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Analysis of the spatial patterns of malnutrition among women in Nigeria with a Bayesian structured additive model

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Abstract Malnutrition among women has severe consequences on their health, households and national development. The different forms of malnutrition among adult individuals are severe thinness, underweight, overweight and obesity which are usually assessed using height and weight indices calculated as body mass index (BMI). In this study, the spatial distributions of the various forms of malnutrition measured at the upper and lower tails of the BMI were accessed among women of reproductive age in Nigeria after accounting for the influence of socio-economic factors. Bayesian quantile regression that permits for inference on conditional quantiles, yielding a complete description of the functional changes among covariates at different quantiles of the response variable was adopted. Markov random field and Bayesian P-splines were used as prior distributions for the spatial and nonlinear effects respectively, while computation was based on MCMC approach. Data were derived from the 2013 Nigeria Demographic and Health Survey. Findings indicate the existence of spatial structure in the various forms of malnutrition with neighbouring states sharing similar patterns and that the socio-economic variables exact dissimilar influence on the various forms of malnutrition. The study provides valuable insights for policy makers in the quest for halting all forms of malnutrition among Nigerian women.

Keywords Malnutrition · Spatial structure · Nigeria · Bayesian method · Quantile regression

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Introduction

Adequate nutrition is necessary for national development and individual's well-being as poor nutrition creates problems not only for the individual but for the entire population. Women and children are particularly at high risk due to their unique physiology and high nutrients requirements. The World Health Organization (WHO) approximated that in 2014, 462 million adults were underweight while 1.9 billion were either overweight or obese (WHO 2017). Women are important agents in any society due to their multiple roles as custodians of household welfare. However, for several social and biological reasons, women of reproductive age (15–49 years) are usually amongst the most vulnerable to malnutrition, aside of young children, in developing countries (Ahmed et al. 2012). Malnutrition remains a major concern among these women in Nigeria deserving more attention by researchers and policy makers. According to the 2013 Nigeria Demographic and Health Survey (NDHS), as high as eleven per cent of women of reproductive age are undernourished while seventeen per cent are overweight. The survey also presents some enormous evidence of geographical variations in these statistics.

Malnutrition among women has severe consequences on their health, households and national development. Some of these consequences include poor pregnancy outcomes, high vulnerability to infectious diseases with slow recovery rates, lethargy and general body weakness leading to reduced productivity, increased risk of maternal complications and death (Muller and Krawinkel 2005; Denison et al. 2010). Scholarly evidence has shown that both under- and over- nutrition lead to poor pregnancy and birth outcomes. During labour and delivery, maternal obesity was found to be associated with maternal death, haemorrhage, caesarean delivery, or infection (Ahmed et al. 2011; Normal and Reynolds 2011). Furthermore, both obesity before pregnancy and inadequate weight gain during pregnancy have negative effects on breastfeeding practices (Liu et al. 2010; Kitsantas and Pawloski 2010), and increase the risk of death due to postpartum haemorrhage thus, enhancing the overall morbidity and mortality in women and their young children (Tomkins 2001). Obesity in particular increases the risk of developing cardiovascular diseases in women and, in pregnancy, it induces gestational diabetes and hypertension (UNICEF 2009). Children of well-nourished women have been reported to have firmer developmental path, both physically and mentally (NPC and ICF 2014).

The geographic environment in which people live and self-awareness of nutritional status play important role in their health conciousness and management. Thus, understanding the association between geographic settings, socioeconomic condition and BMI status is vital to improving quality of life especially in developing countries (Hong and Ye 2018). Consequently, the geographic pattern of malnutrition among women and young children has received considerable attention in a number of studies. A recent study in Afghanistan identified rapid changing political, socioeconomic and insecurity landscape to have both direct and indirect implications on the population nutrition. In particular, the study observed large scale geographical disparity and therefore concluded that district-level approaches are required to reduce inequities and scale up nutrition-specific and nutrition-sensitive interventions in the country (Akseer et al. 2018). Similar findings were obtained in the case of Pakistan where huge geographical inequalities in both maternal and child nutrition are found to be masked by national and provincial averages thus, raising the need for local-level tracking of nutritional status for monitoring and programme evaluation (Cesare et al. 2015). Studies in Luxembourg identified significant nonlinear effect of age on overweight and obesity in both male and female and also found higher likelihood of overweight and obesity among individuals living outside the country's capital with the highest rates found in municipalities located in the South-West of the country (Samouda et al. 2018; Tchicaya and Lorentz 2012).

