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Analysis of Childhood Stunting in Malawi Using Bayesian Structured Additive Quantile Regression Model

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Abstract Analyses of childhood stunting have mainly used mean regression yet modeling using quantile regression is more appropriate than using mean regression in that the former provides flexibility to analyze the determinants of stunting corresponding to quantiles of interest whereas the latter allows only analyzing the determinants of mean stunting. Bayesian structured additive quantile regression models were fitted for childhood stunting. Both quantile and mean regression models were fitted and their estimates were compared. Inference was fully Bayesian using integrated nested Laplace approximation approach for quantile regression and Markov chain and Monte Carlo approach for mean regression. The 2010 Malawi demography and health surveys data was used. Using multistage stratified sampling, more than 19000 eligible reproductive women aged between 15 and 49 years were interviewed in a round of surveys and the anthropometric characteristics of their under 5 children were measured. We found that the dominant determinants of childhood stunting in Malawi include child sex, household head sex, type of residence, mother working status, vitamin A supplementation, availability of radio/TV, source of drinking water, vaccination coverage, infectious diseases, mother education, ethnicity, child age, and duration of breastfeeding. We also observed no any significant structured spatial effects on childhood stunting. In this study, we confirmed that quantile regression fits better than mean regression when modeling childhood stunting.

Keywords Conditional quantile regression, Asymmetric laplace distribution, Integrated nested Laplace approximations, Structured spatial effects, Childhood stunting

1. Introduction

Childhood undernutrition has serious adverse effects on a child, a family and the development of a country. It leads to more than 30% of all deaths in children below five years in all developing countries [1]. An undernourished child is more likely to be sick and die [2]. It can lead to stunted growth [3], impaired cognitive and behaviour development [5], poor school performance, lower working capacity and lower income [4]. It can slow down economic growth and increase level of poverty. Furthermore, it can prevent the society from meeting its full potential through loss in productivity, cognitive capacity and increased cost in health care [5]. The indicators of undernutrition are stunting, wasting and underweight. In Malawi, childhood stunting still remains the highest undernutrition burden. The prevalence rate of childhood stunting has insignificantly dropped from 53% in 2004 to 47% in 2010 [6]. Only childhood stunting was analysed in this study since stunting still remains the most significant undernutrition burdenin developing countries including Malawi.

The reduction of childhood malnutrition (MDG1) is among the United Nations Millennium Development Goals, aiming at halving the proportion of children suffering from hunger by 2015. In addition, the reduction of childhood mortality (MDG4) is also among the United Nations Millennium Development Goals, aiming at reducing the under-five mortality rate by two-thirds between 1990 and 2015. In order to attain both MDG1 and MDG4, a first 1000 child-days project was launched in Malawi about two years ago. However, little effort has been made to statistically understand the social-demographic determinants of childhood undernutrition.

Studies have previously been made to appropriately analyse the childhood stunting in developing countries including Malawi. Unfortunately, most of the analyses have been emphasized on modeling mean regression instead of quantile regression. For instance, the regression studies of risk factors for acute or chronic undernutrition [7] should have used quantile regression instead of mean regression. In fact, even the regression studies for morbidity or mortality [8] should have used quantile regression instead of mean regression. Modeling stunting using quantile regression is more appropriate than using mean regression in that the former provides flexibility to analyze the determinants of

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stunting corresponding to quantiles of interest either in the lower tail (say 5% or 10%) or upper tail (say 90% or 95%) or even median (50%) of the stunting distribution whereas the latter allows only analyzing the determinants of mean stunting.

The main purpose of this study was to fit statistical models that would better explain variability in childhood stunting in Malawi. In order to achieve this, both the mean and quantile regression models for childhood stunting were fitted using the 2010 Malawi DHS data set, the socio-demographic determinants of childhood stunting were identified, the structured spatial effects on childhood stunting were estimated, and the estimates obtained from quantile regression models were compared with those obtained from mean regression models.

The rest of this paper is structured as follows. Section 2 describes the methods used in this study. The results of this study are given in section 3. Finally, the discussion and conclusion are presented in sections 4 and 5 respectively.

2. Methods

This section summarises the conceptual framework of the Bayesian structured additive quantile regression models, the data sources, and data analysis procedures used in this study.

2.1. The Model

2.1.1. Quantile Regression

The quantile regression itself is an old regression method but it is the Bayesian framework that has made the Bayesian structured additive quantile regression arelatively new statistical method for analyzing data like malnutrition. Quantile regression aims at describing conditional quantiles in terms of covariates instead of the mean. Quantile regression is more appropriate for modeling severe malnutrition than mean regression [9]. In general, quantile regression is all about describing conditional quantiles of the response variable in terms of covariates instead of the mean. The general additive conditional quantile model is given by

$$Q_{Y_i|x_i,z_i}(\tau|x_i,\ z_i) = \eta_{\tau_i} = {x_i}^T\beta_\tau + \sum_{j=1}^{J} g_{\tau_j}(\ z_{ij}) \quad (1)$$

where $Q_{Y_i|x_i,z_i}$ is the conditional quantile response, η_{τ_i} is the semi-parametric predictor, $\tau\epsilon(0,1)$ is the τ^{th} quantile response e.g. $\tau = 0.5$ for the medianresponse regression, x is the vector for categorical covariates (assumed to have fixed effects), z is the vector for metric/spatial covariates, β is the vectorfor coefficients for categorical covariates including intercept, $g$is the vector forsmoothing functions for metric/spatial covariates [10, 11]. It is worthy to note that quantile regression duplicates the roles of quartile, quintile, decile, and percentile regressions. This is achieved by selecting appropriate values of τ inthe conditional quantile regression model where $\tau\epsilon(0,1)$.The two unknowns, β and $g$are estimated via the minimization rule given by

