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KHATAB, Khaled <http://orcid.org/0000-0002-8755-3964>

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Childhood Malnutrition in Egypt using Geoadditive Gaussian and Latent Variable Models

Khaled Khatab*

Institute of Occupational and Social Medicine, Medical School, Rheinisch-Westfälische Technische Hochschule Aachen (RWTH) University, Aachen, Germany

Abstract. Major progress has been made over the last 30 years in reducing the prevalence of malnutrition amongst children less than 5 years of age in developing countries. However, approximately 27% of children under the age of 5 in these countries are still malnourished. This work focuses on the childhood malnutrition in one of the biggest developing countries, Egypt. This study examined the association between bio-demographic and socioeconomic determinants and the malnutrition problem in children less than 5 years of age using the 2003 Demographic and Health survey data for Egypt. In the first step, we use separate geoadditive Gaussian models with the continuous response variables stunting (*height-for-age*), underweight (*weight-for-age*), and wasting (*weight-for-height*) as indicators of nutritional status in our case study. In a second step, based on the results of the first step, we apply the geoadditive Gaussian latent variable model for continuous indicators in which the 3 measurements of the malnutrition status of children are assumed as indicators for the latent variable ''nutritional status''.

INTRODUCTION

Childhood undernutrition is amongst the most serious health issues facing developing countries. It is an intrinsic indicator of well-being, but it is also associated with morbidity, mortality, impaired childhood development, and reduced labor productivity.[1,2,3]

To assess nutritional status, the 2003 Demographic and Health survey (DHS)[4] obtained measurements of height and weight for all children below 5 years of age. Researchers distinguish between 3 types of malnutrition: wasting or insufficient weight for height indicating acute malnutrition; stunting or insufficient height for age indicating chronic malnutrition; and underweight or insufficient weight for age which could be a result of both stunting and wasting.

These 3 anthropometric variables are measured through z-scores for wasting, stunting, and underweight defined by

$$Z_i = \frac{AI_i - MAI}{\sigma}, \tag{1}$$

where AI refers to the individual anthropometric indicator (e.g., height at a certain age), MAI refers to the median of a reference population, and σ refers to the standard deviation of the reference population. Each of the indicators measures somewhat different aspects of nutritional status. Note that higher values of a z-score indicate better nutrition and *vice versa*. Therefore, a decrease of z-scores indicates an increase in malnutrition. This has to be taken into account when interpreting the results. The reference standard typically used for the calculation is the National Center for Health Statistics-Centers for Disease Control and Prevention Growth Standard that has been recommended for international use by World Health Organization. The reference population are children from the USA. More exactly, up to an age of 24 months these are children from white parents with high socio-economic status, while older children are from a representative sample of all United States children. The selection of the reference populations can affect the results, for example a higher z-score can be caused by the change of the reference population.

Previous analyses are often based on DHSs as a well-established data source with reliable information on childhood undernutrition, and they rely on statistical inference with various forms of regression models. Because of methodological restraints, it is difficult to detect nonlinear covariate effects, for example of age, adequately, and it is impossible to recover small-scale, district-specific spatial effects with common linear regression or correlation analysis. Recent research has therefore applied geoadditive regression models.[5,6] They have been used in regression studies of risk factors for acute or chronic undernutrition,[7–9] for morbidity.[9,10–12] These models can account for nonlinear covariate effects and geographical variation while simultaneously controlling for other important risk factors. However, in all these studies regression analyses are carried out separately for certain types of undernutrition such as stunting, wasting, or underweight, neglecting possible association among these response variables and without aiming at the detection of common latent risk factors.

In this work, a latent variable model (LVM) for the nutritional status based on continuous indicators is applied. This model permits modeling of covariate effects on the latent variables through a flexible geoadditive predictor. It gives us the opportunity to study the association or interrelationship between the 3 types of malnutrition as indicators for nutritional status. The factor loadings describe the association between these indicators and their impact on the nutritional status of a child. To build a regression model for undernutrition, we first have to define distribution for the response variable. In this application, it is reasonable to assume that z-score is Gaussian distributed; thus in principle, Equation (3) could be applied. The analysis started by employing a separate geoadditive Gaussian model to continuous response variables for wasting, stunting, and underweight. The author then applies geoadditive latent variable models, based on these results, where the 3 undernutrition variables are taken as indicators for nutritional status of a child. All computations have been carried out with BayesX version 2, and R Programs using the Markov Chain Monte Carlo package.[9,13,14] This study consists of 4 sections. Section 1 describes the data set as well as the various bio-demographic and socioeconomic variables which have been used in this study. Section 2 describes the geoadditive Gaussian and geoadditive latent model, whilst section 3 contains statistical inference and results using the geoadditive and the latent variable models. Section 4 includes discussion and comments.

*Address correspondence to Khaled Khatab, Institute of Occupational and Social Medicine, Medical School, RWTH Aachen University, Germany, Pauwelsstraße 30, 52074 Aachen. E-mails: kkhatab@ukaachen.de or khaledkhatab314@yahoo.com

MATERIALS AND METHODS

DHS collects information on household living conditions such as housing characteristics, on childhood morbidity, malnutrition, and child health from mothers in reproductive ages (15–49). There are 6,661 children's records in the 2003 survey of Egypt. Each record consists of malnutrition information and diseases information as well and the list of covariates that could affect the health status and the nutritional status. In the following, we provide some more information about the nutritional indicators, which were used as response variables and information about the covariates considered in this study.

Stunting. Stunting is an indicator of linear growth retardation relatively uncommon in the first few months of life. However it becomes more common as children get older. Children with *height-for-age* z-scores below –2 SD from the median of the reference population are considered short for their age or stunted.

Wasting. Wasting indicates body mass in relation to body length. Children whose *weight-for-height*'s z-scores are below –2 SD from the median of the reference population are considered wasted (i.e., too thin for their height) which implies that they are acutely undernourished, otherwise they are not wasted.

Underweight. Underweight is a composite index of stunting and wasting. This means children may be underweight if they are either stunted or wasted, or both. In a similar manner to the 2 previous anthropometric incidences, children may be underweight when their z-score is below –2 SD and they are severely or moderately so if their z-score is lower than 2 SD. The following variables were considered in the analysis to study child nutritional status:

Metrical covariates. Chage: Child's age in months *BMI*: Mother's body mass index *Mageb*: Mother's age at birth.

Spatial covariates. reg: Governorate where respondent resides.

Categorical covariates. Table 1 provides information on categorical socioeconomic and bio-demographic covariates, their categories, frequencies, and coding used in the models.

