Bayesian Spatial Quantile Interval Model with Application to Childhood Malnutrition in Ethiopia

Abdu Shebeshi
Department of Statistics, Samara University
Zeytu Asfaw (zeytugas@gmail.com)
Hawassa University College of Natural and Computational Science https://orcid.org/0000-0003-3198-1609

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RESEARCH

Bayesian Spatial Quantile Interval Model with Application to Childhood Malnutrition in Ethiopia

Abdu H Shibeshi[1] and Zeytu G. Asfaw[2*]

*Correspondence: zeytugas@gmail.com
[2]Department of Statistics, Hawassa University, Hawassa, Ethiopia
Full list of author information is available at the end of the article

Abstract

Background: The national prevalence of stunting and wasting in Ethiopia is still very high and it is the most common causes of morbidity and mortality among less than five years old children. The aim of the current study was to investigate the determinant of stunting and wasting in Ethiopia.

Methods: Malnutrition data-sets collected through EDHS 2016 were analyzed by Bayesian spatial quantile interval regression models using R-INLA package.

Results: The present study found that child sex, child age, mother's education, mother's age, source of drinking water, mother's BMI, wealth index, region, residence, cooking fuel and toilet facility were significantly associated with childhood malnutrition (stunting and wasting). Furthermore, these findings imply that a multisectorial and multidimensional approach is important to address malnutrition in Ethiopia.

Conclusions: The education sector should promote reduction of gender barriers that contribute to childhood malnutrition and also the health sector should encourage positive behaviors toward childcare and other feeding practices. Moreover, both governmental and non-governmental potential stakeholders should pay attention on the significant factors identified through the current study so that stunting and wasting in Ethiopia minimized optimally.

Keywords: Children; Malnutrition; Spatial quantile interval model; Bayesian approach; R-INLA approach

Background

Malnutrition remains one of the most common causes of morbidity and mortality among under five years old children throughout the World [1]. It leads to at least 47% of deaths among children in sub-Saharan Africa (SSA) [2]. Child malnutrition estimates for the indicators stunting, wasting, underweight and overweight describe the magnitude and patterns of under-nutrition and over-nutrition [3].

In 2018, 149 million children under five years of age were stunted and 49 million were wasted worldwide. The pooled prevalence of stunting in SSA was 42.9% in 2000 and 33% in 2019 [3]. Particularly, in Ethiopia the trend shows a reduction of child under-nutrition between 2000 and 2016. The prevalence of stunting has decreased considerably, from 58% in 2000 to 38% in 2016, but the prevalence of wasting changed little over the same time period (12% to 10%). Evidenced with EDHS 2016, the national prevalence of under five stunting was 38%, which was greater than the developing country average of 25%. Ethiopia's under-five wasting prevalence of 11.9% was also greater than the developing country average of 8.9%.

Though this percentage was slowly declining from 2000 to 2016, the current rate of progress is not fast enough to reach the World Health Organization (WHO) global target of a reduction in the number of stunted children by 2025 [4].

Thus to achieve this global target for 2025 in Ethiopia, a situational analysis is required to determine how many children under age five are malnutrition and to assess key determinants of malnutrition in specific social and geographical locations [5]. This type of analysis will provide evidence for program intervention so that programmatic actions can be tailored to address the contextual needs in Ethiopia Fig 1.

Studies have previously been made to appropriately analyze the childhood stunting and wasting in developing countries including Ethiopia. Unfortunately, most of the analysis have been emphasized on modeling mean regression instead of quantile regression. For instance, the regression studies of risk factors for acute or chronic undernutrition should have used quantile regression instead of mean regression [6]. In fact, even the regression studies for morbidity or mortality should have used quantile regression instead of mean regression [7]. Modeling stunting and wasting using quantile regression is more appropriate than using mean regression because it explained the relationship with extreme childhood nutritional status (i.e moderate and **severe childhood malnutrition**).

The major target of the current study was to perform sensitivity analysis, and use it to analyze the demographic and socio-economic determinants of nutritional status in Ethiopia. Based on the cut-off points for various nutrition indicators according to 2006 WHO growth standards the researcher have been used the weighted mean estimates pooled from quantiles in the interval $\tau = 0.15 \pm 0.05$ which corresponds to $\tau = [0.10, 0.20]$ for modeling childhood stunting and interval $\tau = 0.12 \pm 0.05$ which corresponds to $\tau = [0.07, 0.17]$ for modeling childhood wasting [6].

Methods

Source of data and study population

The source of the data was secondary data obtained from Ethiopian Demography Health Survey, EDHS (2016). All children among age of 6-59 months in Ethiopia, who were participate in the survey were the source of population. A total of 9240 under five children were considered for this study.

Study variables

Variables consider in the current study were based on some previously studies and those that are expected to be factors or determinants of childhood stunting and wasting.

Response variable

Stunting(height-for-age) and wasting(weight-for-height) were considered as the response variable. Z-score (in a standardized form) was used as a continuous variable to maximize the amount of information available in the data set.

Analytical model: Z-score indies of prevalence of malnutrition. The following Z-score is used to carry out the analysis of children's nutritional status [6]. This is represented as

$$Z = \frac{Child's\ measurement - Reference\ median}{Reference\ SD}$$

Where,
Child's measurement = height or weight of a given child at age X
Reference median = mean or 50^{th} percentile of the reference population at age X
Reference SD = standard deviation of the reference population at age X

Explanatory variables

The independent variables were identified based on a conceptual framework developed by UNICEF and previous studies in the area of under-nutrition among children [8, 26, 28]. We have considered both continuous and categorical variables as expected determinants of children malnutrition.

Continuous covariates

Child's age in months (Chag), Mother's age at birth (MAB) and Mother's body mass index (BMI).

Categorical Covariates (as factor coding)

Sex of child (Chsex: 0=female or 1=male), Mother's current work status (MWsts: 0=no or 1= yes), Mother's education level (MED: 0=Illiterate, 1=primary, or 2=secondary and above), Child birth order(Border: 0=First,1=2-4, or 2=>4), Child's size at birth (Chsize: 0=small, 1=average or 2=large), Sex of household head (HHsex: 0=female or 1=male), Locality where child lives (Residence:0=Urban or 1=Rural), Region(1-9 region and 2 city administration), Wealth index (Welnx: 0=poor, 1=medium or 2=rich), Sources of drinking water (Water: 0=not improved or 1=improved), Toilet facility (Toilet: 0=Non improved or1=improved) and Cooking fuel type(Cfuel: 0=Traditional or 1=Modern).

Data cleaning , preparation and management

All available EDHS data sets were not already in the form required by an R-INLA package because the coding style used by EDHS is not compatible with R-INLA. Therefore, prior to data analysis, the researcher performed rigorous data cleaning and preparation for the Bayesian spatial quantile interval regression models. In general, R-INLA approach (R 3.5.1 and R 3.6.1), ENA software , STATA version 14.1, excel, and ArcGIS 10.1 were used for statistical and spatial analysis, respectively.

Method of data analysis

The descriptive analysis was performed using mean, frequency, percentages (cross tabulation), chi-squared test, t-test would be used to summarize, interpret, and to compare childhood nutritional status. Furthermore, the statistical significance of the dummy/discrete variables was tested Using chi-square test and t-test also employed for continuous variables considering the research objective. Bayesian spatial quantile interval models were fitted for stunting, and wasting for years 2016 and were implemented within fully Bayesian framework using R-INLA package to overcome the computational burden experienced in MCMC approaches [9]. By modeling the response as a function of a specified conditional quantile rather than the conditional mean, quantile regression facilitates a complete analysis of the conditional distributional properties of the response variable [10].

Quantile regression (QR) is a statistical tool that extends regression for the mean to the analysis of the entire conditional distribution of the outcome variable [11]. Therefore, location, scale and shape of the distribution can be examined through the analysis of conditional quantile models to provide a complete picture of the distributional effects [12]. Classical linear regression models the conditional mean providing a useful but incomplete summary of a collection of distributions. Quantile regression was meaningful than mean regression because it explained the relationship with extreme childhood nutritional status (i.e moderate and severe childhood malnutrition). As a consequence, compared to standard mean regression model, quantile regression is more robust to outliers and more flexible, because the distribution of the outcome does not need to be strictly specified as certain parametric assumptions.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 in Eq (1).

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

where $Q_{Y_i} \mid x_i,\ z_i$ is the conditional quantile response, $\tau \in (0,1)$ is the response quantile, $j = 1, ..., q$ is number of non-linear or spatial effect, $\eta_{\tau i}$ is semi-parametric predictor evaluated at τ^{th} response quantile level for a given childhood $i, x_i = (x_{i1}, x_{i2}, \cdots, x_{ip})^T$ is the vector of fixed effects categorical covariates for each childhood $i, z_i = (z_{i1}, z_{i2}, \cdots, z_{iq})^T$ is the vector of nonlinear or spatial covariates, $\beta_\tau = (\beta_{\tau 0}, \beta_{\tau 1}, \beta_{\tau 2}, \cdots, \beta_{\tau p})^T$ is the vector of coefficients for categorical covariates together with the baseline intercept at a given τ level, and $g_\tau = (g_{\tau 1}, g_{\tau 2}, \cdots, g_{\tau q})^T$ is the vector of smoothing functions for nonlinear or spatial covariates at a chosen τ level [10, 11, 12].

The unknowns, β_τ and g_τ are estimated using the minimization rule Eq (2)

$$\underbrace{min}_{(\beta_\tau, g_\tau)} \sum \rho_\tau(\eta_{\tau_i}) + \lambda_0||\beta_\tau||_1 + \sum_{j=1}^{q} \lambda_j \vee (\nabla g_{\tau_j}) \tag{2}$$

Where q is the total number of nonlinear and spatial covariates, ρ_τ is the check function (i.e. the loss function) conditioned on the chosen τ level, λ_0 is the constant tuning parameter for all categorical covariates, λ_j represents the tuning parameter to control the degree of smoothness of the function $g_{\tau j}$, $||\beta_\tau||_1 = \sum_{j=1}^{p} |\beta_{\tau j}|$, and $V(\nabla g_{\tau_j})$ is the total variation of the derivative on gradient of function $g_{\tau j}$ [10]

Bayesian posterior inference

Concerned with generating the posterior distribution of the unknown population parameters given both the data and some prior density for these parameters. Let y

be the random observation, Θ is parameter space and p densities the result will be in Eq (3).

$$p(\Theta|y) = \frac{p(y|\Theta)p(\Theta)}{\int p(y|\Theta)p(\Theta)d\Theta} \tag{3}$$

Where, $\Theta = \{g, \beta\}$ which is random, and y=1,2,...,i is child's response vector.
Thus, the posterior distribution can be expressed as :-
$p(\Theta|y) \propto p(y|\Theta)p(\Theta)$ where, $p(y|\Theta)$ is likelihood function, $p(\Theta|y)$ is posterior distribution, and $p(\Theta)$ is prior distribution.

The usual approach for Bayesian inference is to use the Markov chain Monte Carlo (MCMC) simulation techniques. The alternative approach is to use the integrated nested Laplace approximation (INLA) numerical method [9]. Researcher has shown that the INLA method generally converges to the solution faster than MCMC for complex models such as quantile models [9]. For the purpose of our study we would supplement either the RW_1 or RW_2 generated by integrated Wiener processes as priors for metric (nonlinear) co-variates, either ICAR or PCAR or IID as priors for spatial covariates, and either weakly informative Gaussian or log-Gamma or logit-Beta as priors for categorical covariates.

