Weighted Random Effects Multinomial Model with Application to Anaemia and Malnutrition Comorbidity Among Under Five Children in Nigeria.

ABSTRACT

Anemia and malnutrition continue to be major health issues in Sub-Saharan Africa, particularly in Nigeria, where they are significant contributors to mortality and morbidity rates among young children. This study aims to develop multinomial models with weighted random effects in order to better understand the spatial pattern and risk factors associated with anemia and malnutrition, as well as their co-occurrence, among children under the age of five in Nigeria. A Bayesian hierarchical multinomial model with weighted random effects and adjusted Intrinsic Conditional Autoregressive (ICAR) prior for the random effects, was used to account for the comorbid patterns of anemia and malnutrition among young children in Nigeria, utilizing data from the 2018 Demographic and Health Survey. The structured random effects were weighted to reflect state-level variation in precipitation, a climatic factor considered to influence child health outcomes. The results of fixed effects indicated that area of residence, maternal education level, and household wealth status were significant predictors of anemia and malnutrition co-occurrence. The generated map revealed that the north eastern region of the country, where average precipitation is low, was at an increased risk of co-morbidity of anemia and malnutrition. The results suggest the need to mitigate the effects of low precipitation on child health outcome. public health campaigns should focus on empowering mothers with knowledge about child nutrition, hygiene, and disease prevention and Health authorities should consider programs that provide financial or nutritional support to low-income households, such as food subsidies or free healthcare services.

Key words: Anemia, malnutrition, weighted random effects, multinomial model, precipitation, risk factors.

1. INTRODUCTION

Anemia is a serious global public health issue that disproportionately affect young children, particularly those under the age of five and pregnant women. According to the WHO, 40% of children aged 6-59 months and 37% of pregnant women worldwide are affected by anemia (WHO, 2019). These populations are especially vulnerable to the consequences of this condition.

the prevalence of childhood anemia is highest in sub-Saharan Africa, where it affects approximately 67% of children, followed closely by South East Asia, with a prevalence of 65.5%, indicating a significant burden on public health in these regions (Roberts and Zewotir, 2019). Nigeria is unfortunately at the forefront of a significant public health problem, with anemia affecting a large proportion of its population (Bolaji *et. al* 2021, Adebayo et. al 2016). According to the World Health Organization, over 40% of the population suffers from anemia (NPC and ICF, 2019). This staggering figure is further reflected in the alarming rates of anemia among specific groups: 71% among children under the age of 5, 47.3% among non-pregnant women aged 15 to 49, and 57.5% among pregnant women (Esteban 2021). A 2018 Nigeria Demographic Health Survey revealed that anemia among children between the ages of 6 and 59 months was also alarmingly high in the country. Nearly 70% of these children were affected, with mild anemia impacting 27%, moderate anemia affecting 38%, and severe anemia afflicting 3% (NDHS, 2018). The World Health Organization deems any prevalence of anemia above 40% among this age group to be a severe public health problem, emphasizing the critical need for interventions to address this issue (WHO,2022). The geographical variation in the prevalence and etiology of anemia is partially explained by environmental factors that vary across different regions. These environmental factors, such as temperature, as altitude, land surface temperature, are known to cluster geographically and have been linked to the risk of anemia (Kandala, 2011). For instance, malaria, which is a well-known cause of anemia, is more prevalent in regions with specific environmental conditions. Similarly, dietary iron deficiency and anemia-causing helminthic infections are also influenced by environmental factors, which in turn affects the prevalence of anemia in different regions (Adebayo, 2016). Also, in sub-Saharan Africa, childhood malnutrition continues to pose a significant challenge to public health. Malnutrition in children is a significant risk factor for illness, as it weakens the immune system and makes children more vulnerable to diseases. This situation presents a significant challenge for healthcare systems, as it exacerbates the health problems that children in the region already face, such as infectious diseases and poor access to healthcare services (Osafu, 2021). Based on the children's weight, height, and age indices, malnutrition in children is categorized as stunting, wasting, and underweight. Children are considered stunted if their height-for-age z-score (HAZ) is less than negative two standard deviations (−2SD) from the median of the World Health Organization's (WHO) Child Growth Standards (WCGSM). Weight-for-age z-scores (WAZ) less than −2SD from the reference median indicate underweight, while weight-for-height z-scores (WHZ) less than −2SD from the reference median indicate wasting (UNICEF 2019, Gayawan *et. al*, 2019).

Malnutrition and anemia are related conditions that have a major effect on children's growth, development, and general health, especially in developing countries (Adeyemi *et al.,* 2019). Anemia and malnutrition work in tandem because they both make the other worse. Iron, vitamin B12, and folate deficiencies are caused by malnutrition and are necessary for the synthesis of red blood cells. As a result, anemia may result. In a similar vein, anemia, especially iron-deficiency anemia, can exacerbate malnutrition by affecting the metabolism and absorption of nutrients. Furthermore, the joint impact of both disorders on immunological response and physical and mental growth is more detrimental than either illness alone. A more comprehensive knowledge of the intricate relationships between anemia and malnutrition is possible when these two disorders are studied together. It makes it possible to find risk factors and common predictors, which can enhance the creation of focused solutions. For example, since it targets the interrelated pathways that sustain this dual burden, treating both illnesses concurrently in intervention programs may be more effective than treating them separately. A useful technique for identifying regions with high disease burden is the visualization of the spatial distribution of anemia and malnutrition in disease risk maps. By mapping these health outcomes, we can identify hotspots and geographic clusters where they are prevalent. This visualization helps to reveal patterns that may be linked to environmental, socioeconomic, climatic and healthcare access factors unique to specific regions.