STATISTICAL ANALYSIS

Bayesian geoadditive regression and latent variable models of childhood malnutrition. In the following, we focus on geoadditive Gaussian models for continuous response variables to analyze the effects of metrical, categorical, and spatial covariates on stunting, wasting, and underweight response variable in the separate analyses. Furthermore, we use "nutritional status" as the indicator in the analysis of the latent variable models.

Geoadditive Gaussian regression. In this section, we concentrate on separate analyses for the 3 types of anthropometric status of the child. Our analyses focused on children below 5 years of age in Egypt, using a flexible regression method to model the effect of covariates that have linear and nonlinear effects, and the effects of location covariate on the 3 types of undernutrition (stunting, wasting, and underweight) which are measured as standardized Z-scores. Traditionally, the effects of the covariates on the response are modeled by a linear predictor:

TABLE 1

Factors analyzed in malnutrition study

Factor	N (%)	Coding Effect
Place of residence		
Urban	2237 (33.58%)	1
Rural	4424 (66.42%)	–1.ref
Child's sex		
Male	3487 (52.35%)	1
Female	3174 (47.65%)	–1.ref
Working		
Yes	1209 (18.15%)	1
No	5452 (81.85%)	–1.ref
Mother's Education		
No		
Incomp.prim,		
Comp.prim,		
Incomp.sec	4194 (62.97%)	1
Compl.sec,		
Higher	2467 (37.04%)	–1.ref
Pregnancy's treatment		
Yes	697 (10.46%)	1
No	5964 (89.54%)	–1.ref
Drinking water		
Controlled	5374 (80.68%)	1
Not controlled	1287 (19.32%)	–1.ref
Missing	1%	
Had radio		
Yes	5374 (80.68%)	1
No	1559 (19.32%)	–1.ref
Has electricity		
Yes	6203 (93.12%)	1
No	458 (6.88%)	–1.ref
Toilet facility		
Own flush toilet facility	1768 (28%)	1
Other and no toilet facility	4511 (71.8%)	–1.ref
Missing	1%	
Antenatal visit		
Yes	4181 (63%)	1
No	2342 (35%)	–1.ref
Missing	2%	

$$\eta_{ij}^{lin} = x_{ij}'\beta_j + w_{ij}'\gamma_j \qquad j = 1,..,3, \tag{2}$$

where observations (x_i, w_i), i = 1, .., n, on a metrical response y, a vector $x=(x_1,\ldots,x_p)$ of metrical covariates and vector $w=(w_1,\ldots,w_k)$ of categorical covariates.

In our analysis, nonlinear effects of the spatial structure can be included as well as the nonlinear effects of the metrical covariates (*Chage, BMI,* and *Mageb*), categorical covariates (male, urban, having radio, etc.), and the spatial covariate (child's district of residence) on childhood undernutrition. Thus, we replace the strictly linear predictor (2) by the more flexible geoadditive predictor

$$\eta_{ij}^{geo} = \beta_{0j} + f_1(Chage_i) + f_2(BMI_i) + f_3(Mageb_i) + f_{spat_i}(s) + w_{ij}'\gamma_j \tag{3}$$

where w includes the categorical covariates in effect coding. The function f_1, f_2, and f_3 are non-linear smooth effects of the metrical covariates which are modeled by Bayesian P-splines, and f_{spat} is the effect of the spatial covariate $S_i \in 1;\ldots;S$ labeling the districts in Egypt. Regression models with predictors as in (3) are referred to as geoadditive models. In a further step we split up the spatial effect f_{spat} into a spatially correlated (structured) effect modeled by a Markov random field prior and uncorrelated (unstructured) effects which are assumed to be independent and identically distributed random variables.[15]

In a Bayesian approach, unknown functions f_j and γ_j as well as the variance parameter σ^2 are considered as random variables and have to be supplemented with appropriate prior assumptions as developed by Fahrmeir and Lang and Brezeger and Lang.[6,16] For further analysis and to remove the drawbacks of separate Gaussian models for each of the continuous responses, we will use latent variables models described in Raach and Khatab.[9,14]

Latent variable model for continuous responses. A latent variable υ reflects undernutrition status. The LVM for Gaussian responses $y_j, j = 1,\ldots, p$ and scalar υ is given through the *Gaussian measurement model*:

$$y_{ij} = \lambda_0 + a_j' w_i + \lambda_j \upsilon_i + \varepsilon_{ij}, i = 1,.., n, j = 1,.., p, \tag{4}$$

with independent and identically distributed Gaussian errors $\varepsilon_{ij} \sim N(0, \sigma^2)$. In this model, υ_i is the unobservable value of υ for individual i, λ_j is the "factor loading", and $\lambda_j \upsilon_i$ is the effect of υ_i. In addition, w_i are the direct effects which affect the observed variables directly and a_j is the vector of regression coefficients. The restriction to $\sigma_\upsilon = var(\upsilon) = 1$ is necessary for the identifiable reasons.[12,17]

Continuous variables are observed directly, hence the underlying variable is obsolete. *The general form of geoadditive structural model for the latent variable is.*

$$\upsilon_i = u'_i \alpha + f_1(x_{i1}) + \ldots + f(x_{iq}) + f_{geo}(s_i) + \delta_i, \tag{5}$$

with independent and identically distributed Gaussian errors $\delta_i \sim N(0,1)$. The restriction to σ_υ= var (υ) = 1 is necessary a for identifiability reasons.

RESULTS

Different types of covariates, such as the usual covariates with fixed effects, metrical covariates with non-linear effects, unstructured random effects, and spatial covariates, are all treated within the same general framework by assigning appropriate priors with different forms and degrees of smoothness. A main objective of this step was to see which socioeconomic factors have the most influence on the nutritional status of children and which regions are most affected by malnutrition. In the second step, we apply a geoadditive latent variable model, using the 3 types of undernutrition as indicators of latent nutritional status. The decision which covariates should be used in the measurement model, and which should be used in the structural equation, is based on the same criteria that were used in Khatab and Khatab and Fahrmeir.[9,12]

Analysis of childhood malnutrition, using separate geoadditive Gaussian models. In this section, we present results for the Gaussian models. The responses $y_j, j = 1, \ldots, 3$ are stunting, wasting, and underweight as measurements of nutritional status. The predictor of the model considered for the analysis in this section is as follows:

$$y_{ij} = \eta_{ij} + \varepsilon_{ij} \tag{6}$$

$$\eta_{ij} = \beta_{0j} + f_{1j}(Chage) + f_{2j}(BMI) + f_{3j}(Mageb) + f_{strj} + f_{unstrj} + u_i'\alpha \tag{7}$$

In these models, β_{0j} is a constant term and the covariate vector u contains all the bio-demographic and health factors which were included in the analysis of childhood disease in Khatab and Fahrmeir.[12]

The nonparametric function of child's age, mother's body mass index (BMI), and mother's age at birth are assumed to have a nonlinear effect on the nutritional status of children in Egypt, as well as the spatial effects f_{strj} and f_{unstrj}. The main aim is to study child nutritional status by distinguishing among 3 response variables.