In sub-Saharan Africa, a number of studies have focused on the geographical disparity in under-nutrition among young children, demonstrating some environmental and spatio-economic relationships (Uyanga 1981; Gayawan et al. 2017; Rossington 1981; Gewa et al. 2013; Haile et al. 2016). A handful have considered the case of women particular on overweight and obesity notwithstanding the nutritional transition taking place in the region (Popkin 1993, 1998). Due to the persistent poverty that prevail in most of the countries, under-nutrition has been the major focus of most research efforts but the nutritional transition has been characterised with rising proportion of plump women particularly that these women are considered to be sexually attractive, have high social standing and socioeconomic status (Sobal and Stunkard 1989). Using data from the 2008 NDHS, Kandala and Stranges (2014) classified Nigerian women into whether or not they were overweight/obese and examined the socioeconomic and spatial variations in the nutritional status. The study identified significant risk factors to include household wealth, higher educational level and urban residency, while also observing hotspot locations for overweight/obesity to be within states in the south-eastern part of the country. In an analysis of the disparity among the forms of malnutrition among women based on geographical locations in Mali, Gewa et al. (2013) found underweight women to be more prevalent in southern Mali but obesity was more frequent in the north-east and within the major urban areas of the country. Thus, a focus on local disparity in the different forms of malnutrition as undertaken by this study would not only shed light into the possible distinct geographic patterns in the forms of malnutrition but also identify the varying roles of socioeconomic and demographic variables which would be useful in policy formulation and implementation.

According to WHO, malnutrition is defined as the cellular imbalance between supply of nutrients and energy and the body's demand for them to ensure growth, maintenance and specific functions. The different forms of malnutrition among adult individuals are severe thinness, underweight, overweight and obesity. They are usually assessed based on height and weight indices calculated as body mass index (BMI). A woman whose BMI is $< 16\,\mathrm{kg/m^2}$ is considered to be severely thin; women with BMI of $< 18.5\,\mathrm{kg/m^2}$ are said to be underweight. On the other hand, women whose BMI are $> 25\,\mathrm{kg/m^2}$ are said to be overweight while those with BMI $> 30\,\mathrm{kg/m^2}$ are considered obese. This study looks into the extent to which some selected socio-economic factors affect the different forms of malnutrition, and also accesses the spatial patterns among women of reproductive age in Nigeria.

Studies on malnutrition among women and children have largely been based on either mean or binary regression models (Bharati et al. 2007; Kandala et al. 2009; Yadav et al. 2015; Tebekaw et al. 2014). While the former relates the covariates to the average nutritional level neglecting the fact that malnutritions are measured at the extreme ends of the response variable, the latter classifies the variable into whether or not the individual is malnourished but this approach can lead to loss of information. The different forms of malnutrition are measured at the extreme quantiles of the distribution of BMI: severe thinness and underweight at the lower quantiles while overweight and obesity are measured at upper quantiles. It becomes desirable therefore, to adopt statistical methods that take these into consideration in the analysis process. Unlike classical linear regression model which specifies the change in the conditional mean of the response variable associated with a change in the covariates, statistical methods that measure not just the conditional mean but also the extreme quantiles are more appropriate. Inference on conditional quantiles can give a more complete description of functional changes than focusing solely on the conditional mean. It is possible that the upper and lower quantiles of the response variable may depend on covariates different from the center. Further, different types of explanatory variables might be available necessitating the need to combine different variable effects such as nonlinear effects of continuous variables, spatial random effects and the traditional linear effects simultaneously in a single modelling framework. Consequently, Bayesian quantile regression, a completely distribution free approach, is employed in this study since it is capable of giving a complete view of the effects of covariates on the response variable at different quantiles, and can be extended to account for the different types of covariates available (Waldmann et al. 2013). With this approach, we are able to investigate the spatial patterns of the different categories of malnutrition among women in Nigeria at state level, after accounting for the effects of observed variables. Similar approach can explain the distributions of malnutrition among young children (Gayawan et al. 2017; Mtambo et al. 2015).

