Spatio-Temporal Analysis of Childhood Malnutrition in Republic of Congo

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Abstract **Background:** The pooled prevalence of childhood overweight and obesity worldwide dramatically increased between 2000 and 2013. If these increasing trends continue, it is estimated that the prevalence of overweight (including obesity) in children under 5 years of age will rise to 11% worldwide by 2025, up from 7% in 2012 [1, 9]. Research has shown that the pooled prevalence of overweight (including obesity) among children under five years in sub-Saharan Africa was about 5% in 2012 and is expected to reach about 8% by 2025 [1, 9, 38]. The pooled prevalence of stunting among children under five years in sub-Saharan Africa was about 43% in 2000 and about 34% in 2016. [1, 8] To reduce childhood malnutrition, several interventions including scaling-up nutrition programmes are currently operational in most sub-Saharan African countries including Republic of Congo [2]. However, very few studies have ever fitted in-depth statistical models for childhood malnutrition in Republic of Congo. The main objective of this study was to fit newly proposed spatio-temporal quantile interval regression models for childhood stunting, overweight, and obesity in Republic of Congo from 2005 to 2012. **Methods:** The Demographic and Health Survey (DHS) datasets for Republic of Congo from 2005 to 2012 were used in this study. The spatio-temporal quantile interval regression models were used to analyse childhood stunting, overweight, and obesity in Republic of Congo from 2005 to 2012. The statistical inference performed in this study was fully Bayesian using R-INLA package [37, 38] implemented in R version 3.4 [39]. **Results:** We observed that significant determinants of childhood malnutrition ranged from socio-demographic factors to child and maternal factors. In addition, child age and preceding birth interval had significant nonlinear effects on childhood stunting, overweight, and obesity. Furthermore, mother's body mass index had significant nonlinear effects on childhood overweight and obesity. Lastly, I also observed significant spatial and temporal effects on childhood stunting, overweight, and obesity in Republic of Congo. **Conclusions:** To achieve the World Health Organisation (WHO) global nutrition targets 2025 in Republic of Congo [8, 9], scaling-up nutrition programmes and childhood malnutrition policy makers should consider timely interventions based on socio-demographic determinants and spatial targets as identified in this paper.

Keywords Bayesian inference, Spatio-temporal model, Quantile interval regression, R-INLA, Childhood malnutrition, Childhood stunting, Childhood overweight, Childhood obesity

1. Background

Childhood malnutrition has severe adverse effects on the growth of any child and the economy of any nation. The most common indicators of childhood malnutrition are stunting, wasting, underweight, overweight, and obesity. A malnourished child is more likely to fall sick and die [3]. In sub-Saharan Africa, malnutrition often leads to more than 30% of deaths in children below five years annually [4]. Malnutrition is also a strong indicator of retarded growth [5], impaired cognitive and behaviour development [6], poor school performance, and lower working capacity [7]. If not corrected, it can slow down economic growth and increase poverty levels. Furthermore, it can prevent a nation from meeting its full potential through loss in productivity, cognitive capacity and increased cost in health care [6].

The prevalence of childhood overweight and obesity worldwide dramatically increased between 2000 and 2013. If these increasing trends continue, it is estimated that the prevalence of overweight (including obesity) in children under 5 years of age will rise to 11% worldwide by 2025, up from 7% in 2012 [1, 9]. The prevalence of stunting among children under five years in sub-Saharan Africa was about 43% in 2000 and about 34% in 2016 [1, 8]. Doubly surprising, childhood overnutrition is alarmingly becoming more prevalent parallel to existing undernutrition burden in sub-Saharan Africa. The prevalence of overweight (including obesity) among children under five years in sub-Saharan Africa was about 5% in 2012 and is expected to

reach about 8% by 2025 [1, 9, 36].

The consequences of overnutrition can be more devastating than those for undernutrition because it leads to chronic failure problems which in turn lead to increased medical expenditure. Children who are either overweight or obese are at a higher risk of developing serious health problems, including type 2 diabetes, high blood pressure, asthma and other respiratory problems, sleep disorders and liver disease. They may also suffer from psychological effects, such as low self-esteem, depression and social isolation. Childhood overweight and obesity also increase the risk of obesity, noncommunicable diseases (NCD), premature death and disability in adulthood. Finally, the economic costs of the escalating problem of childhood overweight and obesity are considerable, both in terms of the enormous financial strains it places on health-care systems and in terms of lost economic productivity [9].

The overall WHO global nutrition target 2025 is to improve maternal, infant and young child nutrition. One of the specific nutrition targets is the stunting policy which aims at reduction of childhood stunting by 40% from 2014 to 2025 [8]. Another specific nutrition target is the overweight (including obesity) policy which aims at making sure that there is no more increase in prevalence of childhood overweight from 2014 to 2025 [9]. To attain these targets, various malnutrition interventions including scaling-up nutrition programmes are available in most sub-Saharan African countries including Republic of Congo [2]. However, very few studies have ever fitted in-depth statistical models for childhood stunting in Republic of Congo. The main aim of this study was to assess socio-demographic determinants and spatio-temporal variation of childhood stunting, overweight, and obesity in Republic of Congo from 2005 to 2012 using newly proposed spatio-temporal quantile interval regression models and R-INLA package [37, 38] implemented in R version 3.4 [39].

Spatial models have previously been used to analyse childhood malnutrition in most sub-Saharan African countries [11, 12, 40, 41, 42]. Unfortunately, most of them have emphasised on modeling mean regression instead of quantile regression. Modeling malnutrition using quantile regression is more appropriate than using mean regression with extensive literature examples [13, 14, 15, 20, 25, 26, 27, 28, 29, 30, 43] in that it provides flexibility to analyse the determinants of malnutrition corresponding to quantiles of interest either in the lower tail (say 5% or 10%), upper tail (say 90% or 95%) or even median (50%) of the distribution rather than only analysing the determinants of mean distribution. When modeling malnutrition, it makes more sense to model severe responses rather mean responses [13, 14, 15, 20, 25, 26, 27, 28, 29, 30, 43]. For instance, it is more sensible to model severe stunting or severe overweight/obesity which corresponds to the lower and upper tails of the distribution of the same anthropometric measure than to model mean stunting or mean overweight/obesity which corresponds to the average nutritional response.

Furthermore, almost all studies on quantile modeling have emphasised on selecting only one specific response quantile level of interest and report the recommendations based on the only chosen response quantile. Unlike mean response modeling, quantile regression yields model estimates which are stochastic functions of quantiles τ such that $0 < \tau < 1$. This implies that quantile regression modeling using estimates based on only one chosen quantile level τ might be insufficient and not robust enough. In this study, I proposed a new quantile interval modeling approach which is sufficient and robust because it uses weighted mean estimates based on all quantile levels in a specified quantile interval $\tau^* \pm \Delta \tau^*$ of interest.

2. Materials and Methods

This section summarises the conceptual framework of the spatio-temporal quantile interval regression models, the data sources, and data analysis procedures used in this study.

Quantile Regression Model

In general, quantile regression is 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

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

where $Q_{Y_i|x_i,z_i}(\tau|\boldsymbol{x_i},\boldsymbol{z_i})$ is the conditional τ^{th} quantile response given $\boldsymbol{x_i}$ and $\boldsymbol{z_i}$, η_{τ_i} is the semi-parametric predictor, $\tau\epsilon(0,1)$ is the τth quantile of the response e.g. $\tau = 0.5$ for the median response regression, $\boldsymbol{x_i} = (x_{i1}, x_{i2}, \cdots, x_{ip})^T$ is the vector of p categorical covariates (assumed to have fixed effects) for each individual i, $\boldsymbol{z_i} = (z_{i1}, z_{i2}, \cdots, z_{iq})^T$ is the vector of q metric/spatial/temporal covariates, $\boldsymbol{\beta_\tau} = (\beta_{\tau 1}, \beta_{\tau 2}, \cdots, \beta_{\tau p})^T$ is the vector of p coefficients for categorical covariates at a given τ, $\boldsymbol{g_\tau} = (g_{\tau 1}, g_{\tau 2}, \cdots, g_{\tau q})^T$ is the vector of q smoothing functions for metric/spatial/temporal covariates at a given τ [13, 14, 26]. It is worthy to note that quantile regression duplicates the roles of median, tertile, quartile, quintile, sextile, septile, octile, decile, hexadecile, duodecile, ventile, percentile, and permille regressions. This is achieved by selecting appropriate values of τ in the conditional quantile regression model where $\tau\epsilon(0,1)$.

