Confluence University Journal of Science and Technology
Journal of the Confluence University of Science and Technology, Osara, Kogi State
Journal Homepage: www.cujostech.com.ng
CUJoSTech

Bayesian Geo-Additive Modelling of State-Level Heterogeneity in Anaemia Prevalence and Risk Factors among Under-Five Children in Nigeria

[*1]IBRAHIM A., [2]ADEYEMI R. A., [3]USMAN A., [4]MUSA A.O.
[1,4]Department of Statistics, Confluence University of Science and Technology Osara, Kogi state, Nigeria
[2,3]Department of Statistics, Federal University of Technology, Minna, Nigeria
[*]ibrahima@custech.edu.ng

DOI: https://doi.org/10.5455/CUJOSTECH.241011

Research Article

Abstract

Anemia is a very serious global health issue, particularly in sub-Saharan African countries, where it has significant implications for both human health and economic development. This study aims to identify the socioeconomic, demographic and climatic factors as well as geographical variations linked to the prevalence of anaemia in young children in Nigeria, based on the results of the 2018 Nigeria demographic and health survey. The association between various types of covariates and possible spatial variations was explored using a hierarchical Bayesian geo-additive modelling approach. In particular, the study focused on a binary response variable. Out of the four formulated semi-parametric models, geo-additive model with both structured and unstructured random effects was found to be the best fitted. The findings of the study reveal significant spatial variation in anemia risk, with the highest risk observed in the states of Sokoto, Niger, Akwa Ibom, Ebonyi and Bauchi. Besides, educational level of a child's mother, wealth status of household, a child's area of residence, prevalence of malaria and land surface temperature were all associated with childhood anemia. The prevalence of infant anemia decreased with increasing child's age. Mother's Body Mass Index also has inverse relationship with the risk of childhood anaemia. Given the observed state-level patterns of anemia risk, it is important to implement targeted programs that address the specific needs of vulnerable children in each state. This could help reduce the prevalence of childhood anemia in the Nigeria.

Keywords: *Anaemia, geo-additive model, binary, prevalence, spatial variation.*
Article History: *Received: 20 November 2024; Accepted: 22 February 2025; Published: 24 February 2025*

1. Introduction

Anaemia is a major health problem among young children in Africa, especially those under the age of five, and has been linked to increased rates of morbidity and mortality. Anaemia is a condition marked by low hemoglobin levels, resulting in reduced oxygen supply to the body's tissues and organs [1]. Approximately 800 million children and women around the world are affected by anaemia and the highest prevalence of anemia was found in Sub-Saharan Africa [2]. According to WHO estimates, Nigeria is among the countries with a high burden of anemia, with over 40% of the population affected by the condition [3]. Anemia can have multiple causes, and previous studies have shown that approximately half of all incidents of anemia globally are caused by iron deficiency. However, many other factors can also contribute to anemia, including nutritional deficiencies, infectious diseases, and genetic disorders [4]. Countries with a high burden of anemia tend to have a lower proportion of anemia cases that are attributable to iron deficiency, likely due to the higher prevalence of other causes of anemia, such as infection and inflammation [5]. These findings highlight the need for a multifaceted approach to anemia prevention and control, which should consider the specific causes of anemia in each country. Variations in the causes of anaemia can be linked to differences in environmental factors across different regions. The environmental factors that contribute to anaemia often occur in clusters, with certain areas having more cases of anaemia than others. For instance, there is a strong relationship between altitude and temperature and the prevalence of malaria, a major contributor to anaemia [6-9]. Understanding the geographical variation in the prevalence of anaemia and its underlying causes is essential for directing health resources to effectively prevent and control the disease [10]. By accounting for this geographical heterogeneity, we can ensure that interventions are targeted to the areas that need them the most.

Many studies have found that the distribution of anaemia cases follows a pattern of geographical clustering hence Geostatistical models are well-suited for analyzing spatial data such as the distribution of anaemia cases, since they account for spatial autocorrelation by incorporating random effects that are specific to each location [11-12]. Health experts have observed that levels of socio-economic development are linked to the prevalence of anaemia in a population [13-18]. In traditional statistical models, the assumption of independent observations can lead to biased estimates and inaccurate conclusions when the data are spatially correlated. Geostatistical models address this issue by incorporating random effects that account for the correlation between nearby locations.

Bayesian models have the advantage of allowing the effects of covariates and spatial clustering to be modeled together, while also providing a way to quantify the uncertainty in the predictions. In addition to its ability to incorporate prior information and its computational efficiency, the Bayesian approach provides the advantage of posterior probability, which allows for more robust estimates of spatially correlated data. This makes the Bayesian Geo-statistical model a preferred method for analyzing spatially correlated data. Previous studies on the prevalence of anemia in Nigeria have focused primarily on individual-level risk factors, with little consideration of the influence of environmental factors.

