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Spatial Joint Modelling of Children Under-Five Malnutrition in Ethiopia

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ABSTRACT Malnutrition robs children of their futures and leaves young lives being uncertain. The nutritional reputation of children in Ethiopia is still in an alarming scenario as in most developing countries. The central objective of this research was to identify the determinants of childhood undernourishment and hotspot areas for suitable and timely intervention. The multivariate mixed model was employed to pinpoint the geographical dispersion of risk factors of undernourished children under-five years of age. The paper showed that children from malnourished mothers, not breastfed, from low-income families, from families that have no lavatory services, from uneducated mothers, from a rural area, who are male, short birth spacing and who are older are associated with malnutrition problems. The regions such as Afar, Amhara, Benishangul and Somali were identified as high hotspot areas of child under-nutrition in the country. It is recommended that the government should reach the malnutrition hotspot areas with appropriate intervention like family planning programs and mother education to boost child nutritional status.

INTRODUCTION

Childhood undernourishment is a persisting and pressing public health problem in the world. Malnutrition robs children of their opportunities to grow in body and mind to their full potential and continues throughout the rest of their lives. Malnutrition during the first one thousand days of life (0-23 months) can have irreversible consequences on the child's growth leading to an escalated hazard of infectious illnesses and death in children (Akombi et al. 2017), and decreased learning capacity in childhood to increased non-communicable diseases in adulthood (Black et al. 2013). Under-nutrition refers to nutritional deficiency, which is affected by family nutrition insecurity, inadequate knowledge of appropriate childcare, poor nourishing and vaccination practices and underprivileged motherly socio-demographic situations (Kandala et al. 2009; Yadav et al. 2015).

Worldwide, because of malnutrition, at least 1 in 3 children under five years of age are not growing healthily. In 2018, 149 million and nearly fifty- million children under five were stunted and wasted, respectively (UNICEF 2019). As a result, under-nutrition explains around forty-five percent of mortalities between children under five, mainly in poor and medium-income countries (Black et al. 2013). In Africa, around 60 million children are stunted, with millions suffering from wasting (UNICEF et al. 2019). Furthermore, in sub-Saharan Africa, over thirty percent of mortalities of children under five years of age have been attributed to malnourishment (UNICEF 2009). For example, more than ten percent of child deaths are associated with wasting worldwide (Black et al. 2013).

Ethiopia is a low-income country and belongs to the lowliest countries in the world, with low-quality education, health, and social improvement indicators. Child under-nutrition costs Ethiopia 16.5 percent of her GDP and 28.0 percent child mortalities are associated with under-nutrition (African Union et al. 2014). This indicates that like other emerging states, under-nutrition is a severe problem to the health system of the country. The occurrence of growth retardation among children under-5 years is thirty-eight percent, underweight twenty-four percent

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and wasted ten percent (CSA 2016). Hence, efforts designed at attaining a decrease in child malnutrition should comprise exhaustive research into the associates and geographic spreads of the determinants that affect the nutritious status of under-5 children in the state, as this can aid in clarifying target clusters and their areas.

Previous studies conducted in developing countries intended to examine spatial variation in childhood nutritional outcomes have proven the importance of geographic location to improved understanding of childhood nutritional outcomes (Khatab 2010; Kandala et al. 2011; Wand et al. 2012; Adekanmbi et al. 2013). To explicate the potential causes of undernourishment in Ethiopia, diverse regression modelling methods have been employed (Tadiwos et al. 2013; Takele and Taye 2014; Mandefro et al. 2015; Haile et al. 2016). All these studies considered univariate models separately to investigate the possible determinants of malnutrition measures while a child might be stunted, underweight, wasted or a combination of the indicators. Besides, limited studies used spatial models to incorporate the spatial variation in under-five children's nutritional outcomes across the country. However, understanding what drives the geographical disparities is critical to designing appropriate interventions and significantly reducing the prevalence of malnutrition. Consequently, the foremost intent of this research is to simultaneously model the possible correlates of child anthropometric measures in Ethiopia by integrating the spatial dispersion among the regions and generate the spatial occurrence maps of their incidence. It is also of interest to investigate the common drivers of stunting, wasting and underweight.

METHODOLOGY

Source of Data

In this study, the 2016 Ethiopia Demographic and Health Survey (EDHS) data were utilised. The survey was one of the series designed to provide population and health indicator estimates at national and regional levels. Ethiopia embraces nine regions and two administrative cities. The sample for the 2016 EDHS was countrywide representative and enclosed the whole population residing in the country. The survey used a multistage cluster sampling design with urban-rural (region as strata), yielding 21 sampling strata. In all, 645 clusters, consisting of 202 urban, and 443 in rural parts with a representative sample of 15,683 households were selected for the survey interview. Among the households who completed the interview, 5,348 were from urban and 10,335 from rural parts. The data analysis was based on 8,742 samples of children under-five years.

Anthropometric Indices

Children's nutritional status is measured by growth criteria published by the WHO in 2006. The Z-score for child i was defined as,

$$Z_i = \frac{AI_i - M}{\sigma}$$

Where AI_i indicates the child's anthropometric indicator, M and σ refer to the median and the standard deviation in the reference population, respectively. In this investigation, the child's nutritional status categorised as nourished if $Z_i \geq -2.0$ and malnourished if $Z_i < -2.0$. Therefore, the response variable is binary.