The most fundamental aspect of Bayesian modeling is the selection of appropriate latent models and prior distributions. Therefore, when embarking on Bayesian modeling, it becomes essential to perform sensitivity analysis of latent models and prior distributions in order to select the most appropriate ones. To achieve this task, one needs to firstly identify all potential latent models and prior distributions for a given linear predictor of interest and then compare the resulting models based on fitness, complexity, and speed of convergence.

In this study, the researcher was used DIC, WAIC, and -LML because of the following reasons. The DIC is a Bayesian version of AIC, WAIC is a Bayesian version of CV which is good at estimating predictive loss in Bayesian framework, and LML approximates the Bayesian predictive loss using model evidence whereas CV usually uses train-test split or k-folds approaches which are easily computed in non-Bayesian models but too expensive in terms of computational efforts for Bayesian models as there is no standard way to use these approaches in Bayesian framework, AIC is specifically for non-Bayesian models, BIC is for Bayesian models but usually favours complex models as sample size increases, and BF is Bayesian but appropriate when comparing only two Bayesian models [9].

Results

Descriptive Statistical Analysis

The Descriptive Statistics of Continuous Variables

We have considered 9240 children who have under five aged. The average age of the whole sample children in this study was 31.95 months while the average child age is 34.20 and 34.11 months for stunting and wasting respectively with standard deviation 13.90 and 14.78. Based on the result of Table 1 the ages of children have statistical mean difference between both groups at 1% level of significance. This indicates that when the child age increases the probability of affecting by stunting and wasting is low. The average age of children's mother for the whole sample was around 28.89 years. When the research compared the two groups in terms of their mean age, it was found that malnutrition and non-malnutrition groups have average age of 28.87 and 29.16 years, and 28.9 and 28.79 years respectively for stunting and wasting. Hence, this result shows that the children mother age have significant effect only on children wasting. The result of this survey is similar with [5].

Prevalence of childhood malnutrition for categorical variables
The result of this study shows that, 38% of children under age five are stunted, and 17.6 percent of children are severely stunted (Fig 2). In general, the prevalence of stunting increases as the age of a child increases, with the highest prevalence of chronic malnutrition found in children age increase [5]. Fig 2 and Table 2 shows Male children are slightly more likely to be stunted than female children (40% and 35.9% respectively). The chi-squared test result shows that the household place of residence has significance role for child malnutrition status at 1% level of significance in Ethiopia. As shown in Table 2 from malnutrition children 24.41% and 40.94% stunted children are from urban and rural households. From Fig 3 it was showed that 11.9% of children below age five were wasting or too thin for their height; including 3.4% who are severely wasted the remaining 88.1% were normal.

From the given explanatory variables the chi-square test result implies that child sex, household wealth condition, household residence, household drinking water, toilet quality, type of cooking fuel, mother's education level, size at birth and birth order have significance difference on prevalence of wasting in the study area. Table 3 shows that malnutrition status has significantly difference among regions due to various factors. The result of the survey of EDHS, 2016 shows that 48.65%, 46.43%, and 44.40% were the largest three stunting percentage of Afar, Amhara and Benshangule Gumz regions respectively. On the other hand the highest and lowest value of Wasting was recorded 21.12% by Somali and 2.26% by Addis Ababa in respective order.

Studies are limited in pastoral community of Afar region which is lowest infrastructure and implementation capacity than other regions [33]. The three main causes of stunting in some part of Northern Ethiopia, are poor feeding practices, poor maternal nutrition and poor sanitation. Basically, in Amhara region children living in unsanitary conditions and most of them are inadequate nutrition(not eating enough or eating food that luck growth-promoting nutrients). The there is the luck of care and simulation for development [33]. Ethiopia Somali region is one of the highly impacted areas with most people exposed to shortage of food and water. The drought has also resulted in loss of livestock and hence livelihoods that are already vulnerable have been stretched further [33].

Inferential analysis

Selection of latent models and prior distributions

The assumption of a parametric linear predictor for assessing the influence of covariate effects on responses seems to be rigid and restrictive in practical application situation. Besides, practical experience has shown that continuous covariates often have nonlinear effects. For this study, some effects may be of unknown nonlinear form (such as, **childs age**, **mother's age at first birth** and **mother's BMI**).

Goodness of fit for priors in stunting models

For fixed effects on childhood stunting, the Logit-beta prior had smallest DIC = 35992.54, smallest WAIC = 35992.31, and smallest -LML =18066.12. For these reasons, the researcher concluded that the Logit-beta prior was most appropriate for modeling fixed effects on stunting in Ethiopia [13]. For effects of child's age on stunting, the RW2 prior had smaller DIC = 35758.03, smaller WAIC = 35758.32, and smaller -LML = 17970.99. Consequently, the researcher chose the RW2 prior as the more appropriate one for modeling nonlinear effects of child's age on stunting in Ethiopia [13]. For effects of child's age on stunting,the RW2 prior had smaller DIC =35758.03,smaller WAIC = 35758.32, and smaller -LML = 17970.99. Consequently, the researcher chose the RW2 prior as the more appropriate one for modeling nonlinear effects of child's age on stunting in Ethiopia [13].

For effects of mother's age on stunting, the RW2 prior had smaller DIC = 36643.73, smaller WAIC = 36644.16.32, and smaller -LML = 18376.08. Thus, the researcher chose the RW2 prior as the more appropriate one for modeling nonlinear effects of mother's age on stunting in Ethiopia [13]. For effects of Mother's body mass index on stunting, the RW1 prior had smaller DIC = 36625.74, smaller WAIC = 36626.11, and smaller -LML = 18324.63. For these reasons, the researcher concluded that the RW1 prior was preferred for modeling nonlinear effects of Mother's body mass index on stunting in Ethiopia [13]. For spatial effects on stunting, it was found that the ICAR prior was the most appropriate one because it had smallest DIC = 35291.42, smallest WAIC = 35291.30, and smallest -LML = 16175.32 compared to those for PCAR and IID priors (Table 4).

Goodness of fit for priors in wasting models

For fixed effects on childhood wasting, the Log-gamma prior had smallest DIC =30130.10, smallest WAIC = 30130.11, and smallest -LML =15137.70. For these reasons, the researcher concluded that the Log-gamma prior was most appropriate for modeling fixed effects on wasting in Ethiopia [14]. For effects of child's age on wasting, the RW1 prior had smaller DIC = 30492.94, smaller WAIC = 30493.45, and smaller -LML = 15351.12. Consequently, the researcher chose the RW1 prior as the more appropriate one for modeling nonlinear effects of child's age on wasting in Ethiopia [14].

For effects of mother's age on wasting, the RW2prior had smaller DIC = 31331.51, smaller WAIC =30332.23, and smaller -LML = 15005.57. Consequently, the researcher chose the RW2 prior as the more appropriate one for modeling nonlinear effects of mother's age on wasting in Ethiopia [14]. For effects of mother's BMI on wasting, the RW2 prior had smaller DIC = 30503.02, smaller WAIC = 30503.55, and smaller -LML = 15262.87. For these reasons, the researcher concluded that the RW2 prior was preferred for modeling nonlinear effects of Mother's BMI on wasting in Ethiopia [14]. For spatial effects on wasting, it was found that the PCAR prior was the most appropriate one because it had smallest DIC = 28634.56, smallest WAIC = 28786.01, and smallest -LML = 14351.96 compared to those for ICAR and IID priors (Table 5).

Posterior result of explanatory variables on stunting

Fixed effects on stunting in Ethiopia

The researcher found that rural residence (95% credible interval = (-0.4154, -0.1724) , improved source of drinking water (95% credible interval = (-0.1921, -0.0392) were significantly associated with negative effects on HAZ indicating that they significantly increased stunting in Ethiopia in 2016. The researcher also observed that being female child (95% credible interval = (0.0873, 0.2264), improved type of toilet facility (95% credible interval = (0.2331, 0.4632), wealth index being rich (95% credible interval= (0.2244, 0.4053) and children whose mothers' education were secondary (95% credible interval = (0.1861, 0.4602) were significantly associated with positive effects on HAZ meaning that they significantly decreased stunting in Ethiopia(Table 6). In general, the researcher observed that rural residence, poor source of drinking water, and poor type of toilet facility were significantly associated with reduced HAZ and hence were significantly associated with increased childhood stunting in Ethiopia 2016. Evidently, similar results were observed in this study [13].

Although almost all household wealth indexes were significantly positively 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 [13]. It was noticed that female child associated with decreased childhood stunting in Ethiopia 2016. Finally, the researcher found 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 Ethiopia 2016. This finding consistent with previous study [13]. From (Table 6), intercept($\hat{\beta}_{\tau,0}$)= -0.8032, which is the predicted value of the quantile interval ($\tau = [0.10, 0.20]$) under five children stunting when all the explanatory variables are zero. $\hat{\beta}_{\tau,1}\mathbf{rural} = -0.2943$ indicates the rate of change of the quantile level of children stunting distribution per unit change in the value of the first regressor (rural residence) keeping all the other explanatory variables constant.

Nonlinear effects of age of child, mother's BMI and mother's age on stunting in Ethiopia

Fig 4 shows the summary of observed non linear effects and it displays non linear effect of child's age in month, mother's body mass index, and mother's age in year on stunted for under five years old child data. All continuous variables shows significant effect on stunting status of child under age of five years old. The positive and negative linear effect on stunting at lower level of mother body mass index and age of child respectively. And in addition, the non linear effect mother's age on adjusted childhood height for age (stunted) is negative non linear effect and generally followed as **U-shaped** relationship. As a result, childhood stunting sharply increased during the first 20 months of the child, then steadily continued increasing from 20 months up to 44 months after which it started it decreased.

Incremental Spatial Autocorrelation of stunting

To determine spatial clustering for stunting, global spatial statistics were estimated using Moran's I value [14]. As shown in Fig 5, a statistically significant Z-score indicated at 357.42 km distances, where spatial processes promoting clustering are most pronounced. The incremental spatial auto-correlation indicated that a total of 10 distance bands were detected with a beginning distance of 36832.00000 meters.

Spatial Interpolation of stunting

The researcher used ordinary Kriging geostatistical interpolation for the prediction of stunting prevalence of unsampled areas [14]. Based on geostatistical Kriging analysis, in 2016 EDHS, the red color indicates that the risk of sever stunting in Afar, some part of Amhara, and Benshangul had a prevalence of moderately stunting to prevalence of sever stunting Fig 6.

