

Methodology for estimating regional and global trends of child malnutrition

Mercedes de Onis,¹ Monika Blössner,¹ Elaine Borghi,¹ Richard Morris² and Edward A Frongillo³

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Background Child malnutrition is an important indicator for monitoring progress towards the Millennium Development Goals (MDG). This paper describes the methodology developed by the World Health Organization (WHO) to derive global and regional trends of child stunting and underweight, and reports trends in prevalence and numbers affected for 1990–2005.

Methods National prevalence data from 139 countries were extracted from the WHO Global Database on Child Growth and Malnutrition. A total of 419 and 388 survey data points were available for underweight and stunting, respectively. To estimate trends we used linear mixed-effect models allowing for random effects at country level and for heterogeneous covariance structures. One model was fitted for each United Nation's region using the logit transform of the prevalence and results back-transformed to the original scale. Best models were selected based on explicit statistical and graphical criteria.

Results During 1990–2000 global stunting and underweight prevalences declined from 34% to 27% and 27% to 22%, respectively. Large declines were achieved in Eastern and South-eastern Asia, while South-central Asia continued to suffer very high levels of malnutrition. Substantial improvements were also made in Latin America and the Caribbean, whereas in Africa numbers of stunted and underweight children increased from 40 to 45, and 25 to 31 million, respectively.

Conclusion Linear mixed-effect models made best use of all available information. Trends are uneven across regions, with some showing a need for more concerted and efficient interventions to meet the MDG of reducing levels of child malnutrition by half between 1990 and 2015.

Keywords Child, stunting, underweight, malnutrition, trends

Child malnutrition is internationally recognized as an important public health indicator for monitoring nutritional status and health in populations. The devastating effects of malnutrition on human performance, health, and survival are today well-established^{1–6} and a recent global analysis demonstrated that child malnutrition is the leading cause of the global burden of disease.^{7,8} As a result of the increased recognition of the relevance of nutrition as a basic pillar for social and economic development, monitoring trends in childhood malnutrition has gained increasing importance in assessing the progress made by

nations in achieving internationally set goals, such as the Millennium Development Goals.⁹ The objective of this paper is to describe the methodology developed and applied by the World Health Organization (WHO) to calculate regional and global estimates of childhood underweight and stunting and to report trends from 1990 to 2005. This analysis is an update of earlier trend modelling¹⁰ using additional data points that have become available subsequently and new population estimates.

Material and Methods

Data

To estimate regional and global trends in child stunting and underweight, national prevalence of low height-for-age and low weight-for-age (<-2 standard deviation (SD) of the National Center for Health Statistics/World Health Organization international reference population) were derived from the

¹ Department of Nutrition, World Health Organization, Geneva, Switzerland.

² Royal Free and University College Medical School, London, UK.

³ Division of Nutritional Sciences, Cornell University, Ithaca, New York, USA.

Correspondence: Dr Mercedes de Onis, Department of Nutrition, World Health Organization, 1211 Geneva 27, Switzerland. E-mail: deonism@who.int

WHO Global Database on Child Growth and Malnutrition (www.who.int/nutgrowthdb, version January 2003).¹¹

A total of 419 nationally representative surveys giving a prevalence for underweight were available from 139 countries. For 98 countries, national survey data were available from at least 2 surveys and 61 countries had at least 3 surveys. For stunting, 388 national representative survey data points were available from 138 countries. For 96 countries, at least 2 survey data points were available, and for 56 countries at least 3 data survey points were included in this analysis.

Countries providing data were regarded as a representative sample of all countries within their sub-region. Several sub-regions constitute a region. For example within the region of Asia there are four sub-regions: Eastern, South-central, South-eastern, and Western Asia. Hence the data present different hierarchical levels, i.e. at the bottom the countries, then sub-regions, then regions, then the group of all developing regions, and finally global which includes all the regions of developing countries (i.e. Africa, Asia, Latin America and the Caribbean, and Oceania) plus the group of developed countries. Regions and sub-regions were defined according to the UN country classification system.¹²

A data file was constructed consisting of the variables: *region*, *sub-region*, *country*, *survey year*, *sample size*, *minimum* and *maximum* age surveyed, prevalence of *stunting*, prevalence of *underweight*, and *country population* of under 5 year olds at the respective survey year. The methodology followed to obtain standardized country prevalence of underweight and stunting has been described elsewhere.¹¹ The comprehensive list of national prevalence data and their sources included in this analysis are available from authors on request.

Statistical analysis

Fitting trends for the sub-regions of developing countries

The methodology of linear mixed-effect models, as described by Laird and Ware¹³ was used for modelling the data set at sub-regional levels with countries' effect being defined as random. The model used is part of a more general class of models, the multilevel models. In the multilevel modelling literature, notably in Goldstein,¹⁴ the same model is called a 'two-level model', counting the levels of variation, i.e. level one the *survey* and level two *countries*. By regarding countries within a sub-region as random effects, our analysis was able to exploit the common influences throughout the sub-region.

One single linear mixed-effect model was considered for each group of sub-regions belonging to the same region. The basic model contained the fixed factors *sub-region* and *year*, the interaction between *year* and the *sub-region* as fixed effects, and *country* as random effect. Consequently we obtained from each model an intercept and a slope estimate for every sub-region within the region.

One of the advantages of a mixed-effect model over a fixed-effect model is that the former allows for both correlation within level (*countries*) and heterogeneous variances, although the mixed effect models assume normality for the errors in both cases.¹⁵ We considered three different structures for modelling the covariance: compound symmetric, unstructured, and auto-regressive of order 1. The compound symmetry model for a region allows the country to have its own intercept (influencing prevalence estimate) and forces all countries to have a common

slope in prevalence over time. The unstructured model for a region allows each country to have its own intercept and slope. The auto-regressive model of order 1 allows for correlations between observations within the same country to weaken as the time between them increases (see Appendix 1 for model details). Year was centred at the year 1995, around which there was a high concentration of available survey data points. Restricted maximum likelihood estimation method was used, as well as robust estimators for estimating the fixed-effect estimates of standard deviations.¹⁶

The fitting was performed on the logistic transform ('logit') of the prevalence. This transformation ensured that all prevalence estimates and their CI would lie between zero and one. The inherent properties of the logit transform meant (1) that trend lines would curve, decreasing at a slower rate, as zero prevalence was approached, and (2) CI for prevalence estimates close to zero were asymmetric and narrower than for values close to 50%.¹⁷ Because estimates were calculated on the logit scale, prevalence estimates and their respective CI were derived by back-transformation.

