Mapping local patterns of childhood overweight and wasting in low- and middle-income countries between 2000 and 2017

LBD Double Burden of Malnutrition Collaborators*

A double burden of malnutrition occurs when individuals, household members or communities experience both undernutrition and overweight. Here, we show geospatial estimates of overweight and wasting prevalence among children under 5 years of age in 105 low- and middle-income countries (LMICs) from 2000 to 2017 and aggregate these to policy-relevant administrative units. Wasting decreased overall across LMICs between 2000 and 2017, from 8.4% (62.3 (55.1–70.8) million) to 6.4% (58.3 (47.6–70.7) million), but is predicted to remain above the World Health Organization’s Global Nutrition Target of <5% in over half of LMICs by 2025. Prevalence of overweight increased from 5.2% (30 (22.8–38.5) million) in 2000 to 6.0% (55.5 (44.8–67.9) million) children aged under 5 years in 2017. Areas most affected by double burden of malnutrition were located in Indonesia, Thailand, southeastern China, Botswana, Cameroon and central Nigeria. Our estimates provide a new perspective to researchers, policy makers and public health agencies in their efforts to address this global childhood syndemic.

The profound impacts of childhood malnutrition, including both undernutrition and overweight, affect the economic, social and medical well-being of individuals, families, communities and nations1. Undernutrition has been the most common form of malnutrition in LMICs, but as populations experience economic growth, urbanization and demographic change, overweight is an emerging problem, leading to a double burden of malnutrition (DBM). DBM may be manifested at the individual level as stunting in childhood followed by overweight in adulthood1. At the household level, research has focused on maternal and child indicators of malnutrition, whereas at the population level, prevalence of both undernutrition with overweight has been reported6. In children, DBM can be defined using different combinations of the various indicators of undernutrition (wasting and/or stunting) and overweight, obesity and diet-related noncommunicable diseases (NCDs)7. While the most studied type of double burden is that of stunting and obesity, it is mostly applicable at the individual level among overweight adults who were previously stunted from chronic undernutrition during childhood. Wasting is associated with high rate of child mortality, whereas stunting has significant negative impact across the life course and is highly predictive of economic outcomes5. Public health nutrition programs designed to address undernutrition may exacerbate overweight8, thus a comprehensive understanding of DBM at the population level is crucial for the design of effective interventions.

Our aim was to determine the prevalence of overweight among children under 5 years old in LMICs (N=105) for policy-relevant administrative units (district, state, and national level) and determine DBM by combining these estimates with those of wasting prevalence. As there is no broad consensus on the preferred international child growth standards for assessing overweight and obesity among children under 5 (refs. 8,9), we used weight-for-height above established cutoff points defined by the World Health Organization (WHO). This was to analyze overweight estimates in relation to the Global Nutrition Targets (GNTs), which were developed based on WHO standards. Prevalence of early childhood overweight (including obesity) is defined as the proportion of children under 5 with a weight-for-height z score (WHZ) more than two standard deviations (s.d.) above the WHO sex- and age-specific median growth reference standards10. This is different from the definition of overweight for children between the ages of 5–18 years, which is above one s.d. for overweight and above two s.d. for obese. We selected wasting as the comparative indicator against overweight, as both share recommended population prevalence ranges, which can be used to create bivariate categories for DBM. Child wasting prevalence is defined as the proportion of children under 5 with a WHZ more than two s.d. below the median WHO growth standards10. Using WHZs allowed modeling of the three categories in the same distribution and thus enabled us to reliably determine the relative proportions for each category using an ordinal approach. Based on WHO and United Nations Children’s Fund (UNICEF)-defined thresholds, a moderate level of separate or dual conditions is defined as >5–10%, a high level as >10–15% and a very high level as >15% estimated prevalence11. Finally, we have defined DBM in this study as the simultaneous occurrence of >5% estimated prevalence for both wasting and overweight within the same locations in the same year.

Reversing the rise in childhood overweight is indicated in the United Nations (UN) Sustainable Development Goal 2.2 (ref. 12) and WHO’s GNTs to improve maternal, infant and young child nutrition13. WHO has also set an international target to reduce wasting to <5% by 2025 (ref. 14). Quantifying changes in childhood overweight and wasting prevalence can be used to measure progress toward these targets, while identifying locales with simultaneous overweight and wasting will better inform intervention planning. In addition, mapping changes in DBM prevalence will provide a deeper understanding of the impact of past intervention strategies, including insight into overweight in children under 5.

Global and local variation in malnutrition trends

Globally in 2017, an estimated 38.3 million (5.6%) children under 5 were overweight and 50.5 million (7.5%) were wasted15. The majority (91%) of children under 5 affected by wasting and nearly half

* A list of authors and their affiliations appears online. e-mail: sihay@uw.edu
(48%) of overweight children lived in LMICs, with Africa and Asia accounting for the largest shares of the global burden (25% and 46% of overweight and 27% and 69% of wasted children, respectively)\(^6\). Direct comparisons of population-level trends of childhood overweight and wasting generally provide regional- or country-level estimates\(^6\), potentially masking important subnational differences. Previously, we mapped 2000–2017 prevalence and trends in wasting, stunting and underweight among children under 5 across LMICs\(^6\) using Bayesian model-based geostatistical techniques\(^6\). Building from this approach and using data from 420 household surveys representing more than 3 million children, we mapped the relative burdens of overweight and wasting among children under 5 in 105 LMICs from 2000 to 2017. Mapping with a continuous model allows us to incorporate geolocated data and covariates and produce gridded cell-level estimates that can be aggregated to intervention- or policy-relevant geographical areas as boundaries change over time. We present estimates at this local grid cell-level and aggregate or policy-relevant geographical areas as boundaries change over time.

On the basis of 2000 to 2017 weighted annualized rates of change (AROC), which apply more weight to recent data, we predict prevalence of overweight and wasting and estimate their double burden in 2025. The full array of outputs are available at the Global Health Data Exchange (http://ghdx.healthdata.org/record/ihme-data/lmic-double-burden-of-malnutrition-geospatial-estimates-2000-2017) and can be further explored with our customized visualization tools (https://vizhub.healthdata.org/lbd/dbm).

Prevalence and trends in early childhood overweight

Across LMICs, the prevalence of early childhood overweight increased from 5.2% (95% uncertainty interval, 4.5–5.4%) to 6.0% (4.8–6.1%) in the modeled study period. Between 2000 and 2017, there were noticeable differences in estimated levels by area (Fig. 1a,b). Although levels varied broadly across LMICs, every modeling region had areas with high estimated prevalence in 2017 (Fig. 1b and Extended Data Fig. 1). These included large contiguous areas across most Central American, Caribbean and South American countries and areas with ≥15% estimated prevalence in central Cuba, southern Panama, western Paraguay, scattered throughout several eastern Brazilian states (for example, in Rio Grande do Sul, Minas Gerais, Santa Catarina, Paraná and São Paulo) and Peru’s coastal cities of Tacna, Ilo, Callao, Trujillo and Lima. In Africa, most countries bordering the Sahel had low overweight prevalence (0–5%); areas with >15% estimated prevalence were concentrated in North Africa throughout Morocco, Algeria, Tunisia, Egypt and select areas of Libya, as well as along South Africa’s southern coast and in pockets in Botswana and Zambia. Large areas in eastern and northern China and throughout Mongolia had an estimated overweight prevalence >15%. Countries in the Oceania region had moderate to high levels, with estimates over 15%, such as in Indonesia’s Jakarta Pusat and Jakarta Barat regencies (in Jakarta Raya; 17.5% (15.3–18.4%)). The North Africa, Central Asia and Southeast Asia regions showed vast differences across nations; for example, Afghanistan, Sudan and Laos had ≤5% estimated national prevalence, whereas Egypt, Uzbekistan, Morocco, Kyrgyzstan and Thailand had ≥15%. South Asia’s estimated levels ranged from <5% in Bangladesh to ≥10% Bhutan. Estimated prevalence in Karbala city in Karbala, Iraq, increased from 13.6% (12.4–14.1%) in 2000 to 29.3% (22.9–29.1%) in 2017. Thailand’s southern areas experienced large increases in estimated prevalence levels; Sathorn district, Bangkok Metropolitan, had 24.1% (20.1–24.8%) overweight in 2000 and 33.9% (27.5–35.5%) in 2017. Areas with the greatest decrease included Churcampa district, Huancavelica, Peru, decreasing from 17.5% (17.4–17.6%) in 2000 to 10.3% (10.2–10.4%) in 2017. Similarly, overweight in Al Gash district, Kassala, Sudan, declined from 14.1% (13.6–14.5%) to 6.1% (5.2–6.2%).

Within-country differences in estimated overweight levels were found in 37 (35.2%) LMICs, including South Africa, Peru and Indonesia, which had twofold differences in estimated prevalence across second administrative units in 2017. South Africa had high estimated national levels (24.9% (23.9–25.2%)); however, the province of Northern Cape had moderate levels (14.6% (13.6–14.9%)), whereas the southeastern province of Eastern Cape had very high levels (32.7% (30.8–33.9%)). Disparities were further pronounced at the district level. Siyanda (Northern Cape) had 12.5% (11.6–12.9%) prevalence, whereas Ugu (KwaZulu-Natal) had 36.7% (34.0–38.2%). Nearly every modeling region had areas with overweight prevalence that ranked among the highest decile in 2000, 2017 or both years (Fig. 1c).