Weight-for-height measures the BMI of a child about height and designates present nutritional status. For the wasted child, his or her weight-for-height Z-score is less than -2σ (Gayawan et al. 2017).

Height-for-age is a quantity of a child's growth. For the stunted child, his or her height-for-age Z-score is less than -2σ (Gayawan et al. 2017).

Weight-for-age is a combined index of wasting and stunting that accounts for both acute and chronic malnutrition. For an underweight child, his or her weight-for-age Z-score is less than -2σ.

Risk factors include numerous factors concerning the socioeconomic characteristics, child characteristics, spatial factors, and mother characteristics. The variables measured include gender, child's age, birth order number, birth space, maternal body mass index, household economic status, place of residence, mother education level, source of drinking water, toilet facilities, internet use, breastfed and region.

Multivariate Spatial Model

Let y_{ijk} be a binary response corresponding to the children's nutritional situation (where 1 represents undernourished and 0 represents nourished) of the anthropometric measures k, with k=1 for stunting, k=2 for wasting and k=3 for an underweight child j at region i, i=1,2…11. Also, let x_{ijk} be the vector of associated covariates within the generalised linear model framework (GLM) and assume y_{ijk} are identically independently distributed Bernoulli random variables with $E(y_{ijk})=\eta_{jk}$ and model predictors as $g(\eta_{jk}) = x_{ijk}\beta$ where g(.) is a logit link function in the malnutrition risk application. Albeit, the spatial structure of the data renders the independence assumption of y_{ijk} invalid, leading to narrower confidence intervals for β and thus overestimation of the significance of the predictors (Gemperli and Vounatsou 2003). The generalised linear mixed model is an approach that considers spatial dependence particularly for non-Gaussian spatial problems (Breslow and Clayton 1993). To integrate a spatial process, suppose y (s_i/ϕ) is conditionally independent for any site s_i and $E[y(s_i/\phi)]=\mu(s_i)$ is its conditional mean, where ϕ is helping to define the dispersion of s. Therefore, the spatially correlated random effect is integrated into the linear predictor as:

$$g(\mu_k) = X_{ijk}\beta + Z_{ijk}\,\phi'$$

Where β are the vectors of fixed-effect regression parameters, X_{ijk} and Z_{ijk} are the fixed and random effect design matrices and ϕ are random spatial variation parameters. Hence, ϕ is denoted by,

$$\phi = \begin{pmatrix}\phi_1\\ \phi_2\\ \phi_3\end{pmatrix} \sim i.i.d.\,MVN(0,\Sigma) = MVN\left(\begin{bmatrix}0\\0\\0\end{bmatrix}, \begin{bmatrix}\Sigma_{11} & \Sigma_{12} & \Sigma_{13}\\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23}\\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33}\end{bmatrix}\right),$$

Where, Σ_{ij} are entries of the covariance matrices of the spatial effects of stunting, wasting and underweight and $\varepsilon \sim Gau(0,\sigma^2_\varepsilon I)$ and the spatial correlation is parameterised by θ in $\Sigma_\phi(\theta)$ (Schaberger and Gotway 2005).

Spatial Autocorrelation: is used to identify the patterns of spatial correlation by estimating the dependency of covariates with itself within a topographical space (Cliff and Ord 1981). In this paper, the Moran's I and Geary's ratio C statistics were employed to examine the spatial auto-correlation and distribution patterns of malnutrition in Ethiopia. The Moran's I value is obtained from the estimated deviation of the average of two neighbouring values (Moran 1950). The Moran's I is estimated as follows.

$$I = \frac{N\sum_i\sum_j w_{ij}\,(x_i-\bar{x})(x_j-\bar{x})}{W\sum_i(x_i-\bar{x})^2}$$

Where the sample size is represented by N, and $\bar{x}$ is the average of the covariate, x_i is the covariate value at site i, x_j is the covariate value at site j, and w_{ij} is a spatial weight indexing the site of i relative to j. For negative and positive spatial autocorrelation, the Moran's I value range from -1 to +1, respectively. For the Moran's I, the Z-score and p-value are used to evaluate the significance. The null hypothesis states that there is no spatial autocorrelation for the covariate within the geographic area.

Like Moran's I method of measuring spatial autocorrelation, Geary's ratio C also adopts a cross-product term (Getis 1991). Geary's ratio is formally defined as,

$$C = \frac{(n-1)\sum_i\sum_j w_{ij}\,(x_i-\bar{x})^2}{W\sum_j(x_i-\bar{x})^2}$$

The Geary's ratio C ranges from 0 to 2 with 0 indicating a perfect positive spatial autocorrelation (that is, all neighbouring values are the same) and 2 indicating a negative spatial autocorrelation.

Spatial Prediction: Modelling point referenced data is important to identify significant covariates and to produce flat maps of response by predicting unsampled sites. Spatial prediction is commonly known as kriging (Gemperli and Vounatsou 2003). Let Y_0 be a vector of the binary outcome at new, undetected locations s_0i, i= 1,2…n_0. Reliant on the maximum likelihood technique, the distribution defined by (Gemperli and Vounatsou 2003) reads as,

$$p(Y_0|\hat{\beta},\hat{U},\hat{\sigma}^2,\hat{\phi}) = \int P(Y_0|\hat{\beta},U_0)P(U_0|\hat{U},\hat{\sigma}^2,\hat{\phi})d_{U_0}$$

Where $\hat{\beta},\hat{U},\hat{\sigma}^2$ and $\hat{\phi}$ are estimated parameters, $P(Y_0|\hat{\beta},U_0)$ is the Bernoulli maximum likelihood at new sites and $P(U_0|\hat{U},\hat{\sigma}^2,\hat{\phi})$ is the random effect spatial distribution U_0 at new sites, assumed $\hat{U}$ at detected locations and normally distributed (Gayawan et al. 2017).

