*International Journal of Advanced Mathematical Sciences, 11 (2) (2025) 74-82*

SPC

**International Journal of Advanced Mathematical Sciences**

*Website: www.sciencepubco.com/index.php/IJAMS*
*https://doi.org/10.14419/48fnb210*
***Research paper***

# Shared Component Model for Childhood Anaemia, Diarrhoea, and Fever Comorbidities in Nigeria: A Geospatial Perspective

**Aminu Ibrahim [1] *, Rasheed A. Adeyemi [2], Abubakar Usman [2], Muhammed Raji [1], Sule O. Bashiru [1], Isaac Adaji [1], Aisha O. Musa [1]**

[1] *Department of Statistics, Confluence University of Science and Technology Osara, Kogi state, Nigeria*
[2] *Department of Statistics, Federal University of Technology, Minna, Nigeria*
**Corresponding author E-mail: ibrahima@custech.edu.ng*

**Abstract**

Children under the age of five in Nigeria continue to experience significant comorbidities of diseases, contributing to high morbidity and mortality rates. This study applied a Bayesian shared component model to separate the specific and shared risk factors associated with anaemia, diarrhoea, and fever among children across the states in Nigeria. Regional climatic variations were integrated into the spatial modelling framework to enhance the analysis. Childhood disease data were sourced from the 2018 Nigeria Demographic and Health Survey. The identified risk factors common to the three health conditions are wealth index of household, maternal educational level, land surface tempera-ture and regional precipitation. Geospatial analysis of the posterior disease risk estimates revealed that the comorbidities of anae-mia-diarrhoea, anaemia-fever, diarrhoea-fever, and anaemia-diarrhoea-fever are disproportionately higher in the northeastern and southern re-gions of the country. To significantly mitigate the risk of disease comorbidities, policymakers and health authorities in Nigeria should im-plement initiatives to address common risk factors, with priority given to the identified hotspot regions.

***Keywords***: *Shared Component Model; Comorbidities; Anaemia; Spatial Analysis; Climatic Variation.*

## 1. Introduction

Childhood anaemia, fever, and diarrhoea continue to be serious public health concerns in sub-Saharan Africa, especially in Nigeria, where children under the age of five are disproportionately impacted. These conditions have in no small way contributed to illness, death, and developmental challenges in young children, placing a heavy burden on health systems and hindering socioeconomic progress [1], [2]. In sub-Sahara Africa, the likelihood of a child not surviving beyond their fifth birthday is approximately 1 in 13 nearly 15 times higher than the risk faced by children in high-income countries [3].

Anaemia, mainly caused by nutritional deficiencies and infections, impairs both cognitive and physical development, while fever and diarrhoea which are always associated with infectious diseases and poor sanitation further heighten children's vulnerability [4, 19]. Diarrhoea is recognized as the third leading cause of death among young children [5]. Studies have shown that both anaemia and diarrhoea independently contribute to under-five mortality. A meta-analysis found that children with acute malnutrition are at a higher risk of death when they also have comorbid anaemia or diarrhoea [6]. Similarly, a clinical study revealed that malnourished children with diarrhoea are 4.2 times more likely to die if they also suffer from severe anaemia [7]. This underscores the fact that the combination of anaemia, fever, and diarrhoea can lead to more severe outcomes than when any of these conditions occur separately, posing significant threats to the health and survival of children under five.Disease risk estimates rely on data regarding observed disease cases, the population at risk, and potentially covariates such as socioeconomic, demographic and environmental factors [9]. Spatial disease mapping provides an effective approach for identifying geographical patterns and disease hotspots, offering insights into regional disparities in disease burden [8]. However, conventional methods often fail to account for the joint occurrence of multiple diseases, which share similar risk factors [10]. By jointly modelling the spatial distribution of anaemia, fever, and diarrhoea, a shared component model allows researchers to quantify both the common and disease-specific spatial risk patterns, improving the precision of disease risk estimates.

Understanding and unveiling the risk factors of multiple childhood diseases is critical for developing effective and targeted public health interventions. For instance, [23, 24] identified area of residence, maternal education level, household economic status, and ownership of mosquito-treated nets as significant predictors of anaemia and malaria comorbidity among under-five children in Nigeria. Insights from such studies are vital in guiding integrated child health programs and mitigating the compounded effects of multiple infectious diseases in resource-limited settings.

This study utilizes a shared component model to map childhood anaemia, fever, and diarrhoea across states in Nigeria, leveraging spatial statistical techniques to identify disease hotspots and shared underlying risk factors. The shared component approach is particularly appropriate as it enables the analysis of comorbid conditions with spatial dependencies, while borrowing strength across related diseases to improve statistical efficiency [11]. This method also provides robust estimates for regions with sparse data, a common issue in low-resource settings. Also, Conditional autoregressive prior (CAR) prior model will be employed as proposed by [21], on the random field to estimate the spatial risks of anaemia, fever, and diarrhoea. The approach assumes that spatial dependencies across regions can be captured by accounting for the structure of immediate neighboring areas.

In order to promote evidence-based strategies to lower childhood morbidity and enhance health outcomes in Nigeria, this study will educate public health professionals and policymakers about priority areas for intervention by highlighting the spatial distribution and shared risks of these diseases. Analyzing the spatial patterns and common risk factors of these illnesses is key for developing targeted interventions as well as optimizing resource allocation.

Previous ecological studies on childhood diseases in sub-Saharan Africa have predominantly employed univariate spatial statistical methods, even when dealing with multiple diseases [12]. Only a limited number of studies have applied joint spatial models to analyze multiple childhood diseases simultaneously [8], [13], [14]. Besides, despite the considerable progress in understanding the burden of childhood anaemia, fever, and diarrhoea among children in sub-Saharan Africa, existing research often ignores the role of regional climatic variations in shaping the spatial distribution of these diseases. previous studies have focused primarily on socioeconomic and demographic determinants without explicitly considering the influence of climate-related factors such as precipitation, temperature, and aridity, which have a significant impact on disease patterns. This study closes a significant gap in the existing disease-mapping paradigm and improves the accuracy of disease risk estimate by incorporating these climatic factors into a spatial shared component model.