However, our study aims to have this gap bridged by examining the impact of climatic factors, such as temperature, rainfall, and aridity, on the spatial distribution of anemia in Nigeria. This will enable us unveil areas that are particularly vulnerable to anemia due to climatic and ecological factors. The novelty of this study is the use of a spatial mixed model to investigate the impact of geographic location, individual-level factors as well as heterogenous regional climatic factors on childhood anaemia, taking into account the correlation between regions considered as neighbors. The bivariate spline approach used in this study allows for greater flexibility and improved parameter estimates. As far as we know, previous studies have not evaluated geographical differences in childhood anaemia with respect to the three main factors we considered in this study [4, 13, 16, 19-20].

2. Material and Methods

Source of data for the study

This study used 2018 Demographic and Health Survey data. The Demographic and Health Surveys (DHS) data was obtained by submitting an online proposal to the DHS program website, which was subsequently approved. The data on climate were obtained from DHS special data repository. Anaemia status of a child has a dichotomous outcome taking 1 for an anemic child and 0 for a child who is not anaemic. The independent variables consist of a variety of covariates, both categorical and metrical. The categorical covariates include demographic factors (such as the child's parent's area of residence) and socioeconomic factors (such as wealth index, mother's education level, and child's sex). The climatic factors which include average cluster temperature, rainfall and altitude. The metrical covariates include the age of the child, the age of the mother and the mother's Body Mass Index. The spatial covariates include the 36 states of Nigeria and the Federal Capital Territory (FCT). Data cleaning and descriptive analysis were performed using R software, while Bayesian analysis was conducted using BayesX (version 2.1).

Model specification

Let the disease status of a child i in state j be denoted as $Y_{ij,}\ j = 1,2,\ ..\ 37,\ i = 1,2\ ...,n_{j.}$ n_j gives the number of children in state j. Anaemia has dichotomous response as a child is either anaemic with outcome 1, or not anaemic with outcome 0 as represented below

$$Y_{ij} = \begin{cases} 1 & \textit{if a child in state i is anemic} \\ 0 & \textit{if a child in state i is not anemic} \end{cases} \tag{1}$$

The outcome variable $Y_{ij,}$ is assumed in this study to follow a Bernoulli distribution given as $Y_{ij,}|p_{ij} \sim Bernoulli(p_{ij}).\ E(Y_{ij}) = p_{ij}$ is the unknown mean.

$$\text{Model 1:}\quad logit(p_{ij}) = log\left(\frac{p(Y_{ij} = 1|X)}{1-p(Y_{ij} = 1|X)}\right)$$

$$= X_i^T\omega \tag{2}$$

$$\text{Model 2:}\quad logit(p_{ij}) = log\left(\frac{p(Y_{ij} = 1|X,Z)}{1-p(Y_{ij} = 1|X,Z)}\right)$$

$$= X_i^T\omega + f_1(z_{1i}) + f_2(z_{2i}) + \ldots + f_p(z_{pi}) \tag{3}$$

$$\text{Model 3:}\quad logit(p_{ij}) = log\left(\frac{p(Y_{ij} = 1|X,v_j,u_j)}{1-p(Y_{ij} = 1|X,v_j,u_j)}\right)$$

$$= X_i^T\omega + v_j + u_j \tag{4}$$

$$\text{Model 4:}\quad logit(p_{ij}) = log\left(\frac{p(Y_{ij} = 1|X,Z,\ v_j,u_j)}{1-p(Y_{ij} = 1|X,Z,v_j,u_j)}\right)$$

$$= X_i^T\omega + f_2(z_{2i}) + \ldots + f_p(z_{pi}) + v_j + u_j \tag{5}$$

$$i = 1,2,\ \ldots,n_j,\qquad j = 1,2,\ ..\ 37$$

In model 1, all categorical variables (child sex, mothers highest educational level, wealth index of parent, smoking status, child slept under mosquito bed net) are considered as fixed effects.

In model 2, all categorical variables are considered as fixed effects while continuous variables (child's age, mothers age, and mothers BMI) are modelled by smooth function.

In model 3; both the region-specific random effect (unstructured random effects) and spatial random affects (structured random effects) are included in model 1 in what is known as convolution model.

In model 4; also, both the region-specific random effect (unstructured random effects) and spatial random affects (structured random effects) are included in model 2 in what is known as convolution model.