$$\min_{(\beta,g)} \sum \rho_\tau(\eta_{\tau_i}) + \lambda_0\|\beta\|_1 + \sum_{j=1}^{J}\lambda_j \vee \left(\nabla g_{\tau_j}\right) \quad (2)$$

where ρ_τ is the check function (appropriate loss function) evaluated at a given τ, λ_0 is the zeroth (initial) tuning parameter for controlling the smoothnessof the estimated function, λ_j is the j^{th} tuning parameter for controlling the smoothness of the estimated function, $\|\beta\|_1 = \sum_{k=1}^{K}|\beta_k|$ and $\vee\left(\nabla g_{\tau_j}\right)$ denotesthe total variation of the derivative on the gradient of the function g [10].

Bayesian inference requires likelihood. We need an assumption on data distribution for Bayesian quantile inference because the classical quantile regression has no such restriction. A possible parametric link between the minimization problem and the maximum likelihood theory is the Asymmetric Laplace Density (ALD). This skewed distribution appeared in [12, 13] among others.

2.1.2. Prior Distributions

In Bayesian framework, all unknown functions $g's$ for both metric and spatial covariates, all parameters $\beta's$ for categorical covariates, and all variance parameters$\sigma^{2}'s$ are considered as random variables and have to be supplemented by appropriate prior distributions.

In this research, the following prior distributions were supplemented. To facilitate description of our method, we will suppress the subscription τ of regression effects in the following. Priors for unknown functions $f_k(\cdot), k = 1,\cdots,n_f$, belong to the class of Gaussian Markov random fields (GMRF), whose specific forms depend on covariate types, and on prior beliefs about the smoothness of f_k. Although only GMRF is used in this work, there exist some other options like Bayesian P-splines [15].

Let $f = (f(u_1), f(u_1),\cdots, f(u_n))^T$, a random vector of the response at $u_i, i = 1,2,\cdots,n$. We say $f$is a GMRF with mean μ and precision (the inverse covariance) matrix δQ if and only if it has density of form

$$\pi(f|\delta) \propto \delta^{\frac{n-m}{2}}\exp\left(-\frac{\delta}{2}(f-\mu)^T(f-\mu)\right) \quad (3)$$

where Q is a semi-definite matrix of constants with rank$n-m$ $(m \geq 0)$. Theproperties of a particular GMRF are all reflected through matrix Q. For instance, the Markov properties of GMRFs totally depend on the various sparse structures that the matrix Q may have. In this paper we use two kinds of GMRFs: continuous random walk (CRW) models [16] for metric covariates and intrinsic autoregressive models [17] for spatial covariates. Those two GMRFs share equation 5 but with different structures of Q.

For metric covariates, let $u_1 < u_2 < \cdots < u_n$ be the set of continuous locations and $z_i = f(u_i)$ be the function evaluations at u_i, for $i = 1,2,\cdots,n$. Then construction of CRW model is based on a discretely observed continuous time process $z(u)$ that is a realization of an $m-1$ fold integrated Wiener processgiven by

$$z(u) = \int_0^u \frac{(u-h)^{m-1}}{m-1}\mathrm{d}W(h) \quad (4)$$

where $W(h)$ is a standard Wiener process.

For spatial covariates, letting n_i denote the number of neighbors of site u_i, we assume the following spatial smoothness prior for the function evaluations

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

where $j \sim i$ denotes that site u_i and u_j are neighbors. Thus the conditionalmean of $f(u_i)$is an un-weighted average of evaluations of neighboring sites.

For the fixed effect parameters $\beta_j's$, we shall assume independent diffusepriors $\pi(\beta_j) \propto$ constant or a weakly informative Gaussian $\underline{\beta} \sim N(0, \phi^{-1}I)$with small precision ϕ. If $\underline{\beta}$ is a high-dimensional vector, one may consider using Bayesian regularization priors developed in [19], where conditionally Gaussianpriors are assigned with suitable hyper prior assumptions on the variances inducing the desired shrinkage and sparseness on coefficient estimates .

2.1.3. Posterior Inference

When a fully Bayesian framework is adopted, the Asymmetric Laplace Distribution(ALD) is assumed as the likelihood model and three common methods for estimating posterior marginal distribution are available. The standard method is MCMC (Markov chain Monte Carlo). The other two methods are INLA (integrated nested Laplace approximations) and Boosting.

In this study, only two methods (MCMC and INLA) were used. It is worthy to note that the MCMC is so far the standard method for estimating posterior marginal distribution in fully Bayesian framework while INLA [24] is relatively new approach which has so far been guaranteed to outperform MCMC both inaccuracy and computational speed especially for large non-Gaussian response datasets [20]. In Bayesian framework, all unknown functions $g's$ for both metric and spatial.

2.2. Data

For applications of the methodology, we considered data from the 2010 Malawi Demographic and Health Surveys (MDHS). The multistage clustered sampling technique was used with other districts oversampled like Blantyre, Lilongwe, and Mulanje. The 2010 MDHS interviewed a representative sample of more than 19000 eligible reproductive women aged between 15 and 49 years in a round of surveys. The anthropometric assessment of themselves and their children that were born within the previous five years was administered. The data set contains information on family planning, maternal and child health, child survival, HIV/AIDS, educational attainment, and household composition and characteristics [6].

