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Research article

Bayesian Hierarchical Spatial Modelling of Diarrhoea Among Under-Five Children in Nigeria: Regional Disparities and Associated Risk Factors

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Abstract: This study applies a Bayesian geo-additive spatial modelling approach to examine the risk factors and spatial distribution of childhood diarrhoea in Nigeria using data from the 2018 Nigeria Demographic and Health Survey (NDHS). The analysis incorporates socio-demographic characteristics, environmental variables, and regional climatic conditions to identify significant predictors of diarrhoea among children under five. Results indicate that rural residence, lack of access to clean water, malnutrition, and low household wealth significantly increase the likelihood of diarrhoea, while higher maternal education and female gender are protective. Climatic factors, particularly increased temperature and precipitation, were also associated with elevated risk. Spatial analysis revealed distinct geographic clusters of high diarrhoea burden, notably in the northeast, southwest, southeast, and south-south regions of the country. The findings underscore the importance of integrating environmental and spatial components into public health strategies. Targeted, region-specific interventions that address both individual- and community-level determinants are essential for reducing the prevalence of childhood diarrhoea and promoting better health outcomes for Nigerian children.

Mathematics Subject Classification: 62H11, 62M30, 62G08, 92D30
Keywords: Geo-additive; diarrhoea; spatial, distribution; risk factors; temperature; precipitation

1 Introduction

Diarrhoea remains one of the leading causes of morbidity and mortality among under-five children, particularly in low- and middle-income countries [1]. Globally, it accounts for approximately 8% of all deaths in this age group, claiming the lives of over 500,000 children annually [2]. In sub-Saharan Africa,

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especially in Nigeria, childhood diarrhoea persists as a significant public health concern, worsened by inadequate access to clean water, poor sanitation, malnutrition, and limited healthcare services [3-6].

In Nigeria, regional disparities in the burden of diarrhoea diseases are well documented, yet the drivers of this spatial heterogeneity remain inadequately understood. Previous studies have largely focused on individual- and household-level risk factors such as maternal education, wealth index, and sanitation practices [7,8]. Although some have explored spatial patterns of diarrhoea using conventional mapping or regression approaches [9], many have overlooked the potential role of regional climatic factors-notably, average temperature and precipitation, which are known to influence the transmission and persistence of diarrhoea pathogens. This omission leaves an important gap in understanding the ecological context of childhood diarrhoea in Nigeria.

Spatial epidemiological techniques offer powerful tools to bridge this gap. Bayesian geo-additive models, which combine structured and unstructured spatial effects with nonlinear covariate functions, are particularly well-suited for modelling health outcomes influenced by complex spatial processes [10-15]. These models not only account for unmeasured spatial autocorrelation but also allow for the inclusion of continuous environmental covariates, making them ideal for integrating climatic variables such as temperature and precipitation into disease risk assessments. Despite their potential, such advanced spatial modelling techniques have not been widely applied to childhood diarrhoea in Nigeria. Moreover, the influence of regional climatic variation on disease prevalence has yet to be systematically evaluated using robust Bayesian frameworks. This study addresses these gaps by employing a Bayesian geo-additive spatial modelling approach to identify significant socio-demographic and environmental risk factors of diarrhoea among under-five children and detect spatial hotspots of disease risk, while explicitly accounting for regional variation in climatic conditions.

2 Materials and methods

2.1 Summary of Data Sources and Variables

This study utilizes data from the 2018 Nigeria Demographic and Health Survey (NDHS), accessed through an approved request to the DHS Program. Climatic data on average temperature and precipitation were obtained from the DHS spatial data repository.

The outcome variable is childhood diarrhoea, defined as a binary variable indicating whether a child had diarrhoea within two weeks before the survey. Explanatory variables include socio-demographic factors (child's age, sex, area of residence, mother's education, and household wealth index), malnutrition status, and climatic variables (temperature and precipitation). These covariates were selected in line with previous studies on under-five children using national cross-sectional surveys [23-26]. Geographic location was represented by Nigeria's 36 states and the Federal Capital Territory (FCT). The initial dataset comprised 33,924 children. However, the number of valid observations varied across variables because some records contained missing information.