Methods

Data

The data for this study were obtained from the 2013 Nigeria Demographic and Health Survey (NDHS). The survey, executed by the National Population Commission between February and June 2013, was designed to provide population and health indicator estimates at the national, zonal, and state levels. Nigeria comprises of 36 administrative states and a Federal Capital Territory (FCT), Abuja. Details of the sampling procedure for the survey has been reported in NPC and ICF (2014). As with other similar surveys, all women aged 15–49 who were either permanent residents of the selected households or visitors present in the households on the night before the survey were eligible to be interviewed. The Household Questionnaire was used to collect information on characteristics of the household's dwelling unit and was further used to record height and weight measurements for the women and children from where the BMI variable was calculated.

The explanatory variables considered include the following: women's age (in years), women's highest 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 not 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) and type of place of residence. The spatial unit for analysis was based on the state of residence of the respondents.

Ethical consideration

The data used in this study was obtained from The DHS Program (https://dhsprogram.com), who was the main partner that conducted the survey, after approval was given to our request.

Statistical method

Consider a set of variables (y_i, $\boldsymbol{x_i}$, v_i, s_i) where y_i is a response variable, in this case, the BMI, $\boldsymbol{x_i}$ is a vector of possible categorical variables, v_i a vector of continuous variables such as age, and s_i, the state of residence of the ith respondent. A regression model for the analysis of such data can be represented as:

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

where

$$\varepsilon_i \backsim F(\varepsilon_i \mid \theta)$$

and

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

F is an unknown distribution of the error term ε which may depend on some additional parameters θ, η_i is the predictor of the ith observation, $\boldsymbol{\beta}$ is the vector of linear parameters, f_k is the kth smooth function assumed for nonlinear effects, $f(s_i)$ is the spatial effects for the state of residence and b_i accounts for other possible random components. If the distribution of y_i is assumed to belong to the exponential family and its mean 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 $\tau \epsilon (0, 1)$, the τth quantile of the error distribution in (1) is assumed zero, i.e. $F^{-1}(\tau \mid \theta) = 0$. The corresponding quantile function of the continuous variable Y_i is then

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

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

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

where

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

is required to be minimized (Koenker and Bassett 1978). The check function is the appropriate loss function for quantile regression problem.

Fully Bayesian inference for quantile regression has been considered (Yue and Rue 2011; Waldmann et al. 2013). The inference requires an assumption for the error term in order to obtain the needed likelihood to proceed with Bayesian inference. To this end, Y_i is assumed to be independently and identically distributed asymmetric Laplace distributions, that is, $Y_i \backsim \text{ALD}(\eta, \delta_0, \tau)$ where the parameter $\eta \in \mathbb{R}$ is the location parameter, $\delta_0 \in \mathbb{R}^+$ is the scale parameter and $0 < \tau < 1$ is the skewness parameter (Yu and Moyeed 2001; Yue and Rue 2011).

Our choice for prior distributions are based on the work of Waldmann et al. (2013). For the spatial covariate, Markov random field which is based on the idea of predefined neighbours for a spatial location u_i is considered. It assumes that two sites u_i and u_j are neighbours if they share common boundary. Letting n_i denote the number of neighbours for site u_i, the Markov random field prior is assumed for $f(u_i)$ as

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

For the smoothing function for continuous variables, the Bayesian analogue to P(enalized)-splines was adopted (Lang and Brezger 2004; Brezger and Lang 2006). The prior assumes that the unkown smooth function f can be approximated by a polynomial spline of degree l_j. The spline is then represented as a linear combination of B-spline basis function evaluated at equally spaced knots. Diffuse prior are assumed for the linear effects. Markov chain Monte Carlo (MCMC) simulation using Gibbs-sampling technique algorithm was used to draw sample from the posterior distribution in order to circumvent the difficulty of direct inference from the highly dimensional and analytically intractable posterior distribution. Details of this sampling scheme for Bayesian quantile model can be found in Waldmann et al. (2013) and Fahrmeir and Kneib (2011).

Data analysis and results

The results were obtained from Bayesian quantile regression analysis using BayesX, a freely available software for analysing structured additive regression models (Belitz et al. 2015). To access the various forms of malnutrition at the lower and upper tail of the BMI of the women, appropriate quantile needs to be specified for each type of malnutrition. We based this on the proportion of women whose BMI fall below the threshold for each form of malnutrition among those sampled during the NDHS. To this end, severe thinness was analysed at 1% quantile, underweight at 11%, while overweight and obesity were determined based on 75% and 92% quantiles respectively.