The primary outcome in this study was the childhood (under 5 years) stunting in Malawi. It was assessed by using the adjusted child height-for-age z-score (haz) for childhood stunting as a continuous response variable. Considering the literature and the 2010 MDHS data, the following bio-demographic and socioeconomic covariates of childhood stunting were assessed in this study. The categorical covariates included child's sex (csex), household head sex (hhsex), type of residence (residence), ethnicity (ethnicity), mother's education (meduc), current mother working status (mwork), vitamin A supplementation (vitamin),vaccination coverage (vaccin), infectious diseases (infectd), availability/use of radio/TV (radiotv), and source of drinking water (drinkwat). The metric covariates included child's age in months (cage), mother's body mass index (mbmi), and duration of breastfeeding in months (dubreast). The only spatial covariate was district of Malawi (district).

2.3. Analysis

The statistical software packages used in this study were SPSS version 16.0, Rversion 2.15.1, and BayesX version 2.0.1. SPSS was used for data management, R for quantile regression, and BayesX for mean regression. The statistical inference was fully Bayesian using the "INLA" approach for quantile regression in R [20] and the "MCMC" approach for mean regression in BayesX [25].

Firstly, we started with exploratory data analysis where basic descriptive analyses such as cross tabulations for all categorical covariates against childhood stunting indicator variable. The categorized adjusted child height-for-age with two categories, stunted (haz<-2) and not stunted (haz≥-2), was used as a childhood stunting indicator variable in this phase. The statistics (counts, proportions, means, and chi-squarep-values) of cross tabulations were summarized in Table 1. Since there are many covariates, only those with p-values < 0.20 (20%) were included in the subsequent quantile models. The choice of 20% rather than 5% is deliberate in order to tolerate any possible confounding.

Secondly, the Bayesian structured additive quantile regression models were fitted for childhood stunting using R 2.15.1 statistical software [20]. For brevity, only three quantiles (τ = 0.2, 0.4, and 0.5) were assessed. The choice of the quantiles to assess in this study depended on the normal, moderate, and severe cut-points of childhood stunting based on WHO standards such that τ = 0.2 wasequivalent to severe (haz<-3) and τ = 0.4 was equivalent to moderate (-3≤haz<-2).

Thirdly, the Bayesian structured additive mean regression models were fitted for childhood stunting using BayesX 2.0.1 statistical software [25].

Lastly, the fixed effects, nonlinear effects, and structured spatial effects on childhood stunting obtained from quantile regression models were compared with those obtained from mean regression models.

3. Results

This section presents the main findings of this study. The summary of descriptive statistics is presented first in form of tables. A brief discussion of these exploratory results is provided immediately within the text. Thereafter, the findings from the fitted Bayesian structured additive models are presented in form of tables for fixed categorical

covariates, graphs for nonlinear metric covariates, and maps for spatial covariates.

3.1. Significant Categorical Covariates

Table 1 shows the summary of cross tabulations of childhood stunting by categorical covariates. Considering Pearson chi-square p-values < 0.20 (i.e. p-values <20%) together with relevant literature on malnutrition, the following categorical covariates were included in subsequent Bayesian analyses; child's sex, household head's sex, type of residence, ethnicity, mother's education, current mother's working status, vitamin A supplementation, vaccination coverage, infectious diseases, availability and use of radio/TV, and source of drinking water.

Only eight categorical covariates were observed to be highly significant for childhood stunting in this study. These were child's sex, type of residence, mother's education, vitamin A supplementation, vaccination coverage, availability of radio / TV, source of drinking water, and ethnicity. Highly stunted were the children with male sex, rural residence, low mother's education, satisfactory vitamin A supplementation, full vaccination coverage, no radio/TV, non-improved source of drinking water, and ethnic groups Yao, Tonga, Chewa, and Lomwe. All these results were consistent with literature similar previous studies excepton vitamin A supplementation and vaccination coverage.

Table 1. Childhood Stunting by Categorical Covariates

Variable	Category	% Stunted	p-value
Child's Sex	Female Male	997 (38.6%) 1141 (44.6%)	< 0.001**
Household Head's Sex	Female Male	181 (43.9%) 1957 (41.3%)	0.306
Type of Residence	Rural Urban	1966 (42.3%) 172 (34.2%)	< 0.001**
Antenatal Care	Poor Satisfactory	1347 (38.9%) 75 (46.3%)	0.059
Mother's Education	No Education Incomplete Primary Complete Primary Incomplete Secondary Complete Secondary Higher	415 (48.0%) 1303 (41.9%) 197 (40.7%) 170 (34.9%) 50 (27.8%) 3 (13.0%)	< 0.001**
Mother's Working Status	No Yes	906 (41.0%) 1222 (41.8%)	0.59
Early Breastfeeding	Not Immediately Immediately	54 (40.6%) 1371 (39.1%)	0.723
Vitamin A	No Yes	316 (34.3%) 1818 (43.2%)	< 0.001**
Vaccination Coverage	Incomplete Full Vaccination	528 (32.3%) 1165 (47.2%)	< 0.001**
Infectious Diseases	No Diarrhea/Fever /Cough	1073 (40.7%) 727 (42.4%)	0.266
Nutritional Care	Poor Satisfactory	1000 (42.8%) 33 (38.8%)	0.470
Health Seeking	Poor Satisfactory	53 (41.4%) 666 (43.3%)	0.673
Radio/TV	No Yes	1129 (43.3%) 991 (39.5%)	0.006**
Drinking Water	Not Improved Improved	659 (46.0%) 1479 (39.8%)	< 0.001**
Toilet Facility	Not Improved Improved	1869 (41.8%) 269 (39.7%)	0.304
Ethnicity	Chewa Tumbuka Lomwe Tonga Yao Sena Nkhonde Ngoni Others	725 (43.8%) 193 (36.9%) 306 (41.9%) 59 (44.0%) 245 (46.3%) 116 (36.6%) 45 (39.1%) 251 (38.3%) 196 (40.7%)	0.032*

The p-value marked with * indicates that the variable was significant at 5% level.
The p-value marked with ** indicates that the variable was significant at 1% level.
All p-values correspond to Pearson Chi-square test of contingency.

