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Severe acute malnutrition among under-5 children in low- and middle-income countries: A hierarchical analysis of associated risk factors

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ABSTRACT

Objectives: Malnutrition is one of the main reasons for death among children <5 years of age in low- and middle-income countries (LMICs). It accounts for about one-third of preventable deaths among children. Reduction of malnutrition, especially severe acute malnutrition (SAM), is critical, directly or indirectly, to a targeted decrease in child mortality and improvement in maternal health. It would also help achieve sustainable development goal 2 (improvement of nutrition across the board) and sustainable development goal 3 (ensuring healthy lives and well-being promotion for all at all ages). The aim of this study was to develop and test a model of risk factors associated with SAM among under-5 children in LMICs.
Methods: We used 51 recent demographic and health-surveys, cross-sectional, nationally representative data collected between 2010 and 2018 in LMICs. We used multivariable Bayesian logistic multilevel regression models to analyze the association between individual compositional and contextual risk factors associated with SAM. We analyzed information on 532 680 under-5 children (level 1) nested within 55 823 communities (level 2) from 51 LMICs (level 3).
Results: The prevalence of SAM ranged from 0.1% in both Guatemala and Peru to 9.9% in Timor-Leste. Male children, infants, low birth weight children, children whose mothers had no formal education, those from poorer households, and those with no access to any media were more likely to have SAM. Additionally, children from rural areas, neighborhoods with high illiteracy and high unemployment rates, and those from countries with high intensity of deprivation and high rural population percentage were more likely to have SAM.
Conclusion: Individual compositional and contextual factors were significantly associated with SAM. Attainment of sustainable development goals 1, 4, and 10 will automatically contribute to the eradication of SAM, which in turn leads to the attainment of sustainable development goals 2 and 3. These findings underscore the need to revitalize existing policies and implement interventions to rescue and prevent children from having SAM at the individual, community, and societal levels in LMICs.

Introduction

Malnutrition is one of the main reasons for death among under-5 children (U5 C) in low- and middle-income countries (LMIC) and it accounts for about one-third of preventable deaths among children [1–3]. Reduction of malnutrition, especially severe acute malnutrition (SAM), is critical, directly or indirectly, to a targeted decrease in child mortality and improvement in maternal health [3,4].

According to the World Health Organization (WHO), SAM is “a very low weight for height z-score, below −3 z-scores of the median WHO growth standards, by visible severe wasting, or by the presence of nutritional oedema” [3]. In earlier definitions, SAM was said to include the mid-upper arm circumference <115 mm, or the presence of bilateral pitting edema, or both [5,6].

Although the burden of SAM is higher among LMICs than in other countries, inequalities exist in its distribution within these countries. The particular people affected by SAM within LMICs and

OAU conceived the study. AFF and OAU designed the study and analyzed the data. AFF retrieved and merged the data and drew the figures. AFF, OAU, and NBK carried out the literature search, data interpretation, and writing of the manuscript. All authors read and consented to the final version of the manuscript. The authors have no conflicts of interest to declare.

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where they live in the LMIC have not been explored. Rather than using “one cap fits all approach” in the implementation of an intervention aimed at reducing the burden of SAM in these countries, the identification of the most affected subpopulation group and where they live will enable the adoption of appropriate approaches that can substantially reduce the burden. The knowledge of this information and its adoption could further reduce the case fatality rate of SAM beyond the current 55% in hospital settings as stipulated by WHO [3]. The WHO reported that the management of SAM according to its guidelines in hospital settings would include the use of ready-to-use therapeutic foods to reduce the fatality of SAM.

The UNICEF framework for determinants of undernutrition also identified the short-term consequences of malnutrition to include mortality, morbidity, and disability. The identified long-term and intergenerational consequences include adult height, cognitive ability, economic productivity, reproductive performance, and metabolic and cardiovascular diseases [7], as shown in Figure 1. A child with SAM and other medical issues is more difficult to manage. Medical complications with SAM are enormous. They include severe pneumonia, shock, dehydration, convulsions, blinding eye signs, congestive heart failures, severe anemia, hypoglycemia, hypothermia, anorexia, poor appetite, intractable vomiting, hypothermia, and high fever [6,8].

Conceptual framework

We adopted the UNICEF conceptual framework for undernutrition to conceptualize and understand the risk factors and cause of malnutrition among U5 C globally [7], as shown in Figure 1. The framework identified basic, underlying, and immediate causes of undernutrition and depicted interconnectedness [6]. The framework stated that household food insecurity, inadequate care and feeding, unhealthy environment, poor access to education, employment, and income are risk factors for undernutrition among children. Similar factors have been reported in the literature [9–12].

Although a number of studies [9–16] have addressed local and regional levels, distribution, and risk factors for malnutrition in the literature, we were unable to locate published studies that had examined multilevel interconnected contextual factors associated with SAM globally, especially among LMICs. In the present study, we considered the central role of neighborhoods in shaping tendencies of children to develop SAM. The goal of this study was to develop and test a model of risk factors associated with SAM among U5 C in LMICs using individual-, neighborhood-, and country-level socioeconomic factors in a united framework.

Methods

This study was based on an analysis of existing survey data with all identifier information removed. The survey was approved by the Ethics Committee of the ICF Macro at Fairfax, Virginia, and by the National Ethics Committees in their respective countries. All study participants gave informed consent before participation and all information was collected confidentially. The full details can be found at http://dhsprogram.com.

