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Bivariate Spatial Modeling of Malnutrition among Under Five Children in Nigeria. A Bayesian Hierarchical Modelling Approach

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ABSTRACT
Childhood malnutrition continues to be a serious public health concern in Nigeria, with persistent geographic disparities and limited understanding of the joint spatial pattern of malnutrition indicators. This study examined the spatial distribution and determinants of childhood malnutrition in Nigeria using a two-stage Bayesian hierarchical modeling approach. The data were extracted from the 2024 Nigeria Demographic and Health Survey (NDHS). Separate univariate spatial models were fitted for stunting, underweight and wasting, incorporating fixed effects, nonlinear age effects, cluster-specific random effects, and spatial dependence. Spatial effects were extracted to evaluate pairwise correlations and estimate covariate differential fixed effects utilizing a stacked bivariate model. All models were estimated within the Integrated Nested Laplace Approximation (INLA) techniques. The study revealed that the prevalence of stunting, underweight, and wasting was 36.14%, 25.13%, and 8.27%, respectively. Maternal education exhibited the strongest protective effect across all indicators, while household wealth index, child gender, and climatic factors are also identified as significant risk factors. Differential effects analysis showed that maternal education had stronger protective effects on underweight than stunting, while temperature and precipitation showed significant differential effects across malnutrition outcomes. The study also identified strong clustering of stunting and underweight in northern states while wasting exhibited a more dispersed pattern. The findings highlight the need for geographically targeted and outcome-specific interventions that prioritize poverty alleviation programmes, maternal education and climate adaptation to improve child nutrition in Nigeria.

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INTRODUCTION

Childhood malnutrition remains one of the most pressing public health challenges the word is facing and continues to undermine child survival, growth and cognitive development [3]. Approximately 150.2 million children under five were stunted and 42.8 million lost their lives globally in 2024, according to a recent report by the World Health Organization (WHO), United Nations Children's Fund (UNICEF), and World Bank Group Joint Child Malnutrition Estimates. This suggests that efforts to meet the global nutrition targets are still highly inadequate [1]. Although there have been worldwide initiatives to improve nutrition, substantial disparities persist across regions, particularly in low- and middle-income countries where poverty, food security, infectious diseases, environmental degradation and climatic shocks continue to threaten child health and development.

Despite decline in the global prevalence of stunting, the number of stunted children has continued to rise in Sub-Saharan Africa, emphasizing a disproportionate and growing burden of childhood malnutrition [30]. Given this trajectory, it is unlikely for the region to meet the 2030 Sustainable Development Goal target of reducing stunting by 40%. In Sub-Saharan Africa, Nigeria has a significant contribution to the burden of childhood malnutrition. Despite various nutrition-focused programmes and interventions, childhood malnutrition remains a major public health concern particularly in northern Nigeria, where poverty, food insecurity, insecurity, and limited access to health services still aggravate nutritional deprivation [2,3]. Nigeria is ranked the second-largest burden of stunted children globally, with approximately 40% of under-five children affected by chronic malnutrition.

Climatic variability has been identified as an important risk factor of child nutritional outcomes through its influence on agricultural productivity, water resources, food availability, dietary diversity, and transmission of diseases. Also, droughts, high temperatures, erratic rainfall patterns, and flooding have been known to disrupt household livelihoods and food systems, thereby increasing the chance of child vulnerability to chronic and acute forms of malnutrition [4-6].

Geographical disparities in childhood malnutrition in Nigeria have been worsened by recent climatic events, such as frequent flooding and increased rainfall variability in several parts of the country. This development has negatively impacted agricultural output, food availability, and household food security. Despite this potential linkages, socioeconomic and demographic factors have been the main focus of existing studies, with very little emphasis paid to the influence of climatic conditions. Temperature and precipitation fluctuation are examples of climate-related factors that may have an indirect impact on food systems and agricultural productivity, as well as a direct impact on child nutritional outcomes through disease transmission pathways. Incorporating these environmental factors into spatial malnutrition models may offer a more thorough understanding of the geographical distribution of malnutrition and support the development of more efficient, location-specific nutrition interventions, given Nigeria's significant climatic diversity [4,5].

Stunting, wasting and underweight are the three key indicators of malnutrition measured using anthropometric indices based on children's weight, height, and age. Children are considered stunted if their height-for-age z-score (HAZ) is below −2 standard deviations (−2 SD) from the median of the World Health Organization (WHO) Child Growth Standards [7,8]. Wasting occurs when the weight-for-height z-score (WHZ) is less than −2SD from the reference median, whereas underweight occurs when the weight-for-age z-score (WAZ) is less than −2SD from the reference median. These Anthropometric indicators often coexist within the same kid and are generally caused by shared biological, environmental, and socioeconomic pathways.

The geographic distribution and contributing factors of childhood malnutrition in sub-Saharan Africa have been the subject of numerous research. As an illustration of the significance of taking spatial variability into account in malnutrition research, a geo-additive semi-parametric mixed model was used to examine the regional patterns of childhood malnutrition in the Democratic Republic of the Congo [9]. In a similar vein, geo-additive models was also used to determine the factors that contribute to childhood malnutrition in Egypt and found that, in contrast to results from many developing nations, maternal education had no impact on the prevalence of stunting and wasting [10]. A Bayesian geo-additive regression model was employed to examine the factors and geographical variation of childhood malnutrition in Nigeria [11]. The study demonstrated the significance of socioeconomic and demographic factors in explaining nutritional outcomes and found significant regional inequalities, with a larger prevalence of malnutrition centered in northern Nigeria. Nevertheless, the research was limited to a univariate framework and did not take into consideration the potential impact of climatic conditions on malnutrition risk or the combined spatial dependence between multiple malnutrition indicators. A Bayesian quantile regression framework to examine the factors and spatial distribution of childhood undernutrition in Nigeria [12]. The work used Bayesian P-splines to capture nonlinear covariate effects and Markov random fields to simulate spatial effects. Markov Chain Monte Carlo (MCMC) techniques were used to estimate the parameters. The results showed significant regional disparities in undernutrition, with higher levels of undernutrition centered in northern Nigeria and a distinct north-south divide. Additionally, the study showed that the impact of covariates differed across different quantiles of the nutritional distribution, indicating that the factors associated with severe forms of undernutrition may not be sufficiently captured by traditional mean-based regression models. The impact of carbon (IV) oxide concentration on undernutrition in children under five in Nigeria was assessed using a generalized linear mixed model. According to their findings, there is a strong link between CO_2 concentration and an increased risk of undernutrition in Nigeria [13]. Similar risk factors that increase the prevalence of childhood malnutrition were found in the previously stated research. Maternal education, age, body mass index, household wealth quantile, child age and gender, and place of residence are a few of these. Despite the fact that these studies have offered insightful information about the determinant and geographical distribution of malnutrition, the dependence structure that may exist among any pairwise malnutrition indicators within the same child are not taken into consideration. Consequently, vital details on the correlation and co-occurrence of malnutrition indicators could be left out.

