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ORIGINAL RESEARCH ARTICLE

Geo-Additive Discrete-Time Survival Modelling of Geographical Variations in Infant and Child Mortality in Jigawa North East Region

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ABSTRACT
This research examined the lingering regional variations in infant and child mortality in the Jigawa North East area. The study investigated how different categories of risk factors contributed to the spatial disparities observed in the area. A census on population and housing was carried out employing research assistants who collected information from one household to another across the entire region. Geo-additive regression was employed in this study to analyze the factors linked with infant and child mortality within the Jigawa North East region. The findings indicate that, in the Jigawa North East region, Birniwa and Kafin-Hausa have the highest rate of infant and under-five mortality. This can be ascribed to the widespread occurrence of childhood illnesses, overall healthcare practices, persistent poverty levels, and severe malnutrition stemming from food insecurity in areas. The current study has helped to identify geographical 'hotspots' as well as the key factors driving under-5 deaths in Jigawa North East Region. Therefore, policymakers need to pay attention to the findings from this study, as it can help in designing better strategies that will enable the attainment of the SDG 3 targets of reducing under-five mortality to at least 25 per 1000 live births.

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INTRODUCTION
Under-five mortality rates refer to the number of deaths that occurred under five years per 1000 live births or children born in a specified year dying before reaching the fifth birthday subject to current age-specific mortality rates and expressed as a rate per 1,000 live births. Infant mortality can be defined as the number of deaths that occurred under one year per 1000 live births or infant/child born in a specified year dying before reaching the first birthday subject to current age-specific mortality rates and expressed as a rate per 1,000 live births (United Nations 2015).

In the year 2018 alone, there were a total of 5.3 million deaths, indicating a significant global risk for children dying before reaching the age of five, as reported by UNICEF (2020). Despite a general decrease of 59% from 1990 to 2018, the African region still displays the highest under-five mortality rate (U5MR) at 76 deaths per 1000 live births. Sustainable Development Goal 3, which specifically targets "ensuring healthy lives and promoting well-being for all," strives to achieve universal health coverage (UHC) by granting access to high-quality, safe, effective, affordable, and essential healthcare services. Furthermore, the goal is to "end preventable deaths of newborns and children under the age of 5 by 2030," as outlined by the United Nations (2015). The aspiration is that by 2030, each country will have decreased the mortality rate for children under the age of five to no more than 25 deaths per 1,000 live births (United Nations 2015). The elevated under-5 mortality rates (U5MR) in Nigeria serve as an indication of generally poor health outcomes, as deaths among children under five are a metric reflecting the effectiveness of a society's value system in handling its healthcare system (Morakinyo & Fagbamigbe 2017; Yaya et al. 2018).

Jigawa North Northeast region encompasses eight (8) local government areas and represents possibly the most densely populated area with the highest number of local government areas in the State. The region is experiencing the highest incidence of infant and child mortality cases. The current healthcare system in the region is confounded with complexity and significant distinctive interactions between individuals. Currently, the biggest hospital in the region has twenty-three departments offering a wide range of healthcare services to a population of around 300,000. The outpatient department of the hospital is bedevilled with an unprecedented demand for healthcare services,

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lengthening the waiting time of the patient. This occurrence may increase the pressure on the hospital workforce, aggravating patient handling errors and patient dissatisfaction.

There is a wealth of literature that explores patterns in mortality among children under the age of five in diverse contexts, encompassing both developed and developing countries. Many investigations within this field of study have pinpointed various risk factors linked to deaths among children under the age of five. These elements include maternal age, differences in living conditions between rural and urban areas, household wealth status, educational achievement, employment situation, marital status, religious affiliation, birth type, birth order and spacing, gender and weight at birth, as well as the location and manner of delivery (Akinyemi et al. 2015a, b; Alkema et al. 2014; Chao et al. 2018; Ezeh et al. 2015; Morakinyo and Fagbamigbe, 2017; Yaya et al. 2018). As an illustration, Alkema et al. identified noteworthy disparities in survival rates up to the age of five between boys and girls across various nations worldwide (Alkema et al. 2014). The researchers observed that, while there are noteworthy exceptions in specific nations, the sex ratios generally lean towards higher numbers for boys in comparison to girls (Alkema et al. 2014).

The geo-additive regression model is designed to simultaneously screen predictor variables and jointly estimate the fixed effects, nonlinear effects of continuous covariates, spatial effects, and possible random effects accounting for unobserved heterogeneity. Various studies have adopted this methodology, including Amusa & Yahaya (2019), who adopted a stepwise geo-additive regression model and explored fertility preferences using the ideal number of children desired by married women in Nigeria by utilizing the NDHS (Nigeria Demographic Health Survey) data. Gayawan & Adebayo (2015) also employed a geo-additive regression model to examine the determinants and geographical variations of women's employment status in Nigeria using data from the 2008 Nigeria Demographic and Health Survey.