Study design and data

We used sets of successive cross-sectional data obtained from Demographic and Health Surveys (DHS) for this study. The DHS data are nationally representative household surveys and are conducted in LMICs. This study used data from 51 DHS surveys conducted between 2010 and 2018 that were available as of March 2019

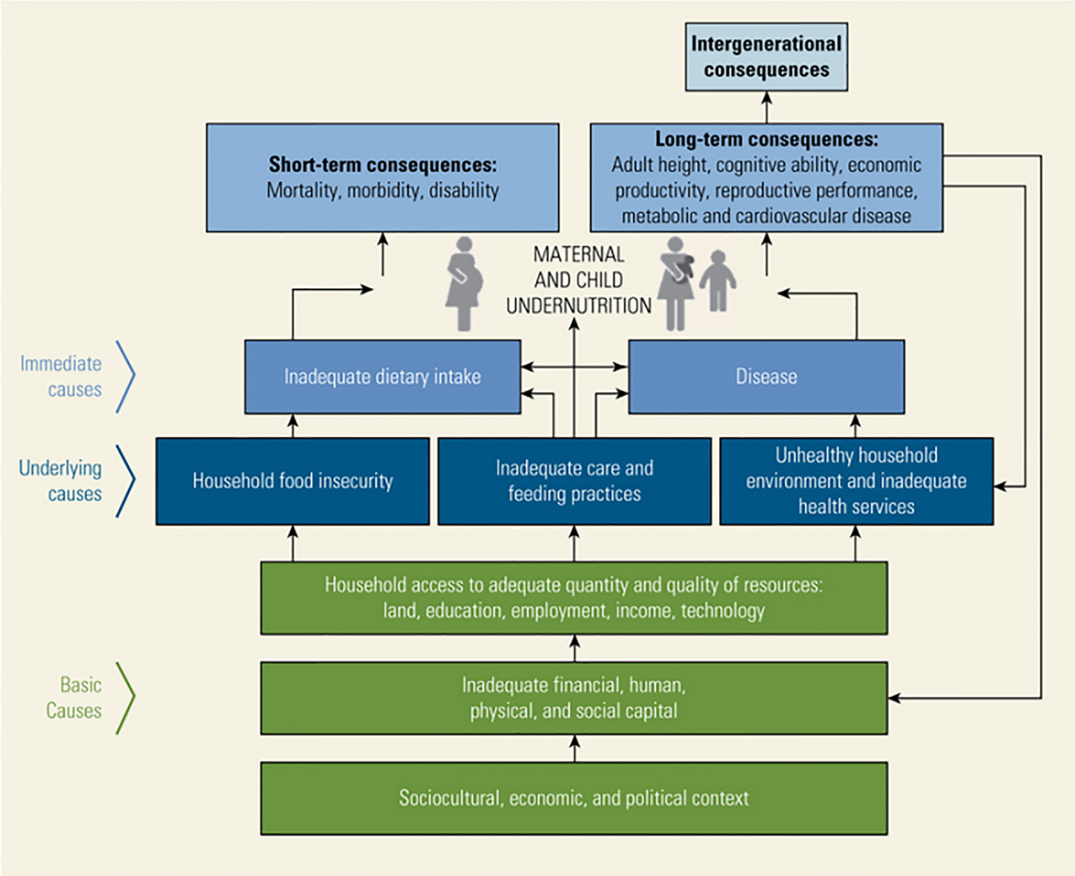

Fig. 1. Conceptual framework of determinants of undernutrition [7].

and that included U5 C anthropometry data. The sample ranged from 1082 children in South Africa to 225 002 children in India, comprising 532 680 total number of children. Typically, the DHS uses a multistage, stratified sampling design with enumeration areas (clusters) as the sampling unit [17,18]. Country-specific sampling methodologies are also available at dhsprogram.com and are available in report forms [19–21]. Within each sampled household, all women and men meeting the eligibility criteria are interviewed. Sampling weights were calculated to account for unequal selection probabilities, including non-response, whose application makes survey findings represent the full target populations. All the DHS questionnaires are standardized and implemented across countries with similar interviewer training, supervision, and implementation protocols. In this study, we used the DHS children recode data. The data covered the health experiences of U5 C born to sampled women within 5 y preceding the survey date. The anthropometry measurements were taken using standard procedures.

Dependent variable

Our dependent variable was SAM, which was determined from composite scores of children's weight and height. We generated the z-scores using WHO-approved methodologies [22]. A child with <−3 SD weight for height z-scores of the median WHO growth standards was classified as having SAM.

Independent variables

We searched PubMed, Hinari, Science direct, and Africa Journal online (between March and August 2019) using the terms "malnutrition," "severe acute malnutrition," "burden," "prevalence," "mortality," "morbidity," "low- and middle-income countries," "African," "Asia," and "sub-Saharan" for the most articles published in English. Our findings from the searches were used to identify the explanatory variables.

We identified three categories of explanatory variables for this study and are depicted in Figure 2.

Individual-level factors

The individual-level factors are sex of the children (male versus female), children age in years (<1 and 1–5 y), maternal age (15–24, 25–34, and 35–49), maternal educational attainment (no education, primary, secondary or higher), occupation (working or not working), access to media, sources of drinking water (improved or unimproved), toilet type (improved or unimproved), weight at birth (average+, small, and very small) birth interval (first born, <36 mo and >36 mo) and birth order (1, 2, 3, and 4+). We used the DHS wealth index as a proxy indicator for socioeconomic status. The methods used in computing DHS wealth index have been described previously [23] .

Neighborhood-level factors

In this study, the term *neighborhood* was used to describe clustering within the same geographic living environment. Neighborhoods were based on sharing a common primary sample unit within the DHS data. The primary sample units were identified using the most recent census in each country where DHS was carried out. The neighborhood-level factors included in the models that were examined in the present study were place of residence (rural or urban), neighborhood poverty, illiteracy, and unemployment rates. The neighborhood factors were categorized into two (low and high) each to allow for nonlinear effects and offer useful results for policy decisions. The median values were used as the reference category for comparison, as illustrated in Figure 2.