To account for the different country populations and ensure that the influence in the regional trend analysis of a country's survey estimate was proportional to the country's population, we carried out weighted analysis. The population weights were derived from the UN Population Prospects, revision 2000.¹² For each data point, we obtained the respective under-5 population estimate for the specific survey year. If a survey was performed over an extended period, for example 1995–1997, the mean year, i.e. 1996, was used as the year from which to choose the respective population estimate. For countries with multiple data points the weights were calculated by dividing the mean of the country's under-5 population (over the observed years) by the sum of the countries' mean population in the whole region. Weights of countries with single data points were derived by dividing the under-5 population at the time of the survey by the sum of the countries' mean population in the whole region.

The decision on how to choose the best model among different covariance structures was based on the model-fit criterion Akaike's Information Criterion (AIC), which is essentially log-likelihood values penalized for the number of parameters estimated.¹⁵ Lower AIC values mean better fit. In parallel, we examined the graphed display of the fitted trend line against the survey data points and discarded models which did not present a reasonable fit with respect to the empirical data.

Analysis of the residuals indicated significant departure from normality at the 5% level of significance for only two of the sub-regions of Latin America, one sub-region in Asia, and one in Africa. The application of a more general class of models, the generalized mixed-effect models which allows for the errors to have, for example, a binomial distribution, was considered. However, the increase in complexity compared with the limited gain in using this class of models, and in the interest of keeping a common approach for all the regions, we decided to use the simpler approach, the linear mixed-effect models with a robust estimator for the CI.

The linear trend fitting was adequate, and therefore we did not fit higher-order polynomials. The final models were then used to project the trend of underweight and stunting in children from 1990 to 2005. Using the resulting prevalence estimates (after back-transformation), the total numbers of affected were calculated with a spreadsheet multiplying the prevalence and

lower and upper limits of the CI by the sub-regional population derived from the UN population estimates.¹²

Prevalence estimates and CI for the regions of developing countries

For the regional level, an attempt was made to fit an overall model considering all the countries within the region, including a model with random effects for the sub-region trends. For some regions there was a significant interaction between *year* and *sub-region*, because different sub-regions presented different trends on the logistic scale. This resulted (after back-transformation) in numbers of malnourished children at the regional level that did not match the sum of the sub-regional totals. We therefore adopted the approach of estimating the prevalence for the region using the sum of the estimated numbers of affected in the sub-regions divided by the total under-5 population of that region. This overall regional estimate is thus the weighted average of the sub-region prevalence estimates (weighted by the respective under-5 population proportions). The CI were estimated using the delta method (Appendix 2 for formulae).

Fitting trends for the group of developed countries

Twenty-one observations were for the developed countries. Given that we had few data points and considering the relative homogeneity of the group, we fitted a linear mixed-effects model in the same way as described above for the trend in sub-regions, having as fixed effects only *year*, and keeping *country* as random effect. There was some departure from normality for the residuals, but we considered that there were too few data points to justify moving to a more complex class of models, like the generalized linear mixed-effect models.

Global prevalence estimates and CI

The global prevalence estimates and respective CI were calculated using the same methodology as described for the regional estimates, but adding up regional estimated numbers of affected plus the number of affected for the developed countries group and the number of affected for Oceania.

For the region of Oceania, there were only six data points and, therefore, we estimated the overall prevalence trend using a simple linear regression. The resultant prevalence estimate, the standard error and corresponding numbers of affected were used only to add up the total global number of affected children in order to obtain the global prevalence estimate and respective standard error.

Results

The first step in the process of deciding on the covariance model was to check the AIC fit statistics, being the smaller the better. Table 1 presents the comparison of AIC fit statistics for stunting and underweight by UN regions.

As a second step we produced graphs of the data to inspect the fit of the empirical data points to the modelled trend line. Figures 1–6 show the plots of the individual survey estimates (circles) against the estimated model trend line for the final selected models; the sizes of the circles indicating the weighted contribution according to the population size in the country within the region. The size of country populations influences the trend. For example, for underweight in Eastern and Western Africa (Figure 4), two of the worst regions in terms of trend, there seems to be a ‘large country’ effect in that the larger countries have the highest prevalence. This also works through to a ‘large sub-region’ effect with Eastern and Western Africa being the largest two sub-regions in Africa and their prevalence being the worst and third worst in this region.

For stunting, discrepancies between fitted and empirical values were noticed for Africa (Northern Africa) and Asia (Eastern Asia), when considering the covariance model with the lowest AIC. We thus rejected that model and selected the next best AIC value (Figures 1 and 2). For underweight, model decision was based on AIC value for Africa and Latin America & the Caribbean while in the case of Asia we took a final decision on the basis of the plot. For the latter, the graphs based on the unstructured covariance model (which had the smallest AIC value) did not fit the empirical data points for South-central and Eastern Asia (too low and not giving appropriate weight to the India survey data; too low and not giving appropriate weight to the China data). As with stunting, we rejected that model and selected the next best AIC value, i.e. compound symmetry (Figure 5). Tables 2 and 3 present the prevalence and number of stunted and underweight children, respectively, from 1990 to 2005.

Discussion

The methodology that we have developed was primarily intended to produce precise and accurate estimates of progress made in reducing child malnutrition at the sub-regional,

Table 1 Fitted models’ AIC^a statistics for stunting and underweight by UN regions (✓ indicating selected models)

Regions	Unstructured	Compound symmetry	Autoregressive
Stunting			
Africa	200.3 ^b	249.9✓	256.8
Asia	187.7 ^c	207.5✓	Did not converge
Latin America & Caribbean	192.8✓	244.3	Did not converge
Underweight			
Africa	204.5✓	245.0	260.9
Asia	165.2 ^d	187.2✓	Did not converge
Latin America & Caribbean	195.7✓	208.0	Did not converge

^a Akaike’s Information Criterion.