The two unknowns, $\boldsymbol{\beta_\tau}$ and $\boldsymbol{g_\tau}$ are estimated via the minimization rule given by

$$\min_{(\boldsymbol{\beta_\tau}, \boldsymbol{g_\tau})} \sum \rho_\tau(\eta_{\tau_i}) + \lambda_0 \|\boldsymbol{\beta_\tau}\|_1 + \sum_{j=1}^{q} \lambda_j V(\nabla g_{\tau_j}) \quad (2)$$

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 smoothness of the estimated function, λ_j is the jth tuning parameter for controlling the smoothness of the estimated function, $\|\boldsymbol{\beta_\tau}\|_1 = \sum_{k=1}^{K} |\boldsymbol{\beta_{\tau_k}}|$

and $V(\nabla g_{\tau_j})$ denotes the total variation of the derivative on the gradient of the function g_{τ_j} [13, 15, 16].

Proposed Quantile Interval Regression Estimation

Let the quantile interval $\tau^* \pm \Delta\tau^* = [\tau^* - \Delta\tau^*, \tau^* + \Delta\tau^*]$ be of interest where τ^* is the desired quantile interval median of interest and $\Delta\tau^* > 0$ is the desired quantile bandwidth. I propose a new methodology for estimating the quantile interval weighted mean estimates for $(p + 1)$ fixed effects parameters denoted by $\hat{\beta}_i(\tau^* \pm \Delta\tau^*)$ for $i = 0,1,2,\cdots,p$ and q nonlinear/spatio-temporal effects smoothing functions denoted by $\hat{g}_i(\tau^* \pm \Delta\tau^*)$ for $i = 1,2,\cdots,q$ in three steps as follows.

Step 1: Divide the quantile interval $\tau^* \pm \Delta\tau^*$ into n equally spaced subintervals with a uniform step size of $h > 0$ such that $n = [(\tau^* + \Delta\tau^*) - (\tau^* - \Delta\tau^*)]/h = [\tau^* + \Delta\tau^* - \tau^* + \Delta\tau^*]/h = 2\Delta\tau^*/h$ is a positive even integer. This step ensures that I have discretized the quantile interval $\tau^* \pm \Delta\tau^*$ into $(n + 1)$ odd number of equally spaced quantiles denoted by quantile set $\tau = \{\tau_0^*, \tau_1^*, \cdots, \tau_{n/2-1}^*, \tau_{n/2}^*, \tau_{n/2+1}^*, \cdots, \tau_{n-1}^*, \tau_n^*\}$ such that $\tau_0^* = \tau^* - \Delta\tau^*$, $\tau_{n/2}^* = \tau^*$, and $\tau_n^* = \tau^* + \Delta\tau^*$. The step size h is supposed to be determined by the user in such a way that it is small enough relative to the bandwidth $\Delta\tau^*$. Since it is more natural to use percentiles, I propose a default step size of $h = 0.01$.

Step 2: For each $i = 0,1,2,\cdots,p$ of the $(p + 1)$ fixed effects parameters, compute all $(n + 1)$ quantile estimates $\hat{\beta}_{ij}(\tau_j^*)$ where $j = 0,1,2,\cdots,n$. Similarly, for each $i = 1,2,\cdots,q$ of the q nonlinear/spatio-temporal effects smoothing functions, compute all $(n + 1)$ quantile estimates $\hat{g}_{ij}(\tau_j^*)$ where $j = 0,1,2,\cdots,n$.

Step 3: Compute the quantile interval weighted mean estimates for $(p + 1)$ fixed effects parameters denoted by $\hat{\beta}_i(\tau^* \pm \Delta\tau^*)$ for each $i = 0,1,2,\cdots,p$ using the formula

$$\hat{\beta}_i(\tau^* \pm \Delta\tau^*) = \sum_{j=0}^{n} \omega_j \hat{\beta}_{ij}(\tau_j^*) \qquad (3)$$

where ω_j = normalized j-th weight assigned to τ_j^* such that $\sum_{j=0}^{n} \omega_j = 1$.

Similarly, compute the quantile interval weighted mean estimates for q nonlinear/spatio-temporal effects smoothing functions denoted by $\hat{g}_i(\tau^* \pm \Delta\tau^*)$ for each $i = 1,2,\cdots,q$ using the formula

$$\hat{g}_i(\tau^* \pm \Delta\tau^*) = \sum_{j=0}^{n} \omega_j \hat{g}_{ij}(\tau_j^*) \qquad (4)$$

where ω_j = normalized j-th weight assigned to τ_j^* such that $\sum_{j=0}^{n} \omega_j = 1$.

The normalized weights $\omega_j's$ are supposed to be determined by the user basing on application at hand. For simplicity, I proposed a default of equal weights $\omega_j = 1/(n+1)$ for each $j = 0,1,2,\cdots,n$ which consequently corresponds to quantile interval equally weighted mean estimates (or simply quantile interval mean estimates) as follows.

$$\hat{\beta}_i(\tau^* \pm \Delta\tau^*) = \frac{1}{n+1}\sum_{j=0}^{n} \hat{\beta}_{ij}(\tau_j^*) \text{ for each } i = 0,1,2,\cdots,p \qquad (5)$$

$$\hat{g}_i(\tau^* \pm \Delta\tau^*) = \frac{1}{n+1}\sum_{j=0}^{n} \hat{g}_{ij}(\tau_j^*) \text{ for each } i = 1,2,\cdots,q \quad (6)$$

For childhood stunting, the primary interest was to model the adjusted height-for-age z-value (HAZ) in the quantile interval $\tau^* \pm \Delta\tau^* = 0.15 \pm 0.05$ i.e. $[\tau^* - \Delta\tau^*, \tau^* + \Delta\tau^*] = [0.10, 0.20]$ where $\tau^* = 0.15$ was the desired quantile interval median of interest and $\Delta\tau^* = 0.05$ was the desired quantile bandwidth.

For childhood overweight, the primary interest was to model the childhood body mass index-for-age Z-score (BMIAZ) in the quantile interval $\tau^* \pm \Delta\tau^* = 0.90 \pm 0.05$ i.e. $[\tau^* - \Delta\tau^*, \tau^* + \Delta\tau^*] = [0.85, 0.95]$ where $\tau^* = 0.90$ was the desired quantile interval median of interest and $\Delta\tau^* = 0.05$ was the desired quantile bandwidth.

For childhood obesity, the primary interest was to model the childhood body mass index-for-age Z-score (BMIAZ) in the quantile interval $\tau^* \pm \Delta\tau^* = 0.97 \pm 0.02$ i.e. $[\tau^* - \Delta\tau^*, \tau^* + \Delta\tau^*] = [0.95, 0.99]$ where $\tau^* = 0.97$ was the desired quantile interval median of interest and $\Delta\tau^* = 0.02$ was the desired quantile bandwidth.