Country-level factors

Country-level data were retrieved from the human index reports published by the United Nations database [24,25]. In particular, we included countries' percentage rural population [25] and the intensity of deprivation [24] in the models. Both indicators belong to the body of the Human Development Index (HDI). The HDI was created by the United Nations to emphasize "that people and their capabilities should be the ultimate criteria for assessing the development of a country, not economic growth alone" [26]. The HDI summarizes the following dimensions of human development: the average achievement in a long and healthy life, being knowledgeable, and having a decent standard of living [26]. The intensity of deprivation is a measure of the average percentage of deprivation experienced by people in multidimensional poverty, whereas percentage of the rural population is a measure of the proportion of a countries population that resides in rural areas. The two factors were categorized into two (low and high) levels each, as shown in Figure 2.

Statistical analyses

Descriptive statistics were used to show the distribution of respondents by country and independent variables in percentages. We used the χ^2 test of association to determine the significance of the association between the independent variables and SAM (Table 1).

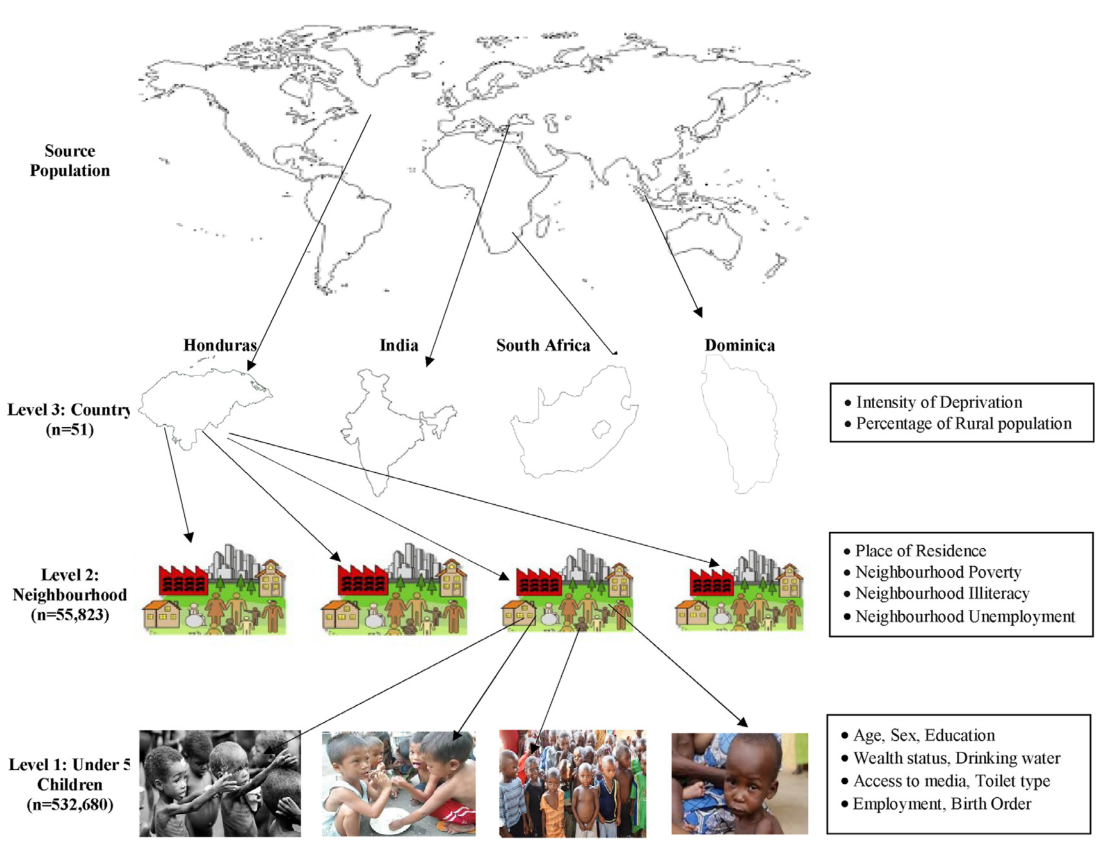

Fig. 2. Hierarchical structure of the source data: author's drawings.

Owing to the hierarchical nature of the available data, as shown in Figure 2, and the dichotomous possibilities of the outcome variable, we used multivariable logistic multilevel regression models to analyze the association between SAM and individual compositional and contextual risk factors. Using the three-level model for binary response specified earlier, with the individual children (at level 1), in a neighborhood (at level 2), living in a country (at level 3; Fig. 2), we modelled the factors associated with SAM. To arrive at a robust model that will help identify risk factors of SAM bearing in mind the hierarchical structure of the data, we constructed five models:

- Model I (an empty model) had no explanatory variables and was specified to decompose the magnitude of variance that existed between country and neighborhood levels.
- Model II contained only individual-level factors.
- Model III had only neighborhood-level factors.
- Model IV contained only country-level factors.
- Model V (the full model) jointly controlled for all the individual-, neighborhood-, and country-level factors.

The multilevel regression model was executed in the MLwinN software, developed by the Centre for Multilevel Modelling University of Bristol, United Kingdom (version 3.03) [27]. Parameters were estimated using the Bayesian Markov Chain Monte Carlo (MCMC) procedures [28] with the following specifications: distribution: binomial; link: logit, burning: 5000, chain: 50000 and refresh: 500.

The results (measures of association) were reported as odds ratios (ORs) with their 95% credible intervals (CrIs). The Bayesian statistical inference provides an opportunity to summarize probability distributions for measures of association alongside the 95% CrI, rather than 95% confidence intervals (CIs) obtained in the frequentist approach. A 95% CrI is easily interpreted as the 95% probability that the parameter takes a value in a particular range.