Table 1 presents the frequency distributions of the women included in the study based on the categories of the covariates. About 36% of the women had no education while about 9% attained higher level of education. Whereas about equal proportion (22%) of the women belong to the richer and richest wealth index, about 17% belong to the poorest households. In support of the fact that the majority of Nigerians reside in rural areas, about 60% of the respondents dwell in rural areas. Majority of the women (62%) are of the working class. As for water source, toilet facilities and presence of electricity in the households of the respondents, many of the women source water from protected sources (64%), use improved toilet facilities (53%) and have electricity in their households (54%). As for mass media, a higher percentage of the women listen to radio (65%) and watch television (55%) at least once in a week but more than three-quarter do not read any newspapers/magazines.

Table 2 presents the results of the Bayesian analysis showing the posterior mean estimates and 95% credible intervals for the four forms of malnutrition considered. In interpreting the results, it should be noted that an explanatory variable with negative estimate for severe thinness and underweight demonstrates negative impact of the covariate on BMI and thereby implying that the women represented suffer from under-nutrition and are thus severely thin or underweight as applicable. Positive estimates for

Table 1 Frequency distribution of the variables included in the analysis

Variables	Frequency	Percentage
Educational level		
No education	13,058	35.67
Primary education	6604	18.04
Secondary education	13,501	36.88
Higher education	3448	9.41
Employment status		
Working	22,735	62.1
Not working	13,876	37.9
Wealth index		
Poorest	6256	17.09
Poorer	7132	19.48
Middle	7463	20.38
Richer	7919	21.63
Richest	7841	21.42
Place of residence		
Rural	21,997	60.08
Urban	14,614	39.92
Water source		
Protected	23,417	63.96
Not protected	13,194	36.04
Toilet type		
Improved	19,307	52.74
Non-improved	17,304	47.26
Electricity		
Yes	19,614	53.57
No	16,997	46.43
Reads newspaper		
Yes	7890	21.55
No	28,721	78.45
Listens to radio		
Yes	23,712	64.77
No	12,899	35.23
Watches television		
Yes	20,307	55.47
No	16,304	44.53
Total	36,611	100

Table 2 Posterior mean estimates for the linear effects

Variables	Severe thinness		Underweight		Overweight		Obesity	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Residence								
Urban	0.075	0.010, 0.142	− 0.08	− 0.159, 0.008	0.307	0.156, 0.464	0.259	0.119, 0.392
Education								
No education	0	0	0	0	0	0	0	0
Primary	− 0.22	− 0.280, − 0.158	− 0.12	− 0.186, − 0.063	− 0.28	− 0.400, − 0.177	− 0.25	− 0.356, − 0.136
Secondary	0.023	− 0.023, 0.071	0.061	0.007, 0.117	− 0.27	− 0.363, − 0.164	− 0.27	− 0.372, − 0.173
Higher	0.428	0.339, 0.512	0.363	0.274, 0.454	1.345	1.147, 1.537	1.359	1.181, 1.527
Wealth index								
Poorest	0	0	0	0	0	0	0	0
Poorer	− 0.02	− 0.089, 0.041	− 0.17	− 0.244, − 0.102	− 1.04	− 1.165, − 0.911	− 1.01	− 1.127, − 0.890
Middle	− 0.09	− 0.140, − 0.034	− 0.11	− 0.172, − 0.054	− 0.16	− 0.267, − 0.057	− 0.19	− 0.295, − 0.088
Richer	0.049	− 0.008, 0.106	0.114	0.038, 0.189	0.769	0.645, 0.897	0.783	0.644, 0.915
Richest	0.209	0.132, 0.282	0.58	0.490, 0.674	2.087	1.901, 2.275	2.053	1.882, 2.216
Water source								
Protected	− 0.23	− 0.291, − 0.165	− 0.14	− 0.207, − 0.064	− 0.3	− 0.407, − 0.185	− 0.29	− 0.408, − 0.172
Toilet facility								
Improved	0.22	0.155, 0.278	0.104	0.032, 0.179	0.217	0.093, 0.356	0.259	0.142, 0.398
Electricity								
Yes	− 0.08	− 0.146, − 0.014	− 0.09	− 0.173, 0.005	0.302	0.164, 0.455	0.347	0.182, 0.493
Mass media newspaper								
Yes	0.024	− 0.048, 0.098	0.12	0.032, 0.216	0.116	− 0.037, 0.282	0.061	− 0.082, 0.205
Radio								
Yes	0.172	0.108, 0.238	0.206	0.130, 0.279	0.216	0.082, 0.337	0.255	0.140, 0.373
Television								
Yes	0.35	0.272, 0.423	0.256	0.159, 0.347	0.36	0.215, 0.498	0.337	0.187, 0.485
Working status								
Working	0.445	0.373, 0.504	0.267	0.201, 0.335	0.618	0.512, 0.736	0.624	0.504, 0.741

