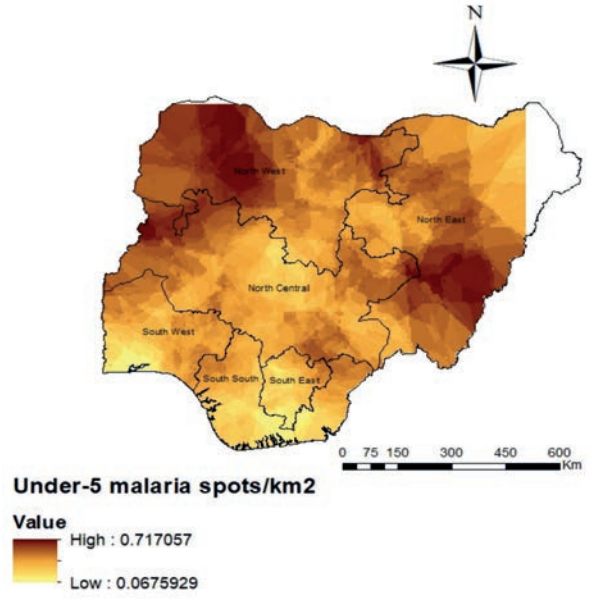

Figure 4. Risk map of under-5 malaria infection as predicted by the spatial generalized linear mixed model for the 6 geopolitical regions of Nigeria. The colorimetric scale represents the number of infected under-5 children per km^2.

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indicated the states Zamfara, Sokoto, Kebbi, Adamawa, Gombe and Jigawa as having the highest risk of under-5 malaria prevalence, followed by Benue, Niger, Kwara, Kano and Plateau. The risk was lowest in the staes Rivers, Akwa-Ibom, Anambra, Enugu and Ogun, which are mostly in the Southern regions.

Table 4 presents summarized estimates of β-coefficients, odd-ratios, the corresponding 95% confidence intervals and P-values estimated by the GLMMs with and without spatial correlation. When the spatial effect was ignored, the estimated fixed effects were inflated by about threefold (over-estimation) as seen in Table 4. Our results show that an over-estimated output would be obtained if the spatial effect was not accounted for in the GLMM. However, the findings of the two models varied slightly, except for the estimated LLIN effect. The availability and usage of LLINs among the under-5 group acted as significant protective factors for malaria infection, only after adjusting for spatial correlation. The result implies that non-availability and non-usage of LLINs are risk factors with respect to under-5 malaria P=0.0373, 0.0427). The low Household Socio-Economic Factor (HSEF) revealed a strong statistical association with under-5 malaria and was consistent after adjusting for the spatial effects (P=<0.0001). The household wealth index (poorest, poorer and middle-range) showed a positive association with malaria regardless of adjusting for spatial correlation. The presence of anaemia in children revealed a statistically significant positive association with malaria infection, regardless of spatial effects and after adjusting for spatial location (P=<0.0001). Several variables appeared to be risk factors for under-5 malaria, regardless of accounting for the spatial effects. They are the type of place of residence, poverty of the household, low mother's educational attainment, family size, age of the child and the head of household.

Table 4. Associations between under-5 malaria prevalence and baseline socioeconomic, demographic and geographic factors.

