SCIENCE FORUM (JOURNAL OF PURE AND APPLIED SCIENCES) 24 (2024), (1), 47 - 57

Science Forum (Journal of Pure and Applied Sciences)

Journal Homepage: https://atbu.edu.ng/science-forum/

Analysis of Nutritional Status of Women of Child-Bearing Age Using Modified Bayesian Geoadditive Quantile Regression Model.

Ben, E, O., Lasisi K. E., Abdulkadir, A., Abdulrasheed B.

Department of Mathematical Sciences (Statistics Option), Faculty of Science, Abubakar Tafawa Balewa University, Bauchi.

ABSTRACT

In a recent research endeavour, an evaluation was conducted to gauge the nutritional status (well-being) of women in Nigeria who are of reproductive age. Utilizing a modified Bayesian Geoadditive Quantile Regression Model, the study delved into data sourced from the 2018 Nigeria Demographic and Health Survey (NDHS), with computational analysis carried out through the R-software. The findings illuminated several pivotal determinants impacting the nutritional health of these women. Specifically, variables such as age, residential location, professional engagement, and the size of the household exerted a favorable influence on their nutritional status. This emphasizes the multifaceted nature of factors influencing nutritional outcomes among Nigerian women of reproductive age. Given these insights, there emerges a palpable imperative for concerted efforts aimed at ameliorating the prevalence of malnutrition in this demographic group. Both governmental bodies and non-governmental entities are thus called upon to formulate and implement targeted interventions. Such interventions could encompass the design and delivery of tailored nutritional education initiatives and other pertinent programs. By aligning interventions with the unique requirements and circumstances of women of reproductive age in Nigeria, it becomes feasible to foster improved nutritional outcomes and overall well-being in this critical demographic.

ARTICLE INFO

Received 18 January 2024
Received in Revised Form
23 January 2024
Accepted 23 January 2024
Published 30 January 2024
Available online 30 January 2024

KEYWORDS

BMI,
Nutritional Status,
Bayesian method
Quantile regression

Corresponding Author Ben, E, O esty2k6.beo@gmail.com *Department of Mathematical Sciences (Statistics Option), Faculty of Science, Abubakar Tafawa Balewa University, Bauchi.*

1. Introduction

The nutritional status reflects the body's acquisition of essential nutrients and protective elements, which are evident in physical, physiological, and biochemical attributes, as well as overall health and functionality. The World Health Organization highlights that a significant number of women, especially during their childbearing years and pregnancies, often lack essential micronutrients in their dietary intake. Given the pivotal roles women play in societies, being central figures in ensuring household well-being, their health and nutrition are of paramount importance. Yet, it's observed that women aged between 15 to 49 years, beyond just young children, are frequently at heightened risk of malnutrition in developing nations. This vulnerability arises from a combination of societal and biological factors (Acharya, Bhatta, Timilsina 2017, Akeresola & Gayawan, 2020).

Mothers who are underweight are notably more prone to having children who experience stunting, putting such children at elevated risks of both illness and death. While there has been a decline in maternal undernutrition, malnutrition remains notably prevalent in Sub-Saharan Africa, as highlighted by the UN in 2015. Proper nutrition plays a pivotal role in the health of both women and children. For women, insufficient nutrition heightens their vulnerability to infections and hampers their recovery from ailments, among other health challenges. The World Health Organization characterizes malnutrition as a cellular discrepancy between the nutrients and energy provided and the body's requirements for growth, upkeep, and specific bodily functions. Severe thinness, underweight, overweight, and obesity are the four types of malnutrition in adults. They are typically evaluated using height and weight indices calculated as body mass index (BMI). A woman whose BMI is ≤16 kg/m^2 is considered to be severely thin; women with BMI of ≤ 18.5kg/m^2 are said to be underweight. On the other hand, women whose BMI is ≥25 kg/m^2 are said to be overweight while those with BMI ≥30 kg/m^2 are considered obese.