The statistical model forms of all fitted models on **stunting** were formulated as:

$$\eta_\tau = \beta_{\tau,0} + \beta_{\tau,1}\mathbf{rural} + \beta_{\tau,2}\mathbf{water} + \beta_{\tau,3}\mathbf{toilet} + \beta_{\tau,4}\mathbf{csex} + \beta_{\tau,5}\mathbf{secondary} + \beta_{\tau,6}\mathbf{richer}$$
$$+ f_{\tau,1}(\mathbf{cage}) + f_{\tau,2}(\mathbf{Mage}) + f_{\tau,3}(\mathbf{MBMI}) + f_{\tau,4}(\mathbf{region}) \quad for \quad \tau = 0.10, 0.11, \cdots, 0.20$$

where η_τ is the linear predictor, $\beta_{\tau,0}$ is the overall model intercept, $\beta_{\tau,p}$, . are the coefficients of all fixed effects covariates, f_τ, . are the smoothing functions of all nonlinear and structured spatial effects for each τ

Posterior result of explanatory variables on wasting

Fixed effects on wasting in Ethiopia

Table 7 summarizes the fixed effects together with their 95% credible intervals in Ethiopia in 2016 based on selected priors. Since the response was WHZ, negative effects on WHZ corresponded to reduced height-adjusted weight of child and hence implied positive effects on wasting. Similarly, positive effects on WHZ implied negative effects on childhood wasting. All the fixed effects (whether negative or positive) were significant because all their 95% credible intervals did not include zero (i.e. were either entirely negative or entirely positive). From (Table 7) the researcher observed that rural residence (95% credible interval = (-0.2045, -0.0275) , improved source of drinking water (95% credible interval = (-0.0741 , -0.0143) were significantly associated with negative effects on WHZ indicating that they significantly increased wasting in Ethiopia in 2016.

Also the researcher noticed that being female child (95% credible interval = (0.0482, 0.1487), improved type of toilet facility (95% credible interval = (0.0345, 0.1223), traditional cooking fuel type (95% credible interval= (0.1740, 0.4485) were significantly associated with positive effects on WHZ meaning that they significantly decreased wasting in Ethiopia. In addition, the researcher observed that middle households (95% credible interval = (0.2173, 0.3632)) and richer households (95% credible interval = (0.0605, 0.1830)) were significantly associated with positive effects on WHZ indicating that they significantly raised wasting in Ethiopia. Similarly, children whose mothers' highest education were primary (95%credible interval = (0.0747, 0.1936) and secondary (95% credible interval = (0.0933, 0.2921) were significantly associated with positive effects on WHZ indicating that they significantly decreased wasting in Ethiopia.

In general, the researcher observed that rural residence, poor source of drinking water, and poor type of toilet facility were significantly associated with reduced WHZ and hence were significantly associated with increased childhood wasting in Ethiopia 2016. Evidently, similar results were observed in this study [13]. It was noticed that female child associated with decreased childhood wasting in Ethiopia 2016. Finally, the researcher found that households with less educated mothers (secondary or below) were significantly negatively associated with WHZ whereas households with more educated mothers (graduates) were significantly associated with positive WHZ which implied that the children of more educated mothers were likely not wasted in Ethiopia 2016. This finding evens the finding in earlier (previous) study [13]. From (Table 7), intercept($\hat{\beta}_{\tau,0}$)= -0.8105, which is the predicted value of the quantile interval ($\tau = [0.07, 0.17]$) under five children wasting when all the explanatory variables are zero. $\hat{\beta}_{\tau,1}$**rural** $= -0.1163$ indicates the rate of change of the quantile level of children wasting distribution per unit change in the value of the first regressor (rural residence) keeping all the other explanatory variables constant.

Nonlinear effects of age of child, mother's age and mother's BMI on wasting in Ethiopia

The negative non linear effect on wasting at lower level of mother age and age of child. And in addition, the non linear effect child's age on adjusted childhood weight for height (wasting) is negative non linear effect and it seems to like reciprocal of **U-shaped**. As a result, the non linear effect of mother's body mass index is slightly positive non linear effect on wasting Fig 7.

The statistical model forms of all fitted models on **wasting** were formulated as:

$$\begin{aligned}\eta_\tau = \beta_{\tau,0} + \beta_{\tau,1}\mathbf{rural} + \beta_{\tau,2}\mathbf{water} + \beta_{\tau,3}\mathbf{toilet} + \beta_{\tau,4}\mathbf{csex} + \beta_{\tau,5}\mathbf{cooking} + \beta_{\tau,6}\mathbf{middle}\\ +\beta_{\tau,7}\mathbf{richer} + \beta_{\tau,8}\mathbf{primary} + \beta_{\tau,9}\mathbf{secondary} + f_{\tau,1}(\mathbf{cage}) + f_{\tau,2}(\mathbf{Mage})\\ +f_{\tau,3}(\mathbf{MBMI}) + f_{\tau,4}(\mathbf{region}) \quad for \quad \tau = 0.07, 0.08, \cdots, 0.17\end{aligned}$$

Incremental Spatial Autocorrelation of wasting

To determine spatial clustering for wasting, global spatial statistics were estimated using Moran's I value [14]. As shown in Fig 8, a statistically significant Z-score indicated at 357.42 km distances, where spatial processes promoting clustering are most pronounced. The incremental spatial autocorrelation indicated that a total of 10 distance bands were detected with a beginning distance of 36832.00000 meters.

Spatial Interpolation of wasting

The researcher used ordinary Kriging geostatistical interpolation for the prediction of wasting prevalence of unsampled areas [14]. Based on geostatistical Kriging analysis, in 2016 EDHS, Afar, Somali, some part of Amhara, some part of Benshagul gumz, and some parts of Tigray had a prevalence of sever wasting than to the prevalence of wasting from other regions Fig 9.

Discussion

The prevalence of childhood malnutrition (stunting and wasting), and associated factors in Ethiopia was assessed. The prevalence of stunting and wasting was 38% (Fig 2) and 11.9% (Fig 3) respectively. This prevalence was consistent with the previous study reported in Ethiopia DHS 2016 year [14]. In general, the current study results show place of residence, drinking water, child age, child sex, mothers' educational status, mother's body mass index, wealth index, mother's age, region, and toilet types had significant association with stunting and wasting where as household sex, mother's working status, birth order, and age at first birth are not statistically significant association.

Age of the child was found to be significantly associated with nutritional status, as the age of child increases the risk of being malnourished increases. This finding is in line with studies done in Ethiopia such as [15, 16]. The reason might be greater energy needs as child age increased. Besides, this could be due to stunting is a chronic malnutrition that can be manifested after long-term nutritional deficiency and wasting reflects acute under-nutrition. Female children were less likely to be stunted and wasted than boys. This finding is consistent with a meta-analysis in SubSaharan Africa [17], a study in the Northern Ethiopia [18] and in Myanmar [19]. However, this study is in contrary to studies in Tanzania [20], Pakistan [21], India [22], and Kenya [23] that found girls had a higher prevalence in stunting than boys.

Children whose mothers had secondary educational level were significantly positively association stunting and wasting. This finding was consistent with the study conducted in Ethiopia [5] and Bangladesh [24] which showed that as mothers' educational level increase, the risk of the children to be stunting and wasting will be decreased. Mothers with BMI less than 18.5 (underweight) were more risk have to have stunting and wasting children as compared to overweight mothers. This finding is similar with other previously conducted studies [25, 26].

The current study indicated that the place of residence (rural) was associated with significant effects of malnutrition (stunting and wasting). This finding evens the finding(s) in earlier (previous) studies [27, 28]. A household's source of drinking water has been shown to be associated with malnutrition of a child in Nigeria (weight-for-height) in separate analysis [29], and that this study has also emphasized the significant of this factor of risk of malnutrition (stunting and wasting).

This study showed association between malnutrition (stunting and wasting) was varies across regions due to variation in cultivated area, traditional living habit, education sector, helth facility and this finding is similar with some developing countries [30]. This study revealed that the levels of wasting status had a significant regional variation ranging from 2.26% in Addis Ababa to over 21.12% in somali regions of the country. This finding is contrary with [5]. This could be due to wasting is characterized by acute malnutrition that can be caused by temporary increased food insecurity from extreme weather events, drought, and shifts in agricultural practices [30].

In the EDHS survey households' wealth were usually measured by increments in household material standards by calculating wealth index. Previous studies in Nepal [23] found that household asset accumulation is an important predictors of nutritional improvement in most countries. The current study found that children from non-improved toilet households were more likely to be stunted. The current study found that children from non-improved toilet and traditional fuel user households were more likely to be wasted. This finding is consistent with [31]. Study [32] noticed U-shaped patterns of effects of age of child on stunting was contrary with the finding researcher observed in this current study because the current study showed the U-shaped patterns of mother's age on stunting. In addition, [32] noticed U-shaped patterns of effects of age of child on wasting which was contrary with the finding researcher observed in this current study because the current study showed that reciprocal of U-shaped patterns of effects of age of child on wasting.

Conclusion

This study was focused on performance of sensitivity analysis on selection of latent models and prior distributions, finding the prevalence, and factors associated with nutritional status of under five years children. Despite efforts made by the Ethiopian government and improvements in reducing malnutrition, rates of stunting and wasting remain high. The findings imply that a multi-sectorial and multidimensional approach is important to address malnutrition in Ethiopia. Thus, the improvement of nutritional status of children requires multi-factorial interventions such as reducing poverty, and educating mothers and their partners. In addition, improving living standards of children is important to get a better health care, reduces child malnutrition, and child mortality. Geographical targeting is important to increases efficiency, allocating more resources to the risky groups, has the potential to maximize program coverage, has low administrative costs, and minimizes the potential for fraud.

Abbreviations

BMI:Body Mass Index; DIC: Deviance Information Criteria;HAZ: Height (for) Age Z-score; ICAR: Intrinsic Conditional AutoRegressive; IID: Independent (and) Identically Distributed; INLA:Integrated Nested Laplace Approximation; LML: Log Marginal Likelihood; RW1:Random Walk (order) 1; RW2: Random Walk (order) 2; UNICEF:United Nations Childrens Fund; WAIC:Watanabe-Akaike Information Criterion; WHO:World Health Organisation; WHZ: Weight (for) Height Z-score.

Declarations

Ethics approval and consent to participate

The protocol for the 2016 EDHS was approved by the Research Ethics Review Committee of College of Natural and Computational Sciences of Hawassa University with reference number RERC/004/2020. Authors have made download survey data-sets from online publicly available at $https://www.dhsprogram.com/data/dataset/Ethiopia\_Standard-DHS\_2016.cfm?flag = 0$. Obviously, researchers have right to access such data-sets for academic purpose and scientific publications.

Consent for publication

Not applicable.

Availability of data and material

The data-sets analyzed during the current study are publicly available at $https://dhsprogram.com/data/dataset/Ethiopia\_Standard - DHS\_2016.cfm?flag = 0$.

Competing interests

The authors declare that no competing interests.

Funding

This study had very limited funding for only data collection by the College of Natural and Computational Science, Hawassa University, Hawassa, Ethiopia.

Author's contributions

Both authors AH and ZGA generated the idea, the first author AH contributed in the data analysis and interpretation, ZGA contributed as an advisory for the entire phase of the study. Both authors read and approved the final manuscript.

Acknowledgments

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Author details

[1]Department of Statistics, Samara University, Samara, Ethiopia. [2]Department of Statistics, Hawassa University, Hawassa, Ethiopia.

