Research Article

Spatially Weighted Multinomial Modelling of Comorbidity of Anaemia and Malaria Among Under Five Children in Nigeria

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Children in sub-Saharan African countries, especially Nigeria, continue to suffer increased mortality owing to the comorbidity of infections such as anaemia and malaria, which are known to epidemiologically overlap. In order to examine the risk factors and spatial patterns of comorbidity of anaemia and malaria using the 2021 Nigeria Malaria Indicator Survey (NMIS), a multinomial logit model was extended by incorporating a spatially weighted random effect. The impact of climatic variation on childhood disease comorbidity was explored by weighting the spatially structured component based on the 2021 NMIS average cluster temperature of each state in Nigeria. A number of spatially weighted geo-additive models were fitted and compared using the deviance information criterion. Inference was fully Bayesian, and an Intrinsic Conditional Autoregressive prior was used for structured random effects. Based on the map generated from the best-fitted model, which unveiled states that are more susceptible to the risk of disease comorbidity, the average temperature used as a weighting factor, however, has a strong relationship with the spatial pattern of disease comorbidity. States with low temperatures have a higher risk of comorbidity of anaemia and malaria compared to states with higher average temperatures. Area of residence, level of education of the mother, economic status of the mother, and owning mosquito-treated nets were identified as significant risk factors associated with the disease comorbidity. Findings from this study will be helpful to policymakers and health authorities in their effort to combat the comorbidity of childhood anaemia and malaria, thereby reducing child mortality in Nigeria.

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1. Introduction

The high prevalence of childhood infections such as anaemia and malaria is a source of great concern to world public health[1]. Anaemia can be thought of as a significant decrease in hemoglobin concentration, which leads to reduced oxygen delivery to the body's tissues and organs[2]. The World Health Organisation (WHO) classified anaemia for children aged 6 months to 59 months based on the level of concentration of hemoglobin in the red blood cells. A child is free of anaemia if the Hb level is at least 11g/dL; it is mild anaemia if the level of Hb is between $(10\ -\ 10.9)g/dL$, it is moderate if the Hb level is between $(7 - 9.9)\ g/dL$, and it is severe if the level of Hb is less than 7g/dL[3]. Anaemia and malaria are two of the leading causes of illness and death in children under the age of five[4]. Young children have a weak immune system to combat malaria, as evident in the 2018 total deaths due to malaria infection, where over 65% of those deaths were children below the age of five. The progress made in ensuring that the burden or cases of anaemia is reduced has been very slow, and the global target of reducing anaemia cases by 50% by the year 2025 may not be achieved[5]. In 2019, about 571 million of reproductive age, representing 29%, and 269 million of children below the age of five years, representing 38.9%, were affected by anaemia, and about 40% of children below the age of five years, 37% of expectant mothers, and 30% of women of reproductive age were also affected[6]. Malaria is regarded as an acute febrile infection caused by a parasite known as P. falciparum. Malaria infection is pervasive in the African region, especially Nigeria, which has a high prevalence of P. falciparum and a reasonable number of anaemia cases, especially among under-five children, attributed to malaria infection[7]. Children with severe anaemia are at a higher risk for contracting malaria, as the condition can weaken the immune system and make it more difficult for the body to fight off infection[8]. In the year 2019, Africa accounted for a whopping share of 94% of the global malaria cases, estimated at 229 million[9]. Anaemia has grave consequences as it makes a young child more susceptible to other infections aside from malaria, thereby increasing the risk of death. It weakens cognitive performance, hinders growth, and retards motor development of a child[10]. Besides, malaria in young children could cause anaemia, damage to the cerebra, and respiratory pain[11]. Anaemia and malaria are considered major indicators of a child's overall well-being[5]. In the past, studies on anaemia and malaria with respect to their risk factors were based on available records or data in hospitals and clinics. Such studies were grossly inadequate to reveal the

required knowledge on the risk factors of these infections. In recent years, a number of national surveys have been conducted to collect comprehensive data on child health outcomes, including the Demographic and Health Survey (DHS) and the Malaria Indicator Survey (MIS). These data are available and accessible to researchers if a due request is made, and they are used to estimate the prevalence of these infections, especially among young children, as well as their risk factors for effective policy formulation. A number of studies have examined the individual risk factors for anaemia and malaria, as well as the spatial variation of these conditions in Nigeria and other sub-Saharan African countries. Phillip *et al.*[6], in their study of anaemia prevalence among children aged 6-59 months, utilized a multiple binary logistic regression model to quantify the risk factors of anaemia and the associated predicted probability across the states in Nigeria, including the Federal Capital Territory. Bilal *et al.*[12] used a geo-statistical model to analyze the risk factors of anaemia among preschool children in Ethiopia using the 2016 Demographic and Health Survey of the country. Alfred and Lawrence[13] investigated the risk factors associated with the severity of anaemia among children in Malawi by proposing an ordered categories model, using multinomial cumulative logistic regression. Abbas *et al.*[14] utilized two national surveys, the DHS and MIS, to examine the association of malaria endemicity and other causes of mortality across varying age strata among under-five children in Nigeria by developing binomial geo-statistical models and a Bayesian piecewise Cox proportional hazard to link mortality to the risk of malaria, considering the spatial disparity of the survey data. Huge efforts have also been made by other authors in the modelling of single diseases[15][16][17].