We also measured the likely contextual effects of the factors considered in the different levels using the intraclass correlation (ICC) and median odds ratio (MOR). The ICC was used to measure the similarity between respondents in the same neighborhood and within the same country. It estimates the percentage of the total variance in the probability of a child having SAM that is related to the neighborhood and country level (i.e., measure of clustering of odds of developing SAM in the same neighborhood and country). The ICC was calculated by the linear threshold (latent variable method) [29]. Adopting the methods recommended by Larsen et al. on neighborhood effects [30], we reported the random effects in terms of the odds. The MORs are the measures of the variance of the OR in higher levels (neighborhood or country), and it estimates the probability of having SAM that can be attributed to any of the neighborhood and country factors. If MOR = 1, there is no neighborhood or country variance. Conversely, the higher the MOR, the more significant are the contextual effects for understanding the probability of having SAM. A similar approach has been used in similar study settings [31,32].

Multicollinearity among explanatory variables was checked by examining the variance inflation factor (VIF) [33]. All diagonal elements in the variance−covariance (τ) matrix for correlation between −1 and +1, and diagonal elements for any elements close to zero were assessed. None of the results of the tests provided reasons for concern. Thus, the models provide robust and valid results. The Bayesian Deviance Information Criterion (DIC) was used to evaluate how well the different models considered in this study fitted the data. A lower value on DIC indicates a better fit of the model.

Results

The regions of the world, countries, year of data collection, numbers of neighborhoods, number of U5 C, and the weighted prevalence of SAM are listed in Table 1. We analyzed data from 532 680 U5 C (level 1) nested within 55 823 neighborhoods (level 2) from 51 LMICs (level 3). The median number of neighborhoods per country sampled was 491, ranging from 251 in Comoros to 28 164 in India. The overall SAM prevalence was 4.7% with a median prevalence of 1.8% ranging from 0.1% in both Guatemala and Peru to 9.9% in Timor-Leste, as shown in Table 2 and Figure 3.

In Table 2, we present the descriptive statistics for the pooled sample by the identified independent variables. Of the children, 20% were infants, 51% were boys, and 53% were from mothers 25 to 34 y of age. Of the mothers, 31% had no formal education, whereas only 16% belonged to households in the richest wealth quintiles. Most of the mothers were currently employed (71%) and currently married (93.8%). Most (81%) of the children had

Table 1
Demographic and Health Surveys data by countries and SAM prevalence among under 5 children in LMICs, 2010 to 2018

Country	Year of survey	Number of neighborhoods	Number of under 5 children	Weighted SAM prevalence
All		55 823	532 680	4.7
Eastern Africa		6283	67 418	1.5
Burundi	2016	554	652	0.9
Comoro	2012	251	2,387	3.9
Ethiopia	2016	640	8919	3.0
Kenya	2014	1592	18 656	1.0
Malawi	2016	850	5178	0.6
Mozambique	2011	610	9313	2.1
Rwanda	2015	491	3538	0.6
Tanzania	2016	607	8962	1.3
Uganda	2016	688	4413	1.4
Middle Africa		3071	37 136	2.5
Angola	2016	625	6407	1.0
Cameroon	2010	575	5033	1.9
Chad	2015	623	9826	4.3
Congo	2012	384	4475	1.6
DRC	2014	536	8059	2.7
Gabon	2012	328	3336	1.2
Northern Africa		872	13 682	3.8
Egypt	2014	872	13 682	3.8
Southern Africa		2,441	20 273	1.7
Lesotho	2016	369	1312	0.7
Namibia	2013	486	1558	2.2
South Africa	2016	466	1082	0.5
Zambia	2014	721	11 407	2.1
Zimbabwe	2015	399	4914	1.1
Western Africa		5734	85 462	4.7
Benin	2018	555	12 033	1.1
Burkina Faso	2010	572	6532	5.8
Cote d'Ivoire	2012	350	3200	1.8
Gambia	2013	276	3098	4.7
Ghana	2014	418	2720	0.7
Guinea	2012	300	3085	3.7
Liberia	2013	322	3171	2.2
Mali	2013	412	4306	5.1
Niger	2012	476	4771	6.2
Nigeria	2013	895	24 505	8.8
Senegal	2017	400	10 787	1.5
Sierra Leone	2013	430	4069	3.8
Togo	2014	328	3185	1.6
Central Asia		315	9883	1.5
Kyrgyz	2012	315	4016	1.1
Tajikistan	2017	366	5867	1.8
South-Eastern Asia		606	4324	2.4
Cambodia	2014	606	4324	2.4
Southern Asia		29,953	240 849	7.1
Bangladesh	2014	600	6965	3.1
India	2016	28,164	225 002	7.4
Maldives	2016	260	2362	2.0
Nepal	2016	375	2369	1.9
Pakistan	2018	554	4151	2.3
Western Asia		304	1561	1.5
Armenia	2016	304	1561	1.5
Central America		1995	21 717	0.2
Guatemala	2012	856	11 744	0.1
Honduras	2016	1139	9973	0.3
South America		1396	9213	0.1
Peru	2012	1396	9213	0.1
South Europe		631	2462	0.5
Albania	2018	631	2462	0.5
Caribbean		1856	18 700	3.9

(*continued*)

Table 1 (*Continued*)

Country	Year of survey	Number of neighborhoods	Number of under 5 children	Weighted SAM prevalence
Dominica	2013	513	3187	0.6
Haiti	2016	449	5598	0.9
Myanmar	2016	439	4197	1.4
Timor-Leste	2016	455	5718	9.9

LMIC, low- and middle-income country; SAM, severe acute malnutrition

drinking water from improved sources but only 50% had improved toilet types. Most of the children were living in rural areas (69%), 21% in high poverty rate neighborhoods, 29% in high illiteracy rate neighborhoods, and 27% in high unemployment rate neighborhoods. At the country level, 27% lived in countries with a high level of intensity of deprivation and 81% in countries with high percent rural population. All the variables considered at the different levels were significantly associated with SAM at 5% χ^2 test. Also, the unadjusted bivariate logistics regression models between each of the explanatory variables and SAM showed that all the variables significantly predicted SAM at $P = 0.05$. Hence, they are all suitable for inclusion in the multivariable models.