Although connections have been established between socioeconomic inequalities, residential geographical locations, and diverse health outcomes, including under-5 mortality, there is a lack of research in the existing literature that delves into the spatial distribution, patterns, and variations of under-5 mortality, specifically in Jigawa State. This shortage has impeded a comprehensive grasp of how the states (regions) of residence contribute to the characteristics of under-5 mortality in children. Therefore, a geo-additive regression model is employed in this study to examine the persisting geographical differences in infant and child mortality, evaluating the contributions of various risk factor categories to the spatial inequality within the Jigawa North East region. The study is significant because the result identified the factors of infant and child mortality in the study area. The result of the study will also help to inform policymakers to consider the important contributing factors and design better strategies that will enable the attainment of the SDG 3 targets of reducing under-five mortality to at least 25 per 1000 live births.

METHODOLOGY

Description of the Study Area

Jigawa state is among the 36 states in Nigeria, situated in the northern part of the country. It is located at approximately latitude 12°00' N and longitude 9°45' E in the northwest region of Nigeria. Covering an expanse of 23,154 square kilometers (8,940 square miles), Jigawa state ranks as the eighth largest state in terms of population, with a census figure of 4,361,002 recorded in 2006 (Nigeria Population Commission, NPC, 2006). This study was conducted in the Jigawa North Northeast region, encompassing eight (8) local government areas and representing possibly the most densely populated area with the greatest number of local government areas. The selection of this area for the study is based on three primary factors: the researcher's residence is Jigawa Northeast region, the region experiencing the highest incidence of infant and child mortality cases, and the availability of easily accessible, accurate, and reliable data for research purposes. Therefore, the conclusions drawn from the research were credible, dependable, and valuable.

Sampling Technique

This is a descriptive cross-sectional study carried out at selected households from various selected communities of the Jigawa Northeast region on geo-additive discrete-time survival modelling of geographical variations in infant and child mortality. A quantitative method research design was employed during data collection. The quantitative data covered information obtained via semi-structured questionnaires. The selection of the communities was done by multistage sampling. Jigawa Northeast was purposefully selected for the study. Jigawa Northeast wards in the 8 LGAs were divided into 10 groups (clusters) in such a way that each cluster represented the potential characteristics of the entire population. One ward was selected from the 10 wards (clusters) using a simple random sampling method by assigning a number to each ward. All women aged 15–49 years present in the selected wards participated in the survey. Information on infant and child mortality was collected from every household in the two randomly selected wards (clusters). All mothers who were unavailable during data collection that consented to be part of the study, the fathers or caregivers have been used in such situations.

Data Collection Tool

The respondents were assessed using an interviewer-administered questionnaire. The research question and the study's goals were guided in the development of the questionnaire. The interviewer-administered questionnaire consisted of multi-choice close-ended questions prepared based on a literature review of previous work done on the subject. The sample size analyzed for each LGA is presented in Table 1. The well-trained research assistants then collected the information from each respondent using an interviewer-administered questionnaire for a brief period of time. The mother and caregiver have reported data on demographic and socioeconomic characteristics. Data refer to children born in the 5 years prior to the surveys. Demographic variables that were considered inherent to the mother and child are maternal age, type of place of residence, child's birth order, whether or not the birth was single, sex of the child, and sex of the household head. Variables classified as mother's status include mother's educational attainment, household wealth index, and mother's working status. Amenity variables include electricity, toilet facility, water source, place of delivery, and exposure to media (newspaper, radio, and television; whether or not the mother was exposed to each of these at least once a week).

Method of Data Analysis

Descriptive statistics for maternal, children, biological, and household characteristics were generated using Stata Version 16. The Infant and Under 5 Mortality Rates were computed using the "table" command in Stata. Inferential analysis was conducted using Bayesian geo-additive regression models.