For decades, a variety of studies have been conducted to gain a better understanding of the spatial distribution of anaemia and malnutrition among children under the age of five in regions of sub-Saharan Africa where the condition is very prevalent (Chuang *et al* 2019; Petry *et al* 2016; Kinyoki *et al* 2016; Takele *et al* 2020; Kinyoki *et al* 2018; Fagbohungbe *et al* 2020 and Aminu *et al.,* 2024). In order to assess the combined spatial distributions of anemia and malnutrition among children in Mozambique and Burkina Faso, Adeyemi *et al*. (2019) used a generalized model and discovered evidence of the co-occurrence of malnutrition and anemia.

In order to ascertain the spatial patterns of undernutrition quantiles among Nigerian children under five, Gayawan *et al.* (2019) employed Bayesian quantile regression. In order to measure the impact of Carbon (IV) Oxide concentration on undernutrition among children under five in Nigeria, Osafu *et al.* (2021) employed a generalized linear mixed model. Their research revealed a strong relationship between increased CO2 concentration and a higher incidence of undernutrition in Nigeria.

Using data from the 2010 Malawi demographic healthy survey, Ngwira and Kezembe (2015) implemented a Bayesian random effect model for child anemia, with district serving as a spatial effect. A binary logistic model was fitted to account for the two types of outcomes: anemia (Hb < 11) and no anemia (Hb ≥ 11). Based on their results, it was recommended that pediatric anemia control techniques be customized to the local environment, taking into account the unique causes and prevalence of anemia.

Bilal *et al.* (2022) used a Bayesian Geostatistical technique to examine the anemia risk factors in Ethiopian preschoolers. The risk factors for anemia that were found were increased fertility, childhood malnutrition, maternal anemia, and low socioeconomic status. In the Namutumba district of Uganda, Kuziga *et al.* (2017) investigated the prevalence of childhood anemia and the contributing factors. After conducting a household survey in 376 randomly chosen households, the researchers discovered that the prevalence of anemia was high (58.8%), with males (61.3%) and children between the ages of 12 and 23 months (68.5%) having the highest rates. The necessity of funding initiatives to prevent anemia was underlined in light of their research findings. Most of the past studies on anemia and malnutrition among young children in Nigeria focused on the risk factors and spatial distribution of these health conditions on individual basis (Ngwira and Kazembe 2016; Ozoka 2018; Yang *et al*. 2018; Kandala *et al*. 2009; Khan and Mohanty 2018 and Gayawan *et al.* 2016). But these diseases exhibit comorbidity as they epidemiologically overlap. Also, the influence of variation in precipitation in the risk of anemia and malnutrition comorbidity have not been previously studied to the best of our knowledge. Regional precipitation affects child health outcome, weighting the spatial structured random effects with the average cluster precipitation of each state will further enhance the model and gives us insight about how the responses vary according to variation in precipitation across the geographical locations.

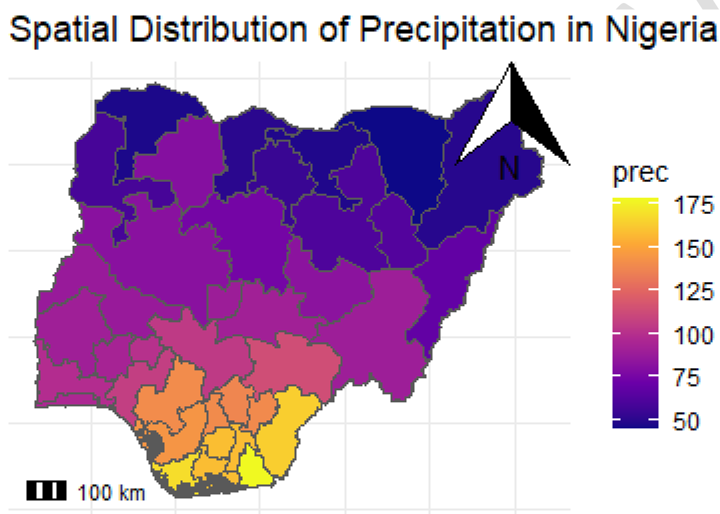


Fig. I: State average spatial distribution of precipitation in Nigeria

The developed weighted model will be compared with unweighted model incorporating only structured spatial effects, unstructured spatial effects or both in order to determine how the model better capture the association between the response variables and the risk factors.

2. METHODS

The data used for this study are sourced from the 2018 Nigeria Demographic and Health Survey. The climate variable data was obtained from the DHS spatial data repository. We used the results of anaemia and malnutrition status of children below the age of five years. A child is considered anaemic if the result of anemia test shows mild, moderate or serious anaemia status. Precisely, a child is positive to anemia if the hemoglobin (Hb) level is less than 11g/dl after adjustment for altitude is made. A child is malnourished if the result shows stunting, wasting or underweight status. Each anaemia and malnutrition have binary status. The covariates (independent variables or risk factors) examined in this study are child's gender, child's age in months and mother's age in years, area of residence, mother's economic status measured in terms of wealth index, state of residence and average cluster precipitation of each state. Formulated models will be compared using the Deviance Information Criterion (DIC). The model with least value of DIC is consider the best fit (Spiegelhalter, 2002). ICAR prior will be used for structure random effects of the unweighted model while the weighted structure random effect will be assigned the adjusted ICAR prior.