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Figures

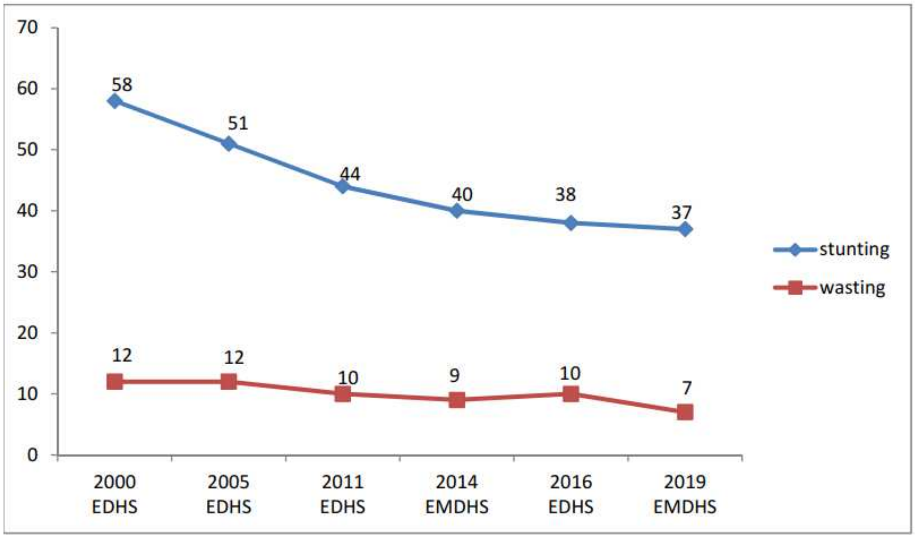

Figure 1 Percentage of children under age 5 who are stunted and wasted in Ethiopia from 2000-2019

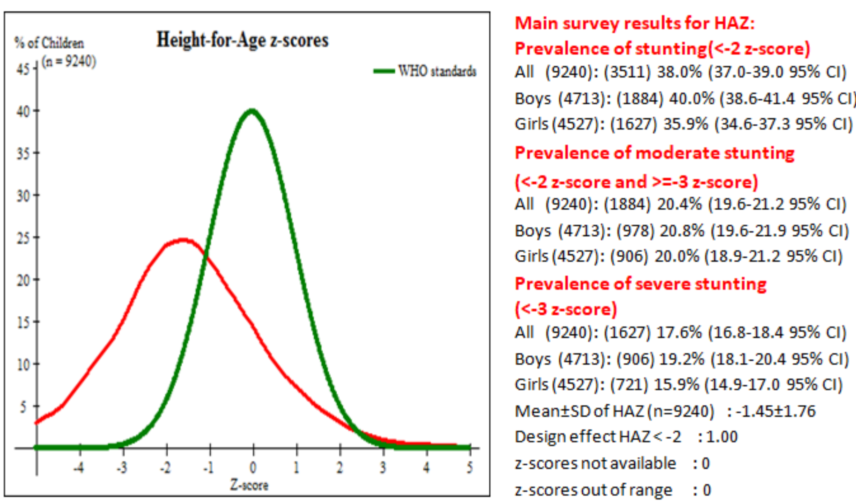

Figure 2 Height-for-Age Z-score(stunting)

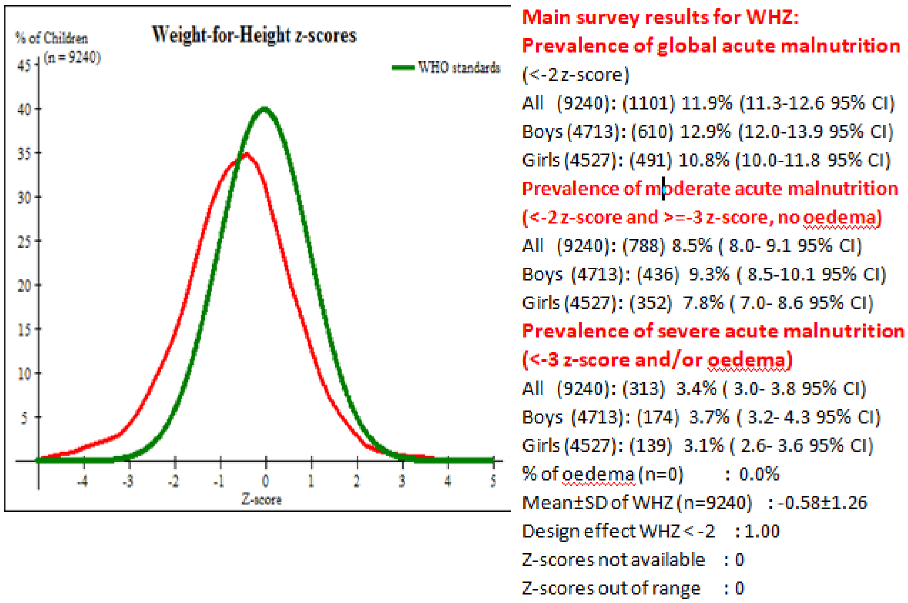

Figure 3 Weight-for-Height Z-score(wasting)

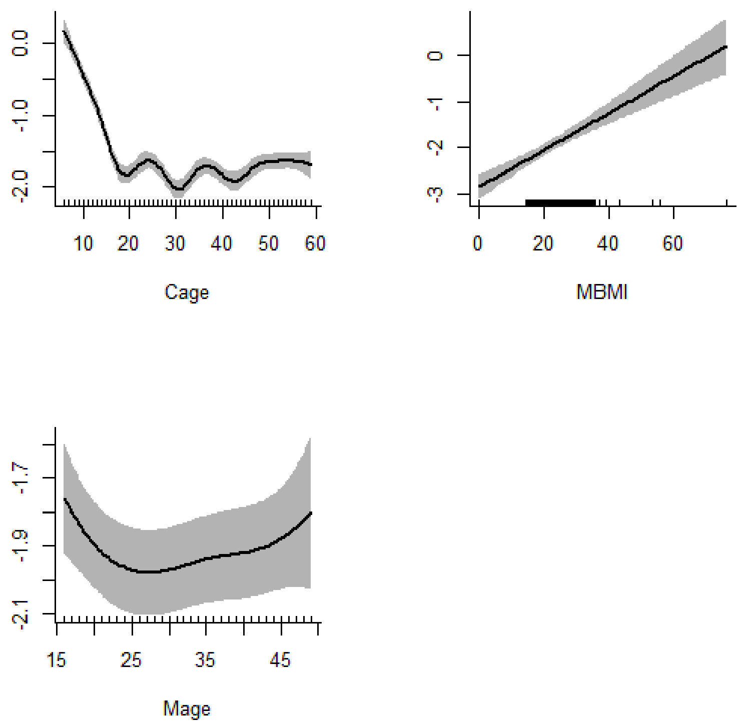

Figure 4 Nonlinear effects of age of child, mother's BMI , and mother's age on stunting

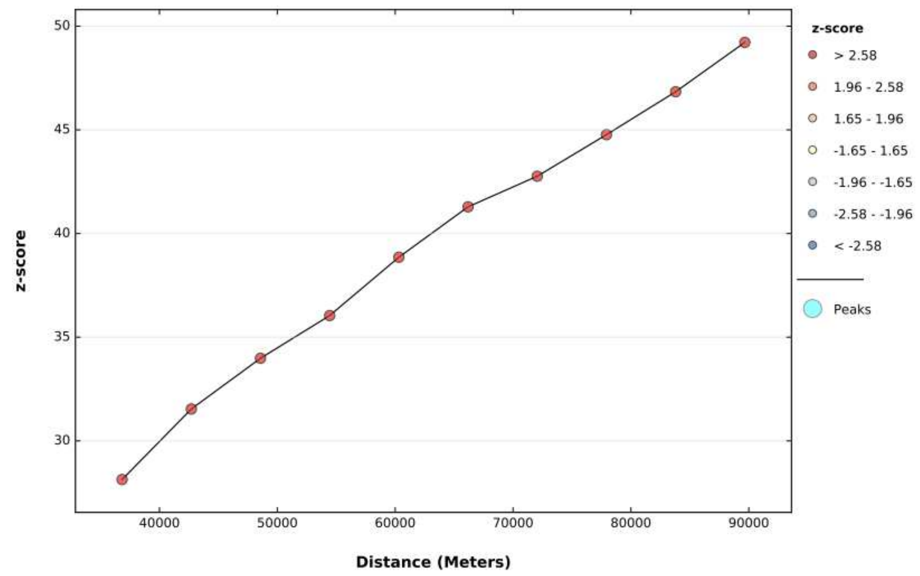

Figure 5 Spatial incremental autocorrelation of stunting in Ethiopia, EDHS 2016

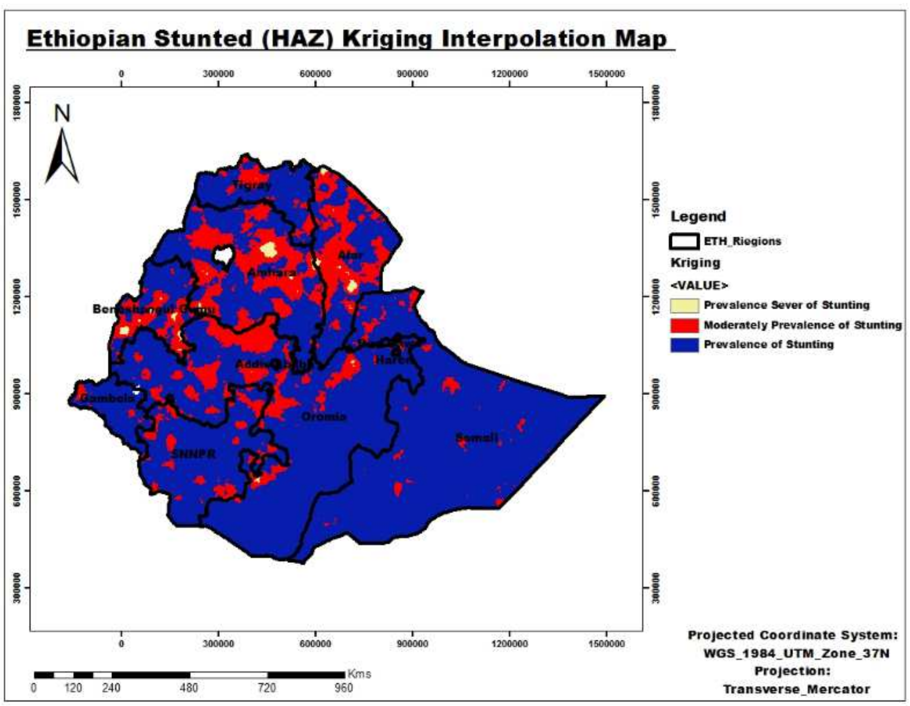

Figure 6 Spatial interpolation of stunting among child's in Ethiopia, EDHS 2016

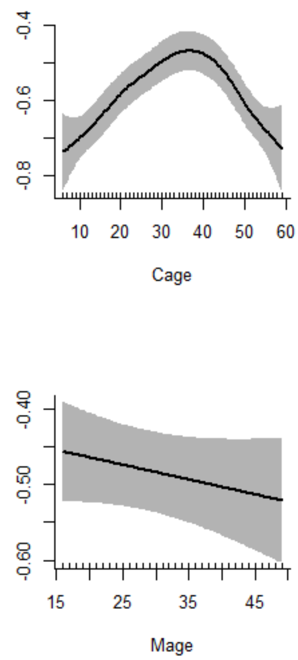

Figure 7 Nonlinear effects of age of child, mother's BMI, and mother's age on wasting

