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

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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 nations. 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 adulthood. 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 reported. 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). 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 outcomes. Public health nutrition programs designed to address undernutrition may exacerbate overweight, 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. 9,10), 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 standards. This is different from the definition 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 standards. 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 prevalence. 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 nutrition. WHO has also set an international target to reduce wasting to <5% by 2025 (ref. 13). 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 wasted. The majority (91%) of children under 5 affected by wasting and nearly half

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Taking into account the largest shares of the global burden (25% and 46% of overweight and 27% and 69% of wasted children, respectively) across LMICs, the prevalence of early childhood overweight and wasting generally provide regional- or country-level estimates potentially masking important subnational differences. Previously, we mapped 2000–2017 prevalence and trends in wasting, stunting and underweight among children under 5 across LMICs using Bayesian model-based geostatistical techniques. 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 to first administrative (such as states and provinces), second administrative (such as districts and departments) and national levels. 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 Metropolis, 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 GNTs for ≤5% prevalence of wasting across all districts based on estimated prevalence (Fig. 3a,b). 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 Asia.
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 × 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 × 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 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.

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.
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 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 conditions. Overall, food security has improved across LMICs in the past decade, which has led to increased availability of calories at the population level. 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 factors.

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 adults. 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 diets. 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 foods. 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 these 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 diarrhea and puts children at greater risk of succumbing to common infections. Childhood overweight is likely to progress into adulthood and is associated with NCDs, including cardiovascular disease, type 2 diabetes, sleep apnea and cancer. 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 transitions.

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. 19). 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 obesity. 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 GNR and Scaling Up Nutrition. Double-duty actions that could simultaneously combat undernutrition, overweight, obesity, and diet-related NCDs have been proposed to address this problem. 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.

Fig. 5 | Overlapping population-weighted quartiles of overweight and wasting prevalence in children under 5 across LMICs in 2017 and 2025. a–d. Prevalence of moderate-to-severe overweight (OVR) and wasting (MSW) among children under 5 years of age in 2017 at the first administrative unit (a) and at a 5 × 5-km resolution (b). c, d, Estimated prevalence of moderate to severe OVR and MSW among children under 5 years of age in 2025 at the first administrative unit (c) and at a 5 × 5-km resolution (d). Quartile cutoffs were 0–5%, ≥5–10%, ≥10–15% and ≥15%. 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 these analyses. Maps were generated using ArcGIS Desktop 10.6.
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
Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41591-020-0807-6.

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Methods
Overview. Our study follows the Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER) (Supplementary Table 1). The analyses used model-based geostatistics to generate local-, administrative- and national-level estimates of children under 5 who are overweight, wasting prevalence and double burden of malnutrition 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 x 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\(^5\). 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 Standard Measurement Survey and Core Welfare Indicators Questionnaire, among other country-specific child health and nutrition surveys\(^5\) (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 (polygon) while accounting for the survey sample design (15,781 each cluster, we assigned data to the smallest available administrative areal unit weight and age data included geographic coordinates or precise place names was associated with a cluster, a group of neighboring households or a ‘village’ during the month in which the survey was conducted. To adjust weight measurements, we fitted a model for each

Spatial covariates. In order to leverage strength from locations with observations of each type of outcome, we applied spatial-temporal models, we compiled several 5 x 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 density. 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\(^6\). 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 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\(^7\).

Analysis. Geostatistical model. In this study, wasting was defined as the proportion of children under 5 who were wasted (z < −2 WHZ); overweight was defined as the proportion of children under 5 who were overweight (z > 2 WHZ); and double burden of was defined as the proportion of children under 5 below 2 WHZ who were wasted and overweight. We used a continuation ratio model to estimate the prevalence of overweight and wasting conditioned on not being wasted using the same Bayesian modeling setup. We estimated the proportion of children under 5 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 who were overweight conditioned on not being wasted using the same Bayesian modeling framework. The estimates from the second conditional model were then combined with the wasting estimates to compute the proportion of overweight children in the full distribution.

Each cluster, \(j\), where \(j = 1, 2, \ldots, n\), and time, \(t\), where \(t = 2000, 2001, \ldots, 2017\), the prevalence of wasting was modeled using the observed number of children in cluster \(c\), who were found to be wasted as a binomial count data \(C_{ij}\) among a sample size \(N_j\) of children within that country at time \(t\). The proportion of wasting was modeled using the observed number of children in cluster \(c\), who were found to be wasted as a binomial count data \(C_{ij}\) among a sample size \(N_j\) of children within that country at time \(t\). The proportion of the children who were overweight conditioned on not being wasted using the same Bayesian modeling framework. The estimates from the second conditional model were then combined with the wasting estimates to compute the proportion of overweight children in the full distribution.