## 2. Methods

### 2.1. Source of data and variables used in the study

The study utilized data from the 2018 Nigeria Demographic and Health Survey (NDHS), complemented by climate data obtained from the DHS spatial data repository. The NDHS is a nationally representative survey adopting a multistage stratified cluster sampling designed to gather comprehensive information on population, health, and nutrition indicators. The survey covers all 36 states in Nigeria as well as the Federal Capital Territory (FCT), which served as the study's spatial framework. It focuses on women between the ages of 15 and 49 living in both urban and rural homes.

Additionally, all surviving children under the age of five (0–59 months) had their illness episodes during the two weeks before the survey recorded. The variables selected for this study are detailed in the table below.

**Table 1:** Description of Variables

| Variables | Description |
|---|---|
| Child sex | A binary variable showing whether the child is male or female |
| Residence | Household's place of residence, categorized as either urban or rural |
| Diarrhoea | A binary variable indicating whether the child experienced diarrhoea in the 24 hours or two weeks preceding the survey |
| Fever | A binary variable indicating whether the child had a fever in the 24 hours or two weeks prior to the survey |
| Anaemia | A binary variable representing the child's anaemia status. |
| Wealth index | A composite measure of household wealth which categorizes households into wealth quintiles, ranging from the poorest to the richest, to reflect socio-economic disparities and allow for comparisons across populations. |
| Mothers' education level | The highest level of education attained by the mother. This standardized variable categorizes education into the following levels: no education, primary, secondary, or higher. |
| Precipitation | It refers to the amount of rainfall received in a given area over a specified period. |
| Aridity | This measures the dryness of a region, often based on the ratio of potential evapotranspiration to precipitation |
| Temperature | Indicates the average air temperature in a specific area during a defined time frame, reflecting the climate's heat characteristics. |

Source: 2018 NDHS.

### 2.2. Statistical methods

Consider $Y_{ij}^{(k)}$ as the disease $(k)$ status of a child $j$ in state $i$ $(i = 1, 2, ..37; j = 1, 2, ...39334; k = 1, 2, 3)$. Let $X_{ij}^{(k)}$ be the covariates vector linked with a child $j$ in state $i$ for disease $k$. Hence, the disease outcome of a child given as $Y_{ij}^{(k)}$ have a Bernoulli random variable with the probability of a child $j$ having disease $k$ defined as $p_{ij}^{k}$. Hence,

$$Y_{ij}^{(k)} \sim \text{Bernoulli}(p_{ij}^{(k)}) \quad (1)$$

The observed covariates $X_{ij}^{(k)}$ and unobserved effects, $u_{jk}$ and $v_{jk}$ could be modelled with a logit function given as;

$$\log\left(\frac{p_{ij}^{(k)}}{1-p_{ij}^{(k)}}\right) = \alpha^{(k)} + \beta^{(k)} X_{ij}^{(k)} + u_j^{(k)} + v_j^{(k)} \quad (2)$$

Where $\alpha_k$, $\beta_k$, are the specific disease baseline and the coefficient of the fixed effects covariates. $u_{jk}$ and $v_{jk}$ are the structured and the non-structure spatial effects known as the state random effects. we examine the comorbidity of multiple diseases at state level, shared random effects are added for joint effects of anaemia and diarrhoea, anaemia and fever, diarrhoea and fever, and anaemia, diarrhoea and fever as given below;

Model 1:

$$p_{ij}^{(1)} = \alpha^{(1)} + \beta^{(1)} X_{ij}^{(1)} + \gamma u_i^{(1,2)} + \omega u_i^{(1,3)} + \delta_1 u_i^{(1,2,3)} + v_i^{(1)} \quad (3)$$

$$p_{ij}^{(2)} = \alpha^{(2)} + \beta^{(2)}X_{ij}^{(2)} + {}^{1}/_{\gamma}\, u_i^{(1,2)} + \varphi u_i^{(2,3)} + \delta_2 u_i^{(1,2,3)} + v_i^{(2)} \quad (4)$$

$$p_{ij}^{(3)} = \alpha^{(3)} + \beta^{(3)}X_{ij}^{(3)} + {}^{1}/_{\omega}\, u_i^{(1,3)} + \frac{1}{\varphi} u_i^{(2,3)} + \delta_3 u_i^{(1,2,3)} + v_i^{(3)} \quad (5)$$

The explanatory variables $X_{ij}^{(1)}$ are decomposed into individual related variables and household variables. climatic variables are incorporated into the above model formulation to examine the impact of varying regional climate on childhood disease outcomes. Aridity reflects moisture availability, temperature captures heat exposure, while precipitation indicates rainfall patterns affecting vector breeding and water quality. These variables help explain spatial heterogeneity beyond socioeconomic and demographic factors.
Model 2:

$$p_{ij}^{(1)} = \alpha^{(1)} + \beta^{(1)}X_{ij}^{(1)} + \vartheta^{(1)}Y_{ij}^{(1)} + \gamma u_i^{(1,2)} + \omega u_i^{(1,3)} + \delta_1 u_i^{(1,2,3)} + v_i^{(1)} \quad (6)$$

$$p_{ij}^{(2)} = \alpha^{(2)} + \beta^{(2)}X_{ij}^{(2)} + \vartheta^{(2)}Y_{ij}^{(2)} + {}^{1}/_{\gamma}\, u_i^{(1,2)} + \varphi u_i^{(2,3)} + \delta_2 u_i^{(1,2,3)} + v_i^{(2)} \quad (7)$$

$$p_{ij}^{(3)} = \alpha^{(3)} + \beta^{(3)}X_{ij}^{(3)} + \vartheta^{(3)}Y_{ij}^{(3)} + {}^{1}/_{\omega}\, u_i^{(1,3)} + \frac{1}{\varphi} u_i^{(2,3)} + \delta_3 u_i^{(1,2,3)} + v_i^{(3)} \quad (8)$$

