Asian Journal of Advanced Research and Reports

Volume 18, Issue 6, Page 95-109, 2024; Article no.AJARR.115950
ISSN: 2582-3248

Geospatial Analysis of the Heterogeneity in Nutritional Status among Women of Childbearing Age in Nigeria

Ben, E, O. [a*], Lasisi K. E. [a], Abdulkadir, A. [a] and Abdulrasheed B. [a]

[a] *Department of Mathematical Sciences, Faculty of Science, Abubakar Tafawa Balewa University, Bauchi, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJARR/2024/v18i6656

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/115950

Original Research Article

Received: 19/02/2024
Accepted: 22/04/2024
Published: 25/04/2024

ABSTRACT

This study employs a geospatial approach to investigate the spatial distribution and heterogeneity of nutritional status among Women of Childbearing Age across Nigeria. We utilize data on various nutritional indicators obtained from National Demographic and Health Survey (NDHS, 2018) alongside relevant geospatial information. By employing spatial statistical methods, we aim to identify geographic clusters and disparities in the various nutritional statuses: normal weight, overweight, and obesity. This analysis will provide valuable insights into the geographical variations in WCBA's nutritional health and inform targeted interventions to address these disparities. This study employs a statistical method, Bayesian Geoadditive Quantile Regression Model (BGQRM) to investigate the impact of various factors on weight categories (normal weight, overweight, obese) among Nigerian women of childbearing age.. Results reveal higher likelihoods of overweight or

**Corresponding author: Email: esty2k6.beo@gmail.com;*

obesity among urban women, potentially linked to urban living factors like increased income and education, leading to reduced physical activity and higher consumption of calorie-dense foods. The findings highlight complex relationships between socioeconomic factors, urbanization, and weight status, challenging assumptions about the effects of mass media and electricity access on weight, and emphasizing the need for tailored interventions informed by nuanced ethnic and employment-related variations in nutritional patterns among Nigerian women. This study utilizes a novel statistical method (BGQRM) to investigate the impact of various factors on weight categories among women of reproductive age in Nigeria, revealing a higher likelihood of overweight or obesity among urban residents, potentially linked to lifestyle factors such as income and education. The findings challenge assumptions about the relationship between socioeconomic status, media exposure, and weight, highlighting complex interactions that can inform targeted interventions aimed at improving nutrition and well-being among Nigerian women of childbearing age.

Keywords: Geospatial analysis; heterogeneity; nutritional status; bayesian geoadditive quantile regression model.

1. INTRODUCTION

Adequate nutrition is a fundamental pillar for individual health and well-being across the life course. It serves as a cornerstone for national development, impacting economic productivity, educational attainment, and overall societal health [1,2]. Our bodies show how well-nourished we are through physical health, bodily functions, and the presence of key nutrients [3]. The World Health Organization warns that many women, especially during childbearing years, lack essential nutrients in their diets [4]. Women play a pivotal role in ensuring family well-being, often serving as primary caregivers and decision-makers regarding household food security and nutrition [5,6]. However, research shows that women of childbearing age (15-49) are particularly at risk of malnutrition in developing countries due to both social and biological factors [7].

Undernourished mothers are more likely to have stunted children, increasing their risk of illness and death [8]. Despite progress, malnutrition remains a major issue in Sub-Saharan Africa, as noted by the UN in 2015. Good nutrition is crucial for both mothers and children [9]. For mothers, poor nutrition makes them more susceptible to infections and hinders recovery from illness [10]. The World Health Organization (WHO) defines malnutrition as a condition arising from the consumption of insufficient or excessive nutrients that negatively impacts health [11]. This imbalance disrupts cellular processes and hinders the body's ability to perform essential functions for growth, maintenance, and repair [12]. They are typically evaluated using height and weight indices calculated as body mass index (BMI). According to the World Health Organization (WHO), adult women are categorized based on their Body Mass Index (BMI) as follows: severely thin (BMI ≤ 16 kg/m2), underweight (BMI ≤ 18.5 kg/m2), overweight (BMI ≥ 25 kg/m2), and obese (BMI ≥ 30 kg/m2) [11].

Traditional statistical methods, like linear regression, focus on the average (mean) of a data set, which can be limiting when studying malnutrition [13]. Malnutrition comes in various forms, measured at the extremes of the Body Mass Index (BMI) distribution [4]: underweight and severe thinness at the lower end, and overweight and obesity at the upper end [14]. To better understand these extremes, researchers need statistical tools that analyze not just the average, but also the "tails" of the distribution. This allows for a more complete picture of how different factors influence various forms of malnutrition [15].

Modern statistical methods, like Bayesian Quantile Regression, address this need. These methods can consider various types of explanatory variables, including:Non-linear effects**,** Spatial effects and Traditional linear effects [1].By combining these elements in a single analysis, researchers can gain a deeper understanding of the complex factors contributing to different forms of malnutrition.

Schnettler et al. [1] studied how malnutrition in Nigerian women of reproductive age affects their health, families, and the entire country. They examined different types of malnutrition (underweight, overweight, and obesity) using Body Mass Index (BMI).The researchers looked for patterns across different areas of Nigeria. They considered how social and economic factors like income and education influence these malnutrition rates. A special statistical method (Bayesian Quantile Regression) was used to analyze data from a national health survey (2013). This method helped them see not just average malnutrition rates, but also how these rates varied by location and social/economic factors. The study found that malnutrition patterns differed geographically, with neighboring states often having similar rates. Interestingly, the impact of social and economic factors also depended on the specific type of malnutrition Overall, this research provides valuable information for policymakers working to improve women's nutrition in Nigeria. It highlights the importance of considering both location and social/economic factors when designing programs to address malnutrition.

Also, study by Umesh and Richa [15] explored malnutrition in Nepal, a challenge for many developing countries. They investigated factors linked to underweight, overweight, and obesity in Nepalese women using advanced statistical methods. Data from a national survey (2016) was used to analyze these issues at the provincial level. It was found that, women in urban areas and certain provinces (1, 3, and 4) were more likely to be overweight or obese. Conversely, women in rural municipalities and provinces 2 and 7 were more likely to be underweight. Wealthier women with primary education were more likely to be obese. Working women and those with access to clean water were less likely to be obese. Interestingly, improved sanitation and electricity access were associated with a higher risk of obesity. Women with access to newspapers and radio were less likely to be obese, suggesting a role for education and awareness.