^b Did not reflect empirical trend in Northern Africa.

^c Did not reflect empirical trend in Eastern Asia.

^d Did not reflect empirical trends in Eastern Asia and South-central Asia.

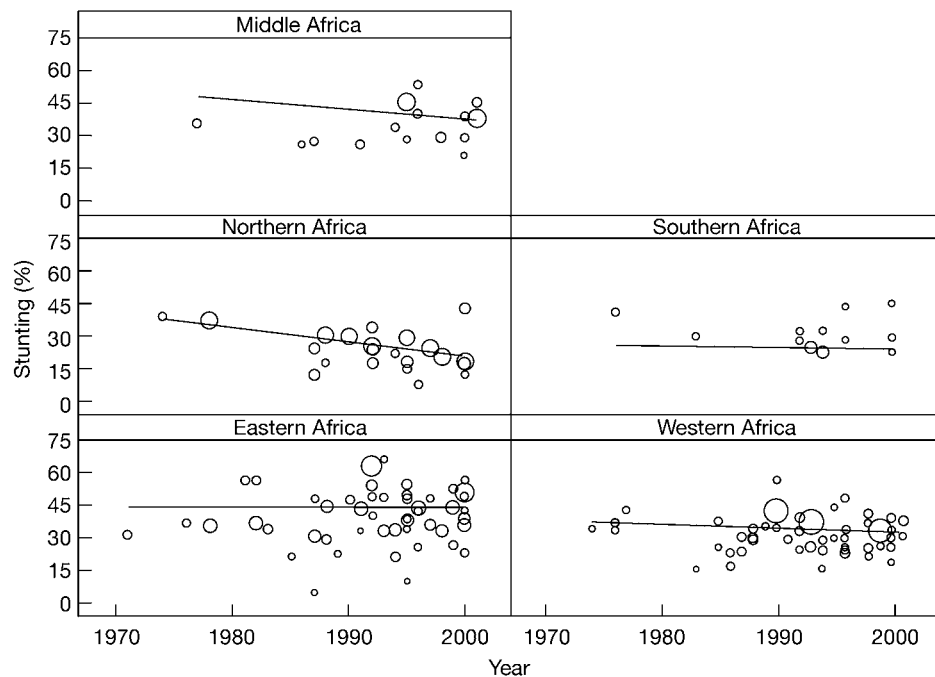


Figure 1 Empirical stunting prevalence (circles) plotted against estimated model trend (line) using compound symmetry covariance structure: Africa

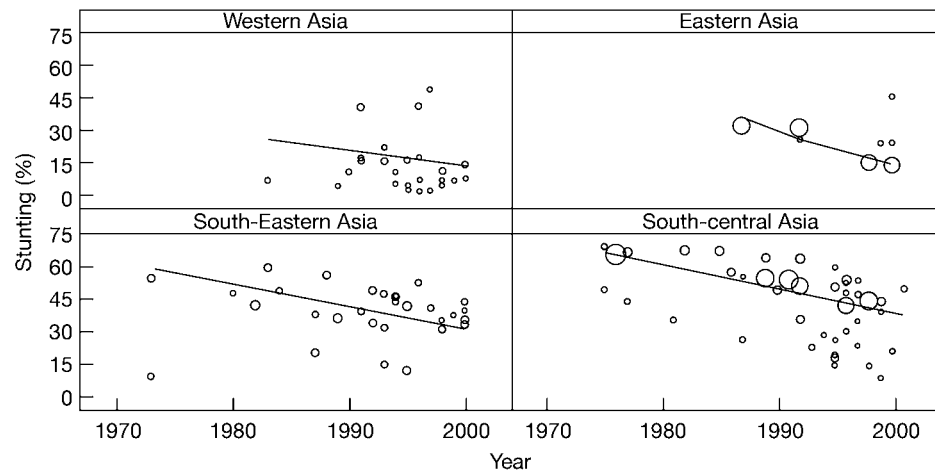


Figure 2 Empirical stunting prevalence (circles) plotted against estimated model trend (line) using compound symmetry covariance structure: Asia

regional, and global levels. The basic elements of the methodology are: (1) estimation for each sub-region, using country-level population weights and assuming linear trend, (2) aggregation from sub-region to region to global using population weights, (3) estimation using random intercept and slope models where data allow and give reasonable results, with simplification to random intercept only models where data do not allow or do not give reasonable results, (4) use of all available country data (i.e. use of all countries that have data and use of all quality data for each country), including countries with only one survey, (5) use of an explicit, multilevel statistical model, (6) use of the delta method to calculate approximate standard errors and CI when an exact formula does not exist.

There are a number of advantages of this methodology. First, multilevel modelling has become a standard approach for this type of task, since software to fit these models became widely available in the past decade. The model specifies the structure across levels through the random effects, the relations among the fixed effects, and the form of the dependency among the residuals (i.e. covariance structure). The use of an explicit statistical model means that assumptions and postulated features of the model (e.g. relations among variables) can be clearly stated and examined.