Overall, the number of overweight children under 5 in LMICs also showed a significant increase from 30.0 million (22.8–38.5) to 55.5 million (44.8–67.9) in the study period (Fig. 2a,b). By 2017, 26.2 million (24.1–27.2 million; 36.0%) of those affected lived in eastern Asia, northern Africa or South America. An estimated 8.6% (8.5–9.9%) of first administrative units had fewer than 1,000 overweight children under 5, 47.5% (47.2–49.5%) had 1,000 to <10,000, 43.8% (40.6–44.3%) had 10,000 to <100,000 and just 3.8% (3.7–3.9%) had 100,000 or more. Some areas, such as northern and central parts of Bolivia, experienced large annualized declines such that their ranking among the highest estimated prevalence decile in 2000 no longer applied in 2017. In contrast, a large area in India, south of the Tropic of Cancer, experienced large annualized increases in overweight: its ranking among the lowest prevalence decile in 2000 was not maintained in 2017. All modeled regions had areas that experienced average annualized increases of ≥1% in overweight prevalence (Fig. 2c). Unless current trajectories change, prevalence of overweight will continue to increase to 2025 (Fig. 2d).

Prevalence and trends in child wasting

The estimated prevalence of early childhood wasting decreased overall across LMICs between 2000–2017, from 8.4% (7.9–9.9%) to 6.4% (4.9–7.9%). The most notable relative reductions were seen across North Africa and in select countries in sub-Saharan African (SSA) regions, Central and Andean America and Southeast Asia regions. In Burkina Faso’s Ganzourgou district, estimated levels declined from 20.2% (19.1–21.3%) in 2000 to 11.6% (10.9–12.1%) in 2017, in Yemen’s Ash Shaikh Outhman district from 25.1% (22.2–26.3%) to 21.3% (18.9–22.2%) and in Sudan’s Al Maghali district from 31.9% (31.4–32.6%) to 12.2% (10.5–12.9%). Increases in estimated prevalence also occurred, such as in Pakistan’s Makran district (Baluchistan), from 7.4% (6.7–7.6%) to 11.4% (10.4–11.8%).

In 2017, there were several instances of contrasting geographic patterns of child wasting compared to those of overweight. Many Central American, Caribbean and South American countries (46%; 11 of 24) affected by overweight (>15% prevalence) met the WHO GNTIs for ≤5% prevalence of wasting across all districts based on estimated prevalence (Fig. 3a,b and Extended Data Fig. 2). Estimated wasting prevalence was ≥15% in 31.9% (850 of 2,661) and ≥20% in 12.9% (342) of second administrative units across Central and South Asian countries, contributing to high prevalence at the national level in India (15.7% (15.4–15.9%)), Pakistan (12.2% (11.8–12.4%)) and Sri Lanka (11.2% (10.5–11.5%)); Afghanistan and Bangladesh maintained high levels (estimated prevalence ≥10%) across many areas. Local-level estimates delineate very high wasting prevalence (≥15%) along the African Sahel from Mauritania to Sudan, in the northeastern Horn of Africa and neighboring countries of Eritrea, Ethiopia, Somalia, Kenya, South Sudan and Yemen, in select areas in Algeria and Egypt, and across Madagascar. In the Middle East, Syria exceeded 15% estimated prevalence throughout most areas and Iraq’s southeastern districts exceeded 10%. Estimated levels of wasting were relatively uniform and low across East Asia, with the exception of a few focal areas exceeding 10% or 20% in central
pockets of east China. Most areas in Southeast Asia and Oceania experienced moderate-to-high estimated wasting levels (~10%), whereas some areas in Indonesia’s southern-most islands in Nusa Tenggara (Timur state) exceeded 15% prevalence. Meanwhile, some areas in Myanmar, Thailand, northern Laos and Vietnam had very low levels, approaching the WHO GNTs.

Fig. 1 | Prevalence of overweight children under 5 in LMICs (2000–2017). a,b, Prevalence of overweight among children under 5 at 5 x 5-km resolution in 2000 (a) and 2017 (b). c, Overlapping population-weighted lowest and highest 10% of grid cells and AROC in overweight from 2000 to 2017. d, Overlapping population-weighted quartiles of overweight and relative 95% uncertainty in 2017. Maps reflect administrative boundaries, land cover, lakes and population; gray colored areas have grid cells classified as ‘barren or sparsely vegetated’ and had fewer than ten people per 1 x 1-km grid cell in 2017 or were not included in this analysis. Maps were generated using ArcGIS Desktop 10.6.
Between 2000 and 2017, the number of children under 5 affected by wasting decreased from 62.3 (55.1–70.8) million to 58.3 (47.6–70.7) million, 28.4% (28.2–28.5) of whom were in Africa and 65.4% (63.6–67.3) in South Asia in 2017 (Fig. 3c,d). Despite maintaining high estimated prevalence in many areas, all regions in Africa had areas that experienced among the highest rates of annualized declines in 2000–2017; only a few areas in Chad, Sudan, South Sudan, Ethiopia and Kenya were among the highest decile of estimated prevalence levels in both 2000 and 2017 (Fig. 4a,b). Progress differed across and within African countries, with some...
nations, such as Nigeria, Ethiopia and Namibia, experiencing both annualized decreases and increases in wasting within their borders (Fig. 4c). Overall, South America and South SSA demonstrated the largest annualized declines (≥5%) across most of their areas and regions of Latin America and the Caribbean, the Middle East, South Asia, Southeast Asia and Oceania experienced mostly

Fig. 3 | Prevalence of wasted children under 5 in LMICs (2000–2017). a–c, Prevalence of moderate and severe wasting among children under 5 at a 5 × 5-km resolution in 2000 (a) and 2017 (b). c, Overlapping population-weighted lowest and highest 10% of grid cells and AROC in wasting from 2000 to 2017. d, Overlapping population-weighted quartiles of wasting and relative 95% uncertainty in 2017. Maps reflect administrative boundaries, land cover, lakes and population; gray colored areas have grid cells classified as ‘barren or sparsely vegetated’ and had fewer than ten people per 1 × 1-km grid cell in 2017 or were not included in this analysis39–45. Maps were generated using ArcGIS Desktop 10.6.
annualized increases. Large areas of India and parts of central Pakistan experienced some of the highest prevalence levels throughout the study period, as well as annualized increases. Nearly all South Asian countries had large contiguous areas of stagnation or

Fig. 4 | Number of wasted children under 5 in LMICs (2000–2017) and progress toward 2025. a, b. Number of children under 5 affected by wasting at the 5 × 5-km resolution (a) and by first administrative units (b). c. AD in wasting prevalence from 2000 to 2017. d. Grid cell-level predicted stunting prevalence in 2025 based on AD achieved from 2000 to 2017 and projected from 2017. Maps reflect administrative boundaries, land cover, lakes and population; gray colored areas have grid cells classified as ‘barren or sparsely vegetated’ and had fewer than ten people per 1×1-km grid cell in 2017 or were not included in this analysis39–45. Maps were generated using ArcGIS Desktop 10.6.

annualized increases in wasting; given recent rates of progress, few will meet the WHO GNTs in all their locations by 2025 (Fig. 4d). By 2025, 68 (64.8%) of LMICs are predicted to fail to meet the <5% target nationally, all of which are in Africa, Asia and the Middle East.
Based on subnational estimates, 88 (83.8%) and 94 (89.5%) will fail to meet the wasting WHO GNTs in all first and second administrative units, respectively.

**Double burden of wasting and overweight**

Nearly every modeling region had subnational areas with at least moderate co-occurrence of wasting and overweight (≥5% estimated prevalence of both conditions) in 2017 (Fig. 5 and Extended Data Fig. 3). Exceptions were Central and South America, where Guyana was the only example of moderate DBM (5%–10% of both conditions). In Africa, much of the Democratic Republic of the Congo, Cameroon, Republic of Congo, Zambia and southern Botswana demonstrated high DBM (≥10% of both overweight and wasting). Areas in central Morocco reached some of the highest levels of DBM (≥15% overweight, 10–15% wasting), whereas much of the rest of North Africa had high estimated overweight (10–15%) and moderate estimated wasting (5–10%). Locations scattered throughout Iraq, India and in Southeast Asia mostly experienced moderate wasting (such as Myanmar at 5–10%) or moderate DBM (such as Indonesia at 5–10%), reaching moderate-to-high DBM levels in select areas (such as central Papua New Guinea and Cambodia at 5–10% overweight, 10–15% wasting; Thailand, 10–15% overweight, 5–10% wasting). Relatively rare in East Asia, DBM was at moderate levels at most (5–10% both conditions), such as in provinces in southeastern China. At the national level, 25.7% (27 of 105) LMICs were moderately affected and 5.7% (6 of 105) were highly affected by both overweight and wasting (≥5% and ≥10% prevalence of both conditions, respectively). Subnationally, however, 70.3% (74 of 105) of LMICs had moderately affected districts, 11.4% (12 of 105) had highly affected districts and 2.9% (3 of 105) had districts with very high DBM (≥5%, ≥10% and ≥15% prevalence of both conditions, respectively).