Results. The estimate of fixed effects of the covariates for the geoadditive Gaussian model (Equation (3)) are given in Tables 2–4 and the nonlinear effects of child's age, mother's BMI, and mother's age at birth are shown in Figure 1. The regional effects are in the maps of Figure 1.

Stunting. The results of the geoadditive Gaussian model show a negative relationship between male children and stunting and a positive relationship between urban area and stunting (Table 2). These results suggest that female children in urban areas are better nourished compared with their counterparts in rural areas. This finding has also been found in some previous studies in developing countries.[8,18] In addition, the educational level of the mother has a slight impact on the level of stunting and; the other categorical covariates have also either a slight or nonsignificant impact on the level of stunting in Egypt.

TABLE 2
Fixed effects on stunting

Variable	Mean	SD	10%	Median	90%
const	−0.715*	0.134	−0.894	−0.712	−0.546
male	−0.078*	0.016	−0.098	−0.077	−0.055
urban	0.029*	0.021	0.002	0.028	0.057
work	−0.004	0.023	−0.034	−0.005	0.025
trepr	0.001	0.027	−0.033	0.002	0.035
anvis	0.014	0.019	−0.010	0.015	0.0388
radio	−0.005	0.022	−0.033	−0.006	0.024
elect	−0.066	0.086	−0.174	−0.067	0.042
water	−0.004	0.026	−0.037	−0.004	0.029
educ	0.017	0.022	−0.010	0.018	0.0455
toilet	−0.028	0.040	−0.077	−0.027	0.0208

*Denotes that effects are significant at a 95% significance level.

TABLE 3
Fixed effects on underweight

Variable	Mean	SD	10%	Median	90%
Const	−0.451*	0.123	−0.610	−0.453	−0.290
male	−0.0757*	0.013	−0.093	−0.075	−0.058
urban	0.005	0.015	−0.014	0.005	0.025
work	0.005	0.0173	−0.016	0.005	0.028
trepr	−0.025	0.0215	−0.053	−0.026	0.0045
anvis	0.034*	0.014	0.017	0.034	0.051
radio	0.017	0.017	−0.005	0.017	0.038
elect	−0.071	0.066	−0.158	−0.074	0.015
water	−0.006	0.020	−0.030	−0.006	0.017
educ	0.029*	0.015	0.010	0.029	0.050
toilet	0.0183	0.032	−0.024	0.017	0.059

*Statistically significant at 0.05%.

TABLE 4
Fixed effects on wasting

Variable	Mean	SD	10%	median	90%
const	0.038*	0.132	−0.132	0.040	0.203
male	−0.055*	0.014	−0.074	−0.056	−0.037
urban	−0.014	0.018	−0.038	−0.013	0.007
work	0.01	0.019	−0.015	0.010	0.035
trepr	−0.030*	0.023	−0.061	−0.030	−0.0005
anvis	0.036*	0.0163	0.0146	0.036	0.057
radio	0.028*	0.019	0.004	0.028	0.053
elect	−0.043	0.072	−0.142	−0.041	0.043
water	−0.007	0.021	−0.036	−0.007	0.019
educ	0.020	0.017	−0.001	0.020	0.045
toilet	−0.051	0.035	−0.123	−0.050	0.017

*Denotes that effects are significant at a 95% significance level.

