Application of Bayesian Spatiotemporal Logistic Regression to Child Mortality in Nigeria

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ABSTRACT

This study investigates the persistent challenge of under-five mortality in Nigeria despite notable global progress in reducing child deaths. Conventional models often assume homogeneous relationships between risk factors and outcomes, neglecting spatial and temporal heterogeneity. To address this limitation, we develop a Bayesian Geographically and Temporally Weighted Logistic Regression (GTWLR) framework an extension of the Geographically and Temporally Weighted Regression (GTWR) model to binary outcomes. The Bayesian GTWLR model incorporates spatial and temporal weighting, prior knowledge, and full uncertainty quantification. Model estimation was implemented using the Integrated Nested Laplace Approximation (INLA) for computational efficiency and robust inference. Using data from the Nigeria Demographic and Health Surveys (NDHS), the model captures local variations in under-five mortality, identifies high-risk regions, and quantifies uncertainty through posterior credible intervals.This approach offers a rigorous statistical foundation for evidence-based policymaking, enabling geographically targeted interventions aligned with Sustainable Development Goal (SDG) 3.2.

Keywords: Child mortality; Bayesian inference; Spatiotemporal modeling; GTWLR; INLA

INTRODUCTION

Health is perceived as the most important part of any national economic growth policy, which aims at ensuring the quality of life for all citizens. The deaths of children between the ages of 0 and 59 months are referred to as under-five mortality. Despite coordinated efforts by all sectors, under-five mortality is still a major problem in Nigeria. According to **[9]**, Child survival continues to be a critical public health issue globally. While the number of under-five fatalities worldwide dropped from 12.6 million in 1990 to 5.2 million in 2019 **[10]**, Sub-Saharan Africa, particularly Nigeria, still represents over 80% of these deaths. The Sustainable Development Goals (SDGs) aim to reduce under-five mortality to a maximum of 25 deaths per 1,000 live births by 2030, yet Nigeria's current statistics remain significantly higher than this target. Previous studies on child mortality in Nigeria **[4]** emphasize its ongoing nature and the differences observed across regions. However, several statistical models employed in such studies presuppose that the impact of risk factors is consistent over both space and time, which restricts their capability to reflect variability. Despite significant advances in public health policy and the expansion of measures such as immunization, antenatal care (ANC), and skilled delivery attendance, Nigeria's child mortality rate remains unacceptable. Recent demographic **[15]** studies in Nigeria have increasingly employed advanced statistical models to examine event processes and time-dependent risk structures in population health outcomes. For example, Cox and extended Cox regression models have been applied to investigate age at first marriage among Nigerian women, highlighting the importance of accounting for temporal dynamics and covariate effects in demographic event analysis. However, while such survival models are well suited for time-to-event data, they do not explicitly account for spatial heterogeneity, which is crucial for understanding geographically varying patterns of under-five mortality." Beyond survival analysis, recent methodological studies **[16]** have also employed asymmetric autoregressive and time-series frameworks to capture dynamic and non-linear temporal behavior in observational data, further underscoring the growing importance of flexible time-dependent modeling in applied statistical research. The recurrence of this problem indicates that national averages disguise significant geographical and temporal variability in mortality risk. For example, rural and conflict-affected northern regions consistently have higher child death rates than their southern counterparts, owing mostly to disparities in maternal education, healthcare accessibility, sanitation, and socioeconomic inequality. These differences represent structural variables that extend beyond individual health behavior, indicating systemic disparities in resource allocation, healthcare infrastructure, and policy execution. Understanding such complex, non-stationary linkages necessitates a scientific approach that can account for local variances and shifting patterns in health outcomes.

Traditional global models, such as classical logistic regression and multilevel models, frequently presume parameter constancy, obscuring spatial relationships and temporal changes. As a result, policy interventions based on these models may be overly broad, failing to address localized causes of death that vary across locations and across time. [1] introduced Geographically Weighted Regression (GWR) to address spatial non-stationarity by allowing regression coefficients to vary across space, while [2] proposed the Geographically and Temporally Weighted Regression (GTWR) model, which captures both spatial and temporal heterogeneity. These frameworks, however, were designed for continuous outcomes, which limits their relevance to binary health outcomes such as life or death. Binary outcomes predominate in demographic and epidemiological studies because survival data is frequently categorized as alive or dead. The logistic regression framework continues to be the most effective statistical technique for modeling such outcomes. However, when applied at the national level, classical logistic regression assumes that the effects of explanatory variables are globally constant, failing to account for regional clustering and temporal evolution of risk factors.