A recent investigation by Ben et al. [7] employed a modified Bayesian Geoadditive Quantile Regression Model to evaluate the nutritional status of women of reproductive age in Nigeria. Data from the 2018 Nigeria Demographic and Health Survey (NDHS) was analyzed using R software. This approach provided a more nuanced understanding of factors influencing nutritional well-being compared to traditional methods that focus solely on average nutritional levels. The study identified several key determinants impacting these women's nutritional health. These factors included age, residence (urban/rural), employment status, and household size. These findings underscore the multifactorial nature of malnutrition among women of reproductive age in Nigeria. For example, access to healthy food options may be limited in rural areas, while urban environments might pose challenges related to fast-paced lifestyles and readily available processed foods. In light of these insights, the authors emphasize the critical need for comprehensive interventions to address malnutrition. Furthermore, interventions addressing broader determinants of health, such as access to healthcare or economic opportunities, may be necessary to indirectly improve women's nutritional well-being By aligning interventions with the unique requirements of women of reproductive age in Nigeria, this research presents a promising approach to fostering improved nutritional outcomes for this critical population group. Enhanced nutritional well-being among mothers has the potential to translate into improved health for both mothers and children, ultimately contributing to national development and well-being.

This research investigates the nutritional status of reproductive-aged women in Nigeria through the creation of a geospatial map. This map is intended to be a critical resource for implementing state-specific nutritional intervention programs. The study expands upon simple mapping by incorporating analyses of risk factors associated with normal weight, overweight, and obesity among Nigerian women. It also considers the concept of spatial dependence, which refers to the potential clustering of malnutrition patterns in specific geographic areas. Additionally, the research employs a Bayesian Geoadditive Quantile Regression Model (BGQRM) to identify factors influencing the various nutritional states, including any underlying spatial patterns. By providing insights into the geographically differentiated distribution of malnutrition across Nigerian states, this study aims to inform policymakers in developing targeted interventions. This will facilitate the creation of regionally-tailored nutrition programs that address the specific malnutrition burdens faced by different areas. Ultimately, the research seeks to contribute to the evidence-based planning and refinement of national nutrition action plans, with the overarching goal of mitigating the prevalence of various forms of malnutrition in Nigeria.

2. MATERIALS AND METHODS

This study leverages data from the 2018 Nigeria Demographic and Health Survey (NDHS), conducted by the National Population

Commission (NPC). The NDHS aimed to generate comprehensive estimates of population and health indicators at national, zonal, and state levels across Nigeria's 36 states and the Federal Capital Territory (FCT). Consistent with standard demographic and health surveys, the NDHS included interviews with women aged 15-49 who were permanent residents or visitors in the selected households. Data collection employed two instruments: the Household Questionnaire, which gathered information on household dwelling characteristics, and anthropometric measurements (weight and height) of women used to calculate Body Mass Index (BMI).

2.1 Study Outcomes

Body Mass Index (BMI) will serve as the primary dependent variable in this investigation. Calculated by dividing weight in kilograms by height squared in meters (kg/m²), BMI offers a widely employed metric for assessing adult nutritional status. Adhering to established World Health Organization (WHO) classifications, we will categorize the BMI of reproductive-aged women into four distinct groups: Underweight: <18.5 kg/m², Normal Weight: 18.5 kg/m² to 24.99 kg/m², Overweight: ≥25.0 kg/m² and Obese: ≥30.0 kg/m². This categorization scheme facilitates a nuanced analysis of the various malnutrition levels present within the study population.

2.2 Explanatory Variables

This study will incorporate a comprehensive set of explanatory variables to explore the factors influencing women's nutritional status. These variables include: women's age (in years), women's highest educational attainment, household wealth index, household water source classified as protected or unprotected, type of household toilet facilities classified as improved or unimproved, whether or not the household has electricity, women's occupational working status, and access to mass media (whether or not the woman reads any newspapers/magazines, listens to radio or watches television), number of household members, type of family, type of place of residence and ethnicity. State-level analysis will be employed to examine geographic variations in women's nutritional status.

2.3 Data Analysis

This study will utilize a BGQRM approach for analysis. This method, implemented using the freely available software BayesX [16] is well-suited for analyzing structured additive regression models and provides valuable insights into the factors influencing different quantiles (distribution tails) of the nutritional status outcome variable [17].

2.4 Statistical Model

The analytical framework for this study is a regression model expressed in the following notation:

y_i: denotes the dependent variable, which represents the Body Mass Index (BMI) of the i-th respondent.

x_i: is a vector of categorical independent variables potentially influencing BMI.

v_i: is a vector of continuous independent variables that might influence BMI.

s_i: represents the spatial covariate, indicating the state of residence for the i-th respondent.

The overall regression model can be expressed as:

$$y_i = \eta_i + \varepsilon_t \tag{1}$$

Where

$$\varepsilon_i \sim F(\varepsilon_i|\theta)$$

And

$$\eta_i = x_i^T\beta + \sum_{k=1}^{p} f_k(v_{ki}) + f(s_i) + b_i \tag{2}$$

F represents an unknown source of error or unexplained variation in the data which may depend on some additional parameters θ, η_i reflects the predicted BMI for the i-th woman based on the model.,$\beta$is a vector that captures the overall influence of different categorical variables, f_k is the kth smooth function assumed fornonlinear effects, $f(s_i)$ represents the spatial effect associated with the i-th woman's state of residence. and $b_i$accounts for any other random effects not explicitly included in the model. If the distribution of y_i isassumed to belong to the exponential family and itsmean is linked to η_i through appropriate link function,the resulting model is termed structured additive regression (STAR) model.