Bayesian hierarchical spatial models provide a flexible and robust framework for concurrently investigating multiple malnutrition indicators while taking into consideration the spatial dependence and latent heterogeneity. Although bivariate conditional autoregressive models have been applied in other sub-Saharan African countries like Ethiopia [13], this study uses a two-stage Bayesian hierarchical approach that is flexible, computationally efficient, and especially well-suited for analyzing differential covariate effects and bivariate spatial relationships in the Nigerian context. Unlike the Ethiopian study, which mainly focused on structured spatial dependence and cluster-level heterogeneity, our study incorporates unstructured heterogeneity and climatic determinants. Thus, this research addresses the need for a robust methodology that jointly analyses correlated malnutrition indicators considering differential covariate effects, spatial heterogeneity, cluster-level variation, and climatic influences particularly in Nigeria, where such studies remain limited.

This study aims to examine the joint spatial distribution and determinants of malnutrition in Nigeria utilizing a two-stage Bayesian hierarchical approach. Separate univariate models are fitted for stunting, underweight, and wasting, incorporating fixed effects, nonlinear covariate effects, structured spatial dependence, cluster-level variability, and unstructured heterogeneity. The spatial effects are then extracted to assess spatial correlations between pairs of indicators and identify covariates with stronger associations with specific malnutrition outcomes. The study also examines the impact of climatic factors on childhood malnutrition outcomes in addition to socioeconomic and demographic variables. The findings are expected to contribute to the growing literature on spatial epidemiology and provide evidence for geographically targeted nutrition interventions and policy formulation in Nigeria.

MATERIALS AND METHODS

Study Area and Data Collection

This study was carried out in Nigeria, which comprises 36 states and the Federal Capital Territory (FCT). The data were extracted from the 2024 Nigeria NDHS, a nationally representative cross-sectional survey implemented by the National Population Commission (NPC) with technical support from the DHS Program. A two-stage stratified cluster sampling design was employed in the survey to provide reliable estimates of demographic and health indicators at national and sub-national levels. Children aged 0–59 months were involved and their information was obtained from their mothers or caregivers. Collection of anthropometric measurements were based on standardized DHS procedures.

Under-five children with complete anthropometric information constituted the study population. In accordance to WHO child growth standards [7], the three malnutrition indicators considered were stunting, derived using height-for-age z-scores (HAZ); underweight, derived using weight-for-age z-scores (WAZ); and wasting, derived using weight-for-height z-scores (WHZ). Explanatory variables included child, maternal, household, and environmental characteristics. The covariates included were carefully selected considering the global burden of disease and risk factors for children [18]. The previous research [15-20] served as a guide for the decisions. The climatic variables included state-level measures of temperature and precipitation variability extracted from the spatial repository of the 2024 NDHS. Table1 gives the details on the explanatory and response variables.

Table 1: Variables of the Study

Variables	Description	Summary
Response variables Stunting (HAZ)	Height-for-age Z-score (chronic undernutrition)	Continuous; min = -5.99, max = 5.88
Wasting (WHZ)	Weight-for-age Z-score (composite undernutrition)	Continuous; min = -4.98, max = 4.8
Underweight (WAZ)	Weight-for-height Z-score(acute undernutrition)	Continuous; min = -5.95, max = 4.7
Maternal education	Mother's highest education attained	Category; 0 = No education, 1 = Primary, 2 = Secondary, 3 = Higher
Wealth status	Wealth status of the family	Category; 1 = Poorest, 2 = Poorer, 3 = Middle, 4 = Richer, 5 = Richest
Gender	Sex of child	Binary; 1= Male, 2 = Female
Area of residence	Settlement place	Binary; 1= Rural, 2 =Urban
Average tepmerature	Land surface temperature (°C)	Continuous; min = 21.15, max = 29.57
Average precipitation	Mean annual precipitation(mm)	Continuous; min = 34.92, max = 198.17
Random effects		
Child's age	Child's age in month	Continuous: min = 0, max = 59
Mother's age	Mother's age in years	Continuous; min = 15, max = 49
Spatial effects		
states	36 states of Nigeria and the FCT	Categorical (1-37)

Statistical Method

The primary aim of this study is to examine the geographical distribution and determinants of childhood malnutrition in Nigeria through a two stage joint analysis of pairwise correlated malnutrition indicators. Spatially structured and unstructured effects within a Bayesian hierarchical framework were incorporated into the model building. The proposed approach captures the complex dependence structure underlying malnutrition outcomes and enables a clearer understanding of the socioeconomic, environmental, and climatic factors associated with childhood malnutrition across the 36 states in Nigeria including the Federal Capital Territory (FCT). The Bayesian hierarchical spatial model offers a flexible framework for joint analysis of correlated malnutrition indicators while accounting for latent spatial dependence and unobserved heterogeneity through a Gaussian Random Field (GRF).

Let $Y_{ik} = (y_{1ik,} y_{2ik})^T$ and $Y_k|\vartheta_k \sim \mathrm{N}(\vartheta_k, \tau^{-1}\mathrm{I})$ be a bivariate standardized malnutrition indicators $y_{1ik,}$, and y_{2ik} of a child i in state k having malnutrition indicator 1, assuming a Gaussian bivariate distribution with mean ϑ_k and a constant covariance matrix $\tau^{-1}I$, where $\vartheta_k = (\vartheta_i, \vartheta_2)^T$ is the expected value of a child's malnutrition indicator in state k, I is an identity matrix, $y_{1k,} y_{2k} \in \{\mathrm{HAZ}_i, \mathrm{WAZ}_i, \mathrm{WHZ}_i,\}$, $y_{1ik} \neq y_{2ik}$ and k = 1,2,...,37. The interest is to account for the factors determining ϑ_k through a hierarchical bi-generalized additive linear mixed models given as:

$$\vartheta_{1k} = x_k^T\beta + \sum_{q=1}^{p} f_q z_k + c_k^T\phi + u_{1k} + v_{1k} \quad (1)$$

$$\vartheta_{2k} = x_k^T\beta + \sum_{q=1}^{p} f_q z_k + c_k^T\phi + u_{2k} + v_{2k} \quad (2)$$

The model formulation in (1) and (2) include fixed-effect covariates, continuous covariates, structured spatial effects, unstructured heterogeneity effects, and cluster-specific random effects. Under this specification, the latent variation in each malnutrition indicator is decomposed into three components: the structured spatial effect, (u_{sk}) which captures spatial dependence among neighbouring states; the unstructured effect, (v_{sk}), which accounts for state-specific heterogeneity that is not spatially correlated; and the cluster-specific random effect, (ϕc_k) which captures residual variation among survey clusters. The complete specification allows the model to simultaneously account for spatial autocorrelation, non-spatial heterogeneity, and cluster-level variability in malnutrition outcomes.