Malnutrition is measured at the extreme quantiles of the BMI distribution: severe thinness and underweight are measured at the lower quantiles, while overweight and obesity are measured at the upper quantiles (Acharya, Bhatta, Timilsina, 2017). As a result, it becomes desirable to employ statistical methods that take these into account in the analysis process. Statistical methods that measure not only the conditional mean of the response variable but also the extreme quantiles are more appropriate than the classical linear regression model, which specifies the change in the conditional mean of the response variable associated with a change in the covariates. Inference on conditional quantiles can provide a more comprehensive description of functional changes than solely focusing on the conditional mean. The upper and lower quantiles of the response variable may be affected by covariates other than the center. Furthermore, different types of explanatory variables may be available, necessitating the need to combine different variable effects in a single modeling framework, such as nonlinear effects of continuous variables, spatial random effects, and traditional linear effects (Umesh and Richa, 2021).

Bayesian statistics employs Bayes' theorem as its foundation, utilizing data to refine our understanding of parameters within a statistical model. This approach calculates the posterior distribution by melding prior beliefs, represented as a prior distribution, with new observational data, depicted through a likelihood function. Notably, this posterior distribution not only informs current insights but can also offer predictive capabilities for future events (Van de Schoot et al., 2021). The strength of Bayesian inferences lies in its ability to integrate prior knowledge with fresh data. By assessing this combined probability distribution, the resulting Bayesian inferences are deemed optimal, with conclusions drawn based on the conditional distribution in light of the observed data.

Academic research indicates that both malnutrition and over-nutrition can result in adverse pregnancy and birth results. Specifically, maternal obesity during labor and delivery has been linked to complications such as maternal mortality, excessive bleeding, the need for cesarean delivery, and infections. Moreover, both pre-pregnancy obesity and insufficient weight gain during gestation can adversely impact breastfeeding behaviors. They also elevate the likelihood of postpartum hemorrhage-related fatalities, thereby amplifying health risks for both mothers and their infants. Specifically, obesity heightens the chances of women developing cardiovascular conditions and, during pregnancy, can lead to gestational diabetes and high blood pressure Akeresola and Gayanwa, 2020).

Furthermore, Previous research often relied on traditional statistical techniques, such as summary statistics or regression models, to discuss women's nutritional status (Gupta et al., 2019; Rai, Gurung, Thapa, & Saville, 2019). Our study aims to overcome the limitations of these earlier works. We utilize a regression method that focuses on the influence of covariates on conditional quantiles, enabling a detailed examination of extreme responses based on covariate changes. This approach offers the advantage of capturing a comprehensive range of outcomes and can effectively account for various types of covariates. Consequently, it's deemed more suitable for studying malnutrition. Additionally, our research delves into the risk factors associated with underweight, overweight, and obesity among Nigerian women, considering spatial dependencies. We also evaluate the key determinants, encompassing the spatial patterns of these malnutrition types, using the Modified Bayesian Geoadditive Quantile Regression model Ghamire and Vatsa, 2021).

Bayesian quantile regression furnishes a holistic view of how various predictors influence the response variable across different quantiles. Furthermore, its versatility allows for the incorporation of diverse types of covariates (Waldmann et al., 2013).

Therefore, this research seeks to determine the severity of the factors that are responsible for the various nutritional status of women of child bearing age in Nigeria,

2.0Material and Method

2.1 Data

The data utilized in this study were sourced from the 2018 Nigeria Demographic and Health Survey (NDHS). Conducted by the National Population Commission between February and June 2018, the survey aimed to offer estimates of population and health indicators at the national, zonal, and state levels. Nigeria comprises 36 administrative states and a Federal Capital Territory (FCT), Abuja. Similar to other surveys of its kind, all women aged 15–49, whether permanent residents of selected households or visitors present on the night before the survey, were eligible for interviews. The Household Questionnaire was employed to gather information on the characteristics of the household's dwelling unit and to record height and weight measurements for women and children, from which the BMI variable was subsequently calculated.

