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Greenspace in relation to childhood undernutrition: A cross-sectional study in 49 low- and middle-income countries

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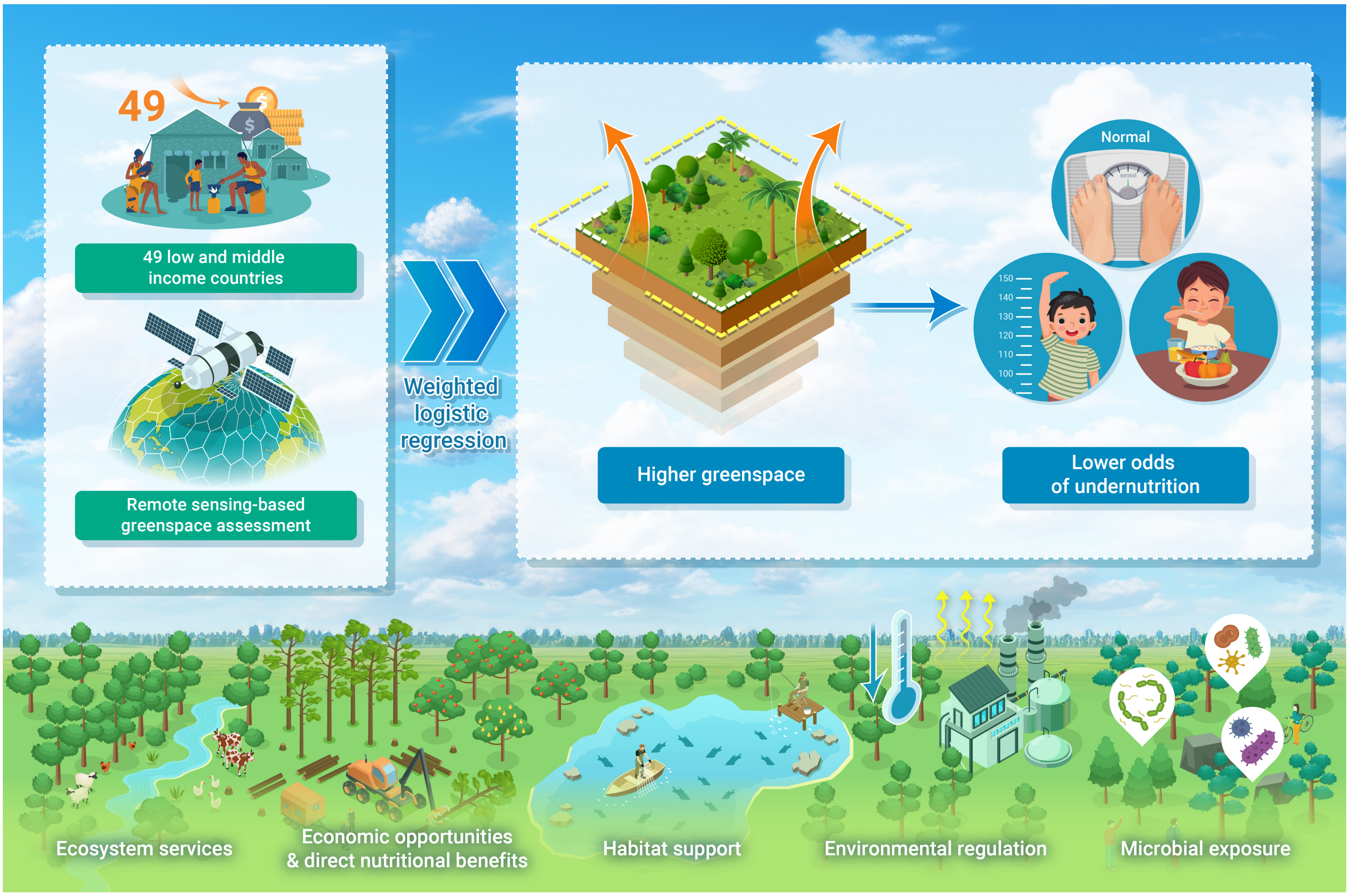
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- The large and multiple-country study estimates the effects of greenspace on childhood undernutrition.
- Living in greenner areas may lower the odds of childhood undernutrition in less developed countries.
- Findings indicate greenspace may protect child health, supporting greener policies to fight undernutrition.

ARTICLE

Greenspace in relation to childhood undernutrition: A cross-sectional study in 49 low- and middle-income countries

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Evidence suggests greenspace may support child nutrition by increasing food availability, reducing environmental hazards, and enhancing microbial diversity, but evidence on the topic is scarce. We used Demographic and Health Surveys (DHS) data from 49 low- and middle-income countries (LMICs) to study the association between greenspace and undernutrition among children aged <5 years. Undernutrition included stunting, underweight and wasting, as determined by z-scores of World Health Organization (WHO) thresholds. A total of 512,013, 509,012, and 507,546 children were included for stunting, underweight, and wasting analysis, respectively. Greenspace was assessed using annual maximum and average values of normalized difference vegetation index (NDVI) as well as proportions of different green land covers, including forest, shrubland, grassland, wetland, and these four combined. Weighted logistic models were constructed to examine the association between greenspace and childhood undernutrition. After adjusting for confounders, we observed that all greenspace indicators were significantly associated with reduced odds of childhood undernutrition. For example, participants in the highest tertile of $NDVI_{max}$ and greenland levels had 17% (95% confidence interval (CI): 13-20%) and 26% (95% CI: 23-28%) lower odds of stunting, respectively, compared to the lowest tertile. The child's sex, age, place of residence, household wealth level, and maternal education modified the associations, but the pattern was mixed. In summary, the study indicates that children living in greener areas may have lower odds of developing undernutrition. Enhancing greenspace may improve children's nutrition status in less developed countries.

INTRODUCTION

Childhood undernutrition remains a great health challenge worldwide and manifests as various child anthropometric issues including stunting, underweight, and wasting.[1] In 2020, approximately 149.2 million and 45.4 million children under five years of age were stunted and wasted, respectively.[2] Furthermore, children experiencing undernourishment are concentrated in low- and middle-income countries (LMICs).[3] Undernourished children are at a higher risk of cognitive, physical, and metabolic developmental impairments, which may subsequently result in various issues including cardiovascular disease, diminished intellectual capabilities, limited academic achievement, and decreased economic productivity in adulthood.[4] Addressing undernourishment is thus a crucial public health concern globally.