overweight and obesity show positive impact on the BMI implying overweight and obesity.

Findings show that women dwelling in urban areas are less likely to be severely thin while estimate for underweight is not significant. However, overweight and obesity are significantly higher among these women. It is evident that women with primary education are significantly more likely to be severely thin and underweight but those with at least secondary education are less likely when compared with women having no education. Women who attained at most secondary level of education are less likely to be overweight or obese but those with higher education are more likely. Findings further show that, compared with non-working women, currently-working women are significantly more likely to be overweight and obese but less likely to be severely thin or underweight. Also, a positive and significant association between household's wealth quintiles and undernutrition is evident. Results reveal that women from the richer and richest households are significantly less underweight and severely thin compared with those from the poorest wealth quintile. However, these women are significantly more prone to overweight and obesity. On the contrary, women from the poorer and middle wealth quintiles are more likely to be severely thin and underweight but less likely to be overweight and obese though estimate for sever thinness is not significant.

Further, women from households that use improved toilet facilities are significantly less likely to be severely thin and underweight but more likely to be overweight and obese when compared with those with non-improved facilities. Women from households having access to protected water sources are significantly more likely to be severely thin and underweight but less likely to be overweight and obese. Further, women having electricity supplied to their households are more likely to be severely thin, overweight and obese than those without electricity in their households. Results for mass media reveal that women who listen to radio, watch television and read newspaper are less likely to be severely thin and underweight but more likely to be overweight and obese when compared with those without such access though only estimate for underweight is significant in the case of newspaper.

Estimates for spatial effects are presented in Figs. 1 and 2. The left panels of the figures present the posterior mean estimates while the right panels show the maps of credible intervals, used in assessing the significance of the posterior means. States shaded black in the credible interval maps are those that are significantly associated with negative estimates implying women from those states are severely thin or underweight in the case of under-nutrition, but less prone to overweight or obese for those models where attention was on the upper quantiles. The reverse is the case for states shaded in white colours while spatial effects estimates for states in grey colour are not significant. From Fig. 1a, b, severe thinness is significantly higher among women in the neighbouring northern states of Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Sokoto and Zamfara, and some states in the southern fringe namely: Lagos, Ogun, Osun, Oyo and Ebonyi states, but significantly lower among women residing in Abia, Anambra, Bayelsa, Delta, Ekiti, Enugu, FCT, Kebbi, Nassarawa, Niger, Ondo, Plateau, Rivers, and Taraba states. Estimates for underweight (Fig. 1c, d) are similar to those of severe thinness except for Kaduna that is now among those with significantly less likelihood of being underweight and for Lagos, Osun, Abia, Ondo and Ekiti states that are no longer significant.

Spatial effects of overweight and obesity show similar patterns as evident from Fig. 2. Women from Abia, Bauchi, Delta, Ebonyi, Ekiti, Enugu, Gombe, Kaduna, Kano, Katsina, Nassarawa, Ondo, Osun, Oyo, Sokoto, and Zamfara states are significantly less likely to be overweight or obese but those from Adamawa, Bayelsa, Borno, Enugu, FCT, Imo, Jigawa, Kogi, Lagos, Nassarawa, Niger, Plateau, Rivers, Taraba, and Yobe states are more likely to be overweight or obese.

Figure 3a–d presents the nonlinear effects of the woman's age for severe thinness, underweight, overweight and obesity respectively, which were obtained using smooth functions. The figures show the posterior means (black unbroken lines) and 80% and 95% credible intervals (dotted lines). There are obvious evidence of nonlinear relationship between the effect of woman's age and the various levels of malnutrition especially for severe thinness and an assumption of linear effect in the modelling process would have been very conservative. Except for bump around ages 21–24 years, the results provide evidence that Nigerian women are less likely to be severely thin as they grow older up to around age 30 years from where a sinusoidal pattern around the positive axis is evident for the rest of the reproductive ages.

