Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Trends in acute malnutrition during a decade of conflict in Yemen from 2015 to 2026

Saleh Mahdi

salehmy10@gmail.com

Ministry of Health

Dhekra Yahya

Ministry of Health

Abdullah Ali Hadi Al-Afad

Sana'a University

Sarah Edhah Mahdy Alheelh

Sana'a University

Research Article

Keywords: nutrition surveys, Yemen, acute malnutrition, wasting, GAM, conflict, ecological analysis, SMART, MICS, EFSNA

Posted Date: November 18th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11131817/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: Competing interest reported. The authors declare that they have no competing interests.

Abstract

Objective

Malnutrition remains a critical public health concern in Yemen. This analysis reviewed whether acute malnutrition among children under five in Yemen has systematically changed over a decade of conflict (2015–2026), described governorate-level trajectories, and examined the influence of survey method on trend estimation.

Methods

We compiled all available anthropometric nutrition surveys in Yemen, from 2015 to 2026, and analysed time trends in GAM and SAM. Ordinary least squares (OLS) regression and linear mixed-effects models were performed to estimate temporal trends in GAM and SAM. Descriptive, paired-method, and ecological sensitivity analyses pooled all survey methods were also conducted.

Results

Among comparable SMART-WHZ observations (n = 67), neither GAM nor SAM showed a national trend (GAM: OLS − 0.033 pp/year, p = 0.879; mixed-effects − 0.124 pp/year, p = 0.335; SAM + 0.002 pp/year, p = 0.975; mixed-effects − 0.015, p = 0.748). Pooling all methods (n = 107) suggested an apparent increase (GAM + 0.37 pp/year, p = 0.119; SAM + 0.232 pp/year, p = 0.025) that disappeared after adjustment for survey method. MICS estimates exceeded paired SMART-WHZ estimates (Wilcoxon p = 0.011; n = 22 pairs), and WHZ-based GAM exceeded MUAC-based estimates by 4.64 pp. In total, 32.3% of observations fell within the WHO Emergency GAM band and 27.7% within the Serious band. Prevalence was higher in lowland/coastal than highland or urban zones, with heterogeneous governorate trajectories.

Conclusion

Acute malnutrition in Yemen remained at severe levels throughout 2015–2026 with no clear evidence of a sustained national increase or decrease. The pattern was one of persistently high prevalence, short-term fluctuations, and recurrent hotspots, with substantial geographic heterogeneity. These findings underscore the need for targeted, context-specific programming, harmonised longitudinal surveillance, and stronger linkage between anthropometric data and contextual drivers to detect genuine change while accounting for geographical and seasonal variation.

1 Introduction

Yemen has experienced protracted conflict and humanitarian crisis since 2015, resulting in one of the world's most severe food security and nutrition emergencies [1]. Acute malnutrition remains one of the most serious threats to child survival in humanitarian settings, closely linked to increased morbidity, infection, and mortality in children under five [1–3]. In conflict, the risk of acute malnutrition is amplified by disrupted livelihood and food systems, displacement, disease outbreaks, and reduced access to health and nutrition services [4]. Yemen represents one of the clearest examples of this interaction between conflict, food insecurity, and child undernutrition. Since 2015, the escalated conflict, compounding pre-existing structural vulnerabilities has worsened child and maternal health outcomes across the country, with large numbers of children remain exposed to recurrent nutritional stress [5, 6].

Yemen has long been recognised as carrying one of the highest burdens of child wasting globally, with repeated SMART surveys and IPC acute malnutrition analyses documenting emergency-level prevalence in hotspot areas since 2015 [7–9]. The drivers are well described as multifactorial and mutually reinforcing. conflict-related disruption of food imports, markets, agricultural production and household livelihoods; damage to water, sanitation and health systems; population displacement; and recurrent disease outbreaks [4, 10].

Nutrition surveillance in Yemen during the conflict period has been carried out by multiple actors using different methodologies. The Standardized Monitoring and Assessment of Relief and Transitions (SMART) methodology is widely used in humanitarian settings as a reference standard for population-level acute malnutrition prevalence. At the same time, other large surveys such as the Multiple Indicator Cluster Survey (MICS) and Emergency Food Security and Nutrition Assessments (EFSNA) apply standard anthropometry within a broader household survey [2, 11]. Methodological research has also established that WHZ and MUAC identify overlapping but non-identical groups of children, and that nutrition surveys in humanitarian settings differ in design, timing, sampling and analytical conventions, limiting direct comparability [2, 12]. What has remained unclear is whether, taken together and after accounting for these methodological differences, the available survey evidence indicates a national trajectory of deterioration, improvement or fluctuation across the full conflict period.

Despite extensive humanitarian analyses, the epidemiology of acute malnutrition trends in Yemen across governorates and over time remains incompletely characterized. Yet it remains unclear whether public narratives of steady deterioration, local improvement, or fluctuation reflect the underlying epidemiology. Understanding temporal trends and geographic variation of acute malnutrition in such a protracted conflict is essential for evidence-based humanitarian. Accordingly, this study aimed to assess national and subnational trends in GAM and SAM among children under five in Yemen from January 2015 to June 2026 using comparable SMART-WHZ estimates as the primary analytic dataset, while also examining the effect of alternative survey methods on trend interpretation.