Second, all available country data points are used, including countries with one data point. This is important for getting the best (i.e. most precise and accurate) estimates of prevalence. A

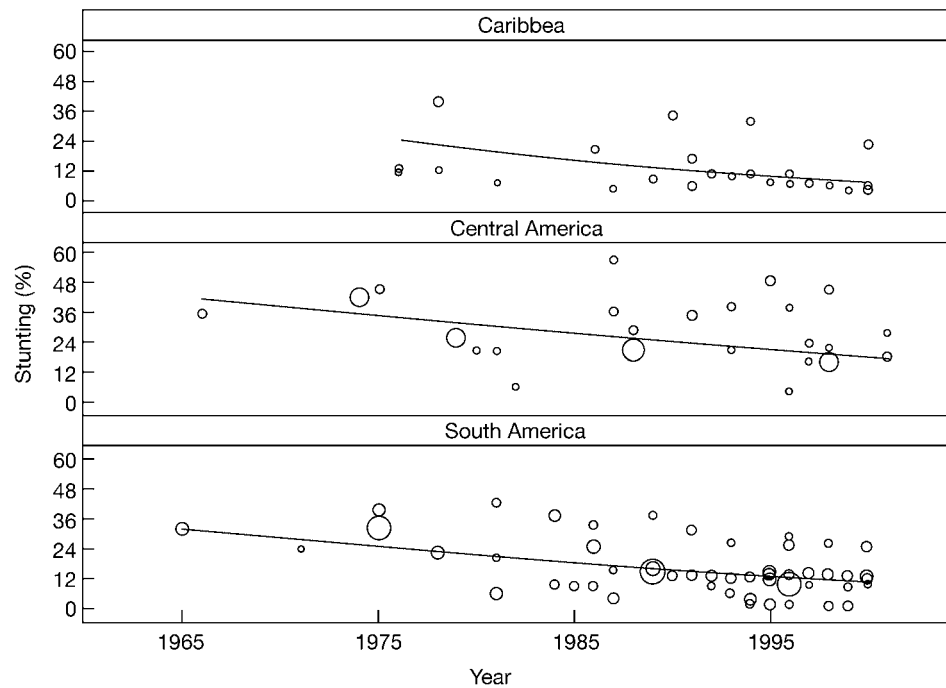


Figure 3 Empirical stunting prevalence (circles) plotted against estimated model trend (line) using unstructured covariance with random intercepts and slopes: Latin America & Caribbean

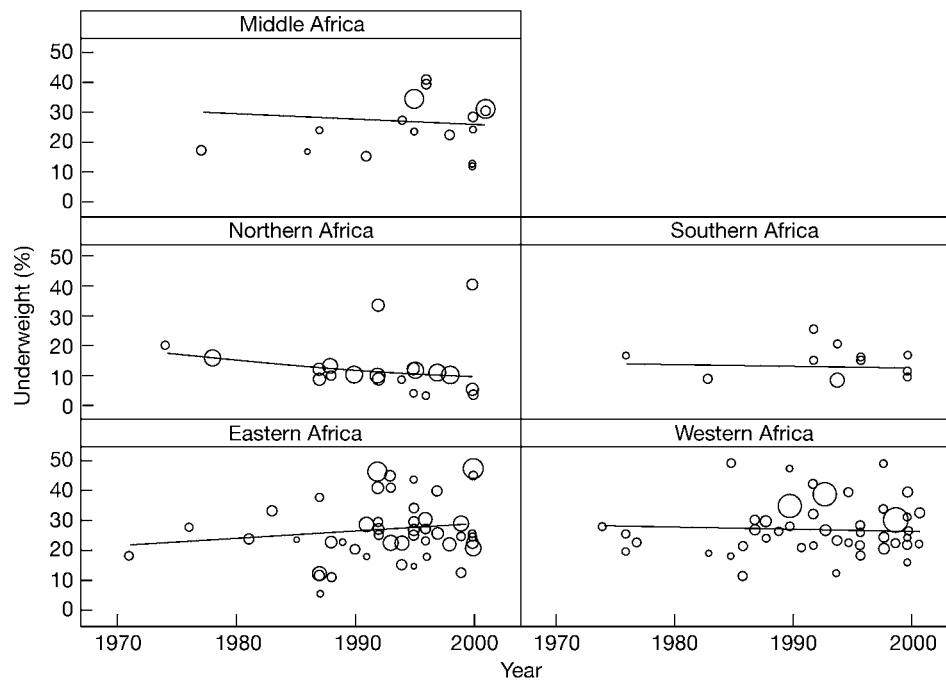


Figure 4 Empirical underweight prevalence (circles) plotted against estimated model trend (line) using unstructured covariance with random intercepts and slopes: Africa

country with only one survey contributes to the prevalence estimate for its sub-region, even though it does not contribute to the estimate of progress over time. The methodology uses all surveys that are available for a country, and does not require that the survey years for each country are the same.

Furthermore, as is desirable, countries with data throughout the interval of interest will have more influence on the trend than countries with data from only a part of the interval of interest.

Third, although we assumed for our analyses a linear (i.e. straight-line) trend among variables, the methodology can

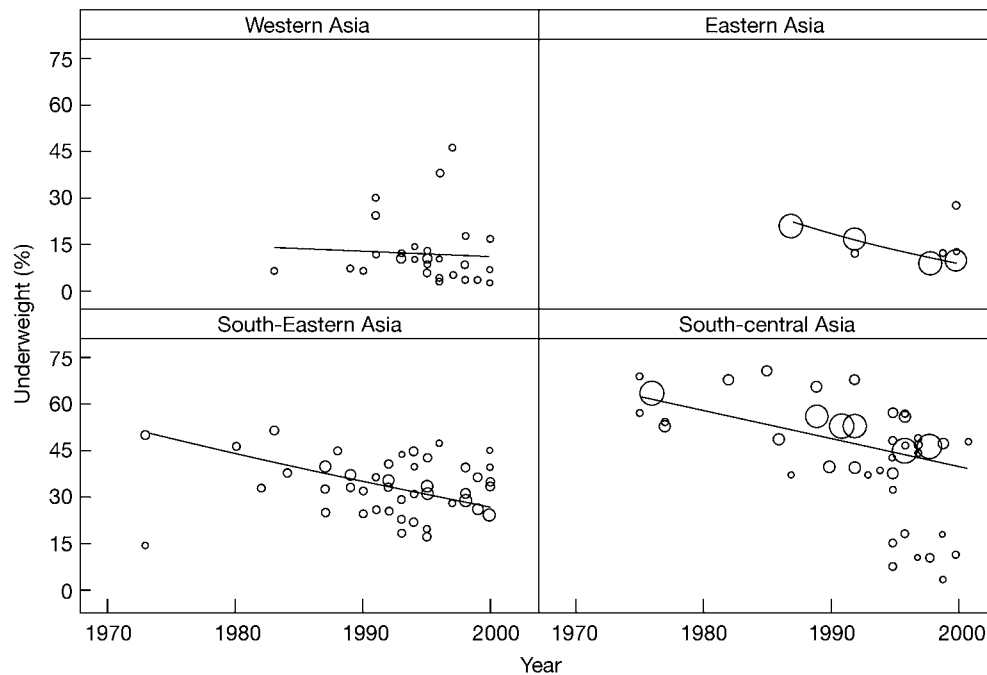


Figure 5 Empirical underweight prevalence (circles) plotted against estimated model trend (line) using compound symmetry covariance structure: Asia