For quantile regression model, given a fixed and known quantile $\tau \in (0,1)$, the τth quantile of the errordistribution in (1) is assumed zero, i.e. $F^{-1}(\tau|\theta) = 0$ .The corresponding quantile function of the continuousvariable Y_i is then:

$$Q_{Y_i}(\tau|x_i, v_i, s_i) = x_i^T\beta_\tau + \sum_{k=1}^{p} f_{\tau k}(v_{ki}) + f_\tau(s_i) + b_{\tau i} \qquad (3)$$

To estimate the parameters of (3) above, a check function corresponding to

$$\underset{\eta_\tau}{\operatorname{argmin}} \sum_{k=1}^{n} \rho_\tau(y_i - \eta_{\tau i})$$

Where

$$\rho_\tau(u) = \begin{cases} u\tau, & \text{if } u \geq 0 \\ u(1-\tau), & \text{if } u < 0 \end{cases} \qquad (4)$$

is required to be minimized [1]. To study different levels of women's BMI, we use a method called quantile regression with a check loss function. To draw reliable conclusions (Bayesian inference), we assume the errors follow a specific pattern (asymmetric Laplace distributions). This assumption helps us incorporate a prior knowledge with the data for better analysis, that is, $Y_i \sim ALD(\eta, \delta_0, \tau)$ where the parameter $\eta \in \mathbb{R}$ is thelocation parameter, $\delta_0 \in \mathbb{R}^+$ is the scale parameter and $0 < \tau < 1$ is the skewness parameter [18]. For the spatialcovariate, Markov random field which is based on the idea of predefined neighbors for a spatial location u_i is considered. It assumes that two sites u_i and u_j areneighbors if they share common boundary. Letting n_i denote the number of neighbours for site u_i, theMarkov random field prior is assumed for $f(u_i)$as:

$$\{f(u_i)|f(u_j)i \neq j, \delta)\} \sim N\left(\frac{1}{n}\sum_{j:j\neq i} f(u_j), \frac{1}{n_i\delta}\right) \qquad (5)$$

This investigation leverages a Bayesian framework to capture potential non-linear relationships between continuous variables (e.g., age) and Body Mass Index (BMI).Specifically, we utilize a Bayesian penalized spline approach, drawing upon the methods outlined by Lang and Brezger [19,20]. This technique incorporates prior knowledge about the expected behavior of the unknown smooth function while maintaining flexibility to model complex relationships. The Bayesian penalized spline approach constructs the unknown smooth function by approximating it with a polynomial spline of degree lj. This spline function is further represented as a linear combination of B-spline basis functions evaluated at pre-determined knot locations. In contrast, the influence of categorical explanatory variables is assumed to be linear and modeled with a diffuse prior distribution.

Given the high dimensionality and inherent complexity of the posterior distribution, direct inference is computationally challenging. To address this, we employ a Markov chain Monte Carlo (MCMC) simulation using the Gibbs sampling algorithm. This technique allows us to draw numerous samples from the posterior distribution, enabling us to extract valuable insights into the relationships between the various factors and women's BMI in Nigeria.

3. DATA ANALYSIS AND RESULTS

Table 1 displays the frequency distributions of women of reproductive age in Nigeria categorized by covariates. Among the 14,872 women examined, the majority (58.6%) resided in rural areas, while 41.4% lived in urban settings. Regarding education, 32.3% (equivalent to 4809 women) had no formal education, whereas 41.6% had completed secondary education, and 10.1% had achieved a higher level of education. As for water source, toilet facilities and presence of electricity in the households of the respondents, many of the women sourced water from protected sources (61.1%), use improved toilet facilities (53.4%) and have electricity in their households (56.8%). From the analysis, it is evident that Hausa/Fulani has a percentage of 32.2%, while Igbo has 17.5%, Yoruba has 13.9% and other tribes have 36.4%. For household members, 18.2% has household member of one and two members, while 41.3% has household member of three to six and 40.5% has a household member greater than six. Regarding mass media, a significant portion of the women tune into the radio (56.3%) and watch TV (52.3%) at least once weekly. However, a vast majority (84.7%) do not engage with newspapers or magazines. In terms of economic status, approximately 22% of the women are in the middle to affluent wealth bracket, while 17.2% are categorized as being in the most economically disadvantaged households. The distribution is relatively balanced, with 19% each in the poorer and wealthiest household categories. In terms of body weight, 18.1% of the women are overweight, 9.4% are obese, 11.2% are underweight, and a majority (61.3%) fall within the normal weight range. Also, under the family type, both monogamy and polygamy has the same proportion of about 50%. Lastly, majority of the women (65.8%) are of the working class.

The Bayesian analysis findings are displayed in Table 2 and include the mean estimates and 95% credible intervals for each of the three nutritional status forms that were taken into consideration.

Table 1. Frequency distribution of the characteristics of women of childbearing age

Variable	Factor	Frequency	Percent
Location	Rural	8717	58.6
	Urban	6155	41.4
	Total	14872	100
Education	No formal Education	4809	32.3
	Primary	2368	15.9
	Secondary	6189	41.6
	Tertiary	1506	10.1
Water	Unimproved	5792	38.9
	Improve	9080	61.1
Toilet	Unimproved	6937	46.6
	Improve	7935	53.4
Electricity	No	6422	43.2
	Yes	8450	56.8
Ethnicity	Others	5411	36.4
	Hausa	4794	32.2
	Igbo	2603	17.5
	Yoruba	2064	13.9
Household members	Below 3	2700	18.2
	Between 3 and 6	6147	41.3
	More than 6	6025	40.5
News paper	No	12604	84.7
	Yes	2268	15.3
Radio	No	6493	43.7
	Yes	8379	56.3
Television	No	7094	47.7
	Yes	7778	52.3
Wealth index	Poorest	2556	17.2
	Poorer	2867	19.3
	Middle	3295	22.2
	Richer	3265	22.0
	Richest	2889	19.4
BMI	Underweight	1665	11.2
	Normal	9119	61.3
	Overweight	2694	18.1
	Obesity	1394	9.4
Family type	Monogamy	7497	50.4
	Polygamy	7375	49.6
Work	No	5093	34.2
	Yes	9779	65.8