Studies on the comorbidities of childhood diseases such as anaemia and malaria are, however, scanty. Jecinta *et al.*[18] used a Bayesian spatial model to analyze the spatial patterns of anaemia and malaria among children under the age of five in Nigeria, using data from the 2015 and 2010 Nigeria Malaria Indicator Surveys. Gayawan *et al.*[19] also modeled childhood morbidity in West Africa using a Distributional Bivariate Probit Model. Adebayo *et al.*[8] adopted a geoadditive latent variable model to examine the effects of different risk factors on anaemia-malaria morbidity among children below the age of five years in Nigeria. Also, Gayawan *et al.*[10], Kezembe *et al.*[20], and Adeyemi *et al.*[21] have also utilized a multinomial model to examine the comorbidity of multiple diseases among under-five children in various Sub-Saharan African countries. However, the impact of climatic variation on the risk of childhood comorbidity of anaemia and malaria has not been explored. The spatial components have not been weighted to reflect the geographical variation in climates across the regions being considered. Children are particularly vulnerable to the effects of climate change because they rely on caregivers to

meet their needs, and their developing bodies are more sensitive to environmental changes, Eduard[22]. In this study, we used different spatially weighted multinomial model formulations to analyze the influence of covariates of different types on the comorbidity of malaria and anaemia. The climatic factors, such as average temperature, were used as spatial weighting factors. The generated maps, which would unveil the risk of anaemia and malaria comorbidity across the 36 states of the federation, including the FCT, and the correlation between climatic variation and the spatial distribution of disease risk, add to the uniqueness of the work. This would provide accurate insight to policymakers in designing relevant strategies to combat the menace of the two most common childhood diseases in the country.

2. Source of Data

This study utilized data from the 2021 Nigeria Malaria Indicator Survey, a cross-sectional survey conducted from August to December 2021. Access to download the data was granted after a proposal submitted to the DHS website was approved. The components of the variables extracted from the 2021 NMIS include the dependent variables, which are anaemia and malaria, each having a binary status of 0 and 1, signifying the absence or presence of the disease in a child. The independent variables are the covariates of different kinds. There are categorical covariates that represent the demographic factors (area of residence of the child's parent), socio-economic factors (wealth index, mothers' level of education, sex). The metrical covariates include the age of the child and the age of the mother. The spatial covariates include the 36 states of the federation, including the FCT, and the cluster average temperature of each state.

3. Methodology

Let the anaemia and malaria status of a child be denoted by y_{ijc} while the probability of comorbidity of the two infections be denoted by p_{ijc}. The child's infection status has four categories as defined below

$$Y_{ij} = \begin{cases} 1 & \text{if a child has neither anaemia nor malaria} \\ 2 & \text{if a child has only anaemia} \\ 3 & \text{if a child has only malaria} \\ 4 & \text{if a child has both anaemia and malaria} \end{cases}$$

This study assumes that $Y_{ijc} \sim MN(1,\, \pi_{ijc})$, a child's infection status follows a multinomial distribution.

Given categorical covariates $(X_{ij,}\,)$, metrical covariates $(Z_{ij,}\,)$, spatial covariates $(\theta_i$, and $\phi_i)$, and ψ_i which represents the weighted parameter, the probability of a child belonging to each of the infection

categories is modeled as:

$$p_{ij}^{(c)} = \frac{exp(\eta_{ij}^{(c)})}{1 + \sum_{s=1}^{c} exp(\eta_{ijs})} \tag{1}$$

$c = 1\ , 2\ 3, 4$, $\eta_{ij}^{(c)}$ is a predictor which is extended so that the spatial weighted multinomial model has the following formulations.

- Model 1: $\eta_{ij}^{(c)} = X_{ij}\ \beta_c$ + $\psi_i\ \theta_i$ (2)
- Model 2 : $\eta_{ij}^{(c)} = X_{ij}\ \beta_c$ + $\psi_i \theta_i$ + ϕ_i (3)
- Model 3: $\eta_{ij}^{(c)} = X_{ij}\ \beta_c + f_c(Z_{ij,})$ + $\psi_i\ \theta_i$ (4)
- Model 4: $\eta_{ij}^{(c)} = X_{ij}\ \beta_c + f_c(Z_{ij}) + \psi_i \theta_i$ + ϕ_i (5)

η_{ijc} is a predictor function having a logit link function, β_c is the regression parameter vector associated with the linear explanatory or categorical variables, f_c represents the smooth function for the metrical covariates assumed to have a non-linear relationship with the response variables, θ_i denotes the state random effects (structured variation) which is geographically weighted with ψ_i and ϕ_i denotes the unstructured variation (heterogeneity).

Model 1 contains the linear covariates (fixed effect model) with spatially weighted structured effects; model 2 contains linear covariates with spatially weighted structured and unstructured effects. Models 3 and 4 include the nonlinear covariates, therefore containing all the covariates. In this study, the reference category is the first group ($for\ c = 1$, when a child has none of the two infections).

A full Bayesian approach is applied in the estimation of model parameters. The regression parameters are assigned informative priors. The smooth functions for the metrical covariates are assigned p-priors, while the spatial effect functions were modeled using priors of Gaussian Markov random fields, in particular the intrinsic conditional autoregressive model (ICAR). This assumes that the mean of each area i written as $\theta_{i,}$ conditional on the rest of its neighbors is normally distributed with the same mean as the average of its neighbors (θ_{-i}) and variance which is inversely proportional to the size of its neighboring areas denoted as m_i. Each pair of areas that shares a border usually takes a weight equal to 1, and 0 otherwise. The full conditional specification of the ICAR prior is

$$\theta_i|\theta_{-i}\ \sim N\left(\frac{1}{m_i}\sum_{-i\sim i}\theta_{-i},\ \frac{\sigma_\theta^2}{m_i}\right) \tag{6}$$

$-i \sim i$ implies that areas $-i$ and i are adjacent to each other on the map. σ_θ^2 represents the spatial smoothing variance. The unstructured or area-specific effect ϑ_i which measures the degree of

heterogeneity, was estimated using normal priors as

$$\vartheta \sim N(0,\ \sigma_{\vartheta}^{2}) \tag{7}$$

To compare the robustness or goodness of fit of the various model specifications, the Deviance Information Criterion (DIC) given by Spiegelhalter[23] is employed

$$DIC = \overline{D} + \rho D \tag{8}$$

$\overline{D}$ is the model deviance which was estimated at the posterior mean, ρD represents the effective number of parameters used to examine model complexity. The model with the smaller value of DIC is considered to have a good fit, be more parsimonious, and hence be a better model.