Table 3 presents the results of all the five different models examined in this study. In the fully adjusted model controlling for the effects of individual-, neighborhood-, and country-level factors, child's age and sex, mother's education, mother's age, place of residence (rural or urban), neighborhood poverty, illiteracy, unemployment rates, intensity of deprivation, and percentage rural population were significantly associated with odds of SAM. In particular, the odds of SAM doubled among infants than those among those 12 to 59 mo of age (OR. 1.99; 95% CrI, 1.92–2.05). Boys were more likely to have SAM (OR, 1.24; 95% CrI. 1.20–1.28). The odds of SAM was also higher among children of younger mothers compared with children whose mothers were 35 to 49 y of age (age 15–24 y: OR, 1.16; 95% CrI, 1.10–1.24; age 25–34 y: OR, 1.05; 95% CrI, 1.01–1.10). Children whose mothers had no formal education were significantly more likely to have SAM than those whose mothers had secondary or higher education (OR, 1.11; 95% CrI, 1.06–1.16). Children from the poorest households were 39% more likely to have SAM than those from the richest households (OR, 1.39; 95% CrI, 1.28–1.49). Also, children whose mothers did not have access to media had higher odds of SAM (OR, 1.08; 95% CrI, 1.04–1.12). The odds of SAM was higher among children who had very low (OR, 1.62; 95% CrI, 1.52–1.4) or low (OR, 1.21; 95% CrI, 1.15–1.26) birth weights than those with average or higher birth weights. Children from rural areas were more likely to have SAM than those from urban areas (OR, 1.11; 95% CrI, 1.06–1.17). Children from neighborhoods with high unemployment rates (OR, 1.15; 95% CrI, 1.08–1.22) were more likely to have SAM than those from neighborhoods with the low rates. At the country-level, respondents from countries with high rates of intensity of deprivation were 77% times more likely to have SAM than those from countries with low rates (OR, 1.77; 95% CrI, 1.02–2.82). Similarly, children living in countries with high percentages of rural population were 134% more likely to have SAM than those living in countries with low percentages (OR, 2.34; 95% CrI, 1.51–3.45).

As shown in Table 3, Model I (the null model) showed a significant variation in the odds of developing SAM across the countries (σ^2 = 0.93; 95% CrI, 0.62–1.40) and across the neighborhoods (σ^2 = 0.92; 95% CrI, 0.87–0.96). On the assessment of the intra-country and intra-neighborhood correlation coefficient, 18.1% and 36% of the variance in odds of having SAM could be attributed to the country- and neighborhood-level factors, respectively. Results from the MOR also confirmed evidence of neighborhood and societal contextual phenomena shaping the distribution of SAM among the children. Model V showed a variation in the odds of developing SAM across the countries (σ^2 = 0.69; 95% CrI, 0.45–1.06) and across the neighboorhoods (σ^2 = 0.97; 95% CrI, 0.92–1.03). If a child is moved to another neighborhood or another country with a higher probability of having SAM, the median increase in their odds of having SAM would be 2.2 (95% CrI, 1.9–2.7) and 2.57 (95% CrI, 2.51–2.64), respectively. Overall, the full model has the lowest DIC, hence we identify it as the best model to fit the data.

Discussion

Since the WHO declared war against SAM, there is a paucity of information on the relationship between contextual and societal factors in the distribution of SAM among UC 5, especially in LMICs. The present study appears to be the first multilevel examination of factors associated with SAM across the globe wherein we considered 51 LMICs using national representative data consisting of 532 680 children found in 55 823 neighborhoods.

We found significant relationships between SAM and the characteristics considered. At the individual level, male infants, low birth weight children, children whose mothers had no education (versus those with secondary or higher), children whose mothers were younger, those from poorer households, those with no access to media, and children who used unimproved toilet types were significantly more likely to have SAM. Sex of the children appeared to be a very important risk factor, with boys significantly more likely to have SAM. The findings corroborate those of previous studies that examined the association between sex of children and nutritional status [14,15,34–37]. There is concise agreement in the literature that poor nutritional outcomes are more common among male children than female children [14,35–37]. We found the older a child is, the less the likelihood of having SAM. There were higher odds among infants than older children, as reported in earlier studies [9,14,15,34,36,38]. Maternal age also played a key role in a UC 5 having SAM. Children of mothers 15 to 24 y of age as well as mothers 25 to 34 y of age had higher odds of having SAM than children of mothers 34 to 49 y of age. Our finding is in consonance with previous studies in child nutrition, which found significant associations between mother's age and nutritional outcomes [12,15].

Children whose mothers had no education or only primary education were at higher odds of developing SAM. The same relationship has been established in the literature [10,14,16,34,35,38,39]. Poor educational attainment could restrict mothers' knowledge on best feeding practices and therefore predispose children to poor nutrition. This is also linked to the wealth status of the family, as education alone is not sufficient to make good decisions and availability of sufficient income to execute such decisions is also vital. Fagbamigbe et al. already established a link among wealth, health, and education in a Nigerian setting [40]. This was evident in the present study, as children from households in the poorest wealth quintiles had higher odds of SAM compared with those from households in the richest wealth quintiles. Similar findings were previously reported [9,10,16,35,38]. Other important findings were the relationships between weight at birth and SAM. U5 C with low birth weight were at higher odds of developing SAM, as reported in earlier studies [9,12,15,34]. It is not unlikely that efforts to control low birth weight are not yielding the expected results.

