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14 February 2011

Full Length Research paper

Multidimensional Nature of Undernutrition: A Statistical Approach

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The statistical assessment of undernutrition is usually restricted to a pairwise analysis of anthropometric indicators. The main objective of this study was to model the associations between underweight, stunting and wasting and to check whether multidimensionality of undernutrition can be justified from a purely statistical point of view. 3742 children aged 0 to 59 months were enrolled in a cross-sectional household survey (2004 Cameroon Demographic and Health Surveys (DHS)). The saturated loglinear model and the multiple correspondence analysis (MCA) showed no interaction and a highly significant association between underweight and stunting (P=0), underweight and wasting (P=0); but not between stunting and wasting (P=0.430). Cronbach's alpha coefficient between weight-for-age, height-for-age and weight-for-height was 0.62 (95% CI 0.59, 0.64). Thus, the study of these associations is not straightforward as it would appear in a first instance. The lack of three-factor interaction and the value of the Cronbach's alpha coefficient indicate that undernutrition is indeed (statistically) multidimensional. The three indicators are not statistically redundant; thus for the case of Cameroon the choice of a particular anthropometric indicator should depend on the goal of the policy maker, as it comes out of this study that no single indicator is to be used for all situations.

Keywords: Stunting, Wasting, Underweight, anthropometric measures, Z-score, Loglinear models, Anthropometric measures

INTRODUCTION

Childhood undernutrition is one of the important health problems in developing countries. There are 170 million underweight children globally, of whom 3 million die each year as a result of underweight (WHO, 2009). The Millennium Development Goals (MDGs) focus on fighting against poverty, mortality, morbidity and undernutrition (United Nations, 2000). Regarding undernutrition, the target is to halve the part of the population suffering from hunger by 2015. Indicators to achieve this goal include reducing the prevalence of underweight in children under 5 years of age and the proportion of the population below minimum level of dietary energy consumption. The United Nations Development Program (UNDP) in its Human poverty index for developing countries (HPI-1) also uses

the percentage of children underweight-for-age for measuring deprivation in a decent standard of living (e.g. UNDP, 2007). This is the evidence that the international community is concerned with fighting undernutrition in developing countries. Socioeconomic factors, demographic and environmental characteristics, food intake, poor absorption and/or poor biological use of nutrients consumed may affect undernutrition (Foraita *et* al., 2008). A survey of the determinants of undernutrition is given in Pelletier (1994), UNICEF (1998), de Onís *et al.* (2000), Smith and Haddad (2002), Caputo *et al.* (2003), Behrman and Skoufias (2004) and Klasen (2008). Anthropometric indicators such as height-for-age, weight-for-height and weight-for-age provide outcome measurements of the nutritional status of young children (0 to 59 months, Gorstein at al., 1994). The evaluation of the nutritional status of young children uses the Z-score which measures the distance, expressed in standard deviations of the standard population between the individual's

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anthropometry and the median of the standard population. For the 2006 WHO Child Growth Standards, the standard population is an international sample from Brazil, Ghana, India, Norway, Oman and the United States of America (USA), whereas the reference one for NCHS/CDC/WHO was constituted solely from a sample population from the USA (Gorstein at al., 1994; WHO, 1995 and de Onís and Habicht , 1996).

A Z-score (with respect to the corresponding anthropometric measure) less than -3; between -3 and -2 and between -2 and -1 is an indication of severe, moderate and mild undernutrition, respectively. A Z-score greater than 2 would indicate over-nourished with respect to the corresponding anthropometric measure (WHO Working Group, 1986).

In the current paper, we shall confine ourselves in both severe and moderate status for each anthropometric measure and term as wasting (height-for-age), stunting (weight-for-height) and underweight (weight-for-age) respectively (the commonly used definition, WHO Working Group, 1986). It is important to note that two other methods for evaluating the children's nutritional status are the percentage of the median and the percentile methods (Cogill, 2003). The WHO Child Growth Standards can serve as a diagnostic tool to assess unhealthy trends (WHO, 2009). In addition, the standard could help in monitoring the nutritional status of communities and alert practitioners and policymakers to unhealthy trends in the population.

Stunting, usually referred as chronic (past) undernutrition (growth retardation) represents a measure of long term effects of malnutrition in a population and does not vary significantly according to the season of data collection (Cogill, 2003 and Rutstein, 2006). Wasting, usually referred to as acute (current) undernutrition (emaciation) is appropriate for examining short-term effects such as seasonal change in food supply or short-term nutritional status due to some factors like an illness. Underweight takes into account both chronic and acute undernutrition and is usually used to monitor nutritional status on a longitudinal basis (Cogill, 2003).