The prior for the fixed effects from a Bayesian viewpoint is given as

$$p\left(X_j\right) \propto const \tag{9}$$

The nonlinear function f_c is modeled by a basis function approach given by

$$f(z) = \sum_{k=1}^{K} (\beta_k B_k(z)) \tag{14}$$

Where B_k are known basis functions and $\beta = (\beta_{1,}\ \ \beta_2\ .\ .\ .\ \ \beta_k)$. A prior for a function f_j is defined by specifying an appropriate design matrix z_j and a prior distribution for the vector β_j of unknown parameters. The prior for β_k with \(K_{j}\\)as the penalty matrix and τ_j^2 as the variance parameter is given as

$$p\left(\beta_j \mid \beta_j\right) \propto \frac{1}{\left(\sigma_j^2\right)^{\frac{rank\left(K_j\right)}{2}}} exp\left(-\frac{1}{2\sigma_j^2}\beta_j^1 K_j \beta_j\right) \tag{10}$$

Highly dispersed gamma priors are assigned for the variance parameter σ_j^2 as provided below.

$$p\left(\sigma_j^2\right) \sim IG(a_j,\ b_j) \tag{11}$$

The corresponding probability density function is given as

$$\sigma_j^2 \propto \left(\sigma_j^2\right)^{-a_j-1} exp\left(-\frac{-b_j}{\sigma_j^2}\right) \tag{12}$$

In this work, $a_j = \ b_j = 0.001$ is the choice for the hyperparameters.

The posterior of the model using the Bayesian approach is given as

$$p\left(\beta_{1,}\ \ldots\ \beta_{p,}\ {\sigma_1}^2\ \ldots\ \sigma_{p,}^2\ \omega_c|y_{ijc}\right) \propto L\left(\beta_{1,}\ \ldots\ \beta_{p,}\ \right)$$
$$\prod_{j=1}^{p}\left(p\left(\beta_j|\sigma_j^2\right)p\left(\sigma_j^2\right)\right)p\left(f_\theta|\sigma_j^2\right)p\left(f_\theta|\sigma_j^2\right) \qquad (13)$$

Where $L(.)$ refers to the likelihood which, under the assumption of conditional independence, is calculated by multiplying the individual likelihood contributions of each observation.

MCMC simulation techniques are used to estimate the parameters of the posterior distribution.

4. Results Analysis

While BayesX, version 2.1, was used for model fitting, descriptive analysis and the two-way cross-tabulation with the Pearson Chi-square test were performed using SPSS software. Descriptive analysis of the variables on the anaemia and malaria status of under-five children is presented in Figure 1 and Table 1 below. The children's infection statuses are; None, Anaemia only, Malaria only, and both Anaemia and Malaria.

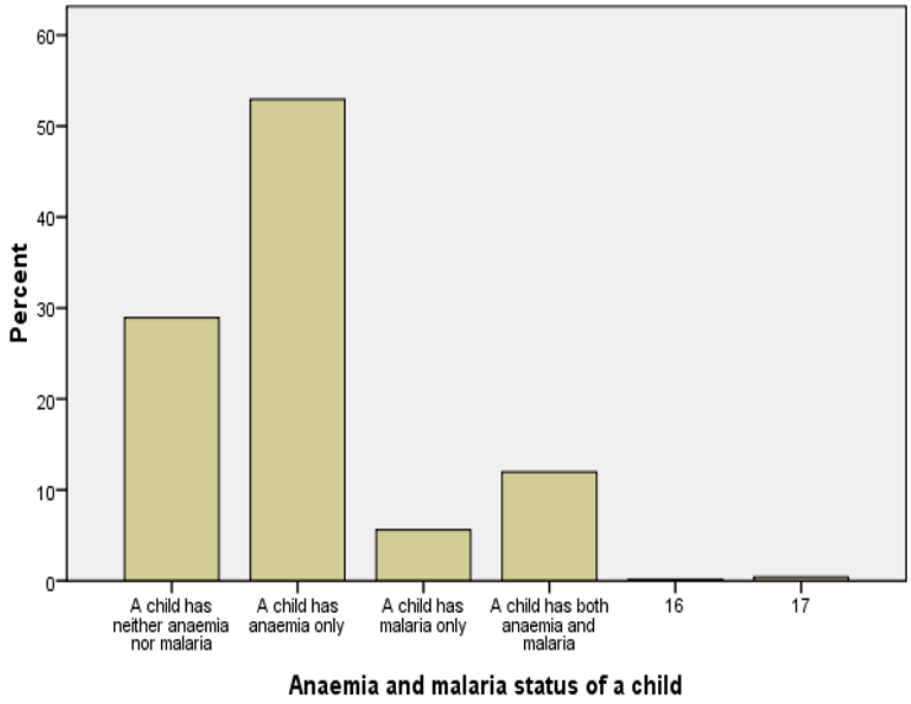

Figure 1. Prevalence of Anaemia and Malaria among Under-five children

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Variables/child illness status	None	Anaemia only	Malaria only	Anaemia and malaria	Total no of children/%	Pearson's ch-square test
Sex						
Male	1357(27.9,14.4)	2630(54.1, 27.9)	277(5.7, 2.9)	596(12.3, 6.3)	4860(51.5)	6.581(0.087)
Female	1388(30.3, 14.7)	2396(52.3, 25.4)	254(5.5, 2.7)	540(11.8, 5.7)	4578(48.5)	
Residence						
Urban	1001(36.2, 10.61)	1354(49.0, 14.3)	147(5.3, 1.6)	260(9.4, 2.8)	2762(29.3)	1.049E2(0.00)
Rural	1744(26.1, 18.5)	3672(55.0, 38.9)	384(5.8, 4.1)	876(13.1, 9.3)	6676(70.7)	
Wealth Index						
Poorest	374(19.6, 4.7)	1161(61.0, 12.3)	95(5.0, 1.0)	274(14.4, 2.9)	1904(20.2)	
Poorer	440(23.3, 4.7)	1056(56.0, 11.2)	99(5.2, 1.0)	291(15.4, 3.1)	1886(20.0)	2.89E2(0.00)
Middle	554(28.6, 5.9)	1028(53.0, 10.9)	129(6.6, 1.4)	229(11.8, 2.4)	1940(20.6)	
Richer	642(33.6, 6.8)	979(51.2, 10.4)	102(5.3, 1.1)	189(9.9, 2.0)	1912(20.3)	
Richest	735(40.9, 7.8)	802(44.7, 8.5)	106(5.9, 1.1)	153(8.5, 1.6)	1796(19.0)	
Highest education						
No education	911(22.6, 9.7)	2330(57.9, 24.7)	212(5.3, 2.2)	574(14.3, 6.1)	4027(42.7)	
Primary	362(26.0, 3.8)	745(53.6, 7.9)	87(6.3, 0.9)	197(14.2, 2.1)	1391(14.7)	2.809E2(0.00)
Secondary	1026(33.7, 10.9)	1553(51.0, 16.5)	177(5.8, 1.9)	292(9.6, 3.1)	3048(32.3)	
Tertiary	446(45.9, 4.7)	398(40.9, 4.2)	55(5.7, 0.6)	73(7.5, 0.8)	972(10.3)	
Availability of mosquito net						
No	1078(31.4, 11.4)	1865(54.3, 19.8)	167(4.9, 1.8)	322(9.4, 3.4)	3432(36.4)	48.3(0.001)
Yes	1667(27.8, 17.7)	3161(52.6, 33.5)	364(6.1, 3.9)	814(13.6, 8.6)	6006(63.6)	
Child age group						2.478E2
6 – 11						