Estimation of model parameters
In the Bayesian framework, each parameter is assigned a suitable prior distribution. Posterior distributions for the parameters of interest are derived by updating these priors using the observed data. The modelling process begins with the formulation of a process model, which connects the observed data to the explanatory variables and incorporates a spatial component. The second stage involves modelling spatial random effects ($u_j$) and non-spatial random effects ($v_j$) through a spatial process model. Prior distributions are specified for parameters ($\alpha, \beta, \vartheta$) while the inverse variances of the non-spatial and spatial random effects, denoted as $\frac{1}{{\tau^2}_u}$ and $\frac{1}{{\sigma^2}_v}$ respectively, represent the hyper-prior distributions. The hierarchical structure of the complete model is summarized below.
First level:

$$X_{ij}^{(k)} | p_{ij}^{(k)} \sim \mathrm{Bernoulli}(p_{ij}^{(k)}) \quad (9)$$

$$\mathrm{logit}\left(p_{ij}^{(k)}\right) = \alpha^{(k)} + \beta^{(k)}X_{ij}^{(k)} + u_j^{(k)} + v_j^{(k)} \quad (10)$$

$i = 1, 2, .. n, j = 1, 2, .., 37, k = 1, 2, 3.$
Second level:

$$u_j | u_{j_{-1}} \sim N\left(\frac{1}{n_j}\sum_{u_j \sim u_{j-1}} u_j, \frac{{\tau^2}_u}{n_j}\right) \quad (11)$$

Priors

$$\beta \sim N(\mu, \Sigma),\ \vartheta \sim N(\mu_{\vartheta, \sigma_\vartheta^2}),\ \alpha \sim N(\mu_{\alpha, \sigma_\alpha^2}),\ \delta \sim \mathrm{Log-Normal}(0, \sigma_\delta^2) \quad (12)$$

Hyperpriors

$$\frac{1}{{\tau^2}_u} \sim G(\alpha_\tau \beta_\tau),\ \frac{1}{{\sigma^2}_v} \sim G(\alpha_\sigma \beta_\sigma) \quad (13)$$

Joint prior

$$p(\Phi) = \prod_{k=1}^{3} p(\alpha^k)\, p(\beta^k) p(\gamma) p(\omega) p(\phi)(\delta_k) p(u^{(1,2)}) p(u^{(1,3)}) p(u^{(2,3)}) p(u^{(1,2,3)}) p(v^{(k)}) \quad (14)$$

Where

$$\Phi = (\alpha^k, \beta^k, \gamma, \omega, \phi, \delta_k, u, v) \quad (15)$$

Posterior Distribution

$$p(\Phi | Y, X) \propto p(Y|X, \Phi) p(\Phi) \quad (16)$$

Expansion of (16) gives:

$$p(\Phi \mid Y) \propto \prod_{k=1}^{3} \prod_i^n \prod_j^{37} p(X_{ij}^{(k)} | p_{ij}^{(k)})\, p(\alpha^k)\, p(\beta^k) p(\gamma) p(\omega)\, p(\phi)(\delta_k)\, p(u^{(1,2)}) p(u^{(1,3)})$$

$$p(u^{(2,3)}) p(u^{(1,2,3)}) p(v^{(k)}) \quad (17)$$

Given the above proper assignment of priors, estimation of the model parameter was done with R-INLA.
Model Diagnostic

The results of the two formulated models were compared using Deviance Information Criterion (DIC) and the Widely Applicable Information Criterion (WAIC). According to standard model selection rules, the model with the lowest values for these diagnostic criteria is preferred [11].

$$\mathrm{DIC} = \bar{\mathrm{D}} + \rho\mathrm{D} \quad (18)$$

$\bar{\mathrm{D}}$ and $\rho\mathrm{D}$ are the deviance posterior mean obtained and effective number of parameters obtained as $\bar{\mathrm{D}} = \frac{1}{nS}\sum_{s=1}^{S}\mathrm{D}(\Phi^{(s)})$ and $\rho\mathrm{D} = \bar{\mathrm{D}} - \mathrm{D}(\bar{\Phi})$. Where $\Phi^{(s)}$ represents the samples from the posterior mean and $\bar{\Phi}$ is the parameter posterior mean.

$$\mathrm{WAIC} = -2(\mathrm{lppd} - \mathrm{pWAIC}) \quad (19)$$

lppd and pWAIC represent the log pointwise predictive density and effective number of parameters, obtained as

$$\mathrm{lppd} = \sum_{i=1}^{n} \log\left(\frac{1}{nS}\sum_{s=1}^{S} p(X_i \mid \Phi^{(s)})\right) \quad (20)$$

$$\mathrm{pWAIC} = \sum_{i=1}^{n} v_{\Phi^{(s)}}\left(\log p(X_i \mid \Phi^{(s)})\right) \quad (21)$$

$v_{\Phi^{(s)}}$ is the posterior sample variance.
Model overview for correlation between diseases
Let $u_j^{(k)}$ and $v_j^{(k)}$ represent the shared and disease-specific spatial effects for disease k in state j respectively. The shared component $u_j$ contributes to all diseases, while $v_j^{(k)}$ is unique to each disease. The spatial random effect for disease k in state j is given as:

$$S_i^{(k)} = \delta^{(k)}u_j + v_j^{(k)} \quad (22)$$

$\delta^{(k)}$ is the scaling parameter for disease k shared component.
Correlation between the spatial random effects for disease k and l is given as

$$\mathrm{corr}(S^{(k)}, S^{(l)}) = \frac{\mathrm{cov}(S^{(k)}, S^{(l)})}{\sqrt{\mathrm{var}(S^{(k)})\,\mathrm{var}(S^{(l)})}} \quad (23)$$

$$\mathrm{cov}\left(S^{(k)}, S^{(l)}\right) = \delta^{(k)}\,\delta^{(l)}\,\mathrm{var}(u) \quad (24)$$

$$\mathrm{var}\left(S^{(k)}\right) = \left(\delta^{(k)}\right)^2\mathrm{var}(u) + \mathrm{var}(v^{(k)}) \quad (25)$$

