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# Spatial Pattern and Determinants of Risk Factors of Malaria among Children under five in Nigeria

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**Abstract.** Malaria remains one of the leading public health problems in developing countries, especially Nigerian. Evidence-based knowledge of interventions are needed to combat the menace of the disease. Pregnant women and under five children have been found to be the most vulnerable groups. Therefore, in this study, we explore the spatial pattern and risk factors of malaria among under five children in Nigeria using data sets from the 2010 and 2015 Nigeria Malaria Indicator Survey. A total of 9360 children aged 6-59 months were included in the analysis. A structured geo-additive model, an approach that simultaneously estimates nonlinear, spatial, fixed and random effects within a Bayesian context in one step was adopted for all estimation. The results reveal a reduction in the proportion of children who had malaria in 2015 compared with those in 2010. Socio-economic status, mother educational level and place of residence have marginal effect on child health. Malaria risk increased with increasing age of child and age of household head. Further, malaria risk was found to be higher in Kebbi, Kwara, Niger and Zamfara states. Findings from this paper are meant to guide policy makers and donor agencies in appropriate identification of the drivers of the disease with the aim of designing and funding of effective intervention strategies to reduce the pattern of the disease endemicity so as to improve child survival-hood.

**Keywords:** Bayesian inference, geo-additive model, malaria, Nigeria, nonlinear, spatial analysis.

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## 1. Introduction

Malaria is one of the deadly diseases endemic in developing countries around the world (WHO, 2017). The 2019 Global Malaria Report by World Health Organization indicates that malaria caused an estimated 228 million clinical

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episodes and 405,000 deaths with the most incidence and mortality occurring in sub-Sahara Africa (WHO,2019). For example, 24 million children were estimated to be infected with *P.falciparum* in 2018 in sub-Sahara Africa (WHO, 2019). Also, about 872,000 children were delivered with low birth weight in 2019 due to malaria in pregnancy, with the highest prevalence occurring in west Africa (WHO, 2019).

According to the 2019 world malaria report, Nigeria suffers the world's greatest malaria burden accounting for 25% of the global cases and death with approximately 51 million cases and 207,000 malaria related deaths (WHO, 2019).

The geographical location of Nigeria makes the climate conducive for malaria transmission throughout the country (Gayawan *et al.* 2014). Also, Nigeria is characterized with a tropical climate of wet and dry season which is driven by the movement of two dominant winds; the rain-bearing Southwesterly winds and the cold-dry-dusty Northeasterly winds, known as the harmattan (NMEP, 2016). These climatic conditions favoured the spread of malaria. The most prevalent specie of malaria in Nigeria is *plasmodium falciparus*, and it is responsible for the most severe form of the disease (NMEP, 2016). Therefore, understanding the burden and contextual risk factors is critical for developing appropriate interventions to control malaria and eliminate malaria.

A number of studies have reported the incidence and determinants of malaria in Nigeria (Adigun *et al.* 2015, Salwa *et al.* 2016, Gayawan *et al.* 2014, Onyiri, 2010, Tobin-West and Kanu, 2016, Ugwu and Zewotire, 2018). However, few studies have modelled the spatial pattern that permits the study of difference in the determinants at local level. In their analysis of co-morbidity of malaria and non-malarial febrile illness among young children in Nigeria, Gayawan *et al.* (2014) modelled spatial variation, thus, shedding light into the geographical distribution of malaria in Nigeria using the data from 2010 Nigeria Malaria Indicator Survey (NMIS). Also, using data from the 2010 malaria indicator survey, Adigun *et al.* (2015) assessed malaria risk in Nigeria. The method of the Bayesian geo-statistical modelling was adopted and the result identified normalized difference vegetation index and rainfall as important environmental/climatic predictors of malaria risk. A similar result was found in Onyiri (2015). This author adopted two models to estimate malaria burden in Nigeria using data from various Nigeria sources. In his first model, the author fitted logistic regression model to demographic and environmental variables.

Significant covariates from this fit were fitted into Bayesian geo-statistical model. The result suggests that rainfall and land surface temperature were associated with the presence of malaria. Recently, Okunlola and Oyeyemi (2019) assess the spatial and temporal association between the incidence of malaria and some environmental risk factors using data from the 2015 Nigeria malaria indicator survey. The authors employed various methods ranging from ordinary least square, spatial lag model and spatial error model as well as moran's diagram to examine relationship between incidence of malaria and the ecological predictors and identify hot spot.