Variables/child illness status	None	Anaemia only	Malaria only	Anaemia and malaria	Total no of children/%	Pearson's ch-square test
12 – 23	162(17.3, 1.8)	619(66.1, 6.7)	32(3.4, 0.3)	123(13.1, 1.3)	936(10.2)	
24 – 35	386(20.2, 4.2)	1161(60.7, 12.6)	77(4.0, 0.8)	288(15.1, 3.1)	1912(20.8)	
36 – 47	515(26.4, 5.6)	1074(55.0, 11.7)	101(5.2, 1.1)	264(13.5, 2.9)	1954(21.3)	
48 – 59	687(33.4, 7.5)	1038(50.5, 11.3)	104(5.1, 1.1)	225(11.0, 2.4)	2054(22.4)	
	839(35.9, 9.1)	1134(48.6, 12.3)	125(5.4, 1.4)	236(10.1, 2.6)	2334(25.4)	
Age group of mothers						
15 – 19	102(25.8, 1.1)	221(55.9, 2.3)	23(5.8, 0.2)	49(12.4, 0.5)	395(4.2)	
20 – 24	417(24.9, 4.4)	938(56.0, 9.9)	107(6.4, 1.1)	213(12.7, 2.3)	1675(17.7)	
25 – 29	771(29.7, 8.2)	1315(50.7, 13.9)	170(6.6, 1.8)	337(13.0, 3.6)	2593(27.5)	44.134(0.01)
30 – 34	690(30.2, 7.3)	1230(53.9, 13.0)	103(4.5, 1.1)	260(11.4, 2.8)	2283(24.2)	
35 – 39	496(31.9, 5.3)	802(51.6, 8.5)	86(5.5, 0.9)	170(10.9, 1.8)	1554(16.5)	
40 – 44	203(28.4, 2.2)	396(55.3, 4.2)	32(4.5, 0.3)	85(11.9, 0.9)	716(7.6)	
45 – 49	66(29.7, 0.7)	124(55.9, 1.3)	10(4.5, 0.1)	22(9.9, 0.2)	222(2.4)	
Zone						
North central (NC)	637(36.2, 6.7)	892(50.7, 9.5)	84(4.8, 0.9)	147(8.4, 1.6)	1760(18.6)	
North East (NE)	438(25.2, 4.6)	1031(59.4, 10.9)	79(4.5, 0.8)	189(10.9, 2.0)	1737(18.4)	
North West (NW)	589(21.6, 6.2)	1433(52.5, 15.2)	202(7.4, 2.1)	505(18.5, 5.4)	2729(28.9)	3.451 (0.00)
South East (SE)	307(29.0, 3.3)	553(52.3, 5.9)	58(5.5, 0.6)	140(13.2, 1.5)	1058(11.2)	
South South (SS)	411(33.1, 4.4)	649(52.2, 6.9)	77(6.2, 0.8)	106(8.5, 1.1)	1243(13.2)	
South West (SW)	363(39.8, 3.8)	468(51.4, 5.0)	31(3.4, 0.3)	49(5.4, 0.5)	911(9.7)	

Table 1. Prevalence of Anaemia and Malaria by risk factors.

Figure 1 shows that out of 9438 children who participated in the survey, 28.9% are free of both anaemia

and malaria, 52.9% had anaemia only, 5.6% had malaria only, and 12.6% had both anaemia and malaria, respectively. Table 1 reveals the prevalence of anaemia and malaria by some risk factors. The percentage of the infection within the covariate group is shown by the first value in the bracket, while the second value shows the percentage of the total children infected. Out of 4860 male children involved in the survey, 27.9% are infection-free, 54.1% had anaemia only, 5.7% had malaria only, and 12.3% had both malaria and anaemia. Similarly, among 4578 female children, 30.3% had none of the diseases, 52.3% had anaemia only, 5.5% had malaria only, and 11.8% had both malaria and anaemia. However, the Pearson chi-square test revealed that sex as a risk factor of childhood infection is not significant. Among children from both rural and urban residences, anaemia had the highest infection rates: 49% (1354/2762) and 55% (3672/6676) for urban and rural areas, respectively. The area of residence is a significant risk factor, as revealed by the chi-square test. The descriptive analyses of other risk factors are similarly captured in Table 1.

Model fit & complexity	Model 1	Model 2	Model 3	Model 4
Deviance $(\overline{D})$	19656.426	19653.137	18836.982	18829.27
ρ_D	125.88701	124.88603	173.18146	173.96167
DIC	19908.2	19902.909	19183.345	19177.193

Table 2. Model fit and complexity

Table 2 gives the model fit and complexity. Model 1, which contains the linear and spatially weighted structured effects, is considered the most complex fitted model given that it recorded the highest value of DIC. Inclusion of both spatially weighted structured effect and unstructured random effects improves the fit of Model 2 as it reduces its DIC value. Model 3 also has an improvement in model fit compared to Model 2. Model 4, which is regarded as a convolution model as both spatially weighted structured and unstructured effects are incorporated, including linear and non-linear covariates, appeared as the best-fitted and least complex model. Estimates of the fixed effects in Table 3 are given in line with the best-

fitted model (Model 4). The estimated odds ratios for probabilities of the comorbidity of anaemia and malaria versus none of the diseases are also contained in Table 3.