Table 2. Fixed Effects on Childhood Stunting

Variable	Category	Severe stunting		Moderate stunting		Median stunting	
		Mean	95% C.I.	Mean	95% C.I.	Mean	95% C.I.
Child's Sex	(Female)	–	–	–	–	–	–
	Male	-0.21*	-0.32 , -0.03	-0.25*	-0.33 , -0.17	-0.25*	-0.34 , -0.17
Head's sex	(Female)	–	–	–	–	–	–
	Male	-0.02	-0.27 , 0.15	0.04	-0.10 , 0.19	-0.05*	-0.09 , -0.19
Type of	((Rural)	–	–	–	–	–	–
Residence	Urban	-0.08	-0.26 , 0.14	0.001	-0.19 , 0.16	0.02	-0.13 , 0.17
Working	(No)	–	–	–	–	–	–
Mother	Yes	-0.02	-0.18 , 0.12	-0.03*	-0.12 , -0.07	-0.02	-0.10 , 0.06
Vitamin A	(No)	–	–	–	–	–	–
	Yes	0.04	-0.11 , 0.17	0.10*	0.02 , 0.23	0.09	-0.02 , 0.20
Radio/TV	(No)	–	–	–	–	–	–
	Yes	0.10*	0.02 , 0.36	0.06*	0.03 , 0.16	0.08	-0.01 , 0.16
Drinking	(Poor)	–	–	–	–	–	–
Water	Improved	0.16*	0.03 , 0.36	0.11*	0.01 , 0.22	0.12*	0.03 , 0.21
Vaccine	(Poor)	–	–	–	–	–	–
Coverage	Full	0.04	-0.12 , 0.4	0.004	-0.11 , 0.17	-0.03	-0.13 , 0.06
Infectious	(No)	–	–	–	–	–	–
Diseases	Yes	0.01	-0.21 , 0.12	-0.003*	-0.10 , -0.002	-0.02	-0.10 , 0.06
	(None)	–	–	–	–	–	–
Mother's	Primary	0.10	-0.03 , 0.22	0.08	-0.04 , 0.21	0.06	-0.002 , 0.17
Education	Secondary	0.26	-0.27 , 0.45	0.23*	0.07 , 0.11	0.22*	0.06 , 0.37
	Higher	0.57	-0.23 , 1.45	0.89*	0.25 , 1.48	0.87*	0.30 , 1.44
	(Others)	–	–	–	–	–	–
	Chewa	0.14	-0.06 , 0.35	0.02	-0.18, 0.22	0.01	-0.16 , 0.19
	Tumbuka	-0.08	-0.63 , 0.17	-0.06	-0.27 , 0.15	-0.06	-0.26 , 0.13
	Lomwe	0.07	-0.29 , 0.31	0.01	-0.19 , 0.21	-0.01	-0.19 , 0.17
Ethnicity	Tonga	0.14	-0.20 , 0.48	-0.05	-0.36 , 0.27	-0.13	-0.42 , 0.17
	Yao	-0.16*	-0.38 , -0.08	-0.18*	-0.38 , -0.03	-0.14*	-0.33 , -0.05
	Sena	0.13	-0.01 , 0.51	0.17	-0.09 , 0.43	0.25	-0.09 , 0.36
	Nkhonde	0.22	-0.17 , 0.61	0.09	-0.37 , 0.43	0.06	-0.27 , 0.37
	Ngoni	-0.03	-0.63 , 0.24	-0.09	-0.11 , 0.30	0.11	-0.08 , 0.31

The categories in parentheses were chosen as reference categories.
The posterior mean marked with * indicates that the variable category was significant at 5% level relative to reference category.

The rest of the categorical covariates were observed not significant at 5% level. For more details about non-significant categorical covariates, refer to the Table 1. It is worth to note that some of these non-significant categorical covariates were still included in the subsequent Bayesian structured additive regression models based on the literature and significance at 20% level.

3.2. Bayesian Structured Additive Quantile Models

Only three conditional quantile regression models were fitted in this study. The first model was fitted to assess severe childhood stunting. The 20% quantile was found to be equivalent to haz = -3 which is the cut-point for severe childhood stunting according to WHO standards. The second model was fitted to assess moderate childhood stunting. The 40% quantile was found to be equivalent to haz = -2 which is the cut-point for moderate childhood stunting according to WHO standards. The third model was fitted to assess median adjusted height for-age. The 50% quantile was found to be equivalent to haz = -1.88 which is within the range of normal adjusted childhood height-for-age according to WHO standards. For each model, fixed effects, nonlinear effects, and structured spatial effects were assessed. In general, the results were as follows.

3.2.1. Fixed Effects

The summary of fixed effects on childhood stunting is shown in Table 2. Since stunting and adjusted height-for-age are negatively associated variables, care was taken in interpreting the effects on childhood stunting. For example, "male child" showed significant negative effect on height-for-age at all observed quantile levels implying that male children had significant positive effect on severe, moderate and median childhood stunting. In other words, stunting is more attributable to male children than to female children in Malawi i.e. male children are at higher risk of stunting than female children in Malawi.