RESULTS

Generalised linear mixed models were employed to analyse the data using SAS 9.4 and R

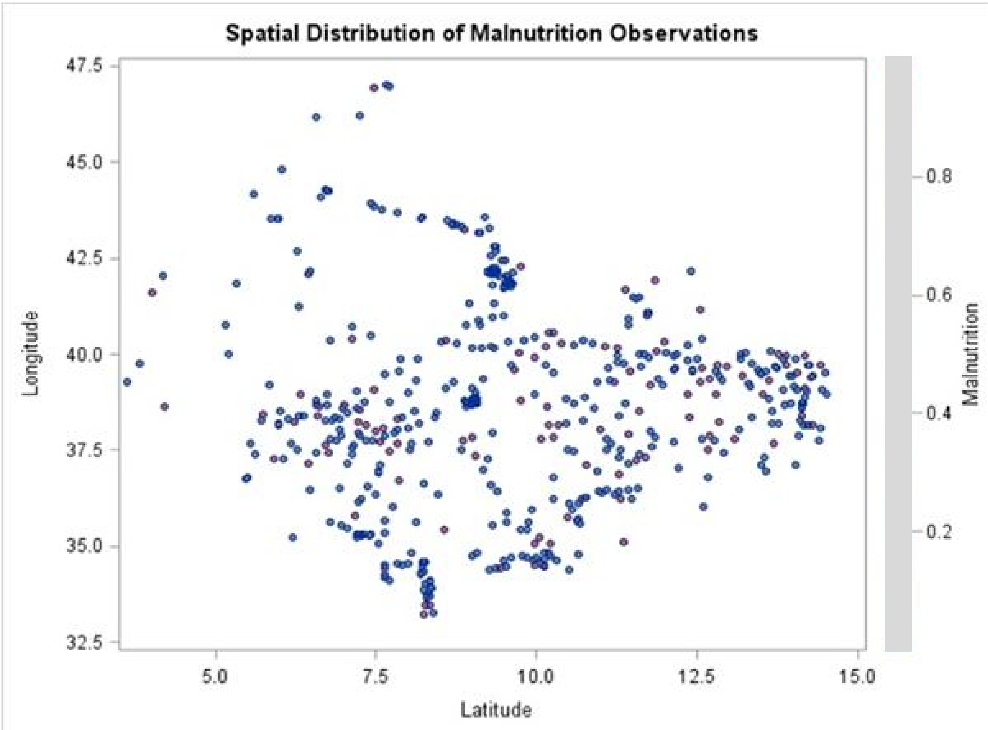

Fig. 1. Spatial distribution of malnutrition outcomes (Stunting, Underweight and Wasting)

5.3.3 to produce smooth maps of undernourishment for each response. In this paper, different covariance structures were considered to identify the appropriate covariance structure. The following are the covariance structures, that is, Exponential, Anisotropic Exponential, 2D Exponential, Geometric Anisotropic, Gaussian, 2D Gaussian, Geometrically Anisotropic, Anisotropic power, Spherical, 2D Spherical, Geometrically Anisotropic, Linear and Linear Log among others. Based on the model selection criteria AIC, the model with a Gaussian covariance structure indicated smaller AIC and is considered as the best model fit to the data. Furthermore, Figure 1 indicates the spatial distribution of undernourishment occurrence for the joint spread of stunting, wasting and underweight. Based on Figure 1, the scatter plot suggests distribution that is not revealing a uniform distribution of the malnutrition dimensions in the prediction area. The red colour indicates locations with high malnutrition cases. From Table 1, Moran's I (Z-score= 44.03 and P < .0001) and Geary's C (Z-score = -3.26 and P= 0.0011) tests show that the spatial spread of feature values is not the outcome of random spatial processes. The result also indicates positive autocorrelation, which suggests that neighbouring values s_i and s_j tend to have similar feature values z_i and z_j, respectively.

Table 1: Results for Moran's I and Geary's C

Assumption	*Estimate*	*Observed*	*Expected*	*Std Dev*	*Z*	*Pr > |Z|*
Randomisation	Moran's I	0.00948	-0.0000396	0.000216	44.03	<.0001
Randomisation	Geary's C	0.98545	1.0000000	0.004466	-3.26	0.0011

Table 2 shows the important factors for the final model that includes spatial variability using a spatial Gaussian covariance structure. Using the GLMM, the result indicates that gender, child's age, birth order number, birth space, mother nutritional status, place of residence, mother schooling level, and source of drinking water, toilet facilities, internet use, family economic status, breastfed and region are significant risk factors of childhood malnutrition in Ethiopia.