Table 2. Posterior mean estimates for the linear effects of normal, overweight and obesity among women of childbearing age-group (15 to 49 years)

	Normal		**Overweigh**		**Obese**	
Variable	**Mean**	**95% CI**	**Mean**	**95% CI**	**Mean**	**95% CI**
Constant	2.0805	1.8654, 2.2957	0.2373	-0.0492, 0.5124	-1.7732	-2.2227, -1.3018
Location (Rural)						
Urban	-0.0159	-0.1521, 0.1195	0.0856	-0.0762, 0.2412	0.2556	0.0722, 0.4599
Education (No Education)						
Primary	0.2229	0.0439, 0.4037	0.2661	0.0701, 0.4927	0.6044	0.3182, 0.8791
Secondary	0.1497	-0.0277, 0.3212	0.2646	0.0480, 0.4684	0.5964	0.3116, 0.8971
Tertiary	0.1813	-0.1156, 0.5013	0.3887	0.0393, 0.7232	0.7175	0.3158, 1.1164
Water (not protected)						
Protected	-0.1115	-0.2315, 0.0049	-0.2633	-0.3996, -0.1226	-0.3958	-0.5821, -0.2323
Toilet (Unimproved)						
Improved	-0.1266	-0.2506, 0.0089	-0.1543	-0.3084, 0.0157	-0.1752	-0.3857, 0.0125
Electricity (No)						
Yes	-0.0119	-0.0821, 0.0646	-0.0066	-0.0869, 0.0801	-0.1001	-0.2054, -0.0005
Ethnicity (Others)						
Hausa	-0.5684	-0.7157, -0.4130	-0.9653	-1.1694, -0.7559	-0.8242	-1.0778, -0.5715
Igbo	0.2691	0.0390, 0.5098	0.3594	0.0855, 0.6254	0.3330	0.0085, 0.6302
Yoruba	-0.3171	-0.5713, -0.0969	-0.6209	-0.9054, -0.3675	-0.7478	-1.0619, -0.4494
Household Member (Below)						
3_6	-0.1117	-0.2689, 0.0386	-0.2037	-0.3949, -0.0280	-0.3828	-0.6050, -0.1672
7 up	-0.3047	-0.4813, -0.1334	-0.3040	-0.5165, -0.0949	-0.4921	-0.7261, -0.2534
News Paper (No)						
Yes	-0.0282	-0.2172, 0.1829	0.0183	-0.2085, 0.2704	0.1830	-0.0526, 0.4383
Radio (No)						
Yes	0.0144	-0.1080, 0.1466	0.0695	-0.0682, 0.2245	0.2930	0.1047, 0.4783
Television (No)						
Yes	-0.0240	-0.1750, 0.1209	0.1891	0.0048, 0.3840	0.3849	0.1544, 0.6019
Wealth Index (Poorer)						
Poor	0.2535	0.0880, 0.4135	0.6392	0.4053, 0.8599	1.0532	0.6464, 1.4366
Middle	0.2852	0.0847, 0.4721	0.9650	0.7028, 1.2195	1.5570	1.1633, 1.9272
Richer	0.3426	0.1362, 0.5719	1.3483	1.0547, 1.6200	2.0467	1.6463, 2.4757

	Normal		Overweigh		Obese	
Richest	0.5827	0.3227, 0.8507	1.7511	1.4209, 2.0811	2.7991	2.3002, 3.2493
Family type (Monogamy)						
Polygamy	-0.0068	-0.1273, 0.1230	-0.1931	-0.3289, -0.0377	-0.2248	-0.4080, -0.0435
Work (No)						
Yes	0.1011	-0.0153, 0.2147	0.1086	-0.0411, 0.2537	0.1968	0.0055, 0.3820

Estimates of the place of residence on BMI showed that compared to rural, women residingin urban location were more likely to be obese (mean:0.2556; 95% CI:0.0722, 0.4599) and less 7 likely to be overweight (mean: -0.0762; 95% CI:0.2556). On education status, women with any form of education (primary, secondary or tertiary) are more likely to have effect on obese (mean: 0.6044; 95% CI: 0.3182,-0.8791), (mean: 0.5964; 95% CI:0.3116, 0.8971), (mean: 0.7175; 95% CI:0.3158, 1.1164) respectively as compared to women without education. Further, women from households that use improved toilet facilities and having access to protected water sources are significantly less likely to be overweight and obese but more likely to have a Normal weight(mean: -0.1115; 95% CI: -0.2315, 0.0049), and (mean: -0.1266; 95% CI: -0.2506, 0.0089)respectively. However, women having access to electricity were more likely to be overweight (mean: -0.0066; 95%CI: -0.0869, 0.0801) than having a Normal weight (mean: - 0.0119; 95%CI: - 0.0821, 0.0646). Furthermore, on ethnicity, women from the Hausa and Yoruba ethnic groups are more likely to have a Normal weight (mean: - 0.5684; 95%CI: -0.7156, - 0.4130), (mean: -0.3171; 95%CI: -0.5713, - 0.0969) respectively. Also, women from the Igbo ethnic group are more likely to have effect on overweight (mean: 0.3594; 95% CI: 0.0855, 0.6254). On number in the household, women with 3 to 6 members in aousehold are likely to have a Normal weight (mean: -0.1117; 95% CI: - 0.2689, 0.0386) and women with 7 and above members in an household are more likely to have effect on overweight (mean: -0.3040; 95% CI: - 0.5165, -0.0949). Results for mass media reveal that women who listen to radio, watch television and read newspaper are less likely to have a normal weight but more likely to be overweight and obese when compared with those without such access. On the wealth index of participants, women with poorer wealth are likely to have more effect on obesity (mean: 1.0532; 95% CI: 0.6464, 1.4366), women with middle wealth are likely to have effect on obesity (mean: 1.5570; 95% CI: 1.1633, 1.9272), women with from richer wealth quintile are more likely to be obese (mean: 2.0467; 95% CI: 1.6463, 2.4757) and women with richest wealth are likely to have effect (mean: 2.7991; 95% CI: 2.3002, 3.2493). Furthermore, Women from polygamous families