Where $\mathbf{x}_i = (x_{k1}, x_{k2}, \dots, x_{kp})^T$represent $p \times 1$ vector of explanatory variables associated with the k^{th} $state$, and $\boldsymbol{\beta}$ is the corresponding $p \times 1$ vector of regression coefficients. The vector $\mathbf{c}_{ik} = (0,0,\dots,0,1,0,\dots,0)^T$is an $m \times 1$ indicator vector identifying the cluster to which the i-th child belongs, with the q-th element equal to 1 if the ith child is sampled from cluster q in $state$ $k$and zero otherwise. The parameter $\boldsymbol{\phi}$ denotes a $m \times 1$vector of cluster-specific random effects that accounts for residual variation among clusters. Furthermore, $f_q(\cdot)$ represents a smooth nonlinear function of the k-th continuous covariate, allowing for possible nonlinear associations with the malnutrition outcomes. Finally, u_{sk}, $s = 1,2$, denotes the structured spatial random effect for state k corresponding to the s-th malnutrition indicator, introduced to account for the spatial dependence and unobserved geographical heterogeneity. Consequently, Equation (1) and (2) can be expressed more compactly in matrix form as

$$\vartheta_k = \begin{bmatrix} x_k \\ x_k \end{bmatrix}^T \beta^* + \begin{bmatrix} c_k \\ c_k \end{bmatrix}^T \phi^* + \sum_{q=1}^{p} f_q \begin{pmatrix} z_k \\ z_k \end{pmatrix} + u_k + v_k \quad (3)$$

Where

$$\phi^* = (\phi, \phi)^T;\ \beta^* = (\beta, \beta)^T,\ u_k = (u_{1k,} u_{2k})^T, \text{ and } v_k = (v_{1k,} v_{2k})^T \quad (4)$$

To investigate the whether the effects of covariates differ between pairs of malnutrition indicators, a stacked bivariate model (Equation 5) was utilized. in contrast to separate univariate models, this approach jointly estimates outcome-specific fixed effects $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$, accounting for the correlation between the two outcomes. Given any pair of malnutrition indicators (y_{1ik} and y_{2ik}) for child i in cluster c and state k. The stacked bivariate model is specified as:

$$\begin{pmatrix} y_{1ik} \\ y_{2ik} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \mathbf{x}_{ik}^T \boldsymbol{\beta}_1 \\ \mathbf{x}_{ik}^T \boldsymbol{\beta}_2 \end{pmatrix} + \begin{pmatrix} \sum_{q=1}^{p} f_q\,(z_{qik}) \\ \sum_{q=1}^{p} f_q\,(z_{qik}) \end{pmatrix} + \begin{pmatrix} \phi_{1c} \\ \phi_{2c} \end{pmatrix} + \begin{pmatrix} u_{1k} \\ u_{2k} \end{pmatrix} + \begin{pmatrix} v_{1k} \\ v_{2k} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1ik} \\ \varepsilon_{2ik} \end{pmatrix} \quad (5)$$

In expanded form, for each outcome $s = 1,2$:

$$\theta_{sk} = \alpha_s + \mathbf{x}_{ik}^T \boldsymbol{\beta}_s + \sum_{q=1}^{p} f_q\,(z_{qik}) + \phi_{sc} + u_{sk} + v_{sk} \quad (6)$$

The differential effect between outcomes which is the primary parameter of interest is given as:

$$\Delta\beta \;=\; \beta_2 \;-\; \beta_1 \quad (7)$$

if $\Delta\beta > 0$, the covariate has a much stronger effect on outcome 2 than outcome 1 and if $\Delta\beta < 0$, the covariate has a stronger effect on outcome 1 than outcome 2

Consequently, this study uses a two-stage approach to relax the independence assumption after fitting distinct univariate models. first, by extracting spatial effects to evaluate pairwise correlations. Second, by fitting a stacked bivariate model to estimate differential fixed effects, allowing us to determine whether a covariate has a significantly stronger association with one malnutrition outcome compared to another.

In the Bayesian framework, every parameter is considered as a random variable and will be assigned appropriate prior distributions. These priors could be non-informative, weakly informative, or elicited from previous studies or expert knowledge [21,22]. The ability to accommodate unobserved regional heterogeneity by explicitly incorporating spatial dependence into the model structure is the major advantage of Bayesian spatial modelling. This is obtained by assigning a spatial prior distribution to the latent spatial effects, thereby enabling neighboring states to exhibit similar risk profiles while taking into consideration geographical variation in malnutrition outcomes.

Let $u^s = \left(u_{s1} + u_{s2} + \ldots + u_{sq}\right)^T$ for $s \in \{1,2\}$ represents the vector of structured spatial random effects associated with the two malnutrition indicators, where q denotes the number of states (36 states and the Federal Capital Territory) included in the analysis. The spatial effects are assumed to follow a Gaussian Random Field (GRF) characterized by a precision matrix Q_s, which captures the spatial dependence structure among neighbouring states.

Let G = (V, E) represent an undirected graph describing the spatial configuration of Nigeria, where V represents the set of states and E denotes the set of edges connecting neighbouring states that share a common boundary. To facilitate efficient computation, the precision matrix Q_s is assumed to be sparse. Let $W = w_{ij}$ denote the n × n adjacency matrix such that w_{ij} = 1, if states i and j are neighbours, w_{ij} = 0, otherwise. Suppose $D = diag(d_1, d_2, \ldots, d_n)$ is a diagonal matrix whose entries correspond to the number of neighbouring states associated with each state.

