EXPLORING THE DETERMINANTS OF BIRTH WEIGHT IN NIGERIA: A BAYESIAN MODELLING FRAMEWORK

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Abstract
This study investigates the determinants of low birth weight (LBW) in Nigeria using a Bayesian spatial modelling approach, leveraging data from the 2018 Nigerian Demographic and Health Survey (NDHS). The outcome variable, LBW, was defined as a binary indicator of birth weight under 2500g. Key explanatory variables included maternal education, wealth index, age, body mass index (BMI), child sex, birth order, and geographic location. The analysis reveals significant associations between LBW and factors such as maternal education, wealth, BMI, and multiple births. Spatial analysis further identifies specific regions in northern Nigeria, particularly Kaduna, Jigawa, and parts of the North-East and North-West, as high-risk areas for LBW. The findings underscore the need for targeted interventions, including improved maternal nutrition, better access to antenatal care, and strategies to address regional disparities in health outcomes. This study contributes to the understanding of LBW determinants in Nigeria and provides insights for policy.

Keywords: Spatial Modelling, binary indicator, explanatory variables, maternal education, Spatial analysis

Introduction

Birth weight is an essential indicator of neonatal health, influencing both immediate survival and long-term developmental outcomes. Low birth weight (LBW), defined by the World Health Organization as a birth weight less than 2.5 kilograms, remains a significant public health concern, particularly in developing countries like Nigeria (Avwerhota *et al.,* 2024; UNICEF, 2019; WHO, 2022). LBW is associated with increased risks of infant morbidity and mortality, as well as chronic health issues later in life. In Nigeria, the prevalence of LBW is influenced by a myriad of factors, including maternal age, nutritional status, socioeconomic conditions, and access to quality antenatal care (Gayawan & Alo, 2024). For instance, a study analyzing data from the 2013 Nigeria Demographic and Health Survey identified key predictors of LBW, such as maternal weight below 70 kg, twin pregnancies, primiparity, and manual paternal employment. Additionally, maternal anemia, particularly prevalent in traditional birth settings, has been linked to higher incidences of LBW (Dahlui *et al.*, 2016; Muula *et al.*, 2011; Oladeinde, *et al.,* 2015).

Socioeconomic disparities further exacerbate the issue. Research indicates that infants born to parents in lower socioeconomic classes tend to have significantly lower mean birth weights compared to those from higher classes, highlighting the impact of parental education and occupation on neonatal outcomes (Kehinde *et al.,* 2021). Preventing low birth weight (LBW) remains a critical focus of public health strategies aimed at improving maternal and neonatal outcomes globally. While LBW prevalence varies widely between and within countries, the burden is disproportionately higher in low- and middle-income regions, particularly among vulnerable populations. A birth weight below 2500 grams typically results from either premature delivery (before 37 weeks of gestation) or inadequate fetal growth during pregnancy [Thapa *et al.,* 2022; Yaya *et al.,* 2022; Adeleke *et al.*, 2018; Mahmud *et al.*, 2020; Kim and Saada, 2013; Desai, S., and Alva, 1998).

To effectively address and mitigate the factors contributing to LBW, it is essential to employ robust analytical methods that can handle the complexity and variability of the data. Bayesian modeling offers a powerful statistical framework for this purpose, allowing for the incorporation of prior knowledge and the handling of uncertainty in parameter estimation (Ugerte *et al.*, 2014; Ibrahim et al., 2025). Recent studies have utilized Bayesian spatial analysis to identify regional patterns and risk factors associated with LBW in Nigeria, providing valuable insights for targeted interventions (Musau *et al.,* 2023; Mahumud *et al.,* 2017; Manyeh *et al.,* 2016).

This study aims to explore the determinants of birth weight in Nigeria using a Bayesian modeling approach, leveraging recent data to identify key risk factors and inform policy decisions aimed at improving maternal and neonatal health outcomes.

Material and Methods

Summary of Data Sources and Variables

This study Uses data from 2018 Nigeria Demographic and Health Survey N(DHS). LBW is the dependent variable defined as a binary outcome variable coded as 1 for children weighing less than 2,500 grams at birth and 0 otherwise. A range of explanatory variables was included to account for socio-demographic and environmental influences. These variables comprise the child's sex and age, area of residence (urban or rural), maternal education level, and household wealth index. Geographic variability was captured using state-level indicators, representing Nigeria's 36 states and the Federal Capital Territory (FCT).

Data management and preliminary descriptive analyses were conducted using R statistical software. For the spatial analysis, Bayesian geo-additive modeling was implemented using **INLA package in R** which allowed for the estimation of both fixed effects and spatially structured random effects, accounting for regional heterogeneity in LBW risk across the country.