Variable	Anaemia vs no infection ROR & 95% CI	Malaria vs no infection ROR & 95% CI	Both Anaemia and Malaria vs No Infection ROR & 95% CI
Residence			
Urban	1	1	1
Rural	1.123(1.00198, 1.646)	1.116(1.021, 1.360)	1.0293(1.165, 2.218)
Child sex			
Male	1	1	1
Female	-0.146(-0.241, -0.0427)	-0.106(-0.354, 0.0830)	-0.152(-0.298, 0.00621)
Own mosquito treated net			
No	1	1	1
Yes	0.0252(0.140, 0.824)	0.202(0.0182, 0.732)	0.310(0.0143, 0.983)
Education status			
No education	1	1	1
Primary education	0.0766(-0.040, 0.0846)	0.381 (0.143, 0.591)	0.313(-0.215, 0.837)
Secondary education	0.235 (0.152, 0.634)	0.114(0.243, 0.821)	0.371(0.214, 1.674)
Tertiary education	0.212(0.0783, 0.872)	0.107(0, 0.104, 0.514)	0.421(0.523, 0.928)
Wealth index			
Poorest	1	1	1
Poorer	-0.214(-0.437, -0.0231)	-0.168(-0.481, 0.217)	0.087(0.04, 0.641)
Middle	0.001(0.092, 0.151)	0.0477(0.023, 0.688)	0.298(0.127, 0.921)
Richer	0.0566(0.041, 0.213)	0.244(0.07, 0.874)	0.021(0.0193, 0.391)
Richest	0.037(0.021, 0.921)	0.231(0.198, 0.329)	0.0109(0.0284, 0.581)

Variable	Anaemia vs no infection ROR & 95% CI	Malaria vs no infection ROR & 95% CI	Both Anaemia and Malaria vs No Infection ROR & 95% CI
Geo-political Zone			
North Central	1	1	1
North East	1.274(1.653, 2.837)	1.165(0.579, 1.982)	1.261(1.004, 1.951)
North West	0.541(0.06, 1.0581)	0.0821(1.139, 2.622)	0.473(0.202884, 0.896)
South east	0.577(0.0833, 0.324)	0.342(0.322022, 0.932)	1.06(1.513, 2.38)
South South	0.461(0.0617, 0.943)	0.165(0.0181, 1.4059)	0.065(0.432, 0.923)
South West	0.363(0.176, 1.942069)	0.132(0.092, 1.576)	**0.224(0.081, 0.873)**

Table 3. Model Estimates and Odd ratios

Area of residence is identified as a significant determinant of anaemia and malaria. Children in rural areas have an increased risk of contracting anaemia (1.123(1.00198, 1.646)), malaria (1.116(1.021, 1.360)), and both infections (1.0293(1.165, 2.218)) compared to urban children. Being female is associated with a reduced risk of contracting anaemia, malaria, or both. Although the results revealed that gender is not a significant determinant of anaemia and malaria among under-five children, the estimate of fixed effects covariates also showed that children from households that own mosquito-treated nets have a reduced risk of being infected with anaemia, malaria, and both compared to those whose parents do not have mosquito-treated nets (0.0252(0.140, 0.0824), 0.202(0.0182, 0.732), 0.310(0.143, 0.483)). The odds of a child in Nigeria having anaemia, malaria, or both are lower for parents who acquired at least primary school education compared with children from parents without education. However, having primary education is only a significant factor for malaria. The likelihood of a child having anaemia, malaria, or both is significantly lower for children from higher socioeconomic backgrounds. Children from poorer, middle, rich, and richest parents have lower odds of contracting diseases compared with children from the poorest parents. However, among the wealth indices observed, only the poorer category is not associated with the odds of a child having anaemia, malaria, or both infections. Also, children from the North East

and South West have the highest and lowest risk of having anaemia compared with children from the Central Geo-political zone. Children from the North East were 27%, 16%, and 26% more likely to have suffered from anaemia, malaria, and comorbidity of both infections, respectively, in comparison with children from the North Central zone. Children from the North West are 54%, 8%, and 47% less likely to contract anaemia, malaria, or both infections, respectively, compared with their counterparts from the North Central zone. South East children have a 57% and 34% reduced chance of being infected with anaemia and malaria, respectively, while they are 6% more likely to suffer from both diseases. Under-five children from South South are 46%, 17%, and 7% less likely to have contracted anaemia, malaria, and both infections compared with children from North Central. Besides, in comparison with children from the North Central part of Nigeria, children from the South Western zone of Nigeria are 36%, 13%, and 22% less likely to have suffered from anaemia, malaria, and both infections, respectively. Figures 2-4 present the non-linear effects of the age of the child and the age of the mother alongside the posterior modes and 95% CI. Essentially, the risk of anaemia decreases as children grow and develop. The sinusoidal curve that describes the nonlinear relationship between the age of the mother and the risk of a child contracting anaemia in Figure 2 shows that a child is at higher risk of contracting anaemia when the mother is between the ages of 15 and 22 years. The chance declines when the mother is between 23 and 30 years, and the risk rises when the mother is between the ages of 31 and 40 years, and declines when the mother is above 40 years. Figures 3 and 4 also describe the non-linear relationship between the child's age and the risk of contracting malaria and the age of the mother and the associated risk of malaria. As presented in Figure 3, the risk of malaria in a child rises sharply from the first month until the 10^{th} month of birth. It maintains a constant high value till the age of five years. Also, the relationship between the mother's age and the risk of a child having malaria can also be described by a nonlinear curve. The risk rises among children from mothers between the ages of 15 and 20 years, and the likelihood of a child having malaria declines sharply as mothers reach the age of 45. However, the finding for the comorbidity of anaemia and malaria, as shown in Figures 4, shows that the likelihood of a child having both infections increases from the first month until the age of the 10^{th} month, after which it maintains a constant pattern till the child reaches the age of 5 years. The nonlinear relationship between the age of the mother and the likelihood of a child contracting both anaemia and malaria is also best described by a sinusoidal curve. The risk was observed to rise sharply when the mother is between the ages of 15 and 20. It maintains a steady pattern when the mother is between 21 and 45 years and declines after the age of 45 years. Figure 5 reveals the residual geographical pattern for anaemia, malaria, and comorbidity of

anaemia and malaria. The left maps show the posterior modes and the 95% CI. The right maps show the states at high and low risk of the infections. As revealed by Figure 7, the odds of a child in Nigeria testing positive for the comorbidity of anaemia and malaria based on NMIS (2021) are significantly higher in four states, which are Bayelsa, Akwa Ibom, Lagos, and Kwara; it is lower in states like Borno, Ogun, and Kaduna. However, the odds are not significant in other states.