2 Methods

2.1 Study design and Data Sources

We conducted a retrospective ecological analysis using repeated cross-sectional nutrition surveys data in Yemen between January 2015 and June 2026. The unit of analysis was the survey observation or, where multiple strata were reported within a governorate and survey period, a harmonised governorate-year summary. We compiled a comprehensive database of all available SMART nutrition surveys, MICS and EFSNA assessments conducted in Yemen between 2015 and 2026. Data sources included: (1) Ministry of Public Health and Population (MoPHP) SMART surveys; (2) UNICEF-supported nutrition assessments; (3) Humanitarian organization surveys (Save the Children, Action Contre la Faim); (4) Joint MoPHP-CSO (Central Statistical Organization) national surveys. All surveys were retrieved from public humanitarian and nutrition information websites, including ReliefWeb/yemen nutrition cluster [13] and UNICEF repositories [14]. We also sought relevant surveillance data directly from the Ministry of Public Health and Population and UNICEF.

We included a source if it: (1) reported data collected in Yemen between 2015 and 2026; (2) reported GAM and/or SAM among children aged 6–59 months; (3) provided a clearly defined geographic unit; (4) provided a survey year or defined data-collection period; and (5) used a sampling design intended to represent a governorate, zone, district, or national population, or was clearly identified as a targeted surveillance estimate. We excluded non-representative facility-based data, local programme monitoring data without a defined population denominator, observations outside the study period, records without an extractable GAM or SAM estimate, and records for which geographic attribution was unclear.

2.2 Variables and definition

The primary outcomes were the prevalence of GAM and SAM among children aged 6–59 months, defined in SMART-WHZ assessments using weight-for-height z-score (WHZ) below − 2 standard deviations from the WHO Child Growth Standards median. WHO defines wasting as score WHZ < − 2, and SAM as WHZ < − 3. MUAC-based GAM was defined as MUAC < 125 mm, and MUAC-based SAM as MUAC < 115 mm [15]. WHZ-based and MUAC-based estimates were not treated as directly interchangeable.

2.3 Data Extraction and Harmonization

For each eligible survey, we extracted the source identifier, survey year, survey title, governorate name, sub-governorate zone or cluster label, sample size, sampling design, survey method ((SMART, MICS, EFSNA) anthropometric criterion, GAM, SAM and MUAC estimates. Each observation was classified according to source type, geographic unit, sampling design, and anthropometric criterion.

Importantly, we standardized all malnutrition metrics to the WHO 2006 child growth standards. By definition, GAM is the percentage of children 6–59m with weight-for-height z-score < − 2 SD (or bilateral edema), and SAM is < − 3 SD [15]. We created a master dataset at the governorate-year level. For each governorate and year, we merged data from all surveys covering that governorate in that year. If surveys included multiple governorates, we assigned observations to each governorate with GAM and SAM. A metadata table records of all included surveys.

2.4 Statistical analysis

We summarized observations by year, governorate, and survey method. Descriptive analyses included the number of observations, mean GAM and SAM prevalence, and the distribution of observations across WHO severity categories. The primary temporal analysis used the 67 governorate–survey-year SMART-WHZ observations. We estimated the average change in GAM and SAM prevalence over time using ordinary least-squares regression and a linear mixed-effects model with a random intercept for governorate.

The primary models were restricted to SMART-WHZ governorate–survey-year observations because this category provided the greatest methodological comparability. Sensitivity analyses included pooled observations from additional survey methods and models that included survey method as an exploratory covariate. For governorates with at least three comparable SMART-WHZ observations from different years, we estimated governorate-specific linear slopes. Governorates with only one or two comparable observations were summarized descriptively and were not used to support inferential claims about temporal trajectories.

We compared MICS estimates with the nearest available SMART-WHZ estimate from the same governorate in a descriptive matched-governorate analysis. We also compared WHZ-based and MUAC-based estimates reported for the same survey round. The statistical distribution of paired differences was examined before applying paired tests, and influential observations was assessed using Cook's distance in the relevant regression models. All tests used a two-sided significance level of 0.05, confidence intervals were reported where available. All analyses were conducted in Python 3.12 using pandas (v2.2.2), statsmodels (v0.14.6), and scipy (v1.13.1).

3 Results

3.1 Survey and Dataset Overview

The harmonized database comprised 107 survey observations from 38 distinct survey reports across all 22 governorates. Of these, 67 were SMART-WHZ observations, 18 were EFSNA, and 22 were MICS observations (Table 1). The composition of the full 107 dataset (Appendix 1). The 67 governorate–survey-year SMART-WHZ observations were used for the primary trend analysis. EFSNA and MICS observations were excluded from the primary trend model because their sampling frames, survey designs, geographic units, and reporting conventions differed from those of the SMART-WHZ assessments. Because the number and geographic distribution of contributing observations varied across years, annual descriptive means should not be interpreted as nationally representative prevalence estimates.