This study utilizes data from both 2010 and 2015 waves of the Nigeria malaria indicator survey. The combined data set allows us to study change in malaria prevalence in Nigeria between 2010 and 2015. The flexible Bayesian modelling approach that jointly models spatial effect, nonlinear effects of continuous covariates, structured and unstructured random effects, as well as, linear effect was adopted in the study. With this approach, we were able to discern not only the geographical distribution of malaria but also the detailed functional relationships between the disease and different nature of covariates.

## 2. Materials and Method

The data for this study comes from two waves of the Nigeria Malaria Indicator Survey (NMIS), which were conducted in 2010 and 2015. The baseline survey was conducted in 2010. The 2015 was a follow-up to the baseline survey and was designed to provide information on malaria indicators and prevalence in Nigeria. In addition, the survey was also designed for monitoring and evaluating Nigeria's national malaria elimination programme for the next 10 years (NMEP, 2016). The sampling frame used for the surveys was based on 2006 National Population and Housing Census (NPHC) of the Federal Republic of Nigeria. The primary sampling unit(PSU), referred to as "cluster" for the 2010 and the 2015 NMIS, was defined on the basis of Enumeration Areas (EAs) from the census frame. Both surveys selected sample using a two-stage stratified design. In the first stage, nine clusters were selected in each state, including the Federal Capital Territory (FCT), while 25 households were selected in each cluster at the second stage. In all, the database consists of 9360 observations.

The survey collected data from women within the reproductive age 15 - 49 years and those with children under 5 years. In addition, blood samples were collected from children age 6 - 59 months, after obtaining informed consent from child's parent or guardian. Two methods of biological data collection were involved; the Rapid Diagnostic Test (RDT) for the detection of histidine rich protein-2 (HRP 2) and the microscopy test to determine both the presence of the parasites and the parasite species (NMEP, 2016). Results of the microscopy test are considered as gold standard, hence they are used as the outcome variable in this study.

The independent variables explored are: "year of study" which was categorized into 2010 and 2015, socio-economic, demographic and geographic factors. The wealth index is a background characteristic used to measure the socio-economic status of household. This was calculated using data from the household ownership of durable goods like radio or a television, sanitation facilities, dwelling characteristic, source of drinking water and other characteristic relating to the household socio-economic status. Using the Principle Component Analysis, each of these asset was assigned a score which was standardized inline with the standard normal deviation with a mean of zero and standard deviation of one. All the households were then grouped into five wealth quintiles with 1 corresponding to the poorest and 5 the richest. The demographic factors consist of age and sex of child, age and sex of household head. The geographic factors include place of residence and region. Use and ownership of bed net were also explored. The metrical covariates include age of child in month and age of household head. Table 3 presents a description of the variables included in the analyses, including their frequency distribution. Data cleaning was handled with R statistical software (R Core Team, 2021), all analyses were performed with Bayes-X; a software for Bayesian semi-parametric modelling through Markov

Chain Monte Carlo (MCMC) techniques and figures were produced using the package Bayes X (Umlauf *et al.* 2019).

## 2.1 *Statistical Model*

Suppose $Y_i$ is a binary response variable, where $y_i = 1$ if child $i$ tested positive to malaria from microscopy diagnosis test and 0 otherwise. The dependence of $Y_i$ on a set of covariates given as $(x_i, s_i, v_i, \xi_i), i = 1, \cdots, n$, is modelled within the framework of geo-additive structured models which extends the generalized additive model (Hastie and Tibshiran, 1990). In this case, $x = (x_1, \cdots, x_p)^{'}$ is the matrix of metrical covariates, $s_i = (1, \cdots, 37)$, the state (district) where respondent $i$ lived during the survey, $v = (v_i, \cdots, v_q)^{'}$ is matrix of the linear effect of the categorical covariates and $\xi_i$ is a random effects for cluster number where the child lived. The geo-additive model is specified as

$$\eta_i = \mathbf{T}_{2015} + \sum_{j=1}^{p} f_j(x_{ij}) + f_{spat}(s_i) + v_i^{'}\beta + \xi_i, \tag{1}$$

where $\eta_i$ is the geo-additive predictor, $\mathbf{T}_{2015}$ is a dummy for year of study with 2010 as the reference category, $f_i, \cdots, f_p$ are the nonlinear effect of metrical covariates $x$, which include age of child in month and age of household head, $f_{spat}$ is the non-linear effect of spatial covariates and $\beta_i = (\beta_1 \cdots, \beta_L)^{'}$ is a vector of fixed effect parameters for the categorical covariates. In this study, we adopted the logit link and set the first categories to reference. The spatial effects $f_{spat}$ can further be split into two component; spatially correlated (structured) and uncorrelated (unstructured) effects such that;