Integrating logistic regression into a GTWR context, resulting in a Geographically and Temporally Weighted Logistic Regression (GTWLR) model, allows for the identification of local effects and temporal patterns in mortality risk while remaining interpretable within a logistic framework. Nonetheless, frequentist estimate of GTWLR can be computationally expensive and unstable, particularly when data is scarce in specific locations or times. The Bayesian technique, which is supported by new computing approaches such as the Integrated Nested Laplace Approximation (INLA), offers a strong alternative. Bayesian inference incorporates previous knowledge, generates credible intervals for all parameters, and quantifies uncertainty, resulting in a richer and more flexible inferential framework. INLA outperforms Markov Chain Monte Carlo (MCMC) in terms of computation time and scalability for big datasets, making it ideal for spatiotemporal modeling with Nigeria Demographic and Health Survey (NDHS) data. Ultimately, reducing under-five mortality in Nigeria requires analytical methods that go beyond descriptive statistics or global regression models. The Bayesian GTWLR framework developed in this study offers an advanced methodological tool for exploring complex spatiotemporal interactions among determinants of child survival, quantifying uncertainty, and producing credible, actionable insights for policymakers. By integrating rigorous Bayesian computation with geographic weighting, the study aims to provide not only a methodological innovation but also a scientific basis for regionally targeted health interventions that can accelerate Nigeria's progress toward achieving the SDG child survival targets. This approach offers a rigorous statistical foundation for evidence-based policymaking, enabling geographically targeted interventions aligned with Sustainable Development Goal (SDG) 3.2.

MATERIALS AND METHODS

2.1 Model Formulation

The classical Geographically and Temporally Weighted Regression (GTWR) model is extended to binary outcomes via a logistic link. The coefficient surfaces vary over space and time, allowing covariate effects such as maternal education and household wealth to change geographically and temporally.

Let $Y_i \sim Bernoulli(P_i)$, where:

$$\boldsymbol{P_i = P\left(Y_i = \frac{1}{X_i}\right) = \frac{1}{1+\exp(-\eta_i)}, \eta_i = \beta_0(u_{i,}v_i,t_i) + \sum_{k=1}^{p}\beta_k(u_{i,}v_i,t_i)X_{ik}} \qquad \textbf{(1)}$$

Where $\beta_k(u_{i,}v_i,t_i)$ *is the* Coefficient surface that vary over space and time, and X_{ik} *are* Covariate (e.g maternal education, wealth, etc)

2.2 Likelihood Specification

A Bernoulli likelihood is assumed for each observation, where the probability of child survival or death is governed by a spatiotemporally varying linear predictor. This formulation enables efficient computation while maintaining local variability.

The Bernoulli likelihood for one observation i is given as

$$P\left(\frac{Y_i}{\eta_i}\right) = P_i^{Y_i}(1 - P_i)^{1-Y_i},$$

therefore $$\boldsymbol{P\left(\frac{Y_i}{\eta_i}\right)} = \left(\frac{1}{1+e^{-\eta_i}}\right)^{Y_i}\left(\frac{e^{-\eta_i}}{1+e^{-\eta_i}}\right)^{1-Y_i} \ldots \qquad (2)$$

The probability of each child's outcome is determined exclusively by their spatiotemporally-varying linear predictor η_i, which takes into account local risk factors.

its log $-$ likelihood is given as:

$$\boldsymbol{Log\mathcal{L}(\beta) = \sum_{i=1}^{n}\left[Y_i\left(\beta_0(\mu_\kappa,t_i) + \sum_k^p \beta_k(u_{i,}v_i,t_i)X_{ik}\right)\right] - log(1+exp)\left(\beta_0(u_{i,}v_i,t_i) + \sum_k^p \beta_k(u_{i,}v_i,t_i)X_{ik}\right)} \qquad \textbf{(3)}$$