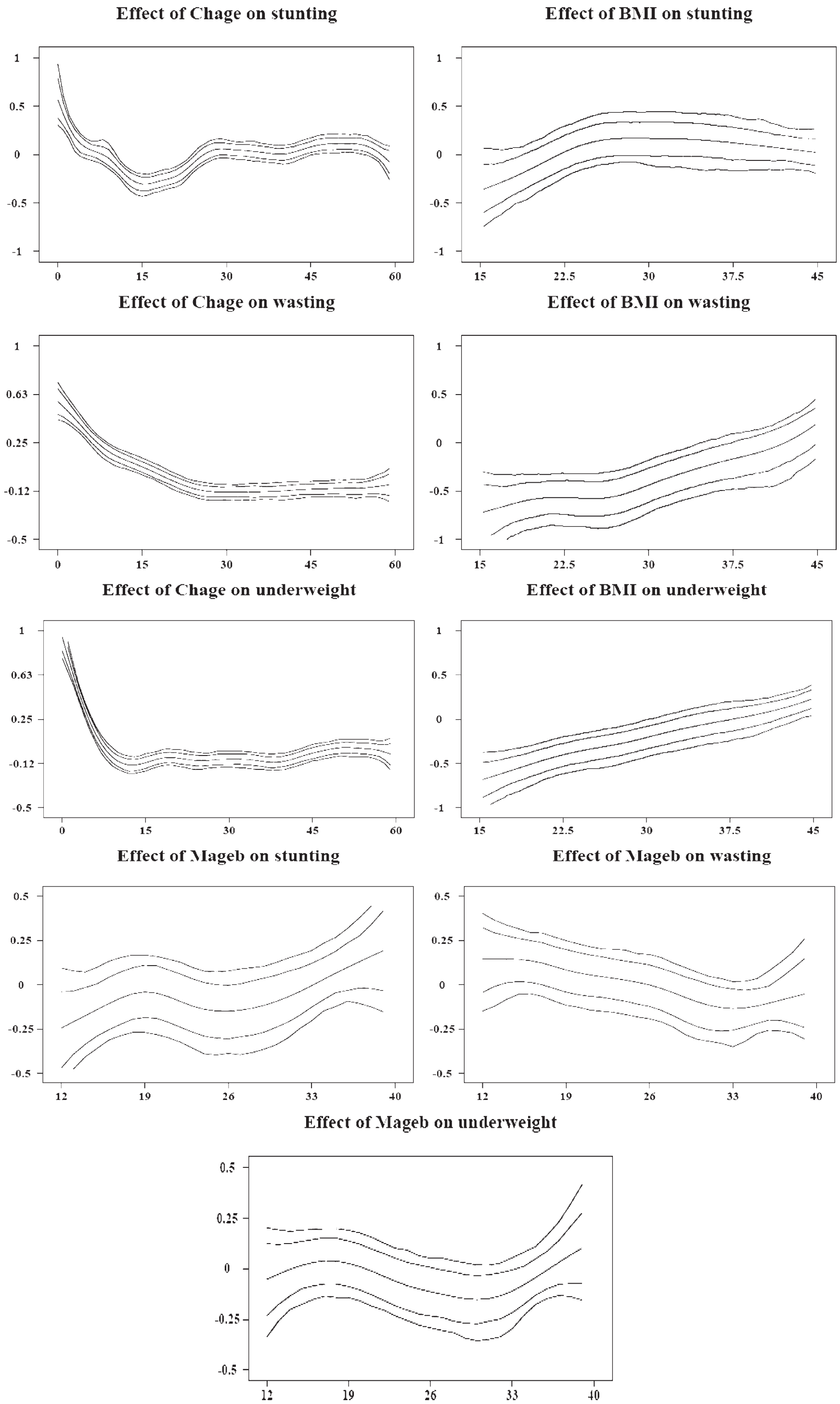

FIGURE 1. Posterior means of nonparametric effects in stunting (top), wasting (second from top), and underweight (bottom) for child's age (left top to third from top), mother's BMI (right top to third from top), and mother's age (last 3 panel from bottom) for Gaussian semiparametric model.

The left panels of Figure 1 display the nonparametric effect of the child's age. Shown are the posterior means together with 80% and 95% pointwise credible intervals. We find the influence of a child's age on its nutritional status is considerably high between the age of 5 months and the age of 15 months. This deterioration in nutritional status of a child begins around 5 months after birth and continues with an almost linear trend until the age of 15 months. After 15 months of age and between the ages of 15 to 30 months, stunting decreases and stabilizes thereafter at a middle level.

In looking at the mother's BMI and its impact on the level of stunting, the right panels of Figure 1 show that the influence is in the form of an inverse U shape. Results show that the mothers with BMI between 23 and 29 have a slightly higher z-score of *height-for-age* (lower stunting) measured by stunting, and the effect stabilizes at the same level thereafter.

Mothers with BMI less than 20 have a lower z-score of *height-for-age*. It shows that BMI has a slight effect on the nutritional status. Low BMIs of less than 18.5 suggest acute undernutrition of the mother. Furthermore, the z-score is around 35 (and thus lowest stunting).

The effect of mother's age on stunting is quite slight (third panel from top of Figure 1). It shows that the *height-for-age* z-score is low for mother between the ages of 12 to 33 years. The z-score of *height-for-age* increases (and stunting decreases) after age of 33 years. After age of 33, the effect of the mother's age stabilizes, with an almost linear trend. It shows that their children are better in their nutritional status compared with children whose mothers are in the middle age group.

Spatial effects are allocated by the model into structured and unstructured effects shown in Figure 2. The model shows that the structured effects are significant. This indicates that the worst nutrition is implying a higher relative risk of stunting in some cities and rural areas on the Nile Delta. Note that the unstructured effect shows that there are no cases found in the governorates with gray color; that is because most of these areas are not populated.

Wasting. Results of fixed effects parameters are shown in Table 4. Female children whose mothers have obtained antenatal visit during their pregnancy, and have access to radio, have higher z-scores of *weight-for-height* (lower level of wasting), which implies that they are better nourished. Astonishingly, children whose mothers had clinical treatment are not associated with higher *weight-for-height*. Gender differences in childhood nutrition have been confirmed by other authors.[2,7,18] It is found that female are better nourished than male children and the effect of gender is similar in this study. In addition, the mother's current employment status, where the mother lives (rural/urban), availability of electricity, access to controlled water, education level of mothers, availability of flush toilet at household have either slight or statistically insignificant effects on a child's *weight-for-height*.

There is evidence that there is deterioration in a child's *weight-for-height* from the age of 5 months until the child is about 20–25 months, where minimum z-scores of *weight-for-height* are attained and go on to stabilize at a low level thereafter.

Figures for the mother's BMI display an almost linear trend with positive slopes. The implication is that children whose mothers have a low BMI are likely to be wasted (Figure 1). There is an almost linear fixed effect from BMI of 20 to 35.

The effect of mother's age on nutritional status of children is high for older mothers (> 30) and it is quite similar for the underweight anthropometric indices. Figure 2 displays structured spatial effects (left panels) on stunting, wasting, and underweight, with corresponding unstructured spatial effects (right panels) on the colored map of Egypt. The geographical panel indicates a significantly high rate of wasted children are associated with some regions in Nile Delta such as Damietta, Dakahlia, and Esmaliyia.

Underweight. This response variable belongs to the index of stunting and wasting. That means, a child may be underweight if s/he is either stunted, or wasted, or both. The factors associated with underweight are presented in Table 3.

The results indicate that male children were at higher risk of being underweight than female children. Children born to mothers with a secondary or higher educational level, and who obtained medical care during pregnancy, were at lower risk of malnutrition compared with the other children.

We also note that having a flush toilet in the household and whether a mother had treatment during her pregnancy are not associated with better nutritional status.

As expected and as confirmed in many previous studies, female children seem to be better nourished than male children, and the gender effect in this application is consistent with the results of these studies. Furthermore, children whose mothers are currently working, have completed at least secondary school or higher education, have made antenatal visits, have electricity, radio, or flush toilet and have access to controlled water are better nourished compared with their counterparts. As previously mentioned, the nonlinear effects of the continuous covariates are shown in Figure 1.

A child may have low z-scores of *weight-of-age* if s/he is either chronically malnourished (stunted), acutely malnourished (wasted), or both. As a consequence, underweight is a combination of stunting and wasting. It is obvious that the deterioration in *weight-for-age* after the first 4 or 5 months of life and low stability level were reached at age 15 months.

The bottom panels of Figure 2 depict the occurrence of underweight children. It shows clearly where the nutritional problems are severe. The occurrence of underweight children was particularly high in the Nile Delta, such as Damietta, Dakhalia, and Esmaliyia, which are associated with high levels of stunting and wasting, and are also affected by underweight.

Analyses using latent variable models for continuous responses. In this section, our interest is in analyzing the 3 types of undernutrition status of children using latent variable models, and in investigating how they can be established as indicators of the latent variable ''undernutrition status''. Based on the previous separate analyses, we are able to determine which factors can have direct effects and which can have indirect effects on the indicators. The analysis begins with 2 major parts, corresponding to continuous outcomes versus mixed outcomes in a further work. Within each part conventional analysis using continuous latent variables will be described first, followed by recent extensions that add binary indicators of childhood disease to the analysis with latent variables.[11]

We start using the easiest model possible, a classic factor analysis for continuous indicators. The predictor of the structural equation of the model yields LMV0:

$$\eta = 0 \tag{8}$$

Estimates of factor loadings are depicted in Table 5. The estimated mean factor loadings show that indicator 2 (*weight-for-age*) has the highest factor loading. The classic factor analysis model has been extended by introducing direct and indirect parametric covariates, which modified the latent construct. The next model was selected based on the previous separate analyses. This leads to the latent variable model (Equation (7)).