In model 1 – 4, X^T is p-dimentional vector of covariates with ω as the associated vector of regression coefficient. v_j which denotes the non- spatial or unstructured random effects are modelled using the normal distribution priors with mean 0, and variance 1. The u_j is the spatial random effects or structured random effects. u_j accounts for the spatial autocorrelation that occurs when regions that are close together are more similar to each other than regions that are further apart. z_j is the vector of continuous variables which will be modelled by a smooth function, f_j approximated by a Bayesian polynomial spline of degree l at equally spaced knots [21, 22] given within the domain of the z_j covariates as

$$z_j^{min} = \xi_{j0} + \xi_{j1} + \ . \ . \ . \ \xi_{js} = z_j^{max} \tag{6}$$

We express the Bayesian spline as a linear combination of $d = s + l$ basis function B_m given as

$$f_j(z_j) = \sum_{m=1}^{d} \varepsilon_{jm} B_m(z_j) \tag{7}$$

the spatial effect u_j is modeled by Markov Gaussian field or conditional Gaussian autoregressive model prior [23]. given u_{-j} as random effect vector excluding the jth region, then the spatial effects prior u_j given all other effects is expressed as:

$$u_j | u_{-j} \sim N\left(\frac{1}{m_i} \sum_{-j\sim j} u_{-i}, \frac{\sigma_u^2}{m_i}\right) \tag{8}$$

m_i is the number of neighbors of region i, σ_u^2 is the variance parameter of the random effects, and inverse gamma hyper-prior is assumed for the normal prior variance.

The posterior distribution is proportional to the product of the likelihood and priors and as given below.

$$p(\omega, u, v, \varepsilon, \sigma_\omega^2,\ \sigma_u^2, \sigma_v^2 | Y) \propto p(Y |\ \omega, u, v, \varepsilon). p(\omega|\sigma_\omega^2). p(u|\sigma_u^2). p(v|\sigma_v^2). p(\varepsilon). p(\sigma_\omega^2). p(\sigma_u^2). p(\sigma_v^2) \tag{9}$$

Breaking down equation (9)

The likelihood is given by:

$$p(\omega, u, v, \varepsilon) = \prod_{ij} \left({p_{ij}}^{Y_{ij}} (1 - p_{ij})^{1-Y_{ij}} \right) \tag{10}$$

With:

$$logit(p_{ij}) = X_i^T \omega + f_2(z_{2i}) + . . . + f_p(z_{pi}) + v_j + u_j \tag{11}$$

And priors

$$\omega \sim \exp\left(-\frac{1}{2}\sigma_\omega^2 \omega^T \omega\right)\ u_j \sim \exp\left(-\frac{1}{2}\sigma_u^2 u^T u Q\right);\ v \sim \exp\left(-\frac{1}{2}\sigma_v^2 v^T v\right) \tag{12}$$

the precision matrix Q defines the spatial structure and the hyper-priors on the variance components $\sigma_\omega^2, \sigma_u^2,\ \sigma_v^2$ are modelled as $p(\sigma_\omega^2),\ p(\sigma_u^2), p(\sigma_v^2)$ ~Inverse Gamma. Distribution.

The model parameters were estimated using fully integrated Bayesian procedures which use techniques of Markov Chain Monte-Carlo (MCMC). The estimated posterior odd ratio is interpreted in terms of the odd ratio obtained from the logistic regression. Model comparison was done using the Deviance information criterion as established by [23].

$$DIC = \overline{D} + \rho D \tag{13}$$

The model posterior mean deviance is denoted by $\overline{D}$ while ρD establish the effective number of parameters in the model. According to [24], the better model is the one with the least value of DIC.

3. Results and Discussion

The children with complete information of covariates were used for the study. This study involves 11284 children.

Table 1: Variable description and Pearson Chi-square test

Covariates	Total (% anaemic)	Pearson Chi-square (P-value)
Sex		
Male	5718 (58.8)	0.05(0.48)
Female	3311(59.5)	
Residence		
Urban	4374 (54.3)	68.4(0.00)
Rural	6910 (62.2)	
Working Status		
No	3421 (62.4)	21.5 (0.00)
Yes	7863 (57.7)	
Geopolitical Zone		
North Central	1966(56.4)	
North East	2028 (60.8)	
North West	2712 (59.6)	87.6 (0.00)
South East	1649 (66.3)	
South South	1264 (60.9)	
South West	1635 (51.3)	
Smoking Status		
Yes	26 (50.0)	0.904 (0.225)
No	11258 (59.2)	
Highest Educational Level		
No education	4285 (63.9)	
Primary education	1899 (59.3)	104.96 (0.00)
Secondary education	4057 (57.1)	
Tertiary education	1043 (47.6)	
Wealth index		
Poorest	2245 (66.3)	
Poor	2246 (61.8)	
Rich	2504 (60.5)	160.77 (0.00)
Richer	2384 (57.6)	
Richest	1905 (47.8)	