Under the intrinsic conditional autoregressive (ICAR) specification [29], the precision matrix of the structured spatial effects is defined as

$$Q_s = \tau_{u^s}(D \;-\; W) \quad (8)$$

Where τ_{u^s} is the precision parameter which controls the degree of spatial smoothing for the s^{th} malnutrition indicator? This specification enables neighbouring states to exhibit similar spatial effects, thereby accounting for residual spatial dependence and unobserved geographical heterogeneity in childhood malnutrition.

The continuous covariates such as child age and mother's age whose effects are nonlinear was assigned A second-order random walk (RW2).

Let $f_d = (f_{d1}, f_{d2}, \,..\, .f_{dT})^T$ denote the vector of nonlinear effects associated with the d^{th} continuous covariate, where $(f_{dt}\})$ represents the effect at the t^{th} knot. Under specification of the RW2, the 2^{nd} order differences are assumed to be independent and normally distributed, such that

$$\delta_{f_{dt}}^2 = f_{dt} - 2f_{d(t+1)} + 2f_{d(t+2)} \sim N(0, \sigma_{ft}^2) \quad (9)$$

the prior distribution of f_d is given by

$$\pi(f_d) \propto \left(\frac{1}{\sigma_{f_d}^2}\right)^{(n-2/2)} exp\left\{-\frac{1}{\sigma_{f_d}^2} \sum_{t=1}^{n-2} (\Lambda_{f_{dt}}^2)^2\right\},$$

$$\Delta^2 f_{dt} = f_{dt} - 2f_{d(t+1)} + f_{d(t+2)} \quad (10)$$

Here f_1 captures the effect of child's age, and f_1 captures mother's age effects among under five children.

The RW2 prior specified in (10) corresponds to the formulation given by [23] for regularly ordered covariates. In this study, child age and maternal age were considered as ordered covariates and modelled using RW2 priors adequately capturing nonlinear relationships with malnutrition outcomes. The RW2 model is suitably applicable due to its flexibility in accounting for the smooth nonlinear effects and its computational efficiency arising from the Markov property.

For the cluster-specific random effects, independent Gaussian priors with mean zero and variance σ_ϕ^2 were assigned. Similarly, the regression coefficients were assigned diffuse multivariate Gaussian priors, $\beta \sim N\left(0, \sigma_p^2 I\right)$, The precision parameter was assigned a Gamma prior, $\tau \sim Gamma(a, b)$

Penalized Complexity (PC) priors were specified for $(\sigma_{f_d}^2)^{1/2}$. specifically, the PC prior was parameterized (σ_0, α), such that $p(\sigma_{f_d}^2)^{1/2} > \sigma_0 = \alpha$. the distribution follows

$$\pi\left(\sigma_{f_d}^2 \propto \frac{\lambda}{2}\left(\sigma_{f_d}^2\right)^{-3/2 \exp(-\lambda\left(\sigma_{f_d}^2\right)^{-1/2})}\right) \quad \sigma_{f_d}^2 > 0, d = 1,2 \;\;;$$

$$\lambda = -\log(\,\alpha)/\,\sigma_0 \quad (11)$$

The joint posterior distribution of all unknown parameters of interest is obtained by combining the likelihood function with the corresponding prior distributions through Bayes' theorem expressed as

$$\pi(\beta, u, v, f_1, f_2, \Lambda, \sigma_{\beta,}^2 \sigma_{\phi,}^2 | Y, X) \propto$$
$$L(.)\pi(\beta)\pi(\phi)\pi(u, v|\Lambda)\pi(f_1)\pi(f_2)\pi(\Lambda)\pi(\tau)|\sigma_{f_1,}^2 \sigma_{f_2}^2)\pi(\sigma_\beta^2)\pi(\sigma_{\phi,}^2) \quad (12)$$

Estimation

Parameters were estimated within a Bayesian framework using the Integrated Nested Laplace Approximation (INLA) approach implemented by [25]. INLA provides accurate and computationally efficient approximations to posterior marginal distributions for latent Gaussian models and has become widely applicable in spatial epidemiological studies. Posterior summaries were obtained for all model parameters which are the fixed effects, cluster-specific random effects, structured spatial and unstructured heterogeneity effects, and hyperparameters. Penalized Complexity (PC) priors were specified for the variance parameters, while setting hyperparameters at $\sigma_0 = 1$ and $\alpha = 0.001$. the remaining hyperparameters were assigned default INLA prior. Details of the INLA estimation procedures and its application to Bayesian spatial models have been duly discussed in previous studies [25-27].

State-specific posterior probabilities were derived from the posterior marginal distributions of the spatial random effects to pinpoint geographical areas with elevated malnutrition risk. Since lower values of the spatial effects gives indication of a higher prevalence of malnutrition relative to the national average, the posterior probability of excess risk for each state was computed from the estimated spatial effect distributions as given below:

$$p(u_{sk} > 0|D) = \int_0^\infty \pi(u_{sk}\,|D)du_{sk},\ \ \forall\, s,k \qquad (13)$$

The posterior marginal distribution of state k for indicator s is denoted by $\pi(u_{sk}|D$. A threshold value of zero was adopted as the reference level which represents the national average risk. Under this parameterization, states having posterior probabilities near one indicate a higher likelihood of experiencing an elevated burden of malnutrition relative to the national average, whereas smaller probabilities suggest lower risk. The posterior probabilities were obtained by evaluating the posterior distribution of the spatial effects through Monte Carlo integration; $E(I(u_{si} > 0|D$ expressed as;

$$p(u_{sk} > 0|D) = \frac{(\sum_h^n (I(u_{sk}>0)}{n} \qquad (14)$$

Where $u_{sk}^{(h)}$ is the h^{th} realization from the posterior marginal distribution of the spatial effect associated with state k and malnutrition indicator$s$. $I(\cdot)$ Represents the indicator function, taking a value of 1 if the condition holds and 0 otherwise.

To examine the bivariate spatial correlation between the pairwise combinations of malnutrition indicators, a two-stage post-estimation approach was employed. This was achieved by first separating the fitted univariate BYM2 models for each malnutrition indicator (stunting, underweight, wasting), and extracting the state-specific spatial effects (u_{sk}). The pairwise Pearson correlation coefficients between the spatial effects of different indicators was then calculated.

$$r_{12} = \frac{\sum_{k=1}^{37}(u_{ik} - \bar{u}_1)((u_{2k} - \bar{u}_2)}{\sqrt{\sum_{k=1}^{37}(u_{ik} - \bar{u}_1)^2}\sqrt{\sum_{k=1}^{37}(u_{2k} - \bar{u}_2)^2}} \qquad (15)$$

Where u_{1k} and u_{2k} represent spatial effects for malnutrition indicators 1 and 2 in statek, (where k=1-37). A positive correlation shows that states with high risk for one indicator also tend to have high risk for the other. A negative correlation indicates inverse relationship between the indicators.