In the fundamental analysis (LVM1), the vector a_j comprises the covariates urban, mother working, treatment during pregnancy, educational level of mothers, access to flush toilet, and availability of electricity with direct effects on y_j; and u'_i comprises the remaining categorical covariates sex, antenatal visits, and access to controlled water, having common effects on the latent variable υ.

The results of geoadditive latent variable models are shown in Table 6 for model LVM1. They indicate that female children whose mothers obtained antenatal visits during pregnancy are more likely to be better nourished, and these factors have significant effect on the latent variable (nutritional status). But

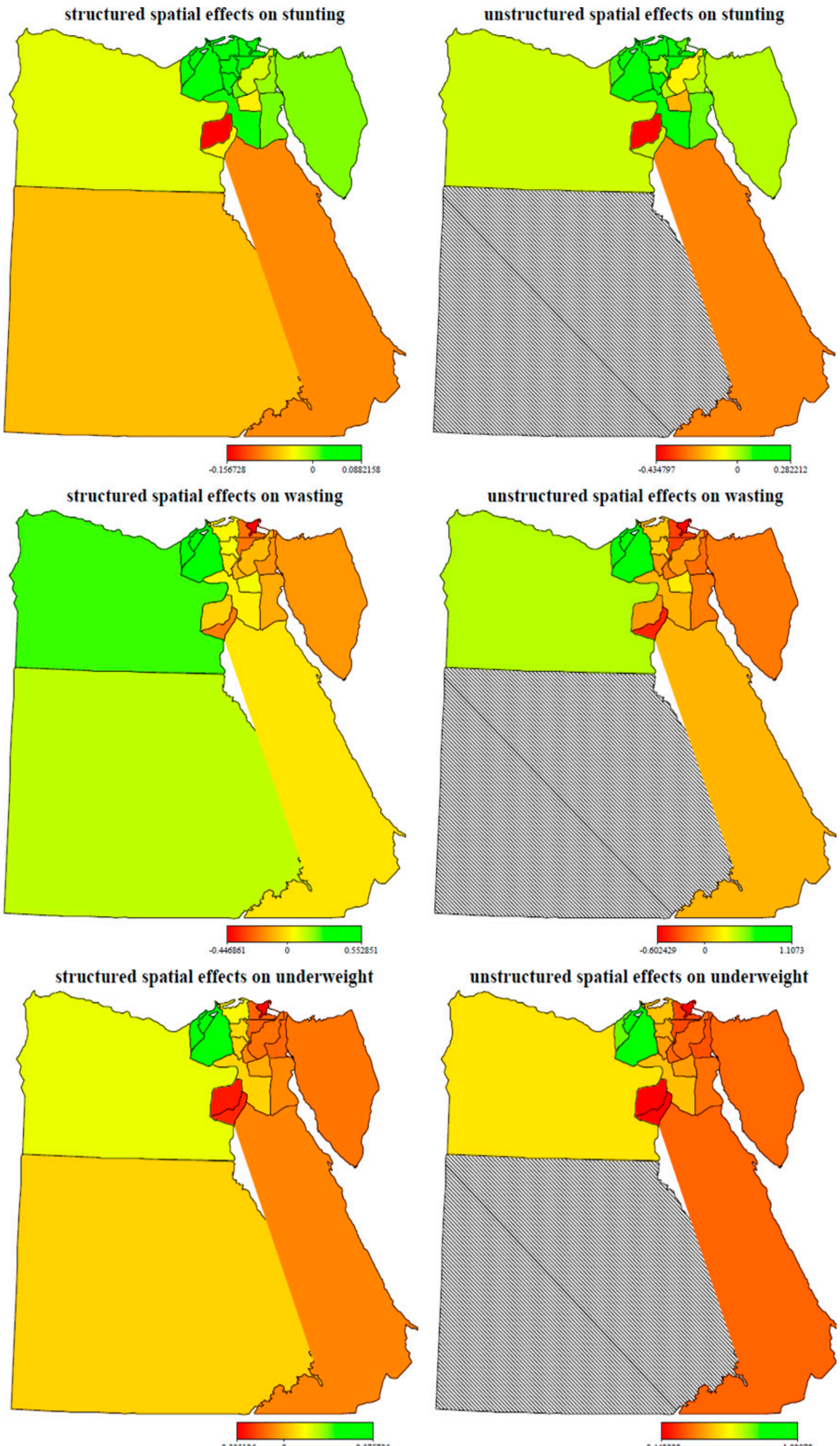

FIGURE 2. Colored maps of Egypt, showing posterior means of structured (left) and unstructured (right) spatial effects in stunting (top), wasting (middle), and underweight (bottom) for Gaussian semiparametric model. This figure appears in color at www.ajtmh.org.

on the other hand, the access to controlled water has a slight effect on the nutritional status of children. Regarding parametric direct effects, the results indicate a significant effect of urban location, education level of mothers, treatment during her pregnancy, availability of electricity, radio, and type of toilet on the factor loading of *weight-for-age* (λ_{21}). The covariates of radio, treatment during pregnancy, type of toilet, urban (at 90%), and electricity (at 90% confidence intervals) have significant effect on *weight-for-height*. Effects of toilet, electricity and place of residence are, however, negative on the indicators y_2 (underweight) and y_3 (wasting). The cause of these negative signs could be due to the following reasons:

First, in the analysis of latent models, we used 3 indicators (which were assumed to have high level of correlations among

Table 5
Results of Model LVM0 of z-scores indicators with $\eta = 0$

Parameter	Mean	SD	2.5%	97.5%
Factor loadings				
Stunting λ_{11}	0.72	0.0149	0.69	0.74
Underweight λ_{21}	1.053	0.0079	1.04	1.06
Wasting λ_{31}	0.757	0.0123	0.734	0.781

each other) instead of one indicator, which was used by the separate analysis. Because of that, it is difficult to compare the results of the LVM with the previous separate analysis. Second, it has been found that 66.4% of the households that have access to electricity and flush toilet are located in the rural areas and 33.7% of the households are located in the urban areas, therefore the corresponding effects of the rural areas (which were assumed to be reference category) are higher than their counterparts in the urban areas. Third, it is observed that the indicators have a higher correlation which can affect the results, so we have made a further analysis excluding the indicator of wasting (*weight-for-height*) to examine the effects of various factors on the other indicators (underweight and stunting), and results are compared with analysis of all 3 indicators.