The explanatory variables considered include the following: women’s age (in years), women’s educational attainment, household wealth index, household water source classified as being protected or not protected, type of household toilet facilities classified as improved or non-improved, whether or ot the household has electricity, women’s working status, exposure to mass media (whether or not the woman reads any newspapers/magazines, listens to radio or watches television at least once a week), type of place of residence, Ethnicity, Family Type and Household Number.

2.2 Statistical Model

In the given equation below, consider t_i as the nutritional status of the ith group of women, categorized as 'normal weight,' 'overweight,' and 'obesity.' Let x_i represent the covariate vector associated with t_i through a multinomial logit model, specifically defined as follows:

$$P[ti = r] = \frac{\exp(\eta i,r)}{1 + \sum_{s=1}^{k-1} \exp(\eta i,s)} \quad r = 1:(K-1).$$

The symbol r represents a specific nutritional status category, and K denotes the total number of categories. In relation to the category indexed by r,

$$\eta_{I,r} = u_i'\beta_r + f_r(z_i) + gr(S_i), r = 1:(K-1),$$

Using u_i as a categorical covariate vector, where z_i represents age and S_i denotes geographical divisions, the term β_r is associated with linear effects. Additionally, f_r represents a nonlinear smooth function of age, while g_r signifies the spatial effects of divisions. The geoadditive regression model described above is a modification of the Generalized Linear Model (GLM). It incorporates adjustments to accommodate nonlinear effects of the continuous covariate 'age,' spatial effects from geographical divisions in the country, and linear effects of other categorical covariates within the same framework.

In this research, we adopted a Bayesian approach for inference to model fitting. Diffuse priors, $P(\beta_r) \propto const$, were assigned to the linear effects β_r. Bayesian p-spline priors were employed for the unknown nonlinear smooth function f_r (Fahrmeir, Kneib & Lang, 2004), while a Gaussian Markov random field (GMRF) prior was applied to the unknown spatial effects g_r (Rue H & Held L, 2005). A non-informative inverse-gamma hyper-prior, with default hyper-parameters a=b=0.001, was specified for the variance parameter of the Bayesian p-spline prior and the smoothing parameter of the GMRF prior. For further details on the geoadditive regression model for categorical response variables, refer to [Kneib T & Fahrmeir L., 2006]. The inferences were drawn using Markov Chain Monte Carlo (MCMC) techniques, implemented through the BayesX software using the R-package BayesXSrc.

3.0 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.

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

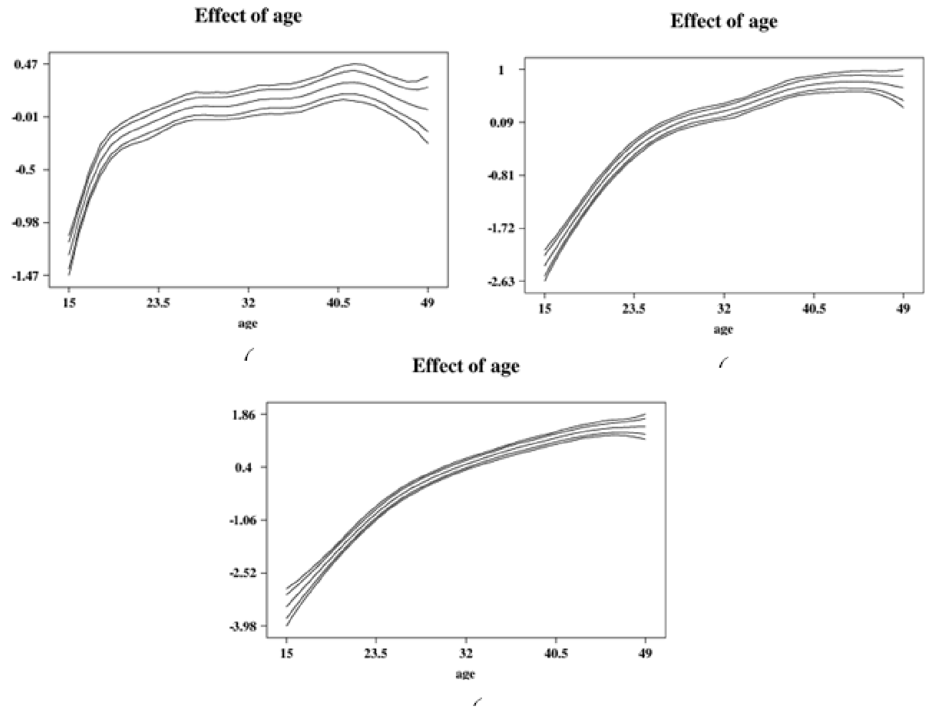
Table 2; Posterior mean estimates for the linear effects of normal, overweight and obesity among women of childbearing age-group (15 to 49 years).