Substituting (24) and (25) in (23)

$$\mathrm{corr}(S^{(k)}, S^{(l)}) = \frac{\delta^{(k)}.\delta^{(l)}.\mathrm{var}(u)}{\sqrt{\left(\delta^{(k)}\right)^2\mathrm{var}(u) + \mathrm{var}(v^{(k)})\,.\mathrm{var}\left(\delta^{(l)}\right)^2\mathrm{var}(u) + \mathrm{var}(v^{(l)})}} \quad (26)$$

Following the procedure above the correlation for three diseases (k, l and q) is computed utilizing;

$$\mathrm{corr}\left(S^{(k)}, S^{(l)}, S^{(q)}\right) = \frac{\delta^{(k)}.\delta^{(l)}\,\delta^{(q)}\,\mathrm{var}(u)}{\left(\delta^{(k)}\right)^2\mathrm{var}(u) + \mathrm{var}\left(v^{(k)}\right)\mathrm{var}\left(\delta^{(l)}\right)^2\mathrm{var}(u) + \mathrm{var}\left(v^{(l)}\right)\mathrm{var}\left(\delta^{(q)}\right)^2\mathrm{var}(u) + \mathrm{var}\left(v^{(q)}\right)} \quad (27)$$

## 3. Results

**Table 2:** Characteristic of the Study Population

| Variables | Number of respondents |
|---|---|
| Political Zones | |
| North Central | 5875 |
| North East | 7211 |
| North West | 10305 |
| South East | 3798 |
| South South | 3202 |
| South west | 3533 |
| Residence | |
| Urban | 11699 |
| Rural | 22225 |
| Mother's Education | |
| No education | 15391 |
| Primary | 5274 |
| Secondary | 10623 |
| Tertiary | 2636 |
| Wealth Index | |
| Poorest | 8066 |
| Poorer | 7743 |
| Middle | 7171 |
| Richer | 6166 |

| | |
|---|---|
| Richest | 4778 |
| Child sex | |
| Male | 17257 |
| Female | 16667 |
| Fever status | |
| Positive | 7536 |
| Negative | 23177 |
| Diarrhoea status | |
| Positive | 3956 |
| Negative | 26757 |
| Anaemia status | |
| Positive | 7003 |
| Negative | 3179 |
| Anaemia and Diarrhoea | 1022 |
| Anaemia and Fever | 2131 |
| Diarrhoea and fever | 2148 |
| Anaemia Diarrhoea and Fever | 603 |

Table 2 reveals the characteristics of the study population. A total of 33924 children were involved in the survey. North West and South South had the largest and least percentage (30% and 9%) respectively of the respondents who participated in the survey. Majority of the children (65.5%) lived in rural area. Mothers' education is categorized into four and while the larger percentage of the mothers (45.5%) had no formal education only approximately 7.8% had tertiary education. Majority of the respondents belongs to the poorest and poor categories in terms of the wealth index of the household. About 47% of the mothers lived below average life. As regards gender distribution of the children, 51% and 49% are male and female respectively. Among the children involved in the survey, 7534 had fever, 3956 had diarrhoea and 7003 suffered from anaemia. comorbidities among anaemia, diarrhoea, and fever as examine by the study shows that 1002 children had anaemia and diarrhoea, 2131 had anaemia and fever, 2148 suffered from both diarrhoea and fever while 603 children had all the three diseases. The number of children with Diarrhoea and Fever (2,148) is the highest among the comorbid conditions.

**Table 3:** Model Comparison

| Information criterion | Model 1 | Model 2 |
|---|---|---|
| DIC | 67233.95 | 65231.11 |
| WAIC | 67229.37 | 65231.49 |

Table 3 presents the DIC values for the five formulated models. Among them, model five, which incorporates spatial components with weighted structured components, has the lowest DIC value. According to model selection criteria the model with the least DIC value was considered the best fit. Therefore, all subsequent posterior analyses are based on this model.

**Table 4:**

| Variables | Anaemia ROR (95% CI) | Diarrhoea ROR (95% CI) | Fever ROR (95% CI) |
|---|---|---|---|
| Child sex | | | |
| Male | 1 | 1 | 1 |
| Female | 0.943 (0.201, 1.448) | 1.006 (0.413, 1.742) | 1.026(0.517, 1.836) |
| Residence | | | |
| Urban | 1 | 1 | 1 |
| Rural | 1.292 (1.061, .892) | 0.943(0.321, 1.062) | 1.01(0.314, 1.763) |
| Mother's Education | | | |
| No education | 1 | 1 | 1 |
| Primary | 0.978(0.407, 1.615) | 1.025(0.654, 1.825) | 0.681(0.205, 0.966) |
| Secondary | 0.859(0.182, 1.125) | 0.456(0.223, .979) | 0.412 (0.141, 0.872) |
| Tertiary | 0.234(0.051, 0.932) | 0.250(0.062, 0.655) | 0.291(0.092, 0.673) |
| Wealth Index | | | |
| Poorest | 1 | 1 | 1 |
| Poorer | 0.789(0.367, 1.327) | 1.04(0.520, 1.914) | 0.423(0.222, 0.866) |
| Middle | 0.933(0.397, 1.46) | 0.519(0.216, 0.807) | 1.054(0.223, 1.972) |
| Richer | 0.465(0.187, 0.88) | 0.234(0.093, 0.762) | 0.255(0.031, 1.521) |
| Richest | 0.201(0.169, 0.768) | 0.064(0.035, 0.345) | 0.561(0.231, 0.922) |
| Precipitation | 1.185(1.418, 2.309) | 0.489(0.193, 0.571) | 1.702 (1.241, 2.093) |
| Aridity | 1.153(1.005, 1.530) | 0.848(0.359, 1.490) | 0.764(0.144, 1.03) |
| Temperature | 1.43(1.012, 1.439) | 1.442(1.092, 1.982) | 1.603 (0.354, 1.984) |