Moreover, the level of the education of the mother is the only covariate which has a significant effect on y_1. Note that some variables, such as radio and electricity, were associated with nonsignificant effect on the *weight-for-age* in the separate analysis, and they become significant on the second indicator y_2 as shown by model LVM1. Still, the difference is not large between the results of model LVM1 and the previous results that were obtained using Gaussian geoadditive models. For further analysis, we included the parametric direct covariates which were insignificant in LVM1 in the indirect parametric effects of the model LVM2, and they still seem to be insignificant or have slight effects on the nutritional status of children.

The results of the further analysis using only 2 indicators (stunting and underweight) show that the child's sex and antenatal visits have significant indirect effects on the nutritional status by LVM3 Table 7. On the other hand, the results for the covariates of direct effects are yet more reasonable compared with the results by LVM1. It shows that education level of mothers are associated with higher *height-for-age* (thus lowest level of stunting) and with higher *weight-for-age* (thus lowest level of underweight). Furthermore, the results indicate that the variable flush toilet has a negative effect on the indicator of underweight. The factor loadings estimates show that *weight-for-age* is more serious (due to its high factor loading of 0.968) compared with its reference population. With regards to nonlinear effects on the latent variable nutritional status, their patterns are similar to the patterns of the separate analysis, therefore they are not shown here, and in addition, the patterns of LVM1 and LVM2 are quite similar. The nonlinear effects and the spatial effect of LVM3 are shown in Figures 3 and 4, respectively.

Table 6
Results of LVM1, including direct and indirect effects

Parameter	Mean	SD	2.5%	10%	90%	97.5%
Factor loadings						
Stunting λ_{11}	0.66**	0.014	0.636	0.673	0.681	0.692
Underweight λ_{21}	0.982**	0.005	0.974	0.976	0.989	0.996
Wasting λ_{31}	0.712**	0.011	0.691	0.698	0.727	0.736
Parametric indirect effects						
male	–0.116**	0.039	–0.192	–0.106	–0.066	–0.038
anvis	0.117**	0.040	0.039	0.066	0.169	0.197
water	0.123	0.101	–0.074	–0.006	0.253	0.321
Parametric direct effects						
urban (α_{11})	0.031	0.032	–0.03	–0.009	0.072	0.094
work (α_{12})	–0.004	0.038	–0.080	–0.052	0.045	0.073
trepr (α_{13})	–0.042	0.049	–0.140	–0.106	0.019	0.050
elect (α_{14})	–0.165	0.151	–0.469	–0.360	0.029	0.126
radio (α_{15})	0.027	0.038	–0.048	–0.022	0.077	0.103
educ (α_{16})	0.063**	0.023	0.0184	0.033	0.091	0.108
toilet (α_{17})	–0.061	0.072	–0.200	–0.154	0.029	0.076
urban (α_{21})	–0.006*	0.005	–0.019	–0.014	–0.0009	0.004
work (α_{22})	–0.003	0.012	–0.031	–0.024	0.010	0.016
trepr (α_{23})	–0.076**	0.0175	–0.109	–0.103	–0.055	–0.048
elect (α_{24})	–0.192**	0.075	–0.368	–0.337	–0.117	–0.105
radio (α_{25})	0.075**	0.012	0.0560	0.0608	0.090	0.109
educ (α_{26})	0.047**	0.0068	0.027	0.0369	0.053	0.056
toilet (α_{27})	–0.1740**	0.018	–0.204	–0.197	–0.146	–0.136
urban (α_{31})	–0.035*	0.025	–0.084	–0.067	–0.001	0.013
work (α_{32})	–0.01	0.031	–0.071	–0.050	0.030	0.050
trepr (α_{33})	–0.056*	0.039	–0.132	–0.107	–0.005	0.022
elect (α_{34})	–0.120	0.127	–0.376	–0.290	0.043	0.121
radio (α_{35})	0.077**	0.032	0.016	0.036	0.118	0.140
educ (α_{36})	0.011	0.018	–0.026	–0.012	0.034	0.047
toilet (a_{37})	–0.154**	0.058	–0.268	–0.228	–0.079	–0.037
Smoothing parameters						
Chage	0.014**	0.011	0.003	0.005	0.026	0.042
BMI	0.002**	0.004	0.0003	0.0005	0.005	0.013
Mageb	0.003**	0.004	0.0004	0.0006	0.006	0.012
Reg	0.570**	0.242	0.026	0.33	0.867	1.189

** Statistically significant at 2.5% and 10%

TABLE 7
Estimates of factor loadings of the LVM3 with only 2 indicators in Egypt

Parameter	Mean	SD	2.5%	97.5%
Factor loadings				
Stunting λ_{11}	0.655*	0.014	0.626	0.684
Underweight λ_{21}	0.968*	0.008	0.952	0.983
Parametric indirect effects				
male	−0.152*	0.027	−0.201	−0.099
anvis	0.077*	0.030	0.016	0.140
work	0.0137	0.036	−0.063	0.079
trepr	0.032	0.034	−0.036	0.098
elect	−0.047	0.045	−0.131	0.039
radio	0.008	0.133	−0.223	0.303
Parametric direct effects				
water (α_{11})	−0.012	0.051	−0.117	0.078
educ (α_{12})	0.055*	0.022	0.011	0.104
toilet (α_{13})	−0.045	0.084	−0.212	0.104
urban (α_{14})	0.048	0.036	−0.020	0.121
water (α_{21})	−0.020	0.0413	−0.102	0.050
educ (α_{22})	0.043*	0.0148	0.005	0.063
toilet (α_{23})	−0.138*	0.067	−0.260	−0.0518
urban (α_{24})	0.023	0.0275	−0.026	0.068
Smoothing parameters				
Chage	0.003*	0.0071	0.0004	0.017
BMI	0.007*	0.009	0.0006	0.032
Mageb	0.002*	0.005	0.0003	0.013
reg	0.558*	0.241	0.244	1.177

*Statistically significant at 0.05%.