Considering 95% credible intervals, we found that the effects of "male child" and "Yao ethnic group" had significant positive relations with severe childhood stunting where as "availability of radio/TV" and "improved source of drinking water" had significant negative relations with severe childhood stunting. The effects of "male child", "working mother", "infectious diseases" and "Yao ethnic

group" had significant positive relations with moderate childhood stunting where as" availability of radio/TV", "improved source of drinking water", "vaccine coverage" and "mother's education" had significant negative relations with moderate childhood stunting. The effects of "male child", "male household head", and "Yao ethnic group" had significant positive relations with median childhood stunting where as "improved source of drinking water" and "mother's education" had significant negative relations with median childhood stunting.

3.2.2. Nonlinear Effects

Figure 1 shows the summary of observed nonlinear effects. The first row corresponds to severe childhood stunting. The second and third rows correspond to moderate and median childhood stunting respectively.

The summary of nonlinear effects of child's age in months on childhood stunting was displayed along the left column in the Figure 1. We found that the general relationship of the effects of child age with adjusted height-for-age followed aU-shape. We observed that adjusted height-for-age remained constantly high (constantly low childhood stunting) for the first 6 months after which it steadily deteriorated (increasing childhood stunting) until 18 months. The adjusted height-for-age remained constantly low (constantly higher childhood stunting) from 18 months up to 30 months. Thereafter, adjusted height-for-age stabilized back to normal (reducing childhood stunting).