2.1 Formulation of spatially weighted multinomial model

Let Y_j be a vector of categorical response variable capable of taking any of k categories: $\{1, 2, \ . \ . \ . k\}$. A vector of predictor variables $X_j = (x_{j1}, x_{j2}, \ . \ . \ . \ x_{jp})^T$ is defined for each jth observation. The probability that the jth observation belongs to category r is given as

$$p_{jr} = P\left(Y_j = r \middle| X_j\right) \tag{1}$$

a linear predictor $\tilde{\eta}_{jr}$ is defined for each category r as

$$\tilde{\eta}_{jr} = X^T \zeta_r \tag{2}$$

The relationship between the linear predictors and the probabilities is specified by the multinomial model as

$$p_{jr} = \frac{\exp(\tilde{\eta}_{jr})}{(\sum_{s=1}^{k} \exp(\tilde{\eta}_{is})} \tag{3}$$

Given c as the reference category $\exp(\tilde{\eta}_{jc}) = 1$, the probabilities of an observation belonging to r category relative to reference category are

$$p_{jr} = \frac{\exp(\tilde{\eta}_{jr})}{1 + (\sum_{s=1}^{k-1} \exp(\tilde{\eta}_{is})} \tag{4}$$

$$p_{jc} = \frac{1}{1 + (\sum_{s=1}^{k-1} \exp(\tilde{\eta}_{is})} \tag{5}$$

The log-odds ratio for category r relative to the reference category c is:

$$\log\left(\frac{p_{jr}}{p_{ic}}\right) = \tilde{\eta}_{jr} \tag{6}$$

$$\log\left(\frac{p_{jr}}{p_{ic}}\right) = X^T \zeta_r \tag{7}$$

With all the categories combined, the multinomial model can be expressed for $r = 1, \ 2, \ . \ . \ . \ k-1$, and for c category respectively as

$$p_{jr} = \frac{\exp(X^T \zeta_r \ )}{1 + (\sum_{s=1}^{k-1} \exp(X^T \zeta_s \ )} \tag{8}$$

$$p_{jc} = \frac{1}{1 + (\sum_{s=1}^{k-1} exp(X^T \zeta_s \ )} \tag{9}$$

Incorporating the linear predictor $\tilde{\eta}_{ijr} = X^T \beta_r + u_{is\_str} + v_{is\_un_{str}}$ which represents the spatial components into (8), we define the spatial multinomial model as:

$$p_{ijr} = \frac{\exp(X^T \zeta_r \ + u_{is\_str} + v_{ir\_un_{str}})}{1 + \left(\sum_{s=1}^{k-1} \exp(X^T \zeta_s \ + u_{is\_str} + v_{is\_un_{str}}\right)} \tag{10}$$

For the reference category

$$p_{ic} = \frac{1}{1 + \left(\sum_{s=1}^{k-1} \exp(X^T \zeta_s \ + u_{is\_str} + v_{is\_un_{str}}\right)} \tag{11}$$

To further extend the spatial multinomial model, we introduce a weighting factor ω_{si} and a coefficient γ. The linear predictor is then modified to include interaction term as given below

$$\tilde{\eta}_{ijr} = X^T\zeta_r + u_{ir\_str} + v_{ir\_un_{str}} + \gamma\omega_{si}u_{ir\_str} \tag{12}$$

Incorporating the weighting factor into (10) we have a spatially weighted multinomial model given below

$$p_{ijr} = \frac{\exp(X^T\zeta_r + u_{ir_{\_str}} + v_{is_{un_{str}}} + \gamma\omega_{si}u_{is\_str})}{1 + \left(\sum_{s=1}^{k-1}\exp(X^T\zeta_s + u_{is_{\_str}} + v_{is\_un_{str}} + \gamma\omega_{si}u_{is_{\_str}}\right)} \tag{13}$$

the reference category is expressed as

$$p_{ijc} = \frac{1}{1 + \left(\sum_{s=1}^{k-1}\exp(X^T\zeta_s + u_{is_{\_str}} + v_{is\_un_{str}} + \gamma\xi_{si}u_{is_{\_str}}\right)} \tag{14}$$

the following flexible models are formulated and incorporated into (8), (10) and (13)

Model 1, $\tilde{\eta}_r = x^T\zeta_r$

Model 2, $\tilde{\eta}_r = x^T\zeta_r + g(z_i)$

Model 3, $\tilde{\eta}_r = x^T\zeta_r + u_{is_{\_str}}$

Model 4, $\tilde{\eta}_r = x^T\zeta_r + g(z_i) + u_{is_{\_str}}$

Model 5, $\tilde{\eta}_r = x^T\zeta_r + g(z_i) + u_{is_{\_str}} + v_{ij_{un_{str}}}$

Model 6, $\tilde{\eta}_r = x^T\zeta_r + g(z_i) + \gamma\xi_{si}u_{is_{\_str}}$

Model 7, $\tilde{\eta}_r = x^T\zeta_r + g(z_i) + \gamma\xi_{si}u_{is_{\_str}} + v_{ij_{un_{str}}}$

(15)

$x^T\zeta_r$ is a vector of categorical covariate effects with its coefficient

$(g(z_i)$ denotes the estimate of the nonlinear smoothing effects of the metrical covariates

u_{ir_str} and $v_{ir\_un_{str}}$ is the structured spatial components and unstructured (spatially uncorrelated) component

$\gamma\xi_{si}u_{is_{\_str}}$ denotes the structured spatial effects with spatially weighting factors $\gamma\xi_{si}$.