DISCUSSION

The results of estimating the separate Gaussian models (set out in Equation (7)) and from estimating the geoadditive latent variable models with continuous response variables are indicated and suggest the following:

Child's sex. The likelihood of being stunted and underweight was lower for girls than for boys; a finding consistent with others; on the other hand, Gibson[21] did not find any significant gender difference between the *height-for-age* and the *weight-for-age* in Papua, New Guinea.[2,7,8,18,19]

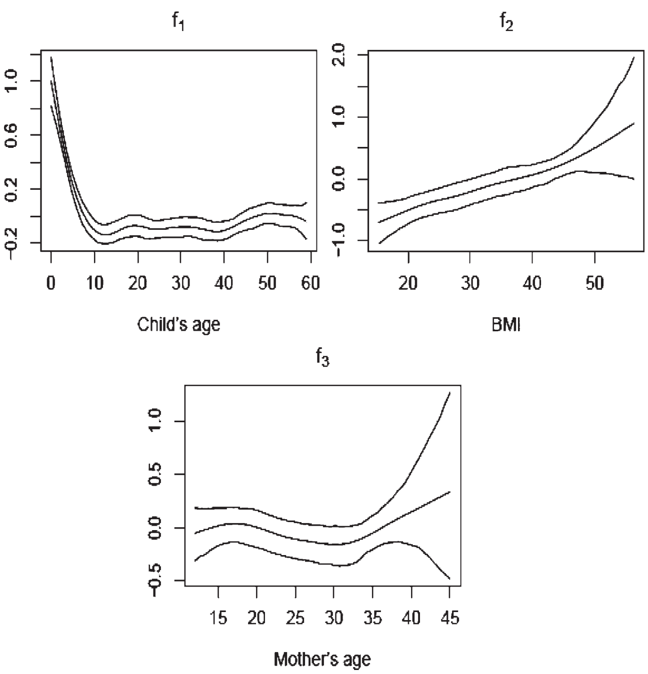

FIGURE 3. Non-linear effects from top to bottom: child's age, mother's BMI, and mother's age at birth using only 2 indicators of a latent variable "Malnutrition status" of children for Egypt, using Bayesian latent variable model.

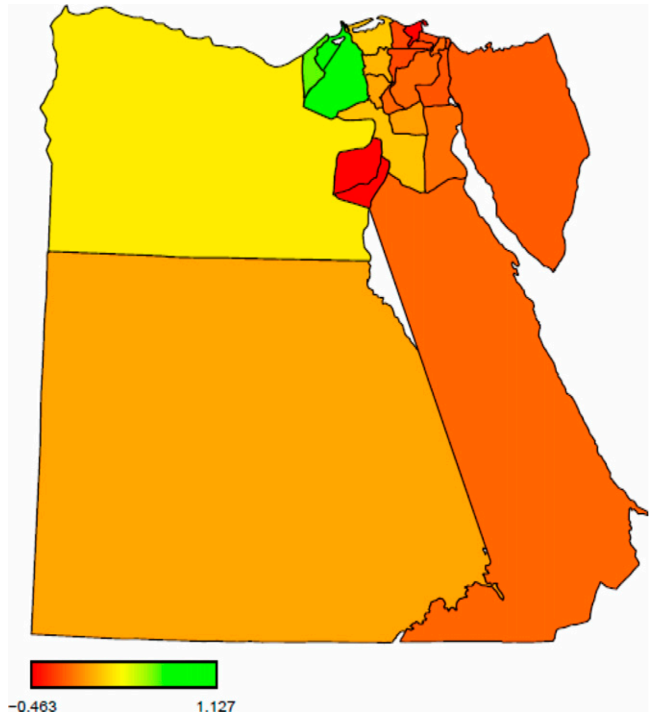

FIGURE 4. Posterior mean for latent variable model, using only 2 indicators of a latent variable "Malnutrition status" for Egypt. This figure appears in color at www.ajtmh.org.

Stunting, underweight, and wasting among children by residence. Urban children are less likely than their rural counterparts to be stunted, as shown in the separate analysis, where the quality of health environments and sanitation are found in urban areas and these results are reasonable. On the other hand, although, rural living was expected to have many problems, such as poor health, use of unprotected water supplies, lack of charcoal as fuel, lack of milk consumption, and lack of personal hygiene, which were the risk factors for stunting, wasting, and underweight, the results indicate that the place of residence is not associated with significant effects on wasting and underweight. This is consistent with some studies, but not with others: Adebayo[7] found that where the mother lives (rural/urban) has no statistical significance for child's *weight-for-height*, and a similar impact of where the mother lives, as in *height-for-age*, is observed in *weight-for-age*, though Kandala[20] found that urban areas have a statistical significance for a child's *height-for-age* in Tanzania and Malawi.[19,21,22]

Mother's education. Maternal education, which is related to household wealth, is a determinant of good child-care knowledge and practices. The education attainment of mothers is mostly significant in the analysis of LVM, it has a significant effect on the underweight of a child in separate analyses, and it reduced the likelihood of children being malnourished. The results with 2 indicators are quite similar to the results with 3 indicators with regard to this variable. This result supports the suggestion that an educated mother assumes the responsibility of taking a sick child to receive health care. Further, the time that mothers spend discussing their child's illness with a doctor is almost directly proportional to their level of education: in consequence, illiterate women (and their sick children) get much less out of visiting a doctor than do literate women. These findings are consistent with many studies in the context of developing countries, which reported that maternal education has a strong and significant effect on stunting.[19,23] They found that, at low levels of education, effects on stunting are small or negligible, and they increase only at secondary or higher levels. On the other hand, the result is the opposite of the cases of some developing countries which are in Latin America and Andean countries.

Mother who is currently working. The fact that nutritional status of children of all socioeconomic levels, as represented by current employment of mothers, suggests that insufficient food intake may be not affected by the current working status of mothers. The results are consistent with some previous studies and not consistent with others. Some studies reported that when mothers are working, the household income is increased and the access to better food will be increased, as well as the access to a quality level of medical care. On the other hand, and as mentioned previously in the analysis of childhood disease, when mothers are used outside the home, it curtails the duration of full breastfeeding and necessitates supplementary feeding, usually by illiterate care-takers, which might affect the health of children negatively.

Source of drinking water. The results indicate that the source of water has no statistical significant effect on child nutritional status. This suggests that socioeconomic differences, represented by source of water, can not fully explain the level of stunting, underweight, and wasting.

Type of toilet. The type of toilet seems to have a nonsignificant statistical effect on the nutrition status of children in separate analyses, and negative significant effects in LVM analysis even when we used 2 indicators instead of 3.

Availability of electricity and radio in household. Although ownership of electricity and or/radio facilitate the acquisition of nutritional information allowing more successful allocation of resources to produce child health, the availability of electricity and radio in households is not associated with the nutritional status of children.[20] The reasons for these results may be that mothers allocate their leisure time to radio or television, but it doesn't help improve the level of nutrition of their children. At the same time, it reduces the length of time spent engaging in their children's affairs.

Antenatal visits and treatment during pregnancy. The covariate of *trepr* has a slight effect on the nutritional status, but *anvis* seems to be significant and has a positive influence on the underweight and wasting. The results with 2 indicators also indicate that the *anvis* has a positive effect in both countries.

In addition, the reason for the nonsignificant effects of toilet, mother's working status, and source of water could be that, because most children are living in rural areas (66%) where many problems are found, such as the level of health or educational level of mothers, most women are not working (81%), and lack sanitation and water supply.