Table 2: Type III tests of fixed effects for the GLMM with spatial correlation

Effect	*Num DF*	*F Value*	*Pr > F*
Child's sex	3	8.79	<.0001
Child's age	6	105.68	<.0001
Birth order	6	3.45	0.0021
Birth space	6	8.02	<.0001
Mother nutritional status (BMI)	3	38.22	<.0001
Household economic status	6	13.18	<.0001
Place of residence	3	7.06	<.0001
Mother education level	6	4.76	<.0001
Drinking water source	9	2.73	0.0035
Toilet facility	6	2.19	0.0410
Internet use	3	4.47	0.0038
Breastfeeding	3	5.27	0.0012
Region	30	11.00	<.0001

Results from Spatial Joint Multivariate GLMM

The current study found that male children are 1.236 (P=0.002) times higher expected to be wasted as compared to the female counterpart. From Table 3, the results suggest that the child's age is significantly affecting a child's nutritional status. The prevalence of stunting and underweight are lower between children aged 0-11 months (OR=0.186, P<.0001, OR=0.385, P<.0001) as compared to older children (24-59 months). Further, the occurrence of underweight is lower among children aged 12-23 months (OR=0.834, P=0.008) in contrast to older children (24-59 months). Also, the occurrence of height-for-age is higher in children aged between 12-23 months (OR=1.305, P<.0001) as compared to older children (24-59 months). However, the result indicates that the incidence of wasting is greater among children aged between 0-11 months (OR=1.88, P<.0001) and 12-23 months (OR=1.68, P<.0001) in comparison to older children (24-59 months). Based on the analysis, a child born at second to third order has 89.5 percent, 85.0 percent, and 88.6 percent lesser odds of being wasted, stunted and underweight (OR=0.895, P=0.050, 0.85, P=0.042, OR=0.886, P=0.050) respectively, as compared to a child born at fourth-order and above. Likewise, a child born at first order has 75.1 percent lower odds of being underweight (OR=0.751, P=0.001) in contrast to a child born at the fourth-order and above.

The other important significant risk factor affecting child nutritional status is birth spacing. A child born to birth space of more than or equal to 48 months is less probable to be wasted, stunted and underweight when compared to a child with birth space below or equal to 24 months (OR=0.783, P=0.002, OR=0.85, P=0.004, OR=0.625, P<.0001), respectively. Furthermore, the mother's nutritional status (BMI) significantly affects the nutritional status of a child. The result revealed that children from a mother's nutritional status (BMI) more than or equal to 18.5 are 0.815, 0.657 and 0.599 (P<.0001, P=0.001, P<.0001) less probable to be wasted, stunted and underweight than a child from mother BMI less than 18.5, correspondingly. The other important risk factor affecting child nutritional status is household economic status. The present finding indicates that children from the poor and middle-income households have (OR=1.21, P<.0001, OR=1.48, P=0.024, OR=1.43, P=0.003, OR=1.39, P=0.013, OR=1.82, P<.0001, OR=1.50, P<.0001) higher probability to be stunted, wasted and underweight than children from rich families, in turn (Table 3). Correspondingly, the place of residence is significantly affecting the nutritional status of a child (Table 3). Children living in urban areas are (OR=0.807, P=0.047, OR=0.591, P=0.0003, OR=0.784, P=0.047) less probable to be stunted, wasted and underweight as compared to children living in a rural counterpart.

Furthermore, the mother's level of education is considerably influencing the stunting and underweight of the children (Table 3). As a result, a child from an uneducated mother or mother with primary level education is (OR=1.43, P=0.001) or (OR=1.31, P=0.016) at high risk of stunting than children born to mothers with a secondary and higher education. Similarly, children born to an uneducated mother is 1.52 (P=0.002) times at a high risk of being underweight than a child born to a mother with secondary and higher level. For

Table 3: Spatial joint model of malnutrition estimates

Covariates	*Stunting*		*Underweight*		*Wasting*	
	Estimate (S.E)	*P-value*	*Estimate (S.E)*	*P-value*	*Estimate (S.E)*	*P-value*
Intercept	2.049 (0.377)	<.0001	2.076 (0.380)	<.0001	-2.901 (0.452)	<.0001
Sex of child (Female=ref))						
Male	-0.686 (0.457)	0.457	-0.685 (0.485)	0.158	0.204 (0.068)	0.002
Age of child (24-59 months)						
0-11 months	-1.684 (0.0805)	<.0001	-0.955 (0.082)	<.0001	0.633 (0.089)	<.0001
24-59 months	0.266 (0.062)	<.0001	-0.182 (0.069)	0.008	0.518 (0.088)	<.0001
BORD (4th and above =ref)						
1st birth order	-0.135 (0.084)	0.109	-0.287 (0.092)	0.001	-0.183 (0.118)	0.120
2-3rd birth order	-0.111 (0.057)	0.050	-0.121 (0.062)	0.050	-0.162 (0.082)	0.046
Birth space (? 24 months =ref)						
24-47 months	-0.116 (0.065)	0.073	-0.109 (0.068)	0.108	-0.052 (0.088)	0.560
≥48 months	-0.245 (0.0807)	0.002	-0.47 (0.089)	<.0001	-0.335 (0.117)	0.004
Mother nutritional status (less than 18.5=ref)						
≥18.5	-0.205 (0.058)	<.0001	-0.512 (0.061)	<.0001	-0.420 (0.076)	<.0001
Household economic status (Rich =ref))						
Middle	0.194 (0.087)	0.0249	0.409 (0.100)	<.0001	0.331(0.134)	0.013
Poor	0.392 (0.078)	<.0001	0.600 (0.090)	<.0001	0.358 (0.121)	0.003
Residence (Rural=ref)						
Urban	-0.214 (0.107)	0.047	-0.243 (0.122)	0.047	-0.526 (0.144)	0.0003
Mother's education level (S and Higher=ref))						
No education	0.357 (0.114)	0.001	0.416 (0.138)	0.002	0.165 (0.165)	0.317
Primary	0.266 (0.112)	0.016	0.161 (0.137)	0.240	0.095 (0.162)	0.560
Breastfeeding (No = ref))						
Yes	-0.185 (0.055)	0.0007	-0.116 (0.060)	0.052	-0.062 (0.083)	0.453
Type of toilet facility (No toilet facility=ref)						
Flush	-0.390 (0.162)	0.016	-0.441 (0.197)	0.025	-0.183 (0.224)	0.415
Latrine	-0.068 (0.062)	0.270	-0.106 (0.067)	0.116	-0.045 (0.088)	0.608
Drinking water (public tap=ref)						
Other	-0.066 (0.056)	0.240	-0.049 (0.061)	0.412	0.062 (0.077)	0.426
Piped	-0.261 (0.121)	0.030	-0.181 (0.144)	0.212	-0.444 (0.175)	0.011
protected spring	0.032 (0.093)	0.728	0.192 (0.101)	0.058	0.232 (0.135)	0.085
Internet (Yes=ref)	0.774 (0.234)	0.001	0.228 (0.285)	0.424	0.485 (0.356)	0.173