Greenspace exposure, which refers to the availability and access to vegetated areas such as forests, grasslands, shrublands, and parks, has been shown to be protective against overweight and obesity in children living in urban areas, especially in high-income countries.[5,6] However, greenspace may also serve ecosystem functions related to food availability and sustenance, and thus be beneficially related to undernutrition.[7] For example, previous work has suggested that greenspace in LMICs provides grazing areas for livestock, supporting the availability of animal-sourced foods such as milk and meat.[8] Additionally, greenspace enhances agricultural productivity by improving soil quality and maintaining water cycles,[9-11] which can increase crop yields and food security. Also, greenspace provides access to forest products, such as lumber, which can generate income for families,[12,13] and native plants that offer fruits, nuts, and medicinal properties, further supporting nutrition and well-being.[14-16] In addition, evidence also suggests that greenspace can mitigate air pollution and high temperatures,[17] while also enriching microbial diversity,[18] all of which have been linked to undernutrition.[19-21]

We are aware of three previous studies that have investigated the association between greenspace and stunting in LMICs.[20,22,23] However, these studies were performed in a few countries, used greenspace indicators with rough resolution (i.e., 5 km × 5 km), and had small sample sizes. In addition, findings from these studies were inconsistent. For instance, while Amegber et al.[20] observed a positive association between greater greenspace levels and elevated odds of undernutrition, Kinyoki et al.[22] found that greenspace exposure was associated with reduced odds of undernutrition, and Khan et al.[23] reported no significant association between them. To help fill this literature gap, our study aimed to assess the associations of different types of greenness with childhood undernutrition by analyzing a large dataset of children's records across 49 LMICs.

MATERIALS AND METHODS

Study design and population

Our analysis used data from Demographic and Health Surveys (DHS), a program that has been collecting data in over 90 LMICs across Africa, Asia, Latin America, the Caribbean, and Eastern Europe since 1984.[24] These surveys have been carried out at 3- to 5-year intervals and are designed to provide comprehensive data on health and health-related indicators for a country.[24] Most DHS surveys follow a stratified, two-stage sampling approach, in which enumeration areas (clusters of households) are selected

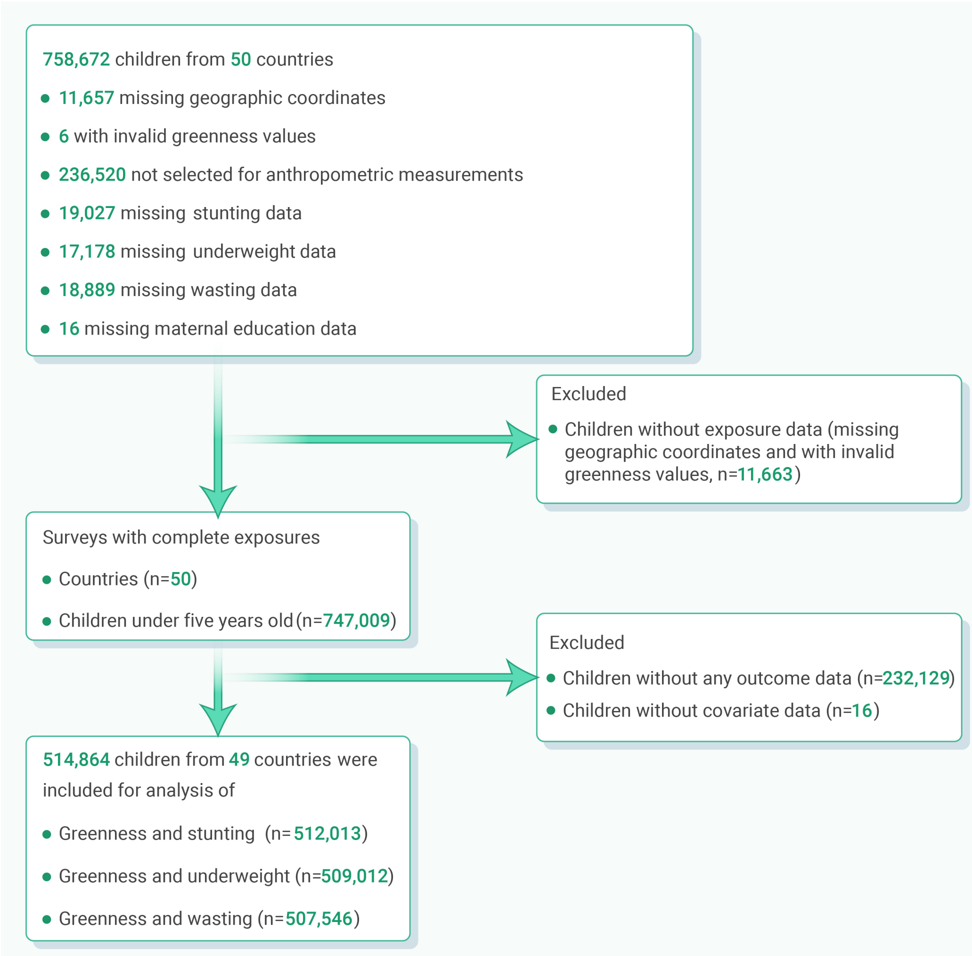

Figure 1. Flowchart showing the selection of samples included in the analysis of children under five years old participating the Demographic and Health Surveys (DHS) program, 2008-2018.

with probability proportional to the size of the cluster in the strata.[25] Households are then randomly selected and interviewed in each cluster to generate a dataset representative at national and sub-national levels.[25] The surveys measure indicators of population health and nutrition, with a special emphasis on women of reproductive age and children aged less than five years. DHS also collects information on households' and mothers' sociodemographic characteristics as well as the geographic coordinates of the sampled clusters.

For the current analysis, we initially examined survey data from 2008 to 2018 covering 758,672 children in 50 countries. After excluding 11,663 children who lacked exposure data due to missing geographic coordinates and invalid greenness values, we further excluded 232,129 children without any outcome data, either because they were not selected for outcome measurements or had invalid measurements, and then we excluded 16 children without covariate data (maternal education). Ultimately, 512,013 children have stunting data, 509,012 children have underweight data, and 507,546 children have wasting data (Figure 1). The included countries are Armenia, Angola, Bangladesh, Burkina Faso, Benin, Bolivia, Burundi, Congo DR, Cote d'Ivoire, Cameroon, Colombia, Dominican, Egypt, Ethiopia, Gabon, Ghana, Guinea, Guatemala, Guyana, Honduras, Haiti, India, Jordan, Kenya, Cambodia, Comoros, Krigiztan, Liberia, Madagascar, Mali, Myanmar, Malawi, Mozambique, Nigeria, Namibia, Napel, Philippines, Pakistan, Rwanda, Seira Leone, Senegal, Chad, Togo, Tajikistan, Timor-Leste, Tanzania, Uganda, South Africa, Zambia, and Zimbabwe.