This log-likelihood summation allows efficient computation across all Nigerian regions while maintaining the spatial and temporal variability in risk patterns

2.3 Bayesian Framework and Prior Specification

The GTWLR model is embedded within a Bayesian framework to enhance estimation reliability. Weakly informative priors are assigned to spatial and temporal precision and range parameters to control smoothness and avoid overfitting. Incorporating the linear predictor (as defined by [2], the GTWLR model can be expressed as:

$$P\left(\boldsymbol{Y_i} = \frac{\boldsymbol{1}}{\boldsymbol{X_i}}\right) = \boldsymbol{P_i} = \frac{\boldsymbol{1}}{\boldsymbol{1+exp[-\beta_0(u_{i,}v_i,t_i) + \sum_{k=1}^{p}\beta_k(u_{i,}v_i,t_i)X_{ik}]}} \qquad \textbf{(4)}$$

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Where $Y_i \in [0, 1]$: Binary indicator of child mortality, X_{ik}: Covariate (e.g maternal education, wealth, etc) and $(u_{i,} v_i, t_i)$: Spatial (longitude, latitude) and temporal (year) Coordinates, $\beta_k(u_{i,} v_i, t_i)$: Coefficient surface that vary over space and time.

Weakly informative log-precision and log-range priors are specified to capture uncertainty while avoiding over fitting.

Log- precision prior (τ_s)

$$\mathbf{log}\boldsymbol{P(\tau_s) = -\frac{1}{2} log\left(2\pi\sigma^2_{\tau_s}\right) - log\tau_s - \left(\frac{\left(log\tau_s - \mu_{\tau_s}\right)^2}{2\sigma^2_{\tau_s}}\right)} \quad \textbf{(5)}$$

This represents the logarithm of the prior probability density function for the spatial precision parameter $\boldsymbol{\tau_s}$

Log- precision prior (τ_t)

$$\mathbf{log}\boldsymbol{P(\tau_t) = -\frac{1}{2} log\left(2\pi\sigma^2_{\tau_t}\right) - log\tau_t - \left(\frac{\left(log\tau_t - \mu_{\tau_t}\right)^2}{2\sigma^2_{\tau_t}}\right)} \quad \textbf{(6)}$$

This is the log of the prior probability density **for the** temporal precision parameter $\boldsymbol{\tau_t}$. It assumes that the logarithm of the temporal precision follows a **Normal (Gaussian)** distribution:

Log – Range Prior (P_t)

$$\mathbf{log\ Plog}\boldsymbol{P(P_t) = -\frac{1}{2} log\left(2\pi\sigma^2_{P_t}\right) - logP_t - \left(\frac{\left(logP_t - \mu_{P_t}\right)^2}{2\sigma^2_{P_t}}\right)} \quad \textbf{(7)}$$

The Joint Log-Prior Expression for Hyper-parameter is given as:

$$\boldsymbol{logp(\theta) = \sum_{k=1}^{4} p(\theta) = -log\tau_s - \left(\frac{\left(log\tau_s - \mu_{\tau_s}\right)^2}{2\sigma^2_{\tau_s}}\right) - logp_s - \left(\frac{\left(logp_s - \mu_{p_s}\right)^2}{2\sigma^2_{p_s}}\right) - log\tau_t - \left(\frac{\left(log\tau_t - \mu_{\tau_t}\right)^2}{2\sigma^2_{\tau_t}}\right) - logP_t - \left(\frac{\left(logP_t - \mu_{P_t}\right)^2}{2\sigma^2_{P_t}}\right) + Constant} \quad \textbf{(8)}$$