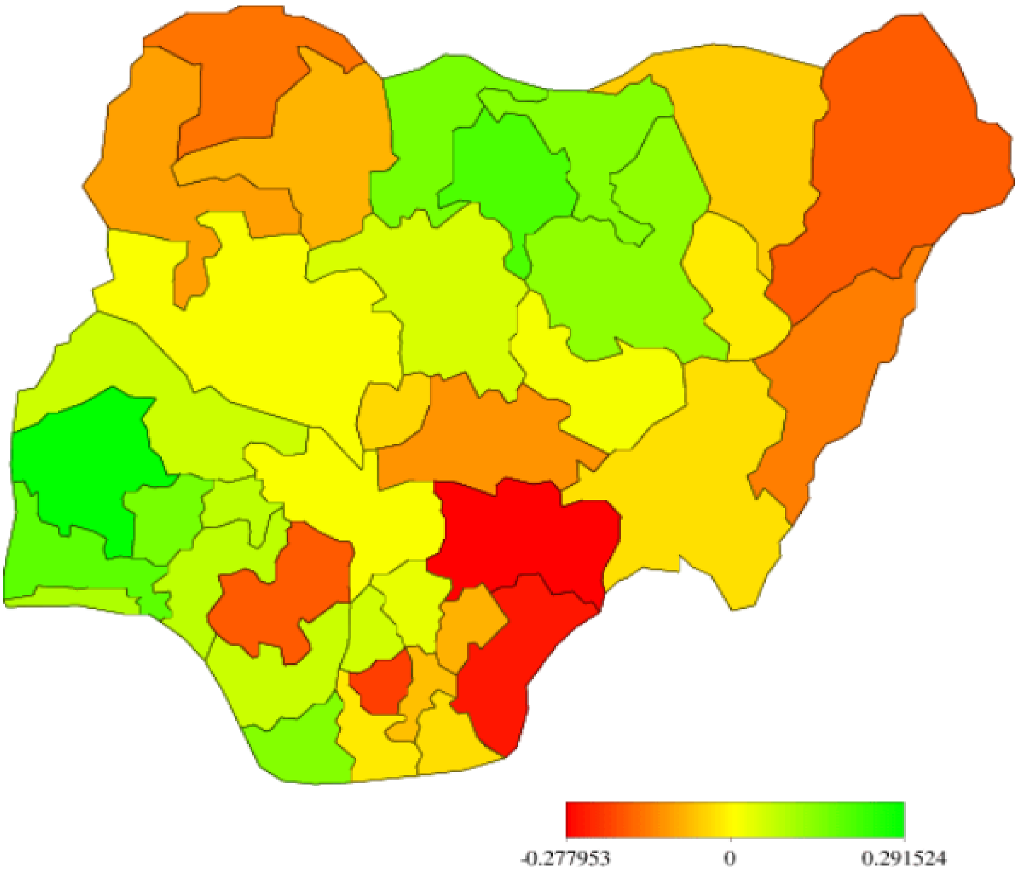

Fig. 1. Maps of Nigeria showing the spatial effects of normal weight

are likely to have a Normal weight (mean: -0.0068; 95% CI: -0.1273, 0.1230) than being overweight or obese. Lastly, Findings further show that, compared with non-working women, currentlyworking women are significantly more likely to be obese (means: 0.1968; 95% CI: 0.0055, 0.3820).

Fig. 1 explores the geographic distribution of mothers with normal weight across Nigeria. The analysis reveals a concentration in some regions. All states in the southwest appear to have a positive effect with normal weight. In other regions, the picture is less uniform. Only Kwara state shows a positive effect in the north-central region, while Kaduna, Katsina, Kano, and Jigawa states exhibit positive effects in the northwest. Similarly, just Bauchi state in the northeast and Anambra state in the southeast have a positive effect with normal weight. The south-south region shows a positive effect in Delta and Bayelsa states.

These findings suggest potential geographic variations in factors influencing a healthy weight among mothers. Further investigation into these regional differences could be valuable for informing policies and programs that promote healthy weight across Nigeria.

Fig. 2 suggests regional disparities in the prevalence of overweight mothers across Nigeria. Southern regions appear to have a higher risk. All states in the southwest (except Osun) and Delta and Rivers states in the south-south exhibit a positive effect with overweight. A similar trend is observed in the north-central region (except Kwara and Niger states) and the northwest (except Sokoto and Kaduna). In the northeast, all states except Borno and Adamawa show a positive effect. The southeast seems to have a lower risk, with only Anambra state having a positive effect with overweight.

These findings highlight potential geographic variations in factors contributing to overweight mothers. Understanding these variations could be crucial for designing targeted interventions to address overweight and obesity in different regions of Nigeria.