Prior Distributions

In fully Bayesian framework, all unknown functions $\{g\}'s$ for both metric and spatio-temporal covariates, all parameters $\{\beta\}'s$ for categorical covariates, and all variance parameters $\{\sigma^2\}'s$ are considered as random variables and must be supplemented by appropriate prior distributions. In this research, the following prior distributions were supplemented. The priors for unknown functions $f_k(\cdot), k = 1, \cdots, n_f$, do belong to the class of Gaussian Markov random fields (GMRF), whose specific forms actually depend on covariate types and also on the prior beliefs about the smoothness of f_k. Although only GMRF was used in this study, there exist some other options like Bayesian P-splines [15, 17].

Let $\boldsymbol{f} = (f(u_1), f(u_2), \cdots, f(u_n))^T$, a random vector of the response at $u_i, i = 1,2,\cdots,n$. The vector $\boldsymbol{f}$ is a GMRF with mean $\boldsymbol{\mu}$ and precision (the inverse covariance) matrix $\delta\boldsymbol{Q}$ if and only if it has density of form

$$\pi(\boldsymbol{f}|\delta) \propto \delta^{(n-m)/2}\exp\left(-\frac{\delta}{2}(\boldsymbol{f} - \boldsymbol{\mu})^T\boldsymbol{Q}(\boldsymbol{f} - \boldsymbol{\mu})\right) \quad (7)$$

where $\boldsymbol{Q}$ is a semi-definite matrix of constants with rank $(n - m)$ where $m \geq 0$. The properties of a particular GMRF are all reflected through matrix $\boldsymbol{Q}$. For instance, the Markov properties of GMRFs totally depend on the various sparse structures that the matrix $\boldsymbol{Q}$ may have. In this paper, I used two kinds of GMRFs: second order random walk (RW2) models [18] for metric covariates and intrinsic conditional autoregressive (ICAR) models [19] for spatial covariates. These two GMRFs share equation 7 but with different structures of $\boldsymbol{Q}$.

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 RW2 model is based on a discretely observed continuous time process $z(u)$ that is a realization of an $(m - 1)$ fold integrated Wiener process given by

$$z(u) = \int_0^u \frac{(u-h)^{m-1}}{(m-1)!}dW(h) \qquad (8)$$

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

For spatial covariates, letting n_i denote the number of neighbours of site u_i, I assumed the following spatial smoothness prior for the function evaluations

$$f(u_i)|\{f(u_j), j \neq i\}, \delta \sim N\left(\frac{1}{n_i}\sum_{j:j\sim i} f(u_j), \frac{1}{n_i\delta}\right) \quad (9)$$

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

For the fixed effect parameters $\{\beta_j\}'s$, I assumed independent diffuse priors $\pi(\beta_j) \propto$ constant or a weakly informative Gaussian $\boldsymbol{\beta} \sim N(\mathbf{0}, \phi^{-1}\boldsymbol{I})$ with small precision ϕ on the identity matrix $\boldsymbol{I}$. If $\boldsymbol{\beta}$ is a high-dimensional vector, one may consider using Bayesian regularization priors developed in [17], where conditionally Gaussian priors are assigned with suitable hyper prior assumptions on the variances inducing the desired shrinkage and sparseness on coefficient estimates.

Spatio-temporal models

The spatio-temporal data can be defined by a stochastic process $\boldsymbol{Y}(s,t) \equiv \{y(s,t), (s,t) \in \boldsymbol{D} \subseteq \mathbb{R}^2 \times \mathbb{R}\}$ and are observable or measurable at n spatial locations or areas and at given T time points. Since the space and time dimensions are always correlated, a valid spatio-temporal covariance function given as $\text{Cov}(\theta_{it}, \theta_{ju}) = \sigma_C^2 C(s_i, s_j; t, u)$ must always be defined and assessed [31, 44]. If an assumption of stationarity in space and time is made, then the space-time covariance function can simply be written as a function of both the spatial Euclidean distance $\Delta_{ij} = \|s_i - s_j\|$ and the temporal lag $\Lambda_{tu} = |t - u|$, as $\text{Cov}(\theta_{it}, \theta_{ju}) = \sigma_C^2 C(\Delta_{ij}; \Lambda_{tu})$. Note that many valid non-separable space-time covariance functions are also possible as are reported in [32].

To overcome the computational complexity of non-separable models, many simplifications have been introduced in practice. For instance, basing on the separability hypothesis, the space-time covariance function can be decomposed into either sum or the product of a purely spatial component and a purely temporal component, e.g. $\text{Cov}(\theta_{it}, \theta_{ju}) = \sigma_C^2 C_1(\Delta_{ij})C_2(\Lambda_{tu})$, as described in [33]. In some cases, it is also possible to assume that the spatial correlation is constant over time so that a space-time covariance function becomes purely spatial when $t = u$, i.e. $\text{Cov}(\theta_{it}, \theta_{ju}) = \sigma_C^2 C(\Delta_{ij})$, and is zero otherwise. Consequently, the temporal evolution can also be introduced with an assumption that the spatial process evolves with time following some autoregressive dynamics [34].

Similarly, the GMRF framework for area level spatio-temporal data analysis can be extended to include a precision matrix that is defined also in terms of time with a neighbourhood structure assumption. It is worthy to note that if a space-time interaction is included, then its precision can be obtained through the Kronecker product of the precision matrices for the space and time effects interacting [35].

In this research, I performed spatio-temporal data analysis of childhood stunting, overweight, and obesity in Republic of Congo. In this case, the datasets were defined by stochastic processes of the form $\boldsymbol{Y}(s,t) \equiv \{y(s,t), (s,t) \in \boldsymbol{D} \subseteq \mathbb{R}^2 \times \mathbb{R}\}$ where $\boldsymbol{Y}(s,t)$ were childhood height-for-age Z-score (HAZ) and childhood body mass index-for-age Z-score (BMIAZ) as a continuous response variable at a given 2-dimensional (latitude and longitude) spatial location s which was a region of Republic of Congo at a given time point (year) T which ranged from 2005 to 2012. For simplicity, I assumed stationarity in space and time to easily decompose the space-time covariance function into a sum or product of purely spatial and purely temporal terms.

Posterior Inference

The well-known method for estimating Bayesian posterior marginal distribution is Markov chain Monte Carlo (MCMC). The alternative method is Integrated Nested Laplace Approximations (INLA). In this study, INLA method was used because it is generally faster than MCMC for quantile models [21, 22, 23, 24, 37, 38, 45].

Data Sources

For applications of the newly proposed methodology, I considered the Demographic and Health Survey (DHS) datasets of Republic of Congo from 2005 to 2012. A multi-stage clustered sampling technique was used to interview eligible women of reproductive age between 15 and 49 years. The anthropometric assessment of themselves and their children that were born within the previous 5 years preceding the survey were administered. These DHS datasets contained information on family planning, maternal and child health, child survival, educational attainment, and other household composition and characteristics.

Data Analysis

Firstly, I started with estimating the crude prevalence rates of childhood stunting, overweight, and obesity in the Republic of Congo from 2005 to 2012. The categorized adjusted childhood stunting with two categories, stunted ($HAZ < -2$) and not stunted (otherwise), was used as a childhood stunting indicator variable in this phase. The categorized adjusted childhood overweight with two categories, overweight ($2 \leq BMIAZ \leq 3$) and not overweight (otherwise), was used as a childhood overweight indicator variable in this phase. The categorized adjusted childhood obesity with two categories, obese ($BMIAZ > 3$) and not obese (otherwise), was used as a childhood obesity indicator variable in this phase.

Finally, I performed spatio-temporal data analysis of childhood malnutrition in Republic of Congo from 2005 to 2012. The primary outcomes in this study were the childhood (under 5 years) stunting, overweight, and obesity in Republic of Congo from 2005 to 2012. On one hand, childhood stunting was assessed by using the childhood height for age Z-score (HAZ) as a continuous response variable. On the other hand, childhood overweight and obesity were assessed by body mass index-for-age Z-score (BMIAZ) as a continuous response variable. The statistical inference was fully Bayesian using the newly proposed quantile interval estimation approach and INLA approach implemented in R

version 3.4 with reference to examples cited in [21, 22, 23, 24, 37, 38, 45].