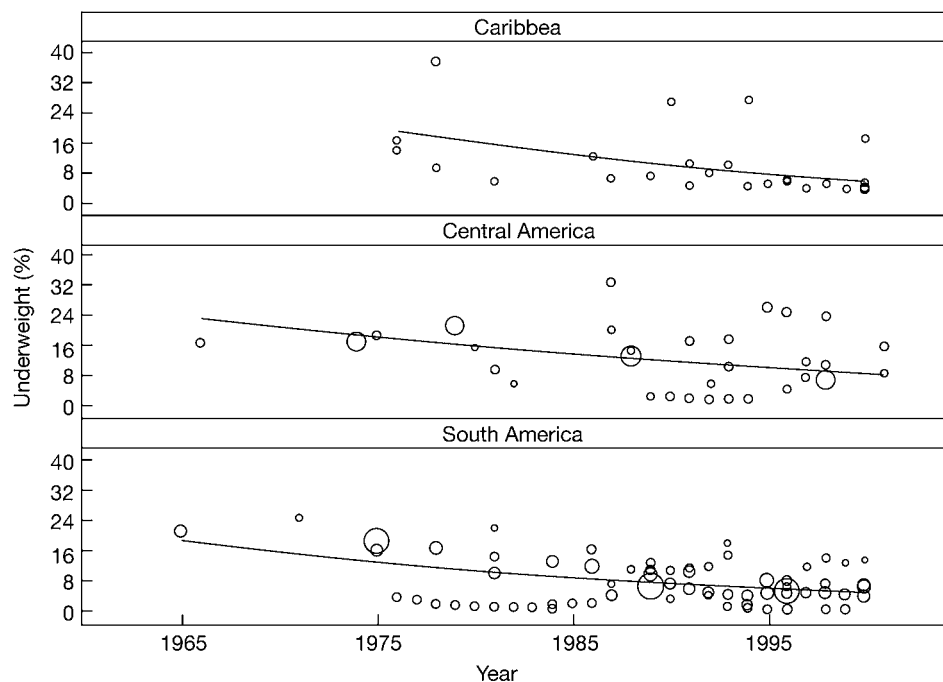


Figure 6 Empirical underweight prevalence (circles) plotted against estimated model trend (line) using unstructured covariance with random intercepts and slopes: Latin America & Caribbean

easily incorporate deviations from the linear trend. This can be done by specifying second-degree and higher polynomial terms. In this analysis we examined this and no evidence of non-linear relationships was found for any region.

Fourth, the fact that not all the countries have available underweight and/or stunting prevalence data has to be considered and incorporated in the model. The best way to do

this is to include countries as random effects in the model, under the assumption that the countries without data are missing at random.^{19,20} This also allows exploitation of common influences operating on the prevalence of underweight and stunting for countries when making estimates for the sub-region.

Fifth, specifying random intercept and slope models means that the trend in each country with multiple surveys is captured

Table 2 Estimated prevalence and numbers of stunted preschool children 1990–2005 with 95% CI

UN regions and sub-regions	% Stunting				No. stunted (in millions)			
	1990	1995	2000	2005	1990	1995	2000	2005
Africa	36.9 33.3–40.5	36.1 33.0–39.1	35.2 32.5–38.0	34.5 31.7–37.4	39.6 35.7–43.5	41.9 38.4–45.5	45.1 41.6–48.7	48.5 44.5–52.6
Eastern	44.4 36.6–52.4	44.4 37.3–51.8	44.4 37.6–51.4	44.4 37.6–51.4	15.8 13.0–18.7	17.3 14.5–20.2	19.4 16.5–22.5	21.6 18.3–25.0
Middle	42.2 34.2–50.5	40.0 34.0–46.2	37.8 33.7–42.1	35.8 33.0–38.6	5.6 4.5–6.7	6.3 5.4–7.3	6.8 6.0–7.6	7.4 6.9–8.0
Northern	27.4 21.1–34.7	24.4 18.7–31.2	21.7 16.1–28.6	19.1 13.5–26.5	5.8 4.5–7.4	5.1 3.9–6.5	4.6 3.4–6.1	4.2 2.9–5.8
Southern	25.4 23.7–27.1	25.0 22.6–27.6	24.6 21.5–28.1	24.3 20.4–28.6	1.5 1.4–1.6	1.4 1.3–1.6	1.5 1.3–1.7	1.4 1.2–1.7
Western	34.7 28.7–41.2	33.8 29.9–37.9	32.9 30.2–35.7	32.0 28.4–35.7	10.9 9.0–13.0	11.8 10.4–13.2	12.7 11.7–13.8	13.9 12.4–15.5
Asia	41.1 38.6–43.6	35.4 32.6–38.2	30.1 27.1–33.1	25.7 22.5–28.9	154.6 145.1–164.1	130.8 120.5–141.0	109.4 98.6–120.2	92.4 80.9–103.8
Eastern	30.0 28.7–31.3	21.5 20.4–22.6	14.8 13.9–15.8	10.0 9.3–10.7	37.5 35.9–39.1	23.5 22.3–24.7	15.2 14.3–16.1	9.5 8.8–10.2
South-central	50.8 46.1–55.4	45.2 40.2–50.3	39.7 34.4–45.3	34.5 29.0–40.5	88.0 79.9–96.0	81.0 72.0–90.2	71.5 62.0–81.6	63.5 53.3–74.4
South-eastern	41.8 33.6–50.4	36.8 29.3–44.9	32.1 25.2–39.7	27.7 21.3–35.1	23.9 19.2–28.8	21.3 17.0–26.0	18.1 14.3–22.5	15.3 11.8–19.4
Western	25.0 20.2–30.4	21.7 15.1–30.1	18.7 10.9–30.1	16.1 7.8–30.3	5.2 4.2–6.3	5.0 3.5–6.9	4.5 2.7–7.3	4.1 2.0–7.8
Latin America & Caribbean	18.3 13.6–23.0	15.9 11.3–20.5	13.7 9.1–18.4	11.8 7.0–16.5	10.0 7.4–12.6	8.8 6.2–11.3	7.6 5.0–10.2	6.5 3.9–9.2
Caribbean	12.4 6.8–21.5	9.6 5.1–17.3	7.4 3.8–14.1	5.7 2.7–11.5	0.5 0.3–0.9	0.4 0.2–0.7	0.3 0.1–0.5	0.2 0.1–0.4
Central America	25.9 16.3–38.4	23.0 14.4–34.8	20.4 12.5–31.5	18.0 10.8–28.4	4.0 2.5–5.9	3.7 2.3–5.6	3.3 2.0–5.1	2.9 1.8–4.6
South America	15.7 10.8–22.2	13.3 8.6–20.0	11.3 6.5–18.9	9.6 4.9–18.2	5.5 3.8–7.8	4.7 3.0–7.1	4.0 2.3–6.7	3.4 1.7–6.5
Oceania	n/a ^a	n/a	29.3 7.9–66.7	n/a	n/a	n/a	0.32 0.09–0.72	n/a
All developing countries	37.9 35.9–39.8	33.5 31.4–35.6	29.6 27.5–31.7	26.5 24.2–28.7	204.3 193.7–214.9	181.5 170.4–192.7	162.1 150.4–173.8	147.5 135.0–159.9
Developed Countries	2.8 0.8–9.1	2.8 0.8–8.9	2.7 0.8–8.7	2.6 0.8–8.4	2.2 0.7–7.1	2.0 0.6–6.4	1.8 0.5–5.7	1.6 0.5–5.2
Global	33.5 29.5–44.9	29.9 23.0–40.0	26.7 17.4–35.5	24.1 12.9–31.4	206.5 195.7–217.2	183.5 172.2–194.8	163.9 152.1–175.7	149.1 136.6–161.6