$Y_j \sim MN(r,\ \pi),\ j = 1,\ 2,\ .\ .\ .\ n,\ r = 1,\ 2,\ .\ .\ \mathrm{k},\ \ n = 10988.$

A child's sickness status of anemia and malnutrition, designated as Y_j is further divided into four categories as shown below in order to apply a multinomial model to the data.

$$Y_j = r = \begin{cases} 1 & \text{if a child is free from both anemia and malnutrition} \\ 2 & \text{if a child has malnutrition only} \\ 3 & \text{if a child has Anaemia only} \\ 4 & \text{if a child has both anaemia and malnutrition} \end{cases}$$

2.2 Assignment of priors for the spatial components

The unweighted structured spatial effects are assigned ICAR prior as given below

$$u_{si}|u_{s_{-1}} \sim N\left(\frac{1}{n_i}\sum_{si\sim s_{-1}} u_{si}, \frac{\sigma^2}{n_i}\right) \tag{17}$$

The spatially weighted effect is assigned a modified ICAR prior

$$u_{si}|u_{s_{-1}} \sim N\left(\frac{1}{\sum_{i\sim s_{-1}} \xi_{si}}\sum\nolimits_{si\sim s_{-1}} \xi_{si}u_{si}\ ,\ \ \frac{\sigma^2}{\sum_{i\sim s_{-1}} \xi_{si}}\right) \tag{18}$$

The unstructured or uncorrelated component is assigned normal prior as given below

$$v_i \sim N(0,\ \sigma_v^2) \tag{19 }$$

u_{si} is the structured random effects for state i. $u_{s_{-1}}$is the structure random effects for all states except state i

n_i is the number of neigbouring location for state s_i, $\frac{1}{\sum_{i\sim s_{-1}} \xi_{si}}\sum_{si\sim s_{-1}} \xi_{si}u_{si}$ represents the weighted mean of the spatial random effects of the neighbors of s_i,

$\frac{\sigma^2}{\sum_{i\sim s_{-1}} \xi_{si}}$ represents the variance of the spatial random effect for s_i adjusted by the sum of the weights.

For n number of observation, the joint likelihood is given as

$$L(Y|\eta) = \prod\nolimits_{i=1}^{n}\prod_{r=1}^{K}\left(\frac{\exp(X^T\zeta_r\ + u_{is\_str} + v_{is_{unstr}} +\ \gamma\xi_{si}u_{is\_str})}{1 + \left(\sum_{s=1}^{k-1}\exp(X^T\zeta_s + u_{is\_str} + v_{is\_un_{str}} +\ \gamma\xi_{si}u_{is\_str}\right)}\right)^{I(Y_i=K)} \tag{19}$$

The posterior distribution combines the likelihood and the priors using Bayes' theorem:

$$p(\alpha,\ \zeta,\ \gamma,\ v,\ u|Y,X,Z)\ \propto L(Y|\eta)\ .\ P(\alpha)\ .\ P(\zeta)\ .P(\gamma)\ .\ P(u)\ .\ P(v) \tag{20}$$

Where;

$L(Y|\eta)$ is the likelihood$P(\alpha) = \prod_{r=1}^{K} N(\alpha_k|0.\ \sigma_\alpha^2)$, $P(\beta) = \prod_{r=1}^{K} N\left(\zeta_k|0.\ \sigma_\zeta^2 I\right)$, $P(\gamma) = \prod_{r=1}^{K} N\left(\gamma_k|0.\ \sigma_\gamma^2 I\right)$,

$$P(v) = \prod\nolimits_{r=1}^{K} N(v_k|0.\ \sigma_v^2 I)$$

$$P(u) = \prod\nolimits_{i=1}^{n}\prod_{s=}^{S} N\left(\frac{1}{n_i}\sum_{si\sim s_{-1}} u_{si}, \frac{\sigma^2}{n_i}\right),\quad P(\xi_{si})$$

$$= \prod\nolimits_{i=1}^{n}\prod_{s=}^{S} N\left(u_{si}|\frac{1}{\sum_{i\sim s_{-1}} \xi_{si}}\sum\nolimits_{si\sim s_{-1}} w_{si}u_{si}\ ,\ \frac{\sigma^2}{\sum_{i\sim s_{-1}} \zeta_{si}}\right)$$

3. RESULTS AND DISCUSSION

Table 1 shows that out of 10171 children below the age of five considered, 2167 representing 21.3% are free of Anemia or malnutrition, 1007 ((9.9%) suffered from anemia only, 3855 (37.9 %) are malnourished only while 3142 (30.9 %) suffered from both anaemia and malnutrition.

50.6% of the children are male while 40.6 are female. A larger percentage of the children considered (61%) are from rural area. Only 29% of the children's mothers are working. As regards the educational qualification of the mothers, 38% have no formal education, 17 % has primary education, 36 % has secondary education while only 9% has Higher or tertiary education. 73% and 13% of the children experience fever and diarrhea respectively two weeks prior to the survey. Geo-political distribution of the data shows that North West and South South respectively have the highest and lowest number of children who participated in the Survey. 68% of the household own mosquito bed net. Regarding the economic status of the parent, 20%, 20%, 22%, 21% and 17 percent respectively belong to poorest, poorer, middle, richer and riches categories. The table also reveals that 52% of the households have electricity.