Under-five and Infant Mortality Rates

Infant Mortality Rate (IMR)

The IMR is the number of deaths of infants under age 1 per year per 1000 live births in the same year, i.e.

$$IMR = \frac{No\ of\ death\ under\ 1\ year}{Total\ live\ births} * 1000 \quad (1)$$

Under-five Mortality Rate (U5MR)

The U5MR is the number of deaths of infants under age 5 per year per 1000 live births in the same year, i.e.

$$U5MR = \frac{No\ of\ death\ under\ 5\ years}{Total\ live\ births} * 1000 \quad (2)$$

The Bayesian Geo-Additive Model

To investigate the influences of important socioeconomic and socio-demographic factors, along with the potential impact of geographical location on the likelihood of a child's death before the age of 5, hierarchical Bayesian geo-additive regression models were employed. Specifically, our model is a binomial regression, where the binary response y_{ij} is assigned a value of 0 if the child (ij) aged < 5 years is alive and 1 if the child died before reaching the age of 5 $(i = 1, \ldots, S; j = 1, \ldots, n)$. In this context, $S(= 10)$ denotes the number of clusters (wards) in the Jigawa North East Region, serving as the geographical units of interest. Hence, the variable y_{ij} is distributed according to a Bernoulli distribution, where π_{ij} denotes the probability of a favorable outcome, specifically the likelihood that a randomly chosen child succumbed before turning 5. This relationship is formally expressed as $y_{ij} \sim$ Bernoulli (π_{ij}), with the mean (expected value) $\mu_{ij} = E[Y_{ij}|\pi_{ij}]$ equating to π_{ij}. The variance $Var[Y_{ij}|\pi_{ij}]$ is determined by $\pi_{ij}(1 - \pi_{ij})$. Furthermore, the probability mass function (pmf) governing the occurrence of the response is outlined by this distribution.

$$(f; \pi) = \pi^y (1 - \pi)^{1-y} \quad \text{for} \quad y \in \{0,1\} \quad (3)$$

In the context of the semi-parametric geo-additive mixed models utilized in this research, the response variable y is affected by a group of covariates through a linear predictor η_{ij}, which is connected to a function of its mean via a link function $g(\mu_{ij})$. This modeling approach, as described in Equation (4), is based on previous works such as Brezger (2006), Kandala et al. (2019), and Kneib and Fahrmeir (2006).

$$\eta_{ij} = f_1(x_{ij1}) + \cdots + = f_p(x_{ijp}) + f_{spat}(s_i) z'_{ij}\gamma + \omega_i \quad (4)$$

In this context, the mean μ_{ij} is determined by the inverse logit link function $g^{-1}(\eta_{ij})$, where η_ij is the linear predictor. The functions f_$f_1, \ldots, f_p$ are nonlinear (not necessarily smooth) functions of continuous covariates $x_{ij1}, \ldots, x_{ijp}$, such as maternal age. Additionally, the function $f_{spat}(s_i)$ represents a non-parametric function of the spatial covariate, which belongs to the set $s_i \in \{1, \ldots, S\}$ and corresponds to the ith geographical location. This function takes into account the cumulative unobserved effects associated with different geographical locations.

The variables $z'_{ij}s$ represent individual-specific attributes that are categorical, such as Gender, Educational level, Wealth index, etc. The corresponding coefficients for these variables are captured by the vector γ. The term ω_i accounts for the random effects at the cluster level, specifically at the ward level, incorporating unobserved factors inherent in the survey design that are not explained by the spatial function $f_{spat}(.)$. This term is assumed to follow a Gaussian distribution with a mean of zero, denoted as $\omega_i \sim Normal(0, \sigma_\omega^2)$, where the parameter σ_ω^2 represents the variance and needs to be estimated. This method has been widely applied in various instances, as evidenced by multiple examples in existing literature. Notable references include works by Gelman and Little (1997), Little (1993, 2012), Malec et al. (1999), Molina et al. (2014), Rao and Molina (2015), Si et al. (2015), Sugasawa (2020), and Zhang et al. (2014).

It is justifiable to posit that neighboring geographical locations, specifically Local Government Areas (LGAs), exhibit greater similarities, consistent with the first law of geography articulated by Tobler in 1970. This principle asserts that proximate entities tend to share more similarities than those located at a greater distance from each other. On the contrary, it is reasonable to presume that observations within local government districts that are farther apart are independent of each other and lack shared boundaries and characteristics. Thus, to effectively account for both the inherent spatial autocorrelations among nearby local government areas (LGAs) and the spatial independence among more distant LGAs, the spatial effect denoted as f_{spat} in Equation (3) is deconstructed into two components: a spatially correlated (structured) part represented by $f_{str}(.)$ and an uncorrelated (unstructured) part denoted as $f_{unstr}(.)$, as depicted in Equation (4).

$$f_{spat}(s_i) = f_{str}(s_i) + f_{unstr}(s_i) \quad (5)$$

The breakdown presented in Equation (5) offers a notable advantage by allowing for the measurement of spatial dependency within the data. This enables a direct comparison between the two effects, as a larger unstructured effect signifies a lower level of spatial dependency and vice versa. For clarity and ease of identification, all functions are standardized to be centered around zero. The research questions will be simultaneously investigated using equations (6) and (7). Equation (6) examines the unadjusted effects of spatial geography, considering only the spatial aspect without incorporating other covariates. On the other hand, equation (7) assesses the adjusted effects of spatial location, taking into account the influence of additional covariates. In the second equation, the evaluation incorporates the consideration of individual- and community-level covariates, enabling a simultaneous examination of the effects of these factors.