These priors control smoothness and prevent over fitting of spatial and temporal random effects. Estimation via INLA The Integrated Nested Laplace Approximation (INLA) is used for making posterior inferences. In contrast to Markov Chain Monte Carlo (MCMC), INLA eliminates the need for expensive iterative sampling, which enhances its efficiency for large datasets like NDHS. It delivers precise approximations of posterior marginals while ensuring computational practicality ([11], [12]). The posterior distributions for the parameters in Bayesian Hierarchical spatio-temporal models in this study are simulated in the software R-INLA, to reduce the computation time often incurred when analyzing large spatial datasets. A variety of prior distributions for model parameters and random effects can be specified in R-INLA. The Bayesian spatiotemporal modeling method leverages information from both counties and years to generate smoothed annual estimates at the county level and facilitates the analysis of spatial and temporal variations in rare mortality causes over time. This approach can be utilized for many uncommon causes of death outcomes to analyze minor geographic differences and changes over time using model-based, smoothed, and reliable small area estimates. The precision of the INLA estimates in relation to MCMC estimates has been assessed across numerous study regions [13].

DESCRIPTIVE STATISTICS AND TRENDS

Descriptive statistics reveal improvements in maternal education, antenatal care utilization, and urban residence across survey years, alongside persistent challenges related to sanitation, cooking fuel, and breastfeeding practices.

Table 1: Summary of Key Child and Maternal Characteristics, NDHS 2008-2018

Indicator	2008	2013	2018	Trend
Child outcome (Alive)	20,140	20,239	18,220	Slight decline
Child deaths	84,668	99,147	109,325	Increase
Urban residence (%)	25.4	32.5	34.6	Rising
Rural residence (%)	74.6	67.5	65.4	Declining
No maternal education	58,550	60,778	63,699	Slight
Primary education	24,785	27,945	25,311	Stable
Secondary education	17,039	24,388	30,756	Substantial
Higher education	4,434	6,275	7,779	Increasing
No antenatal visits	7,013	6,662	5,365	Improving
Inadequate ANC (1–3)	1,963	2,483	3,793	Slight rise
Adequate ANC (≥4)	9,688	10,507	12,307	Increase
Still breastfeeding	76,161	10,690	10,309	Sharp drop
Breastfed until stopped	26,223	20,304	22,781	Mild decline

Table 1 presents key child and mother characteristics from the 2008, 2013, and 2018 Nigeria Demographic and Health Survey (NDHS) waves. It demonstrates gradual advances in maternal education, antenatal care use, and the use of contemporary fuels. The number of women with secondary or higher education has risen dramatically, indicating improved female literacy and potential increases in health awareness. Over three survey years, there was a continuous increase in adequate prenatal care attendance (≥ four visits), indicating higher engagement with maternal health services.

However, the descriptive analysis indicates ongoing health and environmental challenges. Breastfeeding rates fell substantially, biomass fuels like wood remained popular, and insufficient sanitation facilities persisted. These characteristics provide substantial challenges to improving child health outcomes, especially in rural and low-income areas.

Table 2: Maternal and Environmental Health Indicators (% of total per year)

Indicator	**2008 (%)**	**2013 (%)**	**2018 (%)**	**Direction**
At least one ANC visit	60.8	66.8	75.4	Increasing
Adequate ANC (≥4 visits)	45.0	52.3	60.0	Increasing
Access to improved toilet	88.9	88.0	89.0	Stable
LPG as primary cooking fuel	0.2	0.5	4.2	Increasing

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Wood as primary cooking fuel	79.8	74.6	71.0	Decreasing
Urban residence	25.4	32.5	34.6	Increasing
Mothers with secondary/higher education	21.5	30.6	38.1	Increasing