Month is the integer-valued month of the year (1, \ldots, 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 determined the periods using scikit_learn\(^{12}\), using 12 cyclic cubic \((cc)\) regression splines basis functions and we accounted for a smooth longer time temporal trend using four thin-plate \((p)\) splines. The country effects and the long-term temporal spline were included only to avoid confounding during fitting of the spatial spline fit and neither country effects nor the long-term temporal 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.

Seasonality adjustment. WHZs were used to calculate individual child wasting status. As a data preprocessing step, we performed a seasonality adjustment on individual-level child weight 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:

\[
\text{WHZ} \sim \text{sgp}(\text{month}) + \text{sg}(t) + \text{as.factor}(\text{country}).
\]
For indices $i$, $j$ and $t$, *(index)* is the value of *t* at the index. The annual prevalence of overweight ($\rho_{e,t}$) in cluster $i$, in time $t$, was modeled as a logistic link function with $\logit(\rho_{e,t})$, with unstructured country random effects $\gamma_c$, with country-specific variance $\sigma^2_c$, and clustered spatiotemporal random effects $Z_{c,i,t}$, with country-level random effects $\epsilon_c$ and the country-specific variance $\sigma^2$. The residuals $\epsilon_c$ were modeled as a multi-dimensional Gaussian process in space–time centered at zero and with a covariance matrix constructed from a Kroncker product of spatial and temporal covariance kernels. The spatial covariance, $\Sigma^{sp}$, was modeled using an isotropic and stationary Matérn function and temporal covariance, $\Sigma^{tm}$, as an annual autoregressive (AR1) function over the 18 years represented in the model. In the stationary Matérn function, $\theta$ is the modified Bessel function of order $\nu > 0$, $\kappa > 0$ is a scaling parameter, $D$ denotes the Euclidean distance and $\alpha^2$ is the marginal variance. The scaling parameter, $\kappa$ is defined to be $\kappa = \sqrt{5\nu/\theta}$, where $\theta$ is a rounding parameter (where the distance covariance approaches 0.1) and $v$ 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. The number of columns of the spatial Matérn covariance matrix are both equal to the number of temporal 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 space–time covariance matrix, $\Sigma^{ws} \otimes \Sigma^{tm}$, 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. The posterior distributions were fitted using computationally efficient and accurate approximations in R-INLA $\sim \loggamma$ (integrated nested Laplace approximation) and the stochastic partial differential equations $\sim \loggamma$ approximation to the Gaussian process residuals using R package v3.5.1. The stochastic partial differential equations approach using INLA has been demonstrated elsewhere, including the estimation of health indicators, indicate air matter and population age structure. Uncertainty intervals were generated from 1,000 draws (statistically plausible candidate maps) created from the posterior-estimated distributions of modeled parameters.

**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. 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. Areas where the total population density was less than ten individuals per 1 x 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 WHO 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 $t$:

$$\text{AROC}_{m,n} = \logit\left(\frac{\rho_{m,n} - \rho_{m,n+1}}{\rho_{m,n} - \rho_{m,n+1}}\right)$$

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:

$$W_t = (t - 2000 + 1)$$

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:

$$\text{AROC}_{m,n} = \frac{\sum_t W_t \times \text{AROC}_{m,n,t}}{\sum_t W_t}$$

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

$$\text{Proj}_{m,n,2025} = \logit^{-1}\left(\logit(\rho_{m,2017}) + \text{AROC}_{m,n} \times 8\right)$$

This projection scheme is analogous to the methods used in the Global Burden of Disease 2017 study $\sim \loggamma$ 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:

$$\rho_1 \sim N(\mu_1, \sigma^2 = 3^2)$$

$$\rho_2 \sim \loggamma(\mu_2 = \frac{1}{\text{ensemble models}}, \sigma^2 = 3^2)$$

$$\logit(\rho_{10}) \sim N(\mu_{10}, \sigma^2 = 1.2^2)$$

$$\logit(\rho_{20}) \sim \loggamma(\alpha = 1, \gamma = 5 \times 10^{-5})$$

$$\logit(\rho_{50}) \sim \loggamma(\alpha = 1, \gamma = 5 \times 10^{-5})$$

$$\theta_1 = \log(\sigma^2_{\text{country}}) \sim N(\mu_{\text{sigma}}, \sigma^2_{\text{sigma}})$$

$$\theta_2 = \log(k) \sim N(\mu_{\text{sigma}}, \sigma^2_{\text{sigma}})$$

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 $N(0, \sigma^2 = 3^2)$ and the prior for the fixed-effect coefficients to be $N(\text{mean ensemble model}, \sigma^2 = 3^2)$. The prior on the temporal correlation parameter, $\rho$, was chosen to be zero mean, 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 $\gamma$. In our parameterization, we represent $\kappa$ and $\gamma$ 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 sets 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 $\sim \loggamma$ (both for nugget and country random effects). The hyper-prior for the AR1 rho, $\rho_1$, was retained as shown below.