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

Variables	None	Anemia only	Malnutrition only	Anaemia and malnutrion	Total
Sex					
Male	1037	481	1934	1699	5151
Female	1130	526	1921	1443	5020
Residence					
Urban	1132	360	1622	846	3960
Rural	1035	647	2233	2296	6211
Working Status					
No	1624	708	2805	2061	7198
Yes	543	299	1050	1081	2973
Educational level					
No education	468	471	1126	1825	3890
Primary	317	184	715	514	1730
Secondary	983	288	1666	706	643
Tertiary	399	64	348	97	908
Fever status					
Yes	1769	764	2813	2054	7400
No	398	243	1042	1088	2771
Diarrhea					
Yes	162	159	435	586	1342
No	2005	848	3420	2556	8829
Electricity					
Yes	1437	541	2106	1254	5338
No	730	466	1749	1888	4833
Geo-Zone					
North Central	456	149	767	406	1778
North East	307	243	493	779	1822
North West	314	365	610	1170	2459
South East	358	84	792	258	1492
South South	267	49	578	250	1144
South West	465	117	615	279	1476
Wealth Index					
Poorest	203	215	605	1019	2042
Poorer	285	211	698	839	2033
Middle	450	278	877	639	2244
Richer	563	173	976	428	2140
Richest	666	130	699	217	1712
Own mosquito bed net					
No					

Yes	790	290	1323	789	3192
	1377	717	2532	2353	6979

Table 2 shows the model diagnostic statistics. Seven models were formulated which are subset of fixed, metrical and spatial covariates. Model one contains only the fixed effects covariates. Model 2 expands on Model 1 by including metrical (continuous) covariates alongside the fixed effects. model three incorporates the structured random effects to the fixed covariates accounting for spatial variation. Model four contains fixed effects covariates, metrical covariates, and the structured random effects. Model five builds on Model 4 by adding unstructured random effects, allowing for both structured spatial variations and individual-level random variations. Model six incorporate average cluster precipitation as weighting effects to the structured random effects to reflect potential regional disparities in climate in addition to fixed and metrical covariates while model seven added the unstructured or area specific random effects to model six. The model with the lowest value of DIC is considered as the best fitted model. Models with weighted structured random effects have lower values of DIC suggesting that weighted random effects model have more improved explanation of the risk of disease comorbidity compared to unweighted model. However, model six has the least value of defiance criterion and it is considered as the best model to capture the variation in our data. The further analysis is based on the best fitted model.

Table 2: Values of the model diagnostic criterion

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
$\bar{D}$	24502.963	23989.63	23779.843	23264.297	23254.811	23264.175	23255.089
ρ_D	44.601	74.995	133.340	163.26632	164.751	162.231	163.353
DIC	24592.164	24139.617	24046.561	23590.83	23594.313	23588.863	23591.795

Table 3 presents the posterior Mean estimates of the fixed effects of demographic characteristics, environmental and socioeconomic risk factors of the comorbidity of anaemia and malnutrition using multinomial model with structured weighted random effects. the results contains 95 % credible interval which is used to determine the significance of the risk factors. The risk factors are considered as not statistically significant if the credible interval includes zero. Based on the results, female children have a reduced risk of being malnourished or anemic and comorbidity of both illnesses compared to male children. The results also reveal that child sex is not a significant risk factor for malnutrition but significant for anaemia and coexistence of anaemia and malnutrition. Children in rural area has a higher odd of illness compared to their counterparts in urban settlement. This covariate is only significant for anaemia. The results also shows that children who had fever or diarrhea are more susceptible to being anemic, malnourished or suffer from both infections. Having fever or diarrhea are significant risk factors for the comorbidity pf anaemia and malnutrition. Owning a mosquito treated bednet is not considered as a significant risk factor for child illnesses. This could be based on the fact that owning mosquito bed net does not translate to using them. The results also reveal that the education status of a child mother is consider as a significant risk factors for child illnesses as it concerns anaemia and malnutrition. Children from mothers with higher educational qualification have lesser odds of being malnurisshed, anaemic, having both illnesses. The socioeconomic status of a child mother is also found to be significant with the odds of illnesses. According to the results, a child from wealthy home has a lower odd of being tested positive to anaemia and being malnourished or having both illnesses. A child from a house without electricity has higher odds of comorbidity of anaemia and malnutrition. However, electricity is not a significant risk factor of the infection being considered.

Table 3: Odd ratio for the fixed effect estimates and their 95 % credible interval