3. Results

Firstly, the exploratory results were assessed in terms of trends in crude prevalence rates of stunting, overweight, and obesity in Republic of Congo from 2005 to 2012. Secondly, the results of spatio-temporal quantile interval regression models were assessed in terms of fixed effects, nonlinear effects, and spatial effects.

Prevalence of Childhood Malnutrition

Table 1 and Figure 1 show the trends in prevalence rates for childhood stunting, overweight, and obesity in Republic of Congo from 2005 to 2012. Firstly, the prevalence of childhood stunting in Republic of Congo slightly decreased from 28.1% in 2005 to 26.5% in 2012. Secondly, the prevalence of childhood overweight in Republic of Congo decreased from 10.3% in 2005 to 4% in 2012. Lastly, the prevalence of childhood obesity in Republic of Congo also decreased from 3.1% in 2005 to 0.9% in 2012.

Table 1. Trends of childhood malnutrition prevalence rates in Republic of Congo

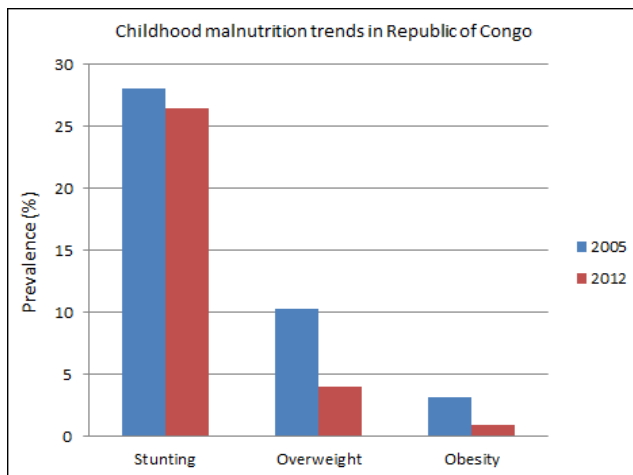|		Stunted	Overweight	Obese
Year	Total	Count (%)	Count (%)	Count (%)
2005	2879	809 (28.1)	296 (10.3)	88 (3.1)
2012	3090	820 (26.5)	124 (4)	29 (0.9)

Figure 1. Trends of childhood malnutrition prevalence rates in Republic of Congo

Fixed Effects

Table 2, Table 3, and Table 4 show the estimated fixed effects plus their 95% credible intervals for childhood stunting, overweight, and obesity, respectively.

In general, I observed that rural residence, poor source of drinking water, poor type of toilet facility, male-headed household, and male child were significantly associated with reduced HAZ and hence were significantly associated with increased childhood stunting in Republic of Congo over the

period from 2005 to 2012. I found that, although almost all household wealth indexes were significantly negatively associated with HAZ, the pattern of the magnitudes of their fixed effects revealed that richer households were associated with reduced childhood stunting compared to poor households. It was noticed that availability of TV was associated with decreased childhood stunting in 2005 but with increased childhood stunting in 2012. Finally, I found out that households with less educated mothers (secondary or below) were significantly negatively associated with HAZ whereas households with more educated mothers (graduates) were significantly associated with positive HAZ which implied that the children of more educated mothers were likely not stunted in Republic of Congo over the period 2005 to 2012.

The fixed effects on both childhood overweight and obesity revealed similar pattern of associations as follows. It was observed that urban residence, poor source of drinking water, poor type of toilet facility, availability of TV, male-headed household, and male child were significantly positively associated with BMIAZ and hence were significantly associated with increased childhood overweight and obesity in Republic of Congo over the period from 2005 to 2012. I observed that all household wealth indexes were significantly positively associated with BMIAZ in a such a way that the richer households were associated with reduced childhood overweight and obesity compared to poor households. However, I found out that households with highly educated mothers (graduates) were also associated with lower prevalence rates of childhood overweight and obesity compared to households with less educated mothers (secondary or below) in Republic of Congo from 2005 to 2012.

Nonlinear Effects

Figure 2, Figure 5, and Figure 9 show the summary of observed nonlinear effects of child's age on childhood stunting, overweight, and obesity, respectively in Republic of Congo from 2005 to 2012. On one hand, I noticed that child's age exhibited a U-shaped pattern of effects on HAZ such that childhood stunting rapidly increased as child's age increased from birth to about 24 months (in the first 2 months), then remained stationary between ages 24 months and 36 months, and then finally started decreasing (coming back to normal nutritional status) from 36 months up to 59 months. On the other hand, I observed that child's age exhibited an inverse U-shaped pattern of effects on BMIAZ such that childhood overweight and obesity rapidly increases for children aged between 36 and 48 months.

Figure 3, Figure 6, and Figure 10 show the summary of observed nonlinear effects of preceding birth interval on childhood stunting, overweight, and obesity, respectively in Republic of Congo from 2005 to 2012. I noticed that shorter preceding birth intervals were associated with increased childhood stunting whereas longer preceding birth intervals were associated with reduced childhood stunting in Republic of Congo from 2005 to 2012. Similarly, I observed that

shorter preceding birth intervals were associated with increased childhood overweight and obesity whereas longer preceding birth intervals were associated with reduced childhood overweight and obesity in Republic of Congo from 2005 to 2012.

Figure 7 and Figure 11 show the summary of observed nonlinear effects of mother's BMI on childhood overweight and obesity, respectively in Republic of Congo from 2005 to 2012. It was found that children whose mothers had higher BMIs were more likely to be either overweight or obese than childhood whose mothers had lower BMIs in Republic of Congo from 2005 to 2012.

Spatial Effects

Figure 4, Figure 8, and Figure 12 show the summary of observed spatial effects on childhood stunting, overweight, and obesity, respectively in Republic of Congo from 2005 to 2012.

Maps on the left show distributions of posterior means for spatial effects on childhood stunting, overweight, and obesity. A band of colours ranging from black (strongest negative effect) to yellow (strongest positive effect) were used to display the intensity of spatial effects within regions of Republic of Congo.

Maps on the right show significance of observed spatial effects on childhood stunting, overweight, and obesity. Only three colours were used for discriminating significance of observed effects. Firstly, black colour (-1) corresponded to significant negative spatial effects on HAZ or BMIAZ. Secondly, yellow colour (+1) corresponded to significant positive spatial effects on HAZ or BMIAZ. Lastly, purple colour (0) corresponded to non-significant spatial effects on HAZ or BMIAZ.

It was observed that most of the regions in Republic of Congo had significant spatial effects (some negative and others positive) on childhood stunting, overweight, and obesity. Note that only four regions were used for 2005 DHS data set in Republic of Congo.