Table 4 presents the fixed effects result for each of the diseases including their 95% credible interval. The findings reveal that the sex of a child is not a significant risk factors for each of the three diseases as the odds of female children compared to male children are not significantly different for anaemia [0.943 (0.201, 1.448), diarrhoea 1.006(0.413, 1.742) and fever 1.026(0.517, 1.836)]. Mother's area of Residence has a significant impact only on anaemia [1.292 (1.061, 1.892)], with rural children having higher odds compared to urban children. There is no significant difference in the odds of diarrhoea 0.943(0.321, 1.062) or fever 1.01(0.314, 1.763) based on residence. Tertiary education significantly reduces the odds of anaemia, [0.234(0.051, 0.932))] while primary and secondary education show no significant effects. Tertiary education significantly reduces the odds of diarrhoea; [0.250(0.062, 0.655)], but primary and secondary education do not show significant effects. Both secondary and tertiary education significantly reduce the odds of fever; [0.412 (0.141, 0.872), 0.291(0.092 0.673] while primary education does not show a significant effect. Mothers' higher education levels (secondary and tertiary) are associated with reduced odds of these health outcomes in children, emphasizing the protective role of maternal education. There is no significant difference in the odds of anaemia between children from poorer and middle households and those from the poorest households. Children from richer as well as richest households have significantly lower odds of anaemia; 0.465(0.187, 0.88); 0.201 (0.169, 0.768)] compared to those from the poorest households. There is no significant variation in the odds of diarrhoea between children from poorer and middle households and those from the poorest households. Children from wealthier and the wealthiest households have significantly lower odds of diarrhoea [0.234(0.093, 0.762); 0.064(0.035, 0.345)] compared to their counterpart from the poorest households. Children from middle, richer and richest-income households have significantly lower odds of fever when compared with those from the poorest households: 0.255(0.031, 1.521); 0.054(0.223, 0.972); 0.561(0.231, 0.922)]. While higher precipitation is significantly associated with increased odds of anaemia and fever, [1.185(1.418, 2.309), 1.702 (1.241 2.093)], it is significantly associated with reduced odds of diarrhoea, 0.489(0.193, 0.571). Increased aridity is significantly associated with increased odds of anaemia 1.153(1.005, 1.530) but reduced odds of fever, 0.764(0.144, 1.03). This climatic covariate is however not significant for diarrhoea, 0.848(0.359, 1.490). Higher temperatures are significantly associated with increased odds of anaemia, 1.43(1.012, 1.439) and diarrhoea 1.442(1.092, 1.982). higher temperature also increase the odds of fever but this effect is however not statistically significant.

**Table 5:** Odds Ratio for Shared Fixed Effect Risk of Disease Comorbidities

| Variables | Anaemia/diarrhoea ROR (95% CI) | Anaemia/Fever ROR (95% CI) | Diarrhoea/fever ROR (95% CI) | Anem/Diarrh/Fev ROR (95% CI) |
|---|---|---|---|---|
| Child sex | | | | |
| Male | 1 | 1 | 1 | 1 |
| Female | 0.949(0.371, 1.799) | 0.968(0.241,1.674) | 0.632(0.257,1.131) | 0.973(0.206,1.590) |
| Residence | | | | |
| Urban | 1 | | | 1 |
| Rural | 1.001(0.549, 2.001) | 1.071(0.627, .491) | 0.953(0.238,1.815) | 1.011(0.214,1.764) |
| Mother’s Education | | | | |
| No education | 1 | | 1 | 1 |
| Primary | 1.211 (0.432, 1.686) | 0.947(0.236,1.794) | 0.991(0.247,1.972) | 0.970(0.205,1.573) |
| Secondary | 0.106(0.023, 0.632) | 0.869(0.332,1.483) | 0.468(0.266,0.281) | 0.494(0.194,0.827) |
| Tertiary | 0.397(0.503, 0.983) | 0.246(0.091,0.921) | 0.81(0.334, 1.871) | 0.493(0.188, .939) |
| Wealth Index | | | | |
| Poorest | 1 | 1 | 1 | 1 |
| Poorer | 0.821(0.414, 1.293) | 0.783(0.195,1.142) | 1,03(0.784, 1.145) | 0.815(0.374,0.846) |
| Middle | 0.951 (0.537, 1.508) | 0.983(0.456,1.939) | 1.075(0.568,1.620) | 1.002(0.512,2.727) |
| Richer | 0.916(0.453, 1.487) | 0.935(0.233,1.746) | 1.431(1.072,1.981) | 0.367(0.092,0.975) |
| Richest | 0.401(0.201, 0.944) | 0.863(0.215,1.464) | 1.12(0.772, 1.744) | 0.173(0.485,0.723) |
| Precipitation | 1.691(1.022, 2.052) | 1.672(1.076,2.214) | 0.374(0.073,0.911) | 0.181(0.096,0.875) |
| Aridity | 1.212(0.301, 1.875) | 1.114(0.497,1.785) | 0.819(0.375,1.742) | 1.945(1.182,2.918) |
| Temperature | 0.968(0.241, 1.674) | 1.752(1.132,2.043) | 0.280(0.068,0.731) | 0.230(0.056, 0.66) |