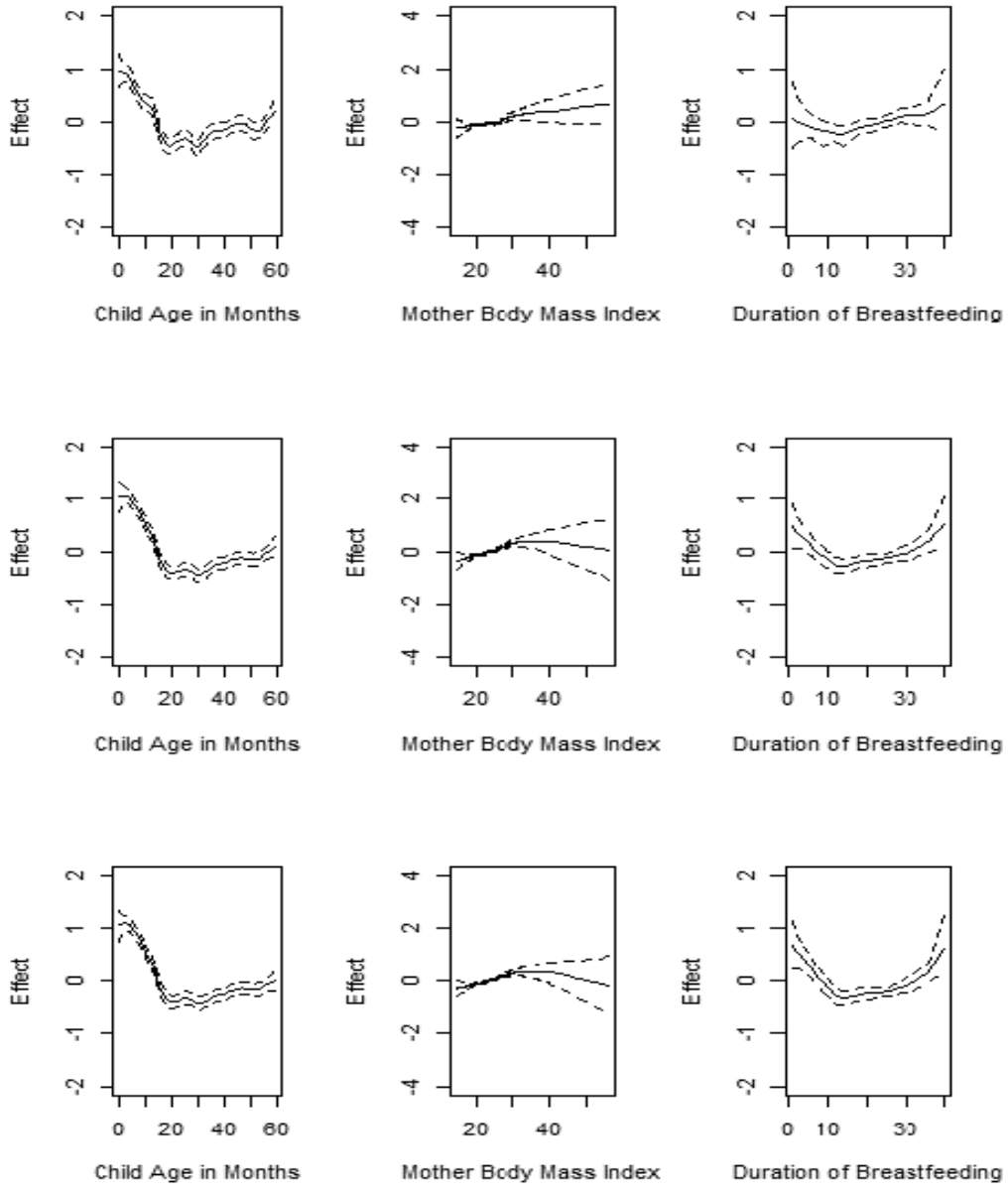

Figure 1. Nonlinear effects on childhood stunting

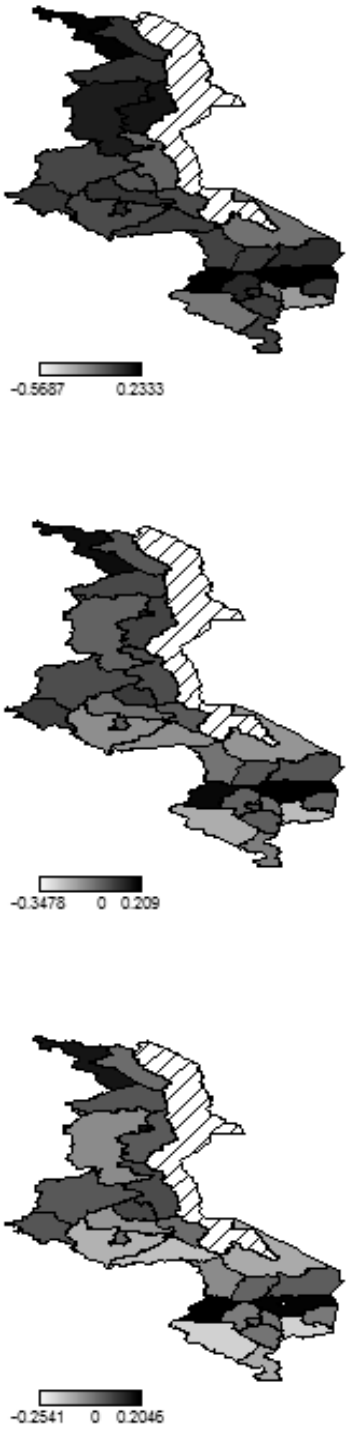

Figure 2. Posterior means of structured spatial effects on childhood stunting

The summary of nonlinear effects of mother body mass index on childhood stunting was displayed along the middle column in the Figure 1. We found that the general relationship of the effects of mother's body mass index with adjusted height-for-age followed an inverse U-shape. We observed that very low mother's body mass index (lower than 20 kg/m^2) as well as very high mother's body mass index (higher than 35 kg/m^2) reduced adjusted height-for-age (increased childhood stunting). An exception was observed only for severe childhood stunting model in which mother's body mass index continued increasing the adjusted height-for-age (continued reducing severe childhood stunting) beyond35 kg/m^2. We observed that, for mother's body mass indices between20 kg/m^2 and 35 kg/m^2, increase in mother's body mass index slightly increased adjusted height-for-age (reduced childhood stunting).

The summary of nonlinear effects of duration of breastfeeding in months on childhood stunting was displayed along the right column in the Figure 1. We found that the general relationship of the effects of duration of breastfeeding with adjusted height-for-age followed a U-shape. We observed that very short duration of breastfeeding (less than 6 months) and very long duration of breastfeeding (more than 18 months) were associated with higher adjusted height-for-age (reduced childhood stunting). We observed that durations of breastfeeding between 6 months and 18 months were associated with constantly lower adjusted height-for-age (increased childhood stunting). It was noted that duration of breastfeeding was complex to interpret. On one hand, it was quiet in order to observe that long duration of breastfeeding increased adjusted height-for-age (reduced childhood stunting). On the other hand, it was a surprise to observe that very short duration of breastfeeding also increased adjusted height-for-age (reduced childhood stunting). Likely, there should be an expert explanation for this surprise.

3.2.3. Structured Spatial Effects

Figure 2 shows the posterior means of structured spatial effects on childhood stunting. The top map corresponds to severe childhood stunting model. The middle and bottom maps correspond to moderate and median childhood stunting models respectively. In general, we observed that only Chitipa, Machinga, Zomba, and Mwanza districts depicted high positive structured spatial effects on adjusted height-for-age (high negative structured spatial effects on childhood stunting). However, these effects were not significant at 95% nominal level.

3.3. Bayesian Structured Additive Mean Models

The mean regression model was fitted for childhood mean adjusted height-for-age. The fixed effects, nonlinear effects, and structured spatial effects were assessed. It is important to note that with mean regression, we cannot talk of childhood stunting but simply childhood average adjusted height-for-age. This model was fitted to assess childhood mean adjusted height-for-age. As already pointed out earlier, mean regression has a major drawback of explaining the relations of covariates with average nutritional status. Since the mean response is heavily influenced by outliers, it is difficult to validate whether the observed relations are with respect to undernutrition, or overnutrition, or normal nutrition status. With conditional quantile regression, we were able to validate whether the observed relations were not

only with respect to undernutrition, or overnutrition, or normal nutrition but also whether with respect to moderate or severe nutritional status. This is the main reason why quantile regression should be preferred to mean regression in modeling nutritional status. The results of the fitted mean regression were as follows.

3.3.1. Fixed Effects

The summary of fixed effects on childhood mean adjusted height-for-age is shown in Table 3. The posterior means and 95% credible intervals of all categorical covariates were summarized in this table. Considering 95% credible intervals, we found that only the effect of male child had significant negative relation with childhood mean adjusted height-for-age. On the other hand, we found that the effects of improved source of drinking water, and secondary or higher mother education had significant positive relations with childhood mean adjusted height-for-age.

3.3.2. Nonlinear Effects

Figure 3 (left) shows display of nonlinear effects of child's age in months on average childhood adjusted height-for-age. We found that the general relationship of the effects of child's age with average adjusted height-for-age followed aUshape. We also observed that average adjusted height-for-age steadily deteriorated until 20 months. The average adjusted height-for-age remained constantly low from 20 months up to 40 months. Thereafter, average adjusted height-for-age started stabilizing gradually. Figure 3 (middle) shows display of nonlinear effects of mother's body mass index on average childhood adjusted height-for-age. We found that the general relationship of the effects of mother's body mass index with adjusted height-for age followed an inverse U-shape. In general, we observed that mother's body mass indices beyond 30 kg/m^2 were associated with higher average childhood adjusted height-for-age. Figure 3 (right) shows display of nonlinear effects of duration of breastfeeding in months on average adjusted childhood height-for-age. We found that the general relationship of the effects of duration of breastfeeding with adjusted height-for-age followed an inverse U-shape. We observed that very short durations of breastfeeding (less than 10 months) reduced average adjusted height for-age. We observed that, for durations of breastfeeding beyond 10 months, increase in duration generally increased the average adjusted height-for-age.