$$f_{spat}(s_i) = f_{str}(s_i) + f_{unstr}(s_i). \tag{2}$$

## 2.2 *Bayesian prior probability distribution*

To estimate smooth effect functions and model parameters, Bayesian approach was used as developed by Fahrmeir and Lang (2001), and Lang and Brezger (2004). All parameters had appropriate priors assigned to them. Fixed effect parameters were considered to have diffuse prior, whereas nonlinear effects $f_j(x_{ij})$ were assumed to have Bayesian P-spline based on Brezger and Lang (2006). The semiparametric estimates of $f$ as a linear combination of basis functions (B-spline) is possible using the P-spline prior;

$$p(z) = \sum_{j=1}^{j} \beta_j B_j(z), \tag{3}$$

Table 1: **Emperical frequency of the district variables across the two levels of microscopy test results for 9360 observations.**

| | | Microscopy | | |
|---|---|---|---|---|
| Factors | Factor level | Negative | Positive | P-Value |
| Year of study | 2010 (ref) | 2676(62.1%) | 1636(37.9%) | $< 0.0000$ |
| | 2015 | 4166(72.8%) | 1560(27.2%) | |
| Wealth Index | Poorest (ref) | 929(53.8%) | 798(46.2%) | $< 0.0000$ |
| | Poorer | 1094(56.9%) | 830(43.1%) | |
| | Middle | 1260(64.4%) | 696(35.6%) | |
| | Richer | 1483(75.7%) | 588(24.3%) | |
| | Richest | 1602(89.3%) | 192(10.7%) | |
| Mother Edu. Level | No Education (ref.) | 2396(57.4%) | 1778(42.6%) | $< 0.0000$ |
| | Primary | 1242(68.4%) | 575 (31.6%) | |
| | Secondary | 2173(78.4%) | 597(21.6%) | |
| | Higher | 557(93.0%) | 42(7.0%) | |
| Child Sex | Male (ref.) | 3203(67.7%) | 1530(19.2%) | 0.4629 |
| | Female | 3165(68.4%) | 1462(31.6%) | |
| Sex of household head | Male (ref.) | 5800(67.5%) | 2790(32.5%) | 0.0004 |
| | Female | 732(71.9%) | 286(28.1%) | |
| Ownership of bed net | No (ref) | 1965(65.2%) | 1047(34.8%) | $< 0.0000$ |
| | Yes | 4403(69.4%) | 1943(30.61%) | |
| Use of bed net | No(ref.) | 3497(68.4%) | 1614(31.6%) | 0.3909 |
| | Yes | 2871(67.6%) | 1378(32.4%) | |
| Place of residence | Urban (ref.) | 2493(84.9%) | 445(15.1%) | $< 0.0000$ |
| | Rural | 3875(60.3%) | 2547(39.7%) | |
| Region | North Central (ref.) | 1106(63.4%) | 639(36.6%) | $< 0.000$ |
| | North East | 1282(71.2%) | 518(28.8%) | |
| | North West | 1324(57.0%) | 998(43.0%) | |
| | South East | 846(80.3%) | 207(19.7%) | |
| | South South | 1026(73.4%) | 371(26.6%) | |
| | South West | 784(75.2%) | 259(24.8%) | |

where $B_j(z)$ denotes B-splines and $\beta_j$ are coefficients defined to follow a second order Gaussian random walk smoothness priors

$$\beta_j = 2\beta_{j-1} - \beta_{j-2} + \varepsilon_1$$

with independence and identically distributed errors $\varepsilon_i \sim N(0, \tau^2)$. The smoothness of $f$ is controlled by variance $\tau^2$. With $\varepsilon$ very small and assigning a weakly informative inverse gamma prior $(\tau^2 \sim IG(\varepsilon, \varepsilon))$, $f$ is computed together with the basis function coefficients. The random effects were modelled using an exchangeable normal prior, $b_{ij} \sim N(0, \tau_b)$, where $\tau_b$ is the variance component that accounts for heterogeneity and over dispersion.
A Gaussian Markov random fields prior was assumed for the spatial effects, $f_{spat}(s), s = 1, \cdots, S$. This prior is commonly used in spatial statistics and it is given as (Gayawan *et al.* 2013) ;