CHILDHOOD STUNTING

Table 2.   Fixed effects on childhood stunting in Republic of Congo

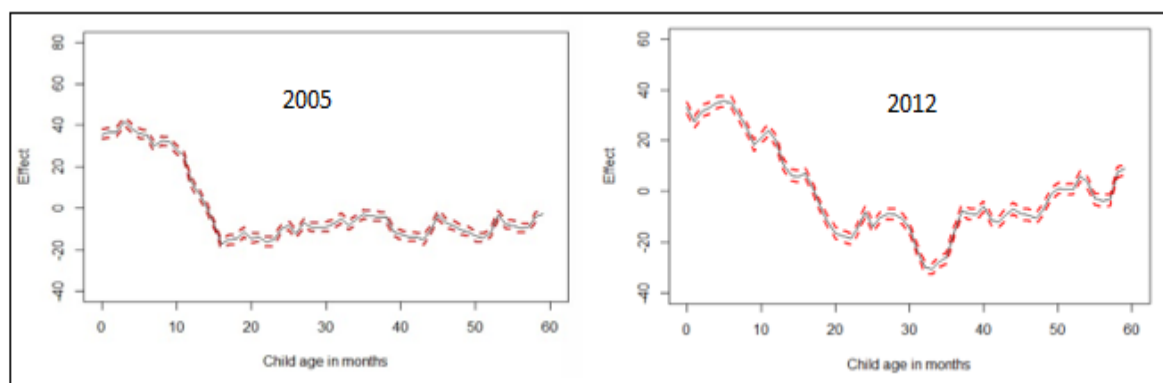|	2005		2012	
Variable	Posterior mean	95% Credible interval	Posterior mean	95% Credible interval
(Intercept)	-39.57	-39.65, -39.50	-55.28	-55.35, -55.21
Rural residence	-10.04	-10.13, -9.94	-7.89	-8.01, -7.76
Poor water source	-8.58	-8.67, -8.48	-1.12	-1.23, -1.00
Poor toilet facility	-28.44	-28.52, -28.37	-3.89	-4.00, -3.77
Television available	1.27	1.17, 1.38	-1.96	-2.04, -1.88
Male household head	-26.49	-26.57, -26.42	-37.37	-37.44, -37.30
Male child	-24.95	-25.03, -24.87	-24.67	-24.77, -24.57
Poor household	-15.87	-15.98, -15.76	-14.83	-14.93, -14.74
Middle household	-16.36	-16.48, -16.25	-3.89	-4.03, -3.74
Richer household	-13.26	-13.40, -13.13	-3.95	-4.14, -3.77
Richest household	-8.42	-8.57, -8.27	11.14	10.95, 11.32
Primary education mother	-32.21	-32.31, -32.11	-38.62	-38.71, -38.53
Secondary education mother	-13.17	-13.26, -13.08	-21.91	-22.00, -21.82
Higher education mother	-1.59	-1.99, -1.18	2.20	2.20, 2.63

Figure 2.   Nonlinear effects of child's age in months on childhood stunting in Republic of Congo
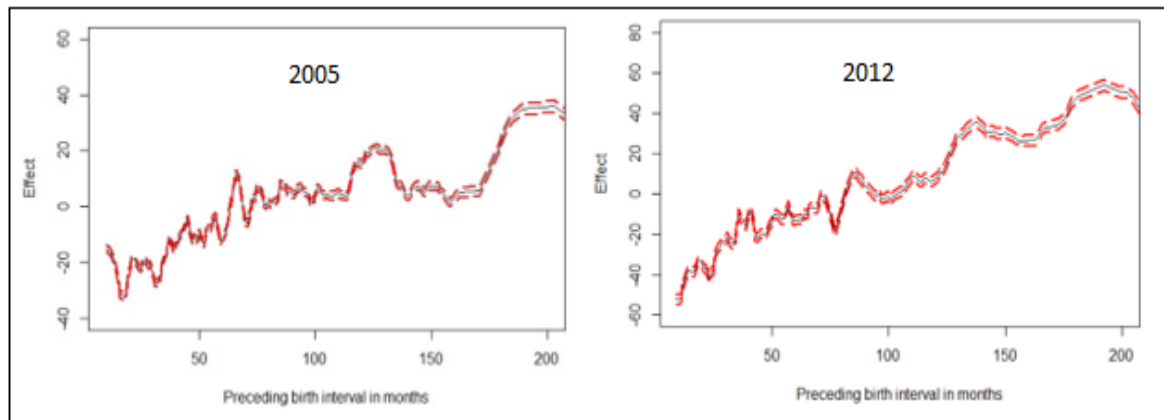
Figure 3. Nonlinear effects of preceding birth interval in months on childhood stunting in Republic of Congo
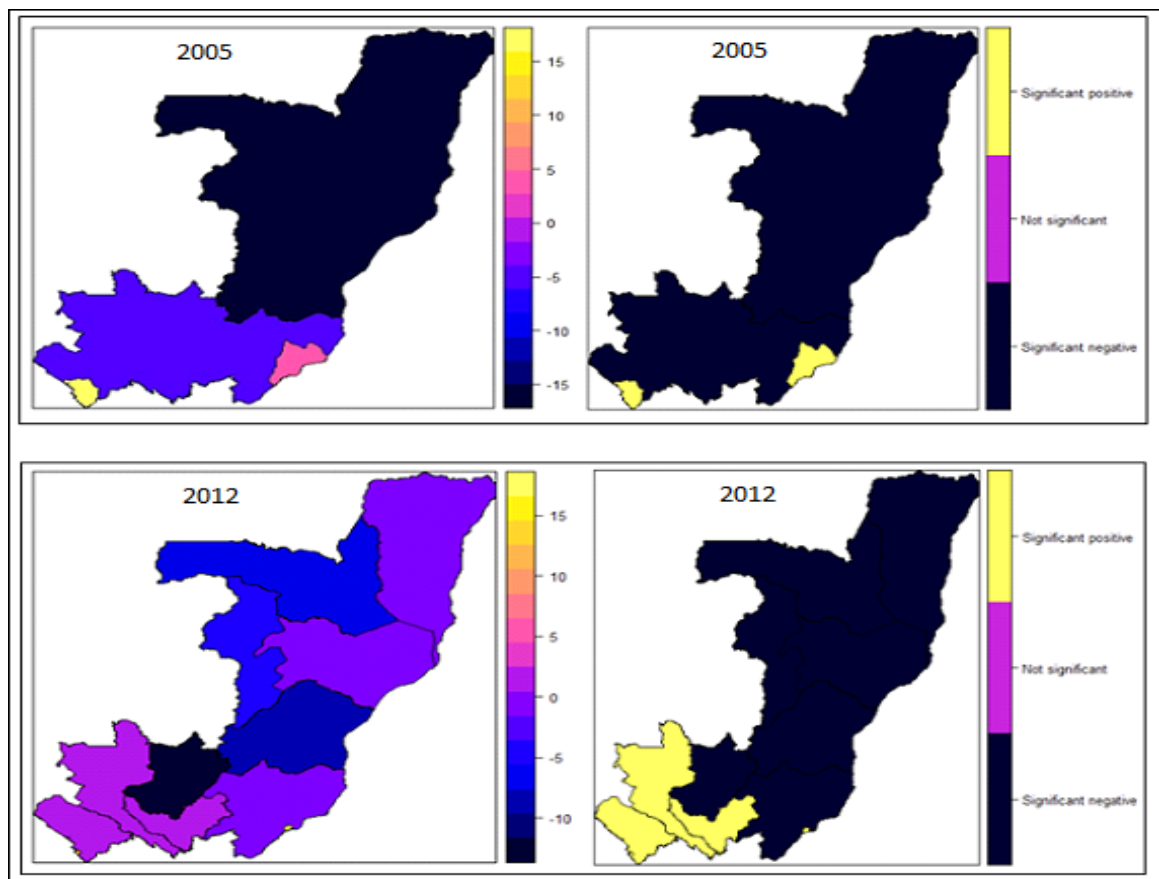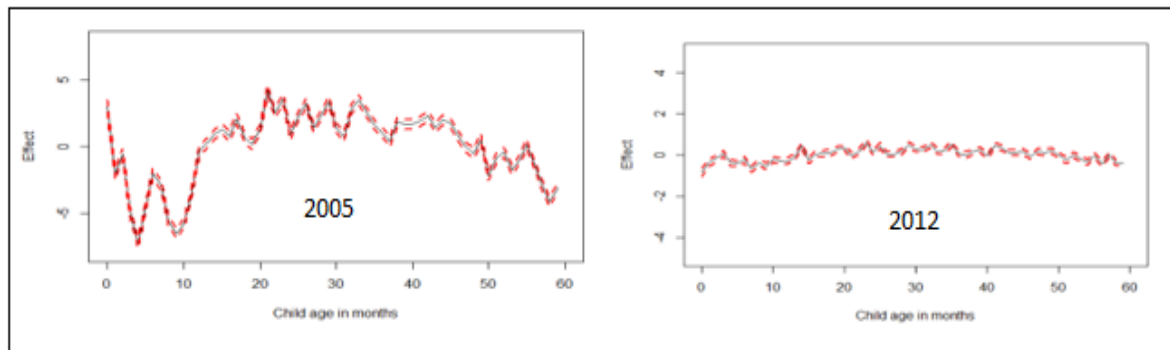