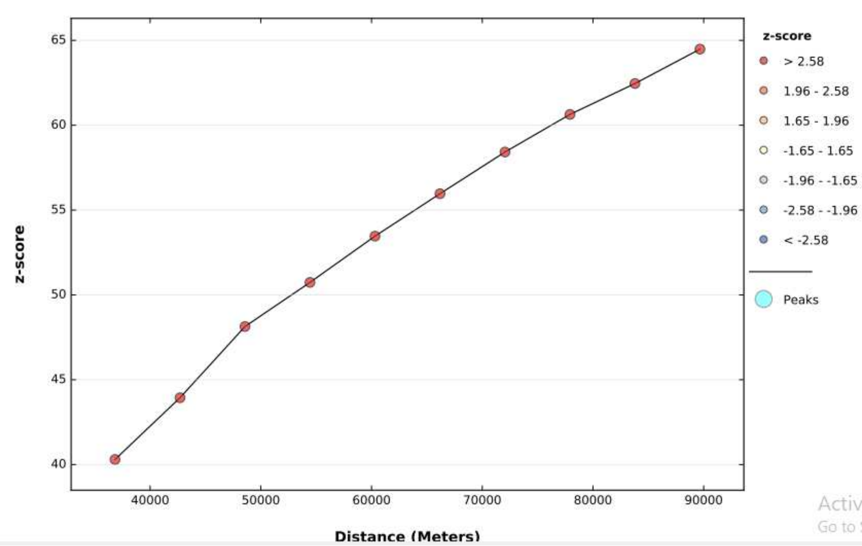

Figure 8 Spatial incremental auto-correlation of wasting in Ethiopia, EDHS 2016

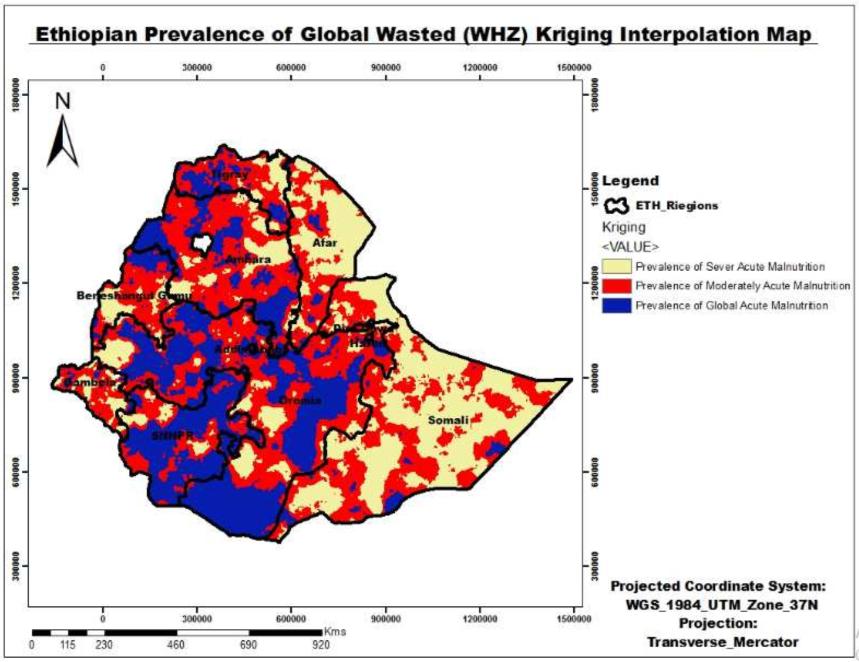

Figure 9 Spatial interpolation of wasting among child's in Ethiopia, EDHS 2016

Table 1 Descriptive statistics for continuous variables

	Normal(5729)	stunting(3511)	Combined(9240)	
Variables	Mean(Std.)	Mean(Std.)	Mean(Std.)	t-value
HHAge	38.61(12.29)	38.78(12.31)	38.68(12.30)	-0.64
Cage	30.57(16.43)	34.20(13.90)	31.95(15.62)	-10.92***
Mage	28.90(8.57)	28.87(8.36)	28.89(8.49)	0.16
MBMI	21.82(3.29)	21.51(3.06)	21.70(3.20)	4.61***
Age-fb	18.16(3.27)	18.30(3.29)	18.22(3.28)	-1.99**
	Normal(6863)	wasting(2377)	Combined(9240)	
Variables	Mean(Std.)	Mean(Std.)	Mean(Std.)	t-value
HHAge	8.71(12.34)	38.57(12.19)	38.68(12.30)	0.49
Cage	31.21(15.83)	34.11(14.78)	31.95(15.62)	-7.84***
Mage	28.79(8.53)	29.16(8.38)	28.89(8.49)	-1.79*
MBMI	21.80 (3.26)	21.44(3.01)	21.70(3.20)	4.74***
Age-fb	18.16(3.22)	18.38(3.43)	18.22(3.28)	-2.83***

Source EDHS, 2016

∗ ∗ ∗, ∗∗ and ∗ means statistically significant at 1%, 5% and 10% level of significance

Table 2 Descriptive statistics for Categorical variables

Variables		Stunting (< -2HAZ) n(%)	p-value	Wasting (< -2WAZ) n(%)	p-value
Combined		3511(38.00)		1101(11.9)	
Residence	Urban	401(24.41)		149(9.07)	
	Rural	3110(40.94)	0.00*	952(12.53)	0.00*
HHsex	Male	2779(38.31)		828(11.44)	
	Female	737(36.85)	0.23	273(13.65)	0.01**
Dwater	Non-Imroved	1524(10.91)		502(13.48)	
	Improved	1987(36.03)	0.00*	599(10.86)	0.00*
Toilet	Non-Improved	3143(40.82)		969(12.58)	
	Improved	368(23.90)	0.00*	132(8.87)	0.00*
CgFuiel	Tradition	3442(39.31)		1086(12.40)	
	Modern	69(14.29)	0.00*	15(3.11)	0.00*
Wealth	Poor	2207(42.39)		786(15.10)	
	Midium	550(36.96)		138 (9.27)	
	Rich	754(29.62)	0.00*	177(6.95)	0.00*
Csex	Male	1884(40.00)		610 (12.94)	
	Female	1627(35.9)	0.00*	491 (10.85)	0.00*
Border	First	598(33.50)		186 (10.42)	
	2-4	1526(36.84)		47 (11.35)	
	≥ 5	1387 (41.87)	0.00*	445(13.43)	0.00*
Sizebi	Small	928(36.61)		325(12.82)	
	Average	1501(38.56)		479 (12.30)	
	Large	1082 (38.48)	0.24	297(10.56)	0.02**
Mowork	No	2559(38.05)		798(11.96)	
	Yes	972(37.85)	0.86	303(11.80)	0.83
Moedu	No.edu	2513(41.93)		806(73.21)	
	Primray	799 (34.66)		230 (20.89)	
	$\geq$Secondary	199(21.13)	0.00*	65(5.90)	0.00*

Source EDHS, 2016

$***$, $**$and $*$ means statistically significant at 1%, 5% and 10% level of significance

Table 3 Status of Malnutrition by regions

Region	Stunting n	Stunting %	Wasting n	Wasting %
Tigray	389	41.21	102	10.81
Afar	434	48.65	158	17.71
Amhara	429	46.43	88	9.52
Oromiya	525	37.58	140	10.02
Somali	377	30.50	261	21.12
Benshangul	329	44.40	94	12.69
SNNP	463	39.67	71	6.08
Gambela	172	27.74	96	15.48
Hareri	162	35.14	43	9.33
Addis Ababa	51	12.81	9	2.26
Diredawa	180	39.13	39	8.48
Total	**3511**	**38.00**	**1101**	**11.90**

Source EDHS, 2016

Table 4 Measures of goodness of fit for priors on stunting

Effects	Prior	DIC	WAIC	- LML
Fixed	Gaussian	35992.55	35992.32	18068.89
	Logit-beta	35992.54	35992.31	18066.12
	Log-gamma	35992.56	35992.33	18067.14
Age of child	RW1	35772.34	35772.42	17972.23
	RW2	35758.03	35758.32	17970.99
Mother's body mass index	RW1	36625.74	36626.11	18324.63
	RW2	36625.77	36626.13	18325.55
Mother's Age	RW1	36664.23	36664.65	18637.74
	RW2	36643.73	36644.16	18376.08
Spatial	ICAR	35291.42	35291.30	16175.32
	PCAR	36210.14	36220.28	18080.40
	IID	36292.33	36292.46	18183.32

Table 5 Measures of goodness of fit for priors on wasting

Effects	Prior	DIC	WAIC	- LML
Fixed	Gaussian	30130.12	30130.67	15141.48
	Logit-beta	30130.12	30130.67	15138.57
	Log-gamma	30130.10	30130.11	15137.70
Age of child	RW1	30492.94	30493.45	15351.12
	RW2	30521.19	30521.31	15416.42
Mother's body mass index	RW1	30503.03	30503.57	15263.79
	RW2	30503.02	30503.55	15262.87
Mother's Age	RW1	31417.78	30431.20	15336.56
	RW2	31331.51	30332.23	15005.57
Spatial	ICAR	29637.31	29640.32	14893.23
	PCAR	28634.56	28786.01	14351.96
	IID	30009.78	30010.35	15043.05

Table 6 Fixed effects on stunting in Ethiopia in 2016

Covariates	Posterior mean	95%credible interval
(Intercept)	-0.8032	[-0.9633, -0.6433]
Rural	-0.2943	[-0.4154, -0.1724]
Water	-0.1164	[-0.1921, -0.0392]
Toilet	0.3481	[0.2331, 0.4632]
Female child	0.1562	[0.0873, 0.2264]
Wealth(rich)	0.3154	[0.2244, 0.4053]
M.education(secondary)	0.3234	[0.1861, 0.4602]

Table 7 Fixed effects on wasting in Ethiopia in 2016

Covariates	Posterior mean	95%credible interval
(Intercept)	-0.8105	[-0.9262, -0.6943]
Rural	-0.1163	[-0.2045, -0.0275]
Water	-0.0186	[-0.0741 , -0.0143]
Toilet	0.040	[0.0345, 0.1223]
Cooking	0.3114	[0.1740, 0.4485]
Female child	0.0985	[0.0482, 0.1487]
Wealth(middle)	0.2901	[0.2173, 0.3632]
Wealth(rich)	0.3834	[0.0605, 0.1830]
M.education(primary)	0.121	[0.0747, 0.1936]
M.education(secondary)	0.1932	[0.0933, 0.2921]