Unadjusted model:

$$u5m_i \sim f_{str}(LGA_i) + f_{unstr}(LGA_i) \quad (6)$$

Adjusted model:

$$u5m_i \sim f_{str}(LGA_i) + f_{unstr}(LGA_i) + Ethnicity + Gender + \cdots + f\ (Age) \quad (7)$$

Here, the variable $u5m_i$ represents the response variable, taking a value of 1 if the *ith* child succumbed before reaching the age of 5, and 0 if the child survived beyond that age.

Following this, the models will be applied using R2BayesX, an R interface for BayesX, a well-established statistical program designed for the fitting of various generalized additive mixed models. The analysis will be carried out using the R statistical programming language, specifically version 3.6.1, following the guidelines provided by Belitz et al. (2011).

The Deviance Information Criterion (DIC), introduced by Spiegelhalter et al. (2002), will be employed as the metric for evaluating and choosing models based on their goodness of fit. The results will be presented and discussed with a focus on models that demonstrate the lowest DIC values, signifying superior fits.

RESULTS AND DISCUSSION

Table 1 presented the under-five and infant mortality rates for the eight Local Government Areas of Jigawa north-east region. The number of under-five deaths per year per one thousand live births for the various LGAs during the period of the study is contained in the second column of the table. The number of infant deaths per year per one thousand live births for the various LGAs during the period of the study is subsequently contained in the third column of the table.

The weighted descriptive statistics are outlined in Table 2, encompassing a sample size of 870 cases of infant and child mortality across eight local government areas within the Jigawa North East region, as analyzed in this study. Concerning the residence parameter, out of the 870 deceased infants, 197 (22.6%) resided in the urban area of the region, while 673 (77.4%) resided in the rural area. In terms of the birth order parameter, among the 870 deceased infants, 146 (16.8%) were the firstborn, 298 (34.3%) were second or third births, and 426 (48.9%) were fourth or higher births. Regarding the sex parameter, within the 870 cases of deceased infants and children, 424 (48.7%) were female, while 446 (51.3%) were male. About the sex of the household head, 768 (88.3%) were male, and 102 (11.7%) were female. Regarding the educational attainment parameter, among 870 household heads, 418 (48.0%) had not attended school, 203 (23.4%) had attended primary education, and 249 (28.6%) had attended secondary or higher education. In terms of the wealth index parameter, out of 879 household heads with cases of infant and child mortality, 142 (16.3%) were categorized as the poorest, 226 (26.0%) as poorer, 283 (32.5%) with a middle wealth status, 114 (13.1%) as richer, and 105 (12.1%) as the richest. In terms of the working status parameter, within the 870 household heads associated with cases of infant and child mortality, 266 (30.6%) indicated no working status, 582 (66.9%) reported having a working status, and 22 (2.5%) did not respond to the question. Out of the 870 household heads linked to cases of infant and child mortality, 609 (70.0%) did not have electricity in their compound, 252 (29.0%) had electricity in their compound, and 9 (1.0%) did not respond to the question.

Concerning the toilet facility parameter, among the 870 household heads associated with cases of infant and child mortality, 577 (66.3%) were utilizing a non-improved toilet facility, 285 (32.8%) were using an improved toilet facility, and 8 (0.9%) did not respond to the question. Regarding the water sources used by the 870 household heads with cases of infant and child mortality, 59 (6.8%) relied on other water sources for domestic purposes, 172 (19.8%) used surface water, 438 (50.3%) used well water, 194 (22.3%) used pipe water, and 7 (0.8%) did not respond to the question. Examining the place of delivery for the 870 women associated with cases of infant and child mortality, 392 (45.1%) delivered in a location other than a hospital, 475 (54.6%) delivered in a hospital, and 3 (0.3%) did not respond to the question. In terms of exposure to mass media, among the 870 household heads linked to cases of infant and child mortality, 776 (89.2%) had never used newspapers as a form of mass media, 88 (10.1%)

used newspapers for mass media, and 6 (0.7%) did not respond to the question. Out of the 870 household heads associated with cases of infant and child mortality, 297 (34.1%) had never used radio as a means of mass media, 572 (65.8%) used radio for mass media, and only 1 (0.1%) did not respond to the question. Moreover, within the 870 household heads associated with cases of infant and child mortality, 567 (65.2%) had never used television as a means of mass media, 301 (34.6%) used television for mass media, and 2 (0.2%) did not respond to the question. Concerning the type of cooking fuel used by the 870 households with cases of infant and child mortality, 116 (13.3%) utilized a cooking fuel other than electricity, gas, kerosene, or wood, 36 (4.1%) used electricity or gas, 35 (4.1%) used kerosene, while 683 (78.5%) used wood as their cooking fuel.