In addition, bivariate spatial maps are constructed by overlaying the probability of excess prevalence maps for each pair of malnutrition indicators.

RESULTS AND DISCUSSION

The results of the independent univariate analysis of stunting, wasting and undernutrition and the bivariate spatial analyses of pairwise childhood malnutrition indicators in Nigeria are presented in this section. The results are arranged as follows: first, the fixed effects from the separate univariate spatial models and the bivariate fixed effects which show differential covariate effects between pairs of malnutrition indicators are presented; second, the nonlinear effects of maternal and child age are explained; third, probability maps are explored to visualize the spatial patterns of each indicator; and finally, the correlation analysis and bivariate mapping are used to analyze the bivariate spatial relationships between pairs of indicators.

To interpret the results, positive coefficients indicate that the covariate is associated with higher z-scores (HAZ, WAZ, or WHZ), corresponding to lower malnutrition risk. Conversely, negative coefficients indicate lower z-scores, corresponding to higher malnutrition risk. The statistical significance of the estimated effects is determined by the inclusion or non-inclusion of zero in the 95% credible intervals. A Bayesian framework using INLA was utilized in estimating all models with cluster-specific random effects incorporated to capture within-cluster heterogeneity.

As revealed in Table 2, children in rural areas have significantly higher prevalence of stunting (43.4%) than urban children (26.2%). Similarly, underweight prevalence is 8% higher in rural areas compared to urban children (28.5% vs 20.5%). There is a different pattern in Wasting, with slightly higher prevalence in urban centre (9.1%) compared to rural areas (7.6%). Female children are 4.8%, 1.4% and 0.5% higher in stunting, underweight and wasting prevalence respectively compared to their male counterpart. The sample is balanced with nearly the same representation of male (49.4%) and female (50.6%) children. Considering the effects of maternal education on child malnutrition, there is a noticeable 39.6% and 26.1% decline in the prevalence of stunting and underweight respectively among children of mothers with no education and children of mothers with higher education. The effect was however less pronounced for wasting. There is a noticeable consistent decrease in stunting and underweight as wealth increases. Poor household children have more than double the stunting prevalence (50.7%) compared to their counterpart from the rich households (21.3%). Underweight also shows a similar pattern: 34.5% (poor) and 16.1% (rich). However, wasting shows similar prevalence across wealth groups. Besides, children from households with improved toilet facilities have considerably lower stunting (31.0% vs 43.1%) and underweight (21.6% vs 30.0%). Wasting shows no clear difference (8.4% vs 8.1%) on the use of improved toilet. The prevalence of stunting, underweight, and wasting among children under five in Nigeria was 36.14%, 25.13%, and 8.27%, respectively. These indicate that stunting which is a form of chronic malnutrition remains the most prevalent form of malnutrition, affecting more than one-third of children, while acute malnutrition (wasting) affects approximately one in twelve children.

Table 2: Prevalence of Malnutrition Indicators by Covariates

Variable	Category	Stunting	Underweight	Wasting	Total
Residence	Rural	2384 (43.4%)	1565 (28.5%)	419 (7.6%)	5487
	Urban	1057 (26.2%)	828 (20.5%)	368 (9.1%)	4035
Gender	Female	1854 (38.5%)	1244 (25.8%)	411 (8.5%)	4817
	Male	1587 (33.7%)	1149 (24.4%)	376 (8%)	4705
Highest Education Level	Higher	159 (13.2%)	116 (9.7%)	74 (6.2%)	1202
	No Education	1867 (52.8%)	1267 (35.8%)	313 (8.9%)	3535
	Primary	425 (36.6%)	281 (24.2%)	87 (7.5%)	1162
	Secondary	990 (27.3%)	729 (20.1%)	313 (8.6%)	3623
Household Wealth Index	Middle	688 (36.8%)	458 (24.5%)	128 (6.8%)	1869
	Poor	1939 (50.7%)	1320 (34.5%)	326 (8.5%)	3825

Variable	Category	Stunting	Underweight	Wasting	Total
	Rich	814 (21.3%)	615 (16.1%)	333 (8.7%)	3828
Improved Toilet System	Improved	1700 (31%)	1182 (21.6%)	458 (8.4%)	5484
	Unimproved	1741 (43.1%)	1211 (30%)	329 (8.1%)	4038
Total		3441(36.14%)	2393(25.13%)	787(8.27%)	9522

Table 3 presents the fixed effects estimates of separate malnutrition indicators. Based on the table, children resident in urban areas is associated with significantly higher stunting risk compared to their counterpart from rural areas (β = -0.107, 95% CI: -0.195, -0.020). Also, urban children had significantly higher WHZ scores (β = 0.079, 95% CI: 0.013, 0.146), indicating lower wasting risk. However, no significant urban-rural difference was observed for underweight. With respect to gender, male children had significantly higher HAZ (β = 0.161, 95% CI: 0.106, 0.216) and WAZ (β = 0.055, 95% CI: 0.009, 0.101) than female children, implying that female children are at greater risk of chronic malnutrition. There is no significant gender difference observed for wasting. There was a consistent protective effect of Maternal protective across all malnutrition indicators, with the strongest effect observed for stunting (β = 0.736, 95% CI: 0.610, 0.862) and the weakest for wasting, indicating that maternal education is among the most critical factors to be considered when it comes to preventing chronic malnutrition. Household wealth showed a strong significant effect for all the three malnutrition indicators, with children from rich households having significantly higher z-scores (stunting: β = 0.393, 95% CI: 0.282, 0.505; underweight: β = 0.286, 95% CI: 0.194, 0.378), but the effect on wasting is not that pronounced, suggesting wealth is more protective against chronic than acute malnutrition. There is no significant association of improved toilet facility with malnutrition. With respect to the role of climate in childhood malnutrition, higher temperature was consistently linked to increased wasting and underweight risk, and higher precipitation was protective against stunting and underweight but increased wasting risk. This underscores the complex role of climate in childhood nutrition. The climatic variables are all significant across malnutrition indicators except temperature that shows insignificant effects on stunting.