Table 5 presents the odds ratios for fixed covariates associated with pairwise comorbidities of the studied childhood diseases, as well as the combined effects of all three diseases. Based on the results, being a female child is associated with about 5.1%, 3.2%, 37.8%, and 2.7% reduced likelihood of being affected by anaemia and diarrhoea, anaemia and fever, diarrhoea and fever and anaemia diarrhoea and fever respectively. however, a child's gender does not significantly influence the comorbidity of these childhood infections. Being in rural is linked with 0.001%, 7.1% and 1.1% higher chance of being affected with anaemia and diarrhoea, anaemia and fever, anaemia diarrhoea and fever respectively but with 4.7% reduced chance of fever and diarrhoea compared to being in urban area. Having secondary education is a significant protective factor only for the comorbidity of anaemia and diarrhoea, as A child whose mother attained a secondary level of education is 89.4% less likely to be affected by both conditions compared to a child whose mother has no formal education. However, having primary or secondary education is not a significant factor for any other combinations of the diseases compared to having no formal education. A child whose mother has higher education has a reduced likelihood of testing positive for the combined effects of anaemia and diarrhoea (60.3%), anaemia and fever (75.4%), diarrhoea and fever (19%), and anaemia, diarrhoea, and fever (50%) compared to a child whose mother has no formal education. This covariate is not statistically significant for diarrhoea and fever. Based on the household wealth index, the poorer and middle categories are not statistically significant. However, children from richer households have 63.3% reduced odds of experiencing the combined effects of the three diseases. Additionally, children from the richest wealth category have a lower likelihood of having anaemia and diarrhoea (50.9%), anaemia and fever (13.7%), and the combination of anaemia, diarrhoea, and fever (82.7%) compared to children whose mothers have no formal education. While higher average annual precipitation increases the odds of a child experiencing the combined effects of anaemia and diarrhoea (69.1%) and anaemia and fever (67.2%), it is associated with a reduced likelihood of diarrhoea and fever (62.6%) and the combined effects of anaemia, diarrhoea, and fever (81.9%). Aridity has no significant effect on the comorbidities of anaemia and diarrhoea, anaemia and fever, or diarrhoea and fever. However, higher aridity is associated with a 95.4% increase in the odds of a child experiencing the combined effects of all three diseases. The effect of land surface temperature is not statistically significant for the comorbidity of anaemia and diarrhoea. However, it is associated with an increased odds of contacting anaemia and fever (75.2%), while reducing the odds of diarrhoea and fever (71%) and the combined effects of anaemia, diarrhoea, and fever (77%) in children.

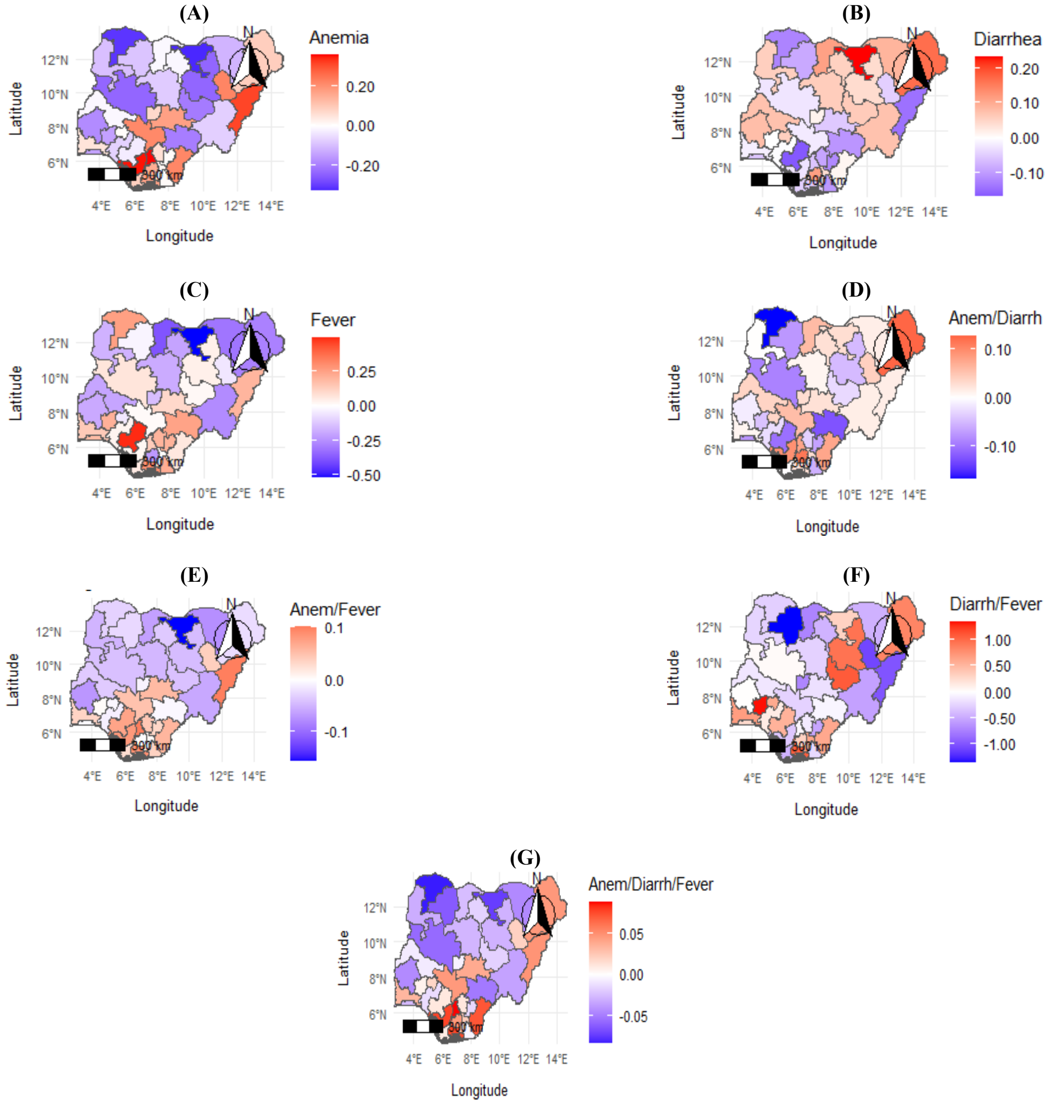
**Table 6:** Spatial Correlation Estimates among Anaemia, Diarrhoea and Fever

| | Correlation | Standard error | p-value |
|---|---|---|---|
| Anaemia/diarrhoea | 0.083 | 0.025 | 0.230 |
| Anaemia/fever | 0.239 | 0.013 | 0.208 |
| Diarrhoea/fever | 0.636 | 0.035 | 0.048 |
| Anaemia/diarrhoea/fever | 0.862 | 0.061 | 0.00 |