As for underweight, for every unit increase in age of the women, there is a sharp decline in the likelihood of being underweight up to around age 30 years from where the decline is no longer as sharp. Findings on overweight and obesity as shown in Fig. 3c, d present indistinguishable patterns, showing that the tendency of being overweight or obese increases with every unit increase in the woman's age.

Discussions and conclusion

This study was aimed at understanding the spatial distributions of the various forms of malnutrition among women of reproductive age in Nigeria and

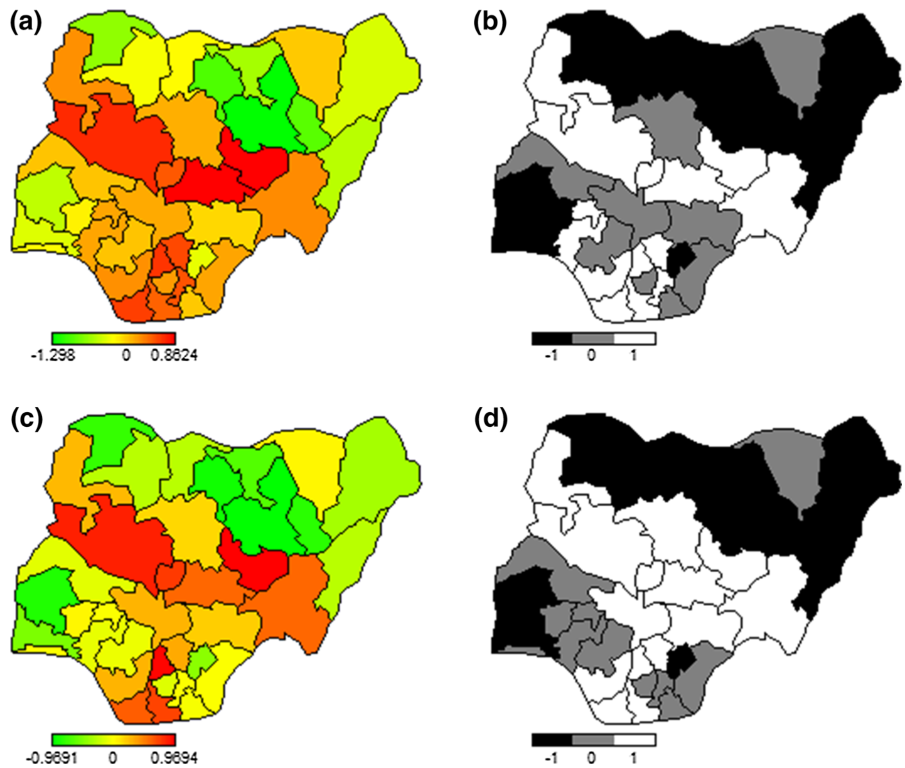

Fig. 1 Maps of Nigeria showing the spatial effects of **a** severe thinness and **b** its 95% CI; **c** underweight and **d** its 95% CI