Additionally, our findings showed that neighborhood- and country-level factors influence the development of SAM among U5 C besides the individual-level factors. The estimates of the only neighborhood-level factor model (Model III) showed that U5 C

Table 2
Demographic and Health Surveys data by background characteristics and SAM prevalence among under 5 children in LMIC, 2010 to 2018

Characteristics	Weighted n	Weighted %	Weighted SAM prevalence	Pearson χ^2 test *P*-value value
Individual level				
Age (mo)				
<12	103 379	20	7.4	<0.0001
12–59	413 718	80	4	
Sex				
Female	252 541	48.8	4.3	<0.0001
Male	264 556	51.2	5.1	
Maternal age (y)				
15–24	160 133	31	5.2	<0.0001
25–34	273 802	52.9	4.6	
35–49	83 162	16.1	3.8	
Maternal education				
No education	160 999	31.1	5.8	<0.0001
Primary	130 816	25.3	3.1	
Secondary	225 260	43.6	4.8	
Marital status				
Never married	12 550	2.3	1.9	<0.0001
Currently married	498 898	93.8	4.8	
Previously married	20 520	3.9	2.4	
Wealth index				
Poorest	122 991	23.8	5.6	<0.0001
Poorer	112 755	21.8	4.8	
Middle	104 194	20.1	4.5	
Richer	96 896	18.7	4.2	
Richest	80 261	15.5	3.8	
Employment				
Yes	366 033	70.8	5	<0.0001
No	151 064	29.2	3.9	
Access to media				
No	188 357	36.5	5.3	<0.0001
Yes	328 311	63.5	4.3	
Drinking water sources				
Unimproved	95 544	19.2	4.1	<0.0001
Improved	402 688	80.8	4.8	
Toilet type				
Unimproved	248 331	49.9	5.2	<0.0001
Improved	249 753	50.1	4.1	
Weight at Birth				
Average+	423 017	85.4	4.6	<0.0001
Low	52 939	10.7	5	
Very low	19 624	4	6.4	
Birth interval				
First	157 067	30.4	4.8	<0.0001
<36	193 030	37.4	4.9	
36+	165 780	32.1	4.2	
Birth order				
1	157 065	30.4	4.8	<0.0001
2	134 436	26	4.9	
3	83 134	16.1	4.6	
4	142 462	27.6	4.3	
Neighborhood factors				
Place of residence				
Urban	158 938	30.7	4.2	<0.0001
Rural	358 159	69.3	4.9	
Poverty rate				
Low	408 434	79	4.4	<0.0001
High	108 663	21	5.7	
Illiteracy rate				
Low	365 564	70.7	4.2	<0.0001
High	151 533	29.3	5.9	
Unemployment rate				
Low	375 508	72.6	5	<0.0001
High	141 589	27.4	3.8	
Community SES quintiles				
1 (highest)	117 186	20.2	4.2	<0.0001
2	101 302	20	4.3	
3	103 795	20.1	4.2	
4	100 611	20	5	
5 (lowest)	94 203	19.7	5.8	
Country level				
Intensity of deprivation				
Low	377 408	73	5	<0.0001
High	139 689	27	3.8	
Percent rural population				
Low	96 289	18.6	3	<0.0001
High	420 808	81.4	5.1	
Multidimensional poverty Index				
Low	386 418	74.7	5.7	<0.0001
High	517 097	25.3	1.8	
Total	532 680	100	4.7	

LMIC, low- and middle-income country; SAM, severe acute malnutrition; SES, socioeconomic status.

who reside in a neighborhood with low rates of socioeconomic factors had higher odds of developing SAM. A similar pattern of the significance of the neighborhood-level factors was found in the only country-level model (Model IV) where children in high rural percentage and high intensity of deprivation are at higher odds of developing SAM.

However, in the full model, when individual-, neighborhood-, and country-level factors were adjusted for at the same time, we found evidence that, in addition to the individual-level factors, living in a neighborhood with low rates of the socioeconomic position increases the odds of developing SAM. The findings are supported by the reports from previous studies [15,16,38]. It is evident in the present study that geographic clustering affects the odds of developing SAM as corroborated in the literature [9,14]. About 18.1% and 35.9% of the variation in developing SAM is conditioned by differences between neighborhoods and countries, respectively. The odds of a U5 C developing SAM after moving to another neighborhood or another country with a higher probability of developing SAM may increase by about 157% and 122%, respectively. This finding demonstrated that SAM is clustered among neighborhoods and countries. A clear demonstration of this is shown in Table 1 and Figure 3, where we reported wide differences in the prevalence of SAM among countries. U5 C living in the same neighborhood tend to have similar tendencies in developing SAM. It is therefore possible that there are some evidences of possible neighborhood and country contextual phenomenon affecting tendencies of children in developing SAM. Literature is replete with the fact that the odds of poor nutrition are higher among U5 C residing in communities with low levels of urbanization and low-level well-being index [12,35,36].

The present findings showed the need to strengthen existing policies on child nutrition and implement public health prevention strategies targeted at all children especially in most-at-risk and high-risk neighborhoods and countries. There is a need for further decomposition analyses to explore how the significant factors identified in the present study could help explain the disparities in SAM among high-risk children residing in high-risk places.