Figures

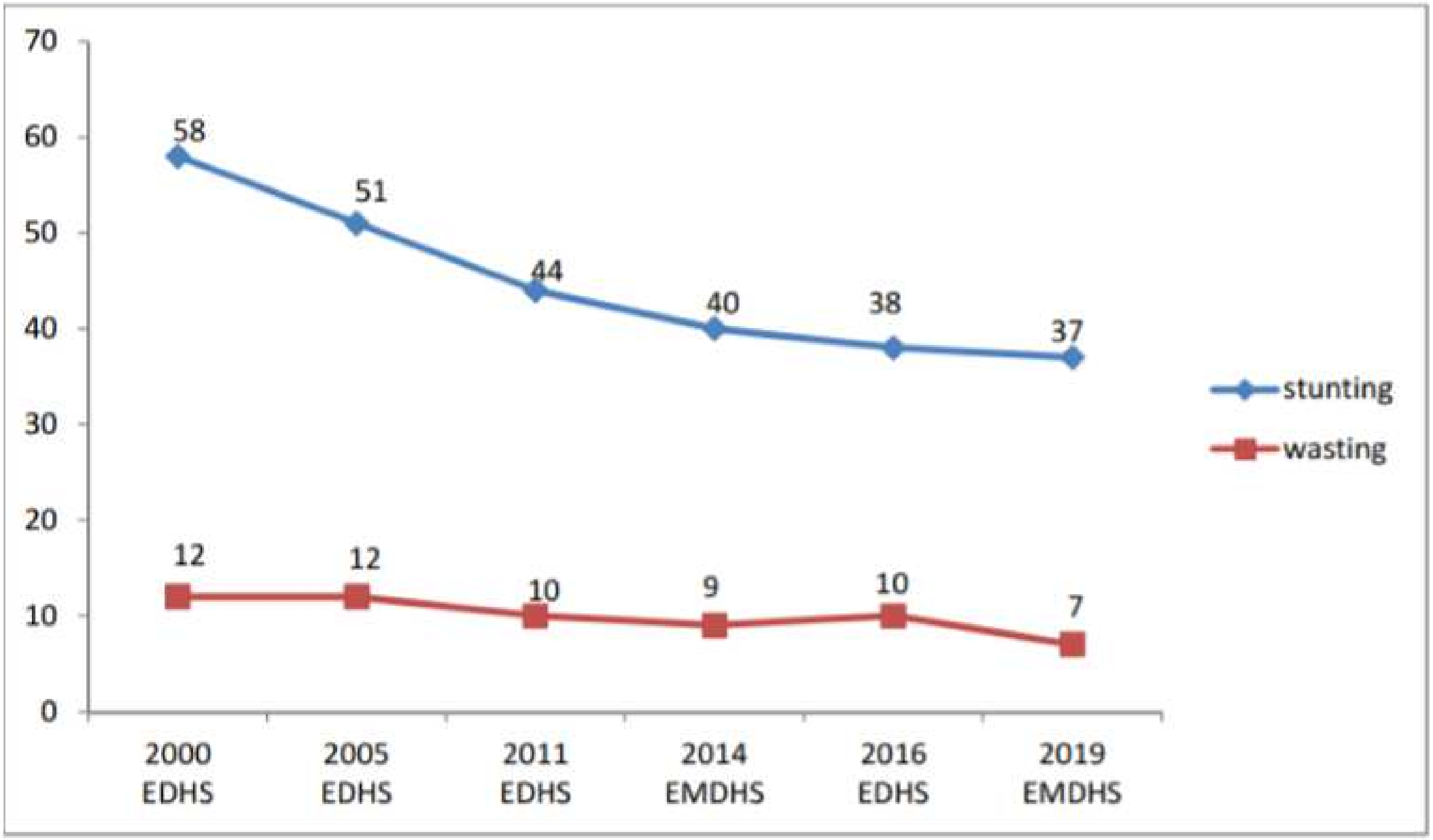

Figure 1

Percentage of children under age 5 who are stunted and wasted in Ethiopia from 2000-2019

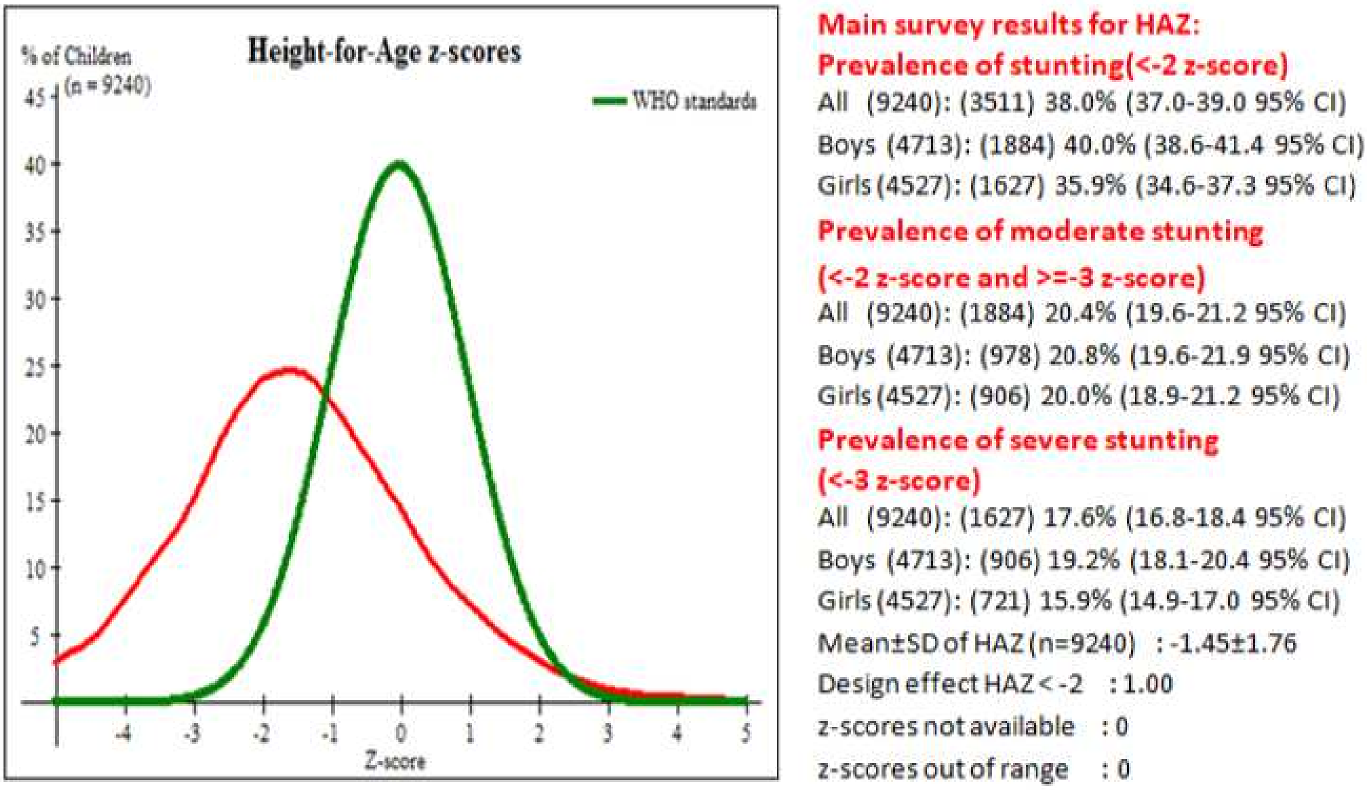

Figure 2

Height-for-Age Z-score(stunting)

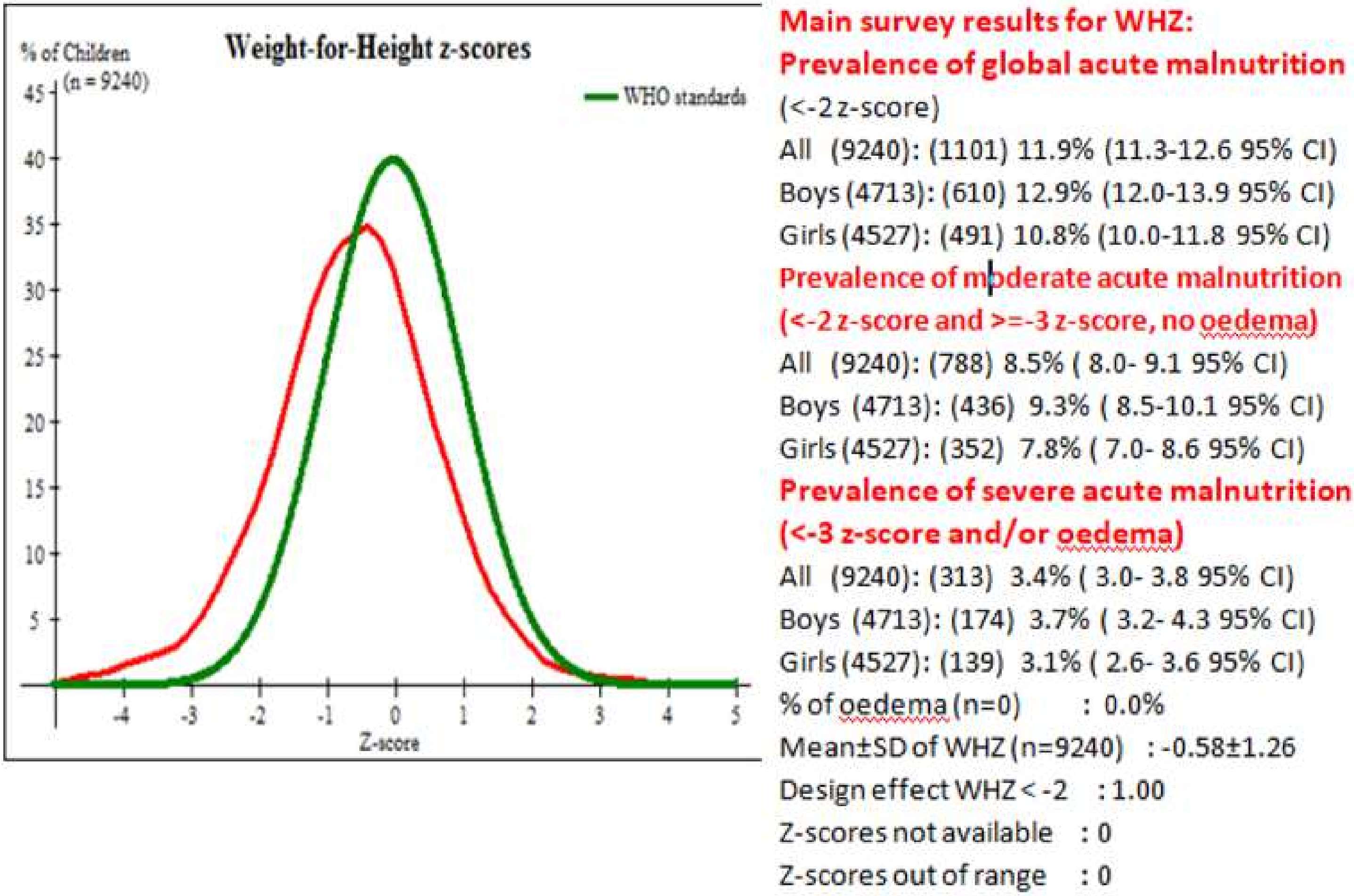

Figure 3

Weight-for-Height Z-score(wasting)