the same reason, from Table 3, the result indicates that children who are breastfed are (OR=0.831, P=0.0007, OR=0.891, P=0.052) less affected to stunting and underweight than children not breastfed. Likewise, the family's drinking water source was considerably affecting the child's nutritional status (Table 3). A child born in a household that uses piped water in their home is (OR=0.771, P= 0.03, OR=0.641, P=0.011) less exposed to stunting and wasting than a child born in a family who uses public tap water. However, children born in a household that consumes water protected from springs in their households are 1.21 (P= 0.058) times more prone to being underweight than a child born in a family that uses water from public tap water. Equally important the other risk factor affecting child growth is access to toilet facilities. Children born in a family who have access to flush toilet facilities are 0.677 and 0.643 times less probable to have stunted and underweight than children born in a family who have no access to toilet facilities, respectively. Furthermore, children from households with no access the Internet are 2.17 more likely to get affected by stunting.

Another important finding was that the region was found to affect the nutritional status of a child (Table 4). A child born in Afar, Amhara, Benishangul, Dire Dawa, SNNPR or Tigray regions has high odds of stunting at 1.23 (P=0.0334) or 2.14 (P<.0001) or 1.69 (P=0.0057) or 1.75 (P=0.0039) or 1.48 (P=0.0343) or 1.61 (P=0.0085), compared a child born in Addis Ababa city.

Lastly, the predicted mean values of each anthropometric index were obtained from the final GLMM model fitted using SP (GAU). Then, using the R 5.3.3 the researchers portrayed the smooth maps of stunting, wasting and underweight. As a result, from the spatial joint model, the predicted mean effects for height-for-age is as depicted in Figure 2. The incidence of growth retardation is higher in the Amhara region and lower in Addis Ababa city (Fig. 2).

In this study, a child born in Afar, Amhara, Benishangul, Dire Dawa, Harari, Oromia, SNNPR, Somali and Tigray regions has high odds of stunting at 3.19 (P<.0001), 2.96 (P<.0001), 3.75 (P<.0001), 2.74 (P=0.0003), 1.18 (P=0.0106), 1.99(P=0.0120), 2.15 (P=0.0048) and 2.25 (0.0029) compared to a child born in Addis Ababa city. Figure 3 shows the predicted mean spatial effects for weight-for-age from the joint model. The incidence of weight-for-age is higher in Afar and Benishangul regions and lower in Addis Ababa city.

Additionally, a child born in all regions of Ethiopia had high odds of wasting compared to a child born in Addis Ababa city excluding a child born in SNNPR (Table 4). The incidence of weight-for-height is higher in the Somali region and lower in Addis Ababa and SNNPR (Fig. 4).

Table 5 presents the estimated spatial covariance parameter. The estimated variance and range are 0.1675 and 0.6293, respectively. The estimate of the sill is 0.9761. Based on this result, it indicates variability between the districts.

Table 5: Random parameter estimates

Effect	*Estimate*	*Standard error*	*P>Z*
Variance	0.1603	0.02507	0.045
SP (GAU)	0.6293	0.9033	0.027
Residual	0.9761	0.009333	0.012

Table 4: Extension of the spatial joint model of malnutrition estimates

Covariates	*Stunting*		*Underweight*		*Wasting*	
	Estimate (S.E)	*P-value*	*Estimate (S.E)*	*P-value*	*Estimate (S.E)*	*P-value*
Region (Addis Ababa =ref)						
Afar	0.398(0.187)	0.0334	1.159(0.274)	<.0001	1.198(0.327)	0.0002
Amhara	0.761(0.186)	<.0001	1.085(0.275)	<.0001	0.679(0.334)	0.0420
Benishangul	0.526(0.190)	0.0057	1.321(0.277)	<.0001	0.730(0.339)	0.0312
Dire Dawa	0.557(0.193)	0.0039	1.008(0.281)	0.0003	0.718(0.346)	0.0383
Gambela	-0.274(0.196)	0.1629	0.476(0.283)	0.092	0.911(0.334)	0.0063
Harari	0.329(0.195)	0.0908	0.866(0.283)	0.0022	0.862(0.341)	0.0115
Oromia	0.252(0.183)	0.1674	0.697(0.273)	0.0106	0.691(0.328)	0.0350
SNNPR	0.389(0.183)	0.0343	0.691(0.275)	0.0120	0.142(0.339)	0.6749
Somali	-0.342(0.184)	0.0635	0.764(0.271)	0.0048	1.369(0.321)	<.0001
Tigray	0.477(0.182)	0.0085	0.811(0.272)	0.0029	0.819(0.326)	0.0121