^a Not available due to insufficient data.

well by the model. This results in a more precise model than if only random intercepts are used, and is more realistic than assuming that all countries in a sub-region progress similarly. Furthermore, constructing overall regional and global prevalence estimates by using the sub-regional estimates is preferred, considering the relative homogeneity within sub-regions, except for the case of South-central Asia. The heterogeneity found in this sub-region would have justified splitting it into two distinct groups; however, we chose not to do so to maintain this UN sub-region as an entity and to be consistent with the country grouping used in earlier reports.

Sixth, the methodology yields explicit estimates of uncertainty in the form of CI. When needed, the delta method

was used to estimate standard errors by using a Taylor series expansion to obtain the asymptotic distribution, a standard technique for this purpose. The delta method produces an estimator of the standard error that is straightforward and intuitive.

Seventh, the methodology can theoretically provide country-level estimates that are statistically most efficient by using principles of shrinkage (i.e. empirical Bayes in this case) estimation that borrow information from neighbouring countries when a given country has limited data.¹⁸ This approach has been highly successful in small-area estimation, for example. Whether this theoretical advantage can be realized in this case, however, is not clear. Most countries may not

Table 3 Estimated prevalence and numbers of underweight preschool children 1990–2005 with 95% CI by UN regions and sub-regions

UN regions and sub-regions	% Underweight				No. underweight (in millions)			
	1990	1995	2000	2005	1990	1995	2000	2005
Africa	23.6 21.0–26.2	23.9 21.5–26.3	24.2 21.9–26.4	24.5 22.1–26.8	25.3 22.6–28.1	27.8 25.0–30.6	30.9 28.0–33.8	34.5 31.1–37.8
Eastern	26.7 22.0–32.0	27.9 23.3–33.0	29.2 24.6–34.3	30.6 25.7–35.8	9.5 7.8–11.4	10.9 9.1–12.9	12.8 10.8–15.0	14.8 12.5–17.4
Middle	27.8 19.8–37.5	26.9 21.0–33.8	26.1 21.8–30.8	25.3 21.6–29.3	3.7 2.6–5.0	4.2 3.3–5.3	4.7 3.9–5.5	5.3 4.5–6.1
Northern	12.3 7.4–19.6	10.9 5.9–19.4	9.7 4.6–19.4	8.6 3.6–19.5	2.6 1.6–4.1	2.3 1.2–4.1	2.1 1.0–4.2	1.9 0.8–4.3
Southern	14.0 9.9–19.5	13.9 9.8–19.2	13.7 9.7–19.0	13.6 9.6–18.8	0.8 0.6–1.1	0.8 0.6–1.1	0.8 0.6–1.2	0.8 0.6–1.1
Western	27.8 23.6–32.4	27.5 24.2–31.0	27.1 24.2–30.3	26.8 23.6–30.3	8.8 7.4–10.2	9.6 8.4–10.8	10.5 9.4–11.7	11.7 10.3–13.2
Asia	35.1 31.7–38.5	31.5 27.8–35.1	27.9 24.0–31.7	24.8 20.8–28.8	131.9 119.2–144.7	116.3 102.7–129.8	101.2 87.3–115.0	89.2 74.9–103.5
Eastern	18.5 17.6–19.4	13.2 12.5–13.9	9.3 8.8–9.9	6.5 6.1–6.9	23.1 22.0–24.2	14.5 13.7–15.3	9.5 9.0–10.1	6.1 5.7–6.5
South-central	49.6 42.4–56.8	45.2 37.9–52.6	40.8 33.5–48.5	36.5 29.3–44.4	86.0 73.5–98.5	80.9 67.9–94.3	73.4 60.3–87.3	67.1 53.9–81.5
South-eastern	35.2 30.8–40.0	31.2 27.1–35.6	27.4 23.4–31.8	23.9 19.9–28.5	20.2 17.6–22.9	18.1 15.7–20.7	15.5 13.2–18.0	13.2 11.0–15.7
Western	12.9 9.9–16.7	12.1 7.3–19.4	11.3 5.0–23.7	10.6 3.3–28.9	2.7 2.1–3.5	2.8 1.7–4.5	2.8 1.2–5.8	2.7 0.9–7.5
Latin America & Caribbean	8.7 6.1–11.3	7.3 5.0–9.6	6.1 4.0–8.1	5.0 3.2–6.8	4.8 3.4–6.2	4.0 2.8–5.3	3.4 2.2–4.5	2.8 1.8–3.8
Caribbean	10.0 5.9–16.4	7.8 4.5–13.3	6.1 3.3–10.8	4.7 2.5–8.7	0.4 0.2–0.7	0.3 0.2–0.5	0.2 0.1–0.4	0.2 0.1–0.3
Central America	12.4 7.5–19.9	10.7 6.3–17.6	9.2 5.2–15.7	7.9 4.3–14.0	1.9 1.2–3.1	1.7 1.0–2.8	1.5 0.9–2.6	1.3 0.7–2.3
South America	7.0 4.5–10.8	5.7 3.6–8.9	4.6 2.9–7.4	3.7 2.3–6.1	2.5 1.6–3.8	2.0 1.3–3.1	1.6 1.0–2.6	1.3 0.8–2.2
Oceania	n/a ^a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
All developing countries	30.1 27.6–32.5	27.3 24.8–29.9	24.8 22.2–27.3	22.7 20.1–25.4	162.2 149.1–175.3	148.2 134.4–162.0	135.5 121.3–149.7	126.5 111.8–141.2
Developed Countries	1.6 0.8–3.0	1.4 0.6–3.2	1.3 0.5–3.5	1.1 0.3–3.7	1.2 0.6–2.4	1.0 0.4–2.3	0.8 0.3–2.3	0.7 0.2–2.3
Global	26.5 24.3–28.6	24.3 22.1–26.6	22.2 19.9–24.5	20.6 18.2–22.9	163.4 150.3–176.6	149.2 135.3–163.1	136.4 122.2–150.6	127.2 112.5–141.9