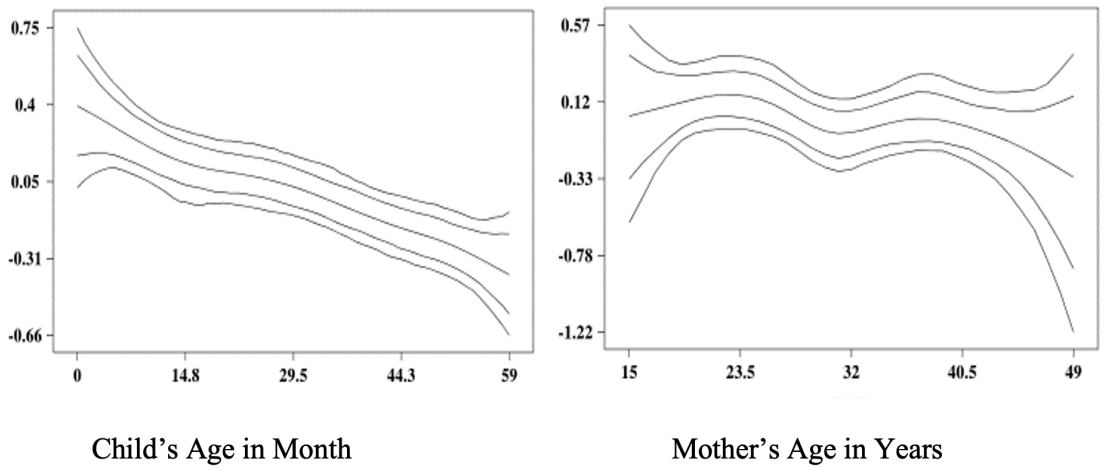

Figure 2. Nonlinear effect of child's age and mother's age on the risk of childhood anaemia

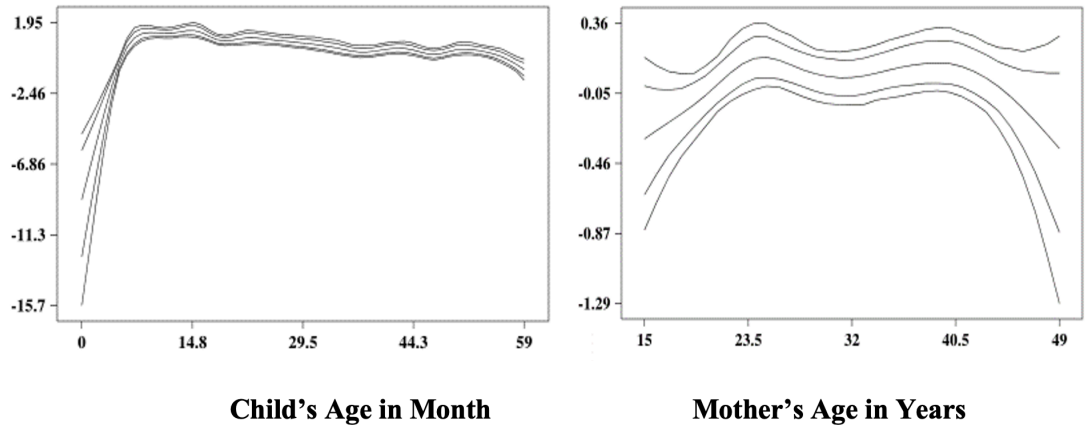

Figure 3. Nonlinear effect of child's age and mother's age on the risk of childhood malaria in Nigeria

doi.org/10.32388/MBSNRX.2

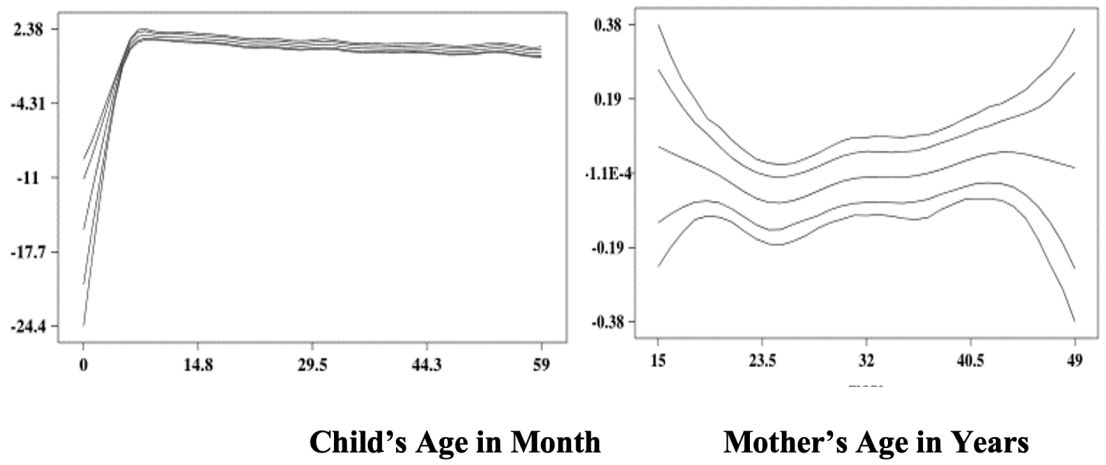

Figure 4. Nonlinear effect of child's age and mother's age on the risk of childhood comorbidity of anaemia and malaria