Table 1: Infant and Child Mortality Rates for the Jigawa North-East Region

LGA	Under-five mortality rate	Infant mortality rate
Auyo	80	18
Birniwa	92	24
Guri	85	20
Hadejia	90	23
Kafin-Hausa	95	26
Kaugama	86	22
Kiri-kassama	83	20
Malam Madori	85	21

Tables 3 and 4, respectively, presented the results of posterior estimates from model one and model two. The results for infants closely correspond to those for under-five children and are hence not presented separately. The reported values include the posterior means along with their corresponding 95% credible intervals (CI). The table also features the DIC values. Based on the DIC values, it is observed that the model fits improve with the inclusion of more variables; as a result, the full model demonstrates the most favorable fit. The results concerning the fixed effects are largely in line with prior research on child mortality in the Jigawa North East region. Children living in rural areas experience higher mortality risks compared to their counterparts in urban areas.

Furthermore, children with second or higher birth orders, as well as those born singly, demonstrate reduced mortality risks when compared to children of first births and multiple births, respectively. The findings also suggest elevated risks for male children, while no significant impact of the sex of the household head is evident. Moreover, children whose parents have completed secondary education or higher exhibit reduced mortality risks compared to those whose parents lack formal education. On the contrary, children with parents having primary education showed higher risks. Regarding the wealth indicator, findings indicate that, in comparison to children from the poorest households, those from the wealthiest households experience lower mortality risks, while results for the other categories are not statistically significant. Women who are employed face elevated risks of child mortality when contrasted with those who are not working.

Additionally, children from households with access to electricity, improved toilet facilities, and a water source from a pipe, as well as those born in hospitals, exhibit lower risks of mortality compared to their counterparts without these amenities. The findings regarding mass media reveal that children whose mothers listen to the radio at least once a week face increased risks of mortality, whereas the estimates for television and newspapers are not statistically significant. Similarly, the results for the type of cooking fuel used are not significant.

Analyzing the variables sequentially aids in gaining a comprehensive understanding of the varied impacts of different variable categories across different spatial locations. Two models were examined, with the initial model incorporating a demographic component, a socioeconomic component, and the nonlinear effect of age. In the second model, the spatial effect and amenity variables were included, making it the comprehensive or full model.

The figures presented, Figure 1, illustrate the estimated posterior means along with their corresponding 95% confidence intervals (CI) for the baseline child's age and mother's age in relation to children under five and infants, respectively. Comparable estimates were obtained for all models, and consequently, only those stemming from the full models are depicted. The baseline for children under five indicates a sharp decrease in the risks of mortality between ages 0 and 1, followed by a relatively stable pattern until around 12 months, where a slight increase is noted, possibly due to data heaping. Following that, there is a gradual decline until approximately 16 months, after which the curve undergoes a slight upward movement between ages 21 and 24 months. Subsequently, a sinusoidal pattern emerges before a substantial decline around the age of 50 months. Similarly, the baseline for infant data shows a significant decrease in the risks of mortality during the neonatal period. The nonlinear effect of the mother's age, as estimated, indicates a gradual rise in the risks of mortality for children under 5 years old until around age 49 years, with a slight bend observed around ages 23–25 years. When compared to the curve for children under five, the estimated effects for infants exhibit a somewhat contrasting pattern. The baseline effects show a sustained level for ages 15 to 30 years before gradually increasing. Significantly, the baseline effects highlight that the risks of mortality are most elevated in the first month of life and decrease subsequently. To tackle these trends, cost-effective interventions such as strengthening early post-natal home visits and improving the management of neonatal infections are essential across all regions of the Jigawa North East region.