^a Not available due to insufficient data

accept an estimate for their country that is statistically adjusted with data borrowed from other countries.

As shown in Table 1, in all three regions, for both stunting and underweight, the unstructured covariance model with random intercepts and slopes presented lower AIC than did the compound symmetry covariance model with random intercepts only (the auto-regressive structure performed worst in all cases). However, in three out of six cases the model with the lowest AIC was rejected in favour of the model with fixed effect for the slope (i.e. compound symmetry) because the estimated trend line did not reflect the empirical trend (footnotes to Table 1). The fact that models with random slopes fitted better than models with fixed slopes indicates that there is heterogeneity between trends in prevalence at the country level. As can be seen in Figure 5, there appear to be some outliers which have lower levels of prevalence of underweight

in South-central Asia in surveys conducted from 1995 to 2000. If these countries had earlier surveys, the sub-regional trend line might have been steeper. There also appear to be outliers in the graphs for stunting in Northern Africa and Eastern Asia that would also might have impact the sub-regional trends if they had earlier surveys (Figures 1 and 2). For these sub-regions we therefore decided to use the model with fixed effect for the slope, that is less affected by outliers and fitted better the empirical data.

While the methodology described above presents various strengths, there are also some inherent weaknesses. One potential drawback is its complexity. Although it has become a standard approach for many applications—and software is included in most of the statistical packages—mixed-effect model fitting requires understanding and caution to ensure appropriate use. In this analysis, both sound knowledge of the

nutritional situation in countries and the expertise in developing models were needed to derive valid estimates. Alternatively, the use of individual simple regression models at country level would be conceptually more straightforward, but would lack the ability to deal with the complexities of the data that are available for global, regional, and sub-regional monitoring.

Another limitation of this methodology is a by-product of one of its biggest advantages. The fact that the model enables inclusion and achieves best use of all the available information for a region, assuming relative homogeneity within sub-regions, makes it highly dependent on the country grouping. Consequently, overall estimates can be different depending on what regional classification is applied. To overcome this problem, it is recommended to present trends always using the same regional classification.

There has been global progress in the reduction of child malnutrition during the 1990s, with stunting and underweight prevalence declining from 34% to 27% and 27% to 22%, respectively (Tables 2 and 3). The largest decline was achieved in Eastern Asia where stunting and underweight levels decreased by one-half between 1990 and 2000. South-eastern Asia also experienced substantial improvements with stunting rates declining from 42% to 32% and underweight from 35% to 27%. South-central Asia continues to suffer from staggeringly high levels of child malnutrition but rates are showing significant declines in stunting, from 51% to 40% and underweight from 50% to 41% during this period. Substantial improvements were also made in Latin America and the Caribbean where a relative decrease of 25% in stunting (from 18% to 14%) and one-third in underweight (from 9% to 6%) occurred over the last 10 years. In Africa, however, there has been little or no change in the last decade, and 35% and 24% of all under 5s remain stunted and underweight, respectively. The actual number of malnourished children in Africa has actually increased between 1990 and 2000, from 40 to 45 million stunted and 25 to 31 million underweight. The lack of progress observed in Africa is likely to be partly due to the effect of the human immunodeficiency virus (HIV)/AIDS epidemic. The disease has both a direct and indirect effect: infected children are more likely to be underweight, but also AIDS orphans or children of parents affected by AIDS are at increased risk of becoming malnourished. In sub-Saharan Africa, an

estimated 333 000 children below 5 years of age died in 1999 with HIV infection²¹ and 11 million are estimated to be orphaned because of AIDS.²² The predictions of stunting and underweight made for 2005 might be underestimates if the HIV/AIDS epidemic worsens in Africa or other regions.

The overall reduction in the prevalence of underweight is consistent with the increasing rates in childhood overweight observed in many developing countries. A recent global analysis reported that 16 of the 38 developing countries with more than one national survey available, showed a rising trend in childhood overweight.²³ The comparison of both ends of the weight-for-height distribution suggest a population-wide shift, with overweight replacing wasting as countries undergo the nutrition transition.²³ Because of this transition, indicators of malnutrition based on weight will be more complex to interpret, and stunting will increasingly provide a more accurate indication of undernutrition than will underweight.