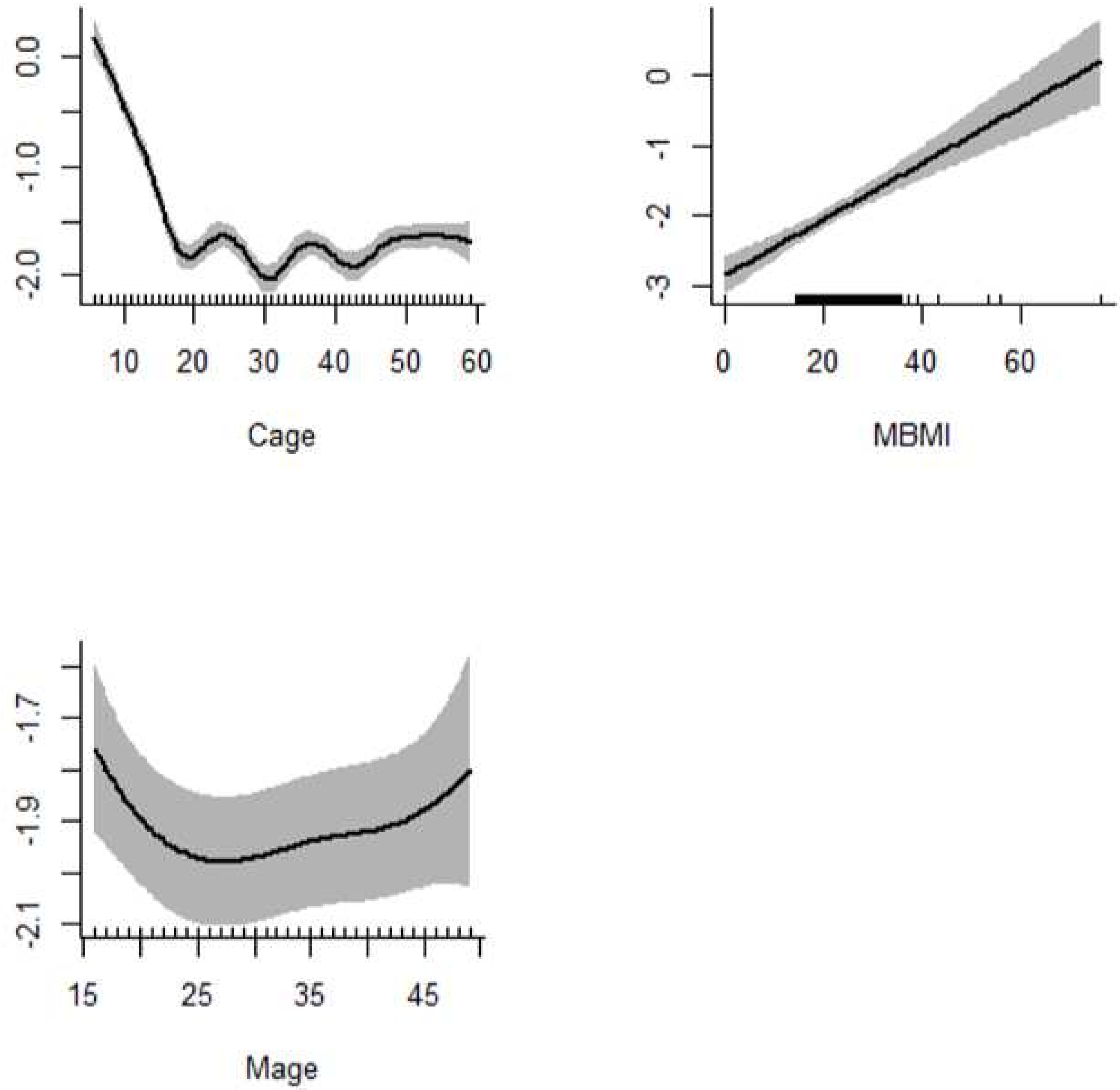

Figure 4

Nonlinear effects of age of child, mother’s BMI , and mother’s age on stunting

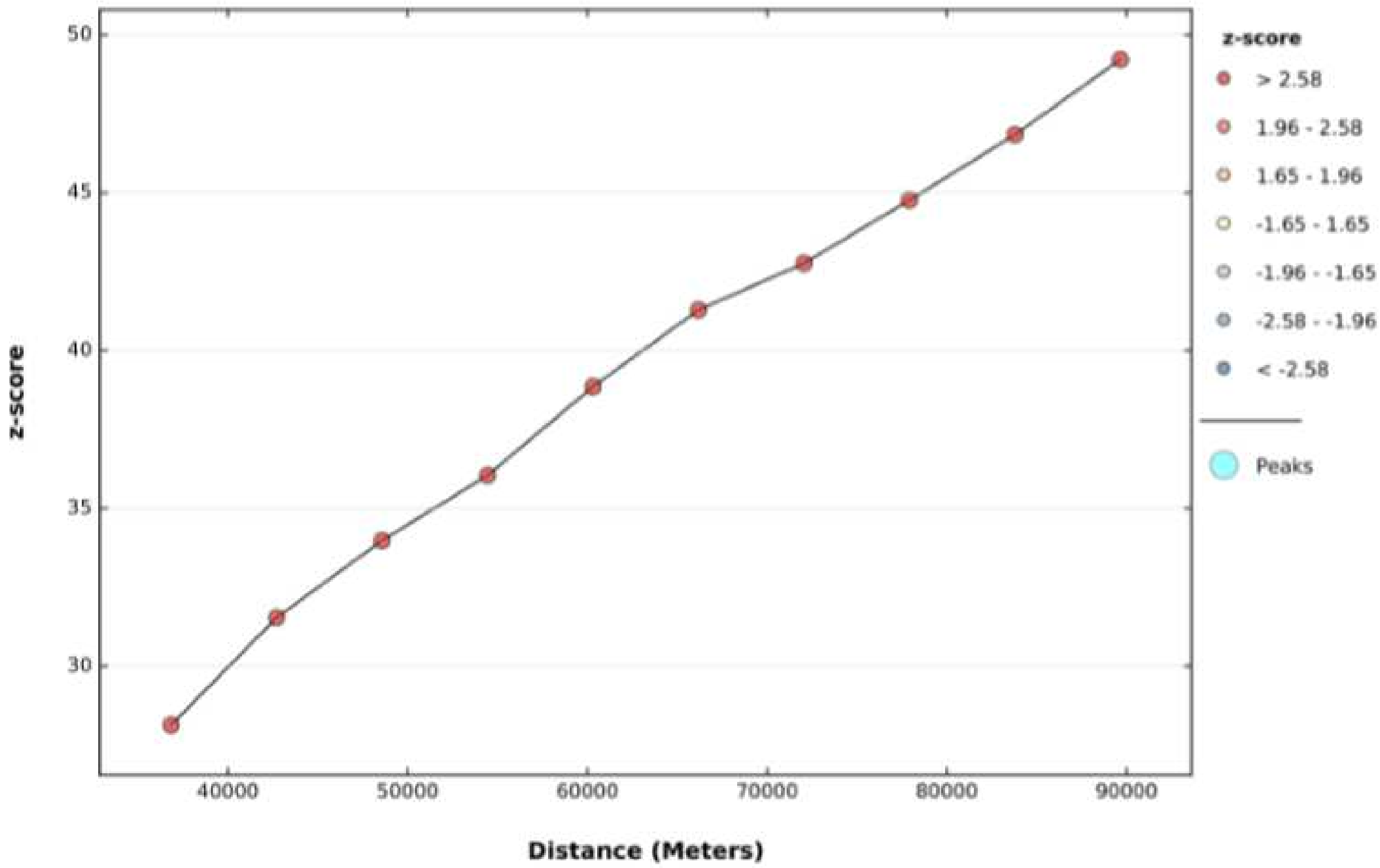

Figure 5

Spatial incremental autocorrelation of stunting in Ethiopia, EDHS 2016

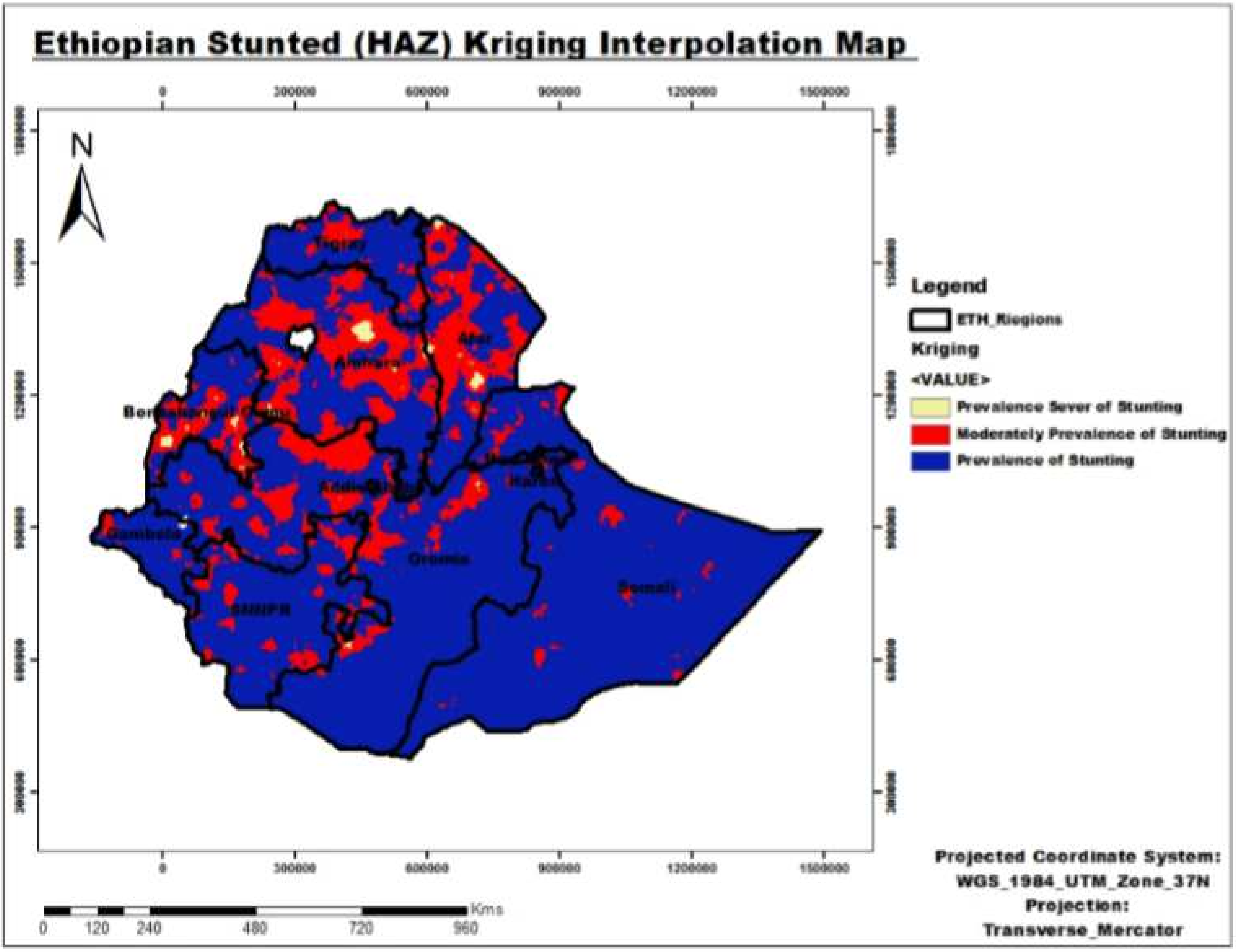

Figure 6

Spatial interpolation of stunting among child's in Ethiopia, EDHS 2016