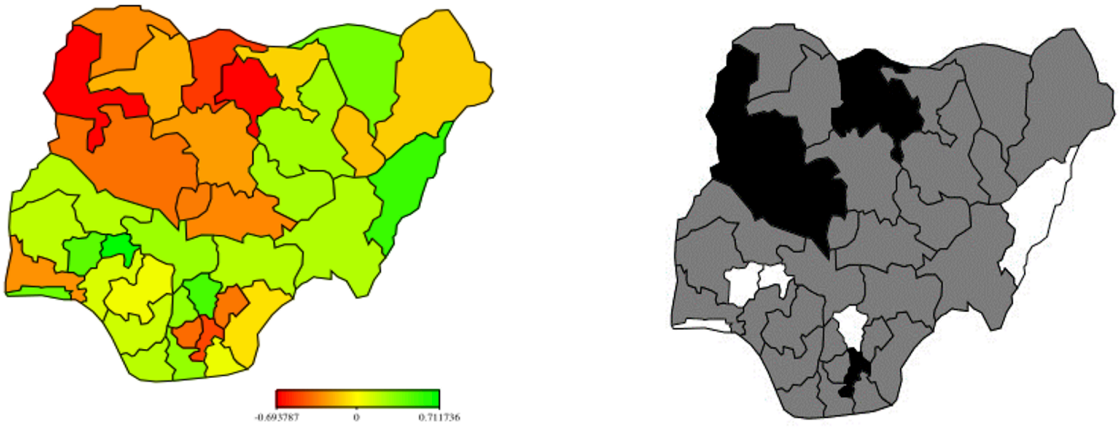

Figure 5. Residual spatial weighted effects at state levels for anaemia only versus no infection.

The left map (Map I) shows the relative risk ratio, and the right map (Map II) shows the corresponding posterior probability for a nominal level of 95%. Black denotes states with a strictly negative credible interval, white denotes states with a positive credible interval, and grey denotes states with a non-significant probability of the relative risk ratio.

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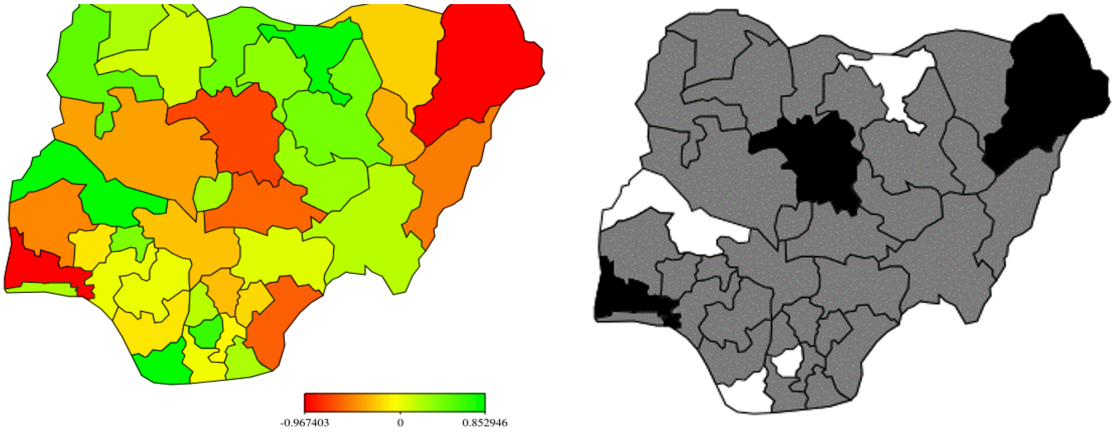

Figure 6. Residual spatially weighted effects at state levels for malaria only versus no infection.

The left map (Map III) shows the relative risk ratio, and the right map (Map IV) shows the corresponding posterior probability for a nominal level of 95%. Black denotes states with a strictly negative credible interval, white denotes states with a positive credible interval, and grey denotes states with a non-significant probability of the relative risk ratio.

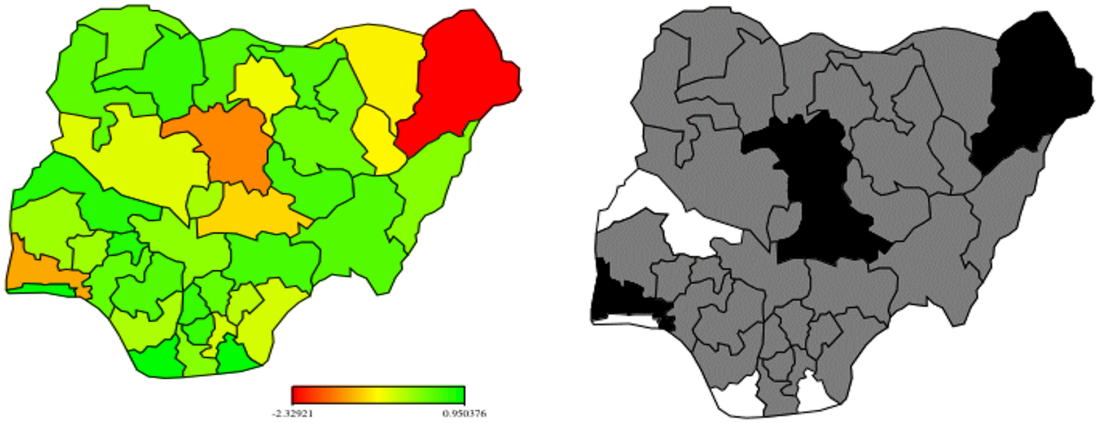

Figure 7. Residual spatial weighted effects at state levels for comorbidity of anaemia and malaria versus no infection.

The left map (Map III) shows the relative risk ratio, and the right map (Map IV) shows the corresponding posterior probability for a nominal level of 95%. Black denotes states with a strictly negative credible

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interval, white denotes states with a positive credible interval, and grey denotes states with a non-significant probability of the relative risk ratio.