The aim of this paper was to construct statistical models to study the relationship between underweight, stunting and wasting; and to check whether the multidimensionality of undernutrition can be justified from a purely statistical point of view.

METHODS

Sample design

Data for 3742 children aged 0 to 59 months were obtained from the 2004 Cameroon Demographic and Health Survey (DHS) that was carried out by Cameroon's National Institute of Statistics and ORC Macro (USA).

The sample of Cameroon's DHS was a nationally representative household survey that used a two-stage stratified random sampling design. The first stage was the selection of primary sampling units (PSU) within each of the 22 strata and the second was the selection of households within each PSU. The survey consisted of a household questionnaire and a women's questionnaire. On the average, 22 households were selected in an urban PSU and 28 in a rural PSU for a total of 11584 households. Women aged 15-49 years identified in the households were interviewed. The women's questionnaire contained information on several topics including: background characteristics, contraceptive knowledge and use, maternity and breastfeeding, immunization of children, diarrhoea, fever, and cough in children, marriage, fertility preferences, husband's background, work status, age, height and weight of children. A more general description of the DHS methodology can be found in Rutstein and Rojas (2006).

The methodology for computing the indicators was based on the 2006 WHO Child Growth Standards (WHO, 2009). Since our focus was only the deficits on Z-scores, the variables were categorized as follows: from weight-for-age to underweight (Yes or No); from height-for-age to stunting (Yes or No); from weight-for-height to wasting (Yes or No). Yes was coded 1 and No was coded 0.

Statistical analysis

Statistical models used were loglinear models, Cronbach's alpha coefficient (Cronbach, 1951) and multiple correspondence analysis (MCA).

Loglinear models can be interpreted as a generalized linear model (GLM) which treats the cells counts as independent observations from a Poisson random component with corresponding means equal to the expected cell counts. They are useful when all the three factors can be treated as response (Agresti, 2002, 2007); it is indeed the case for *underweight*, *stunting* and *wasting*; and our focus is on their structure of association. Since there are three factors, 2^3 +1 (9) models are possible with loglinear models:

-Mutual (Complete) Independence *(*Model 1*)*: *stunting*, *wasting* and *underweight* are completely independent, i.e they are pairwise independent. This results in a loglinear model in which all interaction parameters are zero.

Partial Independence (Independence of one factor)*:* Joint independence of one factor and the combined classification of the two others; leading to a loglinear model with one possible nonzero interaction parameter.

-*Underweight* is partially independent of *stunting* and *wasting* (Model 2).

-*Wasting* is partially independent of *stunting* and *underweight* (Model 3).

-*Stunting* is partially independent of *wasting* and *underweight (*Model 4*)*.

Table 1: Cross classification of underweight by stunting and wasting

Stunting	Wasting	Underweight		All
		Yes	No	
Yes	Yes	67	0	67
	No	327	934	1261
No	Yes	68	70	138
	No	22	2254	2276
Total		484	3258	3742

Table 2: Goodness-of-fits tests for loglinear models relating stunting (S), wasting (W) and underweight (U)

Model	Loglinear Model Symbol	G^2 (Likelihood Ratio)	X^2 (Pearson)	df	P	
					G^2	X^2
1	(S, W, U)	1000.47	1063.74	4	0	0
2	(U, SW)	999.72	1091.48	3	0	0
3	(W, SU)	501.71	1036.05	3	0	0
4	(S, WU)	660.25	620.16	3	0	0
5	(SW, SU)	500.96	1013.25	2	0	0
6	(SW, WU)	659.50	620.26	2	0	0
7	(SU, WU)	161.50	153.63	2	0	0
8	(SW, SU, WU)	3.55	1.99	1	0.06	0.17
9	(SWU)	0	0	0	1	1

Conditional Independence of one factor: Two factors are conditionally independent on the other if independence holds within each partial table conditioning on a given value of that factor. This results in a loglinear model with two possible nonzero interactions parameters.

-*Wasting* and *underweight* are conditionally independent of *stunting* (Model 5).

-*Stunting* and *underweight* are conditionally independent of *wasting* (Model 6).

-*Stunting* and *wasting* are conditionally independent of *underweight* (Model 7).