Although childhood nutritional status generally improved over 2000–2017, subnational variation in childhood overweight, wasting and DBM was apparent. Declines in wasting and overweight prevalence in South Africa’s western areas led to a decrease in DBM prevalence, from high levels in Siyanda district in 2005 (10–15% estimated wasting and overweight) to moderate levels in 2017 (5–10% both conditions); overweight remains very high, however, on the southern coast (≥15%). On the basis of annualized trends, 25.7% (27 of 105) of LMICs are predicted to have districts with at least moderate DBM by 2025 and 34.3% (36 of 105) are predicted to have high DBM districts (Fig. 5). Between 2000 and 2017, 8.6% (9 of 105) of LMICs had first administrative units that experienced transition from high estimated prevalence of wasting (≥10%) to normal weight (<5% both wasting and overweight). Nearly one-third, 32.3% (34 of 105) of LMICs had first administrative units that transitioned from normal weight to high overweight and 7.6% (8 of 105) transitioned from high wasting to high DBM.

**Discussion**

This study provides overweight estimates and combines them with wasting estimates to highlight DBM across LMICs at a fine geospatial scale. This enables efficient targeting of local-level interventions to improve nutrition outcomes in vulnerable populations. The figures presented here, as well as our online visualization tools, allow for comparing overweight and wasting levels and trends across and within countries for each year from 2000 to 2017, leveraging the spatially resolved underlying data and covariates to produce detailed spatial estimates across all modeled regions. Our estimates show the global trend in early childhood wasting is declining, but areas with high prevalence and little progress, such as in the Sahel and South Asia, remain. Meanwhile, childhood overweight prevalence has increased, especially in tropical South America and regions in the Middle East, Central Asia and Africa.

Across LMICs, trends in childhood overweight have increased while wasting decreased by different magnitudes from 2000–2017, leading to the emergence of DBM in several areas. As countries experience economic growth, they may undergo nutritional transitions wherein the challenges of undernutrition are replaced by those of overweight or the co-occurrence of both conditions4. Overall, food security has improved across LMICs in the past decade, which has led to increased availability of calories at the population level12. Although overweight is a reflection of excess calorie intake and reduced energy expenditure, there is a growing recognition that at the root of the rising rates of overweight are complex interactions between societal, environmental, food industry and individual factors, including biological, psychological and economical factors41. Understanding the factors underpinning these trends is key to predicting how nutrition programs can accelerate amelioration of wasting without incurring high rates of childhood overweight.

Although we included urbanicity as a covariate in our models, we were unable to reliably stratify our results by urban and rural areas. Urbanization is widely viewed as a key driver of the rise in overweight, but an increase in rural body mass index has recently been recognized as a main driver of the global epidemic of obesity in adults42. Such an analysis would thus add important context to our estimates. Case studies in China, Egypt, India, Mexico, the Philippines and South Africa have demonstrated a consistent trend of increased energy content of diets43. Relatively rural areas in China have experienced an increase in the intake of animal source foods and edible oils, likely due to the decreasing cost of these products. Further, increased use of motor vehicles and labor-saving technologies in agriculture have caused a decrease in energy expenditure in all these countries. In Brazil, household consumption of high-calorie ultra-processed foods has steadily replaced that of fresh or minimally processed foods44. Nutritious diets consisting of the latter can help prevent both wasting and stunting, thus work is needed to identify how dietary patterns differ between wasted and overweight children and the underlying factors causing those differences. Widespread collection and assembly of nutrition data from older children and adults would also contribute to a more complete understanding of longitudinal nutrition patterns.

In addition to tracking progress, child nutrition measurements are important for predicting and averting morbidity and mortality. Wasting is often indicative of short-term weight loss due to food shortages, famine or diseases such as diarrhea28–30 and puts children at greater risk of succumbing to common infections45. Childhood overweight is likely to progress into adulthood and is associated with NCDs46, including cardiovascular disease, type 2 diabetes, sleep apnea and cancer47–49. Routine monitoring and reporting of child nutrition status can highlight trends and act as an early warning for health systems, particularly in the context of epidemiological transitions48.

Although overall spending on development assistance and investments to address malnutrition from government donors has remained steady, those from multilateral institutions have increased since 2013, amounting to US$856 million in overseas development assistance in 2016 (ref. 50). These investments, however, fall short of the estimated US$3.5 trillion per year that malnutrition costs society, US$500 billion of which is attributable to overweight and obesity51. By focusing on prevention and early action, healthcare costs can be reduced and human capital increased. One difficulty, however, is addressing the different forms of malnutrition in tandem. Multiple forms of malnutrition are the new normal, according to the GNR52 and Scaling Up Nutrition53,54. Double-duty actions that could simultaneously combat undernutrition, overweight, obesity, and diet-related NCDs have been proposed to address this problem55–58. Despite progress in identifying such actions, such as the promotion of breastfeeding, double-duty approaches have not been widely adopted. To better respond to the diverse and rapidly
evolving nutrition challenges facing LMICs, sustainable and health-promoting food systems are needed to slow the development of DBM. Due to the multiple causality of malnutrition, multisector collaboration is required, including agriculture, trade and industry, environment, communication and education, all working towards policy and intervention coherence.
There are several limitations to these analyses, mainly concerning the quantity and quality of the underlying data in the models, as shown in our uncertainty maps (Figs. 1f and 2f). Missing or improbable values in the primary data may contribute bias in the estimates and thus we have incorporated covariates to improve the estimates in areas where data are sparse. Additionally, differences in measurement techniques between surveys, scale miscalibration or equipment failure and poor training and standardization of measurers may contribute bias. Although our estimates were produced at a high spatial resolution, they were limited to prevalence by area, rather than the co-occurrence of wasting and overweight experienced by the same households or individuals. Additional work is required to identify the immediate and basic causes that lead to both wasting and obesity coexisting in the same geographical areas so that appropriate solutions can be identified. Future studies will consider maternal indicators associated with child nutritional outcomes, such as anemia and examine the co-distribution of overweight and stunting to broaden our assessment. New modeling approaches are currently in development to provide full distributions of height, weight and age, for more complete assessments of DBM using all important indicators of undernutrition. Commendable gains have been made globally against child malnutrition over the past two decades. Our mapped estimates, however, show that high rates of wasting persist and overweight is increasing among young children in many LMICs. Identifying the causes underlying the presence of wasting or overweight in children living in the same community is necessary to formulate appropriate solutions. The estimates provided by this study can aid in the identification of specific areas where further insight can be gathered and trials of policy interventions administered, ultimately contributing to the UN Decade of Action on Nutrition process of sustained and coherent implementation of policies and programs.

Online content
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Methods

Overview. Our study follows the Guidelines for Accurate and Transparent Health Estimates Reporting (GÂTEL) (Supplementary Table 1). The analyses used model-based geostatistics to generate local-, administrative- and national-level estimates of child under 5 overweight, wasting prevalence and double burden over time. Using an ensemble modeling framework that fed into a Bayesian generalized linear mixed-effects model with a correlated space-time random effect and 1,000 draws from an approximate posterior distribution, we generated annual prevalence estimates for overweight and wasting on a 5×5-km grid over 105 LMICs from 2000 to 2017 and aggregated these to administrative and national levels (Supplementary Table 2). Countries were selected for inclusion in this study using the socio-demographic index (SDI), a summary measure of development that combines education, fertility and poverty. Selected countries were in the low, lower-middle and middle SDI quintiles, with several exceptions (Supplementary Table 2). China, Libya, Malaysia, Panama and Turkmenistan were included despite higher-middle SDI for geographic continuity with other included countries. Albania, Bosnia-Herzegovina and Moldova were excluded due to geographic discontinuity and lack of available survey data. We did not conduct estimates for the island nations of American Samoa, Federated States of Micronesia, Fiji, Kiribati, Marshall Islands, Samoa, Solomon Islands or Tonga, as no survey data could be sourced.

Data. Surveys and child anthropometry data. We extracted individual-level weight, height and age data for children under 5 from household survey series including the Demographic and Health Surveys, Multiple Indicator Cluster Surveys, Living Standards Measurement Survey and Core Welfare Indicators Questionnaire, among other country-specific child health and nutrition surveys (Supplementary Tables 3 and 4). Included in our models were 420 georeferenced household surveys representing over 3 million children under 5. Each individual child record was associated with a cluster, a group of neighboring households or a ‘village’ that acted as a primary sampling unit. Approximately 185 surveys with height, weight and age data included geographic coordinates or precise place names for each cluster within that survey. In the absence of geographic coordinates for each cluster, we assigned data to the smallest available administrative area unit in the survey (polygons) while accounting for the survey sample design (15,781 survey polygons for overweight and wasting). Boundary information for these administrative units was obtained as shapefiles either directly from the surveys or by matching to shapefiles in the Global Administrative Unit Layers database or the Database of Global Administrative Areas. In select cases, shapefiles provided by the survey administrator were used or custom shapefiles were created based on survey documentation. These raw data were resampled to points locations using a population-weighted sampling approach over the relevant area unit with the number of locations set proportionally to the number of grid cells in the area and the total weights of all the resampled points summing to one.

Select data sources were excluded for the following reasons: missing survey weights for areal data, missing sex or age variable, incomplete sampling (for example, only children ages 0–3 years measured) or untrustworthy data (as determined by the survey administrator or by inspection). Details on the survey data excluded for each country can be found in Supplementary Table 5. Data extraction and processing methods have been described previously.