Table 1
Dataset composition of the harmonized 107 observation by survey method

Data source / analytical unit	observation n (%)	# of Governorates	Covered Years	Mean GAM (%)	Mean SAM (%)
Governorate-round SMART-WHZ	67 (62.6)	22	2015–2026	12.4	2.0
EFSNA	18 (16.8)	18	2016	11.2	1.7
MICS	22 (20.5)	22	2023	18.0	5.8
All observations	107 (100)	22	2015–2026	13.4	2.5

3.2 Temporal trends in GAM and SAM

Among the 67 comparable SMART-WHZ governorate–survey-year observations, GAM and SAM fluctuated over time, but neither outcome showed a statistically detectable linear trend. The estimated GAM slope was approximately − 0.03 percentage points per year in the unadjusted OLS model (slope − 0.033 pp/year, 95% CI − 0.47 to 0.40, p = 0.879) and approximately − 0.12 percentage points per year in the mixed-effects model (95% CI -0.38 to 0.13, p = 0.335). Both confidence intervals included zero. (Table 2; Fig. 1–2)

SAM showed a similarly flat pattern. The estimated OLS slope was approximately 0.002 percentage points per year (95% CI -0.13 to 0.13; p = 0.975), while the mixed-effects estimate was approximately − 0.014 percentage points per year (95% CI -0.11 to 0.08; p = 0.773). Neither estimate provided statistically robust evidence of an average increase or decrease in SAM prevalence. Results for all models are summarized in Table 2.

The annual mean GAM among the 115 zone-level SMART-WHZ observations varied across the observation period, ranging from approximately 9.9% in 2017 to 17.5% in 2026. These annual means describe the available surveys only. They should not be interpreted as national estimates because the number, geographic distribution, and composition of contributing governorates differed substantially across years (Fig. 1–2).

Table 2
National pooled trend models for GAM and SAM (primary and sensitivity models)

Outcome / dataset	Model	N	Slope (pp/year)	95% CI	p-value
GAM - (SMART-WHZ)	OLS (governorate-year)	67	-0.033	[-0.47, 0.40]	0.879
GAM - (SMART-WHZ)	Mixed-effects (random intercept, governorate)	67	-0.124	[-0.38, 0.13]	0.335
SAM - (SMART-WHZ)	OLS (governorate-year)	67	+ 0.002	[-0.13, 0.13]	0.975
SAM - (SMART-WHZ)	Mixed-effects (random intercept, governorate)	67	-0.015	[-0.11, 0.08]	0.748
GAM - Sensitivity (all methods pooled)	OLS (governorate-year)	107	+ 0.37	[-0.10, 0.84]	0.119
GAM - Sensitivity (all methods)	Mixed-effects	107	+ 0.346	[-0.05, 0.74]	0.087
GAM - method-adjusted as covariate	OLS (method as covariate)	107	-0.033	[-0.63, 0.57]	0.912
SAM - Sensitivity (all methods)	OLS (governorate-year)	107	+ 0.232	[0.03, 0.43]	0.025*
SAM - Sensitivity (all methods)	Mixed-effects (governorate-year)	107	+ 0.24	—	0.022 *

*percentage points (pp) GAM or SAM per year. * = nominally significant at p < 0.05; disappears in the methodologically consistent core (SMART-WHZ-only) subset (see Discussion). The 107 is the total governorates rounds observations (67 SMART-WHZ, 22 MICS, 18 EFSNA),*

3.3 Governorate-level patterns

Governorate-level slopes were heterogeneous. Several governorates had positive estimated slopes, whereas others had negative or near-zero slopes. However, the individual governorate slopes were not statistically significant after the available number of observations and uneven coverage were taken into account (Fig. 3; Appendix 2).

The apparent positive slope for Al Jawf was largely driven by the high MICS estimate in 2023. In contrast, the SMART-WHZ-only observations for Al Jawf suggested a different pattern. This illustrates the sensitivity of governorate-level classifications to single observations and to the inclusion of methodologically heterogeneous data. One further governorate, Sa'ada, had only two comparable observations; it showed a descriptive two-point increase (9.3% → 22.1%) but was not evaluated by slope testing and is reported separately from the statistically classified trajectories. The other governorates had ≥ 3 years of comparable observations. Al Hodeidah showed a negative overall slope across its entire 6 available years (− 0.38 pp/year, p = 0.607) although it included two influential observations at the

beginning and end of the series. This is because intermediate observations were lower than these high values, demonstrating why comparisons based only on the first and last available observations can obscure important fluctuations (Appendix 2).

3.4 Survey zone and temporal period differences

GAM prevalence varied significantly by ecological zone. Lowland/coastal surveys had higher mean GAM (17.2%) than highland/mountainous (10.1%) or urban (11.3%) surveys (ANOVA $p < 0.001$). GAM also varied significantly across time periods (Kruskal-Wallis $p = 0.034$), with the Mid period (2017–2018) showing the lowest median GAM (9.5%) and the Latest period (2025–2026) the highest (17.4%). As noted above, the Latest-period estimate is based on only 4 surveys and should be interpreted with caution. Governorate-level variation was substantial, with coastal lowland governorates/zone (Al Hodeidah, Taiz, Lahj, Hajjah) consistently showing critical GAM prevalence (≥ 15%). In contrast, highland and eastern governorates (Al Mahrah, Hadhramaut Valley) maintained lower prevalence. These geographic patterns should be interpreted cautiously because the availability, timing, sampling design, and geographic coverage of surveys differed among governorates (Appendix 3).

3.5 Influence of survey methodology

When observations from multiple survey methods were pooled without adjustment, the estimated GAM and SAM slopes were more positive than those observed in the SMART-WHZ-only analysis. The pooled SAM association reached nominal statistical significance, whereas the pooled GAM association was not statistically significant. GAM (OLS + 0.37 pp/year, $p = 0.119$; mixed-effects + 0.346 pp/year, $p = 0.087$), SAM (OLS + 0.232 pp/year, $p = 0.025$; mixed-effects + 0.240 pp/year, $p = 0.022$) (Table 2). However, after survey method was included as an exploratory covariate, the estimated temporal associations were attenuated toward the null (GAM: −0.033 pp/year, $p = 0.912$; SAM: +0.00 pp/year, $p = 0.987$) (Table 2, Fig. 4B). This pattern indicates that differences among survey methods and their distribution across years may contribute substantially to the apparent pooled trend.