Outcomes

Our outcomes of interest included three childhood undernutrition indicators (stunting, underweight, and wasting). For children under five years of age, DHS field investigators weighed each child using a solar-powered digital scale. Standing height was measured for children older than two years, and lying length was obtained in children less than two years old using an adjustable board.[26] Stunting, underweight, and wasting were defined as z-scores that were two or more standard deviations below the World Health Organization (WHO) healthy population reference median for length/height-for-age, weight-for-age, and weight-for-length/height, respectively, for age- and sex-specific curves.[27]

Exposures

We calculated two indicators for total vegetative cover ("greenness") and five types of green land cover. Greenness indicators included the annual maximum normalized difference vegetation index ($NDVI_{max}$) and the annual mean normalized difference vegetation index ($NDVI_{average}$). $NDVI_{average}$ reflects year-round exposure, whereas $NDVI_{max}$ captures the peak greenness level within a year. We focused more on $NDVI_{max}$ as it more accurately captures peak-season greenness, which is closely linked to food availability and ecosystem services relevant to nutrition. Additionally, in high-latitude regions, snow cover or leaf fall during winter can obscure true vegetation levels. Green land covers included the percent cover of the forest, shrubland, grassland, wetland, and these four types combined.

NDVI values were derived from cloud-free Landsat 5 Thematic Mapper satellite images at a spatial resolution of 30m × 30m and a temporal resolution of 16 days.[28] NDVI is calculated from the near-infrared minus the red reflectance divided by the near-infrared plus the red reflectance.[28] Resulting values range from -1 to +1, with higher values representing areas with more healthy, denser vegetation. We downloaded satellite images for the study area across the study period (2008 to 2018) and calculated the maximum and average values for each survey year. For sensitivity analysis, we also calculate the annual maximum and average values of enhanced vegetation index (EVI) and soil adjusted vegetation index (SAVI), which are derived from cloud-free Landsat 5 Thematic Mapper satellite images. NDVI is widely used for general vegetation monitoring due to its simplicity and broad applicability.[29] Compared to NDVI, EVI further includes correction factors for soil and canopy background, and is more suitable for areas with high biomass density (e.g., dense forests).[30] SAVI additionally corrects NDVI for the influence of soil background, and is particularly effective in arid and semi-arid regions, where soil brightness may influence vegetation measurements.[31]

Green land covers were derived from two moderate-resolution datasets: GlobeLand 30 and Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC). GlobeLand 30 was produced based on Landsat satellite images using a pixel-object-knowledge approach, having an overall global accuracy exceeding 85%.[32,33] FROM-GLC was produced based on Sentinel-2 data using a random forest approach, having an overall accuracy exceeding 72%.[34] Both datasets divide the earth's surface into 10 homogeneous categories at a resolution of 30m × 30m: cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surfaces, bareland, and permanent snow and ice. We quantified the percentage of green land within each buffer by summing the areas classified as forest, shrubland, grassland, and wetland, then dividing this total by the overall buffer area and multiplying by 100%. Similarly, the percentage of each specific greenspace type (i.e., forest, shrubland, grassland, or wetland) was calculated by dividing the area it occupied within the buffer by the total buffer area and multiplying by 100%. Since land cover data were available for 2010 and 2015 from the GlobeLand30 dataset, and for 2017 from the FROM-GLC dataset, we assigned the 2010, 2015, and 2017 data to surveys conducted in 2008–2014, 2015–2016, and 2017–2018, respectively. This approach follows the methodology of a previous study, which assigned exposure data to the nearest corresponding survey year.[35]

We calculated the average greenspace exposure within circular buffers around the reported locations of DHS clusters, which are groups of adjacent households that serve as the primary sampling units in the survey procedure. It should be noted that the survey authorities randomly displaced the cluster locations within 0–2 km for urban areas and 0–5 km for rural areas with approximately 1% of the rural clusters displaced up to 10 km to ensure the confidentiality of the respondent.[36] As recommended by the DHS guidelines, displacement effects can be mitigated by generating average values within neighborhood buffers.[36] Therefore, we used the recommended buffer radius to estimate exposures (2 km for urban areas and 5 km for rural areas). For each cluster, we assigned the same exposure estimate to all children within that cluster. These calculations were conducted using ArcGIS 10.4 (ESRI, Redlands, CA, USA).

Covariates

We extracted child's age and sex, place of residence (rural, urban) and maternal education (no education, primary, secondary, and higher) from DHS database. Additionally, we calculated household wealth levels (poorest, poorer, middle, richer, and richest). In the DHS survey, the household wealth level was originally determined based on the assets and services possessed by each household within the survey, and then standardized according to the specific asset distribution of that survey. However, this wealth index cannot be compared across surveys given differences in absolute wealth levels across countries and calendar years. We therefore adopted the method approach proposed by Bendavid,[37] in which household wealth index was calculated as a score of the following assets and services: source of drinking water, toilet facilities, electricity, type of flooring, number of rooms per person living in the household, and possession of radio, television, landline, cellphone, refrigerator, motorcycle, and car. Collection of this information occurred during home surveys conducted by DHS investigators, and we drew data using the following variable codes: HV201, HV205, HV206, HV213, HV012, HV216, HV207, HV208, HV221, HV209, HV211, and HV212. This information was then pooled using a principal components analysis method and we used the quintiles (i.e., poorest, poorer, middle, richer, and richest) of this index in our analyses.

We downloaded the standardized precipitation evapotranspiration index (SPEI) from the Global SPEI database (https://spei.csic.es/spei_database), with a spatial resolution of 0.5° x 0.5°. SPEI is a drought monitoring and assessment tool used to quantify and monitor the severity and duration of meteorological droughts. Positive SPEI values indicate surplus water availability while negative SPEI values indicate a deficit in water availability. Subsequently, we associated each child in our study with the corresponding annual SPEI value. Additionally, we gathered Köppen-Geiger climate zone data at a resolution of 0.0083° x 0.0083° created by Beck et al, which was predicted based on climate conditions for the period from 1980 to 2016.[38] We divided the participants into five climate zones according to the Köppen-Geiger climate classification system,[38] including tropical climate zone, dry climate zone, temperate climate zone, continental climate zone, and polar climate zone. Similarly, when extracting these variables, a 5 km buffer was employed for rural settings, while a 2 km buffer was used for urban settings around the geolocations provided in the DHS.