	Nonspatial-GLMM					Spatial-GLMM				
Variable	Mean	SD	OR	95% CL	P-value	Mean	SD	OR	95% CL	P-value
Intercept	-4.2937	0.5687	0.0137	0.0045 0.042	<.0001	-0.1614	0.1237	0.8511	0.6677 1.0844	0.1931
Region (Ref. North West)										
South East	0.3081	0.3786	1.3608	0.6479 2.8580	0.4163	-0.0499	0.1278	0.9513	0.7405 1.2221	0.6965
South South	-0.4598	0.4612	0.6314	0.2557 1.5591	0.3196	-0.0651	0.1346	0.9371	0.7197 1.2198	0.6285
South West	0.2795	0.3599	1.3225	0.6532 2.6776	0.4381	-0.0538	0.1393	0.9476	0.7212 1.2451	0.6992
North Central	-0.3401	0.4435	0.7117	0.2983 1.6975	0.4438	-0.1901	0.0937	0.8269	0.6881 0.9936	0.0427
North East	-1.2204	0.4895	0.2951	0.1131 0.7703	0.0132	-0.1088	0.1111	0.8969	0.7215 1.1151	0.3269
Place of residence (Ref. Urban)										
Rural	1.4641	0.4575	4.3236	1.7637 10.5994	0.0015	0.2948	0.0721	1.3429	1.1659 1.5467	<.0001
Wealth index (Ref. Richest)										
Poorest	1.3989	0.4114	4.0507	1.8086 9.0723	<.0001	0.2226	0.0731	1.2536	1.0826 1.4418	0.0023
Poorer	1.9532	0.3503	7.0512	3.5489 14.0102	<.0001	0.2973	0.0593	1.3462	1.1985 1.5121	<.0001
Middle-range	1.1308	0.2445	3.0981	1.9186 5.0029	<.0001	0.1621	0.0401	1.1759	1.0871 1.2721	<.0001
Richer	0.6536	0.1832	1.9224	1.3425 2.7529	0.0007	0.0596	0.0269	1.0614	1.0069 1.1189	0.0273
Mother's education (Ref. Higher)										
No education	0.6759	0.2018	1.9659	1.3236 7.3939	0.0009	0.0984	0.0295	1.1034	1.0414 1.3381	0.0009
Primary	0.4381	0.1979	1.5498	0.6567 2.2841	0.0273	0.0509	0.0286	1.0522	1.1129 1.1129	0.0347
Secondary	0.4052	0.1815	1.4996	1.0507 2.1403	0.0261	0.0549	0.0247	1.0564	1.1129 1.1129	0.0261
Bed net (Ref. All used)										
No bed-net	-0.1908	0.1318	0.8263	0.6382 1.0699	0.1481	0.0396	0.0224	1.0404	0.9957 1.0871	0.0373
Some used	-0.1747	0.1103	0.8397	0.6765 1.0423	0.1137	-0.0299	0.0192	0.9705	0.9347 1.0078	0.1187
No child used	-0.1791	0.1188	0.8361	0.6624 1.0552	0.1322	0.0272	0.0204	1.0276	0.9873 1.0695	0.0427
Spraying (Ref. Yes)										
No	-0.1041	0.3492	0.9012	0.4545 1.7866	0.7676	-0.0168	0.0555	0.9833	0.8819 1.0963	0.7624
Child's age (Ref. 6-12 months)										
13-24 months	0.5316	0.1201	1.7017	1.6834 2.1533	<.0001	0.0865	0.0199	1.0904	1.0486 1.1337	<.0001
25-36 months	0.9618	0.1203	2.6164	2.0668 3.3121	<.0001	0.1567	0.0201	1.1696	1.1245 1.2166	<.0001
37-48 months	1.2587	0.1198	3.5208	2.7840 4.4527	<.0001	0.2074	0.0198	1.2305	1.1836 1.8476	<.0001
49-59 months	1.5432	0.1235	4.6795	3.6735 5.9611	<.0001	0.2554	0.0203	1.2909	1.2406 1.3433	<.0001
Child's sex (Ref. Male)										
Female	-0.0585	0.0661	0.9432	0.8286 1.0736	0.3777	-0.0112	0.0113	0.9889	0.9672 1.0111	0.3211
Anaemic status (Ref. No)										
Yes	1.1072	0.0791	3.0259	2.5913 3.5333	<.0001	0.1871	0.0132	1.2057	1.1750 1.2374	<.0001
Age of head of household	0.0132	0.0055	1.0133	1.0024 1.0243	0.0161	0.0023	0.0009	1.0023	1.0005 1.0041	0.0108
Family size	0.0671	0.0329	1.0694	1.0026 1.1406	0.0421	0.0111	0.0055	1.0116	1.0003 1.0221	0.0443
Number of rooms	-0.0199	0.0251	0.9803	0.9332 1.0297	0.4257	-0.0024	0.0045	0.9976	0.9888 1.0064	0.5961

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Discussion

The study investigated important associations between different socioeconomic, demographic and geographic factors and under-5 malaria prevalence in Nigeria. Risk maps of this prevalence were developed based on the available data, to also identify high-risk regions. We observed that the geographical inequalities in health are strongly associated with the socioeconomic conditions and inefficient public health resource allocations as pointed out by Onwujekwe *et al.* (2009). The results show that, the unavailability and non-usage of LLINs among the under-5 part of the population increased the likelihood of malaria infections. It is evident from the results that households where all children or some children had slept under LLINs prior to the survey reduced the risk of malaria as compared to those households without LLINs. These results are in line with previous findings, that the use of LLINs reduces malaria infection (Ayele *et al*., 2013; Samadoulougou *et al.*, 2014; Yaya *et al.,* 2018). However, whether dwelling has been sprayed against mosquitoes or not in the last 12 months prior to the survey was insignificant in this study. We found that under-5 malaria infections were more common among children living in low-income households, thus supporting the view that low socioeconomic factors such as poverty influences the vulnerability of under-5s to malaria infection (Diggle *et al.*, 2002; Onwujekwe *et al.*, 2009; Adigun *et al.*, 2015; Adebayo *et al.*, 2016; Samadoulougou *et al*., 2014).