$$\left[f_{spat}(s)|f_{spat}(t) \neq s, \tau^2\right] \sim N\left[\sum_{t\in\delta_s} \frac{f_{spat}(t)}{N_s}, \frac{\tau^2}{N_s}\right]$$

where $N_s$ denotes the number of nearby sites and $t \in \delta_s$ indicates that site $t$ is a neighbour of sites $s$. Patterns in neighbouring locations are believed to have comparable tendencies. Thus, the prior classified areas as neighbours if they

share boundary.
Highly distributed yet appropriate hyper-priors are applied to nonlinear and spatial effects in order to estimate their smoothing parameters. As a result, an inverse distribution with hyper-parameters $a$ and $b$ is chosen for all variance components. The hyper parameters $a = 1$ and $b = 0.005$ or $a = b = 0.001$ are the standard hyper-parameter. In this study, the default choice was used (Brezger*et al.* 2005). The default option was used in this study.
The inference was completely Bayesian. The posterior distribution is intractable, thus samples from the prior distribution were generated using Markov Chain Monte Carlos (MCMC) process. When using the MCMC to fit Bayesian models, all parameters are treated as randomly distributed according to certain prior distributions. The parameters can be estimated and inferred using MCMC techniques which model spatial, nonlinear, and linear fixed effects. All analyses are performed in BayesX a software for Bayesian inference in Structured Additive Regression Models version 3.0.2. For all the models considered in this study, 12000 iterations with 2000 burn-in period were used. Model diagnostics were based on the Deviance Information Criterion(DIC) given by (Spiegelhaiter *et al.* 2002).

$$DIC = \bar{D}(\theta) + pD$$

where $\bar{D}$ is the posterior mean of the deviance and $pD$ is the effective number of parameters measuring model complexity. The model with the lowest DIC is considered the best model, while small values of $pD$ indicate a parsimonious model.

## 3. Results and Discussion

### 3.1 *Results*

Descriptive statistics were used to display the distribution of the independent variables by the outcome variable of interest which is presence or absence of malaria parasites among the respondents. The Pearson Chi-square $(\chi^2)$ test of association was used to determine which variables are significantly associated with presence or absence of malaria parasite at bivariate level. The Bayesian semi-parametric model was used to identify the predisposing factors and hot spot for malaria prevalence across the states.
Four models with different specifications were considered to investigate the influence of observed covariates and unobserved heterogeneity on response variable. In the first model $(M_1)$, we modelled the dependence of the presence or absence of malaria on year of study and categorical variables. Model $M_1$ was extended in the second stage to include the nonlinear effect of child age and age of household head. The resulting model was labeled $M_2$. The third model $M_3$ included spatial effect and unobserved random effects of cluster number to identify the hot spot for malaria prevalence across the states. Finally, in model $M_4$, the spatial effect was split into structured and unstructured effect. The fitted models are defined as follows

$$
\begin{aligned}
M_1: &\quad \eta = T_{2015} + v_i^{'}\beta \\
M_2: &\quad \eta = T_{2015} + v_i^{'}\beta + f_1(childage) + f_2(household\_headage) \\
M_3: &\quad \eta = T_{2015} + v_i^{'}\beta + f_1(childage) + f_2(household\_headage) + f_{spat}(s_i) + \xi_i \\
M_4: &\quad \eta = T_{2015} + v_i^{'}\beta + f_1(childage) + f_2(household\_headage) + f_{str}(s_i) + f_{unstr}(s_i) + \xi_i
\end{aligned} \tag{4}
$$

The four models were implemented in Bayes X. Table 2 presents model diagnostics statistics for all the fitted models. Obviously, Model $M_4$ that split the spatial component into spatially correlated and uncorrelated performed best when compared with all other models (DIC = 9508.5697). However, there was not a significant difference between models $M_3$ and $M_4$. Furthermore, the results for fixed effects, spatial components and nonlinear effects are indistinguishable from the two models. Therefore, discussions of results will be based on model $M_3$.