	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
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

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. Estimates of the place of residence on BMI showed that compared to rural, women residing in urban location were more likely to be obese (mean:0.2556; 95% CI:0.0722, 0.4599) and less 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 a household 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 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, currently-working women are significantly more likely to be obese (means: 0.1968; 95% CI: 0.0055, 0.3820).

3.1 Nonlinear Effects

Figures 1, 2, and 3 illustrate the nonlinear impacts of a mother's age on Normal weight, overweight, and obesity, respectively, utilizing smooth functions. These visuals display the posterior means with thick black lines and the corresponding 80% and 95% credible intervals in shaded areas. Clearly, the relationship between a mother's age and these weight categories isn't linear, suggesting that assuming a linear relationship would be erroneous.



4.0 Discussion and Conclusion

This research delved into a comprehensive examination of how covariates influence various Nutritional status categories using the Modified Bayesian Geoadditive Quantile regression approach. By employing this method, the study addresses the constraints observed in earlier research that relied on traditional regression techniques (Waldmann et al., 2013). Regarding the socio-economic factors examined, findings related to residential location indicate that women in urban settings are at a higher risk of experiencing overweight and obesity. It is widely recognized that women residing in urban settings are prone to having elevated income and educational levels. This circumstance may contribute to adopting more sedentary lifestyles and possessing additional disposable income that can be allocated to the consumption of processed and calorie-dense foods (Balogun, Adebayo, and Ullah, 2019). The processes of urbanization and westernization often lead to reduced physical activity and an uptick in food availability, notably including high-calorie fast foods and sugary beverages. This observation aligns with the conclusions drawn by Akeresola and Gayanwa (2020). In terms of educational background and wealth index, the study indicates that women with any level of education are susceptible to experiencing overweight and obesity. But as the level of education increases, the estimate increases showing that as the educational status increases, the women of child bearing age are more likely to be overweight or obese. This agrees with the study of Austin & Stover (2021). Women with education may possess greater awareness of healthy dietary practices and physical exercise, yet they might face constraints in terms of time or resources to implement this knowledge. Those with a higher socioeconomic status might have increased access to leisure and sedentary activities like watching television and using the internet, factors that could contribute to weight gain (Tyagi, *et al* 2019). Additionally, women who have access to safe water and upgraded toilet facilities are more likely to maintain a normal weight than those lacking these amenities. This finding aligns with studies from Kenya and other regions in sub-Saharan Africa. Enhanced access to clean and advanced sanitation facilities might promote better hygiene behaviors, potentially lowering the chances of water-related illnesses and enhancing general health. Moreover, better access to safe water and improved sanitation could positively influence nutrition and food security, subsequently impacting overall health and weight (Samb *et al,* 2021; Aliko *et al*, 2021). Access to mass media serves as a primary conduit for health-related information, leading to the assumption that women who engage with radio, television, or newspapers would be more knowledgeable about healthy dietary habits and lifestyles. However, our research indicates that individuals with exposure to mass media are actually less inclined to maintain a normal weight. This observation is consistent with the findings of Akeresola and Gawayan in 2018. Moreover, women with access to electricity in their homes tend to have a higher likelihood of being overweight compared to those without such access. Research from Bangladesh indicates that having electricity can result in a rise in the intake of processed foods. This is because refrigerators and cooking devices facilitate the storage and preparation of such foods. Additionally, having electricity might correlate with a superior socioeconomic position, which is associated with elevated obesity rates (Kristal et al., 2018). Research also indicated that Hausa/Fulani and Yoruba women tended to maintain a healthier weight, whereas Igbo women were more susceptible to obesity. These variations may be attributed to differences in dietary habits, levels of physical activity, and socioeconomic factors, as highlighted in the studies by Ogunjuyigbe et al. (2017) and Okolo et al. (2018). Furthermore, the research indicated that employed women have a higher tendency to be overweight or obese but are less likely to maintain a normal weight compared to those who are not employed. This contrasts with the findings from Bangladesh, where non-employed women were predominantly underweight (Kamal and Islam 2010). In Nigeria, working women often experience greater empowerment and increased purchasing power. Consequently, they can independently decide on their dietary choices. In contrast, non-working women typically rely on their husbands or their husbands' families for sustenance, which can restrict the diversity and types of foods they consume.