Table 3: Independent Analysis of Stunting, Wasting and Underweight

Covariates/estimates	Stunting			Wasting			Underweight		
	Mean	**Sd**	**2.5%-97.5%**	**Mean**	**Sd**	**2.5%-97.5%**	**Mean**	**Sd**	**2.5%-97.5%**
Intercept	-1.914	0.065	-2.041, -1.786	-0.59	0.049	-0.69, -0.50	-0.156	0.055	-1.67, -1.45
Residence (ref=Rural)									
urban	-0.107	0.044	-0.195,-0.020	0.079	0.033	0.013, 0.146	-0.0046	0.037	-0.067,0.076
Gender (ref=female) male	0.161	0.028	0.106, – 0.161	-0.012	0.022	-0.055, 0.030	0.055	0.023	0.009, 0.101
Highest education level (Ref=No education)									
Primary education	0.179	0.054	0.073-0.285	0.086	0.044	0.0043, 0.167	0.15	0.045	0.068, 0.024
Secondary education	0.229	0.050	0.131-0.327	0.019	0.042	0.056, 0.094	0.15	0.041	0.071, 0.23
Higher education	0.736	0.064	0.610-0.862	0.23	0.038	0.133, 0.328	0.59	0.053	0.48, 0.69
Household wealth index (ref= poor)									
Middle	0.152	0.048	0.058 , 0.245	0.033	0.036	0.040, 0.105	0.121	0.039	0.043, 0.199
rich	0.393	0.057	0.282, 0.505	0.041	0.043	0.044, 0.126	0.286	0.047	0.194, 0.378
Improved Toilet system (ref= no)									
yes	-0.013	0.039	-0.091, -0.064	-0.033	0.03	-0.093, 0.026	-0.007	0.033	-0.071, 0.056
Mean temperature	0.036	0.027	-0.016, 0.087	-0.11	0.019	-0.15, -0.076	-0.059	0.022	-0.102, -0.017
Mean Precipitation	0.272	0.043	0.187, -0.357	-0.080	0.028	-0.14, -0.023	0.101	0.034	0.036, 0.167

Table 4 presents the differential outcome between pairs of malnutrition indicators. it indicates significance if the 95% credible interval does not contain zero. Δβ Represent the difference in effect between the pairs of outcomes. Positive values indicate a stronger effect on the second outcome; negative values indicate a stronger effect on the first outcome. Area of residence, household wealth index, and improved toilet system has no differential effects between any pairs of malnutrition indicators indicating that their protective effects are consistent across stunting, underweight, and wasting. However, gender has a significant differential effect on only stunting and underweight pair, suggesting that the effects of gender is much stronger on underweight that stunting. Education had the strongest differential effect on stunting versus underweight (Δβ = 0.372, 95% CI: 0.322, 0.422), demonstrating that education is more protective against underweight than stunting. Considering the differential effects of climatic variables, both temperature and precipitation reveal negative significant differential effects across all pairs, with the strongest effect for precipitation on stunting vs wasting ($\Delta\beta = -0.460$). This implies that these variables show stronger effects on the first outcomes of the pairs.

Table 4: Fixed Effects Estimates of Bivariate Analysis

Variable	Stunting and Underweight $\Delta\beta$ 95%CI	Stunting and Wasting $\Delta\beta$ 95%CI	Wasting and underweight $\Delta\beta$ 95%CI
Residence : Urban	0.015* (0.005, 0.035)	0.043* (0.013, 0.073)	0.053* (0.027, 0.079)
Gender: Male	0.053* (0.030, 0.076)	0.024 (0.000, 0.047)	0.004 (-0.016, 0.024)
Highest education Level			
Primary education	0.090* (0.048, 0.133)	0.052* (0.009, 0.095)	0.062* (0.025, 0.099)
Secondary education	0.085* (0.047, 0.124)	0.021 (-0.018, 0.060)	0.025 (-0.009, 0.058)
Higher education	0.372* (0.322, 0.422)	0.210* (0.159, 0.261)	0.201* (0.157, 0.245)
Household wealth index			
Middle	0.087 (-0.045, 0.113)	0.159 (-0.435, 1.221)	0.43 (-0.132, 1.154)
Rich	0.462 (-0.128, 1.118)	0.463 (-0.271, 0.985)	0.189 (-0.081, 0.593)
Improved Toilet system			
Yes	-0.002 (-0.032, 0.029)	0.010 (-0.021, 0.041)	0.000 (-0.027, 0.026)
Mean temperature	-0.071* (-0.089, -0.052)	-0.114* (-0.133, -0.095)	-0.091* (-0.107, -0.074)
Mean Precipitation	-0.240* (-0.274, -0.205)	-0.460* (-0.495, -0.425)	-0.273* (-0.303, -0.243)

As revealed by table 5, there is high positive correlation between stunting and underweight ($r = 0.820$), suggesting that both forms of chronic malnutrition have similar geographic risk factors. in contrast, moderate negative correlation *(r = 0.048)* between stunting and underweight. This indicates that there is distinct spatial association between chronic and acute malnutrition. Wasting and underweight have negligible spatial correlation ($r = 0.034$). this highlights the need for outcome-specific intervention strategies.

Table 5: Pairwise Spatial Correlation between Malnutrition Indicators

Indicators	correlation
Stunting and underweight	0.820
Stunting and wasting	-0.480
Underweight and stunting	0.034

Fig 1 - 6 display the nonlinear effects of the child age and mother's age on separate malnutrition indicators. Fig 1 shows that the age of the child exhibited a strong nonlinear relationship with stunting with risk showing a sharp decline between 6 and 20 months. This critical period coincides with the transition to complementary feeding suggesting possible necessary intervention is essential to prevent chronic malnutrition. The nonlinear effects of maternal age curve reveal that children of younger mothers are at higher risk of chronic malnutrition. There is a sharp increase in underweight risk between 6 and 24 months and maternal age is protective, with children of younger mothers at higher risk as shown in figures 3 and 4. Child age and maternal age exhibited weaker effects on wasting compared with other forms of malnutrition as show in figures e and 5. While the risk of wasting rises slightly during the weaning period (6–18 months), it remains relatively stable across other age groups. Besides, younger mothers show slightly higher risk.