Table 2: **Model Diagnostic Statistics**

| Model | $\bar{D}$ | $P^D$ | DIC |
|---|---|---|---|
| $M_1$ | 1046.451 | 19.07576 | 10502.6030 |
| $M_2$ | 10301.028 | 26.461831 | 10353.9510 |
| $M_3$ | 8999.7838 | 254.44591 | 9508.6756 |
| $M_4$ | 8998.7401 | 254.9148 | 9508.5697 |

Findings from the bivariate analyses are presented in Table 3. Overall, there is 10.7% significant reduction in the prevalence of malaria in children under five in 2015 compared with those in 2010. Findings reveal statistical significance in wealth index, educational attainment, sex of household head, ownership of bed net, place of residence, geopolitical location of the respondents and prevalence of malaria. Malaria prevalence decreases with increase in wealth index of the child's household. Children from wealthiest household are less likely to have experienced episodes of malaria. Evidently, there is a significant positive association between mother's educational attainment and presence of malaria in children under five. Only seven (7.0) percent of children whose mothers attained higher education compared with 42.6% of those whose mothers do not have any formal education tested positive to malaria. It is interesting to know that children from female-headed households are less likely to experience malaria (28.1% vs. 32.5%). This may not be unconnected with known care from women to children in African settings especially in Nigeria. This may further be as a result of experience in caring for children that are peculiar to women in Nigeria. Astonishingly, ownership of bed nets was found to be associated with lower prevalence of malaria. Only 31% of children from households that own bed nets compared with 35% of those who do not own bed net experienced malaria episodes. On place of residence, children who reside in rural areas are more susceptible to episodes of malaria. Prevalence of malaria was 39.7% among children who dwelled in rural areas compared with 15.1% of their counterparts in urban areas. Findings from this bivariate analysis shows a significant geographical variations in prevalence of malaria among children under five. While prevalence of malaria was least and about one-fifth in South East, the prevalence among children in North West was highest and put at above two-fifths.

Table 3: **Empirical frequency of the district variables across the two levels of microscopy test results for 9360 observations.**

| | | Microscopy | | |
|---|---|---|---|---|
| Factors | Factor level | Negative | Positive | P-Value |
| Year of study | 2010 (ref) | 2676(62.1%) | 1636(37.9%) | $< 0.0000$ |
| | 2015 | 4166(72.8%) | 1560(27.2%) | |
| Wealth Index | Poorest (ref) | 929(53.8%) | 798(46.2%) | $< 0.0000$ |
| | Poorer | 1094(56.9%) | 830(43.1%) | |
| | Middle | 1260(64.4%) | 696(35.6%) | |
| | Richer | 1483(75.7%) | 588(24.3%) | |
| | Richest | 1602(89.3%) | 192(10.7%) | |
| Mother Edu. Level | No Education (ref.) | 2396(57.4%) | 1778(42.6%) | $< 0.0000$ |
| | Primary | 1242(68.4%) | 575 (31.6%) | |
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| Child Sex | Male (ref.) | 3203(67.7%) | 1530(19.2%) | 0.4629 |
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| Sex of household head | Male (ref.) | 5800(67.5%) | 2790(32.5%) | 0.0004 |
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| Place of residence | Urban (ref.) | 2493(84.9%) | 445(15.1%) | $< 0.0000$ |
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| | South West | 784(75.2%) | 259(24.8%) | |

Based on the selected model $M_3$, findings from the fixed effects component of predictor (4) are presented in Table 3. After adjusting for some covariates, there is a significant in presence/absence of malaria based on the odds ratio (OR) for year of study. The odds of having malaria declined by 51% in 2015 (OR=0.4927, CI: 0.4315, 0.5680) compared with 2010. Episodes of malaria decline with increase in household wealth indices. Findings show that the odds of having malaria decrease by 74% among children from richest wealth index (OR=0.263, CI: 0.198, 0.356) compared with children from Poorer wealth index who are 12% less likely to experience malaria (OR=0.884, CI: 0.754, 0.970). Also, mother's educational attainment was positively associated with episodes of malaria in which children from mothers with higher education are least likely to experience episodes of malaria. Children whose mothers attained higher education are 66% less likely to experience malaria compared with their counterparts whose mothers do not have any education (OR=0.341, CI: 0.233, 0.492). Similarly, compared to their counterparts whose mothers have no education, children whose mothers have a secondary and those whose mothers have a primary education are respectively 20% and 15% less likely to contract malaria (Secondary education OR=0.801, CI: 0.666, 0.958 and Primary OR=0.853, CI: 0719, 0.998). Considering place of residence, children from ru-