Children living in rural areas in poor households constitute the vulnerable group, whose needs should be adequately weighed in future intervention policies, as they were found to be highly affected by malaria, which might be as a result of inaccessibility of health facilities and LLINs in the remote rural areas. In concurrence with the findings of Onwujekwe *et al*. (2009), Ayele *et al.* (2013), Samadoulougou *et al.* (2014) and Adebayo *et al.* (2016), children residing among what was called richer and richest households and those in families in urban areas were significantly less prone to malaria infection than their counterparts. According to Onwujekwe *et al.* (2009) and Okeke and Okeibunor (2010), children living in the rural areas show a higher rate of mortality than those living in urban areas, and this may last until the child reaches about 10 years of age. The analysis of socioeconomic factors shows that a low education of the mother is associated with under-5 malaria (Kreuels *et al.,* 2008; Ayele *et al.*, 2013; Njau *et al.,* 2014). In concurrence, our study found that the higher the level of the mother's education the more significantly negative is the correlation with under-5 malaria. The result implies that, an educated mother s likely to have the adequate knowledge required for malaria prevention, control and total care of her children. Moreover, the likelihood of an under-5 malaria infection vulnerability increased with age as observed from our results, with lower likelihood among children less than 25 months (Diggle *et al*., 2002; Ayele *et al.,* 2013; Gayawan *et al*., 2014; Adebayo *et al.*, 2016;). This can be attributed to the fact that children <20 months old are protected through maternal immunity (Adebayo *et al.*, 2016). The age of the household head is known to influence malaria among children, with malaria infection being significantly more common among children living with heads of households 60 years old and above (Ayele *et al*., 2013; Gayawan *et al*., 2014; Adebayo *et al.,* 2016). Regarding the anaemia status, there is a strong statistically significant association between anaemia and malaria prevalence among under-5s. The positive malaria outcome was higher among the anaemic children than the non-anaemic children as they are seen to be highly inter-correlated (Yusuf *et al.,* 2010). Therefore, malaria preventive measures can also protect the anaemic children, since both diseases share a common influence.

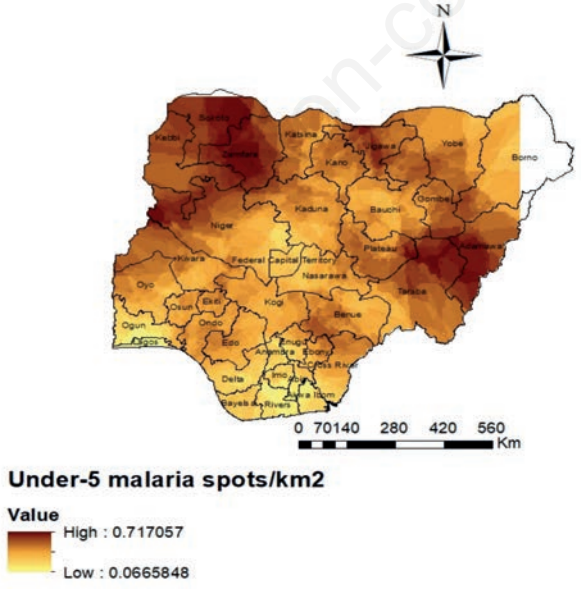

Figure 5. Risk map of under-5 malaria infection as predicted by the spatial generalized linear mixed model for the 36 states including the Federal Capital Territory of Nigeria. The colorimetric scale represents the number of infected under-5 children per km^2.

The identification of hotspots, which may reflect malaria eradication-limiting factors will allow the focusing of public health resource allocation to areas that have particularly high malaria burdens. Indeed, some areas in Nigeria show particularly high burdens of under-5 malaria, including hotspots. Our results suggest that the distribution of malaria is geographically structured and there are factors that influence certain areas to be more vulnerable than others. For instance, a strong correlation was observed between under-5 malaria prevalence and areas where problem of poor socioeconomic conditions and rural population are predominant (Onwujekwe *et al*., 2009; Adigun *et al.*, 2015). Indeed, other studies show that gaining a better understanding of the socioeconomic factors that favour malaria infection can raise the profile of malaria control management in both rural and urban areas through spatial analysis (Diggle *et al.,* 2002; Ayele *et al.,* 2013; Kazembe and Mathanga, 2016; Adebayo *et al.,* 2016; Kreuels *et al*., 2008).

The following limitations should be considered when interpreting the results of this study: i) The study utilized a cross-sectional data from the 2015 NMIS, which lacks the capacity to make any casual inference; ii) the study did not examine other important factors such as: the entomology-vector variables, the vector breeding-sites, climatic factors, environmental factors and geographic covariates, such as forest cover. The limitations may lead to insufficient analytical conclusions. However, despite these limitations, the study has identified potential other risk factors based on the available variables extracted from the 2015 NMIS database and has filled a gap in the spatial analysis of under-5 malaria prevalence in Nigeria based on GLMMs.

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Conclusions

The results presented provide important insight for public health practitioners working towards malaria eradication in Nigeria, which should specifically target children between ages 37-59 months residing with illiterate-poor mothers in the rural households across the identified high-risk regions of Nigeria. Under-5 malaria predictive risk maps show a clear spatial heterogeneity, which to an extent may be explained by variations in socioeconomic factors. The odds of malaria among the under-5s increase with family poverty, non-availability and non-usage of LLINs, low education of the mother, family size, age of the child, presence of anaemia and increased age of the head of household. Children in the rural areas were more at the risk of malaria than their urban counterparts, indicating a rural disadvantage in terms of malaria control and intervention. This need to be addressed under public health education and intervention programmes at the community or state level.

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