Figure 4. Spatial effects on childhood stunting: posterior means (left); significance at 95% level (right)

CHILDHOOD OVERWEIGHT

Table 3. Fixed effects on childhood overweight in Republic of Congo

	2005		2012	
Variable	Posterior mean	95% Credible interval	Posterior mean	95% Credible interval
(Intercept)	3.88	3.85, 3.91	0.44	0.44, 0.45
Urban residence	2.11	2.08, 2.14	0.23	0.22, 0.24
Poor water source	2.35	2.32, 2.38	0.17	0.07, 0.10
Poor toilet facility	3.31	3.28, 3.34	0.09	0.15, 0.18
Television available	1.70	1.66, 1.74	0.14	0.13, 0.15

Variable	2005		2012	
	Posterior mean	95% Credible interval	Posterior mean	95% Credible interval
Male household head	3.49	3.47, 3.52	0.38	0.37, 0.39
Male child	3.33	3.30, 3.36	0.20	0.18, 0.21
Poor household	3.22	3.17, 3.27	0.31	0.30, 0.32
Middle household	2.63	2.58, 2.67	0.19	0.17, 0.20
Richer household	2.74	2.70, 2.79	0.24	0.22, 0.26
Richest household	2.62	2.56, 2.67	0.26	0.24, 0.29
Primary education mother	3.06	3.02, 3.10	0.37	0.36, 0.38
Secondary education mother	2.40	2.36, 2.43	0.35	0.34, 0.36
Higher education mother	3.21	3.07, 3.35	0.01	-0.04, 0.07

Figure 5.   Nonlinear effects of child's age in months on childhood overweight in Republic of Congo
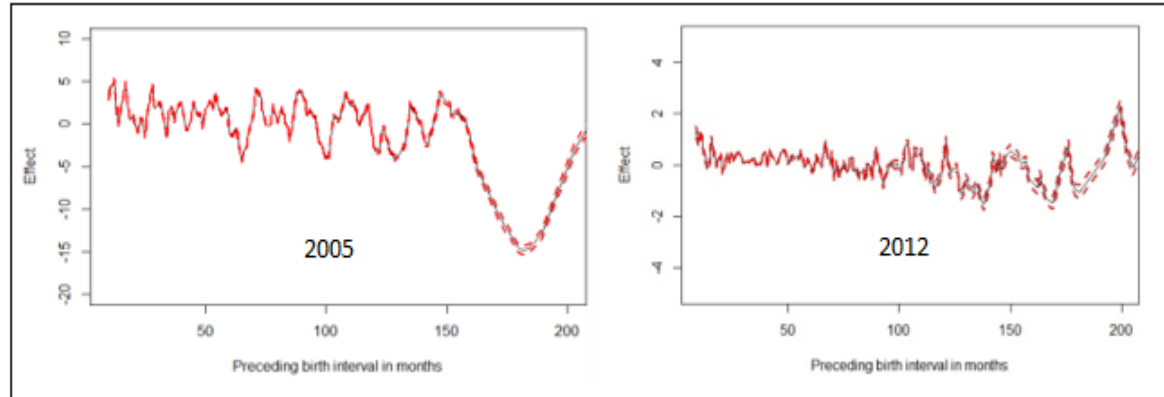

Figure 6.   Nonlinear effects of preceding birth interval in months on childhood overweight in Republic of Congo
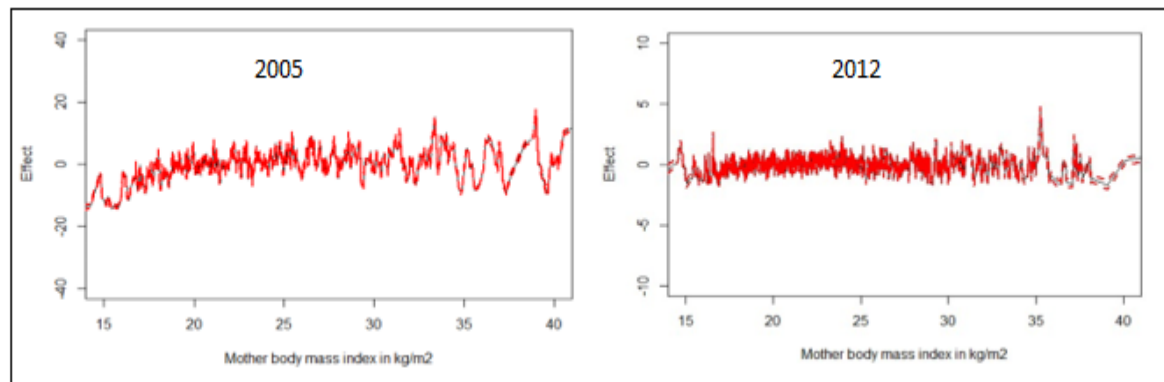

Figure 7.   Nonlinear effects of mother's BMI in kg/m^2 on childhood overweight in Republic of Congo
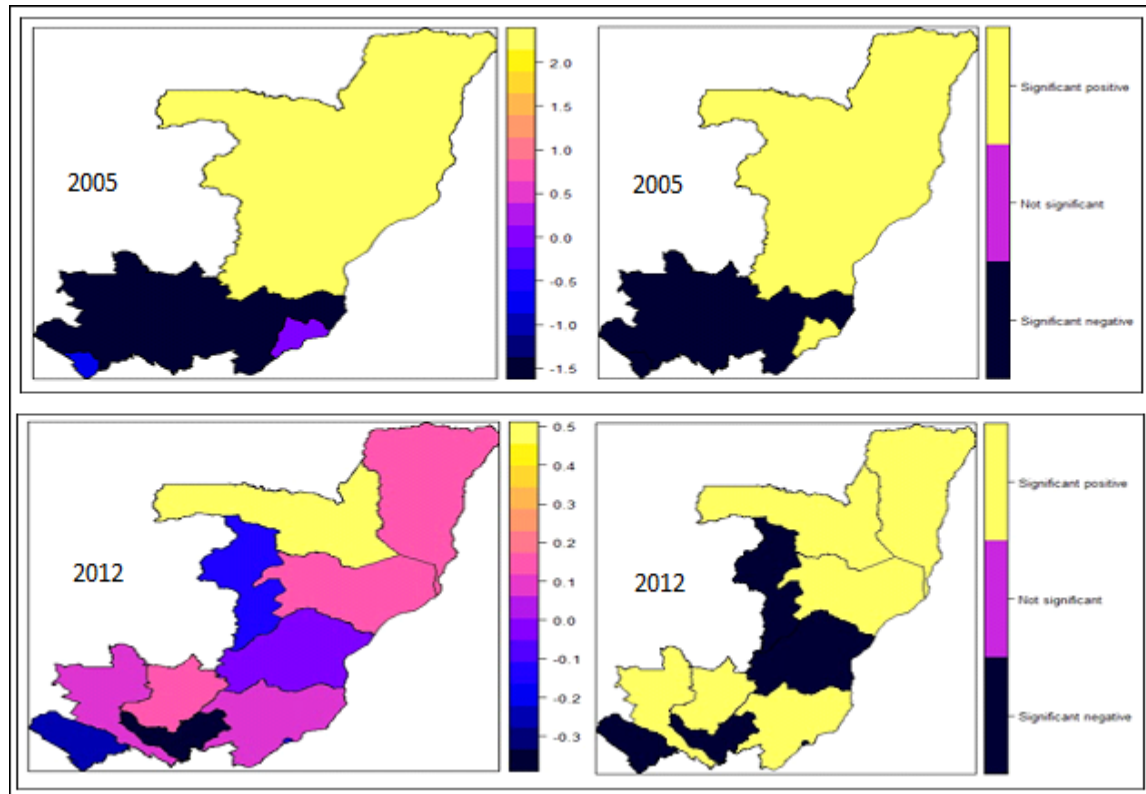
Figure 8. Spatial effects on childhood overweight: posterior means (left); significance at 95% level (right)