Table 4: **The posterior estimates of the fixed-effects covariates within 95% credible interval.**

| Coefficients | Odd ratio | SD | 95% C.I |
|---|---|---|---|
| Intercept | 1.2827 | 0.2592 | 0.7609 - 2.2380 |
| Year of study(ref. 2010) | 1.000 | | |
| 2015 | 0.4946 | 0.0672 | 0.4315 - 0.5649 |
| Wealth Index(ref. Poorest) | 1.000 | | |
| Poorer | 0.8835 | 0.0812 | 0.7535 - 0.9700 |
| Middle | 0.6495 | 0.0943 | 0.5412 - 0.7805 |
| Richer | 0.4935 | 0.1145 | 0.3972 - 0.6219 |
| Richest | 0.2627 | 0.1424 | 0.1978 - 0.3564 |
| Mother Edu. Level (ref. No Education) | 1.000 | | |
| Primary | 0.8532 | 0.0817 | 0.7186 - 0.9980 |
| Secondary | 0.8005 | 0.0917 | 0.6663 - 0.9575 |
| Higher | 0.3409 | 0.1906 | 0.2328 - 0.4922 |
| Child Sex(ref. Male) | 1.000 | | |
| Female | 0.9238 | 0.0513 | 0.8390 - 1.0273 |
| Head of household sex(ref. Male) | 1.000 | | |
| Female | 0.9416 | 0.1049 | 0.7663 - 1.1726 |
| Ownership of bed net(ref. No) | 1.000 | | |
| Yes | 0.9694 | 0.0808 | 0.8379 - 1.1375 |
| Bed net use(ref. No) | 1.000 | | |
| Yes | 0.9008 | 0.0736 | 0.7760 - 1.6377 |
| Place of residence(ref. Urban) | 1.000 | | |
| Rural | 2.5185 | 0.1017 | 2.0508 - 3.0774 |
| Region (ref. North Central) | 1.000 | | |
| North East | 0.6733 | 0.4210 | 0.2882 - 1.6044 |
| North West | 1.0385 | 0.3583 | 0.5220 - 2.08842 |
| South East | 0.8806 | 0.4442 | 0.3778- 2.2321 |
| South South | 1.1098 | 0.4767 | 0.4405 - 2.8467 |
| South West | 1.6796 | 0.4191 | 0.6950 - 3.9687 |

ral areas are 150% more likely to experience episodes of malaria compared with those from urban areas (OR=2.519, CI: 2.051, 3.0774).

Figure 1a and 1b displays the results of the nonlinear effects of child's age and age of household head. There is a positive increase in episodes of malaria as child's age increases and similarly as the head of household's age increases.

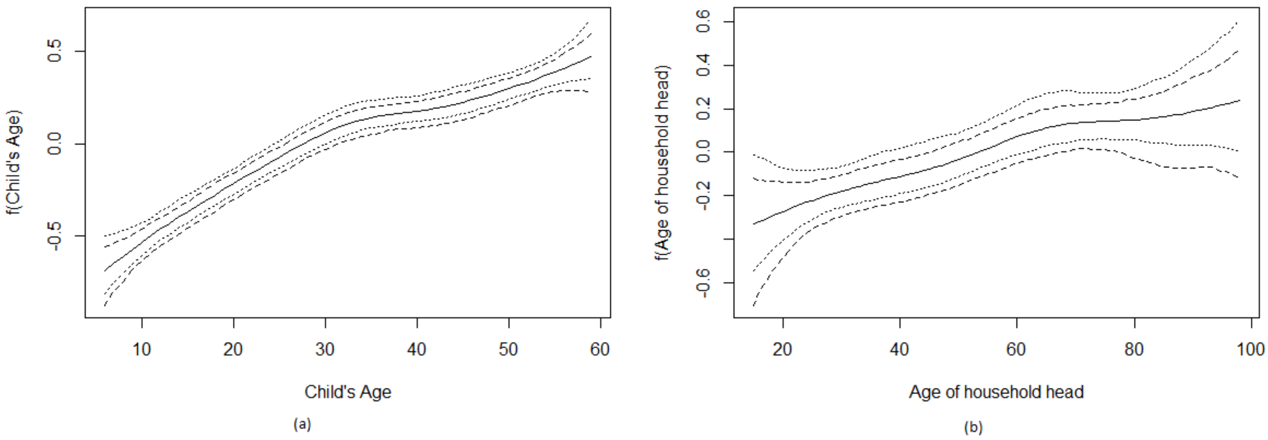


Figure 1: Nonlinear effect of: (a) child age (b) Age of household head.

Turning attention to the results of the spatial component, findings show significant spatial variations in episodes of malaria among children under 5 in Nigeria. Figure 2a depicts the results of the spatial effect, while Figure 2b displays the map of the spatial effect's significance. States in white are significantly associated with higher episodes of malaria (credible intervals above 1.0) whereas states in black are significantly associated with lower episodes of malaria (credible intervals between 0 and lower than 1.0). Spatial variations of states in grey are found not to be significant (credible intervals include zero (0.0)). From this, Kebbi, Kwara, Niger and Zamfara states are found to be significantly associated with higher episodes of malaria, while the geographical variations in Borno and Lagos states are significantly lower. The spatial variations in the remaining states are not significant.