-Homogenous association (Model 8): Every factor interacts with each other factor, but there is no interaction between all three factors. The conditional odds ratios between any two factors are identical at each category of the third factor. The logs of these odd ratios are functions of the parameters and the functions do not depend on the level of the conditioning factor. This model is usually hard to interpret.

- The saturated model (Model 9): This model contains the three factors being analyzed and all possible relationships between these factors. The only interpretation of this model is the fact that apparently all other models failed to represent the data in a suitable way (i.e. all the other models do not fit the data quite well). It provides a perfect fit. The goodness of fit of the models was assessed using Chi-squared and G-squared.

Cronbach's alpha coefficient was used to check whether dimension reduction was possible.

Another multivariate method used was MCA which is a graphical multivariate technique for performing an exploratory data analysis of a multi-way contingency table (see e. g., Greenacre,1993; Khattree and Naik, 2000). It can be used to determine the association (if any) between sets of variables.

Data were analysed with the Statistical Analysis Systems (SAS) version 6.12 (SAS Institute, 1996 Cary, NC, USA) and R (version 2.7.1, R Development Core Team, 2010).

RESULTS

Table 1 shows that *stunting* was observed in 35.17% of children, *wasting* in 5.45% and *underweight* in 12.88%. Pearson's correlations between weight-for-age with both *height-for-age* and *weight-for-height* were 0.67 and 0.63 respectively; and -0.14 between *weight-for-age* and *height-for-age*. *Underweight* was associated with *stunting* (P=0) and also with *wasting* (P=0) whereas *stunting* and *wasting* were not (P=0.43). Table 1 shows the raw data from which the loglinear model was fitted.

Table 2 shows the goodness of fits of the 9 different models. For models 1-7, P=0 for both likelihood ratio statistics and Pearson statistics. Model 8 gives P=0.06 and P=0.17 for likelihood ratio statistics and Pearson statistics respectively. Thus the fits of unsaturated models are very poor. This means that there is no best model that is close to the saturated model (Model 9). This

Table 3: Estimates for fitting saturated loglinear model for stunting, wasting and underweight

Coefficients	Estimate	Standard. Error	z value	P value
Intercept	7.72	0.02	366.54	0
Stunting	-0.88	0.04	-22.64	0
Wasting	-3.47	0.12	-28.61	0
Underweight	-4.63	0.21	-21.61	0
stunting:wasting	-25.67	42250	-0.001	1
stunting:underweight	3.58	0.22	16.005	0
wasting:underweight	4.60	0.27	16.81	0
stunting:wasting:underweight	22.96	42250	0.001	1
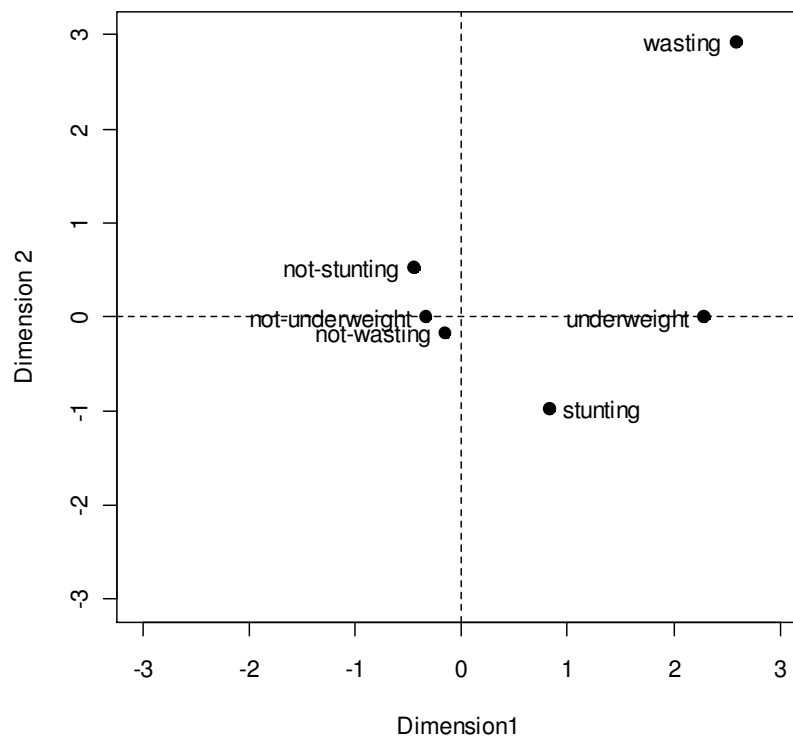
Figure 1: Multiple correspondence analysis for wasting, underweight and stunting

indicates that we have no good fitting restricted model that does not differ from the saturated model. In this case, it is not possible to select the more parsimonious restricted model because it cannot still explain the data equally well as the saturated model while possess fewer relationships between the variables. Thus, only the saturated model should be considered.