We then constructed a directed acyclic graph (DAG)[39] (Figure S1) to identify a minimally sufficient set of factors to adjust for confounding and finally retained maternal education level, household wealth level, place of residence, and drought episodes as covariates in the main models.

Statistical analysis

Descriptive statistics were used to describe the characteristics of participants and their greenspace exposures. Spearman rank correlations were also performed to evaluate the associations across different greenspace indicators.

We tested the linearity of the associations between greenspace and the outcomes using restricted cubic spline models with three degrees of freedom. To assess the associations of greenspace with stunting, underweight, and wasting, we fitted multivariable logistic regression models. Sample weights were applied in the above regression models to account for complex survey design.[40] This adjustment accounts for any biases that may arise due to differences in the probability of being selected for the survey. Outliers and influential data points were assessed using Cooks'distance. The odds ratio (OR) and corresponding confidence intervals (CIs) were calculated by tertiles.

We conducted several sensitivity analyses to assess the robustness of our results. First, we used inverse-probability-of-attrition weighting (IPAW) to address potential selection bias in our study. The primary reasons for attrition were missing geographic coordinates data (n=11,657) and invalid outcome measurements (n=26,192). Since it was challenging to predict attrition due to missing geographic coordinates data, we focused solely on attrition caused by invalid outcome measurements. Specifically, after excluding 236,520 participants who were not sampled for outcome measurements (which has been accounted for in the sample weights in the main analysis), the remaining 522,152 participants were used for IPAW analysis. For each specific outcome, IPAW was estimated as $1/[Pr(C=0)|Z]$, where $C=0$ indicates responders with missing covariates and Z represents a set of predictors. In this context, we used logistic regression models to predict the probability of missing covariates and incorporated country, survey year, and the age of children as predictors.[41] IPAW was then incorporated into the main models by multiplying it by the sample weights. Second, to assess the stability of the associations across climate zone classification, we repeated the analysis within each of the distinct Köppen-Geiger climate zones. Third, given that India contributed the largest proportion of children (43.5%, Table S1), we conducted a sensitivity analysis by excluding India to examine whether the results were disproportionately influenced by a single country. Fourth, given the weak to moderate correlations among stunting, underweight, and wasting (Phi coefficient range: −0.02 to 0.46), we explored their association with greenspace by combining these indicators into a single composite outcome. Fifth, to account for spatial heterogeneity, we grouped countries into ten regions (Western Asia, Caribbean, Central Asia, Central Latin America, Central Sub-Saharan Africa, Eastern Sub-Saharan Africa, North Africa, South Asia, Southeast Asia, and Southern Sub-Saharan Africa) and included region as an adjustment factor in the models. Sixth, we repeated the analyses using alternative vegetation indices — annual maximum and average values EVI and SAVI) to evaluate the robustness of the results across different greenness metrics.

We examined the effect modification of child's sex, age group (≤24 months and >24 months), place of residence, household wealth level, and maternal education on the association between greenspace and childhood undernutrition by introducing interaction terms between greenspace indicators and the potential modifiers into the adjusted models.

Data analyses were completed using R software 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria). We used R package "survey" to obtain effect estimates for weighted regression models and a two-tailed *p* value less than 0.05 was considered statistically significant.

RESULTS

A total of 514,864 children from 49 LMICs (32 in Africa, 10 in Asia, and 7 in America) were included in our analyses (Figures 1-2). Compared with the excluded dataset, the included participants tended to report higher household wealth and maternal education, along with higher prevalence of stunting, underweight, and wasting (Table S2). Similarly, compared with the overall dataset, the included participants also tended to report higher household wealth and maternal education, along with higher prevalence of undernutrition (Table S2). The prevalence of stunting, underweight, and wasting was 34.3%, 23.8%, and 12.6%, respectively (Table 1). The median (IQR) age of the participants was 29.2 (17.1) months, and about half were girls (48.8%). Among the sampled children, 70.7% lived in rural areas, 30.2% lived with parents who had no formal education, and 21.6% were from households reporting the lowest levels of wealth in the DHS dataset. Compared to participants without growth issues, those underweight, stunted, or wasted were more likely to be boys, have parents with lower education levels, come from wealthier families, and reside in rural areas.

The median (IQR) values of $NDVI_{max}$, $NDVI_{average}$, green land, forest, shrub-

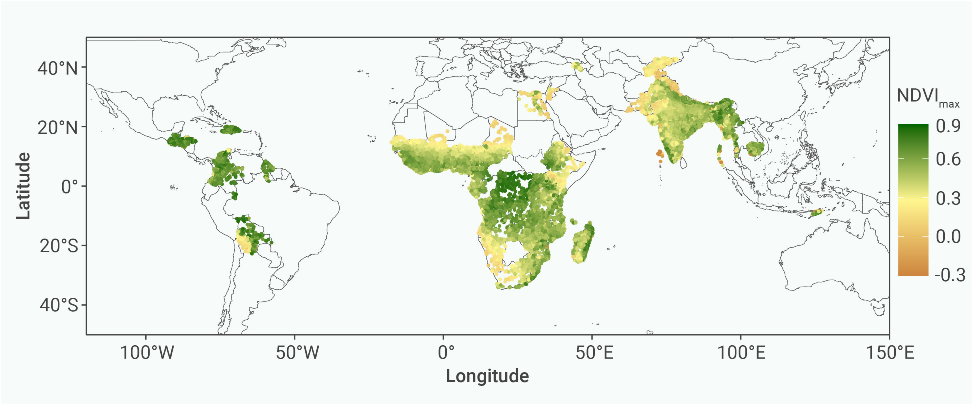

Figure 2. World map showing cluster locations by greenness level among participants in the Demographic and Health Surveys (DHS) program, 2008-2018 Clusters are visualized as dots with maximum normalized difference vegetation index in the survey year ($NDVI_{max}$) determining the dot color.

land, grassland and wetland were 0.49 (0.19), 0.45 (0.18), 43.71% (72.09%), 1.91% (22.55%), 1.01% (10.10%), 9.32% (26.53%), and 0.00% (0.04%), respectively (Figure 3 & Table 2). $NDVI_{max}$ and $NDVI_{average}$ had a high correlation, with a Spearman's correlation coefficient of 0.90. Also, we observed low to moderate correlations of green land with all the other studied greenspace indicators. (Spearman's correlation coefficients ranged from -0.23 to 0.55, Figure 3 & Table S3).