The plot of the kernel density displaying the inclusion of random component into the predictor in (4) is presented in Figure 3. Comparing the two plots in Figure 3, a slight departure from normality was noticed at the peak of the curve.

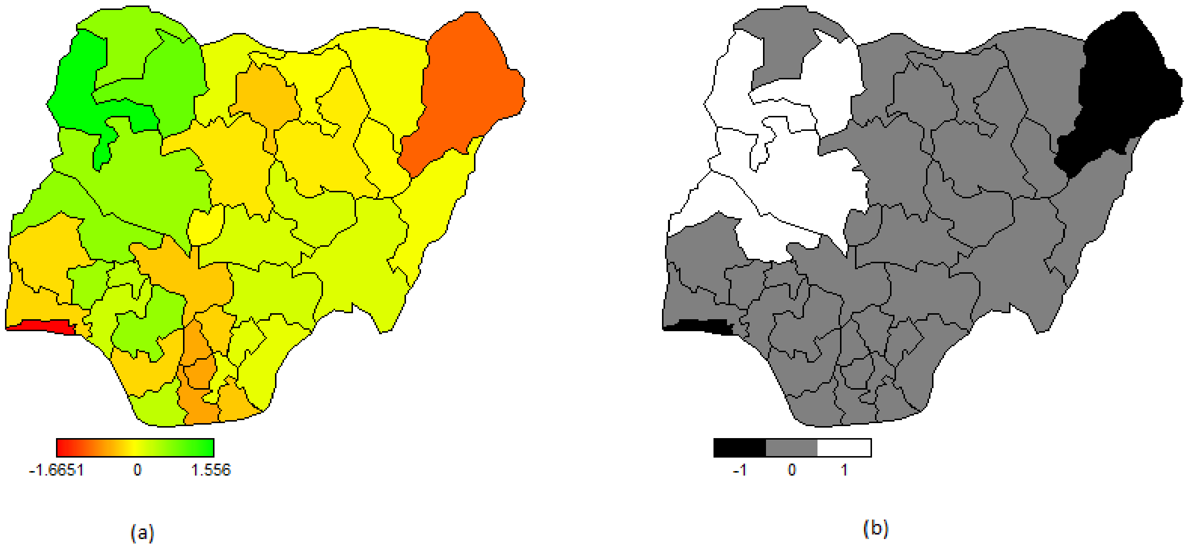


Figure 2: Nonlinear estimate of the spatial pattern of: (a) structured effect, (b)corresponding 95% posterior probabilities.

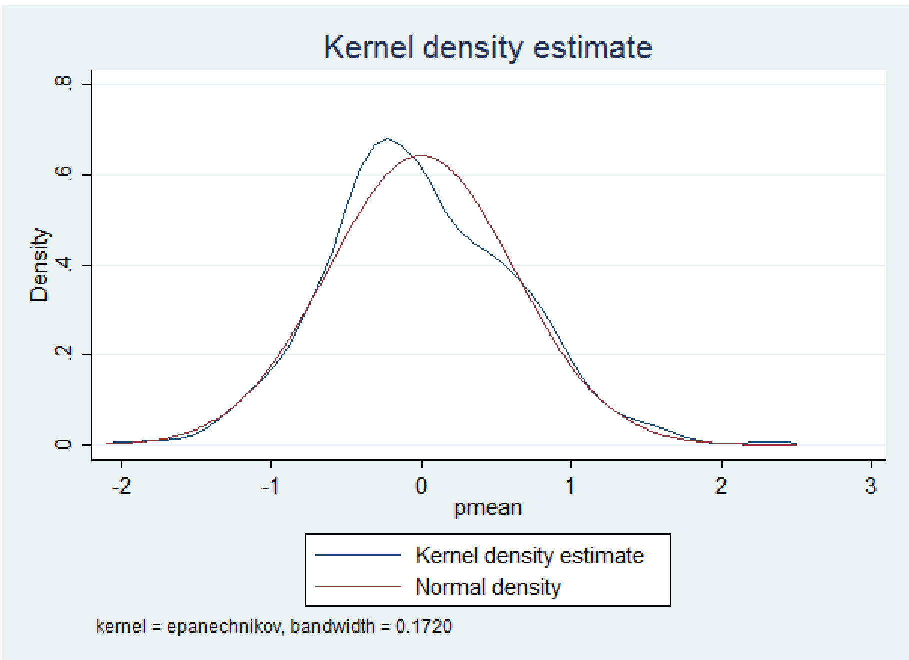


Figure 3: Kernel density estimates for cluster number random effect for model $M_3$.