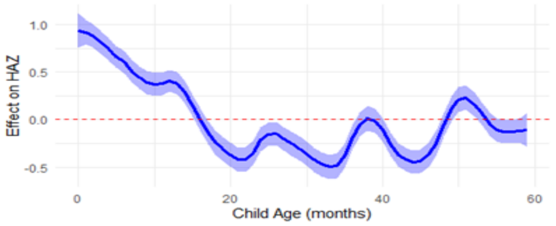

Figure 1: Non-linear effects of child age on stinting

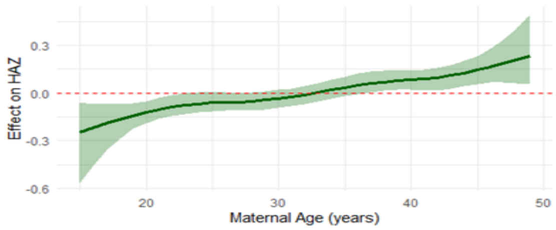

Figure 2: Non-linear effects of maternal age on stunting

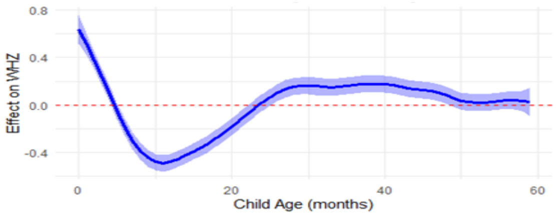

Figure 3: Non-linear effects of child age on underweight

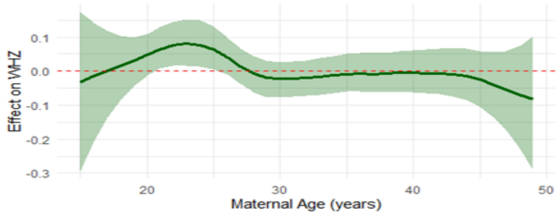

Figure 4: Non-linear effects of maternal age on underweight

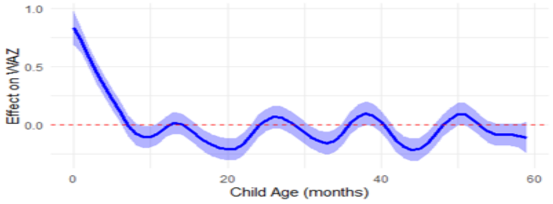

Figure 5: Non-linear effects of child age on wasting

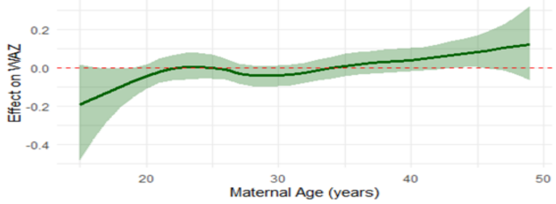

Figure 6: Non-linear effects of maternal age on wasting

Figures 7 – 9 shows the distribution of separate malnutrition risks across the states in Nigeria. States in dark red have elevated risk, while states in lighter shades show lower risk. As revealed by Fig 8, stunting is most prevalent in northern states with significantly higher risk probability in Sokoto, Zamfara, Katsina, Jigawa, Yobe, and Borno. However, south-south and south-east regions like Rivers, Akwa Ibom, Anambra, and Enugu show lower probabilities which indicate better nutritional status. The prevalence pattern of underweight is similar to stunting with northern states such as Sokoto, Zamfara, Katsina, Kebbi, and Niger states. Consistently showing elevated risk. in contrast, southern states particularly Lagos, Ogun, and Bayelsa exhibit lower prevalence. Fig 7 indicates that wasting show different prevalence pattern compared to stunting and underweight. Elevated probability of stunting is noticed in Borno, Yobe, and parts of the North-East, including some southern states like Rivers and Delta. This indicates that wasting which is a form of acute malnutrition has a more dispersed spatial distribution compared to stunting and underweight, known to be heavily concentrated in the Northern regions. Figures 10-12 display the bivariate maps of pairwise malnutrition indicators. as shown in figure I there is concurrent high prevalence of both stunting and underweight malnutrition with states like Sokoto, Zamfara, Katsina, Jigawa, and Yobe experiencing elevated risk. This pattern is most pronounced in the northwest and northeast regions. The bivariate map of fig 11 reveals that stunting and wasting do not always occur together. Borno and Yobe experience high stunting and wasting while other northern states show low wasting but high stunting. Fig 12 also shows a minimal overlap between wasting and underweight. Parts of be and Borno are observed to experience high concurrent risk of both malnutrition forms.

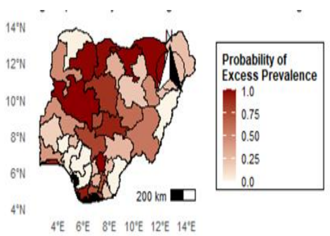

Figure 7: Excess stunting prevalence by state

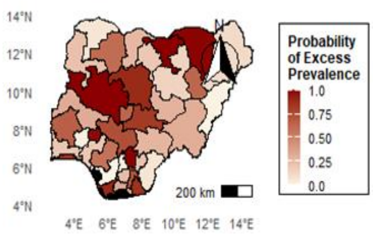

Figure 8: Excess underweight prevalence by state

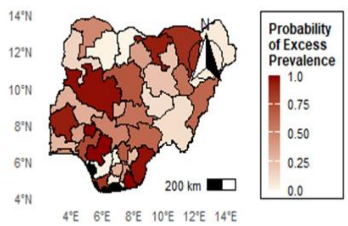

Figure 9: Excess wasting prevalence by state

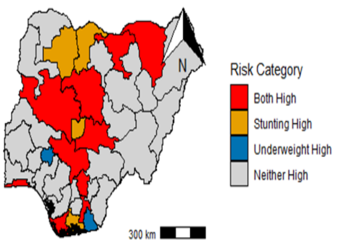

Figure 10: bivariate map of stunting and underweight

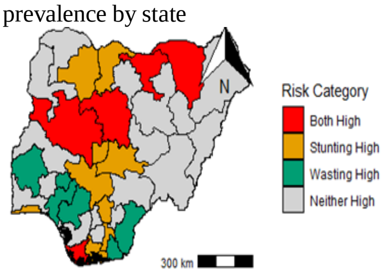

Figure 11: Bivariate prevalence map of stunting and wasting

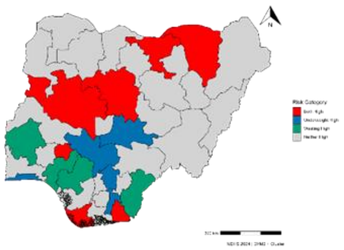

Figure 12: Bivariate prevalence map of underweight and wasting

Discussion

This study used a two-stage Bayesian hierarchical modeling approach to examine the joint spatial distribution and determinants of childhood malnutrition in Nigeria. The analysis reveals that stunting is the most prevalent form of malnutrition, affecting more than one-third of children, while underweight affects one in every four children, and wasting affects approximately one in every twelve children.