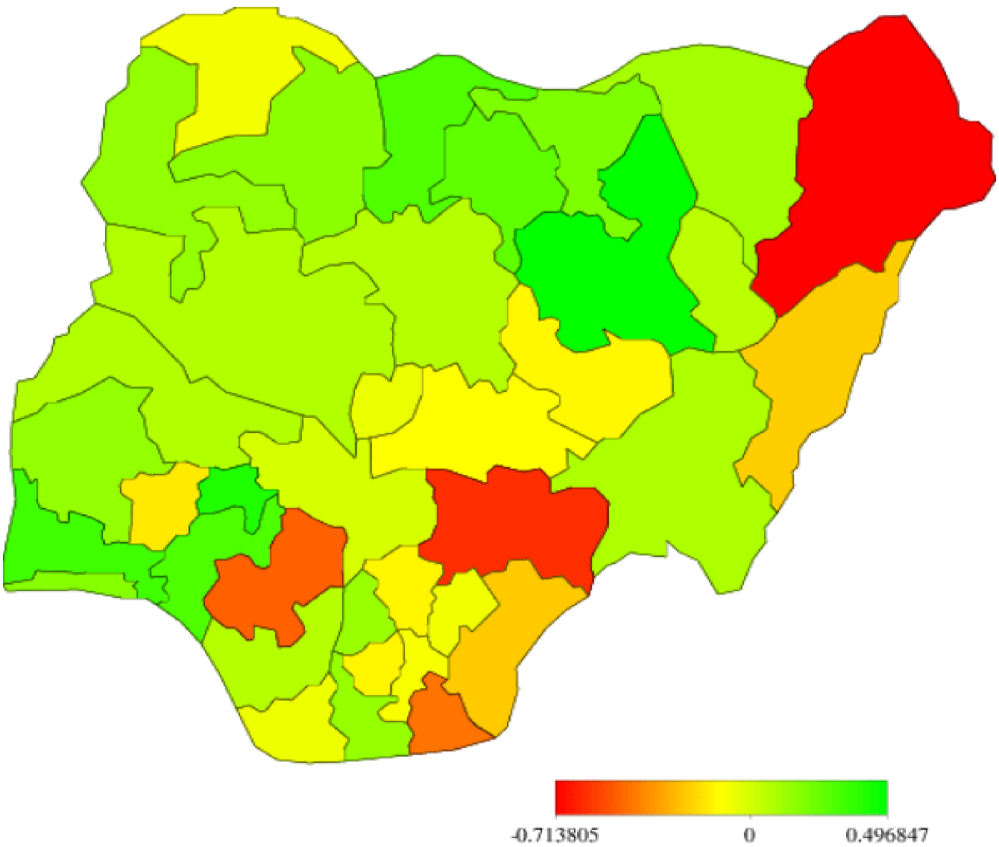

Fig. 2. Maps of Nigeria showing the spatial effects of Overweight

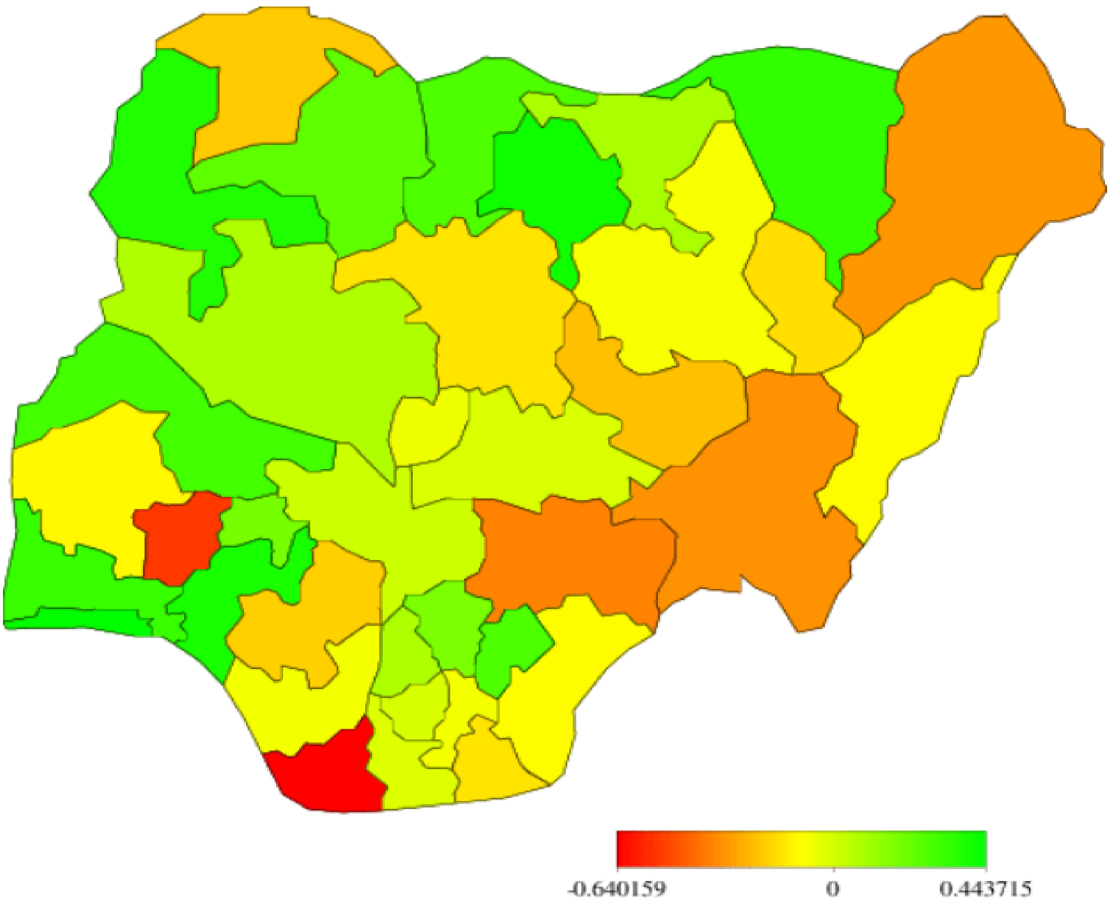

Fig. 3. Maps of Nigeria showing the spatial effects of obesity

Fig. 3 reveals geographic variations in the likelihood of maternal obesity across Nigeria. In the southwest, all states except Oyo and Osun show a positive effect with maternal obesity. A similar trend is observed in the northwest (except Sokoto) and north-central (except Kwara and Niger). Interestingly, only Yobe state in the northeast exhibits a positive correlation with maternal obesity. In contrast, the southeast shows a lower risk, with only Imo and Anambra having a positive effect. The south-south region appears to have the lowest risk, with no states showing a positive contribution to maternal obesity.

This suggests potential regional differences in factors influencing maternal weight. Further investigation into these variations could be valuable for tailoring nutrition interventions to specific regions of Nigeria.

4. DISCUSSION AND CONCLUSION

This study used a novel statistical method (Modified BGQRM) to explore how different factors influence various weight categories (Normal weight, overweight, obesity) among women of reproductive age in Nigeria. This approach overcomes limitations of prior research that relied solely on traditional methods. These methods often focus on average outcomes, neglecting the heterogeneity within the data [21-23]. In contrast, this approach allows us to examine how different factors influence the nutritional status across the entire spectrum. Additionally, it incorporates spatial analysis, enabling researchers to identify geographical variations in these factors and tailor interventions accordingly.