$$\logit(\rho_{10}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$

$$\logit(\rho_{20}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$

$$\logit(\rho_{50}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$

**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, $\rho_1$, were retained the same as model 1.

$$\logit(\rho_{10}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$

$$\logit(\rho_{20}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$

$$\logit(\rho_{50}) \sim \loggamma(\alpha = 1.5 \times 10^{-5})$$
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.

\[
\log(\frac{\sigma}{\rho}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}) \text{ and } \\
\log(\frac{\sigma}{\text{country}}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 2) \\
\log(\frac{\sigma}{\text{nugget}}^2) \sim \text{Normal}(\mu = 4, \sigma^2 = 1.2^2) 
\]

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.

\[
\log(\frac{\sigma}{\rho}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}) \text{ and } \\
\log(\frac{\sigma}{\text{country}}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}) \\
\log(\frac{\sigma}{\text{nugget}}^2) \sim \text{Normal}(\mu = 0, \sigma^2 = 2.58^2) 
\]

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.

\[
\log(\frac{\sigma}{\rho}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}) \text{ and } \\
\log(\frac{\sigma}{\text{country}}^2) \sim \text{loggamma}(\alpha = 1, \gamma = 5 \times 10^{-5}) \\
\log(\frac{\sigma}{\text{nugget}}^2) \sim \text{Normal}(\mu = 0, \sigma^2 = 1.2^2) 
\]

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\(^{76,77}\) 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 SSA mesh is described by Kinyozi et al.\(^{69}\).

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\(^{48}\) (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/ihme-data/ihme-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\(^{39}\). 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\(^{68}\). 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\(^{49,50}\). Populations were retrieved from WorldPop\(^{43,44}\).

Code availability

All code used for these analyses is publicly available online at http://ghdx.healthdata.org/record/ihme-data/ihme-double-burden-of-malnutrition-geospatial-estimates-2000-2017 and at http://github.com/ihmeuw/lbd/tree/dbm-lmic-2020.

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Author contributions
D.K.K., J.M.R., A.A. and S.I.H. conceived and planned the study. A.L.-A. and D.K.K. obtained, extracted, processed and geopositioned data. D.K.K. carried out statistical analyses. The first draft of the manuscript was written by D.K.K, J.M.R., S.B.M., L.E.S., A.A. and S.I.H.; D.K.K., S.B.M. and J.M.R. finalized the manuscript based on comments from other authors and reviewer feedback. D.K.K., A.L.-A. and S.B.M. managed the Supplementary Information. All authors provided intellectual input into aspects of this study. Additional details on author contributions are in the Supplementary Information.

Competing interests
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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 cell49–45, 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.

46. Murray, C. J. et al. GBD 2010: design, definitions and metrics. *Lancet* **380**, 2063–2066 (2012).
# Reporting Summary

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## Statistics

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

| Item                                                                 | Confirmed |
|----------------------------------------------------------------------|-----------|
| The exact sample size \( (n) \) for each experimental group/condition, given as a discrete number and unit of measurement | n/a       |
| A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly | n/a       |
| The statistical test(s) used AND whether they are one- or two-sided  | n/a       |
| A description of all covariates tested                              | n/a       |
| A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons | n/a       |
| A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals) | n/a       |
| For null hypothesis testing, the test statistic (e.g. \( F, t, r \)) with confidence intervals, effect sizes, degrees of freedom and \( P \) value noted | Yes       |
| Give \( P \) values as exact values whenever suitable.              |           |
| For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings | n/a       |
| For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes | n/a       |
| Estimates of effect sizes (e.g. Cohen's \( d \), Pearson's \( r \)), indicating how they were calculated | Yes       |

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/](http://ghdx.healthdata.org/). Maps were generated using ArcGIS Desktop 10.6.

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## Data

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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
- A description of any restrictions on data availability

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/](http://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.

| Materials & experimental systems | Methods |
|----------------------------------|---------|
| n/a | Involved in the study |
| ☒ | Antibodies |
| ☒ | Eukaryotic cell lines |
| ☒ | Palaeontology |
| ☒ | Animals and other organisms |
| ☒ | Human research participants |
| ☒ | Clinical data |
| n/a | Involved in the study |
| ☒ | ChIP-seq |
| ☒ | Flow cytometry |
| ☒ | MRI-based neuroimaging |