Restricted cubic spline models indicated that the associations of greenspace with undernutrition were nonlinear (Figures S2-S4). After adjusting for maternal education level, household wealth level, place of residence, and drought episodes, all greenspace indicators were significantly and inversely associated with the prevalence of childhood undernutrition (Table 3), and the results were not influenced by outliers (Figures S5-S6). For example, when participants with the highest tertile of $NDVI_{max}$ values (≥0.56) were compared with those with the lowest tertile of $NDVI_{max}$ values (<0.45), the ORs for stunting, underweight, and wasting were 0.83 (0.80, 0.87), 0.62 (0.60, 0.65), and 0.60 (0.56, 0.63), respectively.

Incorporating inverse-probability-of-attrition weighting into our models did not substantially alter these results (Table S4). Additionally, we repeated the analysis within each of the distinct Köppen-Geiger climate zones, and observed that the effect estimates in tropical, dry, and temperate climate zones were consistent with those in the main models, whereas the associations in continental and polar climate zones became non-significant (supplemental excel table, sheet 1). Excluding India from the analysis yielded results largely consistent with the main findings, except that the association between wetland exposure and undernutrition became statistically non-significant (Table S5). Combining stunting, underweight, and wasting into a single composite outcome did not significantly change the associations (Table S6). Furthermore, the results remained robust after adjusting for geographic regions (Table S7) and when using the EVI or SAVI as alternative measures of greenness (Table S8).

We did not observe strong and consistent effect modification by the child's sex, age, place of residence, household wealth level, or maternal educational levels in the association between greenspace and childhood undernutrition (supplemental excel table, sheet 2). For example, the associations between $NDVI_{max}$ and stunting were stronger among children aged ≥24 months (p for interaction < 0.05 for both the middle and highest tertiles of $NDVI_{max}$). In contrast, an opposite pattern was observed for the association between $NDVI_{max}$ and wasting (p for interaction = 0.21 for the middle tertile and < 0.01 for the highest tertile of $NDVI_{max}$).

DISCUSSION

Summary and interpretation of main findings

To our knowledge, this represents the first large-scale investigation of the association of greenspace with childhood undernutrition in LMICs. Across various greenness indicators, we identified protective associations between greenness and childhood undernutrition.

We observed an inverse correlation between NDVI and grassland, likely due to differences in vegetation density and abundance. NDVI primarily reflects overall greenness and biomass, which are typically higher in forests and densely vegetated areas than in grasslands.[29] Grasslands often have lower biomass, greater seasonal variation, and regions with sparse vegetation, all of which can result in lower NDVI values.[42]

Prior studies have also investigated greenspace and child nutrition status, but most were conducted in high-income regions.[5,6] The prior studies mainly concluded that greenspace exposure can reduce the risk of childhood overweight and obesity.[5,6] For example, in the U.K., a cross-sectional study found an inverse association between the density of trees around children's homes and obesity risk.[43] A cohort study in Spain found that higher NDVI levels and the proportion of green land cover were associated with smaller body mass index among children under five years old.[44]

In contrast to most prior research, we examined child undernutrition in LMICs. We found that proximity to greenspace areas was associated with a reduced risk of undernutrition. We are aware of three previous studies that have investigated the association between greenspace and stunting in LMICs, but their findings have been inconsistent.[20,22,23] These studies, which analyzed the cross-sectional associations between greenspace and stunting in children under five years old, used the enhanced vegetation index (EVI) as a proxy for greenspace and measured EVI at a resolution of 5 km at cluster level. Consistent with our findings, Kinyoki et al.[22] found that EVI was associated with reduced odds of stunting in Somalia among 73,778 children. However, contrary to our results, Khan et al.[23] reported non-significant associations among 22,789 children in Bangladesh, and Amegber et al.[20] found a positive association between EVI and stunting among 185,591 children in Sub-Saharan Africa. Our study shared similarities with the earlier studies in study design, outcome assessment, and participants' basic characteristics. However, our study had a much larger sample size, which enabled us to detect modest associations with greater statistical power. Furthermore, we collected multiple childhood undernutrition indicators and objectively measured a comprehensive panel of seven greenspace indicators, therefore our results may be more comprehensive.

We observed a non-linear, inverse-U-shaped association between NDVI and undernutrition. One possible explanation is that the transition from low to moderate NDVI levels reflects a shift from barren or sparsely vegetated areas to moderately green environments. In such contexts, even small increases in vegetation at low NDVI levels can substantially improve environmental conditions and yield health benefits, particularly among low socioeconomic status (SES) populations.[17] However, moderate NDVI levels may correspond to urban–rural transitional zones or fragmented agricultural landscapes, which often lack the ecological integrity, biodiversity, and infrastructure necessary for sustained food production or meaningful environmental enhancement.[45] At high NDVI levels, stronger protective effects re-emerge, likely due to forested or agroforestry landscapes that promote dietary diversity, income generation, and ecological stability.[7]

As for the mechanisms underlying the effects of greenspace exposure on undernutrition status, they are yet to be established. However, there have been several explanations (Figure 4). First, in rural areas, greenspace may be more closely related to a wide range of ecosystem services that impact food availability and safety.[7,46] These services may play important roles in underdeveloped areas where sufficient amounts of food for children may not readily be available. For instance, grasslands sustain livestock that provide protein-rich meat and dairy products through grazing, supporting both subsistence and commercial livestock production.[8] Additionally, forests and wetlands play a crucial role in purifying water, improving soil fertility, and supporting small-scale agriculture with high yields.[9] By retaining moisture and preventing soil degradation, these ecosystems enhance agricultural productivity, ensuring a more stable food supply. Second, forest products, including timber and non-timber forest products offer economic opportunities for local communities.[12,13] The harvesting of wildfood such as bushmeat, wild fruits,

Table 1. Characteristics of children under five (n=514,864) from 49 low or middle-income countries participating in the Demographic and Health Surveys (DHS) program, 2008-2018.