MICS estimates were generally higher than the nearest available SMART-WHZ estimates from the same governorates. In the matched-governorate comparison involving 22 pairs, the distribution of MICS–SMART-WHZ differences was shifted upward (Wilcoxon signed-rank $p = 0.011$; Fig. 4A), with only weak, non-significant overall correlation between the two methods (Pearson $r = 0.31$, $p = 0.159$). The largest positive differences occurred in Al Jawf (+ 52.7 percentage points), Hajjah (+ 22.8 pp), Raymah (+ 19.7 pp), and Lahj (+ 17.7 pp). The Al Jawf estimate was particularly influential because the MICS GAM estimate was substantially higher than the corresponding SMART-WHZ estimate. (Appendix 3)

3.6 Influential observations

Influence diagnostics identified five observations with relatively high leverage or influence in the pooled GAM model. These included the MICS estimate from Al Jawf (60.6%, MICS, Cook's D = 0.29, the most extreme) and several high GAM estimates from Al Hodeidah, Hajjah, and Lahj. Three of the five observations were from the MICS 2023 dataset (Appendix 3).

Excluding these observations reduced the magnitude of the pooled GAM slope, but did not materially change the national trend estimate, which remained non-significant (+ 0.168 pp/year, p = 0.264). Statistical influence was not considered evidence of data error, and all observations were retained in the primary descriptive database.

3.7 WHZ- and MUAC-based estimates

Among survey rounds reporting both WHZ-based and MUAC-based GAM, WHZ-based estimates were higher on average than MUAC-based estimates. The mean WHZ-based estimate was approximately 12.8%, compared with 8.2% for the MUAC-based estimate, corresponding to an average difference of approximately 4.6 percentage points (Appendix 4).

These findings are consistent with the fact that WHZ and MUAC identify overlapping but non-identical groups of children. The difference should not be interpreted as a direct comparison of diagnostic accuracy because the estimates may have been affected by the characteristics of the surveyed populations, the sampling design, and the way each indicator was collected and reported.

3.8 Severity classification and contextual patterns

Across all 107 observations, 32.3% were classified in the emergency GAM category (GAM ≥ 15%), 27.7% in the serious category (10–14.9%). These percentages refer to the distribution of survey observations, not to the proportion of children or the proportion of Yemen's population living in each category. The proportion of observations classified as emergency increased from 37.5% during 2015–2016 to 50.0% during 2025–2026. The latter estimate was based on only four observations which limits the precision of this comparison. The comparison did not provide statistically robust evidence of a temporal change in the proportion of observations classified as emergency (chi-square p = 0.623).

4 Discussion

This repeated cross-sectional ecological analysis found that acute malnutrition in Yemen remained persistently high across available survey observations between 2015 and 2026. However, neither GAM nor SAM showed a statistically detectable national-level linear trend across the methodologically consistent WHZ-based SMART surveys. The absence of a detectable trend should not be interpreted as evidence of improvement or stabilisation; rather, it indicates a chronic humanitarian crisis that has remained severe over the study period. The uneven temporal and geographic coverage of the survey database means that substantial subnational changes may have occurred without producing a detectable national average trend. The principal pattern was one of persistently high prevalence, short-term fluctuation, and recurrent hotspots rather than a clear monotonic increase or decrease. This contrasts with other protracted crisis settings where sustained multi-sectoral interventions have achieved reductions in acute malnutrition [16–18].

The distribution of survey observations across severity categories, with 74% classified as Emergency or Serious, indicates a substantial and sustained burden of acute malnutrition. This pattern is consistent with a chronic, spatially heterogeneous humanitarian crisis, though the study design does not permit estimation of the independent effect of conflict on malnutrition. It is important to emphasise that these severity categories describe survey observations and should not be interpreted as population-weighted national estimates. The concentration of emergency-level observations in coastal and lowland areas, particularly in southern Hodeidah and Taiz lowlands where IPC AMN Phase 5 (extremely critical) classifications have been documented [7–9], suggests that national averages alone are insufficient for operational decision-making and resource allocation. This pattern of emergency stagnation despite more than a decade of humanitarian intervention reflects persistent underlying determinants, including protracted conflict, economic collapse, disease outbreaks, and severe structural barriers to nutrition recovery. In crisis-affected settings, malnutrition can operates not merely as a health outcome but as a systemic barrier to recovery and long-term development, reinforcing cycles of vulnerability that short-term humanitarian responses alone cannot interrupt [1, 16, 19, 20].

The significant governorate-level and ecological heterogeneity observed in this analysis is epidemiologically and operationally plausible. Lowland and coastal surveys had significantly higher mean GAM than highland or urban surveys, and several coastal or frontline governorates such as Al Hodeidah, Taiz, Lahj, and Hajjah showed persistently elevated values. The persistent high-GAM zones we identified were also those repeatedly cited as malnutrition hotspots by IPC-AMN analyses, UNICEF and WFP [7–9]. This is also consistent with evidence from other conflict settings showing that wasting clusters geographically and is shaped by livelihood, environmental, and conflict-related factors [21, 22]. Chronic underinvestment and direct conflict-related damage, including food insecurity, limited access to health and nutrition services, and adverse socioeconomic conditions, likely sustained high rates in these locations [23].