Child anthropometry. Using height, weight, and age data for each individual, WHZs were calculated from the age- and sex-specific lambda-mu-sigma values from the 2006 WHO Child Growth Standards. The lambda-mu-sigma methodology allows for Gaussian z score calculations and comparisons to be applied to skewed, non-Gaussian distributions. A child was classified as overweight or wasted if their weight-for-height/length was more than two s.d. (z scores) above or below the WHO growth reference population, respectively. These individual level data observations were then collapsed to cluster-level totals for the number of children sampled and total number of children under 5 affected by overweight and the total number of children who were wasted out of the children who were not overweight.

Temporal resolution. We estimated prevalence of overweight and wasting annually from 2000 to 2017 using a model that allowed us to account for data points measured across survey years, and as such, allows us to predict at monthly or finer temporal resolutions. We were limited, however, both computationally and by the temporal resolution of covariates (Supplementary Table 6) and thus produced only annual estimates.

Seasonality adjustment. WHZs were used to calculate individual child wasting status. As a data preprocessing step, we performed a seasonality adjustment on individual-level weight weights in order to account for differences in observed child weight that may have been due to food scarcity during the month in which the survey was conducted. To adjust weight measurements, we fitted a model for each region with a 12-month seasonal spline, a country-level fixed effect and a smooth spline over the duration of our data collection using the mgcv package in R and the following formula:

\[ \text{WHZ} \sim s_D(\text{month}) + s_T(t) + \text{as.factor}(\text{country}) \]

Month is the integer-valued month of the year (1, …, 12), \( t \) is the time of the interview in integer months since the earliest observation of any child in the dataset and country is a factor variable representing the country where the observation was recorded. We then estimated the period effect using 12 cyclic cubic (cc) regression splines basis functions and we accounted for a smoother longer time temporal trend using four thin-plate (tp) splines. The country effects and the long-term temporal spline were included only to avoid confounding during fitting of the seasonal spline fit and neither country effects nor the long-term trend was used in the seasonal adjustment. We then adjusted all observations to account for the difference in the seasonal period between the month of the interview and an average day of the year as determined by which days aligned with the mean of the periodic spline.

Spatial covariates. In order to leverage strength from locations with observations the most temporal–spatial detail, we compiled several 5×5-km raster layers of putative socioeconomic and environmental correlates of malnutrition in the 105 LMICs (Supplementary Table 6). These covariates were selected based on their potential to be predictive for overweight and wasting, according to literature review and plausible hypothesis as to their influence. Acquisition of temporally dynamic datasets, where possible, was prioritized to best match our observations and thus predict the changing dynamics of the two indicators. Of the 12 covariates included, 6 were temporally dynamic and were reformatted as a synoptic mean over each estimation period or as a mid-period year estimate. These included average daily mean rainfall (precipitation), educational attainment in women of reproductive age (15–49 years old), enhanced vegetation index, fertility, urbanicity and population. The remaining six covariate layers were static throughout the study period and were applied uniformly across all modeling years; these covariates included growing season length, irrigation, nutritional yield for vitamin A, nutritional yield for protein, nutritional yield for iron and travel time to nearest settlement >50,000 inhabitants.

To select covariates and capture possible nonlinear effects and complex interactions between them, an ensemble covariate modeling method was implemented. For each region, three submodels were fitted to our dataset, using all of our covariate data as explanatory predictors: generalized additive models, boosted regression trees and lasso regression. Each submodel was fitted using fivefold cross-validation to avoid overfitting and the out-of-sample predictions from across the five holdouts were compiled into a single comprehensive set of out-of-sample predictions from that model. Additionally, the same submodels were also run using 100% of the data and a full set of in-sample predictions were created. The three sets of out-of-sample submodel predictions were fed into the full geostatistical model as the explanatory covariates when performing the model fitting. The in-sample predictions from the submodels were used as covariates when generating predictions using the fitted full geostatistical model. A recent study has shown that this ensemble approach can improve predictive validity by up to 25% over an individual model.

Analysis. Geostatistical model. In this study, wasting was defined as the proportion of children under 5 below 2 WHO z score (≤−2) and overweight was defined as the proportion of children under 5 above positive 2 WHO z score (>2) as defined in the WHO growth reference population. To model the full distribution of possible indicators of nutritional status in WHO wasting (≤−2 WHO z, normal (−2 <−2 and ≤2 WHO z) and overweight (>2 WHO z), we used an ensemble modeling approach to estimate the relative proportion of each indicator. A similar modeling approach was used to estimate vaccine coverage in Africa.

We used a continuation ratio model to estimate the prevalence of three categories: wasting, normal weight and overweight. We first modeled the proportion of wasting children within a Bayesian hierarchical framework using logistic regression with a spatially and temporally explicit generalized linear mixed-effects model. Second, we modeled the proportion of the children that were overweight conditioned on not being wasted using the same Bayesian modeling framework. To achieve this, we used an ensemble modeling approach to estimate the changing dynamics of the two indicators. Of the 12 covariates included, 6 were temporally dynamic and were reformatted as a synoptic mean over each estimation period or as a mid-period year estimate. These included average daily mean rainfall (precipitation), educational attainment in women of reproductive age (15–49 years old), enhanced vegetation index, fertility, urbanicity and population. The remaining six covariate layers were static throughout the study period and were applied uniformly across all modeling years; these covariates included growing season length, irrigation, nutritional yield for vitamin A, nutritional yield for protein, nutritional yield for iron and travel time to nearest settlement >50,000 inhabitants.

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For indices $i$, $j$ and $t$, *(index)* is the value of $*$ at the index. The annual prevalence of weightings, $\pi_{ijt}$ in cluster $i$, in time $t$, was modeled as a linear combination of the three submodels, (generalized additive models, boosted regression trees and lasso regression), rasterized covariate values, $X$, a correlated spatiotemporal random effect term $Z_t$, country random effects $\epsilon_c(i)$, with one unstrung country random effect fitted for each country in the modeling region and all $\epsilon_c(i)$ sharing a common variance parameter, $\gamma$, and an independent nugget random effect $\epsilon_0$, with variance parameter, $\sigma$. Coefficients $\beta$ in the three submodels $h=1, 2, 3$ represent their respective predictive weights in the logit link, while the joint error term $Z_t$ accounts for residual spatiotemporal autocorrelation between individual data points that remain after accounting for the predictive effect of the submodel covariates, the country-level random effect $\epsilon_c(i)$, the nugget and $\epsilon_0$. The residuals $Z_t$ were modeled as a three-dimensional Gaussian process in space–time centered at zero and with a covariance matrix constructed from a Kronecker product of spatial and temporal covariance kernels. The spatial covariance, $\Sigma_{sp}$, was modeled using an isotropic and stationary Matérn function and temporal covariance, $\Sigma_{te}$, as an annual autoregressive (AR1) function over the 18 years represented in the model. In the stationary Matérn function, $\nu$ is the gamma function, $K$ is the modified Bessel function of order $\nu>0$, $\sigma>0$ is a scaling parameter, $D$ denotes the Euclidean distance and $\sigma_0$ is the marginal variance. The scaling parameter, $\kappa$, is defined to be $\kappa = \sqrt{8\nu}/\delta$, where $\delta$ is a range parameter (where the distance where the covariance function approaches 0.1) and $\nu$ is a scaling constant, which is set to 2 rather than fitted from the data. The number of rows and the number of columns of the spatial Matérn covariance matrix are both equal to the number of spatial mesh points for a given modeling region. The number of rows and the number of columns of the spatial Matérn covariance matrix are both equal to the number of spatial mesh points for a given modeling region. In the AR1 function, $\rho$ is the autocorrelation function and $k$ and $j$ are points in the time series where $|k-j|$ defines the lag. The number of rows and the number of columns of the AR1 covariance matrix are both equal to the number of temporal mesh points (18). The number of rows and the number of columns of the spatial–time covariance matrix, $\Sigma_{sp} \otimes \Sigma_{te}$, for a given modeling region are both equal to the number of spatial mesh points times the number of temporal mesh points.

This approach leverages the residual correlation structure to more accurately predict prevalence estimates for locations with no data, while also propagating the dependence in the data through to uncertainty estimates\(^1\). The posterior distributions were fitted using computationally efficient and accurate approximations in R-INLA\(^{22}$ (integrated nested Laplace approximation) and the stochastic partial differential equations\(^{22}$ approximation to the Gaussian process residuals using R project v3.5.1. The stochastic partial differential equations approach using INLA has been demonstrated elsewhere, including the estimation of health indicators, particulate air matter and population age structure\(^{69–71}$.

**Post estimation.** To transform grid cell-level estimates into a range of information useful to a wide constituency of potential users, estimates were aggregated at first and second administrative units specific to each country and at national levels\(^1\). Although the models can predict all locations covered by available raster covariates, all final model outputs for which land cover was classified as ‘barren’ or sparsely vegetated on the basis of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data (2013) were masked\(^1\). Areas where the total population density was less than ten individuals per 1 km×1 km grid cell in 2015 were also masked in the final outputs.

**Model validation.** Models were validated using spatially stratified fivefold out-of-sample cross-validation. In order to offer a more stringent analysis by accounting for some of the spatial correlation in the data, holdout folds were created by combining sets of all data falling with first administrative level areas. Validation was performed by calculating bias (mean error), variance (root-mean-square error), 95% data coverage within prediction intervals and correlation between observed data and predictions. All validation metrics were calculated on the out-of-sample predictions from the fivefold cross-validation. All validation procedures and corresponding results are provided in Supplementary Tables 7–18.