The fitted saturated model (Table 3) shows a highly significant interaction between *underweight* and *stunting* (P=0) and *underweight* and *wasting* (P=0), but no interaction between *stunting* and *wasting* (P=1). Furthermore, the saturated loglinear model shows the lack of a three-factor interaction between *stunting, wasting* and *underweight*.

MCA in Figure 1 shows the two dimensional display of all points corresponding to the six categories. 84.55% of the total inertia is explained by the first two dimensions; i.e. the loss is only 15.45%. The points corresponding to the levels of the same variable are clearly separated (i.e. *not-stunting*, *not-underweight* and *not-wasting* belong to the first and third quadrants of the plot; whereas *stunting*, *underweight* and *wasting* belong to the second and fourth). More interesting, stunting and wasting fall in two completely different quadrants (second and fourth),

indicating that they are not associated. *Underweight* is at the border line of the second and fourth quadrant, indicating that it is associated both with *wasting* and *stunting*.

Cronbach's alpha coefficient between *weight-for-age*, *height-for-age* and *weight-for-height* is 0.62 (95% CI 0.59, 0.64) and is therefore below the recommended 0.7 as an indication of data reduction.

DISCUSSION

Underweight status is associated with both *stunting* and *wasting* whereas *stunting* and *wasting* are not. This is consistent with the result of Gorstein at al. (1994). Furthermore, it is also well known that *underweight* could reflect *stunting* and/or *wasting*; or a composite measure of both; thus its inability to distinguish between both (e.g., Gorstein *et al.*, 1994; WHO, 1995; Cogill, 2003; Rutstein and Rojas, 2006).

Loglinear models analysis provide a coherent method for studying three factors considered as response variables like *underweight*, *wasting* and *stunting*. Bishop et al. (1975) advocate the use of log-linear models because they provide a richer analysis of the structure of association among all variables, not just between the predictors and response. The most common problem in loglinear modeling is to find the most suitable model. Suitable in this context means that the model includes as few interaction terms as possible and declares as much of the deviation from mutual independence as possible (Theus and Lauer, 1999). The stepwise model selection procedures for loglinear models (Christensen, 1997) usually use Chi-squared and G-squared statistics to judge the adequacy (fit) of a model; we used these approaches here. Interaction parameters are useful for interpreting associations (Agresti, 2002, 2007; Thompson, 2006). An extensive analysis of loglinear models can be found e.g. in Agresti (2002, 2007). The pairwise comparison as usually performed cannot give insight on the three-way interaction. This can be assessed using loglinear model analysis and MCA. The lack of three-factor interaction and the value of the Cronbach's alpha coefficient indicate the three anthropometric measures cannot be reduced to one or two dimensions, thus for the Cameroon example undernutrition is indeed (statistically) multidimensional.

The results of these studies only apply to this sample and associations may change depending on sample's settings and age range. A multi-country study could be carried out to find out how the results found here vary across countries. One can also perform ecological study across selected countries. However, drawbacks of such studies are well known, e.g. results found may be very different at the individual level. As stressed by Kelsey et al. (1986), ecological correlation studies should be interpreted with caution. De Onís et al. (1993) performed

an ecological correlation analysis of 22 African countries and found that the prevalence of *underweight* was positively associated with *wasting* and *stunting* and a very low correlation between *wasting* and *stunting*. Victora (1992) showed similar results for others African countries. Similar results can be found in Centers for Disease Control (1991). To the best of our knowledge, we did not find in the literature a similar study as ours using loglinear models or MCA as method for studying the associations between *stunting, wasting* and *underweight.*

Unlike a pairwise study of the associations between anthropometric measures, this paper uses unified modeling approaches such as MCA and loglinear models. As result, the lack of three-factor interaction and the value of the Cronbach's alpha coefficient indicate that undernutrition is indeed (statistically) multidimensional. The three indicators are not statistically redundant, thus for the case of Cameroon, the choice of a particular anthropometric indicator should depend on the goal of the policy maker, because no single indicator is useful in all situations.

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