Table 3. Fixed Effects on Mean Childhood Stunting

Variable	Category	Mean Stunting	
		Mean	95% C.I.
Child's Sex	(Female)	–	–
	Male	-0.25*	-0.33 , -0.16
Head's sex	(Female)	–	–
	Male	0.03	-0.13 , 0.19
Type of Residence	((Rural)	–	–
	Urban	-0.004	-0.17 , 0.17
Working Mother	(No)	–	–
	Yes	-0.02	-0.11 , 0.07
Vitamin A	(No)	–	–
	Yes	0.07	-0.06 , 0.19
Radio/TV	(No)	–	–
	Yes	0.10	-0.003 , 0.19
Drinking Water	(Poor)	–	–
	Improved	0.12*	0.02 , 0.22
Vaccine Coverage	(Poor)	–	–
	Full	-0.07	-0.18 , 0.05
Infectious Diseases	(No)	–	–
	Yes	-0.05	-0.13 , 0.04
Mother's Education	(None)	–	–
	Primary	0.02	-0.10 , 0.14
	Secondary	0.19*	0.001 , 0.38
	Higher	0.72*	0.01 , 1.40
Ethnicity	(Others)	–	–
	Chewa	0.03	-0.14 , 0.24
	Tumbuka	-0.09	-0.31 , 0.13
	Lomwe	0.02	-0.17 , 0.22
	Tonga	-0.11	-0.45 , 0.21
	Yao	-0.10	-0.31 , 0.11
	Sena	0.14	-0.12 , 0.40
	Nkhonde	-0.07	-0.45 , 0.31
	Ngoni	0.10	-0.11 , 0.32

The categories in parentheses were chosen as reference categories.
The posterior mean marked with * indicates that the variable category was significant at 5% level relative to reference category

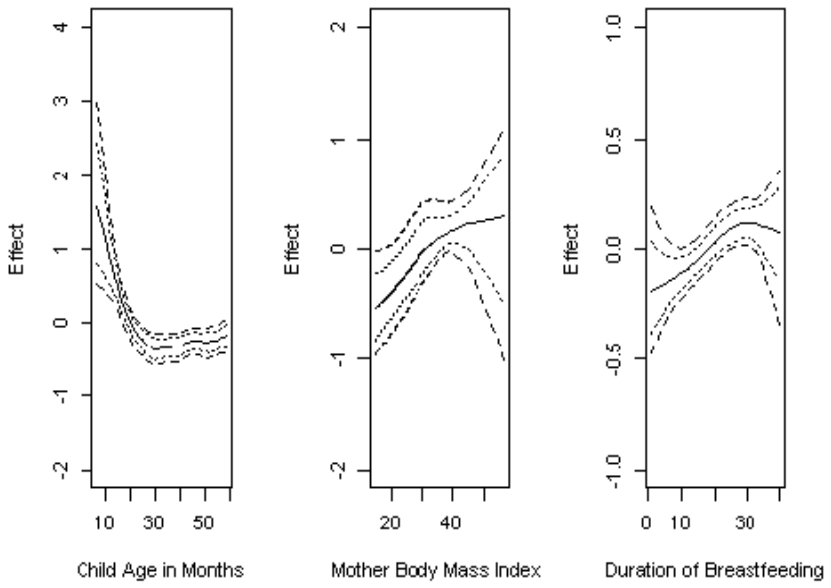

Figure 3. Nonlinear effects on childhood mean adjusted height-for-age

3.3.3. Structured Spatial Effects

Figure 4 shows the posterior means of structured spatial effects on average adjusted childhood height-for-age. We observed that only Karonga and Phalombe districts depicted high positive structured spatial effects on average adjusted childhood height-for-age but not significant at 95% nominal level. On the other hand, we observed that only Dowa and Chiradzulu district depicted high negative structured spatial effects on average adjusted childhood height-for-age but not significant at 95% nominal level.

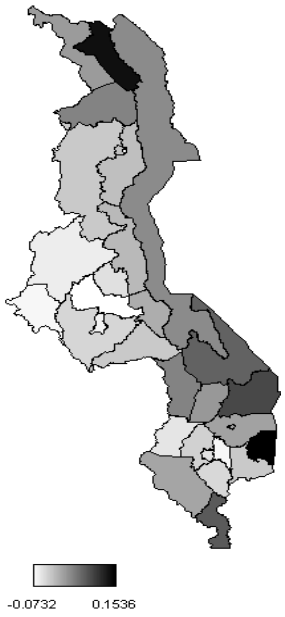

Figure 4. Nonlinear effects on childhood mean adjusted height-for-age

3.4. Comparing Bayesian Quantile and Mean Models

In order to compare the fit of quantile and mean regression models, we compared the deviance information criterion (DIC) computed for each model that was fitted. Table 4 displays the summary of DIC for all the models that were fitted in this study. In Table 4, D stands for "Deviance evaluated at the posterior mean", p stands for "Effective number of parameters", and DIC stands for "Deviance Information Criterion". The mathematical relationship used to compute DIC is given by DIC = D + 2p where D is minus twice the log likelihood (-2LL). The DIC is an appropriate tool for assessing the adequacy of the fitted models. The rule of thumb is that the smaller DIC values correspond to better model fit i.e. the model with smaller DIC is better than a model with larger DIC.