The spatial structure comprised Nigeria's 36 states and the Federal Capital Territory (FCT), represented using Nigeria's administrative shapefile. Spatial adjacency was defined based on shared-boundary contiguity, such that two geographical units were considered neighbours if they shared a common boundary. The

resulting binary adjacency matrix specified the neighbourhood relationships used in defining the structured spatial random effects under the Intrinsic Conditional Autoregressive (ICAR) prior. The climatic covariates, namely average temperature and precipitation, were assigned to their corresponding states and the FCT to ensure geographical consistency with the spatial units used in the Bayesian modelling. *R* software was used for data cleaning and descriptive analysis, while BayesX (version 2.1) was used for the Bayesian spatial modelling.

2.2 Model specification

Y_{ij} represent the diarrhea status of the ith child in the jth state, where $j = 1, 2, \ldots, 37$, (36 states plus the FCT). The binary outcome variable is coded as

$$Y_{ij} = \begin{cases} 1 & \text{if a child in state } j \text{ had diarrhea} \\ 0 & \text{if a child in state } j \text{ was free of diarrhea} \end{cases} \tag{1}$$

$$Y_{ij} \sim \text{Bernoulli}(\pi_{ij}) \tag{2}$$

where π_{ij} denotes the probability that child i in state j experienced diarrhea.

We developed four hierarchical models of increasing complexity:

Model 1: Fixed Effects Model

$$\text{Logit}(\pi_{ij}) = X_{ij}^T \beta \tag{3}$$

This model includes only fixed effects for categorical covariates such as the child's sex, mother's education level, wealth index, access to clean water, area of residence, and malnutrition status.

Model 2: Fixed Effects + Smooth Continuous Effect

$$\text{Logit}(\pi_{ij}) = X_{ij}^T \beta + f(Z_{ij}) \tag{4}$$

In addition to the categorical covariates, this model incorporates smooth functions for continuous variables like the age of the child, modelled using Bayesian penalized splines.

Model 3: Convolution Model Based on Model 1

$$\text{Logit}(\pi_{ij}) = X_{ij}^T \beta + u_j + s_j \tag{5}$$

This model introduces spatial heterogeneity by including both structured random effects u_j and unstructured spatial effects (s_j) jointly known as the convolution prior.

Model 4: Convolution Model Based on Model 2

$$\text{Logit}(\pi_{ij}) = X_{ij}^T\beta + f(Z_{ij}) + u_j + s_j \tag{6}$$

This is the full model combining fixed effects, smooth continuous effects, and both types of spatial random effects.

The unstructured random effects (s_j) are assumed to follow a normal distribution:

$$s_j \sim N(0, \sigma_s^2) \tag{7}$$

The structured spatial effects (u_j) are modelled using an Intrinsic Conditional Autoregressive (ICAR) prior [16]:

$$u_j \mid u_{(-j)} \sim N\left(\frac{1}{m_j}\sum_{k\in\delta_j} u_k, \frac{\sigma_u^2}{m_j}\right) \tag{8}$$

where δ_j denotes the set of neighbors of region j and m_j is the number of such neighbours.

2.3 Spline Approximation for Continuous Covariates

Continuous covariates like age are modeled using Bayesian P-splines [22]. The smooth function $f(Z)$ is approximated by a linear combination of basis functions:

$$f(Z) = \sum_{r=1}^{R} \gamma_r B_r(Z) \tag{9}$$

where $B_r(Z)$ are the spline basis functions and γ_r are spline coefficients with appropriate priors.

2.4 Bayesian Inference and Estimation

Bayesian estimation was performed using Markov Chain Monte Carlo (MCMC) techniques implemented in BayesX (version 2.1). The posterior distribution is proportional to the product of the likelihood and the prior distributions:

$$p(\theta \mid Y) \propto p(Y \mid \theta)\, p(\theta) \tag{10}$$

Hyperpriors for variance components (σ_u^2, σ_s^2) are assigned Inverse Gamma distributions.