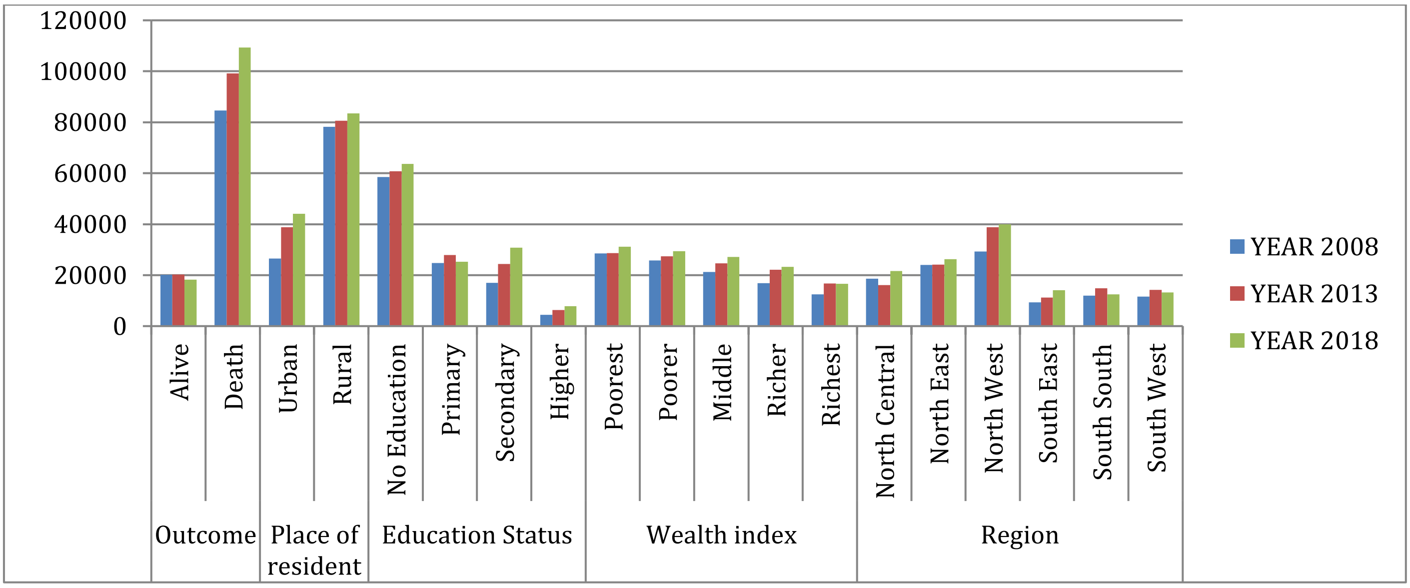
Table 2 further illustrates that, while access to maternal health services has improved, as has urbanization. Women receiving at least one prenatal care visit increased from 60.8% to 75.4%, while those receiving enough ANC (≥ 4 visits) climbed from 45% to 60%. The use of LPG as a cooking fuel increased dramatically, demonstrating progressive modernization. Nevertheless, more than 70% of homes continued to rely on wood, and sanitary coverage improved only little. These mixed patterns show that, while health-care consumption has improved, environmental health variables remain major restrictions.

Table 3: Summary of Child Mortality-Related Factors

Category	2008	2013	2018	Observation
Health service use (ANC ≥ 4)	9,688	10,507	12,307	Access improved
Poor environmental condition (no toilet)	11,936	12,045	11,365	Stable
Traditional cooking fuel (wood)	24,169	25,539	26,859	Persistent use
Child ever breastfed (%)	99.3	97.3	96.5	Slight decline
Never breastfed (%)	0.7	2.7	3.5	Increase

Table 3 Summarize proximate risk variables for child death. The rise of appropriate ANC utilization demonstrates growth in maternal health awareness; nevertheless, continued reliance on traditional fuels and limited sanitation access suggest ongoing exposure to household air pollution and infection risks. Breastfeeding indicators show a little decrease in "ever-breastfed" proportions and a slight increase in "never-breastfed," implying behavioral or socioeconomic factors that require additional exploration using the Bayesian spatiotemporal model.

3.1 Spatial and Socioeconomic Patterns of Child Mortality



3.2 depicts trends in child survival and mortality from 2008 to 2018, using NDHS data. The total number of reported child fatalities grew during the period, indicating that, despite governmental actions and global attention, under-five mortality remains a significant public health burden in Nigeria. This tendency may reflect population increase and improved data collection, but it also highlights that national progress toward Sustainable Development Goal (SDG) 3.2 has been gradual. Regional study indicates major differences. Child mortality rates are consistently higher in the North East and North West, whereas they are lower in the South West, South East, and South South regions. These spatial inequities are directly related to differences in maternal education, household wealth, and healthcare access. Rural communities continue to have disproportionately high death rates due to inadequate health infrastructure, low skilled birth attendance, poor sanitation, and nutritional deprivation. Child survival rates are higher in urban settings, which is most likely due to better access to health services, improved water and sanitation facilities, and higher levels of maternal education. Socioeconomic gradients are also evident. Children from poorer households and those born to mothers without formal education are significantly more likely to die before age five. Conversely, maternal education and household wealth act as strong protective factors, reinforcing the evidence that social determinants remain pivotal in shaping child survival outcomes.