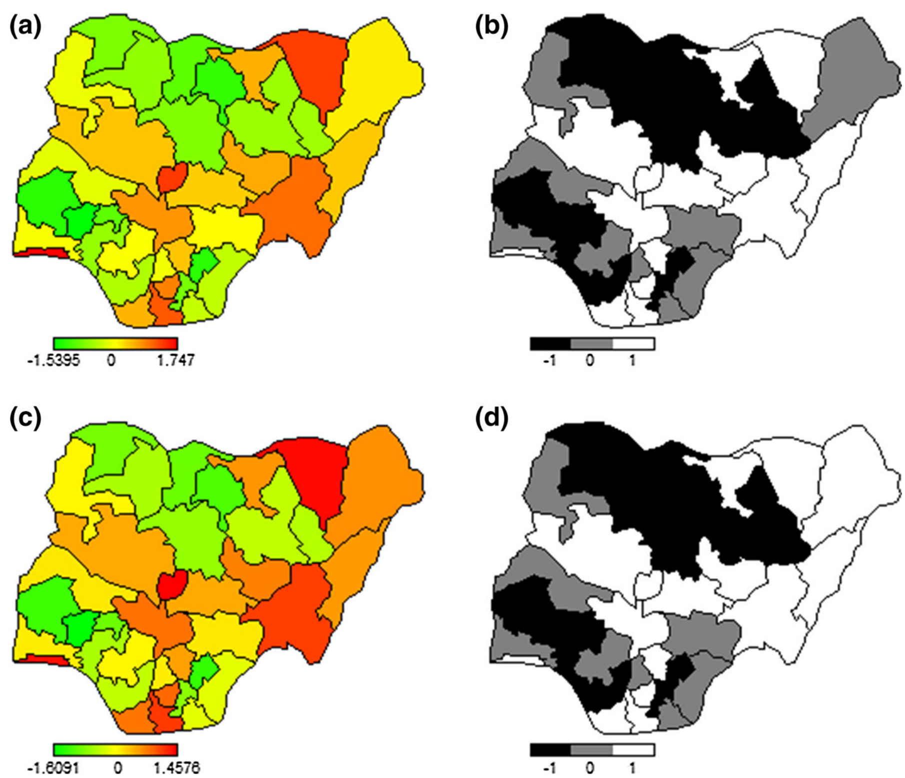

Fig. 2 Maps of Nigeria showing the spatial effects of **a** overweight and **b** its 95% CI; **c** obesity and **d** its 95% CI

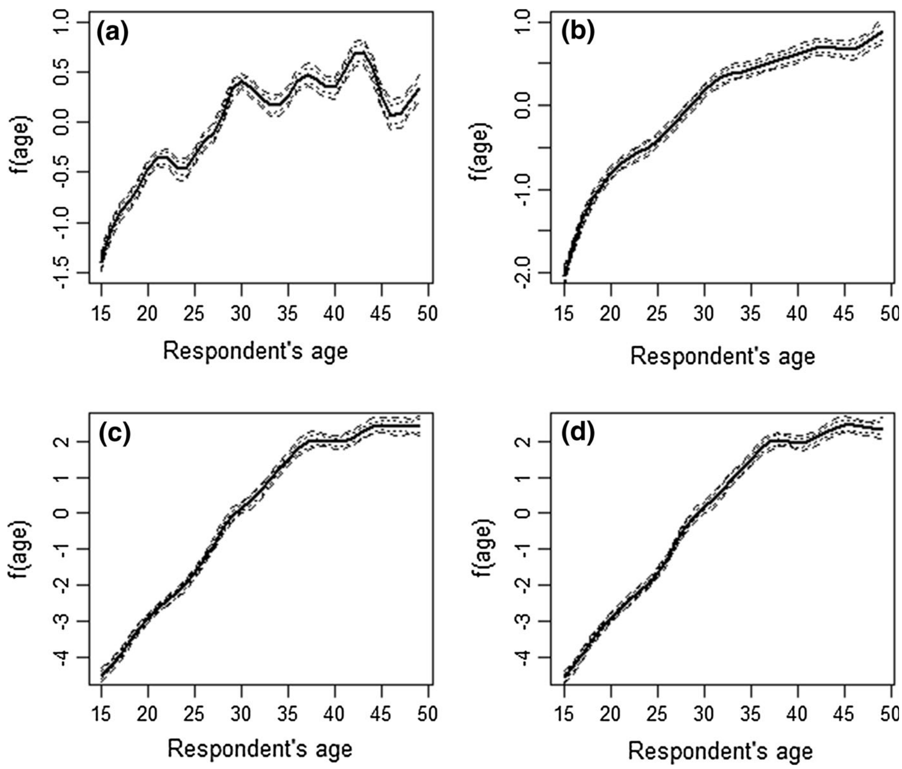

Fig. 3 Nonlinear effects of respondent's age for **a** severe thinness, **b** underweight, **c** overweight and **d** obesity

therefore, offers some insights into the disparity in the burden of malnutrition among the vulnerable group. The structured additive quantile regression approach employed made it possible to estimate the covariates at different levels of malnutrition based on a nutritional indicator of the women, the BMI and to simultaneously account for the different types of covariates available.

Findings on the spatial effects have shown, interestingly, that malnutrition among women in Nigeria both as under-nutrition and over-nutrition have spatial structures that show neighbouring states at the different geo-political zones of the country sharing similar patterns. This may be partly explained by shared cultural norms that affect women, general healthcare practices and belief as well as other residual spatial variations influenced by unexplained state-specific traits. In some Nigerian states, ignorance and socio taboos influence food intake of women and use of healthcare services even during pregnancy (Babalola and Fatusi 2009; Gayawan 2014).