### 3.2 *Discussion*

In this study, geo-additive model was used to determine the change, drivers and hot spots of malaria among under five children in Nigeria using data from two waves of the Nigeria Malaria Indicator Survey in 2010 and 2015. We found that there was a reduction in malaria prevalence in 2015 compared with 2010. This is in line with findings from other research that show a considerable decrease in the prevalence of malaria infection in children under the age of five in Nigeria (Oyibo *et al.* 2021). This reduction might be a reflection of the gains in the efforts Nigeria government has put in to achieve pre-elimination status and reduce malaria-related deaths to zero by 2020. So far, Nigeria has implemented three national malaria strategic plans and is currently implementing a fourth plan, which covers the period of 2014-2020 (NMEP, 2016).

Although there was a considerable reduction in malaria in 2015, yet the prevalence was still high. Our findings revealed that socio-economics status, mother educational level and place of residence have marginal effects on child health. Previous studies corroborate our position that children from the richest household are less likely to had malaria compared with children from the poorest household (Ayele *et al.* 2012, Chirombo *et al.* 2014 and Ugwu and Zewotire 2018). Belonging to households in the poorest wealth quintile may be associated with poor environmental conditions which may lead to breeding of mosquitoes. There are a lot of other challenges associated with living in households in the poorest wealth quintile. Food insecurity, poor hygienic condition, water from unimproved sources and unimproved toilet facilities are among several other factors associated with living in the lowest wealth index (Ajao *et al.* 2010 and Morakinyo and Fagbemigbe, 2017). These factors may negatively affect the socio-economic and well-being of individuals in this group.

The relationship between mother's educational level and her child's vulnerability to malaria infection as revealed in our study is well documented in previous studies (Gayawan *et al.* 2014, Ugwu and Zewotire, 2018 and Ukwajunor *et al.* 2020). Children whose mothers attained higher education were found to be less likely to had episodes of malaria compared with children whose mother have little or no education. A higher level of mother education has been associated with improved income, better health education particularly with regards to strategies for malaria prevention.

Further, findings from our study reveal that malaria prevalence is higher in rural area than in urban area. A similar trend have been reported by previous studies in Nigeria (Adigun *et al.* 2015, Oyewale, 2018, Salwa *et al.* 2016).

Findings from the nonlinear effect revealed that malaria risk increased with increasing age of the child. This is consistent with past studies that have found a direct link between age and malaria infection (Chirombo *et al.* 2014, Gayawan *et al.* 2014). It's possible that this pattern of findings is related to the fact that very young infants receive more care from there mothers and are protected by maternal immunity as a result of breastfeeding (Gayawan *et al.* 2014). Older children, on the other hand, are more likely to contract malaria as a result of the outdoor activities in which they participate (Ugwu and Zewotire, 2018).

Result from the spatial effect shown that, after taking into account other relevant determinants, four states (Kebbi, kwara, Niger and Zamfara) possess higher risk in comparison to others.

## 4. Conclusion

A structure geo-additive model was adopted to explore the spatial pattern and risk factors of malaria among under five children in Nigeria. Several authors have considered similar models to study malaria prevalence in Nigeria using either the 2010 or 2015 Nigeria malaria indicator survey data. However, in our work, we analyses data from two waves of survey – 2010 and 2015 data set. The combined data construct allows us to study change in malaria prevalence in Nigeria within the study period. The result from these analyses shows a considerable reduction in the prevalence of malaria infection among under five children in 2015 compared with 2010.
In addition, the study utilized cluster number as random component. Findings from this analysis indicate that there is still some effect of cluster variables that need to be address in order to reduce episodes of malaria and achieve pre-elimination status.
In conclusion, findings from this study provide insight into possible determinants of malaria, and assists in identifying states with significantly high risk allowing policymakers to design intervention to reduce episodes of malaria in such states. Mother educational level, wealth index and place of residence significantly influence a child vulnerability to malaria infection. Although these factors have earlier been pointed out in literature, malaria still remains a burden in Nigeria. Therefore, a greater efforts is needed to improve the prevalence of malaria in Nigeria. Findings from this study when implemented, could be beneficial to government at all levels because it will aid planning and optimal allocation of health resources especially when they are limited.

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