DISCUSSION

Despite gains in healthcare coverage and maternal education, under-five mortality in Nigeria remains high, emphasizing the need for models that go beyond national averages. Traditional regression models assume constant effects of covariates, which obscures local variability and changing risk dynamics. This study tackles these limitations by using a Bayesian Geographically and Temporally Weighted Logistic Regression (GTWLR) framework that allows for parameter variation across space and time.

The descriptive findings are similar with earlier research [14]; [8]; [7], which found regional variation in child mortality across Nigeria and Sub-Saharan Africa. However, the Bayesian GTWLR approach improves statistical rigor by quantifying uncertainty using posterior credible intervals and borrowing strength across geographical and temporal dimensions. This is especially crucial for health surveillance in low-resource settings, because sample numbers can fluctuate between states and years. From a policy standpoint, these findings highlight the critical necessity for regionally tailored interventions. Policies aimed at northern Nigeria should prioritize maternal education, antenatal care access, vaccine coverage, and improved sanitation. In the south, where mortality is lower but inequities persist among the poor, interventions should focus on household poverty reduction and child feeding initiatives.

Furthermore, Bayesian spatiotemporal modeling generates actionable data for resource allocation and progress tracking. Posterior predictive mapping of mortality risk allows policymakers to visualize local hotspots, identify new high-risk areas, and assess the long-term impact of current health measures. This localized evidence base promotes the fair deployment of health interventions, ensuring that no region falls behind as Nigeria strives to achieve SDG 3.2.

CONCLUSION

This study created a Bayesian Geographically and Temporally Weighted Logistic Regression (GTWLR) framework for analyzing under-five mortality in Nigeria, extending the traditional GTWR model to binary outcomes and using Bayesian inference with the Integrated Nested Laplace Approximation (INLA) for efficient estimation. The proposed model effectively captures regional and temporal variability, includes prior knowledge, and quantifies uncertainty in model parameters, thus providing deeper insights into the localized determinants of infant mortality. By identifying region-specific risk factors and high-mortality areas, the framework lays the groundwork for evidence-based health interventions aimed at achieving equity and accelerating progress toward SDG 3.2, which aims to reduce under-five mortality to 25 deaths per 1,000 live births by 2030. Furthermore, the framework emphasizes continuing regional inequalities in Nigeria related to maternal education, household wealth, healthcare access, and environmental circumstances.

Future research should extend this framework across multiple NDHS waves to capture longer-term temporal dynamics, incorporate Gaussian Process priors or hierarchical Bayesian structures to improve predictive performance, and expand to multivariate or multilevel settings to model related health outcomes such as neonatal and infant mortality. The use of posterior predictive mapping to visualize high-risk locations will also help policymakers devise spatially targeted interventions. Overall, the Bayesian GTWLR framework represents a thorough and robust methodological development for modeling complex health disparities, with significant potential to guide data-driven policy and improve child survival outcomes in Nigeria.

List of Abbreviations

GTWR – Geographically and Temporally Weighted Regression
GTWLR – Geographically and Temporally Weighted Logistic Regression
INLA – Integrated Nested Laplace Approximation
NDHS – Nigeria Demographic and Health Survey
SDG – Sustainable Development Goal

Competing Interests

The authors declare no competing interests.

Authors' Contributions

OLUBIYI, Adenike Oluwafunmilola: Manuscript review and approval.
AYODELE, Oluwasola Joshua: Methodology development.
OYINLOYE, Adedeji Adigun: Data analysis.
ABIFADE, Victor Oluwatobi: Modeling and interpretation.
ONIYINDE, Yetunde Omolara: Manuscript preparation.
FAYODE, Taiwo Eniola: Manuscript editing.

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