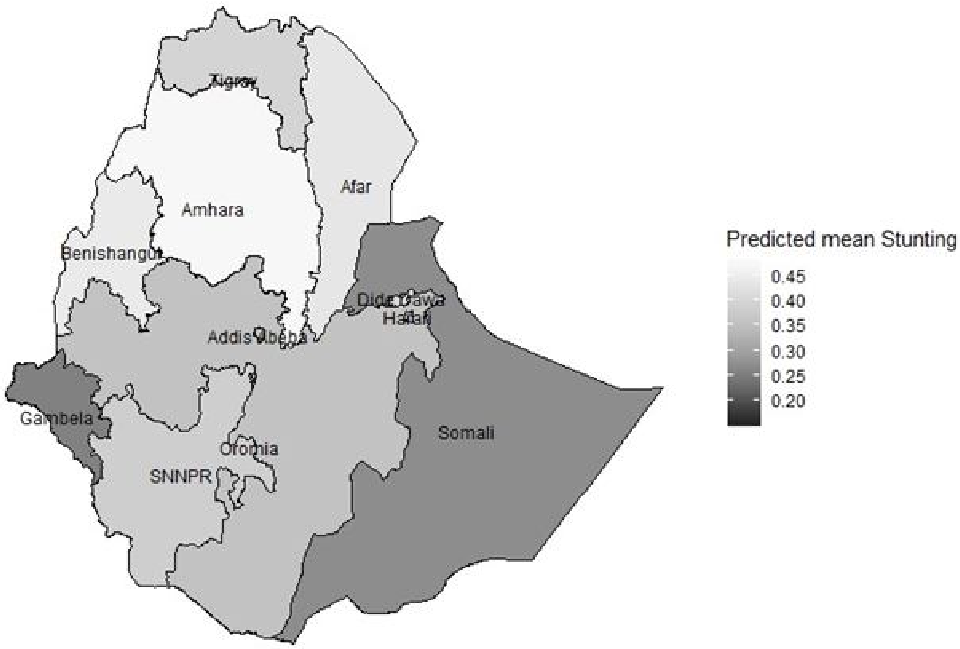

Fig. 2. Predicted mean effects for height-for-age from the joint model

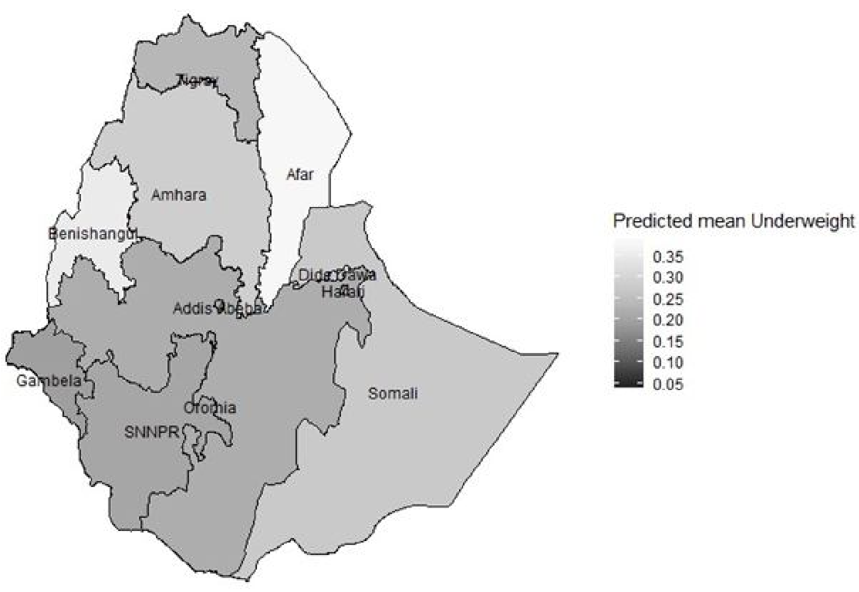

Fig. 3. Predicted mean effects for weight-for-age

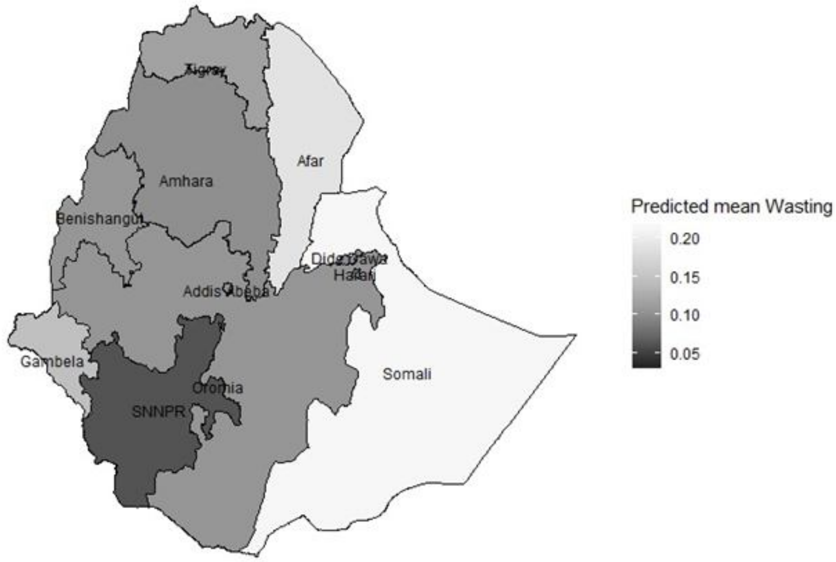

Fig. 4. Predicted mean effects for weight-for-height

DISCUSSION

This study employed the multivariate joint spatial model to examine all possible risk factors of child under-nutrition and produce the prevalence maps at the sub-national level through predicting at unsampled locations. Malnutrition among children in Ethiopia is still considerably high with thirty-eight percent stunted, twenty-four percent underweight and ten percent wasted. Detecting more prudently within clusters of contributing factors, this study indicates the age of the child, birth order, preceding birth interval, households' wealth index, households' place of residence and region as the main statistically significant determinants of stunting, wasting and underweight.

Child age is a significant covariate that affects the dietary status of children. Those aged between 0 to 11 months were at a lower threat of height-for-age and being underweight than children whose ages were among 24 to 59 months. Though, the result indicates that children aged between twelve to twenty-three months are at a more hazard risk of stunting than children whose ages are among 24 to 59 months. Similarly, a child aged among 0 to eleven months and twelve to twenty-three months is more at a threat of wasting. The findings are similar to that of Khatab (2010) and Habyarimana et al. (2016). The likelihood of being wasted was lower for females than for a male, the findings agree with (Khatab 2010; Takele and Taye 2014; Habyarimana et al. 2016). Furthermore, depending on demographic determinants related to malnutrition, the investigation revealed that under-nutrition rises with the birth order of the child. The outcomes of this study agree with that of Habyarimana et al. (2016). The other important risk factor significantly negatively associated with child malnutrition is the preceding birth interval. This study found that under-nutrition decreases with increasing preceding birth interval. This result agrees results from other studies (Chukwuma et al. 2015; Habyarimana et al. 2016; Haile et al. 2016).

Similarly, the mother's nutritional status (BMI) is significantly negatively related with the child's nutritious status. Children from undernourished mothers are more prone to nutritional deficiency. This result agrees to the results of other studies (Felisbino-Mendes et al. 2014; Chukwuma et al. 2015; Haile et al. 2016). Furthermore, the analysis revealed that the household economic status is a significant socioeconomic determinant that affects the nutritional status of children in the country. The result shows that children in poor families are at high risk of malnutrition difficulties when compared to children from rich families. This result agrees with the previous findings (Chukwuma et al. 2015; Gayawan et al. 2017). Children in rural settlements are more prone to nutritional