**Projections.** To compare our estimated rates of improvement in overweight and wasting prevalence over the last 18 years with the improvements needed between 2017 and 2025 to meet WH0 GNTIs, we performed a simple projection using estimated AROC applied to the final year of our estimates. Both AROC and projections were calculated at the draw-level to obtain the uncertainty of the estimates. For each indicator $i$, we calculated AROC at each grid cell ($m$) by calculating the AROC between each pair of adjacent years $t$:

$$\text{AROC}_{i,m} = \log\left(\frac{\text{Prom}_{m}}{\text{Proc}_{m-1}}\right)$$

We then calculated a weighted AROC for each indicator by taking a weighted average across the years, where more recent AROCs were given more weight in the average. We defined the weights to be:

$$W_t = \left(1 - \frac{t - 2000}{1}\right)$$

where $\gamma$ may be chosen to give varying amounts of weight across the years. For each indicator, we then calculated the average AROC to be:

$$\text{AROC}_{i,m} = \left(\sum_{t=1}^{2017} W_t \times \text{AROC}_{i,m,t}\right)$$

Finally, we calculated the projections (Prom) by applying the AROC in our 2017 mean prevalence estimates to produce estimates in 8 years from 2017 to 2025:

$$\text{Prom}_{i,m,2025} = \log^{-1}\left(\log\left(\text{Prom}_{i,m,2017}\right) + \text{AROC}_{i,m} \times 8\right)$$

This projection scheme is analogous to the methods used in the Global Burden of Disease 2017 study\(^1\) for measurement of progress and projected attainment of health-related Sustainable Development Goals. Our projections are based on the assumption that areas will sustain the current AROC, and the precision of the AROC estimates is dependent on the level of uncertainty emanating from the estimation of annual prevalence.

**Priors.** The following priors were used for our overweight and wasting models:

$$\begin{align*}
\rho_0 & \sim N(\mu = 0, \sigma^2 = 3), \\
\beta_0 & \sim \text{iid } N(\mu = 1, \sigma^2 = 3), \\
\log(\sigma_{\text{nu}}^2) & \sim N(\mu = 4, \sigma^2 = 1.2^2), \\
\log(\sigma_{\text{te}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}), \\
\log(\sigma_{\text{sp}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}), \\
\theta_1 & \sim \text{iid } N(\mu = 0, \sigma^2), \\
\theta_2 & \sim \text{iid } N(\mu = 0, \sigma^2), \\
\theta_3 & \sim \text{iid } N(\mu = 0, \sigma^2), \\
\theta_4 & \sim \text{iid } N(\mu = 0, \sigma^2)
\end{align*}$$

Given that our covariates used in INLA (the predicted outputs from the ensemble models) should be on the same scale as our predictive target, we believe that the intercept in our model should be close to zero and that the regression coefficients should sum to 1. As such, we chose the prior for our intercept to be $N(0, \sigma^2 = 3)$ and the prior for the fixed-effect coefficients to be $\text{loggamma}(\mu = 1, \gamma = 5 \times 10^{-5})$. The prior on the temporal correlation parameter, $\rho$, was chosen to be mean zero, showing no prior preference for either positive or negative autocorrelation structure and with a distribution wide enough such that within three s.d. of the mean, the prior includes values of $\rho$ ranging from $-0.95$ to 0.95. The priors on the random effect variances were chosen to be relatively loose given that we believe our fixed-effects covariates should be well correlated with our outcome of interest, which might suggest relatively small random effects values. At the same time, we wanted to avoid using a prior that was so diffuse as to actually put high prior weight on large random effect variances. For stability, we used the uncorrelated multivariate normal priors that INLA automatically determines (based on the finite elements mesh) for the log-transformed spatial hyperparameters $\kappa$ and $\tau$. In our parameterization, we represent $\kappa$ and $\tau$ in the log gamma distribution as shape and inverse-scale, respectively.

**Prior sensitivity analysis.** Sensitivity analysis was undertaken to assess the impact of the hyper-priors for the nugget, country random effects, and space–time correlation. We considered two different sets of priors related to the nugget and country random effects and three set related to space–time correlation, resulting in six different combinations of hyper-priors as outlined below.

Model 1: In this model, we used the default hyper-priors in INLA\(^{22}$ (for both nugget and country random effects). The hyper-prior for the AR1 rho, $\rho$, was retained as shown below.

$$\begin{align*}
\log(\sigma_{\text{nu}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5})\text{ and } \\
\log(\sigma_{\text{te}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}), \\
\log(\rho^2) & \sim \text{Normal}(\mu = 4, \sigma^2 = 1.2^2)
\end{align*}$$

Model 2: The hyper-priors for nugget were changed as indicated below, where hyper-priors for country random effect were the default hyper-priors in INLA. The hyper-priors for the AR1 rho, $\rho$, were retained the same as model 1.

$$\begin{align*}
\log(\sigma_{\text{nu}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 2)\text{ and } \\
\log(\sigma_{\text{te}}^2) & \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}), \\
\log(\frac{1}{\rho^2}) & \sim \text{Normal}(\mu = 4, \sigma^2 = 1.2^2)
\end{align*}$$
Model 3: In this model the hyper-priors for country random effects and nugget were exchanged, where hyper-priors for nugget were the default hyper-priors in INLA. The hyper-priors for the AR1 rho, \( \rho \), were retained the same as model 1.

\[
\log(\frac{\rho}{1-\rho}) \sim \log\text{gamma}(\alpha = 1, \gamma = 5 \times 10^{-5})
\]

\[
\log(\frac{\sigma_n}{\sigma}) \sim \log\text{gamma}(\alpha = 1, \gamma = 2).
\]

\[
\log(\frac{\sigma}{2}) \sim \text{Normal}(\mu = 4, \sigma^2 = 1.2^2)
\]

Model 4: In this model, we used the default hyper-priors in INLA for less informative nugget and country random effects. The hyper-priors for the AR1 rho, \( \rho \), were changed.

\[
\log(\frac{\rho}{1-\rho}) \sim \log\text{gamma}(\alpha = 1, \gamma = 5 \times 10^{-5})
\]

\[
\log(\frac{\sigma_n}{\sigma}) \sim \log\text{gamma}(\alpha = 1, \gamma = 5 \times 10^{-5}).
\]

\[
\log(\frac{\sigma}{2}) \sim \text{Normal}(\mu = 0, \sigma^2 = 2.58^2)
\]

Model 5: In this model, we used the default hyper-priors in INLA for both nugget and country random effects. The hyper-priors for the AR1 rho, \( \rho \), were the default in INLA.

\[
\log(\frac{\rho}{1-\rho}) \sim \log\text{gamma}(\alpha = 1, \gamma = 5 \times 10^{-5})
\]

\[
\log(\frac{\sigma_n}{\sigma}) \sim \log\text{gamma}(\alpha = 1, \gamma = 5 \times 10^{-5}).
\]

\[
\log(\frac{\sigma}{2}) \sim \text{Normal}(\mu = 0, \sigma^2 = 1.2^2)
\]

The predicted estimates for all models with different sets of hyper-priors were highly correlated at the grid-cell level and yielded low mean absolute differences (Supplementary Table 7). We ultimately selected the less informative priors for nugget and country random effects as they are default priors in the INLA package and have been applied widely, and selected a more stringent parameterization of our space–time correlation, as indicated in model 1.

Mesh construction. We constructed the finite elements mesh for the stochastic partial differential equation approximation to the Gaussian process regression using a simplified polygon boundary (in which coastlines and complex boundaries were smoothed) for each of the regions within our model. We set the inner mesh triangle maximum edge length (the mesh size for areas over land) to be 0.75 degrees and the buffer maximum edge length (the mesh size for areas over the ocean) to be 5 degrees. An example finite elements mesh constructed for Eastern ocean is shown in Supplementary Figure 5.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
Our study follows the Guidelines for Accurate and Transparent Health Estimates Reporting (Supplementary Table 1). The findings of this study are supported by data available in public online repositories, data publicly available upon request of the data provider and data not publicly available due to restrictions by the data provider. Nonpublicly available data were used under license for the current study but may be available from the authors upon reasonable request and with permission of the data provider. Details of data sources and availability can be found in Supplementary Tables 2–5. The full output of the analyses are publicly available in the Global Health Data Exchange (http://ghdx.healthdata.org/record/dhme-data/mlmic-double-burden-of-malnutrition-geospatial-estimates-2000-2017) and can further be explored via customized data visualization tools (https://vizhub.healthdata.org/lbd/dbm/). Administrative boundaries were retrieved from the Database of Global Administrative Areas. Land cover was retrieved from the online Data Pool, courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center. USGS/Earth Resources Observation and Science Center, Sioux Falls, South Dakota. Lakes were retrieved from the Global Lakes and Wetlands Database, courtesy of the World Wildlife Fund and the Center for Environmental Systems Research, University of Kassel. Populations were retrieved from WorldPop.