Table 1 shows that 58.8% and 59.5% of male and female children respectively who participated in the survey were anaemic. Classification by the residence of a child's parent reveals that 54.3% and 62.3% of children whose parent reside in urban and rural areas respectively are also positive to anaemia. Working status analysis shows that 62.4% of children whose parents are not working are anaemia while 57.7% of children with working parents are also anaemic. Classification by geopolitical zone reveals that South East with a total of 1649 recorded the highest percentage of anaemic children considering the population of anemic children within each zone. Analysis of smoking status of parents shows that out of 26 parents who are smoker, half of their children are positive to anaemia while 59.2% of children whose parents are not smokers are also anaemic. Classification by highest level of education attained by mothers shows that 63.9%, 59.3%, 57.1% and 47.6% of children whose mothers have no qualification, primary, secondary and higher education respectively are tested positive to anaemia. Wealth index analysis also show that the percentage of anaemic children decreases with increasing social status of the parents as 63.3% of children from poorest parents are anaemic while only 47.8% of parents whose parents are in excellent socio-economic standing are anaemic. According to the p-value of the bivariate Ch-square test, sex of a child and mothers smoking status are not significant determinant of childhood anaemia in Nigeria.

Table 2: Defiance Information Criterion for Model Selection

Models	defiance (ρ)	ρD	DIC
I	14961.251	15.119367	14991.49
II	15093.298	15.551321	15124.401
III	14704.851	44.002882	14792.857
IV	14621.121	44.069333	14709.26

Selection of best fitted models

Deviance Information Criterion (DIC) is often used in choosing the best fitted among the models considered. As shown in Table 2, model IV which contains both structured and unstructured random effects otherwise known as convolution model is considered as the best fitted model as it has the least value of DIC.

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

COVARITES	est ω	odds ratio $Exp(\omega)$	95% $CI\ for\ Exp(\omega)$ Lower	Upper
Residence				
Rural	1	1		
Urban	0.163	1.177	1.053	1.305
Sex				
Male	1	1		
Female	0.0163	1.016	0.939	1.101
Smoking Cigarette				
No	1	1		
Yes	-0.314	0.731	0.313	1.704
Wealth Index				
Poorest	1	1		
Poorer	-0.078	0.925	0.812	1.055
Middle	-0.125	0.882	0.767	1.009
Richer	-0.257	0.773	0.664	0.898
Richest	-0.585	0.557	0.467	0.668
Highest education				
No education	1	1		
Primary	-0.203	0.816	0.713	0.925
Secondary	-0.215	0.807	0.713	0.913
Higher	-0.369	0.691	0.578	0.824
Temperature	0.299	1.349	1.273	1.428
Aridity	0.61	1.841	0.981	1.036
Rainfall	-3.589e-07	0.996	1.0007	1.00087
Malaria Prevalence	1.126	3.083	2.726	10.206

Fixed effects Analysis

Coefficients of fixed effects are contained in Table 3. The covariates that are significant to childhood anaemia are place of residents, wealth index, educational attainment, and temperature. Considering the place of residence, a child whose mother is in urban area has a lower likelihood of being anaemic compared to the rural counterpart, 1.177(1.053, 1.305). The odd value of 1.016 and the credible interval of (0.939, 1.101) reveals that female children have a higher chance of contracting anaemia but the sex of a child is not a significant determinant of anaemia. A child from a cigarette smoking mother has a higher odd of testing positive to anaemia, though the credible interval shows smoking cigarette as a covariate is also not a significant risk factors of anaemia 0.731(0.313, 1.704). regarding the economic status of a child's parent, the child from a poorer and middle parents have lesser odd of being anemic compared to a child from the poorest parent. Although, the wealth status index at this level is not significant 0.925(0.812, 1.055), 0.882(0.767, 1.009). A child from the richer and richest parents also has highly reduced odd of testing positive to anaemia with their respective odd ratios and credible intervals as 0.773(0.664, 0.898), 0.557(0.467, 0.668). Level of education of a child's parent is also discovered to have significant effects as a risk factor of anaemia. Children from parents with primary education, secondary and higher education have reduced odds of testing positive to anaemia infection with their respective odd ratios and credible interval as 0.816(0.713, 0.925), 0.807(0.713, 0.824), 0.691(0.578, 0.824). climatic factor such as temperature is also identified as a significant risk factor of childhood anaemia. A child from a region with high temperature has a reduced odd of being anaemic with odd ratios and credible interval as 1.349(1.273, 1.428). However, other climatic factors considered such as Aridity and Rainfall are not significant factors of childhood anaemia infection. Children from region with high malaria prevalence are also identified to have an increased chance of being infected with anaemia given the odd ratio and credible interval as 3.083(2.726, 10.206).