deficiencies. This might be due to problems of poor health, lack of hygiene and poverty (Gayawan et al. 2017). This finding is similar to the findings of other (Takele and Taye 2014; Ibidolapo et al. 2016; Gayawan et al. 2017). The result indicates that children from uneducated mothers are more exposed to growth retardation and being underweight compared to children from educated mothers. The reason might be that education helps mothers to understand the essential nutrition and hygiene required for children to reduce malnutrition-related problems. This result agrees with that of Gayawan et al. (2017). The finding indicated that children not breastfed have more prevalence of stunting and underweight as compared to children breastfed in Ethiopia. The result revealed that a child born in a family who has access to flush toilet facilities are less vulnerable to stunting and underweight compared to children born in a family who have no access to toilet facilities. The finding agrees with that of Khatab (2010). Besides, the finding of this paper indicated that a child born in a family that has access to piped water is less vulnerable to stunting and wasting compared to children born in a household who have access to public tap water. From Figure 4, the occurrence of wasting is high in the Somali and Afar regions. Similarly, the finding indicated that a high hotspot of stunting and underweight was found in Afar, Amhara, and Benishangul, whereas the low hotspot was found in Addis Ababa city.

CONCLUSION

In this study, vital determinants of child malnutrition were identified using spatial mixed models. The results revealed that child malnutrition was not random in the country. The study found that gender, child's age, birth order number, birth space, maternal nutritional status, household's economic status, place of residence, education level of the mother, and drinking water source, toilet facilities, use of the internet, breastfed and region are significant risk factors of childhood malnutrition in the country. Children from malnourished mothers, from low-income families, non-breastfed, from families that have no lavatory facilities, from uneducated mothers, from a rural area, who are male, with short birth spacing and who are older are associated with malnutrition problems. Furthermore, regions such as Afar, Amhara, Benishangul and Somali were high hotspot areas of child malnutrition in the country.

RECOMMENDATIONS

The study recommends improving access to clean toilet facilities and clean water for households to reduce problems of child malnutrition in Ethiopia. The improvement of child nutritional status in the country requires interventions such as ensuring adequate birth space, elimination of child hunger, improvement of mother's education level and nutrition. The hotspot regions identified for child malnutrition should be highlighted for nutritional interventions.

REFERENCES

Adekanmbi VT, Kayode GA, Uthman OA 2013. Individual and contextual factors associated with childhood stunting in Nigeria: A multilevel analysis. *Maternal & Child Nutrition,* 9(2): 244-259.