5. Discussion and Conclusion

In this study, the multinomial logit model was extended to a Bayesian spatially weighted model to analyze areas of high and low risk of comorbidity of anaemia and malaria after adjusting for different risk factors. A cross-sectional nationally representative survey, precisely the 2021 Nigeria Malaria Indicator Survey data, was used to measure residual spatial patterns across the 36 states of the federation, including the FCT. The average monthly cluster temperature of the year 2020 for each state of the federation, as realized in the survey, was used in this study as a weighting factor. The results of our study showed that the location of children can have an impact on their health and that this can be linked to socio-economic, climatic, and environmental factors. Transforming binary data into multi-categorical data is appropriate for the analysis of two diseases with overlapping characteristics. This approach captures the complex relationships between the diseases and better understands their patterns. The overall comorbidity prevalence of anaemia and malaria was found to be 12%. The residual risk estimates for the comorbidity of both diseases, as shown by the spatial map, range from -0.967 to 0.853. The place of residence was found to be a significant factor in determining the risk of childhood diseases. A child who resides in a rural area has a greater likelihood of contracting anaemia, malaria, and even both infections compared with children in urban areas. Our findings also showed that a child's gender is not a significant risk factor for childhood diseases. Owning a mosquito-treated net is a significant risk factor for anaemia, malaria, and both diseases. This means that owning a mosquito net reduces the risk of a child contracting diseases. The educational level of a mother is also associated with the likelihood of her child testing positive for childhood diseases. As regards the comorbidity of childhood diseases, only tertiary education is significant. This means that a child from a mother who acquired tertiary education is less likely to contract diseases compared with their counterpart from uneducated mothers. This is also the same for the risk of contracting anaemia only and malaria only. Having secondary education was a significant factor and reduced the likelihood of a child contracting either anaemia or malaria compared to a child from a mother who does not possess any academic qualification. The findings also revealed that the wealth index, which is a determinant of socio-economic status, is also a determinant of childhood illness. In comparison with children from the poorest mothers, the risk of a child having the comorbidity of anaemia and malaria is lower among mothers in the middle, rich, and richest wealth index. Also, our

findings show that while children from the North East and South East parts of the country have a higher chance of contracting both anaemia and malaria compared with their counterparts from the North Central, those from other geo-political zones are less likely to contract childhood disease comorbidity. Considering the findings from the study, the area of residence of a child, possessing tertiary education by a child's mother, and belonging to at least the middle wealth index are significant risk factors for disease comorbidity among under-five children in Nigeria. The relationship between a child's age and the risk of contracting diseases was found to be non-linear. The risk of a child having anaemia reduces as the child increases in age. In terms of malaria, the risk of infection increases up until the age of 10 months, after which it remains high but relatively stable. The non-linear effects of a child's age and the risk of comorbidity of anaemia and malaria follow the same pattern as that of malaria only, with both peaking around 10 months of age. The effects of the mother's age on the risk of a child being tested positive for diseases follow a sinusoidal pattern, increasing and decreasing over time. This suggests that environmental and seasonal factors may play a role in the risk of infection, with certain ages being more vulnerable than others. This pattern is similar for both single and multiple diseases. The results of the spatial analysis suggest that while there is variation in the risk of comorbidity of anaemia and malaria among children across the 37 states of the federation, Bayelsa, Akwa Ibom, Lagos, and Kwara states are at high risk of the disease comorbidity, Borno, Ogun, and Kaduna states are at very low risk, while the rest of the states have a risk that can be said to be indifferent. States with low average temperatures have a higher risk of comorbidity of anaemia and malaria among under-five children in Nigeria compared to states with high average temperatures. The average temperature used as weighting factors, however, has a strong relationship with the spatial pattern of disease comorbidity across the 36 states of the federation, including the Federal Capital Territory. The study recommends that, to better account for spatial variation in risk and identify states that are more susceptible to disease comorbidity among children under five years of age, future studies should incorporate weighted spatial random effects into the modelling approach. This will help to more accurately estimate the risks of disease and target interventions to the areas of greatest need. Also, future studies should consider other weighting factors, such as average levels of carbon monoxide, average amount of rainfall, and other climatic factors. These factors may help to further improve the accuracy of estimates of risk, thereby making the model more robust. Based on the findings of this study, the identified areas with a high risk of childhood comorbidity of anaemia and malaria illness should be prioritized for interventions.

Statements and Declarations

Ethics Statement

This study is based on secondary analysis of publicly available, anonymized data from the 2021 Nigeria Malaria Indicator Survey (NMIS), conducted as part of The Demographic and Health Surveys (DHS) Program. The original NMIS 2021 survey protocol was reviewed and approved by the National Health Research Ethics Committee of Nigeria (NHREC) and the Institutional Review Board of ICF International (as the body overseeing DHS). Informed consent was obtained from the parents or guardians of all participating children prior to data collection and biomarker testing, in accordance with the ethical guidelines of the approving bodies.

Data Availability Statement

The data analyzed in this study were sourced from the 2021 Nigeria Malaria Indicator Survey (NMIS), administered by The Demographic and Health Surveys (DHS) Program. These data are publicly available to registered users upon reasonable request from The DHS Program website (www.dhsprogram.com).

Author Contributions

Conceptualization, Aminu Ibrahim (A.I.) and Rasheed A. Adeyemi (R.A.A.); methodology, Aminu Ibrahim (A.I.), Rasheed A. Adeyemi (R.A.A.), Abubakar Usman (A.U.); software, Aminu Ibrahim (A.I.); validation, Aminu Ibrahim (A.I.), Rasheed A. Adeyemi (R.A.A.), Abubakar Usman (A.U.), Nasiru Usman Adabara (N.U.A.); formal analysis, Aminu Ibrahim (A.I.); investigation, Aminu Ibrahim (A.I.); resources, Aminu Ibrahim (A.I.); data curation, Aminu Ibrahim (A.I.); writing—original draft preparation, Aminu Ibrahim (A.I.); writing—review and editing, Rasheed A. Adeyemi (R.A.A.), Abubakar Usman (A.U.), Nasiru Usman Adabara (N.U.A.); visualization, Aminu Ibrahim (A.I.); supervision, Rasheed A. Adeyemi (R.A.A.); project administration, Aminu Ibrahim (A.I.).

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Declarations

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