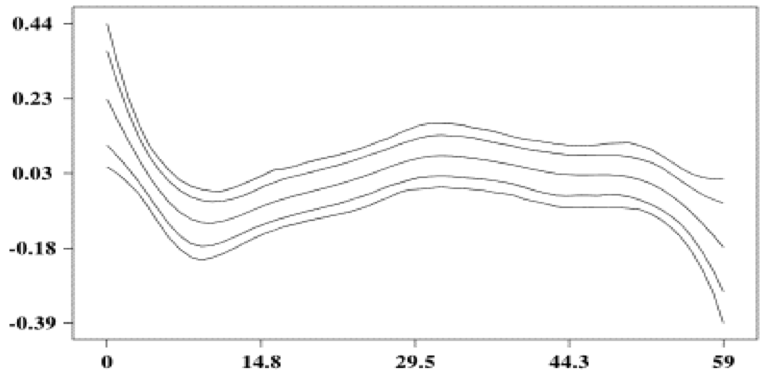

Figure I: Nonlinear Effect of Child's age on Anaemia Status

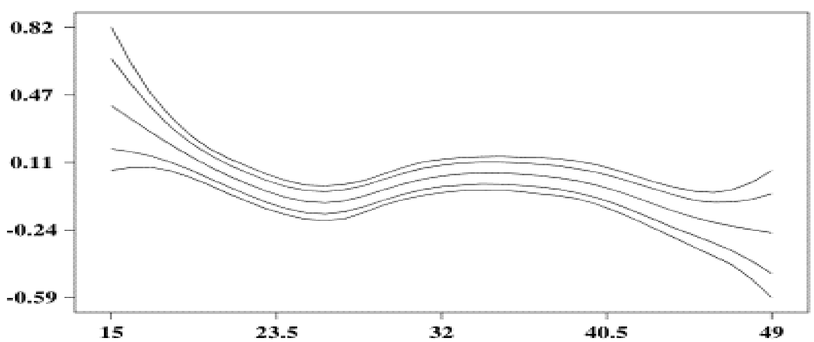

Figure II: nonlinear effects of mother's age on a child anaemia status

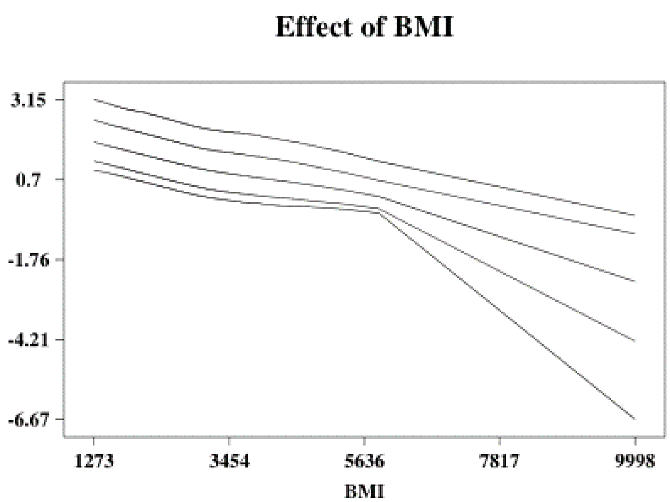

Figure III: Nonlinear Effect of Mother's body Mass Index on a child Anaemia Status