African Union 2014. NEPAD Planning and Coordinating Agency, UN Economic Commission for Africa, and UN World Food Programme 2014. *The Cost of Hunger in Africa: Social and Economic Impact of Child Undernutrition in Egypt, Ethiopia, Swaziland, and Uganda.*

Akombi BJ, Agho KE, Merom D, Renzaho AM, Hall JJ 2017. Child malnutrition in sub-Saharan Africa: A meta-analysis of demographic and health surveys (2006-2016). *PloS One,* 12(5): e0177338.

Black RE, Victora CG, Walker SP, Bhutta ZA, Christian P, De Onis M, Uauy R 2013. Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet,* 382(9890): 427-451.

Breslow NE, Clayton DG 1993. Approximate inference in generalized linear mixed models. *Journal of the American Statistical Association,* 88(421): 9-25.

Chukwuma BD, Uche RO, Kelechi AU, Kelvin CD, Irene AM, Ifeadike OC, Anthony CI 2015. Prevalence and sociodemographic determinants of malnutrition among under-five children in rural communities in Imo State, Nigeria. *American Journal of Public Health Research,* 3(6): 199-206.

Cliff AD, Ord JK 1981. *Spatial Processes: Models & Applications.* UK: Taylor & Francis.

CSA 2016. *Ethiopia Demographic and Health Survey.* Addis Ababa, and Rockville: CSA and ICF.

Felisbino-Mendes MS, Villamor E, Velasquez-Melendez G 2014. Association of maternal and child nutritional status in Brazil: A population-based cross-sectional study. *PloS One,* 9(1): e87486.

Gayawan E, Adebayo SB, Komolafe AA, Akomolafe AA 2017. Spatial distribution of malnutrition among children under five in Nigeria: A Bayesian quantile regression approach. *Applied Spatial Analysis and Policy*, 1-26.

Gemperli, A, Vounatsou P 2003. Fitting generalized linear mixed models for point-referenced spatial data. *Journal of Modern Applied Statistical Methods*, 2(2): 23.

Getis A 1991. Spatial interaction and spatial autocorrelation: A cross-product approach. *Environment and Planning A,* 23(9): 1269-1277.

Habyarimana F, Zewotir T, Ramroop S, Ayele DG 2016. Spatial distribution of determinants of malnutrition of children under five years in Rwanda: Simultaneous measurement of three Anthropometric Indices. *Journal of Human Ecology,* 54(3): 138-149.

Haile D, Azage M, Mola T, Rainey R 2016. Exploring spatial variations and factors associated with childhood stunting in Ethiopia: A spatial and multilevel analysis. *BMC Pediatrics,* 16(1): 49.

Ibidolapo IT, Adebiyi OA, Fatiregun A 2016. Urban-rural disparities and determinants of nutritional status of under-five children: An example of Akinyele Local Government Area, Ibadan. *International Journal of Tropical Disease and Health,* 16(1): 1-11.

Kandala NB, Fahrmeir L, Klasen S, Priebe J 2009. Geo?additive models of childhood undernutrition in three Sub-Saharan African countries. *Population, Space and Place,* 15(5): 461-473.

Kandala NB, Madungu TP, Emina JB, Nzita KP, Cappuccio FP 2011. Malnutrition among children under the age of five in the Democratic Republic of Congo (DRC): Does geographic location matter? B*MC Public Health,* 11(1): 261.

Khatab K 2010. Childhood malnutrition in Egypt using geoadditive Gaussian and latent variable models. The American *Journal of Tropical Medicine and Hygiene, 8*2(4): 653-663.

Mandefro A, Mekitie W, Mohammed T, Lamessa D 2015. Prevalence of undernutrition and associated factors among children aged between six to fifty-nine months in Bule Hora district, South Ethiopia. *BMC Public Health,* 15(1): 41.

Moran PA 1950. Notes on continuous stochastic phenomena. *Biometrika,* 37(1/2): 17-23.

Schabenberger O, Gotway CA 2005. *Statistical Methods for Spatial Data Analysis.* New York: Chapman and Hall/CRC.

Tadiwos Z, Abebaw D 2013. Determinants of child malnutrition: Empirical evidence from Kombolcha District of Eastern Hararghe Zone, Ethiopia. *Quarterly Journal of International Agriculture,* 52(892-2016-65185): 357.

Takele K, Taye A 2014. Bayesian modelling of growth retardation among children under-five years old. *Far East Journal of Theoretical Statistics,* 48(2): 87.

UNICEF 2009. *Tracking Progress on Child and Maternal Nutrition: A Survival and Development Priority.* USA: UNICEF.

UNICEF, WHO, World Bank 2019. *Joint Child Malnutrition Estimates. Levels and Trends in Child Malnutrition: Key Findings of the 2019 Edition.*

UNICEF 2019. *The State of the World's Children in 2019. Children, Food and Nutrition: Growing Well in a Changing World.* UNICEF, New York.

Wand H, Lote N, Semos I, Siba P 2012. Investigating the spatial variations of high prevalence of severe malnutrition among children in Papua New Guinea: Results from geoadditive models. *BMC Research Notes,* 5(1): 228.

Yadav A, Ladusingh L, Gayawan E 2015. Does a geographical context explain regional variation in child malnutrition in India? *Journal of Public Health*, 23(5): 277-287.

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