The higher WHZ-based than MUAC-based estimates we found in this analysis are also consistent with the complementary nature of these indicators. A recent study in Yemen found that children with dual WHZ and MUAC deficits had worse recovery profiles than those with a single deficit, and that reliance on one criterion at discharge can underestimate the ongoing vulnerability and continuing risk [24, 25]. Other broad studies from Ethiopia and other humanitarian settings report that MUAC alone can either under- or over-detect wasting relative to WHZ, depending on context and cut-offs [26, 27]. This reinforces the recommendation that no single anthropometric indicator should be treated as a complete representation of acute malnutrition burden.

4.1 Implications for Policy and Programming

Our findings have several important implications for policy and practice. First, the persistence of emergency-level GAM prevalence in several zones, despite a decade of humanitarian intervention argues against nutrition programming effectiveness and supports continued scale up high-intensity nutrition response to achieve population-level impact. Second, acute malnutrition in Yemen is driven by multiple

determinants beyond direct nutrition interventions, including food insecurity, poor water and sanitation, and high disease burden [1, 23]. Integrated programming addressing these underlying causes may be necessary for sustained improvement. Third, the observed irregular survey coverage and heterogeneity limit timely detection of deteriorating situations. Investment in routine surveillance systems at site, zone and livelihood levels would enable more focused responsive programming to rapid local deterioration. Fourth, nutrition surveillance should systematically link anthropometric outcomes with multidimensional crisis indicators (conflict exposure, displacement, food insecurity, disease outbreaks, humanitarian coverage, and interruptions in services). Service delivery constraints remain critical in Yemen, qualitative programme and access evidence suggests that deteriorating malnutrition trajectories are closely associated with interruptions in nutrition services, which commonly suffer from access barriers and supply interruptions in fragile settings [18]. Fifth, the strong effect of survey methodology suggests that future national analyses should prioritize standardized SMART-compatible designs where feasible, with explicit documentation of deviations. Surveillance systems should distinguish representative prevalence estimates from targeted assessments and routine programme-monitoring data [2]. Finally, the findings highlight the need for continued trend monitoring linked to both longitudinal prevalence patterns and the spatial distribution of high-risk areas as well as integrating data on service availability, coverage, quality, and population outcomes. The simple start-to-end comparisons can be misleading and obscure severe interim deteriorations or seasonal biases. As demonstrated by the Al Hodeidah trajectory, a governorate may record a lower prevalence at the end of the observation period than at its earliest observation while having experienced a severe interim deterioration.

4.2 Strengths and Limitations

This study draws strength from the use of a broad temporal synthesis of available acute-malnutrition observations across the Yemen's 22 governorates. Important strengths include the separation of the primary SMART-WHZ dataset from methodologically heterogeneous sources, explicit examination of survey-method effects, use of mixed-effects models to account for repeated governorate observations, and transparent consideration of influential observations.

Several limitations should be considered. First, survey coverage was uneven across years and governorates, and no comparable representative survey was available for every year. Second, observations were not independent population samples; some were nested within the same governorate, survey period, report, or sampling framework. Third, seasonal information was incomplete and could not be consistently incorporated into the models. Fourth, conflict-related access restrictions may have produced selection bias by excluding inaccessible populations (especially in North). Fifth, differences between survey methods may introduce bias beyond seasonal timing effects alone, and some observations may reflect restricted-access or hotspot-oriented sampling. Finally, the ecological design does not permit individual-level inference or estimation of the independent causal effect of conflict, food insecurity, humanitarian response, or service disruption.

5 Conclusion

Acute malnutrition in Yemen remained persistently severe between 2015 and 2026, with no detectable national linear trend in GAM or SAM. The dominant pattern was one of persistently high prevalence, short-term fluctuation, and recurrent hotspots, with substantial geographic heterogeneity. The burden was concentrated in coastal and lowland governorates, and apparent pooled trends were sensitive to survey method and indicator choice, underscoring the importance of methodologically harmonised surveillance and subnational, hotspot-targeted responses.

The principal programmatic priority is not simply to determine whether national GAM is rising or falling. It is to identify where acute malnutrition remains persistently severe, where it is deteriorating rapidly, and which populations remain unreached by effective prevention and treatment services. This requires district- and livelihood-sensitive programming, harmonised longitudinal surveillance, and stronger linkage between anthropometric data and contextual drivers including conflict exposure, food insecurity, disease, displacement, and health-service performance. Without addressing these structural determinants, short-term humanitarian interventions are unlikely to interrupt the cycle of vulnerability in Yemen.

Abbreviations

AMN
acute malnutrition
CMAM
community-based management of acute malnutrition
FAO
Food and Agriculture Organization of the United Nations
GAM
global acute malnutrition
IDP
internally displaced person
IPC
Integrated Food Security Phase Classification
IYCF
infant and young child feeding
MAM
moderate acute malnutrition
MICS
Multiple Indicator Cluster Survey
MUAC
mid-upper arm circumference
NGO
non-governmental organization
OCHA

United Nations Office for the Coordination of Humanitarian Affairs
PLW
pregnant and lactating women
RUTF
ready-to-use therapeutic food
SAM
severe acute malnutrition
SBC
social and behaviour change
SMART
Standardized Monitoring and Assessment of Relief and Transitions
UNICEF
United Nations Children's Fund
WASH
water,sanitation and hygiene
WaSt
concurrent wasting and stunting
WAZ
weight-for-age z-score
WFP
World Food Programme
WHO
World Health Organization
WHZ
weight-for-height z-score.