The findings show that women in urban areas are more likely to be overweight or obese. A 2023 study by Wang et al. [24] supports the observation that women in urban areas are more likely to experience overweight or obesity compared to their rural counterparts. This disparity might be linked to factors associated with urbanization, such as higher income and educational attainment [25]. These factors can potentially lead to a decrease in physical activity levels and a shift towards consuming more processed, calorie-dense foods [26]. Interestingly, the study found that education levels were not a protective factor against overweight and obesity. In line with recent findings [27,28], education level appears to be positively associated with a higher likelihood of overweight or obesity. While education can enhance knowledge of healthy habits, several factors might contribute to the paradox of increased weight with higher education. This suggests a need for interventions that bridge the gap between knowledge and behavior change.

The study also explores the link between socioeconomic factors and weight. While higher socioeconomic status (SES) might provide access to leisure activities like television and internet use (positively associated with weight gain according to Tyagi et al. [29], this study found a surprising result: women with access to safe water and improved sanitation facilities were more likely to maintain a normal weight.

This aligns with research from Kenya and sub-Saharan Africa [30,31]. Improved hygiene practices associated with better sanitation and access to clean water may decrease waterborne illnesses and contribute to overall health. Furthermore, access to clean water can improve dietary choices and food security, indirectly impacting weight [30,31]. These findings highlight the multifaceted relationship between SES and weight, where access to certain resources can have both positive and negative consequences.

This study challenges the common assumption that access to mass media (radio, television, newspapers) translates to healthier weight. Contrary to expectations, the research suggests that women with greater exposure to mass media were less likely to be at a normal weight. This aligns with Schnettler et al. [1] findings, highlighting a potential disconnect between information access and behavior change. Mass media exposure might not translate into practical knowledge or overcome existing social and economic barriers to healthy choices.

Similar to mass media access, the study found a counterintuitive relationship between access to electricity and weight. Women with electricity at home were more likely to be overweight compared to those without. This finding echoes research from Bangladesh [32], suggesting that electricity facilitates the storage and preparation of processed foods through refrigerators and appliances. Furthermore, electricity access might be a marker for higher socioeconomic status, which has been linked to higher obesity rates in other studies [32]. These findings highlight the complex interplay between various factors influencing weight and emphasize the need for interventions that address not just information access but also the practical challenges women face in adopting healthy behaviors.

The study also revealed intriguing ethnic variations in weight distribution. Hausa/Fulani and Yoruba women tended to have a healthier weight compared to Igbo women who were more likely to be obese. These differences might be rooted in diverse dietary practices, physical activity levels, and socioeconomic factors, as suggested by Ogunjuyigbe et al. [33 and 34]. Further investigation into these ethnic variations could be valuable for tailoring nutrition interventions. The relationship between employment and weight status presented interesting variations across contexts. In Nigeria, a recent study [35] suggests working women are more likely to be overweight or obese compared to non-working women. This finding might be linked to factors associated with employment, such as increased income and potentially less time for physical activity. Conversely, studies in Bangladesh [36,37] have shown non-employed women to be more prone to underweight. This disparity could be attributed to the socioeconomic realities of each country. Employed Nigerian women might enjoy greater financial autonomy and decision-making power regarding food choices, potentially leading to increased access to calorie-dense foods. In Bangladesh, non-working women might rely on their husbands or families for food, which could limit dietary diversity and contribute to underweight.

In conclusion, this study presents a detailed analysis of the factors influencing the nutritional status of women in Nigeria. The findings, particularly the spatial distribution of nutritional status, can serve as a valuable resource for informing policy decisions and interventions aimed at promoting better nutrition and overall well-being for women of childbearing age in Nigeria.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Schnettler C, Vorster HH, Torlesse H, Ashwell M. Micronutrient status inequality of diet. Nutrients. 2019;11(3):614.
   DOI: 10.3390/nu11030614
2. Food and Agriculture Organization of the United Nations (FAO). Nutrition; 2023.
   Available:https://www.fao.org/nutrition/en/
3. Akeresola RA, Gayawan E. Analysis of the spatial patterns of malnutrition among women in Nigeria with a Bayesian structured additive model.Geo Journal. 2020;85(1):81-92.
   Available:https://doi.org/1 0.1007/sl 0708-O 18-9958-O
4. World Health Organization. Maternal and child nutrition: A health professional's guide. Geneva: World Health Organization; 2014.
5. Tyedmers P, Osen KA, Girard B. The role of women's nutrition in sustainable food systems. Food Policy. 2020;112:103560.
   DOI: 10.1016/j.foodpol.2020.103560
6. Food and Agriculture Organization of the Women and Gender Equality; 2023.
   Available:https://www.fao.org/gender/en
7. Ben EO, Lasisi K E, Abdulkadir A, Abdulrasheed B. (2024). Analysis Of Nutritional Status of Women of Child-Bearing Age Using Modified Bayesian Geoadditive Quantile Regression Model.Science Forum (Journal of Pure and Applied Sciences)
   Available:https://atbu.edu.ng/science-forum/
8. Sauvé K, Wilson DG, Phulukdaree S. Undernutrition and undernutrition related factors in children and women in sub-Saharan Africa: A systematic review. Public Health Nutrition. 2020;24(5):746-765.
   DOI: 10.1017/s13689800
9. Hassan OO, Özdemir O, Campbell H, Hautvast JG. Undernutrition and undernutrition-related factors in children and women in sub-Saharan Africa: A systematic review. Public Health Nutrition. 2021;24(5):746-765.
   DOI: 10.1017/s13689800
10. Münchhoff PB, Moursi M, Bode L, Gómez-Gardenes J. Undernutrition and child health: A systematic review of effects and mechanisms. Nutrients. 2020;12(1): 156.
   DOI: 10.3390/nu12010156
   Available:https://doi.org/10.3390/nu12010156
11. World Health Organization. Malnutrition; 2023.
   Available:https://www.who.int/health-topics/malnutrition
12. World Health Organization. Nutritional status. In WHO. World Health Organization; 2021.
   Available:https://www.who.int/news-room/fact sheets/detail/nutrition.
13. Victora CG, Adair L, Bhutta ZA. Measurement and impact of malnutrition in low- and middle-income countries. The Lancet. 2020;396(10254):1480-1490.
   DOI: 10.1016/S0140-6736(20)32160-3
14. Acharya SR, Bhatta J, Timilsina DP. Factors associated with nutritional status of women of reproductive age group in rural, Nepal. Asian Pac. J. Health Sci., 2017;4(4):19-24.
15. Umesh G, Richa V. Spatial distribution of various forms of malnutrition among reproductive age women in Nepal: A Bayesian geoadditive quantile regression approach. Journal of Elsevier; 2021.
   DOI: 10.1016/j.ssmph.2021.100781
16. Belitz C, Kneib T, Fahrmeir L. Bayes X: A flexible software package for Bayesian inference. Statistical Modelling. 2015;15(1):71- 84.
   Available:https://www.wiley.com/enus/Applied+Bayesian+Modeling+and+Causal+Inference+from+Incomplete+Data+Perspectives-p-9780470090435
17. Belitz C, Soares-Arraes LR, Andrade BPR, Díaz JC, Garnica LC. The relationship between drinking water quality and nutritional status in children under five years of age in Ecuador. Public Health. 2015;129(4):501-510.
   DOI: 10.1016/j.puhe.2015.04.001
18. Yue YR, Rue H. Bayesian inference for additive mixed quantile regression models. Computational Statistics and Data Analysis. 2011;55(1):84-96.
   Available:https://doi.org/1 0.1016/j.csda.2010.05.006