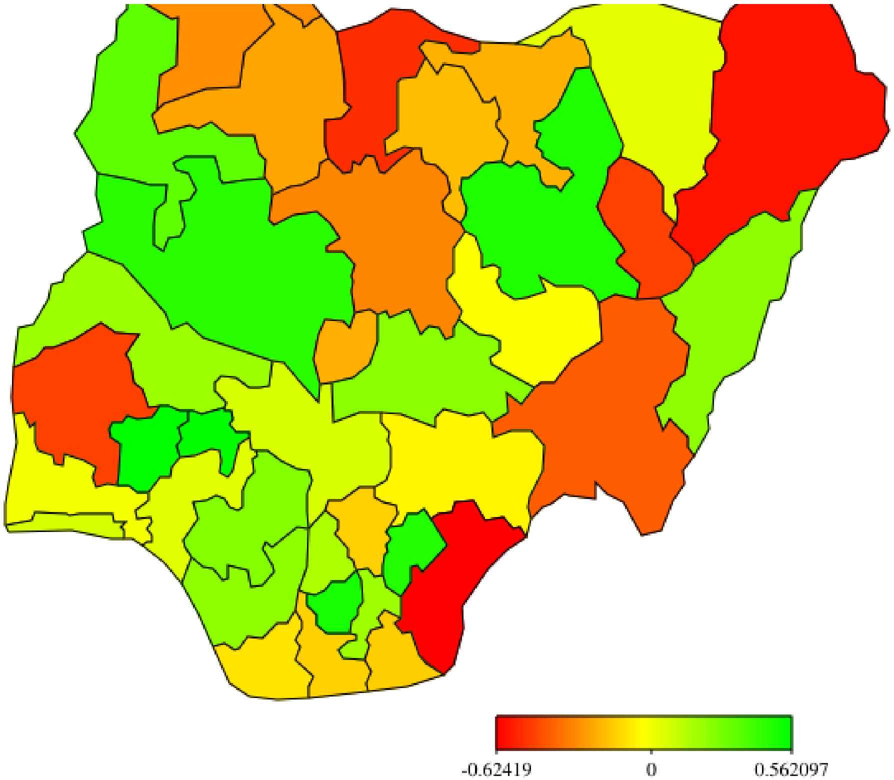

Figure IV: Nigeria's map showing posterior mean spatial effects

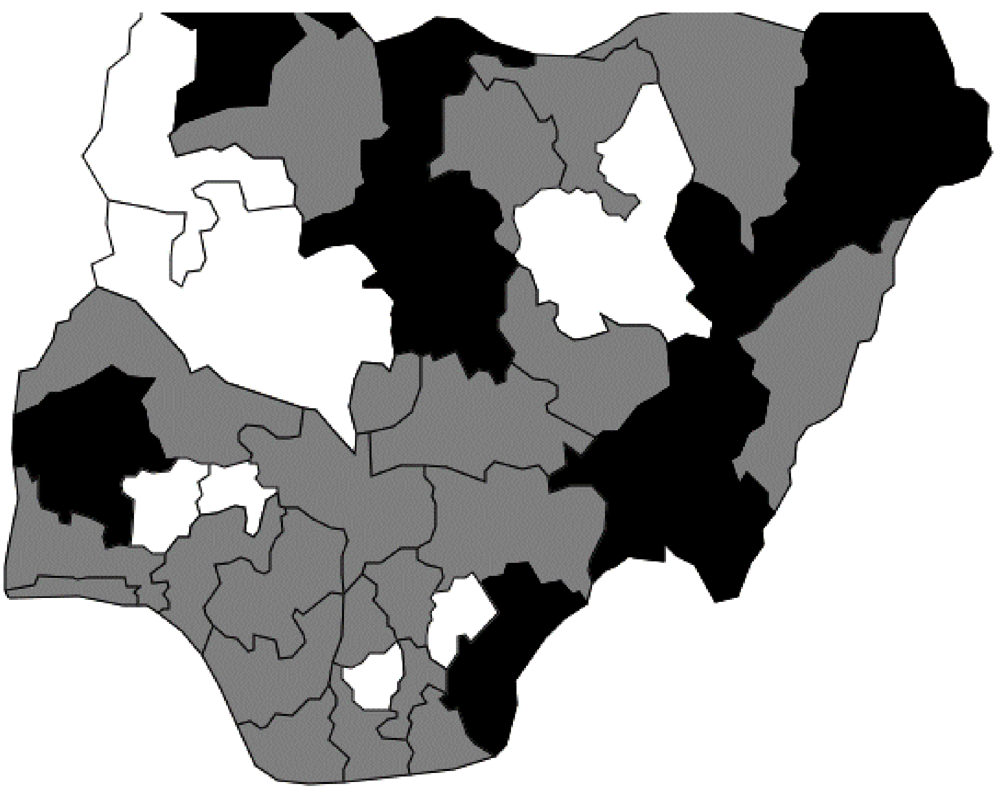

Figure V: Nigeria's map showing 95% posterior credible interval

Effects of non linear covariates

Geo-additive modelling provides a flexible means of including continuous covariates which has non-linear relationship with the response variable. The mother's body mass index (BMI), the child's age, and the mother's age are the continuous covariates that were included in this study and are thought to have nonlinear effects. As revealed in Figure I, a child's early-life anemia risk is very high. When the children reach the age of ten years old, it diminishes. The risk considerably reduces when the child age is above 40 months old. Figure II shows that the risk of childhood anaemia is high among mothers within the age of 15 years to 20 years of age. The risk declines steadily from the age of 21 years to 25 years. The risk continues to increase from the age of 30 years to 40 years and finally declines from the ages of 40 years. Also, the BMI of a mother has inverse relationship with childhood anaemia status. As shown in Figure III, the risk of a child anaemia reduces as the mother's body mass increases. The risk of childhood anaemia has a noticeable sharp decline as the BMI of mothers reaches 5676g.