Model Specification

Y_{ij} denote the birth weight status of the ith child in the jth administrative region of Nigeria (state), where $j = 1,2,\dots,37$ (representing the 36 states and the Federal Capital Territory). The binary outcome variable is defined as:

$$Y_{ij} = \begin{cases} 1 & if\ child\ i\ in\ state\ j\ had\ low\ birth\ weight\ (<\ 2500g) \\ 0 & if\ child\ i\ in\ state\ j\ had\ normal\ birth\ weight\ (\geq\ 2500g) \end{cases} \quad (1)$$

We assume the following Bernoulli distribution for the binary response:

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

where π_{ij}represents the probability that child i in state j had a normal birth weight.

To estimate π_{ij}, we applied a Bayesian hierarchical logistic regression framework of increasing complexity, incorporating the following components:

Fixed effects for individual- and household-level characteristics known to influence birth weight, including child's sex, maternal age, educational attainment, household wealth index, area of residence (urban/rural), parity, and number of antenatal care visits;

Structured spatial effects u_j to capture spatial correlation across neighboring states, modeled using an Intrinsic Conditional Autoregressive (ICAR) prior;

Unstructured spatial effects v_j to account for spatially uncorrelated heterogeneity, modeled with an independent and identically distributed (iid) Gaussian prior.

The linear predictor of the logistic model is defined as:

$$\text{Logit}\ (\pi_{ij}) = X_{ij}^{T}\beta + u_j + v_j \quad (3)$$

where:
$X_{ij}^{T}$is the vector of covariates for child iii in state$j$,
β is the corresponding vector of regression coefficients,
u_j and v_j represent the structured and unstructured spatial effects, respectively.

Likelihood
The likelihood function for all $i = 1,2,\dots,n_j$ children in all $j = 1,2,\dots,37$ states is:

$$p(Y|\beta,\ u,v) = \prod_{j=1}^{37}\prod_{i=1}^{n_j}\left[{\pi_{ij}}^{Y_{ij}}\left(1-\pi_{ij}\right)^{1-Y_{ij}}\right] \quad (4)$$

Where

$$\pi_{ij} = \frac{\exp\ (X_{ij}^{T}\beta + u_j + v_j)}{1 + \exp\ (X_{ij}^{T}\beta + u_j + v_j)} \quad (5)$$

Prior Assignment
Fixed Effects:

$$\beta \sim N\left(0, \sigma_{\beta}^{2}\right) \quad (6)$$

where σ_{β}^{2} is the variance of the prior distribution for the fixed effects
The structured spatial effects (u_j) are modelled using an Intrinsic Conditional Autoregressive (ICAR) prior (Spiegelhalter *et al.,* 2022):

$$u_j|u_{-j} \sim N\left(\frac{1}{m_j}\sum_{k\in\delta_j} u_k, \frac{\sigma_u^2}{m_j}\right) \quad (7)$$

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

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

$$v_j \sim N(0, \sigma_v^2) \quad (8)$$

Posterior Distribution

The joint posterior distribution of all unknown parameters, $\beta,\ u,v,\ \sigma_u^2, \sigma_v^2$ is

$$p(\beta,\ u,v,\ \sigma_u^2,\sigma_v^2|Y) \propto p(Y|\beta,\ u,v)\,.P(\beta)\,.P(u|\sigma_u^2)\ .\ P(v|\sigma_v^2)\,.\ P(\sigma_u^2)\,.\ P(\sigma_v^2) \quad (9)$$

Model Comparison
The performance of the models was evaluated using the Deviance Information Criterion (DIC) (Spiegelhalter *et al.,* 2002), which is defined as:

$$DIC = \overline{D} + \rho D \quad (10)$$

where:
$\overline{D}$ represents the posterior mean of the deviance,
ρD is the effective number of parameters.
A lower DIC value indicates a model that provides a better fit to the data (Spiegelhalter *et al.,* 2002).

Results and Analysis
This section presents the findings of the study based on the specified methodological framework. It begins with a descriptive summary of the variables used, followed by the results from the spatial models fitted to explore the determinants of birth weight in Nigeria. Key findings are illustrated using a table of posterior odds ratios and a spatial map showing states at the highest risk of low birth weight, with interpretations linked to the study's objectives.