Table 2: Categorization of variables and the frequency distribution of the children under age 5

Variables	Sample size	Percentage
Place of residence		
Urban	197	22.6
Rural	673	77.4
Birth order		
1st birth	146	16.8
2nd or 3rd order	298	34.3
4th or higher order	426	48.9
Multiple birth		
Yes	51	5.9
No	819	94.1
Sex		
Female	424	48.7
Male	446	51.3
Sex of the household head		
Male	768	88.3
Female	102	11.7
Educational attainment		
No education	418	48.0
Primary	203	23.4
Secondary or higher	249	28.6
Wealth		
Poorest	142	16.3
Poorer	226	26.0
Middle	283	32.5
Richer	114	13.1
Richest	105	12.1
Working status		
No	266	30.6
Yes	582	66.9
Missing	22	2.5
Has electricity		
No	609	70.0
Yes	252	29.0
Missing	9	1.0
Toilet facility		
Non-improved	577	66.3
Improved	285	32.8
Missing	8	0.9
Water source		
Others	59	6.8
Surface	172	19.8
Well	438	50.3
Pipe	194	22.3
Missing	7	0.8
Place of delivery		
Any other place	392	45.1
Hospital	475	54.6
Missing	3	0.3
Exposure to mass media		
Newspaper		
No	776	89.2
Yes	88	10.1
Missing	6	0.7
Radio		
No	297	34.1
Yes	572	65.8
Missing	1	0.1
Television		
No	567	65.2
Yes	301	34.6
Missing	2	0.2
Type of cooking fuel		
Any other	116	13.3
Electricity/gas	36	4.1
Kerosene	35	4.1
Wood	683	78.5

Table 3: Posterior Estimates for the Fixed Effects Parameters from Model N_1

Variables in Model	Posterior Mean	Std. Error	Lower CI (95%)	Upper CI (95%)
Place of Residence				
Urban	0	0		
Rural	0.212	0.043	0.181	0.245
Birth Order				
1st birth	0	0		
2nd or 3rd order	-0.099	0.312	-0.140	-0.056
4th or higher order	-0.358	0.644	-0.410	-0.307
Multiple Birth				
Yes	0	0		
No	-0.545	0.092	-0.597	-0.496
Sex				
Female	0	0		
Male	0.067	0.050	0.043	0.096
Sex of the Household Head				
Male	0	0		
Female	-0.013	0.035	-0.028	0.052
Educational Attainment				
No education	0			
Primary	0.083	0.0851	0.030	0.136
Secondary or higher	-0.280	0.1207	-0.323	-0.183
Wealth Status				
Poorest	0			
Poorer	0.163	0.088	0.0110	0.217
Middle	0.046	0.015	-0.008	0.101
Richer	-0.018	0.022	-0.073	0.037
Richest	-0.278	-0.092	-0.366	-0.193
Working Status				
No	0		0	
Yes	0.151	0.013	0.120	0.181
Has Electricity				
No	0			
Yes	-0.054	-0.001	-0.099	-0.010
Toilet Facility				
Non-improved	0			
Improved	-0.053	0.032	-0.089	, -0.018
Water Source				
Others	0	0		
Surface	0.014	0.308	-0.065	0.096
Well	0.019	0.365	-0.048	0.085
Pipe	-0.076	0.210	-0.157	0.006
Place of Delivery				
Any other place	0			
Hospital	-0.177	0.051	-0.209	-0.146
Exposure to Mass Media				
Newspaper	0.012	0.012	-0.052	0.079
Radio	0.033	0.211	0.004	0.063
Television	-0.036	0.033	-0.074	0.001
Type of Cooking Fuel				
Any other	0			
Electricity/gas	-0.126	0.075	-0.341	0.088
Kerosene	-0.033	0.073	-0.187	0.116
Wood	0.037	0.052	-0.065	0.141

Table 4: Posterior Estimates for the Fixed Effects Parameters from Model N_2

Variables in Model	Posterior Mean	Std. Error	Lower CI (95%)	Upper CI (95%)
Place of Residence				
Urban	0	0		
Rural	0.093	0.142	0.053	0.135
Birth Order				
1st birth	0	0		
2nd or 3rd order	-0.102	0.413	-0.143	-0.063
4th or higher order	-0.444	0.455	-0.499	-0.392
Multiple Birth				
Yes	0	0		
No	-0.551	0.190	-0.603	-0.502
Sex				
Female	0	0		
Male	0.070	0.051	0.044	0.096
Sex of the Household Head				
Male	0	0		
Female	0.015	0.043	-0.026	0.057
Educational Attainment				
No education	0			
Primary	0.083	0.088	0.030	0.096
Secondary or higher	-0.280	0.170	-0.341	-0.219
Wealth Status				
Poorest	0			
Poorer	0.088	0.121	-0.029	0.049
Middle	0.015	0.115	-0.040	0.072
Richer	0.022	0.122	-0.037	0.080
Richest	-0.092	-0.192	-0.198	0.008
Working Status				
No	0		0	
Yes	0.153	0.013	0.121	0.183
Has Electricity				
No	0			
Yes	-0.052	0.102	-0.089	-0.016
Toilet Facility				
Non-improved	0			
Improved	-0.049	0.134	-0.088	, -0.017
Water Source				
Others	0	0		
Surface	0.018	0.434	-0.060	0.085
Well	0.021	0.311	-0.053	0.082
Pipe	-0.074	0.293	-0.159	0.007
Place of Delivery				
Any other place	0			
Hospital	-0.169	0.051	-0.213	-0.123
Exposure to Mass Media				
Newspaper	0.014	0.023	-0.050	0.081
Radio	0.036	0.244	0.002	0.065
Television	-0.037	0.202	-0.074	0.003
Type of Cooking Fuel				
Any other	0	0		
Electricity/gas	-0.124	0.176	-0.334	0.085
Kerosene	-0.031	0.174	-0.175	0.115
Wood	0.035	0.154	-0.056	0.138