Characteristics	Overall (n=514,864)	Stunted children (n=175,659)	Underweight children (n=120,969)	Wasted children (n=63,995)
Child's age in months [mean (SD)]	29.2 (17.1)	31.7 (15.6)	31.1 (16.5)	26.2 (17.4)
Child's sex [n (%)]				
Boy	263,359 (51.2%) (51.3%)	93,605 (53.3%)	63,993 (52.9%)	34,794 (54.4%)
Girl	251,505 (48.8%) (48.7%)	82,054 (46.7%)	56,976 (47.1%)	29,201 (45.6%)
Maternal education level [n (%)]				
No education	155,737 (30.2%)	67,753 (38.6%)	51,160 (42.3%)	23,882 (37.3%)
Primary	132,269 (25.7%)	48,709 (27.7%)	26,531 (21.9%)	11,444 (17.9%)
Secondary	186,616 (36.2%)	52,191 (29.7%)	38,270 (31.6%)	24,172 (37.8%)
Higher	40,242 (7.8%)	7,006 (4.0%)	5,008 (4.1%)	4,497 (7.0%)
Household wealth level [n (%)]				
Poorest	111,088 (21.6%)	22,491 (12.8%)	15,170 (12.5%)	11,998 (18.7%)
Poorer	105,639 (20.5%)	31,051 (17.7%)	22,245 (18.4%)	13,164 (20.6%)
Middle	105,073 (20.4%)	39,344 (22.4%)	28,573 (23.6%)	14,494 (22.6%)
Richer	97,125 (18.9%)	41,044 (23.4%)	28,158 (23.3%)	13,061 (20.4%)
Richest	95,939 (18.6%)	41,729 (23.8%)	26,823 (22.2%)	11,278 (17.6%)
Place of residence [n (%)]				
Rural	364,186 (70.7%)	136,629 (77.8%)	95,442 (78.9%)	48,627 (76.0%)
Urban	150,678 (29.3%)	39,030 (22.2%)	25,527 (21.1%)	15,368 (24.0%)
Drought episodes (SPEI) [median (Q_{25}, Q_{75})]	-0.4 (-1.1, 0.2)	-0.4 (-1.1, 0.1)	-0.4 (-1.1, 0.1)	-0.4 (-1.1, 0.1)
Köppen-Geiger climate zone				
Tropical climates	240,274 (46.7%)	76,232 (43.4%)	50,035 (41.4)	25,815 (40.3)
Dry climates	106,429 (20.7%)	33,658 (19.2%)	24,977 (20.6)	15,152 (23.7%)
Temperate climates	163,035 (31.7%)	64,403 (36.7%)	45,388 (37.5)	22,683 (35.4%)
Continental climates	3,738 (0.7%)	942 (0.5%)	388 (0.3%)	262 (0.4%)
Polar climates	1,388 (0.3%)	424 (0.2%)	181 (0.2%)	83 (0.1)
Stunting [n (%)]				
Missing	2,851	0	740	228
No	336,354 (65.7%)	0	32,520 (27.0%)	44,090 (69.1%)
Yes	175,659 (34.3%)	175,659 (100%)	87,709 (73.0%)	19,677 (30.9%)
Underweight [n (%)]				
Missing	5,852	2,374	0	87
No	388,043 (76.2%)	85,576 (49.4%)	0	20,274 (31.7%)
Yes	120,969 (23.8%)	87,709 (50.6%)	120,969 (100%)	43,634 (68.3%)
Wasting [n (%)]				
Missing	7,318	2,862	833	0
No	443,551 (87.4%)	153,120 (88.6%)	76,502 (63.7%)	0
Yes	63,995 (12.6%)	19,677 (11.4%)	43,634 (36.3%)	63,995 (100%)

Note: SD, standard deviation. Q_{25}, the 25th percentile. Q_{75}, the 75th percentile. SPEI, standardized precipitation evapotranspiration index. SPEI is a drought monitoring and assessment tool used to quantify and monitor the severity and duration of meteorological droughts. Positive SPEI values indicate surplus water availability while negative SPEI values indicate a deficit in water availability. Stunting, underweight, and wasting were defined as z-scores that were two or more standard deviations below the World Health Organization (WHO) healthy population reference median for length/height-for-age, weight-for-age, and weight-for-length/height, respectively, for age- and sex-specific curves.

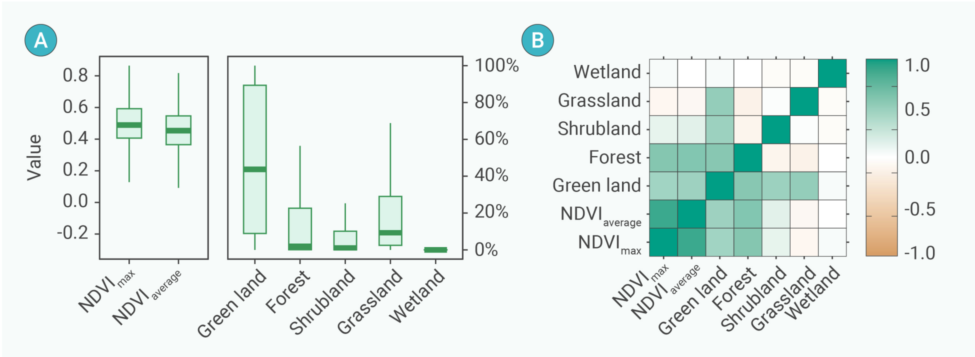

Figure 3. Box and whisker plot (A) and correlation plot (B) of greenness indicators for residences of children under five years old participating in the Demographic and Health Surveys (DHS) program, 2008-2018 Boxes depict the upper and lower quartiles of the data, and whiskers represent the minimal and maximal except for values ≥ 1.5 times the IQR above the upper quartile and below the lower quartile. Color intensity of shaded boxes in the correlation plot indicates the strength of the correlation. Green indicates a positive correlation, and brown indicates a negative correlation. $NDVI_{max}$, maximum normalized difference vegetation index in the survey year. $NDVI_{average}$, annual mean normalized difference vegetation index in the survey year. The corresponding data are presented in Table 2 and Table S3.

nuts, fungi, and edible plants provides direct nutritional benefits.[14-16] Third, forests can provide structures that protect fish and their offspring, and provide habitat for insects that many fish rely on for food, thereby increasing fisheries yields and food availability.[47] Fourth, vegetation in green areas acts as a natural filter for air pollutants,[48] which can impair child growth by increasing respiratory infections, systemic and gut inflammation, and growth hormone resistance.[49] Air pollution may also reduce vitamin D levels, affecting immunity and bone development.[49] Moreover, green areas cool environment through shade and evapotranspiration.[50] Short-term heat exposure can be related to appetite loss, dehydration, and diarrhea,[51-53] while long-term heat can lower crop yields and quality, reducing dietary intake and child nutrition.[54,55] Fifth, exposure to greenspace has been associated with an increase in microbial diversity,[18] a factor that has been shown to decrease the likelihood of childhood undernutrition.[19]