Declarations

Ethics approval and consent to participate

This study was a secondary analysis of previously collected and publicly available aggregated nutrition survey data and did not involve access to identifiable individual-level participant data. Accordingly, ethical approval was therefore not required, in accordance with the ethical standards and guidelines applicable to secondary research using publicly available data.

Consent to participate

Not applicable. This study used previously collected, publicly available aggregated data and did not involve direct recruitment or interaction with human participants or access to identifiable individual-level participant data. Therefore, informed consent to participate was not required.

Consent to publish

Not applicable. No identifiable individual data or images are included in this manuscript.

Clinical trial number

Not applicable

Competing Interests

The authors declare that they have no competing interests.

Funding

Not applicable.

Author Contribution

SMYM conceived and designed the study, developed the research concept and methodology, identified the research themes, and led the writing of the manuscript DY contributed to data extraction, data management, and manuscript review. AAHA participated in data analysis and interpretation, and contributed to the review and revision of the manuscript. SEMA contributed to data extraction, analysis, and manuscript review. All authors contributed to the development of the study, reviewed and approved the final manuscript, and agree to be accountable for all aspects of the work.

Acknowledgement

The authors acknowledge the organisations and assessment teams whose nutrition surveys and humanitarian analyses contributed to the underlying evidence base, including Yemen's Ministry of Public Health and Population, UNICEF, WFP, WHO, Save the Children, ACF, OCHA and other partners.

Data Availability

The datasets generated or analysed during the current study are available as electronic supplementary files accompanying this article. All underlying source data used in this study were obtained from publicly available sources cited in the manuscript.

References

1. Yemen Humanitarian Needs and Response Plan. 2026 (March 2026) | OCHA. 2026. https://www.unocha.org/publications/report/yemen/yemen-humanitarian-needs-and-response-plan-2026-march-2026. Accessed 21 July 2026.
2. Kiarie J, Karanja S, Busiri J, Mukami D, Kiilu C. The prevalence and associated factors of undernutrition among under-five children in South Sudan using the standardized monitoring and assessment of relief and transitions (SMART) methodology. BMC Nutr. 2021;7. https://doi.org/10.1186/s40795-021-00425-3.
3. Nassur A, Daanouni O, Luc G, Humphreys A, Blanárová L, Heymsfield G, et al. Factors associated with acute malnutrition among children aged 6–59 months in Haiti, Burkina Faso and Madagascar: A pooled analysis. PLoS ONE. 2022;17. https://doi.org/10.1371/journal.pone.0278980.
4. Brown ME, Grace K, Billing T, Backer D. Considering climate and conflict conditions together to improve interventions that prevent child acute malnutrition. Lancet Planet Health. 2021;5 9:e654–8. https://doi.org/10.1016/s2542-5196(21)00197-2.
5. Qirbi N, Ismail S. Health system functionality in a low-income country in the midst of conflict: the case of Yemen. Health Policy Plan. 2017;32:911–22. https://doi.org/10.1093/heapol/czx031.
6. Alves R, de Vasconcelos CAC, Vieira NB, Pereira YTG, Feitosa PWG, Maia M, et al. The silence of the lambs: Child morbidity and mortality from malnutrition in Yemen. J Pediatr Nurs. 2022. https://doi.org/10.1016/j.pedn.2021.12.006.
7. Acute malnutrition surges in Government of Yemen-. controlled areas with extremely critical conditions reported in West Coast areas. https://www.unicef.org/press-releases/acute-malnutrition-surges-government-yemen-controlled-areas-extremely-critical. Accessed 18 Sept 2026.
8. Acute malnutrition surges in. southern Yemen with extremely critical conditions reported in West Coast areas | World Food Programme. https://www.wfp.org/news/acute-malnutrition-surges-southern-yemen-extremely-critical-conditions-reported-west-coast. Accessed 18 Sept 2026.
9. IPC Acute Malnutrition Analysis | UNICEF Yemen. 2024. https://www.unicef.org/yemen/reports/ipc-acute-malnutrition-analysis. Accessed 18 Sept 2026.
10. Hussein R, Suprenant M, Al-Dheeb N, Guerrero S, Rogers E, Shafique F, et al. A mathematical model to estimate the incidence of child wasting in Yemen. Confl Health. 2021;15. https://doi.org/10.1186/s13031-021-00400-6.
11. Johnston R, Dhamija G, Kapoor M, Agrawal PK, de Wagt A. Methods for assessing seasonal and annual trends in wasting in Indian surveys (NFHS-3, 4, RSOC & CNNS). PLoS ONE. 2021;16:1–16. https://doi.org/10.1371/journal.pone.0260301.
12. Yaghmaei N, Guha-Sapir D. The use of stunting as a nutrition indicator in Yemen civil war. Glob Health. 2019;15:63. https://doi.org/10.1186/s12992-019-0502-x.
13. Yemen. Sept : Nutrition | ReliefWeb Response. https://response.reliefweb.int/yemen/nutrition. Accessed 22 2026.
14. Nutrition | UNICEF Yemen. https://www.unicef.org/yemen/nutrition. Accessed 22 Sept 2026.