Table 5: The Deviance Information Criterion (DIC)

Model	Model description	pD	DIC
N1	Demographic component, socioeconomic component, and nonlinear effect of age	103.3	23028.3
N2	Demographic component, socioeconomic component, nonlinear effect of age, and spatial effect	103.0	23019.9

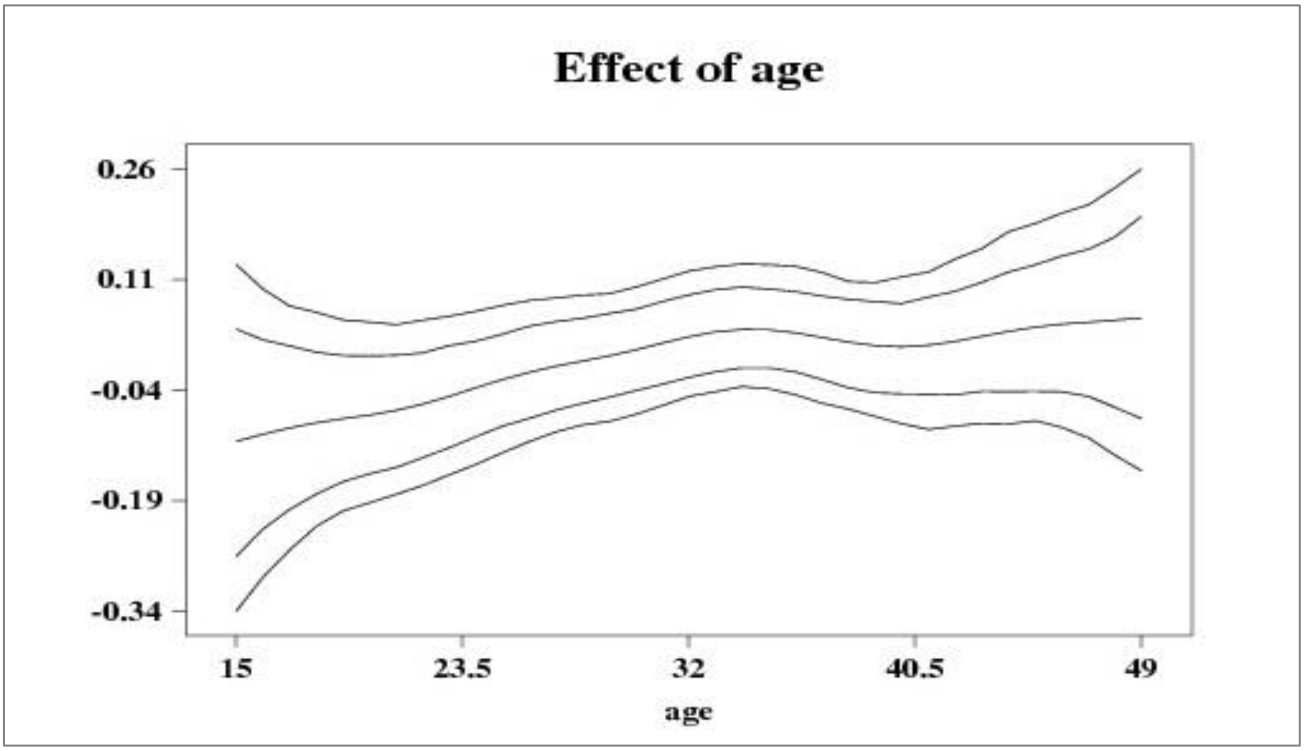

Figure 1: Nonlinear Effects of 'age' (1. Response category) with its 95% credible interval.