Comparing the DIC in the Table 4, we observed much smaller DIC values for all quantile regression models than for mean regression model for stunting (haz). This observation implied that all quantile regression models fitted better than mean regression model.

Table 4. DIC for Bayesian Regression Models

	20% haz	40% haz	50% haz	Mean haz
D	6850.4	6554.72	6555.1	8780.7
p	51.69	28.89	28.80	44.72
DIC	6953.8	6612.5	6612.7	8870.1

4. Discussion

In this study, both the Bayesian structured additive quantile and mean regression models were fitted for childhood stunting. The primary aim of this study was to demonstrate that quantile regression is more appropriate than mean regression in modeling nutritional status. The childhood stunting was assessed because it had shown to be the most prevalent among children under-five (about47%) and that it would provide more information about undernutrition status among under-five children in Malawi.

The inference used in this study was fully Bayesian. For

quantile regression models, the posterior marginals were estimated using INLA approach in R. For mean regression models, the posterior marginals were estimated using MCMC approach in BayesX. The INLA approach was chosen for quantile regression models because it outperforms the MCMC approach in terms of convergence and computational speed for quantile models. For the mean regression models, MCMC approach has no problems.

Using quantile regression models, significant predictors of severe childhood stunting in Malawi include child's sex, availability of radio/TV, source of drinking water, child's age, mother's body mass index, and duration of breastfeeding. The significant predictors of moderate childhood stunting in Malawi include child's sex, mother's working status, supplementation of vitamin A, availability of radio/TV, source of drinking water, infectious diseases, mother's education level, child's age, mother's body mass index, and duration of breastfeeding. The significant predictors of median childhood stunting in Malawi include child's sex, household head's sex, source of drinking water, mother's education level, child's age, mother's body mass index, and duration of breast feeding. Both positive and negative structured spatial effects were observed for all quantile regression models. However, none of them was significant at 95% nominal level.

Using mean regression model, significant predictors of mean childhood stunting in Malawi include only child's sex, source of drinking water, mother's education level, child's age, mother's body mass index, and duration of breastfeeding. Both positive and negative structured spatial effects were also observed for mean regression model. However, none of them was significant at 95% nominal level.

It is worthy to note that most of the results found in this study agreed with the major findings of similar studies. For instance, a study was carried out in order to analyse socio-demographic and spatial determinants of undernutrition in two African countries (Tanzania and Zambia) [7]. Among major findings, the significant risk factors of childhood undernutrition included low mother education, working mother, and male child. It was also found out that increase in child's age significantly increased childhood stunting. Furthermore, it was found that childhood stunting and mother body mass index (mbmi) followed a general inverse U-shape. Evidently, similar results were also observed in this study. Another study was carried out to analyse determinants of undernutrition among children under-2 in Bangladesh in partial fulfillment of the degree of master of public health [26]. Among major findings, the significant risk factors of undernutrition amongunder-2 children in Bangladesh included male child, currently working mother, infectious diseases, lower wealth index quintiles (poverty), food insecurity, poor antenatal care, low mother education, and others. It was also found that increase in child's age significantly increased undernutrition and particularly stunting. Evidently, similar results were observed in this study.

What we see as the most significant strength of this study is that quantile regression was compared to mean regression using the same 2010 MDHS data. The findings obtained from quantile regression were more efficient than those obtained from mean regression. Furthermore, quantile regression was more appropriate in modeling childhood stunting than mean regression in that the former was able to explain the relationship between socio-demographic factors and moderate childhood stunting as well as severe childhood stunting. One significant evident weakness of mean regression was that it explained the relationship between socio-demographic factors and average childhood stunting status which was meaningless. Quantile regression was meaningful because it explained the relationship with extreme childhood nutritional status i.e. moderate and severe childhood undernutrition.

The strength of quantile approach applied in this study was that continuous response variable was used in regression rather than categorized response variables as in the case of binary or multinomial regressions. Use of continuous response variable led to more flexibility in choosing the level of response to consider in regression. In other words, binary or multinomial regressions are limited to the assigned response categories whereas continuous quantile regression is more flexible in such that one can choose any response level by choosing appropriate values of τ which represent desirable response quantiles to regress.

However, what we see as the major limitation of this study is that the 2010MDHS did not capture data on food security which should also have been assessed. Although others argue that food security can be assessed by wealth index, we do not agree with them because it is practically possible for rich households to lack food security due to poor management.

5. Conclusions

Using the fitted quantile regression models, we concluded as follows. The fixed effects of male child, currently working mother, infectious diseases, and Yaoethnic group had significant positive relations with childhood stunting while the fixed effects of vitamin A supplementation, availability of radio/TV, improved source of drinking water, and secondary or higher mother education had significant negative relations with childhood stunting. The general relationship of the effects of child age with adjusted height-for-age followed a U-shape. The general relationship of the effects of mother's body mass index with adjusted height-for-age followed an inverse U-shape. The general relationship of the effects of duration of breastfeeding with adjusted height-for-age followed aU-shape. In general, only Chitipa, Machinga, Zomba, and Mwanza districts depicted high positive structured spatial effects on adjusted height-for-age (highnegative structured spatial effects on childhood stunting). However, these effects were not significant at 95% nominal level. Finally, this paper provided evidence that the Bayesian structured additive quantile

regression models are more appropriate than the Bayesian structured additive mean regression models in modeling childhood stunting. The implication from this study is that when interested in specific levels of response other than the mean (average) response, one should use quantile models rather than mean regressions.

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