Table 1: Frequency distribution of Child Birth Weight (CBW) by Covariates

Covariates	Low Birth Weight (LBW<2500g), %	Normal size (CBW≥2500g), %
Residence		
Urban	1608(13.7)	10091(87.3)
Rural	3490 (15.7)	18735(84.3)
Child sex		
Male	2396(13.8)	14861(87.2)
Female	2702(16.2)	13965(83.8)
Zone		
North Central	860(14.6)	5015(85.4)
North East	1187(16.5)	6024(83.5)
North west	1588(15.4)	8717(84.6)
South East	550(14.5)	3248(85.5)
South South	430(13.4)	2772(86.6)
South west	483(13.7)	3050(86.3)
Mother's wealth Index		
Poor	2646(16.7)	13163(83.3)
Middle	1058(14.8)	6113(85.2)
Rich	1394(12.7)	9550(87.3)
Mother's age		
$15-$	9392(83.8)	1810(16.2)
$24\ yrs$	13846(85.7)	2316(14.3)
$25-$	5588(85.2)	972(14.8)
$34\ yrs$		
$35\ yrs\ \ and\ above$		
Body Mass Index		
Low	943(9.7)	8741(90.3)
Normal	219(7.7)	2617(92.3)
High	55(7.4)	685(92.6)
Multiple Births		
	4684(14.3)	27977(85.7)
No	414(32.8)	849(67.2)
Yes		
Birth order		
First	975(15.1)	5501(84.9)
born	4123(15.0)	23325(85.0)
Later		
Born		

Source: 2018 NDHS

Table 1 shows the frequency and percentage distribution of low birth weight (CBW: <2500g) and normal birth weight (CBW ≥2500g) among Nigerian children, stratified by key demographic and socio-economic characteristics.

Overall, low birth weight was more prevalent among children born in rural areas (15.7%) compared to urban areas (13.7%). Similarly, female children (16.2%) had a higher incidence of LBW than males (13.8%).

Regional variation in LBW is evident. The North East zone recorded the highest percentage (16.5%) of LBW, followed by the North West (15.4%) and North Central (14.6%). Conversely, the South South had the lowest proportion (13.4%).

Socioeconomic status, as measured by the mother's wealth index, shows an inverse relationship with LBW. Children from poor households had the highest LBW prevalence (16.7%), while those from rich households had the lowest (12.7%), suggesting an association between poverty and birth weight outcomes.

With respect to maternal age, the youngest age group (15–24 years) had a slightly higher proportion of LBW births (16.2%) compared to older age groups.

Multiple births had a strong association with LBW, 32.8% of children from multiple births were born with low birth weight, significantly higher than the 14.3% among singletons. Also regarding mothers body mass, mothers with low BMI (underweight) had the highest proportion of LBW births, with 9.7% of children born with LBW in this category. In contrast, mothers with normal BMI and high BMI (overweight/obese) had 7.7% and 7.4%, respectively, of LBW children.

This pattern suggests that maternal nutritional status, as reflected by BMI, is inversely associated with the risk of low birth weight, highlighting the importance of adequate maternal nutrition before and during pregnancy.

Finally, birth order showed little variation: first-born children (15.1%) and later-born children (15.0%) had similar LBW rates.

Table 2: Posterior Odd Ratios and 95% Credible Interval for Low Birth Weight

Covariates	LBW		
	ROR	Std Error	95% CI
Residence			
Urban	1		
Rural	1.214	0.0532	0.916, 1.784
Educational status	1		
No education	1.115	0.032	0.852, 1.665
Primary	0.879	0.0535	0.741, 1.265
Secondary	0.721	0.0613	0.567, 0.942
Tertiary Education			
Birth order			
	1		
Others	1.321	0.0513	1.123, 1.517
Ist born			
Child Sex			
Male	1		
	1.213	0.0110	1.012, 1.621
Female			
Wealth Index			
Lower	1		
Middle	0.763	0.0441	0.514, 0.980
Upper	0.773	0.0536	0.709, 0.951
Child is twins			
	1		
No	1.256	0.0217	1.356, 2.541
Yes			
Body Mass Index	1		
Low	0.783	0.0715	0.634, 0.988
	0.764	0.423	0.465, 0.997
Normal			
High			

Table 2 shows the posterior odds ratios (ROR) and 95% credible intervals (CI) for various factors associated with low birth weight (LBW) in Nigeria. Children born in rural areas had higher odds of being underweight at birth (ROR = 1.214), although the association was not statistically significant as the CI (0.916–1.784) includes 1. Compared to mothers with no formal education, those with tertiary education were significantly less likely to have LBW babies (ROR = 0.721, 95% CI: 0.567–0.942). Other education levels showed no significant effect. First-born children had significantly higher odds of low birth weight than later-borns (ROR = 1.321, 95% CI: 1.123–1.517). Female infants were more likely to be born underweight compared to males (ROR = 1.213, 95% CI: 1.012–1.621). Children from middle and upper wealth households were significantly less likely to have LBW (ROR = 0.763 and 0.773, respectively), indicating a protective effect of improved socioeconomic status. Twins were at a markedly higher risk of LBW compared to singletons (ROR = 1.256, 95% CI: 1.356–2.541). Mothers with normal or high BMI had significantly reduced odds of delivering LBW infants compared to those with low BMI, further emphasizing the role of maternal nutritional status.