Child's age. In the analysis, it was discovered that the stunting of children increases gradually from 5–15 months of age, where the minimum Z-scores of stunting is attained, then rises again through the reminder of the third year. Similarly, deterioration in child's *weight-for-height* sets in during the first 4–5 months of age, as reported in much of the literature, due to supplementation. However, it reaches its minimum level between ages 13 and 15 months, then rises again and reaches its minimum level between ages 26 and 28 months, which is later than the case of stunting. The deterioration in *weight-for-age* sets after 5 months of birth and increases dramatically until age 15 months (which is the low stability level) and goes to be stable thereafter. Previous studies assumed that it is an average effect of low *height-for-age* and *weight-for-height* during this period of life.[7]

The level of wasting suggests that insufficient food intake may be an important factor in the rise of malnutrition. In addition, the implication of this finding is that wasting is not clearly noticeable in the first 4 months of life. As soon as a child is fed with other supplementation such as liquids or other forms of diet which, due to the unhygienic source of preparation of such supplementations, may facilitate infections and diseases such as diarrhea, then acute malnutrition may set in. In other words, the introduction of liquids, such as water, sugar water, juice, tea, powdered or fresh milk, formula, and soiled food, takes place far earlier than the recommended age of about 6 months. This practice has a deleterious effect on nutritional status for many reasons. First, the liquid and solid foods offered are nutritionally inferior to breast milk. Second, the consumption of liquids and solid food decreases the infant's intake of breast milk, which in turn, reduces the mother's supply of milk (breast milk production is determined, in part, by the frequency and intensity of suckling). Third, feeding young infants liquids and solid food increases their exposure to pathogens and thus puts them at greater risk of diseases such as diarrhea.[23,247]

Mother's body mass index. A mother's nutritional status affects her ability to successfully carry, deliver, and care for her children and is of great concern in its own right. The analysis provides that virtually similar patterns are observed for all indices approximately linear trends with positive slopes. Malnutrition in women is assessed using BMI. When the BMI of non-pregnant women fall below the suggested cut-off point, which is around 18.5 kg/m^2, malnutrition is indicated. Women who are malnourished (thinness or obesity) may have difficulty during childbirth and may deliver a child who can be wasted, stunted, or underweight. The results indicate that there is an association between the thinness condition of the mother and the nutritional status of the child.

Mother's age at birth. The results show that the influence of mothers who are younger than 20 years is higher on the nutritional status of children. Possible causes for this are due to childbirth among very young girls, whose bodies are not physically ready to endure the processes of childbirth. The problem is compounded by the fact that some African countries have poor obstetric care. Furthermore, these mothers could not reach health facilities, or, when they do, it is too late. Effective ways must be devised to delay age at first marriage and first birth. These 2 factors will almost certainly determine the number of children she will have in her lifetime. While early age at first birth has health implications, it also has economic implications. Younger mothers are likely to positively affect their children's nutritional status. Moreover, other previous studies which were obtained in some developing countries have shown that some African countries do not allow girls to go back to school after they give birth. As a consequence, a girl who drops out of school will continue the cycle of poverty.[25,26]

Prevalence of stunting, wasting, and underweight among children by region in Egypt. The results indicate that the rural areas in the Nile Delta and some other provenances there or in Lower Egypt are associated with malnutrition in children. One reason, as some previous studies reported, is that obesity among adults, particularly women, has reached very high proportions in Egypt in the last few years, while malnutrition rates in children (in the first 2 years of life) remain stubbornly high. The 1998 national food consumption survey reported that 16.7% of children 2- to 6-years-old were underweight. Overweight and obesity affected 1.6% of 2- to 6-year old children. The prevalence of stunting in preschool children ranged from 13% in Lower Egypt to 24% in Upper Egypt. At the same time, rates of early childhood malnutrition remain stubbornly stable and relatively high. The double burden of obesity and malnutrition is clearly evident. In addition, public awareness of the increasing prevalence of obesity and of diet-related chronic disease is increasing, and attention has turned to documenting the problem. On the other hand, most studies relating diarrhea and malnutrition have been conducted in economically marginal regions, where young children have high rates of diarrhea diseases and severely faltering growth. One study was conducted in an agricultural rural community in the Nile Delta. The population, although relatively uneducated, lived well. The villagers frequently owned their small homes or apartments, had access to municipal water, and often had modest luxuries such as radios and televisions. The incidence of diarrhea in children less than 3 years of age was moderate compared with that in other developing countries, and chronic diarrhea was uncommonly reported.

Summary and conclusions. This study addresses the status of malnutrition in children under 5, using stunting, underweight, and wasting as malnutrition indices. At the same time, it addresses the effects of different roles played by the various socioeconomic factors, such as mother's education, mother who is currently working, etc., in improving the children's nutritional condition. According to the results of this analysis, using separate geoadditive models and geoadditive latent variable models, the mother's education, sex of child, antenatal visits during pregnancy, and source of water were important in both countries on undernutrition of children.

In addition, results showed that the place of residence, mother working, type of toilet, and availability of electricity and radio in household have negligible effects on the undernutrition of children.

We find that the methods identify the association of child's age, mother's age at birth, and mother's BMI. It is found the children are at high risk during the first 15–20 months of life and then stabilize. The effect of BMI on the child's nutritional status is approximately linear with positive slope, which means that there is an association between the thinness condition of mothers and nutritional status. According to the mother's age at birth, it shows that younger mothers are less likely to affect their children's nutritional status positively.

It is found that children living in some provinces in the Nile Delta and Upper Egypt are having undernutrition problems. Furthermore, the results using 2 indicators are quite similar to the results with 3 indicators.

Policy Implications. Integrating nutrition and family planning can help by delaying birth to ensure optimal growth (physical, psychological, and emotional), and to raise the education level and therefore improve the socioeconomic status of mother and children. More attention is needed in some areas which have high rates of poverty, such as the Nile Delta, Upper Egypt, and southeastern Egypt. These areas are more likely to have a higher proportion of undernutrition compared with other areas, due to poor health facilities and complications during childbirth or even careless and misdiagnosis during hospital care. Therefore, the most important issues to address in these areas are health care, proper food, and raising the educational level of parents. Government should improve socioeconomic conditions. There is still a need for research and studies about nutrition and the important components of healthy eating to avoid the increase of illness caused by poor eating habits.

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Author's address: Khaled Khatab, Institute of Occupational and Social Medicine, Medical School, RWTH Aachen University, Germany, Pauwelsstraße 30, 52074 Aachen, E-mails: kkhatab@ukaachen.de or khaledkhatab314@yahoo.com.

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