Our analyses revealed weaker associations between greenspace and stunting compared to underweight and wasting. This disparity may be attributed to the distinct characteristics of these malnutrition outcomes. Stunting, defined as low height-for-age, is a marker of chronic malnutrition, reflecting long-term nutritional inadequacies and influenced by a range of factors, including intergenerational effects, socioeconomic status, access to healthcare, and dietary diversity.[3] This complexity may lead to attenuated associations between greenspace exposure and stunting. In contrast, wasting and underweight, defined as low weight-for-height and weight-for-age, respectively, often indicate recent and severe weight loss. These conditions are often linked to acute nutritional deficiencies and short-term environmental stressors, such as seasonal variations in food supply and climate-related factors like extreme temperatures or droughts.[56] As a result, they may be more responsive to fluctuations in greenspace exposure, which could be related to immediate food availability.[9,50-55]

We observed that the association between greenspace and childhood undernutrition was modified by the child's sex, age, place of residence, household wealth, or maternal education level, but the patterns were inconsistent across different strata and greenspace indicators. The underlying reasons for these variations remain uncertain. One plausible explanation is the potential nonlinearity in the relationship between greenspace and undernutrition, wherein the exposure–response curves may intersect across subgroups, leading to heterogeneous effects. Additionally, some of the observed differences in stratified analyses may reflect chance findings, particularly given the multiple comparisons involved.[57]

Our findings align with the principles of nutrition-sensitive urban planning, which emphasizes the role of urban design in improving nutritional outcomes.[58] Greenspaces, as part of this framework, can function as both direct and indirect enablers of better child nutrition. To translate these findings into policy, integrated strategies are needed that align urban and rural planning with nutritional objectives. Specific actions include supporting urban agriculture —such as Uganda's urban farming initiatives, which improved local food availability and child nutrition[59] —and protecting natural greenspaces, particularly in marginalized communities. Additionally, incorporating green infrastructure into urban design can further promote food security and health. Brazil's Hortas Cariocas program, for example, has increased urban gardens and improved food access in low-income areas.[60]

Strengths and limitations

The current research has several strengths. First, the large and representative sample size of children across nearly 50 countries offered ample statistical power to detect modest associations and minimize the likelihood of a selection bias. Second, we used various measures of greenspace at moderate spatial resolution to minimize exposure misclassification. Moreover, we carefully selected confounders from many candidates by employing a DAG, which allowed us to adjust for a set of covariates selected to reduce confounding. Third, the effect estimates were generally robust to multiple sensitivity analyses, increasing our confidence in our main model's effect estimates. Finally, we fitted non-linear models and observed that only areas with the highest tertile (not the middle tertile) of greenspace levels showed beneficial associations with undernutrition. This indicates that areas with less greenspace should put greater effort to substantially enhancing their greenspace, in order to provide sufficient ecological and economic benefits for improving children's nutritional status.

Table 2. Summary statistics of greenness indicators for participants in the Demographic and Health Surveys (DHS) program, 2008-2018.

	Minimum	Q_{25}	Median	Mean	Q_{75}	Maximum	IQR
$NDVI_{max}$	-0.30	0.41	0.49	0.49	0.59	0.86	0.19
$NDVI_{average}$	-0.30	0.37	0.45	0.45	0.55	0.84	0.18
Green land (%)	0.00	8.93	43.71	48.06	89.35	100.00	80.42
Forest (%)	0.00	0.07	1.91	17.12	22.62	100.00	22.55
Shrubland (%)	0.00	0.03	1.01	11.03	10.13	100.00	10.10
Grassland (%)	0.00	2.48	9.32	19.53	29.01	100.00	26.53
Wetland (%)	0.00	0.00	0.00	0.38	0.04	100.00	0.04

Note: $NDVI_{max,}$ maximum normalized difference vegetation index in the survey year. $NDVI_{average,}$ annual mean normalized difference vegetation index in the survey year. Q_{25}, the 25th percentile; Q_{75}, the 75th percentile.

Table 3. Odds ratios and 95% confidence interval for the association of greenness indicators with undernutrition among children under five years old participating in the Demographic and Health Surveys (DHS) program, 2008-2018.

Greenness indicators	OR (95% CI)[a]		
	Stunting (n=512,013)	Underweight (n=509,012)	Wasting (n=507,546)
$NDVI_{max}$			
Q_1 (<0.45)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (0.45-0.56)	1.01 (0.98, 1.04)	1.01 (0.98, 1.04)	0.96 (0.93, 1.00)
Q_3 (≥0.56)	0.83 (0.80, 0.87)	0.62 (0.60, 0.65)	0.60 (0.56, 0.63)
$NDVI_{average}$			
Q_1 (<0.42)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (0.42-0.53)	1.07 (1.04, 1.11)	1.11 (1.08, 1.15)	1.05 (1.01, 1.10)
Q_3 (≥0.53)	0.90 (0.87, 0.94)	0.72 (0.69, 0.75)	0.66 (0.63, 0.70)
Green land (%)			
Q_1 (<16.12%)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (16.12-77.88%)	0.85 (0.83, 0.88)	0.79 (0.76, 0.81)	0.86 (0.83, 0.90)
Q_3 (≥77.88%)	0.74 (0.72, 0.77)	0.39 (0.37, 0.40)	0.39 (0.37, 0.41)
Forest (%)			
Q_1 (<0.27%)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (0.27-10.59%)	0.92 (0.90, 0.95)	0.96 (0.93, 0.99)	1.00 (0.97, 1.04)
Q_3 (≥10.59%)	0.86 (0.83, 0.89)	0.72 (0.69, 0.75)	0.73 (0.70, 0.77)
Shrubland (%)			
Q_1 (<0.11%)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (0.11-5.10%)	0.96 (0.93, 0.99)	1.00 (0.97, 1.04)	1.09 (1.05, 1.13)
Q_3 (≥5.10%)	0.79 (0.77, 0.82)	0.59 (0.57, 0.62)	0.68 (0.65, 0.72)
Grassland (%)			
Q_1 (<4.04%)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (4.04-19.97%)	1.01 (0.98, 1.04)	0.95 (0.92, 0.98)	0.98 (0.94, 1.02)
Q_3 (≥19.97%)	0.89 (0.86, 0.92)	0.71 (0.68, 0.74)	0.78 (0.75, 0.82)
Wetland (%)			
Q_1 (<0%)	1 (Reference)	1 (Reference)	1 (Reference)
Q_2 (0-0.02%)	1.02 (1.00, 1.04)	1.12 (1.10, 1.15)	1.11 (1.08, 1.15)
Q_3 (≥0.02%)	0.93 (0.90, 0.95)	0.83 (0.81, 0.86)	0.81 (0.78, 0.84)