Overall, our analyses show that progress in reducing child malnutrition has been uneven in distinct regions of the world and some areas even show an aggravating situation. To achieve the Millennium Development target for reduction of hunger,⁹ more concerted efforts are needed in those regions with stagnating and increasing trends of malnutrition, but without diminishing support to those which show progress, given that this is where the majority of children are still to be found.

Well-nourished children have a better chance of surviving, of learning more easily, and of growing into healthy adults who in turn can give their children a better start in life. The three pillars for improving nutritional status are: adequate and safe food intake, freedom from illness, and appropriate family care. Key strategies for achieving the latter include improved breastfeeding and complementary feeding practices. To reduce malnutrition in a sustained manner, there is also a need for micro-nutrient supplementation and fortification, the provision of medical services to help reduce infectious diseases, improvements in access to clean water and sanitation, and increased education.²⁴ Above all, to set the stage for enabling progress along these lines, all populations need peace as well as good governance and equitable distribution of national and international resources. Only when optimal child growth is ensured for the majority will governments be successful in their efforts to accelerate economic development in a sustained way.

KEY MESSAGES

- During the 1990s, rates of child malnutrition improved, as measured by declines in the prevalence of both stunting (34–27%) and underweight (27–22%).
- Large improvements were achieved in Eastern and South-eastern Asia, while South-central Asia continues to suffer very high levels of malnutrition. Substantial progress was also made in Latin America and the Caribbean.
- In Africa numbers of stunted and underweight children increased from 40 to 45 and 25 to 31 million, respectively.
- More concerted and efficient interventions are needed to meet the Millennium Development Goal of reducing levels of child malnutrition by half between 1990 and 2015.
- Linear mixed-effects models have several strengths which make them advantageous to other approaches in deriving trends of child malnutrition.

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Appendix 1

Structures for modelling the covariance

(1) Statistical model for the compound symmetric structure within countries:

$$y_{ij} = \text{logit}(p_{ij}) = \beta_0 \text{ sub-region} + \beta_1 \text{ sub-region} \times \text{year}_j + b_i + \varepsilon_{ij},$$

$$b_i \sim N(0, \sigma_s^2 I) \quad \text{and} \quad \varepsilon_{ij} \sim N(0, R),$$

with

sub-region representing a class variable associated with the sub-regions in the region,

β_0 and β_1 representing, respectively, the intercept and slope sub-region effects,

b_i is the random effect associated with the i^{th} country,

ε_{ij} is the random error associated with the i^{th} country's at time j , b_i and ε_{ij} independent.

The matrix R is block diagonal with Σ being the i^{th} block diagonal element of R , associated with the vector of observations for the i^{th} country over time. In the case of compound symmetry, Σ is such that

$$\text{Var}(y_{ij}) = \sigma_s^2 + \sigma_T^2 \quad \text{and} \quad \text{Cov}(y_{ij}, y_{ij}) = \sigma_s^2.$$

(2) Statistical model for the unstructured covariance matrix with random intercept and random slopes:

$$y_{ij} = \text{logit}(p_{ij}) = \beta_0 \text{ sub-region} + \beta_1 \text{ sub-region} \times \text{year}_j + b_{0i} + b_{1i} \text{ year}_j + \varepsilon_{ij},$$

$$b_i \sim N(0, \Sigma) \quad \text{and} \quad \varepsilon_{ij} \sim N(0, \sigma_T^2 I),$$

with

sub-region representing a class variable associated with the sub-regions in the region,

β_0 and β_1 representing, respectively, the intercept and slope sub-region effects,

$b_i = (b_{0i}, b_{1i})$ is the random effect vector associated with the i^{th} country's parameters intercept and slope,

ε_{ij} is the random error associated with the i^{th} country's at time j .

This model was used with the unstructured covariance model, allowing the variances of b_{0i} and b_{1i} and the correlation between them to be estimated.

Appendix 2

Formulae prevalence estimates and CI for the regions

For a region with n sub-regions with under-5 populations given by N_i ($i = 1, \dots, n$) and prevalence estimates given by \hat{p}_i , the overall prevalence estimator is given by:

$$\hat{p} = \frac{\sum_{i=1}^n N_i \hat{p}_i}{\sum_{i=1}^n N_i}$$

The CI for the sub-regions were derived by back-transforming the lower and upper limits at the logit scale. For constructing a confidence interval for the overall region prevalence estimate, the associated standard error had to be estimated. To do that, we derived approximated standard errors associated with the sub-regions' prevalence estimates \hat{p}_i 's using the delta method, which involves a Taylor series approximation of the logit back-transform function.^{15,18} The logit function is:

$$y = g(p) = \ln\left(\frac{p}{1-p}\right)$$

and the back-transform function is given by:

$$h(y) = g^{-1}(y) = \frac{e^y}{1+e^y}$$

Applying the delta method, the standard error of the sub-region prevalence estimates is given by:

$$s.e.(\hat{p}) = \sqrt{\left[\frac{\partial h(\hat{y}_i)}{\partial \hat{y}_i} \right] [s.e.(\hat{y}_i)]^2} = \hat{p}_i (1 - \hat{p}_i) \times s.e.(\hat{y}_i),$$

where \hat{p}_i 's are the sub-regional estimates on the logit scale. Hence, we were able to calculate an approximate standard error for the regional prevalence estimate \hat{p} , which is given by:

$$s.e.(\hat{p}) = \sqrt{\frac{\sum_{i=1}^n N_i^2 [s.e.(\hat{p}_i)]^2}{\left[\sum_{i=1}^n N_i \right]^2}}$$

An approximate 95% CI for the overall region prevalence estimate was then derived by applying a normal range, i.e.:

$$LowerCL = \hat{p} - 1.96 \times s.e.(\hat{p}) \quad \text{and} \quad UpperCL = \hat{p} + 1.96 \times s.e.(\hat{p})$$