CHILDHOOD OBESITY

Table 4. Fixed effects on childhood obesity in Republic of Congo

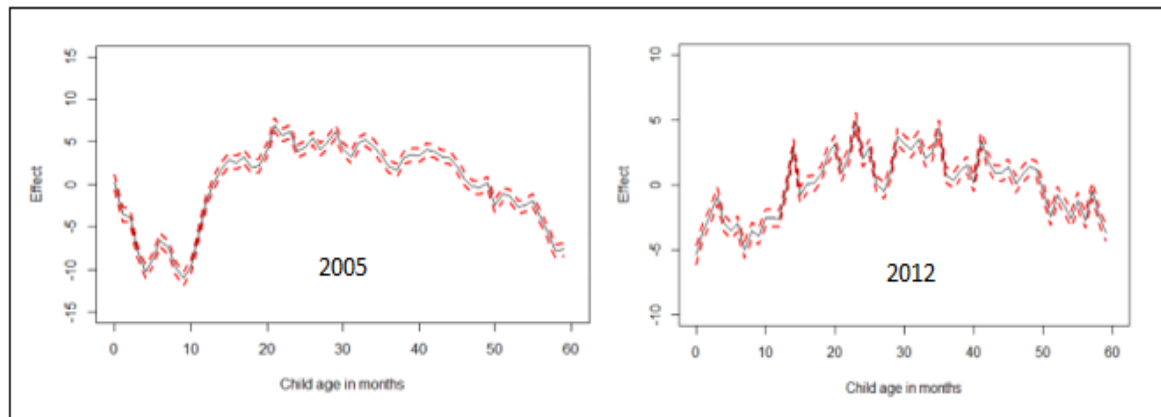| Variable	2005		2012	
	Posterior mean	95% Credible interval	Posterior mean	95% Credible interval
(Intercept)	9.25	9.17, 9.33	4.84	4.81, 4.86
Urban residence	4.55	4.45, 4.65	2.29	2.25, 2.34
Poor water source	5.09	4.99, 5.20	1.42	1.38, 1.47
Poor toilet facility	7.75	7.67, 7.84	0.65	0.61, 0.70
Television available	3.20	3.09, 3.32	1.28	1.25, 1.31
Male household head	7.85	7.77, 7.94	3.90	3.88, 3.93
Male child	7.38	7.29, 7.48	1.64	1.60, 1.68
Poor household	7.38	7.23, 7.53	3.07	3.03, 3.11
Middle household	5.41	5.27, 5.54	2.11	2.05, 2.17
Richer household	6.49	6.34, 6.63	2.42	2.35, 2.48
Richest household	6.13	5.96, 6.71	2.60	2.53, 2.68
Primary education mother	6.59	6.47, 6.71	3.83	3.79, 3.86
Secondary education mother	5.31	5.21, 5.41	3.55	3.52, 3.58
Higher education mother	6.71	6.31, 7.10	1.08	0.93, 1.23

Figure 9. Nonlinear effects of child's age in months on childhood obesity in Republic of Congo
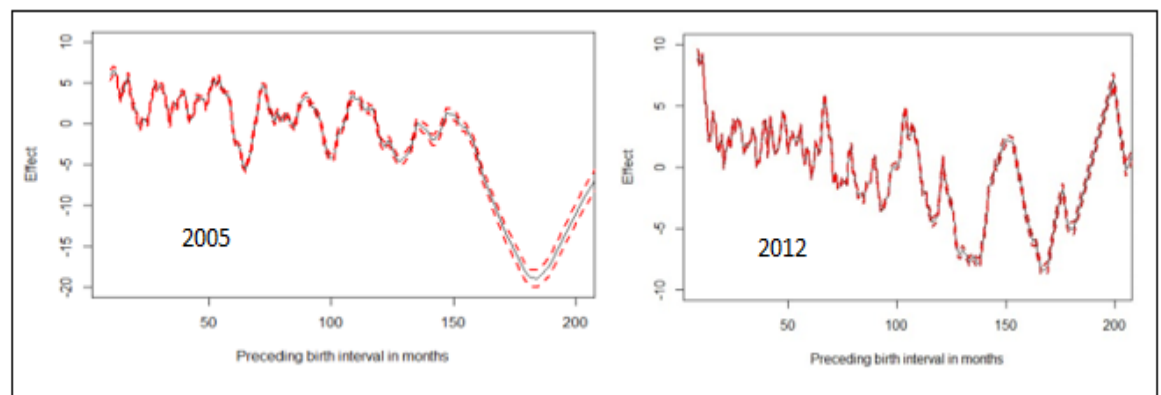

Figure 10. Nonlinear effects of preceding birth interval in months on childhood obesity in Republic of Congo
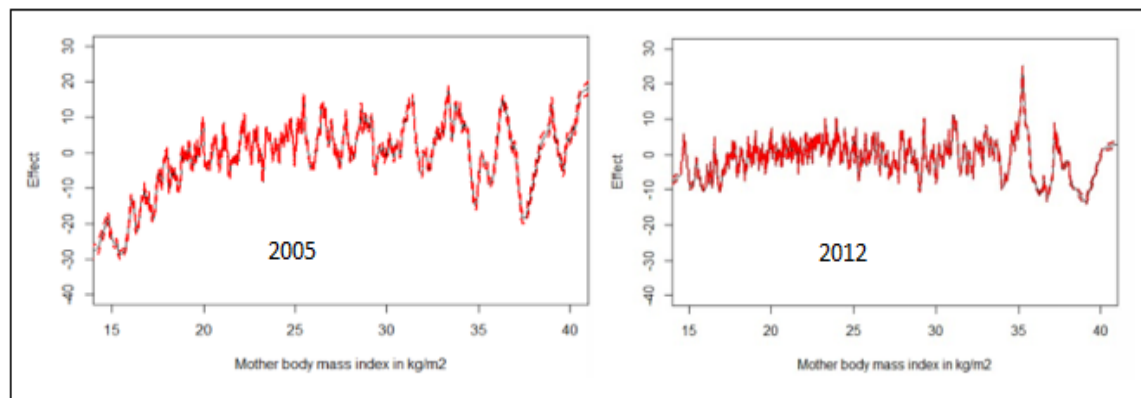