Note: $NDVI_{max}$, maximum normalized difference vegetation index in the survey year. $NDVI_{average}$, annual mean normalized difference vegetation index in the survey year. IDD, inadequate dietary diversity. IQR, interquartile range. OR, odds ratio. CI, confidence interval. Q_1, bottom tertile of the population. Q_2, middle tertile of the population. Q_3, top tertile of the population. Stunting, underweight, and wasting were defined as z-scores that were two or more standard deviations below the World Health Organization (WHO) healthy population reference median for length/height-for-age, weight-for-age, and weight-for-length/height, respectively, for age- and sex-specific curves.

[a] Effect estimates were calculated using weighted logistic models. Associations were adjusted for maternal education level, household wealth level, place of residence (rural/urban), and drought episodes.

Nevertheless, our study has several limitations. Firstly, the cross-sectional design precludes us from establishing causality if the exposure preceded the outcome or vice versa, among other limitations of such studies. Secondly, due to the availability of land use data, we aligned participants with the nearest years of available land use data instead of precisely matching the survey years, which might have potentially introduced exposure bias. However, land-use types typically remain stable over several years, thus the bias would be minimal. In addition, the exposure assessment was based on data from clusters but not from individuals, which might introduce nondifferential measurement bias and thus bias the effect estimates toward null.[61] However, all the effects estimated in our analyses exhibited statistical significance, and the actual effect of the greenspace under investigation might be even more substantial than what was observed in our study. Thirdly, our analysis relies primarily on NDVI and land cover classifications, which serve as useful proxies for vegetation presence but do not necessarily reflect the accessibility, quality, or actual use of greenspaces. There may be significant discrepancies between the quantity of greenness observed through remote sensing and the functional quality of these spaces, including aspects such as safety, maintenance, usability, and cultural relevance. As such, our findings may not fully capture the lived experience of greenspace exposure for children and their

Figure 4. Potential pathways linking greenspace to reduced odds of childhood undernutrition.

caregivers. Fourthly, the samples included in the analyses were considerably reduced from the original dataset due to the missing values for greenspace indicators, outcomes and covariates. Moreover, comparisons of the demographic characteristics between the included and excluded children reveal some disparities, which may potentially compromise the representativeness of the analyzed data. Fifthly, while previous epidemiological studies have primarily utilized smaller buffer sizes (250m, 300m, 500m, or 1km) to investigate greenspace-health associations,[43] our study employs a larger buffer size (2km and 5km), which may impact the comparability of our findings with existing research. Sixthly, the association between greenspace and undernutrition was non-significant in continental and polar climate zones. We speculate that the insignificance of these associations in these regions may be attributed to the limited growth of food-producing plants in such environments,[62] as well as the limited sample size, particularly given that greenspace levels were aggregated at the cluster level. Seventhly, to protect the privacy of DHS survey respondents, random offsets were used for displacement of cluster addresses, which may result in measurement errors in the greenspace indicators at the DHS cluster level. However, a simulation study conducted by the DHS team[36] has indicated that the impact of such displacement could be moderated through the generation of average values using neighbourhood buffers. In addition, point displacements for most countries are constrained to administrative boundaries, which helps reduce potential biases associated with the displacement.[36] Eighth, although the poorest wealth category comprises the largest share of the overall population, the opposite trend is observed among children who are stunted, underweight, or wasted. This raises the possibility that the observed associations may be influenced by residual confounding and selection bias related to socioeconomic status, although we have adjusted for three SES-related covariates to minimize this potential bias. Lastly, given the wide geographic coverage of our study, there may exist considerable heterogeneity in plant types and properties, nutritional status, and socioeconomic conditions across the studied countries. Although we have employed several statistical methods (e.g., such as IPAW) to control for potential effects of the heterogeneity, and sensitivity analyses demonstrated our findings were robust, it is still possible that such heterogeneity has compromised the precision of our effect estimates and has biased findings for some specific countries.

CONCLUSION

This study suggests that children living in areas with more greenspaces such as forest, shrubland, grassland, and wetland may have lower odds of being undernutrition in LMICs. The findings highlight the potential protective role of greenspace in promoting child health, emphasizing the need for enhancing greenspace quality and quantity by governments and taking public health interventions that incorporate greenspace, to address childhood undernutrition in LMICs. Future better-designed longitudinal and intervention studies should be carried out to validate our findings and to investigate how different types of greenspaces may influence child nutrition across various socioeconomic and environmental contexts.

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AUTHOR CONTRIBUTIONS

J.L. and D.B.O. conceived the study, conducted all analyses, and wrote the first draft of the paper. M.H.E.M.B., Y.Z, Y.L., L.H., H.Q., Y.X., G.Z., Y.Z., M.X., S.F., Z.Z., X.Z. and G.D. contributed to the study design, results assessment, and interpretation. L.D.K. and Y.B.Y. conceived the study and supervised the work. All authors contributed to and approved the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

The procedures and questionnaires used in standard DHS surveys have undergone a thorough review and approval process by the ICF Institutional Review Board (IRB). Furthermore, country-specific DHS survey protocols are reviewed by both the ICF IRB and typically an IRB in the host country. We have obtained permission from the ICF-DHS program to utilize the data.

DATA AND CODE AVAILABILITY

Survey data including childhood nutrition status and socioeconomic data in this study are publicly available upon request from the Demographic and Health Surveys Program (https://dhsprogram.com/). Normalized difference vegetation index (NDVI) data can be downloaded from http://earthexplorer.usgs.gov. Global land cover datasets are publicly available including GlobeLand 30 (https://www.webmap.cn/mapDataAction.do?method=globalLandCover) and Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC30, https://data-starcloud.pcl.ac.cn/zh/resource/2). Drought data is available from the Global SPEI database (https://spei.csic.es/database.html). Code is available upon request from the corresponding authors.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/j.xinn-med.2025.100141