Examining the impact of age on women's BMI, the results indicate that with each unit rise in age, the likelihood of having a normal weight, being overweight, or experiencing obesity also increases. Various studies, including Samouda et al. (2018), have consistently reported that factors like diet, physical activity levels, and age significantly influence obesity. The correlation between increasing age and heightened obesity risk is associated with a sedentary lifestyle and decreased metabolic rates.

In conclusion, Bayesian quantile regression provides a holistic approach for thoroughly analyzing the extreme values of BMI. It enables the examination of socio-economic factors across various malnutrition levels, offering a more comprehensive understanding of the impacts of explanatory variables beyond just the average values. Adequate nutrition prevents malnutrition and also reduces the risk of severe illness and diseases among women of childbearing age. Therefore, dealing with the problems associated with women of childbearing age demands pragmatic approach from the government and non-governmental organization.

REFERENCES

Akeresola, R. A., & Gayawan, E. (2020). Analysis of the spatial patterns of malnutrition among women in Nigeria with a Bayesian-structured additive model. *GeoJournal*, *85*(1), 81–92. https://doi.org/10.1007/s10708-018-9958-0

Acharya S.R, Bhatta J, Timilsina DP.(2017) Factors associated with nutritional status of women of reproductive age group in rural, Nepal. Asian Pac. J. Health Sci., 2017; 4(4):19-24.

Aliko, D., DosSantos, S.I., Tiongco, M., Carlier, M., Miller, M. M., Liu, X., Pigeon, S. (2021). Association between access to water. sanitation and hygeine and the nutritional status of children: evidence from sub saharan Africa. Journal of Nutrition, 151 (4), 880-887. doi: 10.1093/jn/nxaa058.

Austin, S. & Stover, E. (2021) . Socioeconomic position and obesity in sub-saharan Africa: a cross-sectional analysis of individual and country level effects. International Journal of Epidermology, 50(3), 1106-1114. d0*i: 10. 1093/ije/dyab288

Balogun, O.A, Adebayo, M. A, & Ullah, S. (2019). Prevalence and Determinants of overweight and obesity among Women of childberaring Age: A Geospatial Approach. BMC Public Health, 19(1), 1-12. https://doi.org/10.1186/s

Brezger, A., & Lang, S. (2006). Generalized structured additive regression based on Bayesian P-splines. *Computational Statistics and Data Analysis*, *50*(4), 967–991. https://doi.org/10.1016/j.csda.2004.10.011

Fahrmeir L, Kneib T, Lang S. (2004). Penalized structured additive regression for space-time data: a Bayesian perspective. Statistica Sinica. 2004;731–61.