Spatial effects

Map of Figure IV and V display the residual spatial effects and the 95% posterior credible interval. In Figure V, white shows states with high anaemia risk, black shows state with negative or very low anaemia risk while grey shows states with indifferent risks. Spatial effects include unobserved effects like environmental conditions, accessibility of good transportation, and availability of child health care. As shown in Figures IV and V, most states show notable positive or negative impacts given by the map of 95% posterior credible interval. This demonstrates quite well the existing spatial effects of childhood anemia in Nigeria. Additionally, the majority of states in the northeast and southwest have very low risk of being tested positive to anaemia.

Discussion of Findings

Geo-additive logistic modelling approach was utilized in this study to examine the spatial heterogeneity of anaemia and its relationship among under-five children and various important risk factors. Under the additiviness assumption, the geo-additive model accounted for non-linear covariate effects and enables the mapping of residual geographical effects to childhood anemia. The subtle implications of metrical continuous covariates that were not visible when modeled linearly were discovered by nonlinear modeling. It is a matter of conjecture to identify the unobserved factors that may be responsible for the observed geographical heterogeneity that are not captured by the covariates in the models. The mother's home location, the wealthiest family's category of wealth, and meteorological factors like temperature are the fixed effects factors of childhood anemia that are relevant in this study. It has been discovered that the age of a child has a nonlinear influence, compared to older children, younger children are more likely to suffer from childhood anemia. This could be explained by the fact that the first year of life is a time of high iron demand due to accelerated physical growth, and that mothers and guardians may find it challenging to ensure enough consumption of iron after the sixth month of life, when stored iron is exhausted and iron demands must be fulfilled by feeding. Children belonging to the wealthier segments of the family have a significantly lower likelihood of being anemic. One possible explanation for this could be that the family can afford healthy food. Temperature is one climatic component that significantly affects childhood anemia. The amount of rainfall and aridity were shown to be non-significant climatic elements that have an impact on childhood anemia.

4. Conclusion

This study underscores significant geographical heterogeneity in childhood anemia prevalence across Nigeria, with hotspots in Sokoto, Niger, Osun, Bauchi, Imo, and Ebonyi states. By employing Bayesian geo-additive modeling approach, key determinants of childhood anaemia were identified, including maternal education, household wealth, child's age, and temperature. These findings highlight the need for targeted, region-specific interventions focusing on socioeconomic improvements and maternal health. Addressing unmeasured community-level factors and exploring other environmental determinants remain essential for future research to provide a more comprehensive understanding of anemia dynamics in Nigeria.

Acknowledgements

We sincerely thank the Demographic and Health Survey for providing access to the data used in this research upon request. We are also grateful to the reviewers for their insightful observations.

Funding

This research received no funding.

Conflict of Interest Statement

The authors declare that there are no competing interests during the preparation of this manuscript.

Authors' Contributions

All authors contributed to the research, participated in the interpretation of results, and approved the final version of the manuscript.

References

1. Kinyoki, D., Zimmerman, A. E., Bhattacharjee, N. V., Kassebaum, N. J. & Hay, (2021). Anemia prevalence in women of reproductive age in low-and middle-income countries between 2000 and 2018. *Journal of Nature Medicine,* 27, 1761–1782.
2. World Health Organization. The global prevalence of anaemia in 2011; 2015. Available from:https://www.who.int/data/gho/data/themes/topics/anaemia_in_women_and_children [Google Scholar]
3. Yang F, Liu X, Zha P. (2018). Trends in socioeconomic inequalities and prevalence of anaemia among children and non-pregnant women in low-and middle-income countries *JAMA Network* 1:e182899. [PMC free article] [PubMed] [Google Scholar]