Study limitations and strengths

We were unable to identify any causal factors of developing SAM owing to the cross-sectional nature of the data. We were limited to establishing only associations. Longitudinal studies may help in this regard. Also, the secondary nature of the data prevented us from including some variables of interest. For instance, the length of time that children had spent in their neighborhoods and the extent of their exposure to the neighborhood environment

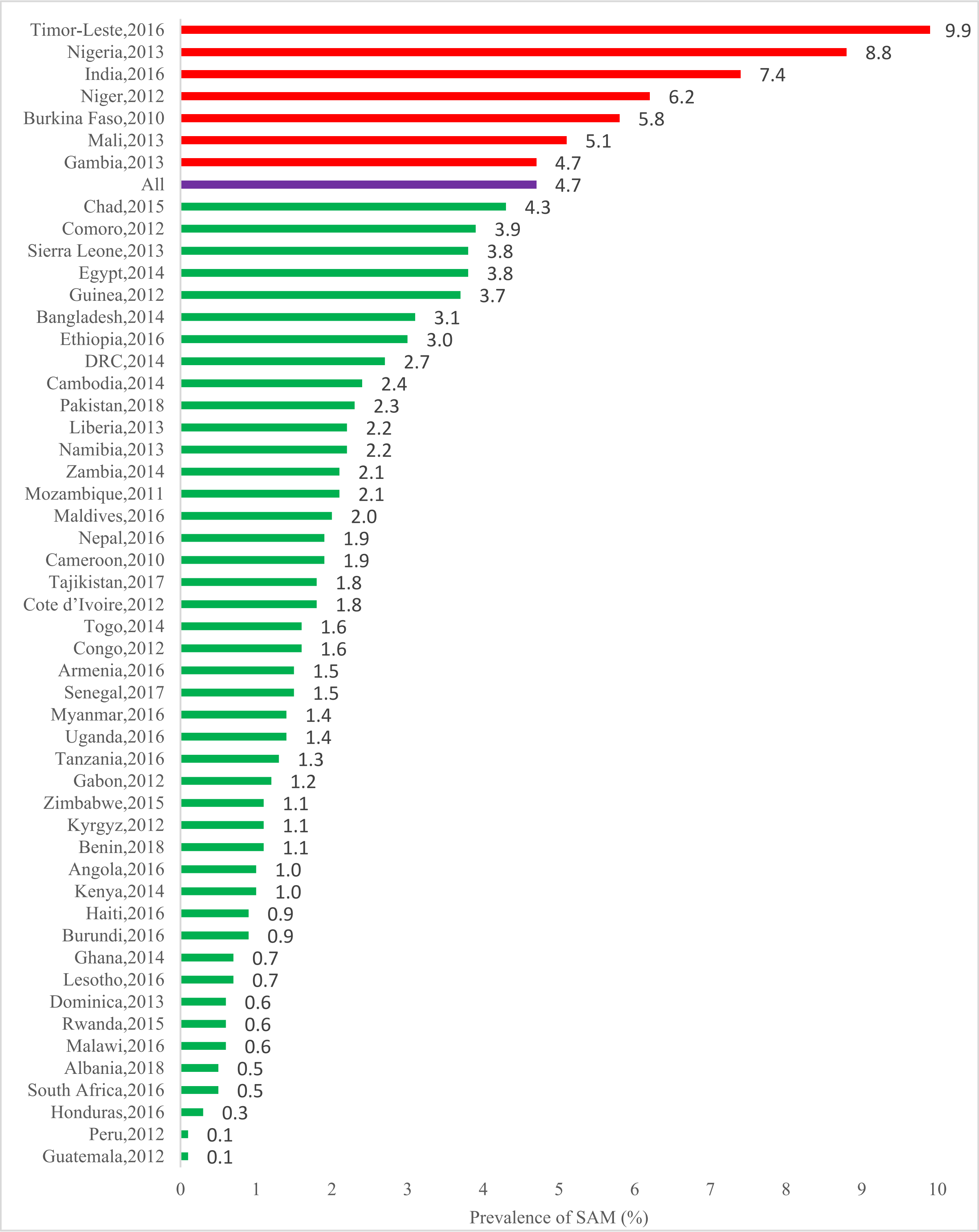

Fig. 3. Prevalence of severe acute malnutrition by countries (Demographic and Health Surveys 20).

were not available. Additionally, we only used wealth index computed from the household asset as a proxy for household income because DHS does not collect data on household income or expenditure, the traditional indicators used to measure wealth.

Despite the highlighted study limitations, the study had significant strengths. This was a multicountry study with a large population spanning 51 countries. Nearly 600 000 U5 C were included. The DHS has a unique advantage of beign nationally representative, with a proven sampling methodology. Also, variables used in DHS were operationalized in the same way and made possible comparison of numerical values across countries. The use of a multilevel approach in studying the distribution of SAM among U5 C was advantageous over non-recognition of the hierarchical nature of the data used. Therefore, we were able to provide more robust

Table 3
Individual compositional and contextual factors associated with SAM identified by multivariable multilevel logistic regression models, DHS data, 2010 to 2018