Variables	Malnutrition vs no infection		Anaemia vs no infection		Anaemia and malnutrition vs no infection	
	ROR	95% CI	ROR	95% CI	ROR	95% CI
Constant	-0.406	-0.766, -0.00246	1.0497	0.784, 1.308	1.312	1.046, 1.586
Gender						
Male	1		1		1	
Female	-0.229	-0.167, 0.123	-0.108	-0.22, -0.0028	-0.292	-0.410, -0.173
Residence						
Urban	1		1		1	
Rural	0.0092	-0.1004, 0.299	0.143	0.0052, 0.282	0.135	-0.011, 0.283
Fever Status						
Yes	1		1		1	
No	0.0068	-0.186, 0.201	0.347	0.204, 0.479	0.426	0.272, 0.571
Diarrhea Status						
Yes	1		1		1	
No	0.449	0.191, 0.706	0.107	-0.00947, 0.318	0.342	0.143, 0.558
Own Mosquito treated net						
Yes	1		1		1	
No	0.0027	-0.174, 0.168	0.109	-0.00621, 0.222	0.140	0.0032, 0.276
Educational level						
No education	1		1		1	
Primary	-0.201	-0.437, 0.0556	-0.104	-0.294, 0.993	-0.427	-0.629, 0.233
Secondary	-0.585	-0.848, -0.366	-0.391	-0.582, -0.198	-0.968	-1.155, -0.775
Tertiary	-1.024	-1.364, -0.659	-0.795	-1.043, -0.555	-1.659	-1.952, -1.366
Wealth Index						
Poorest	1		1		1	
Poorer	-0.154	-0.439, 0.118	-0.117	-0.352, 0.0814	-0.219	-0.437, -.000992
Middle	0.00981	-0.419, 0.207	-0.319	-0.560, -0.0945	-0.634	-0.871, -0.418
Richer	-0.606	-0.991, -0.256	-0.386	-0.658, -0.125	-1.044	-1.303, -0.781
Richest	-0.824	-1.234, -0.441	-0.694	-0.992, -0.387	-1.502	-1.803, -1.176
Electricity status						
Yes	1		1		1	
No	0.217	0.00315, 0.434	-0.0724	-0.229, 0.814	0.0621	-0.105, 0.225

3.1 Spatial Effects

Fig. 2- 4 show spatial results, the left panels display the estimated posterior means, while the right panels present maps of the 95% credible intervals. States shaded in black on the credible interval maps represent significantly lower, states shaded in white represents higher estimates, while gray shading indicates non-significant results for those states. In the case of malnutrition, states with significantly higher risk estimates are Borno, Jigawa, Gombe, Bauchi, Edo and Imo. State with higher estimated risk of anaemia are Yobe, Kebbi, Delta and Ondo state while states with significantly higher risk of comorbidity of anaemia and malnutrition are Borno, Sokoto, Katsina, Kaduna, Ondo, Edo and imo. The spatial effect result indicate that states with lower average precipitation are at higher risk of malnutrition and coexistence of anemia and malnutrition.

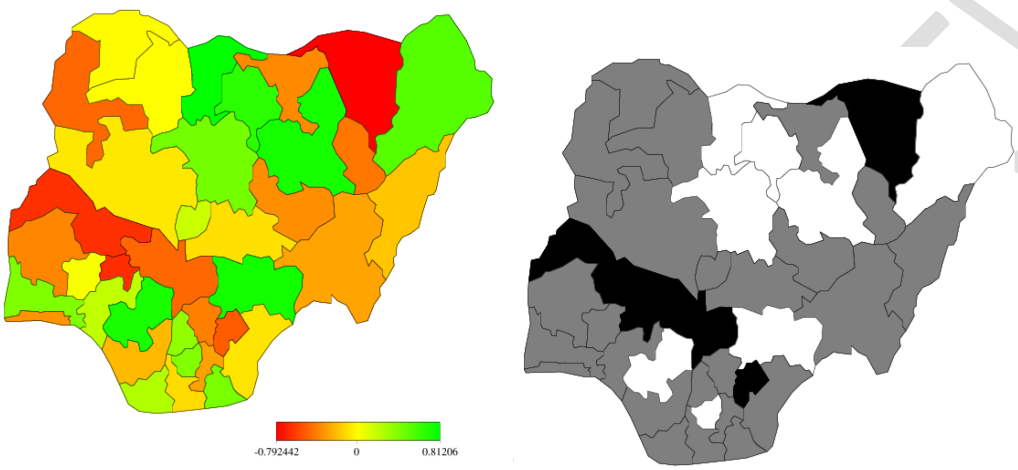


Fig. 2: Residual spatial effects and 95% posterior probability map of malnutrition among under five children.

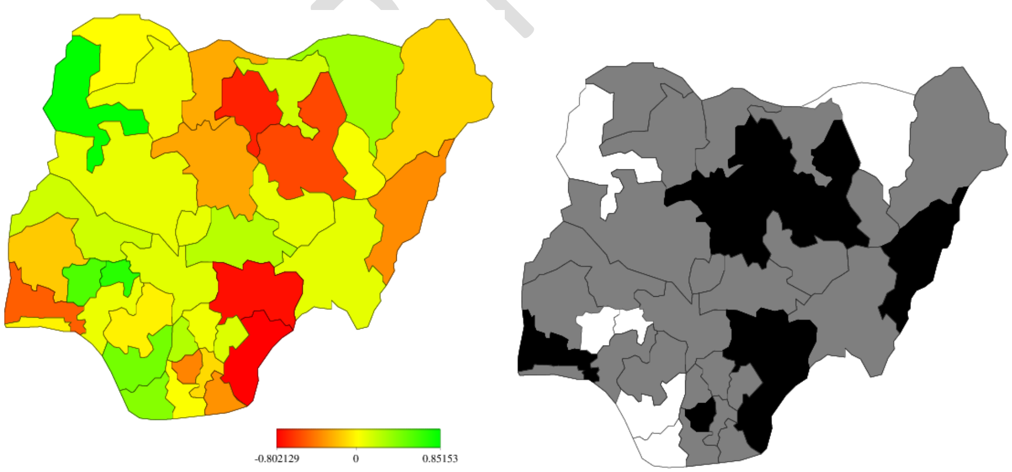


Fig. 3: Residual spatial effects and 95% posterior probability map of Anameia among under five children.