4. Bilal S.E, Geert-Jan D., Seifu H. G. & Mark S. (2022). Risk factors of anemia among preschool children in Ethiopia: a Bayesian geo-statistical model. *BMC Nutrition, 8:2*, https://doi.org/10.1186/s40795-021-00495-3
5. World Health Organisation (2024). Anaemia in Women and Children. Accessed on Wednesday, 8th May, 2024 from https://www.who.int/data/gho/data/themes/topics/anaemia_in_women_and_children
6. Abbas A. (2017). Geostatistical models of malaria and associated morbidity among preschool-aged children in Nigeria. Ph.D Thesis, Swiss Tropical and Public Health Institute (Swiss TPH), Swizerland.
7. Hailu A.A (2016). Ethiopian National Micro Nutrient survey report. Ethiopian Public Health Institute: https://www.researchgate.net/publication/316285242
8. Ibrahim A., Adeyemi R. A., Usman A., Nasiru U. A. (2024). Spatially Weighted Multinomial Modelling of Comorbidity of Anaemia and Malaria Among Under Five Children in Nigeria, *Qeios,* DOI:10.32388/MBSNRX.2
9. Petry N, Olofin I, Hurrell RF, Boy E, Wirth JP, Moursi M, (2016). The proportion of anemia associated with iron deficiency in low, medium, and high human development index countries: a systematic analysis of national surveys. Nutrient.8(11):693.
10. Holendro S. C., Strong, P. M. and Pralip Kumar Narzary (2021). Childhood Anemia in India: an application of a Bayesian geo-additive model. *BMC Pediatrics, 21:529 (2021). https://doi.org/10.1186/s12887-02103008- 0*
11. Kazembe L.N., Namangale J.J. (2007). A Bayesian multinomial model to analyse spatial patterns of childhood co-morbidity in Malawi. *European Journal of Epidemiology,* 22:545–56.
12. Kibret K.T., Chojenta C, D., Arcy E., Loxton D. (2019). Spatial distribution and determinant factors of anaemia among women of reproductive age in Ethiopia: a multilevel and spatial analysis. British Medical Journal; 9(4):e027276.
13. Ejigu B.A., Wencheko E., Berhane K. (2018). Spatial pattern and determinants of anaemia in Ethiopia. *PLoS One.* 13(5):e0197171
14. Habyarimana F, Zewotir T, Ramroop S. (2018).Spatial distribution and analysis of risk factors associated with Anemia among women of reproductive age: case of 2014 Rwanda Demographic and health survey data. *Open Public Health Journal,*. 11(1)
15. Habyarimana F, Zewotir T, Ramroop S. (2017). Structured additive quantile regression for assessing the determinants of childhood anemia in Rwanda. *International Journal of Environmental Reserarch and Public Health*; **14**(6): 652.
16. Gayawan, E., Ekundayo, D. A. and Samson, B. A. (2014). Bayesian multinomial modeling of spatial pattern of co-morbidity of malaria and non-malarial febrile illness among young children in Nigeria. *Transactions of the Royal Society of Tropical Medicine & Hygiene*, 108: 415–424
17. Magalhães R.J.S., Clements A.C. Spatial heterogeneity of haemoglobin concentration in preschool-age children in sub-Saharan Africa. *Bull World Health Organ*. 2011;89:459–68.
18. Rutstein S.O., Rojas J. (2006). Guide to DHS statistics: Demographic Healthy Survey Methodology. Measure DHS/ICF International. Accessed on 10th April, 2024 from http://www.measuredhs.com.
19. Adebayo S. B, Gayawan E., Heumann C., Seiler C. (2016.) Joint modeling of Anaemia and Malaria in children under five in Nigeria. *Spatial Spatiotemporal Epidemiology*, 17, 105-115.
20. Bolaji S. A., Oyepeju M. O. & Kofi A. N. (2021). Prevalence and correlates of anaemia among children aged 6 to 59 months in Nigeria. *World Nutrition; 12(3):58-74.*
21. Fahrmeir L, Kneib T, Lang S. (2004 Penalized structured additive regression for space-time data:a Bayesian perspective. *Stat Sin*.;14:731–61 Available from: http:// www3. stat. sinica.edu. tw/ stati stica/ oldpdf/ A14n36. pdf.
22. Lang S, Brezger A. (2004). Bayesian P-splines. *J Comput Graph Stat*;13(1):183–212. Available from: http://www.tandfonline.com/doi/abs/https:// doi. org/ 10. 1198/ 10618 60043 010.
23. Besag, J., York, J., Mollié, A (1991). Bayesian image restoration, with two applications in spatial statistics. *Ann. Inst. Stat. Math*. 1991, 43, 1–20.
24. Spiegelhalter D.J., Best N.G., Carlin, B.P. & van-der L. A. (2002). Bayesian measures of model complexity and fit (with discussion). *Journal of the Statistical Royal Society, 64*, 583– 639.