On the socio-economic variables considered, results on place of residence reveals that women dwelling in urban areas are more prone to overweight and obesity. It is well known that there are job opportunities in urban areas than available in rural areas. Urbanization and westernization lead to decreased physical activity and also result in increased food supply, which includes access to high caloric fast foods and sugar sweetened beverages (fatty foods) (Duda et al. 2007; Kandala and Stranges 2014). In most rural settings, the main form of occupation is still subsistence agriculture and physical activity based vocations such as fishing, small scale mining and lumbering. An occupation related physical activity is a known protective factor against obesity. In the urban area, however, there is increasing shift from high physical activity based occupations such as construction and working in factories to sedentary and service based occupation (Monda et al. 2008). The study reveals that women who are working are more likely to be obese and overweight but less likely to be severely thin against those not working. This is contrary to findings from Bangladesh where it was found that non-working women were more underweight (Kamal and Islam 2010). In Nigeria, working women are empowered and have higher purchasing power and therefore, can be self dependent to determine the kind of food intake they desire while the non-working ones are by default, dependent on their spouses or his relatives which in turn limits the kind and variety of their food intake.

Furthermore, the results for women's education and household wealth index based on overweight and obesity suggest that women in the higher classes are more prone to becoming overweight and obese as their education and wealth index improve. No doubt, with better education and increased wealth index, a woman stands a better chance of securing good job that pays off and is capable of getting good diet and if not cautioned, the nutrients supplied to the body as a result of food intake might be in excess thus causing over-nutrition. Women of higher socio-economic status may have the resources and knowledge of the importance of physical activity and healthy diet but several socio-cultural barriers may prevent them from putting those into use (Griffiths and Bentley 2005). The majority of women in the poor wealth quantum might have suffered from the aftermath of long history of poor nutrition, frequent illness and poor access to health facilities and hence, their being prone to under-nutrition.

Access to mass media is a key source of information on health related issues and so, it is expected that women who access any of radio, television or newspaper should be better informed on healthy eating behaviour and lifestyles. This can partly explain the reason why respondents with access to mass media are found to be less likely to be thin or underweight. Similar findings have been reported in the case of young adults in Botswana (Letamo and Navaneetham 2014). In the case of toilet facilities and water sources, women of the households with unprotected facilities and unimproved sources are usually from the low socio-economic status, who would suffer from the diseases transmitted from these medium and hence would cause them to suffer nutritional problems but our results show that women with protected water suffer from under-nutrition issues. This is unlike the case of women from Addis Ababa, Ethiopia (Tebekaw et al. 2014).

Considering the effect of age on the BMI of women, the findings have shown that for every unit increase in age, the tendency of being severely thin and underweight reduces while the tendency towards overweight and obesity increases. Issues of underweight have been reported among young people in developing countries (Tebekaw et al. 2014; Letamo and Navaneetham 2014). Factors such as diet, level of physical activity and age have widely been reported to influence obesity (Samouda et al. 2018). Increased obesity with age is related to sedentary lifestyle and reduced metabolic rates.

In conclusion, Bayesian quantile regression offers a comprehensive strategy for complete analysis of extreme ends of the BMI and thus, allows for exploring the spatial patterns and socio-economic variables at different levels of malnutrition thereby providing a complete picture of the effects of explanatory variables rather than focusing only on the average. The study contributes in understanding the spread of under- and over-nutrition indicators among Nigerian women particularly based on their spatial location. Given that adequate nutrition is necessary for national development and well-being of the entire population, findings from the study can provide the basis for policy makers and donor agencies towards intervention strategies for improving national nutritional status. The maps generated have pinpointed the states with high and low likelihood of malnutrition among women and could be useful in targeting developmental efforts or for accessing the associations between welfare indicators and malnutrition among women. The maps could as well be put side-by-side with those of other indicators like poverty, epidemiology, or other socio-cultural factors thus, providing more presumptive explanations for the patterns of the spatial structure observed.

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Compliance with Ethical Standards

Conflict of interest The authors have no conflict of interest to declare.

Ethical Standard The data used in this study was obtained from The DHS Program (https://dhsprogram.com), who was the main partner that conducted the survey, after approval was given to our request.

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