Code availability

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LBD Double Burden of Malnutrition Collaborators

Damaris K. Kinyoki1,2, Jennifer M. Ross3,4, Alice Lazzar-Atwood5, Sandra B. Munro6, Lauren E. Schaeffer7, Mahdieh Abbasalizad-Farhangi8, Masoumeh Abbasi9, Hedayat Abbastabar7, Ahmed Abdelalim8, Amir Abdi9, Mohammad Abdollahi10, Ibrahim Abdollahpour7, Rizwan Suliankatchi Abdulkader12, Nebiyu Dereje Abebe13, Teshome Abuka Abebo15, Carl Abelardo T. Antonio99,100, Ernoiz Antriyandarti101, Davood Anvari102,103, Razique Anwer104, Anurag Agrawal41,42, Tauseef Ahmad43,44, Keivan Ahmadi45, Sepideh Ahmadi46, Cyrus Alinia68, Vahid Alipour69,70, Hesam Alizade71,72, Syed Mohamed Aljunid73,74, Afshin Almasi75, Amir Almasi-Hashiani76, Hesham M. al-Mekhlafi77,78, Rajaa M. al-Raddadi79, Khalid altirkawi80, Abdelrahem I. abushouk22, Manfred Mario Kokou accrombessi23, Dilaram Acharya24,25, Rizwan Suliankatchi Abdulkader12, Nebiyu Dereje Abebe13,14, Teshome Abuka Abebo15, Carl Abelardo T. Antonio99,100, Ernoiz Antriyandarti101, Davood Anvari102,103, Razique Anwer104,非金融支持来自SERVIER，非金融支持来自MICROLIFE，个人费用来自TEVA POLSKA，非金融支持来自SUPERPHARM和非金融支持来自MEDITCOVER，以外的已提交工作。W. Mendoza是目前Program Analyst Population and Development at the United Nations Population Fund-UNFPA Country Office in Peru，它不一定会支持这项研究。Prof. Saxena的报告来自NIHR School for Public Health Research，报告来自NIHR Applied Research Collaboration and grants from The Daily Mile Foundation supported by INEOS，以外的已提交工作。Dr Dunachie的报告来自The Fleming Fund at UK Department of Health and Social Care，作为该研究的首席作者，Dr Mozaffarian的报告研究资金来自National Institutes of Health和the Gates Foundation；个人费用来自GOED，Nutrition Impact，Bunge，Indigo Agriculture，Motif FoodWorks，Amarin，Acasti Pharma，Cleveland Clinic Foundation，America's Test Kitchen and Danone；scientific advisory board，Brightseed，DayTwo，Elysium Health and Filtricine；and chapter royalties from UpToDate；all outside the submitted work。Dr J. Singh的报告来自Crealta/Horizontal，Medasys，Fidia，UBM LLC，Medscape，WebMD，Clinical Care Options，Clearview Healthcare Partners，Putnam Associates，Spherix，the National Institutes of Health and the American College of Rheumatology，stock options in Amarin Pharmaceuticals and Viking Pharmaceuticals and participates in the steering committee of OMERACT，an international organization that develops measures for clinical trials receives arm's length funding from 12 pharmaceutical companies and is also on the speaker's bureau of Simply Speaking.