2.5 Model Comparison

Model performance was assessed using the Deviance Information Criterion (DIC):

$$\text{DIC} = \bar{D} + \rho_D \tag{11}$$

where $\bar{D}$ is the posterior mean of the deviance and ρ_D represents the effective number of parameters. A lower DIC indicates a better-fitting model [17].

3 Results and Analysis

Table 1: Descriptive characteristics of the response variables and the covariates

Variables	**Number of respondents**
Political Zones	
NC	5875
NE	7211
NW	10305
SE	3798
SS	3202
SW	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

Table 1 reveals a summary of the socio-demographic and health characteristics of under-five children included in the study. Out of the total 33,924 respondents, approximately 66% resided in rural areas, while 34% lived in urban settings. Regarding maternal education, a significant proportion of mothers (45.4%) had no formal education, while only 7.8% attained tertiary education. In terms of household wealth, the poorest and poorer households accounted for roughly 47% of the sample, indicating a substantial representation of low-income families. The gender distribution was relatively balanced, with males representing 50.9% and females 49.1%. About 22.2% of children had fever in the two weeks preceding the survey, and 11.7% experienced diarrhoea during the same period. Notably, 60.7% of children belonged to households with access to clean water, while 39.3% lacked such access. Additionally, 37% of children were classified as malnourished. These figures underscore the socio-economic and environmental vulnerabilities that contribute to the burden of diarrhoea diseases among children in Nigeria.

Table 2: Deviance Information Criterion for Model Selection

Models	**Deviance ($\bar{D}$)**	ρ_D	**DIC**
I	8721.511412	65.651332	8787.162744
II	9046.725069	68.542140	9115.267000
III	7845.987100	51.592140	7897.579240
IV	7760.960800	43.696721	7804.657521

Model selection was guided by the Deviance Information Criterion (DIC), a common metric used to evaluate and compare model fit. According to the results presented in Table 2, Model IV, comprising both structured and unstructured spatial random effects, collectively referred to as a convolution model, demonstrated the best performance, having the lowest DIC value among all models assessed. This further underscores the importance of incorporating spatial structure and non-linear relationships in accurately modelling the risk of childhood diarrhoea.

Table 3: Posterior estimates of fixed effect risk factors of anaemia and their odds ratio with 95% credible intervals

Covariates	**Odds ratio**	**STD Error**	**95% Credible interval**	
			Lower	**Upper**
Constant	0.657	0.045	0.134	1.243
Residence				
Urban	1	–	–	–
Rural	1.342	0.032	1.212	1.865
Sex				
Male	1	–	–	–
Female	0.613	0.002	0.432	0.841
Access to Clean water				
Yes	1	–	–	–
No	1.924	0.046	1.341	2.347
Malnutrition Status				
No	1	–	–	–
Yes	1.986	0.021	1.261	2.532
Wealth Index				
Poorest	1	–	–	–
Poorer	0.87	0.540	0.451	1.653
Middle	0.572	0.013	0.243	0.843
Richer	0.421	0.001	0.311	0.942
Richest	0.213	0.022	0.092	0.765
Highest education				
No education	1	–	–	–
Primary	0.98	0.056	0.46	1.210
Secondary	0.874	0.211	0.431	1.422
Higher	0.671	0.031	0.213	0.959
Temperature	1.513	0.430	1.013	2.147
Precipitation	1.938	0.321	1.456	2.662

Table 3 shows the posterior estimates of odds ratios and their corresponding 95% credible intervals for the various covariates included in the final model. A covariate is considered statistically significant

if its credible interval does not include the value 1. Based on this criterion, several variables emerge as significant predictors of childhood diarrhoea in Nigeria.