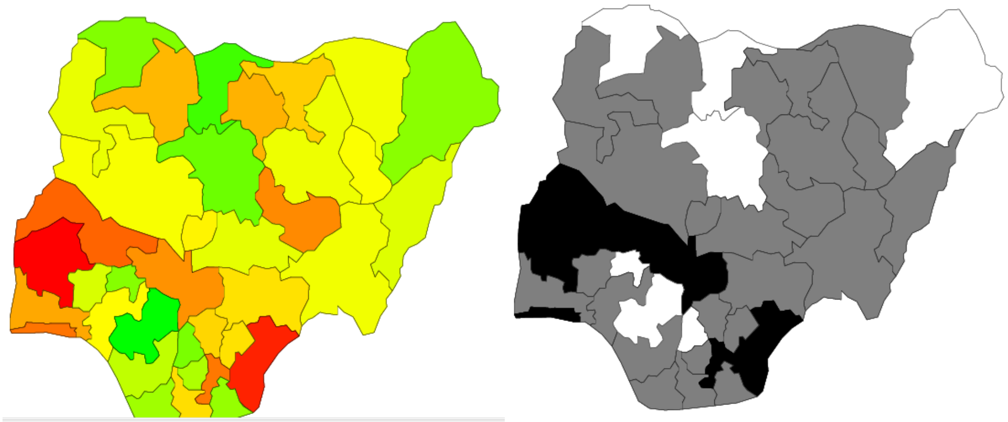
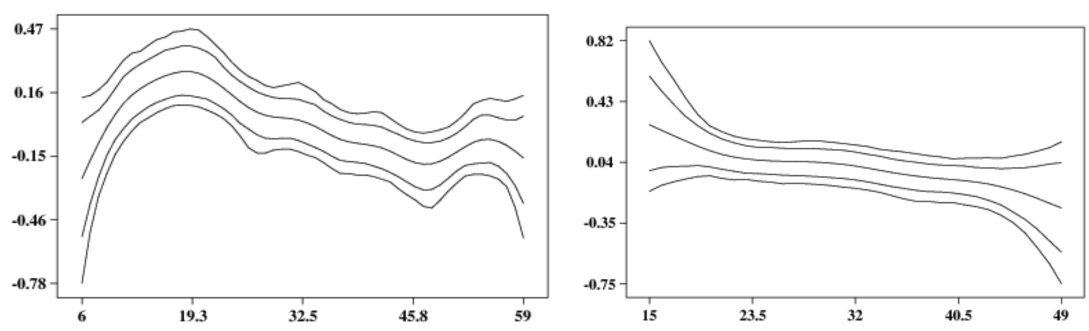


Fig. 4: Residual spatial effects and 95% posterior probability map of disease comorbidity among under five children.

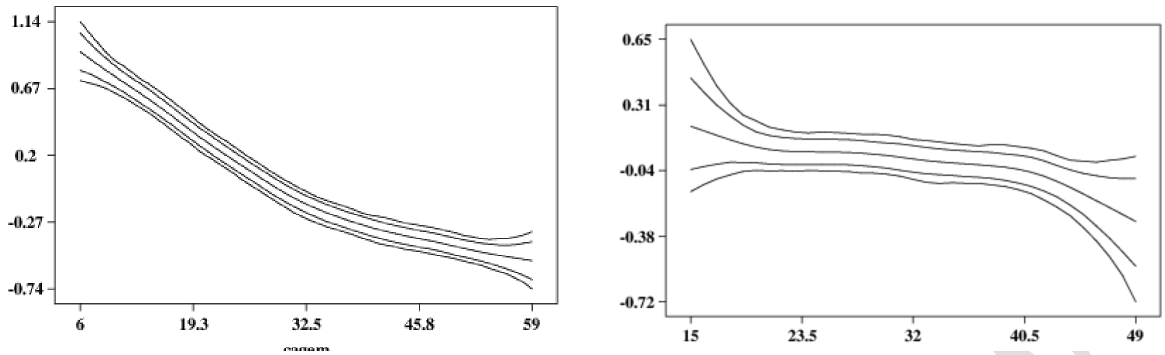
3.2 Non-linear effects of continuous covariates of age on the risk of anemia and malnutrition

Fig. 5 to V7 are spline plot illustrating the nonlinear relationship between a child's and mother's age and the risk of malnutrition and anaemia. As displayed in Figure 4, younger children, particularly those around age 15-25 months, are at higher risk of malnutrition, with the risk diminishing as they age beyond this range. Also, the risk of malnutrition appears to be higher for children born to younger mothers, with the risk decreasing as the mother's age increases. As shown in Figure 5, the risk of anaemia is high at early age of a child but it declines sharply as the child age increases. Also, a child born to younger mother are at higher risk of being anaemic. Figure 4 reveals that the risk of anaemia and malnutrition comorbidity is at the peak between age 10 to 20 months, it starts to decline sharply after 20 months and begins to rise again at age 50 months. The risk of anaemia and malnutrition comorbidity is higher among children of younger and older mothers.