Competing interests
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Additional information
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Ontario, Canada. 220Population Research Centre, Gokhale Institute of Politics and Economics, Pune, India. 221International Institute for Population Sciences, Mumbai, India. 222Department of Medical Entomology and Vector Control, Urmia University of Medical Sciences, Urmia, Iran. 223Department of Biostatistics and Epidemiology, Babol University of Medical Sciences, Babol, Iran. 224Epidemiology Research Center, Royan Institute, Tehran, Iran. 225Department of Nursing, Volaita Sodo University, Sodo, Ethiopia. 226Department of Epidemiology and Preventive Medicine, Monash University, Melbourne, Victoria, Australia. 227Department of Pulmonary Medicine, Christian Medical College and Hospital (CMMC), Vellore, India. 228Hanoi National University of Education, Hanoi, Vietnam. 229School of Public Health and Preventive Medicine, Monash University, Melbourne, Victoria, Australia. 230School of Medicine and Surgery, University of Milan Bicocca, Monza, Italy. 231Institute of Public Health, University of Gondar, Gondar, Ethiopia. 232Discipline of Global Health, Flinders University, Adelaide, South Australia, Australia. 233Department of Human Physiology, University of Gondar, Gondar, Ethiopia. 234Department of Environmental Health, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia. 235Department of Dermatology, Case Western Reserve University, Cleveland, OH, USA. 236Department of Dermatology, University of Milan, Milan, Italy. 237Department of Pediatrics, Tanta University, Tanta, Egypt. 238Toxoplasmosis Research Center, Mazandaran University of Medical Sciences, Sari, Iran. 239Division of Women and Child Health, Aga Khan University, Karachi, Pakistan. 240Department of Epidemiology and Biostatistics, Arnold School of Public Health, University of South Carolina, Columbia, SC, USA. 241Population and Development, Facultad Latinoamericana de Ciencias Sociales Mexico, Mexico City, Mexico. 242Australian Institute for Suicide Research and Prevention, Griffith University, Mount Gravatt, Queensland, Australia. 243Department of Nursing, Woldia University, Woldia, Ethiopia. 244Department of Nursing, Jimma University, Jimma, Ethiopia. 245Department of Neonatal Nursing, St. Paul’s Hospital Millennium Medical College, Addis Ababa, Ethiopia. 246Ambo University, Ambo, Ethiopia. 247School of Pharmacy, Aksum University, Aksum, Ethiopia. 248Addis Ababa University, Addis Ababa, Ethiopia. 249Center for Nutrition and Health Research, National Institute of Public Health, Cuernavaca, Mexico. 250Department of Global Health and Infection, Brighton and Sussex Medical School, Brighton, UK. 251Division of Cardiology, Atlanta Veterans Affairs Medical Center, Decatur, GA, USA. 252School of Nutrition, Food Science and Technology, Harwasa University, Harwasa, Ethiopia. 253School of Nursing and Midwifery, Haramaya University, Harar, Ethiopia. 254Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, New Delhi, India. 255Department of Community Medicine, University of Peradeniya, Peradeniya, Sri Lanka. 256Mathematical Demography and Statistics, International Institute for Population Sciences, Mumbai, India. 257Health Research Section, Nepal Health Research Council, Kathmandu, Nepal. 258Department of Microbiology, Far Western University, Maharanganar, Nepal. 259Department of Epidemiology, Shiraz University of Medical Sciences, Shiraz, Iran. 260Center of Complexity Sciences, National Autonomous University of Mexico, Mexico City, Mexico. 261Facultad de Medicina Veterinaria y Zootecnia, Autonomous University of Sinaloa, Culiacan, Mexico. 262Department of Nursing, Bank Mell, Tehran, Iran. 263Penox Project, Harvard University, Addis Ababa, Ethiopia. 264Ministry of Health and Infectious Disease, Tehran, Iran. 265Center of Excellence in Public Health Nutrition, Nguyen Tat Thanh University, Ho Chi Minh, Vietnam. 266Center of Excellence in Behavioral Medicine, Nguyen Tat Thanh University, Ho Chi Minh City, Vietnam. 267School of Nursing and Midwifery, University of Cape Coast, Cape Coast, Ghana. 268Iran University of Medical Sciences, Tehran, Iran. 269Department of Health Policy and Economy, Tabriz University of Medical Sciences, Tabriz, Iran. 270World Health Programme, New Delhi, India. 271Public Health Department, Harwasa University, Harwasa, Ethiopia. 272Curtin University, Perth, Western Australia, Australia. 273Centre for Tropical Medicine and Global Health, University of Oxford, Oxford, UK. 274Mahidol-Oxford Tropical Medicine Research Unit, Bangkok, Thailand. 275Postgraduate Program in Epidemiology, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. 276School of Medicine, Federal University of Bahia, Salvador, Brazil. 277Medicina Interna, Escola Bahiana de medicina e Saude Publica, Salvador, Brazil. 278Department of Bacteriology and Virology, Tabriz University of Medical Sciences, Tabriz, Iran. 279Department of Pharmacology and Toxicology, Maragheh University of Medical Sciences, Maragheh, Iran. 280Department of Pharmacology and Toxicology, Tabriz University of Medical Sciences, Tabriz, Iran. 281Biomedical Informatics and Medical Statistics, Alexandria University, Alexandria, Egypt. 282Department of Clinical Pathology, Mansoura University, Mansoura, Egypt. 283Pediatric Dentistry and Dental Public Health, Alexandria University, Alexandria, Egypt. 284Institute of Public Health, United Arab Emirates University, Al Ain, United Arab Emirates. 285Department of Statistics, Debre Markus University, Debre Markus, Ethiopia. 286Department of Public Health Sciences, Karolinska Institutet, Stockholm, Sweden. 287World Health Programme, Université du Québec en Abitibi-Témiscamingue, Rouyn-Noranda, Quebec, Canada. 288Endemic Medicine and Hepatogastroenterology Department, Cairo University, Cairo, Egypt. 289Department of Biosciences, Nottingham Trent University, Nottingham, UK. 290Eijkman-Oxford Clinical Research Unit, Eijkman Institute for Molecular Biology, Jakarta, Indonesia. 291Ophthalmic Epidemiology Research Center, Shahroud University of Medical Sciences, Shahroud, Iran. 292Department of Microbiology and Immunology, Suez Canal University, Ismailia, Egypt. 293Department of Midwifery, Wolkit University, Wolkit, Ethiopia. 294Department of Paediatrics, Very, Woldia University, Woldia, Ethiopia. 295Department of Medical Chemistry, Kerman University of Medical Sciences, Kerman, Iran. 296School of Pharmacy, University of Tehran, Tehran, Iran. 297Department of Medical and Surgical Sciences, University of Bologna, Bologna, Italy. 298Department of Psychology, University of Psychotherapy, Bielefeld University, Bielefeld, Germany. 299University of Porto, Porto, Portugal. 300School of Medicine, University of Cape Coast, Cape Coast, Ghana. 301Division of Cancer Epidemiology and Genetics, National Cancer Institute, Bethesda, MD, USA. 302Tehran University of Medical Sciences, Tehran, Iran. 303Unit of Medical Physics, Harwasa University, Harwasa, Ethiopia. 304Berman Institute of Bioethics, Johns Hopkins University, Baltimore, MD, USA. 305School of Public Health, Tehran University of Medical Sciences, Tehran, Iran. 306Department of Political Science, University of Human Development, Addis Ababa, Ethiopia. 307College of Medicine, Imam Mohammad Ibn Saud Islamic University, Riyadh, Saudi Arabia. 308School of Public Health, Tehran University of Medical Sciences, Tehran, Iran. 309Department of Health Research Center, Tehran University of Medical Sciences, Tehran, Iran. 310Multiple Sclerosis Research Center, Tehran University of Medical Sciences, Tehran, Iran. 311Division of Cancer Epidemiology and Genetics, National Cancer Institute, Bethesda, MD, USA. 312Department of Epidemiology, Facultad Latinoamericana de Ciencias Sociales Mexico, Mexico City, Mexico. 313Department of Midwifery, Wolkite University, Wolkite, Ethiopia. 314Department of Pulmonary Medicine, Christian Medical College and Hospital (CMC), Vellore, India. 315Department of Epidemiology and Biostatistics, Jimma University, Jimma, Ethiopia. 316Jamaica University, Jamma, Jamaica. 317Department of Health Services Research, Kaiser Permanente, Fontana, CA, USA. 318School of Health Sciences, A.T. Still University, Mesa, AZ, USA. 319Department of Population Health, The Wistar Institute, Philadelphia, PA, USA. 320Division of Neurology, University of Ottawa, Ottawa, Ontario, Canada. 321Department of Chemistry and Technology, University of Porto, Porto, Portugal. 322Center for Biotechnology and Fine Chemistry, Catholic University of Portugal, Porto, Portugal. 323Department of Health Education & Behavioural Sciences, Jimma University, Jimma, Ethiopia. 324Jimma University, Jimma, Ethiopia. 325Psychiatry Department, Kaiser Permanente, Fontana, CA, USA. 326School of Health Sciences, A.T. Still University, Mesa, AZ, USA. 327School of Public Health, Tobacco Research, Harvard University, Boston, USA. 328Regional Centre for Biotechnology, India. 329Institute of Dermatology, King’s College London, London, UK. 330Institute of Dermatology, National Academy of Medical Sciences of Ukraine, Kyiv, Ukraine. 331Department of Child Dental Health, Obafemi Awolowo University, Ile-Ife, Nigeria. 332Timiryaev Institute of Plant Physiology (IPPRAS), Russian Academy of Sciences, Moscow, Russia. 333Abadan School of Medical Sciences, Abadan University of Medical Sciences, Abadan, Iran. 334Department of Research, Center for Population and Health, Wiesbaden, Germany. 335Department of Family Medicine and Primary Care, University of the Witwatersrand, Johannesburg, South Africa. 336Department of Dermatology, Kobe University, Kobe, Japan. 337Gene Expression & Regulation Program, The Wistar Institute, Philadelphia, PA, USA. 338School of Nursing and Midwifery, Wollo University, Bekoji, Ethiopia. 339School of Health and Medical Sciences, Addis Ababa University, Addis Ababa, Ethiopia. 340School of Medical Sciences, Mekele University, Mekele, Ethiopia. 341Department of Nursing and Midwifery, Addis Ababa University, Addis Ababa, Ethiopia. 342Department of Medical History, Mekele University, Mekele, Ethiopia. 343Haramaya University, Dire Dawa, Ethiopia. 344Pharmacy, Wollo University, Dessie, Ethiopia. 345Department of Nursing, Arba Minch University, Arba Minch, Ethiopia. 346Department of Biostatistics, Mekele University, Mekele, Ethiopia. 347Department of Parasitology and Entomology, Tarbiat Modares University, Tehran, Iran. 348Department of Medical Surgery, Tabriz University of Medical Sciences, Tabriz, Iran. 349Department of Medicine, Tanta University, Tanta, Egypt.
Cardiovascular Disease, South African Medical Research Council, Cape Town, South Africa. 827Department of Psychology, University of Alabama at Birmingham, Birmingham, AL, USA. 828Department of Food Science and Nutrition, Jigjiga University, Jigjiga, Ethiopia. 829Department of Manian Medical Centre, Erode, India. 829Microbiology Service, National Institutes of Health, Bethesda, MD, USA. 830Department of Health Promotion and Education, Alborz University of Medical Sciences, Karaj, Iran. 831Health Policy Research Center, Shiraz University of Medical Sciences, Shiraz, Iran. 832Independent Consultant, Karachi, Pakistan. 833Department of Neuropsychiatry, Ain Shams University, Cairo, Egypt. 834School of Medicine, Alborz University of Medical Sciences, Karaj, Iran. 835Medical Laboratory Sciences, Mazandaran University of Medical Sciences, Sari, Iran. 836Chronic Diseases (Home Care) Research Center, Hamadan University of Medical Sciences, Hamadan, Iran. 837Department of Development Studies, International Institute for Population Studies, Mumbai, India. 838Department of Basic Sciences, Islamic Azad University, Sari, Iran. 839Department of Laboratory Sciences, Islamic Azad University, Sari, Iran. 840University School of Management and Entrepreneurship, Delhi Technological University, New Delhi, India. 841Department of Health Information Management and Informatics, Indian University of Medical Sciences, Tehran, Iran. 842Institute for Population Health, King’s College London, London, UK. 843National Institute of Infectious Diseases, Tokyo, Japan. 844College of Medicine, Yonsei University, Seodamieomu, South Korea. 845Division of Cardiology, Emory University, Atlanta, GA, USA. 846Finnish Institute of Occupational Health, Helsinki, Finland. 847Cancer Research Institute, Tehran University of Medical Sciences, Tehran, Iran. 848Cancer Biology Research Center, Tehran University of Medical Sciences, Tehran, Iran. 849Institute of Medical Epidemiology, Martin Luther University Halle-Wittenberg, Halle, Germany. 849Department of Health Education & Promotion, Kermanshah University of Medical Sciences, Kermanshah, Iran. 850School of Health, University of Technology Sydney, Sydney, New South Wales, Australia. 851Department of Psychology, Reykjavik University, Reykjavik, Iceland. 851Department of Health and Behavior Studies, Columbia University, New York, NY, USA. 852Department of Physical Education, Federal University of Santa Catarina, Florianopolis, Brazil. 853Department of Law, Economics, Management and Quantitative Methods, University of Sannio, Benevento, Italy. 854Menzies Institute for Medical Research, University of Tasmania, Hobart, Tasmania, Australia. 855Global Patient Outcome and Real World Evidence, Eli Lilly and Company, Indianapolis, IN, USA. 856Department of Humanities and Social Sciences, Indian Institute of Technology, Roorkee, Roorkee, India. 857Department of Pulmonary Medicine, Asthma Bhawan, Jaipur, India. 858Department of Medicine, University of Alabama at Birmingham, Birmingham, AL, USA. 859Medicine Service, US Department of Veterans Affairs, Birmingham, AL, USA. 860Department of Forensic Medicine, Khatmandu University, Dhulikhel, Nepal. 861Department of Epidemiology, School of Preventive Oncology, Patna, India. 862Department of Epidemiology, Healis Sekhsaria Institute for Public Health, Mumbai, India. 863Department of Midwifery, Haramaya University, Harar, Ethiopia. 864Department of Physiotherapy and Occupational Therapy, Naestved-Slagelse-Ringsted Hospitals, Slagelse, Denmark. 865Medical Surgical Nursing Department, Urmia University of Medical Science, Urmia, Iran. 866Emergency Nursing Department, Semnan University of Medical Sciences, Semnan, Iran. 867Midwifery Department, Hamadan University of Medical Sciences, Hamadan, Iran. 868Research Center for Environmental Determinants of Health, Academy of Medical Science, Kermanshah, Iran. 869Hospital Universitario de la Princesa, Autonomous University of Madrid, Madrid, Spain. 870Centro de Investigación Biomédica en Red Enfermedades Respiratorias (CIBERES), Madrid, Spain. 871Department of Research Development, Federal Research Institute for Health Organization and Informatics of the Ministry of Health (FRIOHI), Moscow, Russia. 872Laboratory of Public Health Indicators Analysis and Health Digitalization, Moscow Institute of Physics and Technology, Moscow, Russia. 873Hull York Medical School, University of Hull, Hull City, UK. 874Ushe Institute of Population Health Sciences and Informatics, University of Edinburgh, Edinburgh, UK. 875Department of Parasitology and Mycology, Tabriz University of Medical Sciences, Tabriz, Iran. 876Division of Community Medicine, International Medical University, Kuala Lumpur, Malaysia. 877Research Management, Policy, Planning and Coordination, Indian Council of Medical Research, New Delhi, India. 878Clinical Department, Nutrition and Dietetics Department, Federal Research Institute of Nutrition, Biotechnology and Food Safety, Moscow, Russia. 879Department of Internal Disease, Pirogov Russian National Research Medical University, Moscow, Russia. 880Department of Nursing, Muhammediyah University of Surakarta, Surakarta, Indonesia. 881Department of Public Health, China Medical University, Taichung City, Taiwan. 882Department of Community Medicine, Ahmadu Bello University, Zaria, Nigeria. 883Department of Agriculture and Food Systems, University of Melbourne, Melbourne, Victoria, Australia. 884Norwegian Institute of Public Health, Bergen, Norway. 885Department of Community Health, Muhimbili University of Health and Allied Sciences, Dar Es Salaam, Tanzania. 886Muhimbili University of Health and Allied Sciences, Dar Es Salaam, Tanzania. 887Department of Criminology, Law and Society, University of California Irvine, Irvine, CA, USA. 888Department of Medicine, University of Valencia, Valencia, Spain. 889Carlos III Health Institute, Biomedical Research Networking Center for Mental Health Network (CiberSAM), Madrid, Spain. 890Cancer Control Center, Osaka International Cancer Institute, Osaka, Japan. 891Department of Pediatrics, Hawassa University, Hawassa, Ethiopia. 892International Vaccine Institute, Seoul, South Korea. 893Research Center for Molecular Medicine, Hamadan University of Medical Sciences, Hamadan, Iran. 894School of Pharmacy, Mekelle University, Mekelle, Ethiopia. 895University Institute 'Egas Moniz', Monte da Caparica, Portugal. 896Research Institute for Medicines, University of Lisbon, Lisbon, Portugal. 897Department of Public Health, Adigat University, Adigat, Ethiopia. 898Pharmacognosy, Mekelle University, Mekelle, Ethiopia. 899Department of Pediatrics, King Saud University, Riyadh, Saudi Arabia. 900College of Medicine, Alfaisal University, Riyadh, Saudi Arabia. 901Department of Anesthesiology, Perioperative and Pain Medicine, Stanford University, Stanford, CA, USA. 902Department of Anesthesiology, King Fahad Medical City, Riyadh, Saudi Arabia. 903Department of Endocrinology, Christian Medical College and Hospital (CMC), Vellore, India. 904Biology Department, Moscow State University, Moscow, Russia. 905HIV/STI Surveillance Research Center, and WHO Collaborating Center for HIV Surveillance, Kerman University of Medical Sciences, Kerman, Iran. 906Department of Medicine, University of Calgary, Calgary, Alberta, Canada. 907Department of Pathology and Legal Medicine, University of São Paulo, Ribeirão Preto, Brazil. 908Clinical Epidemiology and Public Health Research Unit, Burlo Garofolo Institute for Maternal and Child Health, Trieste, Italy. 909Molecular Medicine and Pathology, University of Auckland, Auckland, New Zealand. 910Clinical Hematology and Toxicology, Military Medical University, Hanoi, Vietnam. 911Department of Neurology, All India Institute of Medical Sciences, Delhi, India. 912Department of Pharmacy, Stamford University Bangladesh, Dhaka, Bangladesh. 913Gomai Center of Biochemistry and Biotechnology, Gomal University, Dera Ismail Khan, Pakistan. 914TB Culture Laboratory, Multi Mehmoon Memorial Teaching Hospital Dera Ismail Khan, Dera Ismail Khan, Pakistan. 915Amity Institute of Biotechnology, Amity University Rajasthan, Jaipur, India. 916Lifestyle Diseases Research Entity, North-West University, Mmabatho, South Africa. 917Division of Health Sciences, University of Warwick, Coventry, UK. 918Department of Epidemiology and Biostatistics, Umeå University, Umeå, Sweden. 919Argentine Society of Medicine, Buenos Aires, Argentina. 920Venezia Sarsfield Hospital, Buenos Aires, Argentina. 921Central Research Institute of Cytology and Genetics, Federal Research Institute for Health Organization and Informatics of the Ministry of Health (FRIOHI), Moscow, Russia. 922Christian Medical College and Hospital (CMC), Vellore, India. 923UKK Institute, Tampere, Finland. 924Psychosocial Research Center, Ilam University of Medical Sciences, Ilam, Iran. 925National AIDS Control Organisation, Ministry of Health, New Delhi, India. 926Raffles Neuroscience Centre, Raffles Hospital, Singapore, Singapore. 927Yong Loo Lin School of Medicine, National University of Singapore, Singapore, Singapore. 928Community & Family Medicine, All India Institute of Medical Sciences, Bathinda, India. 929Department of Neurology & Stroke Unit, Sant'Anna Hospital, Como, Italy. 930Occupational Health Unit, Sant'Orsola Malpighi Hospital, Bologna, Italy. 931Department of Health Care Administration and Economics, National Research University Higher School of Economics, Moscow, Russia. 932Department of Global Health and Population, Harvard University, Boston, MA, USA. 933School of Medicine, University of Belgrade, Belgrade, Serbia. 934Department of Pediatric Endocrinology, Mother and Child Healthcare Institute of Serbia 'Dr Vukan Copic', Belgrade, Serbia. 935Foundation University Medical College, Foundation University, Islamabad, Pakistan. 936Department of Epidemiology and Biostatistics, Wuhuan University, Wuhuan, China. 937Demographic Change and Ageing Research Area, Federal Institute for Population Research, Wiesbaden, Germany. 938Department of Physical Therapy, Naresuan University, Meung District, Thailand. 939Department of Psychology and Counselling, University of Melbourne, Melbourne, Victoria, Australia. 940Department of Medicine, University of Melbourne, St Albans, Victoria, Australia.
Extended Data Fig. 1 | Prevalence of under-5 childhood overweight in LMICs in 2017 at administrative levels 0, 1, 2, and at 5 × 5-km resolution.
Prevalence of overweight among children under 5 at administrative level 0 (national-level estimates) (a), first administrative unit (b), second administrative unit (c), and at the 5 × 5-km resolution (d). Maps reflect administrative boundaries, land cover, lakes, and population; grey-coloured grid cells were classified as “barren or sparsely vegetated” and had fewer than ten people per 1 × 1-km grid cell (39–45), or were not included in this analysis. Maps were generated using ArcGIS Desktop 10.6.
Extended Data Fig. 2 | Prevalence of under-5 child wasting in LMICs at administrative levels 0, 1, 2, and at 5 × 5-km resolution in 2017. Prevalence of wasting among children under 5 at administrative level 0 (national-level estimates) (a), first administrative unit (b), second administrative unit (c), and at the 5 × 5-km resolution (d). Maps reflect administrative boundaries, land cover, lakes, and population; grey-coloured grid cells were classified as “barren or sparsely vegetated” and had fewer than ten people per 1 × 1-km grid cell39–45, or were not included in this analysis. Maps were generated using ArcGIS Desktop 10.6.
Extended Data Fig. 3 | Modelling regions. Modelling regions were based on geographic and socio-demographic index (SDI) regions from the Global Burden of Disease, defined as: Andean South America, Central America and the Caribbean, Central sub-Saharan Africa (SSA), East Asia, Eastern SSA, Middle East, North Africa, Oceania, Southeast Asia, South Asia, South SSA, Central Asia, Tropical South America, and Western SSA. Regions in grey (Stage 3) were not included in our models due to high-middle and high SDI. Map was generated using ArcGIS Desktop 10.6.