Characteristics	Model I OR (95% CrI)*	Model II OR (95% CrI)†	Model III OR (95% CrI)‡	Model IV OR (95% CrI)§	Model V OR (95% CrI)‖
Fixed-effect					
Individual level					
Child age (infant vs 1–5 y)		**1.99 (1.92–2.05)**			**1.99(1.92–2.05)**
Male (vs female)		**1.24 (1.21–1.28)**			**1.24(1.20–1.28)**
Maternal age (y)					
15–24		**1.17 (1.10–1.24)**			**1.16(1.10–1.24)**
25–34		**1.05 (1.00–1.10)**			**1.05(1.01–1.10)**
35–49	1 (reference)				
Maternal education					
No education		**1.14 (1.09–1.19)**			**1.11(1.06–1.16)**
Primary		1.01 (0.96–1.05)			1.00(0.95–1.04)
Secondary or higher	1 (reference)				
Wealth index					
Poorest		**1.30 (1.22–1.40)**			**1.39(1.28–1.49)**
Poorer		**1.13 (1.06–1.20)**			**1.18(1.11–1.27)**
Middle		**1.08 (1.02–1.14)**			**1.12(1.05–1.19)**
Richer		1.02 (0.97–1.08)			1.04(0.98–1.10)
Richest	1 (reference)				
Unemployed (vs employed)		1.04 (1.00–1.08)			1.02(0.98–1.06)
No media access(vs media access)		**1.08 (1.04–1.12)**			**1.08(1.04–1.12)**
Unimproved drinking water		**1.00 (0.96–1.05)**			**1.01(0.97–1.06)**
Unimproved toilet type		**1.11 (1.06–1.15)**			**1.12(1.07–1.16)**
Weight at birth					
Average+	1 (reference)				
Low		**1.21 (1.15–1.26)**			**1.21(1.15–1.26)**
Very low		**1.63 (1.53–1.74)**			**1.62(1.52–1.74)**
Birth interval					
First birth		0.31 (0.20–0.43)			0.62(0.17–1.17)
<36 mo	1 (reference)				
36+ mo		1.01 (0.97–1.05)			1.01(0.97–1.05)
Birth order					
First	1 (reference)				
Second		0.31 (0.20–0.43)			0.62(0.17–1.17)
Third		0.32 (0.21–0.45)			0.65(0.17–1.23)
Fourth+		0.34 (0.22–0.48)			0.69(0.18–1.30)
Neighborhood-level factor					
Rural vs urban			**0.99 (0.95–1.04)**		**1.11(1.06–1.17)**
High vs low poverty rate			**1.16 (1.11–1.21)**		**0.95(0.91–0.99)**
High vs low illiteracy rate			**1.21 (1.16–1.26)**		**1.09(1.04–1.14)**
High vs low unemployment			**1.19 (1.12–1.26)**		**1.15(1.08–1.22)**
Country-level factors					
High vs low deprivation intensity				**2.08 (1.33–2.97)**	**1.77(1.02–2.82)**
High vs low rural population				**2.15 (1.54–3.00)**	**2.34(1.51–3.45)**
Random effects					
Country level					
Variance (95% CrI)	0.93 (0.62–1.40)	0.91 (0.60–1.37)	0.97 (0.65–1.45)	0.67 (0.44–1.01)	0.69(0.45–1.06)
VPC (%, 95% CI)	18.1 (12.9–24.7)	17.6 (12.4–24.0)	18.8 (13.5–26.1)	13.7 (9.6–19.2)	14.1(9.8–19.7)
MOR (95% CrI)	2.51 (2.12–3.09)	2.48 (2.09–3.05)	2.56 (2.16–3.22)	2.18 (1.88–2.61)	2.22(1.91–2.67)
Explained variation (%)	Reference	2.4 (2.8–2.2)	−4.0 (−5.3 to −7.2)	28.2 (28.7–27.8)	25(25.4–24.2)
Neighborhood level					
Variance (95% CrI)	0.92 (0.87–0.96)	0.98 (0.94–1.03)	0.91 (0.86–0.96)	0.91 (0.87–0.96)	0.97(0.92–1.03)
VPC (%, 95% CI)	36 (31.2–41.8)	36.5 (31.8–42.2)	36.3 (31.6–42.8)	32.5 (28.5–37.5)	33.8(29.7–38.8)
MOR (95% CrI)	2.49 (2.44–2.55)	2.57 (2.52–2.64)	2.48 (2.43–2.55)	2.49 (2.44–2.55)	2.57(2.51–2.64)
Explained variation (%)	Reference	−7.1(−7.2 to −7.1)	0.9 (0.3–0.3)	0.0 (0.0 to −0.1)	-6.8(-6.5–7.0)
Model fit statistics					
Bayesian DIC	181 474.44	164 841.15	181 023.99	181 470.94	164750.68
Sample size					
Country level	51	51	51	51	51
Neighborhood level	55 823	55 409	55 823	55 823	55668
Individual level	532 680	491 635	532 680	532 680	491635

DHS, Demographic and Health Surveys; DIC, deviance Information criteria; MOR median odds ratio; SAM, severe acute malnutrition; VPC, variance partition coefficient, OR in **bold** suggest significance at 5%.
*Empty null model, baseline model without any explanatory variables (unconditional model).
†Adjusted for only individual-level factors.
‡Adjusted for only neighborhood-level factors.
§Adjusted for only country-level factors.
‖Adjusted for individual-, neighborhood-, and country-level factors (full model).

evidence about U5 C compositional and contextual measures of socioeconomic position associated with the development of SAM. Additionally, the Bayesian approach we adopted had the advantage of being able to produce a far more robust estimate with better properties and yields unbiased estimates than the frequentist method [28,41].

Conclusions

At 4.7% prevalence, >12 million children <5 y of age in LMICs have SAM at one time or the other in the LMIC. Individual compositional and contextual measures of socioeconomic position were independently associated with having SAM across the 51 LMICs. The odds of SAM are generally higher among children <1 y of age, with low birth weight, mothers with no formal education, mothers 15 to 24 y of age, from households in the poorest wealth quintiles, with no access to media, and using unimproved toilet types. Our findings affected several sustainable development goals (SDGs) and therefore have several policy implications. For instance, on SDG 1, ending poverty and all its forms everywhere will definitely reduce the chances of a child developing SAM. Additionally, our finding is connected to attainment of the SDG 2 on the improvement of nutrition everywhere, SDG 3 on ensuring healthy lives and well-being promotion for all at all ages, and SDG 4 on the provision of quality education for all. Also, our findings on intercountry variabilities suggest a need for renewed efforts to achieve the SDG 10 on the reduction of inequality within and among countries. These findings underscore the need to revitalize existing policies and implement interventions to rescue and prevent children from having SAM at the individual, community, and societal levels.

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