Findings from the separate analysis reveal that across all malnutrition indicators, maternal education showed the largest and most persistent protective effect. There was a clear dose-response gradient, with higher education levels associated with progressively decreased malnutrition risk, especially for stunting. Although the effect was greater for chronic malnutrition (stunting and underweight) than for wasting, household income also established a protective gradient, with children from wealthy homes having considerably higher z-scores than those from poor households. The nutrition transition in urban Nigeria was captured in the paradoxical effect of urban residence: decreased wasting risk but higher stunting risk.

The nonlinear effects of child age reveal that Stunting and underweight showed sharp increases in risk between 6 and 20–24 months which coincide with the transition to complementary feeding. This is consistent with the previous study that children below 20 months are more vulnerable to malnutrition concurrence [21]. There was also a protective effect of maternal age, with children of younger mothers (15–22 years) at higher risk, reflecting lower experience, education, and resources. This also aligns with the findings of previous studies [3,28]. The bivariate differential analysis showed that maternal education had significant differential effects across all pairs of malnutrition, with the strongest effect on underweight versus stunting. This indicates that education is more protective against underweight than stunting. Higher temperatures were more strongly associated with increased wasting and underweight risk than stunting. This finding is consistent with a past study that early-life climate anomalies have complex and differential effects on child growth in Sub-Saharan Africa, indicating that the influence of temperature is not uniform for all forms of malnutrition [5]. With a more apparent negative effect on wasting, precipitation had the highest differential effect on stunting compared to wasting. Area of residence, improved toilet facility and Household wealth index showed no significant differential effects across all malnutrition pairs. This indicates that these factors have similar effects on all forms of malnutrition. There was a strong and positive correlation between stunting and underweight, signifying that these two forms of chronic malnutrition share similar geographic risk factors. In contrast, the correlation between stunting and wasting was moderately negative. These findings also align with previous malnutrition research in Ethiopia where stunting and underweight were also found to be spatially correlated and stunting and wasting exhibit an inverse spatial relationship [22]. There was also a negligible relationship between underweight and wasting.

There was a distinct geographic pattern across Nigeria as revealed by the univariate spatial maps. Stunting and underweight exhibited strong spatial clustering, with higher probabilities concentrated in the North-West and North-East regions predominantly in Zamfara, Sokoto, Jigawa, Katsina, Yobe, and Borno. These findings are in line with previous studies in Nigeria [11,12,28] and reflect the persistent north-south divide in child nutritional outcomes.

However, a different spatial pattern was observed in wasting. Elevated probabilities were detected in Yobe, Borno, Rivers and Delta). This indicates that acute malnutrition has a more dispersed spatial distribution compared to chronic forms. This finding is consistent with previous study on the role of climatic shocks in driving acute malnutrition was highlighted [4].

The maps of the bivariate analysis also reveal distinct spatial association between pairs of malnutrition indicators across Nigeria. The stunting-underweight map shows strong spatial overlap, with states in the North-West and North-East such as Sokoto, Zamfara, Katsina, Jigawa, and Yobe showing concurrent high prevalence of both chronic and all malnutrition, indicating shared geographic risk factors. In contrast, the stunting-wasting map demonstrates moderate spatial divergence. While northern states exhibit high stunting, wasting is higher only in Borno, Yobe, Rivers and Delta. This reaffirms that chronic and acute malnutrition do not always co-occur and reflect distinct risk factors. Besides, minimal spatial overlap was observed in underweight-wasting map, with concurrent elevated risk limited to isolated areas in Borno and Yobe. Overall, the bivariate maps underscore that stunting and underweight share strong spatial patterns as confirmed by their high correlation value while wasting exhibits a more dispersed and distinct distribution, underscoring the need for geographically targeted and outcome-specific nutrition strategies. Also, the significant influence of precipitation and temperature stresses the need to integrate climate adaptation into nutrition programs. The study findings contribute to progress toward SDG 2.2 (Zero Hunger) and SDG 3.2 (Good Health and Well-being) through targeted interventions on ending childhood malnutrition [31].

CONCLUSION

This study utilized a two-stage Bayesian hierarchical modeling approach to examine the joint spatial distribution and determinants of childhood malnutrition in Nigeria/.The study revealed that stunting and underweight are strongly clustered in northern states, while wasting displays a distinct spatial pattern, highlighting the need for geographically targeted interventions. Maternal education was identified as the most consistent protective factor across all forms of malnutrition, with a clear dose-response gradient. Household wealth and climatic variables also had significant but differential roles as risk factors of malnutrition. The analysis of covariate differential effects revealed that education and climate factors have stronger associations with specific outcomes, underscoring the importance of outcome-specific intervention strategies. There was a strong positive spatial correlation between stunting and underweight while stunting and wasting showed moderate negative correlation, and underweight and wasting showed positive but negligible correlation. Findings from this study provide highly essential evidence for designing cost-effective, multi-sectoral interventions that address the complex interplay of socioeconomic, demographic, and climatic factors underlying childhood malnutrition in Nigeria. Reviving poverty alleviation programs, prioritizing maternal education and climate adaptation strategies particularly in northern states with elevated risks is critical for reducing the burden of malnutrition and achieving sustainable improvements in child health. The maps generated identified high-risk areas with specific and concurrent forms of malnutrition, facilitating the creation of evidence-based policies, focused program assessment, and localized interventions in Nigeria.

One of the limitations of this study is that the cross-sectional nature of the data precludes causal inferences, and sampling weights and complex survey design were not accounted for in variance estimation. Furthermore, considering the fact that these variables were not included in the survey data, the study did not incorporate regional factors that are directly related to the nutritional status of under five children, such as food security, nutritional program coverage, and health system capacity. Despite these limitations, the study provides critical evidence for pinpointing high-risk areas of specific and concurrent childhood malnutrition and designing well focused and targeted interventions. Future studies could utilize spatiotemporal approach to assess how malnutrition patterns have changed over time and take sampling design effects into consideration when estimating variance.

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