Table 6 presents correlation coefficients, their standard errors, and associated p-values for the relationships among three childhood illnesses: anaemia, diarrhoea, and fever, as well as their combined effects. There is a weak positive relationship between anaemia and diarrhoea but the p-value of 0.23 implies that the relationship is not statistically significant as it is beyond the threshold of 0.05. Anaemia and fever have a weak positive correlation but the relationship between this combined childhood infection is also not statistically significant. There is a significant positive correlation between diarrhoea and fever suggesting that increase in one condition could possibly lead to increase in the other. The combined effect of anaemia, diarrhoea, and fever shows a strong and significant positive correlation, indicating a strong relationship when all three conditions are considered together. The significant and strong positive correlation when all three diseases are combined suggests a potential interaction or cumulative effect among these childhood health

### 3.1. Spatial effects

The maps from the spatial effects of specific and shared diseases components are presented below




Figures a–c illustrate the spatial distribution of disease specific state-level effects for anaemia, diarrhoea, and fever among children in Nigeria. Anaemia risk (Fig. a) is highest in the northeast and southeast, with hotspots in states such as Borno, Yobe, Adamawa, Nasarawa, Benue, Ebonyi, Anambra, Bayelsa, Rivers, and Ondo. Diarrhoea risk (Fig. b) is elevated in Borno, Yobe, Katsina, and Cross River, while fever risk (Fig. c) is highest in Kano, Kebbi, Yobe, and Lagos.
Figures d–g show the spatial distribution of comorbidities among children in Nigeria. Anaemia–diarrhoea co-occurrence (Fig. d) is highest in Borno, Yobe, parts of Katsina, Adamawa, and Lagos, while anaemia–fever comorbidity (Fig. e) is elevated in Adamawa, Lagos, and coastal states. Diarrhoea–fever overlap (Fig. f) is most pronounced in Borno, Kebbi, Zamfara, and Ogun. The combined comorbidity of anaemia, diarrhoea, and fever (Fig. g) is highest in Borno, Adamawa, Ogun, Lagos, Delta, and Cross River.

### 3.2. Discussion of findings

The shared component model with extra terms to incorporate climatic covariates was considered as the best fitted model having achieved the lower values of DIC and WAIC of 65231.11 and 65231.49 respectively. The improved performance of the model incorporating climatic variables in this study supports the notion, as suggested by [15], that accounting for climatic influences enhances the robustness of health risk assessments.
The fixed effects of the model reveal that acquiring tertiary education, wealth index of household and educational level of a child mothers, land surface temperature and regional precipitation have significant effects on the odds of a child having comorbid effects of anaemia, diarrhoea and fever. The findings on the fixed-effect covariates associated with the specific and shared risks of anaemia, diarrhoea, and fever are largely consistent with those reported in previous studies by [12], [17]; [22]. Besides, the observed effect of temperature on the risk of diarrhoea is consistent with the findings of [16].
The correlation among the three combined diseases is notably high (0.862), suggesting that when all three conditions are considered simultaneously, their interaction or co-occurrence becomes significant. The results of the adopted best fitted shared component model produced spatial risk maps showing specific and shared spatial effects of anaemia, diarrhoea and fever.
The spatial maps reveals that children from North eastern and southern parts of the country have higher odds of disease comorbidities. This finding aligns closely with those of previous studies by [8], [18], [20].

# 4. Conclusion

The study utilized shared component model to examine the specific and shared disease components of anaemia, diarrhoea and fever among children under the age of five across the states in Nigeria. the models were split into two; while model one examined the risk factors of these diseases as a function of demographic, socioeconomic variables, and spatial components the second model incorporates climatic factors in addition to all the variables contained in the first model. The popular model criterion such as DIC and WAIC were used to identify the best fitted model. Model 2 which has lower values of these statistics is considered as the best fitted. All analysis were carried out based on the second model. This study builds upon spatial univariate modelling approach which analyze childhood illnesses on individual bases. the incorporation of climatic variables into our joint models also improved the efficiency of disease risk estimates. According to our results the state level comorbidities of anaemia-diarrhoea, anaemia-fever, diarrhoea-fever, and anaemia-diarrhoea-fever are mostly higher in the north east and southern parts of the country. The higher odds of comorbidity of the three illnesses among children in some states in south-south part of the country could be linked to higher precipitation in that regions which may contribute to favorable breeding conditions for mosquitoes, thereby increasing the burden of vector-borne diseases like malaria, which is a known contributor to anaemia. Additionally, heavy rainfall could lead to water stagnation, promoting the spread of waterborne pathogens responsible for diarrhoea and fever. The region is also impacted by oil spills, which can contribute to air pollution leading to illnesses among children. Our findings on the covariates effects on the risk of the childhood diseases considered in this study are in line with previous studies [2, 8, 18-20].

## 4.1. Recommendation

Since the integration of varying climatic factors across regions in Nigeria in the modelling framework potentially results in more robust estimate of disease risk, future studies on spatial modelling of child health outcome should consider incorporating climatic variation as part of the study covariates. Policy makers and health authorities should support and encourage community-based initiatives that address the impacts of climate change on child health outcome.

# Funding

No funding was received for conducting this study

# Authors Contribution

All authors contributed equally in the preparation of the manuscript.

# Conflict of Interest

The author declares that there is no conflict of interest.

# Acknowledgement

The authors express their sincere appreciation to the Demographic and Health Surveys (DHS) Program for providing access to the survey dataset and spatial data repository used in this study.

# References

[1] Gayawan, E., Egbon, O. A., & Adegboye, O. (2023). Copula-based trivariate spatial modelling of childhood illnesses in Western African countries. *Mathematical Population Studies: An International Journal of Mathematical Demography,* 29 (2). https://doi.org/10.1016/j.sste.2023.100591.

[2] Ibrahim, A., Adeyemi, R. A., Usman, A., & Adabara, N. U. (2025). Weighted random effects multinomial model with application to anaemia and malnutrition comorbidity among under-five children in Nigeria. *Asian Journal of Probability and Statistics, 27*(1), 29–42. https://doi.org/10.9734/ajpas/2025/v27i1701.