Reporting Summary

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For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection

- No primary data collection was carried out for this analysis

Data analysis

- This analysis was carried out using R version 3.5.0. The main geostatistical models were fit using R-INLA version 18.07.12. Additional adjustments were performed using the mgcv package in R (v. 3.5.0). All code used for these analyses is publicly available online at http://ghdx.healthdata.org/. Maps were generated using ArcGIS Desktop 10.6.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

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Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
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The findings of this study are supported by data available in public online repositories, data that are publicly available upon request from the data provider, and data that are not publicly available due to restrictions by the data provider and which were used under license for the current study. A detailed table of data sources and availability can be found in Supplementary Table 2, and online at ghdx.healthdata.org.
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Life sciences study design

All studies must disclose on these points even when the disclosure is negative.

Sample size  Sample size was calculated as the number of unique data source-location pairs with observations of overweight and wasting prevalence. This sample size is reported in the main text under Global and location variation in malnutrition trends,"...using data from 420 household surveys representing more than 3 million children, we map the relative burdens of overweight and wasting among under-5 children in 105 LMICs from 2000 to 2017."

Data exclusions  Reasons for data exclusion were pre-established and are described in supplementary table 5. For a survey to be considered for this analysis, we required information on height, weight, age and sex. Select data sources were excluded from the analysis due to: missing survey weights, missing sex and age variable, incomplete sampling (e.g., only a specific age range), or untrustworthy data (as determined by the survey administrator or by inspection).

Replication  This is an observational study using many years of survey and surveillance data and could be replicated.

Randomization  This analysis is an observational mapping study and there were no experimental groups.

Blinding  Blinding was not relevant to this study, as it was an observational study using survey and surveillance data.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

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