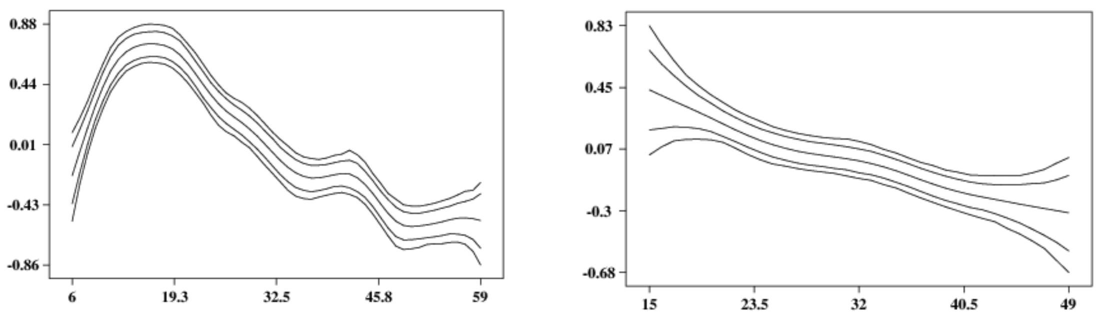
Child's age in Months Mother's age in Years

Fig. 5: Non-linear effects of child's age and mother's age on the risk of malnutrition



Child's age in Months Mother's age in Years

Fig. 6: Non-linear effects of child's age and mother's age on the risk of anaemia



Child's age in Months Mother's age in Years

Fig. 7: Non-linear effects of child's age and mother's age on the risk of anaemia and malnutrition comorbidity

4. Conclusion

The study focused on the spatial analysis of anaemia and malnutrition using multinomial model with weighted structured random effects. By adding weighted structured random effects based on the average cluster precipitation for each state, we have presented a novel method. This adjustment fills a significant gap in the research by capturing the impact of climate variation on the risk of pediatric illnesses. Although earlier research has looked at the geographic distributions of anemia and malnutrition, it frequently ignored how climate conditions, such as precipitation, affect the course of disease. Our model can account for the spatial heterogeneity brought about by regional climatic variations by weighting the structured random effects. This will yield a more precise assessment of illness risk that is impacted by local environmental factors.

In view of the modelling framework adopted in this study, malnutrition is defined by the presence of any one of three indicators: stunting, underweight, or wasting. A child is considered malnourished if they fit any of these criteria. Similarly, anemia is categorized based on severity—whether it is severe, moderate, or mild—such that any level of anemia classifies a child as anemic. This classification allows us to analyze the combined and individual impacts of anemia and malnutrition using a multinomial model with weighted random effects, focusing on the overlap and unique patterns of these conditions.

The results of models with weighted random effects were compared with that of unweighted model using DIC. Based on the values of DIC of each model, it was discovered that model with weighted structured random effects have better fit considering the fact that they have lower values of DIC. The adopted spatial modelling in this study enables us to incorporate the relationship between the regional variation in climate and the risk of childhood anameia and malnutrition. The spatial map reveals that states with lower annual average precipitation like Borno, Sokoto, Katsina, Kaduna have higher estimated risk of anemia and malnutrition comorbidity. Analysis of fixed effects reveals that mother's educational status, the socioeconomic status of a child mother, having fever and diarrhea, child's area of residence are significant risk factors of anaemia and malnutrition comorbidity among children. The spline plot of non-linear effects of a child and mother's age also show that younger children and children born to younger and older mother are at higher risk of childhood disease comorbidity. This finding is in line with the study carried out by [

This method's main benefit is its capacity to increase the model's sensitivity to illness patterns influenced by the climate. Given how precipitation affects agricultural productivity, food security, and general health settings, regions with higher or lower average precipitation also face varying degrees of risk for anemia and malnutrition. By using this weighted technique, hotspots associated to climate change can be identified, providing a more precise spatial picture of disease risk. In turn, this makes it possible to implement focused health interventions in areas that are at risk, especially those where environmental variables significantly influence comorbidity patterns. As a result, our model offers a more accurate and nuanced assessment of disease risk, more in line with the intricate interplay between sociodemographic and climatic factors influencing the health of children.

It is crucial to concentrate health and nutrition services on areas with low average precipitation since these areas are more vulnerable. To combat the effects of environmental vulnerability, these initiatives might focus on enhancing local food security, implementing climate-resilient farming practices, and providing young children with nutritional supplements.

The necessity for early nutritional treatments, especially during infancy and early childhood, is indicated by the vulnerability of younger children. Programs aimed at improving maternal health should also target older and younger moms, offering them information and advice on managing the health and nutrition of their children. Promoting female education and empowering women economically will directly improve child health, as maternal education and socioeconomic position are important variables. Access to proper nutrition and medical treatment could be enhanced by social security programs targeted at low-income households.

Strengthening public health services to prevent, diagnose, and treat fever and diarrhea in children is essential since these illnesses put them at higher risk. These contributing variables can be decreased with the support of health programs that emphasize frequent medical checkups, access to clean water, and good cleanliness.

It is advised to allocate resources to rural areas or places with greater rates of comorbidity because a child's place of living also has a vital role. Mobile health units, community health worker programs, and infrastructural upgrades to provide access to healthcare are a few examples of such projects.

In order to improve the robustness of the findings. Effort should be made by future researchers to integrate a broader range of climatic factors. This expansion would go a long way to enhancing the precision of risk estimates, allowing for more focused and efficient public health interventions in vulnerable populations. In addition to meeting children's immediate medical needs, these focused, research-based interventions would help end the cycle of malnutrition and anaemia among young children, which would eventually improve long-term child health outcomes.

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