Gupta, R. D., Haider, S. S., Sutradhar, I., Hashan, M. R., Sajal, I. H., Hasan, M., et al. (2019). Association of frequency of television watching with overweight and obesity among women of reproductive age in India: Evidence from a nationally representative study. *PloS One*. https://doi.org/10.1371/journal.pone.0221758

Kamal, M., & Islam, M. A. (2010). Socio-economic correlates of malnutrition among married women in Bangladesh. Malasia Journal of Nutrition, 16(3), 349–359.

Kneib T, Fahrmeir L. Structured additive regression for categorical space-time data: A mixed model approach. Biometrics. 2006;62.

Kristal, A. G., Olawoyin, F. B., & Olawoyin, F. B (2018) A comparative study of nutritional status and food habits of three ethnic groups in Nigeria. Annals of Community Health, 3(2), 46-50. doi: 10.4103/AOCH.AOCH_8_18.

Lang, S., & Brezger, A. (2004). Bayesian P-Splines. In *Journal of Computational and Graphical Statistics* (Vol. 13, Issue 1). https://doi.org/10.1198/1061860043010

National Bureau of Statistics Nigeria. National Nutrition and Health Survey (NNHS) 2018.

Ogunjuyigbe, A., Awoniyi, A.O., Adebayo, A.A., &Olatunji, R.O. (2017). Ethnic differences in overweight and obesity prevalence in Nigeria: a population based study. Annals of medicine and health sciences Research, 7(2), 54-60. https://doi.org/10.4103/2141-9248.189174.

Okolo, A., Eziogu, A., Okolo, C., & Oke, B. (2018) Ethnic differences in the prevalence of obesity among women in Nigeria. Journal of obesity, 1-9. http://doi.org/10.1155/2018/9313862.

Rai, A., Gurung, S., Thapa, S., & Saville, N. M. (2019). Correlates and inequality of underweight and overweight among women of reproductive age: Evidence from the 2016 Nepal Demographic Health Survey. *PLoS ONE*. https://doi.org/10.1371/ journal.pone.0216644

Rue H, Held L. Gaussian Markov random fields: theory and applications. CRC press; 2005.

Samb, B.A., Fonkou, A. P., Bayoumi, A., & Bertrand, T.(2021). Water and sanitation access are associated with nutritional status among pre school children i n Kenya. International Journal of Environmental Research and Public Health, 18(5), 2410. doi: 10.3390/ijerph18052410

Samouda, H., Ruiz-Castell, M., Bocquet, V., Kuemmerle, A., Chioti, A., Dadoun, F., et al.(2018) Geographical variation of overweight, obesity and related risk factors: Findings from the European health examination survey in Luxembourg. PLoS ONE, 13(e0197), 021.

Tyagi, S, Pillarisetti, A.R, Verma, S.S, & Jain, A. (2019). 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 43(12), 2440-2448

Umesh, G, & Richa, V. (2021), Spatial distribution of various forms of malnutrition among reproductive age women in Nepal: A Bayesian geoadditive quantile regression approach. Journal of Elsevier. Doi:10.1016/j.ssmph.2021.100781

United Nations. The Millennium Development Goals Report. United Nations; 2015.Public Health. 2018; 152:1–8.

van de Schoot, R., Depaoli, S., King, R., Kramer, B., Märtens, K., Tadesse, M. G., Vannucci, M., Gelman, A., Veen, D., Willemsen, J., & Yau, C. (2021). Bayesian statistics and modelling. *Nature Reviews Methods Primers*, *1*(1), 1–26. https://doi.org/10.1038/s43586-020-00001-2

Waldmann, E., Kneib, T., Yue, Y. R., Lang, S., & Flexeder, C. (2013). Bayesian semiparametric additive quantile regression. *Statistical Modelling*, *13*(3), 223–252. https://doi.org/10.1177/1471082X13480650

Yue, Y. R., & Rue, H. (2011). Bayesian inference for additive mixed quantile regression models. *Computational Statistics and Data Analysis*, *55*(1), 84–96. https://doi.org/10.1016/j.csda.2010.05.006