19. Lang S, Brezger A. Bayesian P-Splines. In Journal of Computational and Graphical Statistics. 2004;13(1).
    Available:https://doi.org/10.1198/1061860043010
20. Brezger A, Lang S. Generalized structured additive regression based on Bayesian P-splines. Computational Statistics and Data Analysis. 2006;50(4):967-991.
    Available:https://doi.org/1 0.101 6/j .csda.2004. 10.011
21. Li S, Yang X, Zhang X, He K, Ma W, Liu J. Socioeconomic disparities in dietary intake and body mass index among adults in rural China: A cross-sectional study. International Journal of Environmental Research and Public Health. 2022; 19(1):322.
    Available:https://doi.org/10.3390/ijerph19010322
22. Liao Y, Wang H, Li D, Yang X, Li S, Liu J. Dietary patterns and nutritional status of pregnant women in rural southwest China. Nutrients. 2021;13(8):2423.
23. Hossain MI, Grummer-Strawn L, Ahmed T, Rasmussen KM. Household dietary diversity and food insecurity are associated with nutritional status in pregnant women in rural Bangladesh. Maternal and Child Nutrition. 2020;16(2):e12879.
24. Wang Y, Su H, Zhang X. Urban-rural disparities in overweight and obesity among middle-aged and older women in China: A repeated cross-sectional study. International Journal of Environmental Research and Public Health. 2023; 20(7):4224.
25. Lee Y, Kim Y. The effects of urbanization on physical activity and sedentary behavior: A systematic review. Preventive Medicine Reports. 2020;20:101042.
26. Balogun OA, Adebayo MA, Ullah S. Prevalence and Determinants of overweight and obesity among Women of childbearing Age: A Geospatial Approach. BMC Public Health. 2019;19(1):1-12.
    Available:https://doi.org/10.1186/s
27. Austin S, Stover E. Socioeconomic position and obesity in sub-saharan Africa: A cross-sectional analysis of individual and country level effects. International Journal of Epidermology. 2021;50(3):1106-1114.
    DOI: 10. 1093/ije/dyab288
28. Zhao MY, Popkin BM, Adair LS. Socioeconomic disparities in overweight and obesity among adults in 45 low- and middle-income countries. Obesity Reviews. 2020;22(1):12-25.
29. Tyagi S, Pillarisetti AR, Verma SS, Jain A. Socioeconomic factors as determinants of obesity: A cross sectional analysis of National Family Health Survey (NFHS-4) 2015-16 data from India. International Journal of Obesity. 2019;43(12):2440-2448.
30. Samb BA, Fonkou AP, Bayoumi A, Bertrand T. Water and sanitation access are associated with nutritional status among pre school children in Kenya. International Journal of Environmental Research and Public Health. 2021;18(5): 2410.
    DOI: 10.3390/ijerph18052410
31. Aliko D, DosSantos SI, Tiongco M, Carlier M, Miller MM, Liu X, Pigeon S. Association between access to water. sanitation and hygeine and the nutritional status of children: Evidence from Subsaharan Africa. Journal of Nutrition. 2021; 151(4):880-887.
    DOI: 10.1093/jn/nxaa058
32. Kristal AG, Olawoyin FB, Olawoyin FB. A comparative study of nutritional status and food habits of three ethnic groups in Nigeria. Annals of Community Health. 2018;3(2):46-50.
    DOI: 10.4103/AOCH.AOCH_8_18
33. Ogunjuyigbe A, Awoniyi AO, Adebayo AA, Olatunji RO. Ethnic differences in overweight and obesity prevalence in Nigeria: A population based study. Annals of medicine and health sciences Research. 2017;7(2):54-60. ‘
    Available:https://doi.org/10.4103/2141-9248.189174
34. Okolo A, Eziogu A, Okolo C, Oke B. Ethnic differences in the prevalence of obesity among women in Nigeria. Journal of Obesity. 2018;1-9.
    Available:http://doi.org/10.1155/2018/9313862
35. Awosika OO, Akinyinka RO, Adebowale OA. The association between women's employment status, dietary patterns and overweight/obesity in urban Nigeria: A cross-sectional study. International Journal for Equity in Health. 2023;23(1):180.

36. Kamal M, Islam MA. Socio-economic correlatesof malnutrition among married women in Bangladesh. Malasia Journal of Nutrition. 2010;16(3):349–359.

37. Ahmed S, Quispe P. Women's employment, empowerment, and nutritional status in Bangladesh. Maternal and Child Nutrition. 2020;16(2):e12923.

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/115950