Figure 11. Nonlinear effects of mother's BMI in kg/m^2 on childhood obesity in Republic of Congo
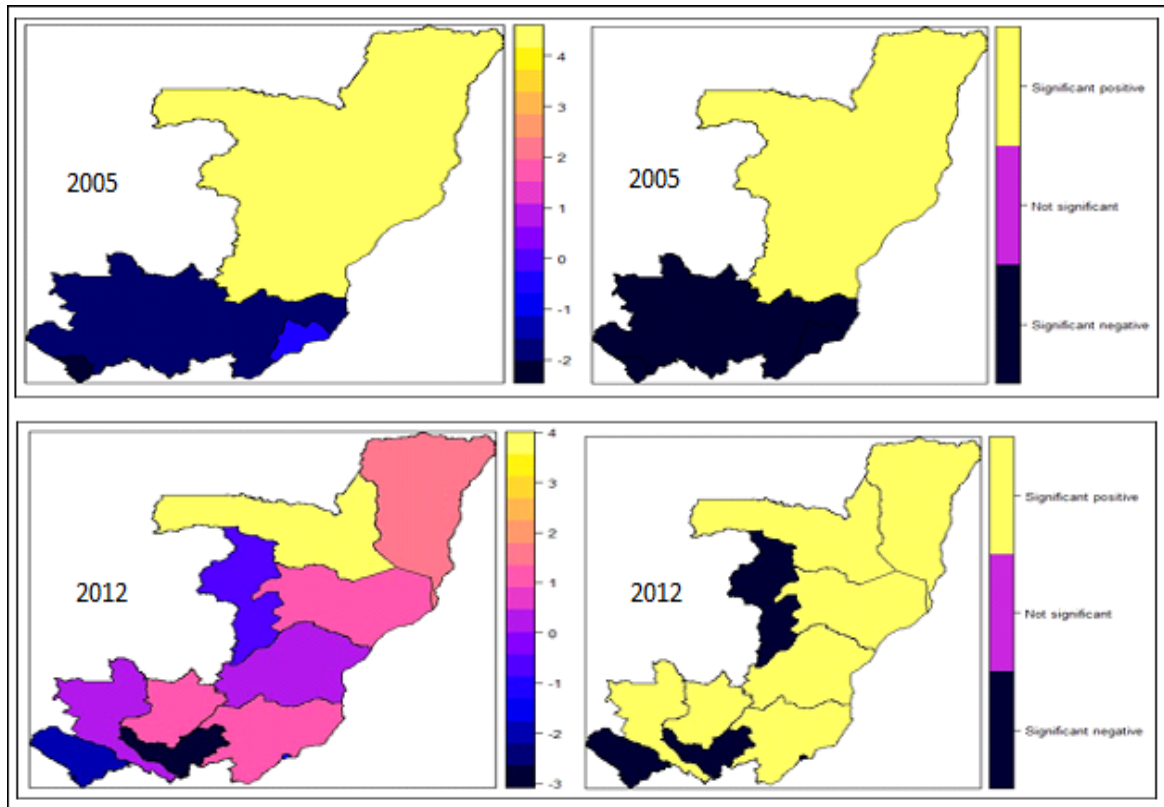
Figure 12. Spatial effects on childhood obesity: posterior means (left); significance at 95% level (right)

4. Discussion

In this study, the spatio-temporal quantile interval regression models were fitted for childhood stunting, overweight, and obesity using the newly proposed weighted mean estimation for the first time. The indicators of childhood undernutrition are stunting, wasting and underweight. However, only childhood stunting was assessed in this study because it has always been the most prevalent undernutrition status among children under-five in sub-Saharan Africa [1, 4]. The indicators of childhood overnutrition are overweight and obesity. Note that I managed to analyse both in this study.

The primary aim of this study was to fit country-specific spatio-temporal quantile interval models in Republic of Congo which are more appropriate than mean regression models when modeling nutritional status.

For childhood stunting, I analysed the height-for-age Z-scores (HAZ) in the quantile interval $\tau^* \pm \Delta \tau^* = 0.15 \pm 0.05$ i.e. $[\tau^* - \Delta \tau^*, \tau^* + \Delta \tau^*] = [0.10, 0.20]$ where $\tau^* = 0.15$ was the desired quantile interval median of interest and $\Delta \tau^* = 0.05$ was the desired quantile bandwidth.

For childhood overweight, I analysed the childhood body mass index-for-age Z-score (BMIAZ) in the quantile interval $\tau^* \pm \Delta \tau^* = 0.90 \pm 0.05$ i.e. $[\tau^* - \Delta \tau^*, \tau^* + \Delta \tau^*] = [0.85, 0.95]$ where $\tau^* = 0.90$ was the desired quantile interval median of interest and $\Delta \tau^* = 0.05$ was the

desired quantile bandwidth.

For childhood obesity, I analysed the childhood body mass index-for-age Z-score (BMIAZ) in the quantile interval $\tau^* \pm \Delta \tau^* = 0.97 \pm 0.02$ i.e. $[\tau^* - \Delta \tau^*, \tau^* + \Delta \tau^*] = [0.95, 0.99]$ where $\tau^* = 0.97$ was the desired quantile interval median of interest and $\Delta \tau^* = 0.02$ was the desired quantile bandwidth.

The inference used in this study was fully Bayesian. The posterior marginal distributions were estimated using R-INLA package [37, 38] in R version 3.4 [39]. The INLA approach was chosen because it is generally faster than MCMC approach for quantile models [23, 27].

Despite a few minor differences in terms of statistical approaches, most of the findings in this study were very similar to those reported in most related studies in sub-Saharan Africa [11, 12, 40, 41, 42]. For example, childhood stunting was analysed in two sub-Saharan African countries; Tanzania and Zambia in 2005 using 1992 DHS datasets [11] and childhood stunting was analysed in Nigeria in 2008 using the 2005 DHS dataset [12]. They both also found that rural residence, poor source of drinking water, poor type of toilet facility, male-headed household, male child, higher household wealth index, and lower mother's formal education were significantly associated with increased childhood stunting in these countries. Furthermore, all of them also observed U-shaped patterns of nonlinear effects of child's age on childhood stunting which was the same finding I observed in our study.

However, a few differences are as follows. Firstly, they used MCMC simulation techniques to estimate the posterior mean effects whereas I used INLA direct computation techniques to estimate the posterior mean effects. Secondly, they analysed mean responses of childhood stunting by using Bayesian semi-parametric geo-additive models whereas I analysed quantile interval responses of childhood stunting in the quantile interval $0.10 \leq \tau \leq 0.20$ by using Bayesian spatio-temporal quantile interval models. Note that my approach is more appropriate than their approaches because it is more appropriate to model severe childhood stunting than to model the average childhood stunting.

5. Conclusions

The prevalence of childhood stunting in Republic of Congo, though still considerably high, decreased from 28.1% in 2005 to 26.5% in 2012. The prevalence of overweight decreased from 10.3% in 2005 to 4% in 2012. Similarly, the prevalence of overweight also decreased from 3.1% in 2005 to 0.9% in 2012.

In general, I found that rural residence, poor source of drinking water, poor type of toilet facility, male-headed household, male child, higher household wealth index, and lower mother's formal education were significantly associated with increased childhood stunting in Republic of Congo from 2000 to 2012.

I observed that urban residence, poor source of drinking water, poor type of toilet facility, availability of TV, male-headed household, and male child significantly increased childhood overweight and obesity in Republic of Congo over the period from 2005 to 2012. In addition, richer households were associated with reduced childhood overweight and obesity compared to poor households. Furthermore, households with highly educated mothers (graduates) were associated with lower prevalence rates of childhood overweight and obesity compared to households with less educated mothers (secondary or below) in Republic of Congo in 2012.

In general, it was observed that childhood stunting, overweight, and obesity increased as age of child increased whereas childhood stunting, overweight, and obesity decreased as preceding birth interval increased. I also found out that childhood overweight and obesity increased as mother's BMIs increased. Finally, I noticed that most of the regions exhibited significant spatial effects on childhood stunting, overweight, and obesity in Republic of Congo from 2005 to 2012.

I recommend that scaling-up nutrition programmes, food security programmes, and childhood malnutrition policy makers should consider timely interventions based on important socio-demographic factors, child age, maternal factors, temporal and spatial variation of childhood stunting, overweight, and obesity in Republic of Congo as reported in this paper.

List of Abbreviations

BMI: Body mass index; BMIAZ: Body mass index-for-age Z-score; DHS: Demographic and health survey; GMRF: Gaussian Markov random field; HAZ: Height-for-age Z-score; ICAR: Intrinsic conditional autoregressive; INLA: Integrated nested Laplace approximations; MCMC: Markov chain Monte Carlo; NCD: Non-communicable diseases; RW2: Random walk order 2; SUN: Scaling up nutrition; TV: Television; UNICEF: United nations children's fund; WFP: World food programme; WHO: World health organisation

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