15. de Onis M, Borghi E, Arimond M, Webb P, Croft T, Saha K, et al. Prevalence thresholds for wasting, overweight and stunting in children under 5 years. Public Health Nutr. 2019;22:175–9. https://doi.org/10.1017/S1368980018002434.
16. FAO, IFAD, UNICEF, WFP and WHO., The State of Food Security and Nutrition in the World 2026. UNICEF DATA. 2026. https://doi.org/10.4060/cd8306en
17. Carroll GJ, Lama SD, Martinez-Brockman JL, Pérez-Escamilla R. Evaluation of Nutrition Interventions in Children in Conflict Zones: A Narrative Review. Adv Nutr. 2017;8:770–9. https://doi.org/10.3945/an.117.016121.
18. Shah S, Padhani Z, Als D, Munyuzangabo M, Gaffey M, Ahmed W, et al. Delivering nutrition interventions to women and children in conflict settings: a systematic review. BMJ Glob Health. 2021;6. https://doi.org/10.1136/bmjgh-2020-004897.
19. Salih M, Satty A, Abdalla FA, Gumma EAE, Adam AMA, Hassaballa AA, et al. Childhood Wasting and its Determinants: A Statistical Analysis Using Cross-sectional Survey Data. J Epidemiol Glob Health. 2026;16:49. https://doi.org/10.1007/s44197-026-00548-5.
20. Al-Hatemi N, Al-Nawd E, Alosoufe L, Alhebshi H, Alhroub N, Alkhawaldeh A, et al. Exploring risk factors for undernutrition in children aged under five years in Yemen. Nurs Child Young People. 2025;37:19–27. https://doi.org/10.7748/ncyp.2024.e1526.
21. Luc G, Kéita M, Houssoube F, Wabyona E, Constant A, Bori A, et al. Community Clustering of Food Insecurity and Malnutrition Associated With Systemic Drivers in Chad. Food Nutr Bull. 2023;44:69–82. https://doi.org/10.1177/03795721231189970.
22. Martin-Cañavate R, Custodio E, Yusuf A, Molla D, Fasbender D, Kayitakire F. Malnutrition and morbidity trends in Somalia between 2007 and 2016: results from 291 cross-sectional surveys. BMJ Open. 2020;10. https://doi.org/10.1136/bmjopen-2019-033148.
23. Duque MP, Alburhomy A, Ahmed A, Saleh Y, Wolz A, Abecasis AB, et al. Acute malnutrition and food insecurity in Yemen, 2021: Evidence from a two-stage cluster randomised survey in a protracted crisis. PLOS Glob Public Health. 2025;5:e0004331. https://doi.org/10.1371/journal.pgph.0004331.
24. Amad MAA, Raja'a YA, Algendari K. Relapse of severe acute malnutrition post-discharge from outpatient programs among children recovered from complicated SAM in a conflict-affected setting: a matched cohort study, Sana'a, Yemen. BMC Nutr. 2026;12. https://doi.org/10.1186/s40795-026-01299-z.
25. Amad MAA, Raja'a YA, Algendari K. Addressing dual deficiencies of SAM indicators; gaps and insights from inpatient admission to outpatient discharge, in conflict-affected Yemen; a retrospective study. Confl Health. 2025;19. https://doi.org/10.1186/s13031-025-00666-0.
26. Farah AM, Hassen HY, Biadgilign S, Kebede A, Desalegn Y, Yilma B, et al. Improving case-detection of wasting among under-five-year-old children in Ethiopia: A secondary analysis of community-based surveys in humanitarian settings. PLOS Glob Public Health. 2026;6:e0005952–0005952. https://doi.org/10.1371/journal.pgph.0005952.

27. Garretson S, Walton S, Alier KK, Grounds S, Khattak Q, Mohamoud SA, et al. Analysing concordance between MUAC, MUACZ, and WHZ in diagnosing acute malnutrition among children under five in Somalia. J Glob Health. 2025;15. https://doi.org/10.7189/jogh.15.04258.