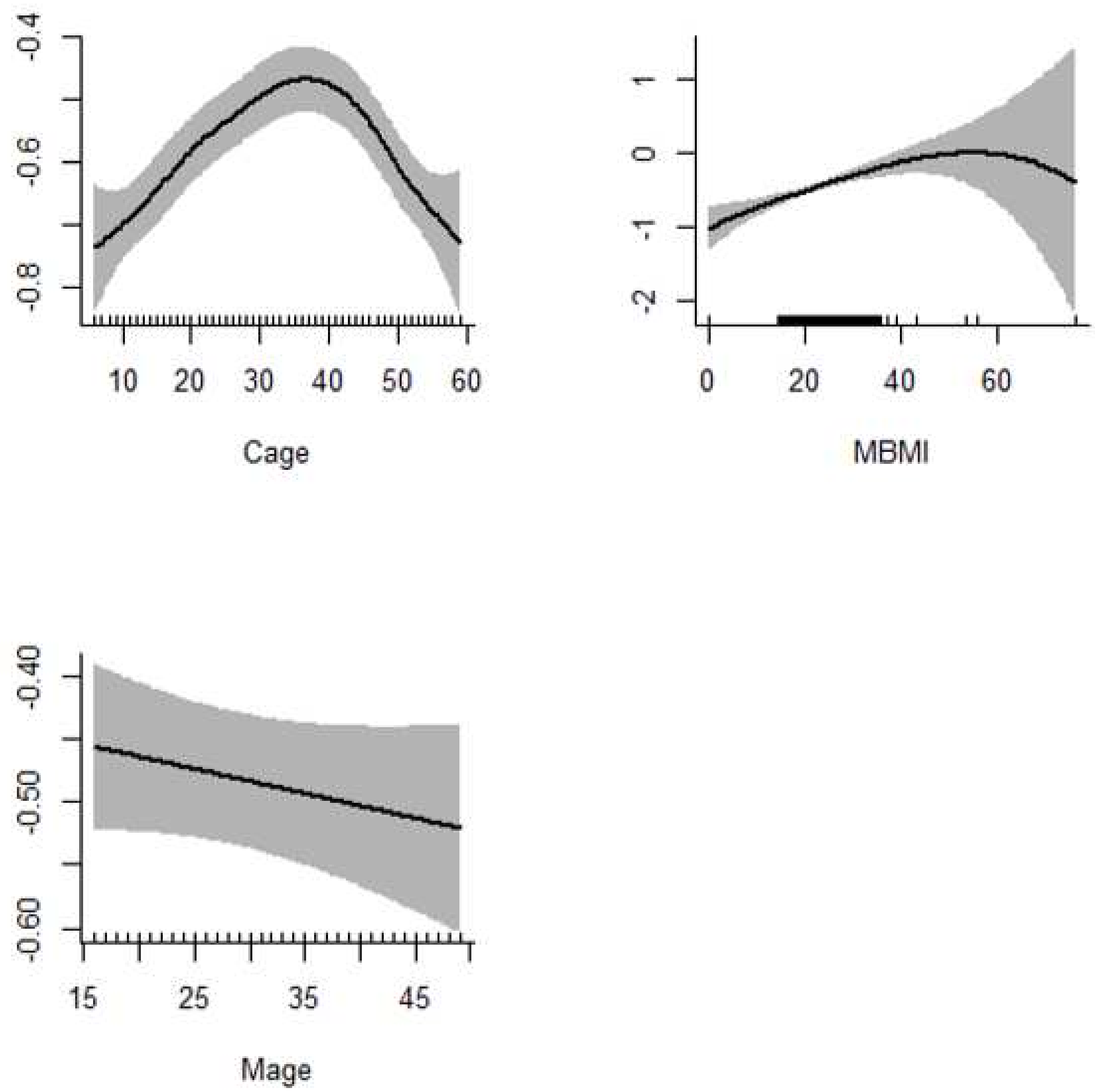

Figure 7

Nonlinear effects of age of child, mother’s BMI, and mother’s age on wasting

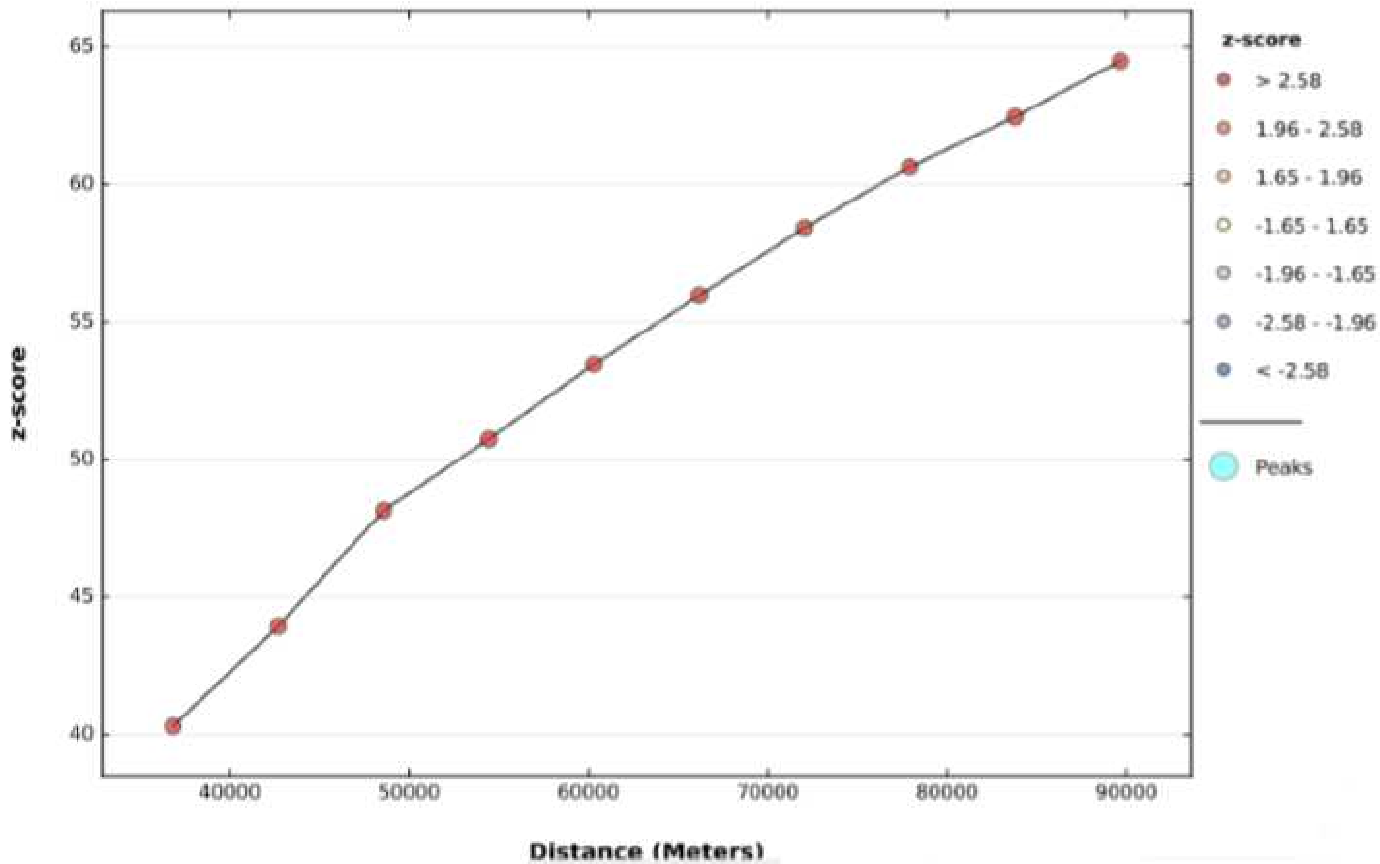

Figure 8

Spatial incremental auto-correlation of wasting in Ethiopia, EDHS 2016

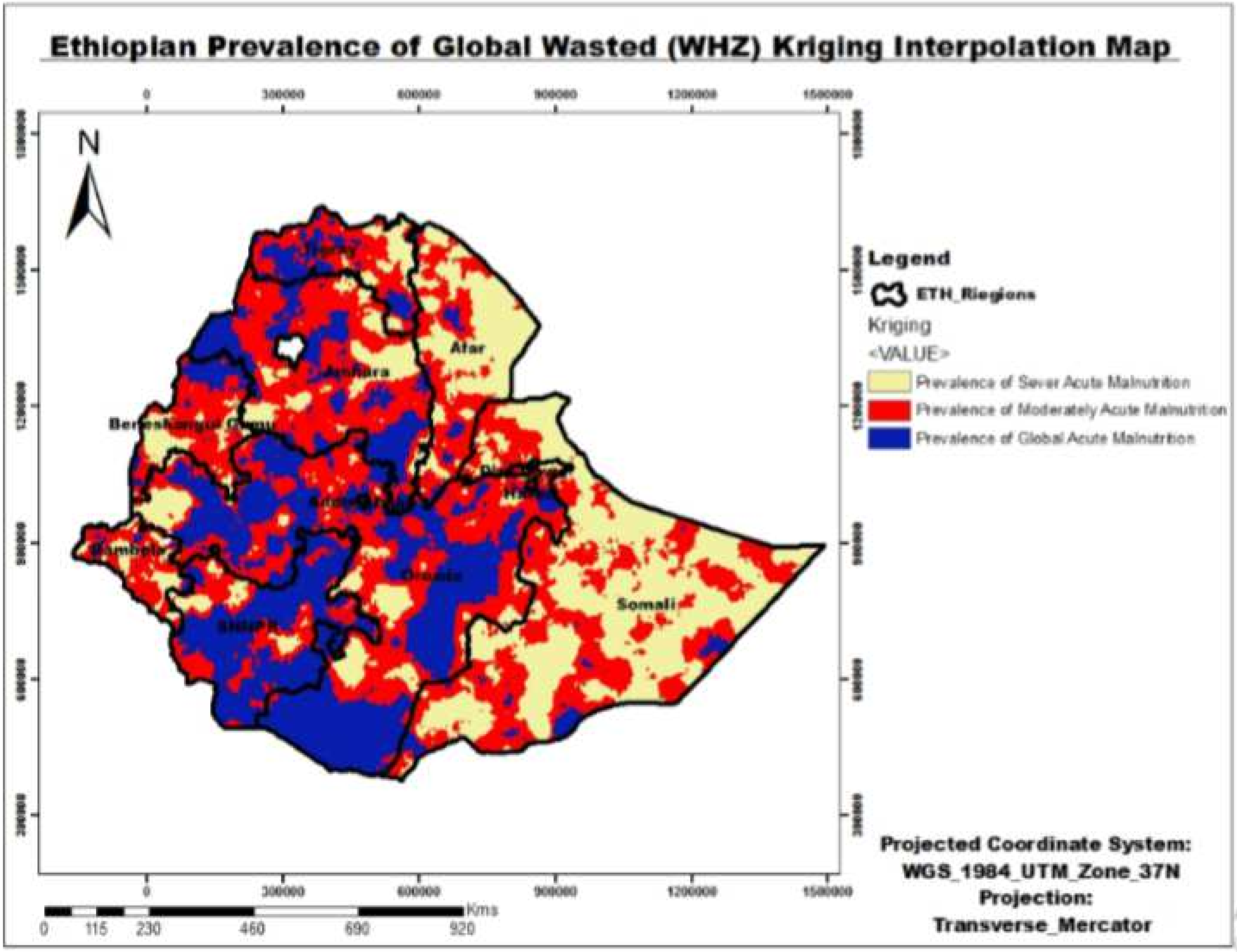

Figure 9

Spatial interpolation of wasting among child's in Ethiopia, EDHS 2016