DISCUSSIONS OF RESULTS

This study explores the spatial variations in infant and under-five mortality in the Jigawa North East region, offering insights into the disparities in child mortality in a region that significantly contributes to child deaths. The analysis methods and strategies used in the study allowed for the identification of region-specific effects and how various categories of variables influence child survival across different areas. The Bayesian geo-additive method employed in this research effectively revealed subtle, region-specific differences. A key finding is that infant and under-five mortality in Jigawa North East exhibits a spatial pattern, with Birniwa and Kafin-Hausa showing the highest mortality rates. After accounting for spatial dependence in the data, most covariates in the fixed part of the models were found to have significant effects in the expected direction. For example, findings on birth order, multiple births, and gender align with existing literature on sub-Saharan Africa (Magadi et al. 2007; Gayawan et al. 2016; Uthman et al. 2008). Multi-fetal pregnancies and multiple births, such as twins and higher-order multiples like triplets and quadruplets, are known to be high-risk, while first births are often associated with inexperienced mothers. Biological resilience and gender preference, particularly due to the perceived value of a bride price, may explain differences in mortality between genders (Fuse 2010).

The educational status of mothers and the household wealth index are key factors in explaining the variations in infant and child mortality. The strong correlation between a mother's education and child survival has led to recommendations that improving maternal education should be adopted as a strategy to reduce infant and child morbidity and mortality (Adebayo et al. 2013; Folasade 2000; Gayawan 2014; Hobcraft 1993). Our findings indicate a higher likelihood of child mortality among children whose parents had only primary education compared to those whose parents had no education. This underscores the need to elevate maternal education to at least the secondary level in the Jigawa North East region. Children from poor households often face challenges such as inadequate nutrition and lack of access to basic healthcare. The findings related to the household wealth index are intriguing. We observed significantly lower risks for children from the wealthiest segment in the model without amenity variables, but this significance disappeared when these variables were included. This suggests that, given the current level of social amenities in the Jigawa North East region, the influence of family wealth on child mortality is diminished. Similar to studies from Nigeria (Adebayo and Fahrmeir 2005), Malawi (Manda 1999), and Bolivia (Forste 1994), working women exhibited higher child mortality rates compared to non-working women. This finding is somewhat unexpected, as one might anticipate the opposite. However, many residents of major cities in sub-Saharan Africa, where employment opportunities are available, live in densely populated areas with poor sanitation (Manda 1999; Mutunga 2004).

The significance of household electricity, improved toilet facilities, and hospital deliveries for child survival, as highlighted by this study, is critical. Household electricity provides essential energy for boiling water and preserving food, which helps prevent diarrheal diseases and respiratory infections, especially in cold climates. However, many households in the Jigawa North East region still lack this crucial resource. The use of pit latrines and other unsanitary methods of waste disposal has been associated with higher risks of morbidity and mortality among children due to the ease of contamination (Folasade 2000). The lack of significance for water sources may be attributed to the fact that in many villages in Jigawa North East, pipes are often dry, forcing residents to find water from alternative sources. Regarding delivery locations, some towns in Jigawa North East have implemented strategies to increase the number of births attended by skilled healthcare professionals, which is contributing to a reduction in maternal and child mortality rates.

The findings on mother's age for both infants and children under five show patterns consistent with earlier studies on Nigerian data by Adebayo and Fahrmeir (2005) and Ghilagaber et al. (2014). The baseline effects indicate that the risk of death is highest during the first month of life and decreases as time goes on. To address this, cost-effective interventions like early postnatal home visits and case management of neonatal infections should be intensified across all towns in the Jigawa North East region.

CONCLUSION

The research extensively investigated the effects of diverse demographic and socioeconomic variables on the spatial distribution of infant and child mortality. The modeling approach successfully identified subtle influences and pinpointed clustering specific to each region. The results suggest that the infant and under-five mortality in the Jigawa North East region displays a spatial structure, where Birniwa and Kafin-Hausa recorded the highest rate of infant and under-five mortality in the region. The observed spatial clustering might be attributed to common factors like the prevalence of shared childhood diseases, consistent healthcare practices, comparable levels of poverty, and acute malnutrition arising from food insecurity. Implementing cost-effective interventions is crucial for addressing the well-being of these infants. The insights obtained from this study can be of significant value to policymakers and international donors when formulating and executing diverse intervention programs intended to safeguard the lives of young children.

Given that infant and under-five mortality are influenced by multiple factors such as socio-demographic characteristics and socioeconomic factors. In future investigations, it might be possible to examine the influence of factors associated with access to healthcare services and utilization of healthcare services. This will provide comprehensive knowledge on the causes of infant and under-five mortality.

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