Children living in rural areas have higher odds of experiencing diarrhoea compared to their urban counterparts, with an odds ratio of 1.342 and a credible interval that ranges from 1.212 to 1.865. Similarly, children without access to clean water are significantly more likely to suffer from diarrhoea, as indicated by an odds ratio of 1.924 (1.341–2.347). Malnutrition is another strong determinant, with malnourished children nearly twice as likely to experience diarrhoea [1.986, (1.261–2.532)]. Gender also shows a significant effect, with female children having reduced odds compared to males [0.613, (0.432–0.841)]. In terms of environmental influences, both temperature and precipitation reveal positive associations with diarrhoea risk. Higher average temperature is linked to increased odds [1.513, (1.013–2.147)], while precipitation has an even stronger association [1.938, (1.456–2.662)], suggesting that climatic conditions may facilitate the spread of diarrhoea pathogens. Socioeconomic status, as captured by the wealth index, reveals a protective gradient: children from richer and richest households have substantially lower odds of diarrhoea, with credible intervals excluding 1. Educational attainment of mothers also plays a role—those with higher education levels are associated with reduced risk, particularly at the tertiary level [0.671, (0.213–0.959)], though primary and secondary levels did not reach statistical significance. Overall, the findings highlight the importance of improving water access, addressing malnutrition, and targeting interventions based on environmental and socioeconomic contexts.

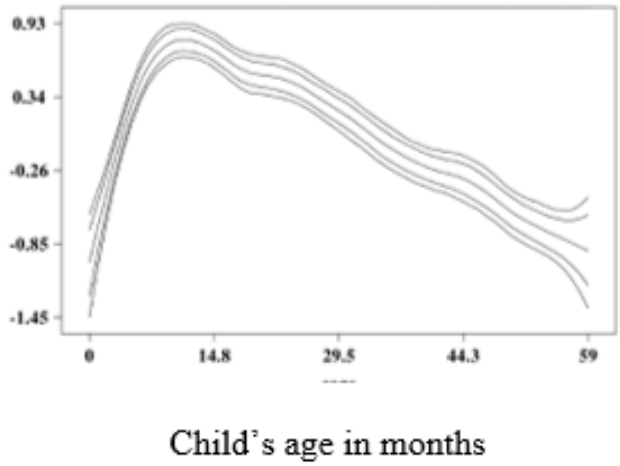
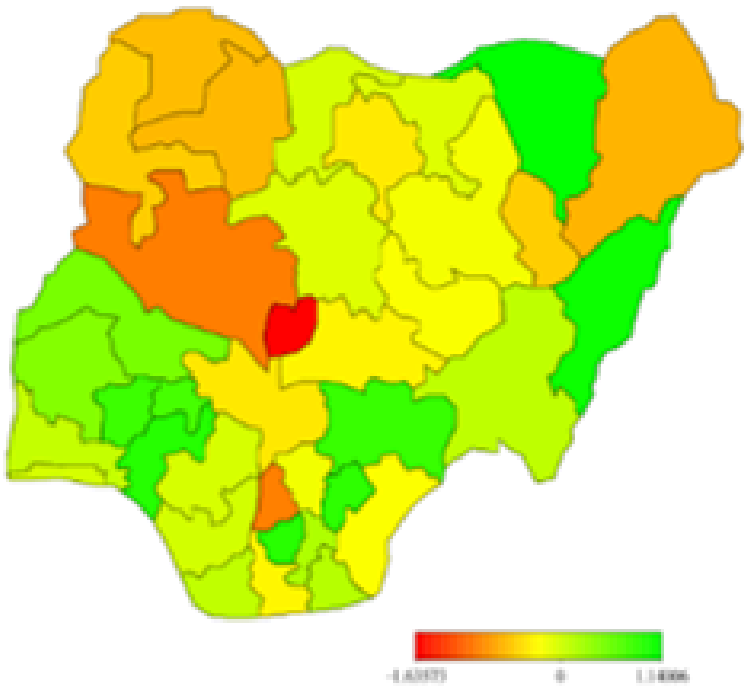


Figure 1: Non-linear effect of child age on the risk of diarrhoea.