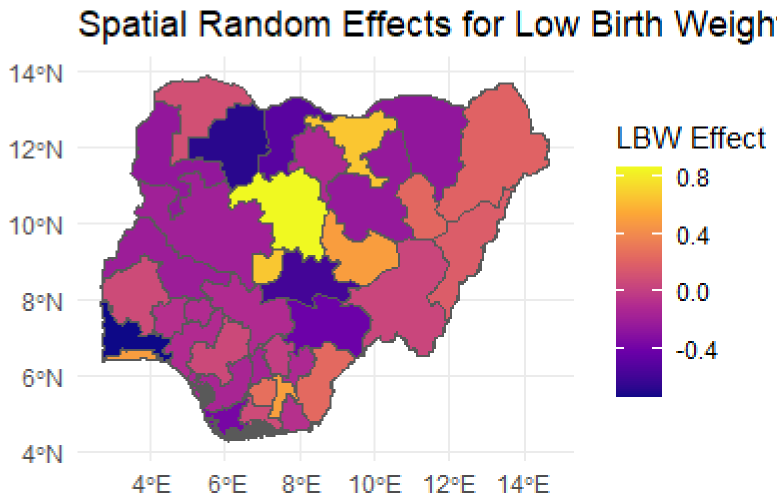

Figure 1: Spatial distribution of mean effects associated with Low Birth Weight across Nigeria

Figure 1 presents the spatial risk distribution of low birth weight (LBW) across Nigeria's states. The map highlights elevated LBW risk in states such as Kaduna, Jigawa, and Plateau. Additionally, several states in the northeastern region including Borno, Adamawa, and Taraba as well as Sokoto in the northwest, also exhibit a significantly higher burden of LBW compared to other areas.

Discussion of Findings

This study identified crucial socio-demographic and spatial factors influencing low birth weight (LBW) in Nigeria. Spatially, higher risks were observed in states like Kaduna, Jigawa, Plateau, Borno, Adamawa, Taraba, and Sokoto, regions consistent with poor maternal health indicators. Maternal education showed a protective effect; mothers with tertiary education had significantly lower odds of having LBW babies, aligning with (Silveira *et al.,* 2013; Ota *et al.,* 2014), who linked higher education with better birth outcomes. First-born children had higher LBW risks compared to later-borns, consistent with findings in Malawi (Muula *et al.,* 2011). Female infants were more likely to be LBW, though this pattern varies across studies (Endalamaw, *et al.,* 2018). Children from wealthier households were less likely to be born with low weight, highlighting the impact of socio-economic status on maternal nutrition and healthcare access (Gathimba *et al.,* 2017). Multiple births and low maternal BMI were both strong predictors of LBW, supporting existing evidence that undernutrition and twin pregnancies increase LBW risk (Oladeinde *et al.,* 2015).

Conclusion

This study employed a Bayesian spatial modeling framework to explore the determinants and geographic variation of low birth weight (LBW) in Nigeria. Findings revealed that maternal socioeconomic status, education, body mass index (BMI), child’s sex, birth order, and multiple births significantly influence the risk of LBW. Spatial analysis further identified northern states, particularly Kaduna, Jigawa, and parts of the North-East and North-West regions, as high-risk areas. These insights underscore the need for targeted public health interventions addressing maternal nutrition, education, and antenatal care, especially in identified hotspots, to reduce the prevalence of LBW and improve neonatal health outcomes in Nigeria.

Recommendation

This study recommends focusing on high-risk areas in northern Nigeria, particularly Kaduna, Jigawa, and parts of the North-East and North-West, for targeted LBW interventions. Strengthening maternal nutrition programs, improving antenatal care, and promoting maternal education and economic empowerment are essential to reduce LBW risks. Also, special care should be provided for first-time mothers and multiple pregnancies, while integrating spatial analysis into health planning can ensure more effective resource allocation.

Conflict of Interest Statement

The authors confirm that there are no conflicts of interest concerning the preparation or publication of this manuscript.

Authors' Contribution

All authors were involved in the research process, contributed to the manuscript review, and approved the final version of the paper.

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