[3] UNICEF. (2022). *Under-five mortality*. Retrieved from https://www.unicef.org/reports/under-five-mortality, 5th March, 2024.

[4] Obasohan, P. E. (2022). Investigating Multiple Overlaps in the Determinants of Risk Factors of Anaemia, Malaria, and Malnutrition, and their Multimorbidity, among Children aged 6 to 59 months in Nigeria [Unpublished Doctoral Thesis]. Dentistry and Health University of Sheffield, England. https://doi.org/10.1101/2023.04.10.23288389.

[5] Duah, H. O., Amankwa, C. E., Adomako, I., Owusu, B., & Agbadi, P. (2021). Comorbid patterns of anaemia and diarrhoea among children aged under 5 years in Ghana: A multivariate complex sample logistic regression analysis and spatial mapping visualisation. *International Health, 13*(6), 562–572. https://doi.org/10.1093/inthealth/ihaa099.

[6] Wagnew, F., Dessie, G., Takele, W., et al. (2019). A meta-analysis of inpatient treatment outcomes of severe acute malnutrition and predictors of mortality among under-five children in Ethiopia. *BMC Public Health, 19*(1), 1–11. https://doi.org/10.1186/s12889-019-7466-x.

[7] Roy, S. K., Buis, M., Weersma, R., et al. (2011). Risk factors of mortality in severely malnourished children hospitalized with diarrhoea. *Journal of Health, Population and Nutrition, 29*(3), 229–235. https://doi.org/10.3329/jhpn.v29i3.7870.

[8] Orunmoluyi, O. S., Gayawan, E., & Manda, S. (2022). Spatial co-morbidity of childhood acute respiratory infection, diarrhoea, and stunting in Nigeria. *International Journal of Environmental Research and Public Health,* 19 (3), 1838. https://doi.org/10.3390/ijerph19031838.

[9] Moraga, P. (2019). *Geospatial health data: Modelling and visualization with R-INLA and Shiny.* CRC Press. https://doi.org/10.3390/ijerph19031838.

[10] Roberts, D., & Zewotir, T. (2019). District effect appraisal in East Sub-Saharan Africa: Combating childhood anaemia. *Anemia*, Article ID 1598920, 1–10. https://doi.org/10.1155/2019/1598920.

[11] Barry, T. S., Ngesa, O., Onyango, N. O., & Mwambi, H. (2022). A Bayesian bivariate model for spatially correlated binary outcomes. *Mathematical Problems in Engineering.* 2 (5), 54-68. https://doi.org/10.1155/2022/7852042.

[12] Bolaji, S. A. & Oyepeju, M. O., (2021). Prevalence and correlates of anaemia among children aged 6 to 59 months in Nigeria. *World Nutrition*, 12 (3), 58-74. https://doi.org/10.26596/wn.202112358-74.

[13] Gayawan, E., Aladeniyi, O. B., Oladuti, O. M., Olopha, P., & Adebayo, S. B. (2019). Investigating the spatial patterns of common childhood morbidity in six neighbouring West African countries. *Journal of Epidemiology and Global Health, 9*(4), 315–323. https://doi.org/10.2991/jegh.k.191030.001.
[14] Adeyemi, R.A., Zewotir, T. & Ramroop, S. (2019). Joint spatial mapping of childhood anaemia and malnutrition in sub-Saharan Africa: A cross-sectional study of small-scale geographical disparities. *African Health Science Journal*, 19(3), 2692-2712. https://doi.org/10.4314/ahs.v19i3.45.
[15] Odjugo, P. (2013). Analysis of climate change awareness in Nigeria. *Academic Journals*, 8 (26), 1203-1211.
[16] Flückiger, M., & Ludwig, M. (2022). Temperature and risk of diarrhoea among children in Sub-Saharan Africa. *World Development, 160*, 106070. https://doi.org/10.1016/j.worlddev.2022.106070.
[17] Atari, D. O., Mkandawire, P., & Lukou, Y. S. (2022). Determinants of co-occurrences of diarrhoea and fever among children under five years of age in South Sudan. *African Geographical Review*, *42*(5), 617–633. https://doi.org/10.1080/19376812.2022.2092161.
[18] Ibrahim, A., Adeyemi, R. A., Usman, A., & Musa, A. O. (2024). Bayesian geo-additive modelling of state-level heterogeneity in anaemia prevalence and risk factors among under-five children in Nigeria. *Confluence University Journal of Science and Technology, 1*(2), 1–15. https://doi.org/10.5455/CUJOSTECH.241011.
[19] Shamenna, A. T., & Goshu, A. T. (2016). Spatial modelling of fever prevalence and suspected malaria cases among children: A cross-sectional study. *International Journal of Tropical Disease & Health, 13*(3), 1–17. https://doi.org/10.9734/IJTDH/2016/13191.
[20] Fagbohungbe, T. H., Gayawan, E., & Orunmoluyi, O. S. (2020). Spatial prediction of childhood malnutrition across space in Nigeria based on point-referenced data: An SPDE approach. *Journal of Public Health Policy, 41*, 464–480. https://doi.org/10.1057/s41271-020-00246-x.
[21] Besag, J., York, J., & Mollie, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics (AISM)*, 43, –59. https://doi.org/10.1007/BF00116466.
[22] Gebremedhin, S. (2017). Vitamin A supplementation and childhood morbidity from diarrhoea, fever, respiratory problems and anaemia in sub-Saharan Africa. *Nutrition and Dietary Supplements*, *9*, 47–54. https://doi.org/10.2147/NDS.S138849.
[23] Ibrahim, A., Adeyemi, R. A., & Abubakar, U. (2024). Spatially weighted multinomial modelling of comorbidity of anaemia and malaria among under-five children in Nigeria. *Qeios*. https://doi.org/10.32388/MBSNRX.
[24] Adebayo, S. B., Gayawan, E., Heumann C., & Seiler C. (2016.) Joint modelling of Anaemia and Malaria in children under five in Nigeria. *Spatial Spatiotemporal Epidemiology*, 17, 105–15. https://doi.org/10.1016/j.sste.2016.04.011.