Figure 1 illustrates the nonlinear effect of a child's age (in months) on the risk of diarrhoea, estimated using Bayesian P-splines. The curve shows how the risk of diarrhoea changes with the child's age, rather than assuming a linear relationship. The x-axis represents the child's age in months while the y-axis shows the log-odds or relative risk of having diarrhoea. The curve shows a peak in diarrhoea risk around 6 to 14 months of age then show a decline in risk as the child grows older, likely due to improved immunity and better hygiene behaviour.



(a)

Figure 2



(b)

Figure 3

Figure 4: Posterior map of diarrhea risk.

3.1 Spatial Effect

Figures II displays the residual spatial effects and their corresponding 95% posterior credible intervals. In Figure II (b), the map color coding indicates varying levels of diarrhea risk: white represents states with high diarrhea risk, black shows states with negative or very low diarrhea risk, and grey highlights states with intermediate or indifferent risk levels.

Spatial effects account for unobserved factors such as environmental conditions, accessibility to transportation, and the availability of child healthcare services. As illustrated in Figures II (a and b), many states exhibit significant positive or negative spatial effects, as indicated by the map of the 95% posterior credible interval. This clearly reflects the spatial variation in the risk of childhood diarrhea across Nigeria. Notable hotspots for childhood diarrhea include the northeastern states of Adamawa and Yobe, southwestern states like Oyo, Osun, and Ondo, as well as Ebonyi in the southeast and Delta in the south-south. These areas are identified as having a heightened risk for diarrhea, warranting focused public health interventions. This closely aligns with the study reported in [1].

3.2 Discussion of Findings

The findings from this study highlight a complex interplay of socio-demographic, environmental, and spatial factors influencing the occurrence of childhood diarrhea in Nigeria. Key individual-level risk factors identified include rural residence, lack of access to clean water, and malnutrition—all of which significantly increase the likelihood of diarrhea among under-five children. In contrast, higher maternal education levels and improved household wealth appear to offer protective effects. The reduced odds among female children further suggest potential gender-related differences in exposure or care-seeking behaviours. These outcomes are consistent with previous research, reinforcing the need for multi-faceted interventions that address both health and socioeconomic inequalities. Specifically, these results are consistent with the findings reported in [1, 4, 7, 21].

Climatic factors, specifically temperature and precipitation, were also found to significantly influence diarrhoea risk, pointing to the broader environmental context within which childhood illnesses occur. Regions experiencing higher rainfall and warmer temperatures had elevated risk levels, likely due to the enhanced transmission and persistence of waterborne pathogens under such conditions. This finding supports the growing body of evidence linking climate variability to child health outcomes and underscores the urgency of integrating climate resilience into public health strategies. Similar findings were also observed in the study cited in [18-20]. Spatial analysis further revealed clear geographic clustering of high-risk areas, with hotspots concentrated in the northeast, parts of the southwest, southeast, and south-south regions. These residual spatial effects, which capture unmeasured regional influences such as environmental sanitation, healthcare access, and infrastructure, underscore the importance of spatially targeted health interventions. Overall, the study emphasizes the need for a geographically informed approach to reducing the burden of childhood diarrhoea in Nigeria, one that addresses both individual and contextual determinants of health.

4 Conclusions

In conclusion, this study demonstrates that childhood diarrhoea in Nigeria is shaped by a combination of socio-demographic, environmental, and spatial factors. The significant roles of rural residence, poor access to clean water, malnutrition, and climatic conditions such as temperature and precipitation emphasize the multifaceted nature of the disease burden. The identification of geographic hotspots further highlights the importance of spatial analysis in public health planning. Targeted interventions that address both individual-level vulnerabilities and region-specific challenges are essential for reducing the incidence of childhood diarrhoea and improving child health outcomes across Nigeria.

4.1 Recommendation

Based on the findings, it is recommended that health interventions prioritize improving access to clean water, enhancing child nutrition, and promoting maternal education, especially in rural and high-risk regions. Public health strategies should also incorporate climate-sensitive planning and spatial targeting to effectively address the environmental and geographic drivers of childhood diarrhea in Nigeria. Future studies should incorporate the appropriate sampling weights, stratification, and clustering information within the Bayesian spatial modelling framework to improve the representativeness and reliability of national-level estimates.

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