Figures

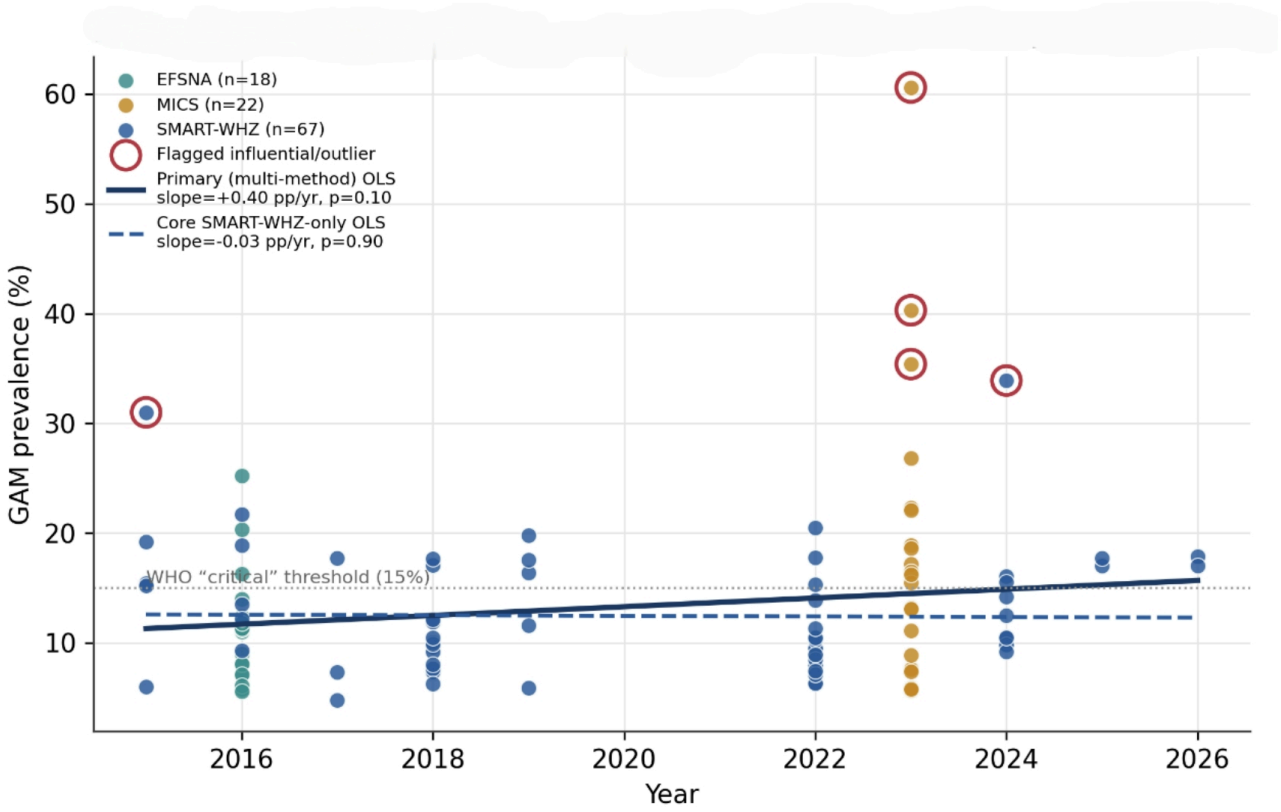


Figure 1

National GAM trend: governorate-round estimates by method, with all and core-SMART-WHZ OLS fits; flagged influential points circled.

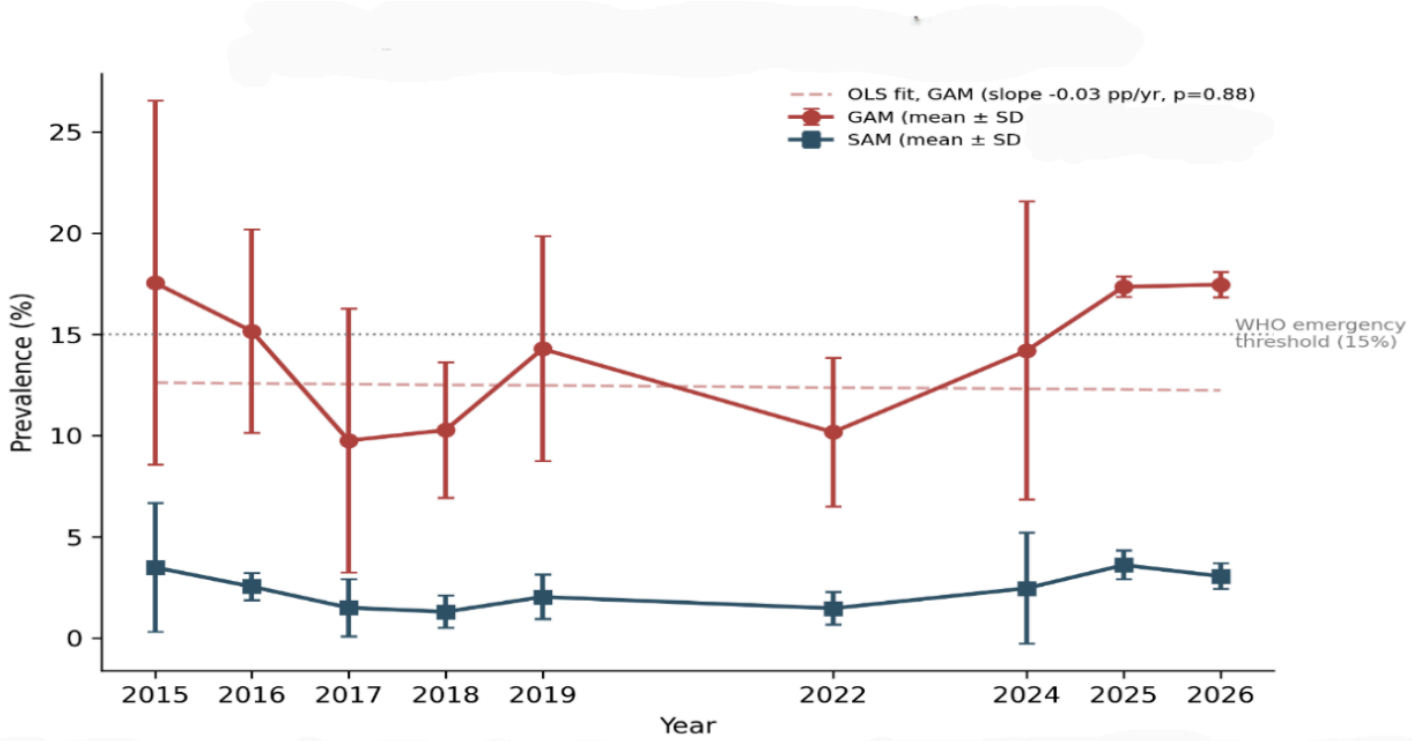


Figure 2

National GAM and SAM trend, 2015–2026, based on governorate-year estimates from the primary SMART-WHZ dataset

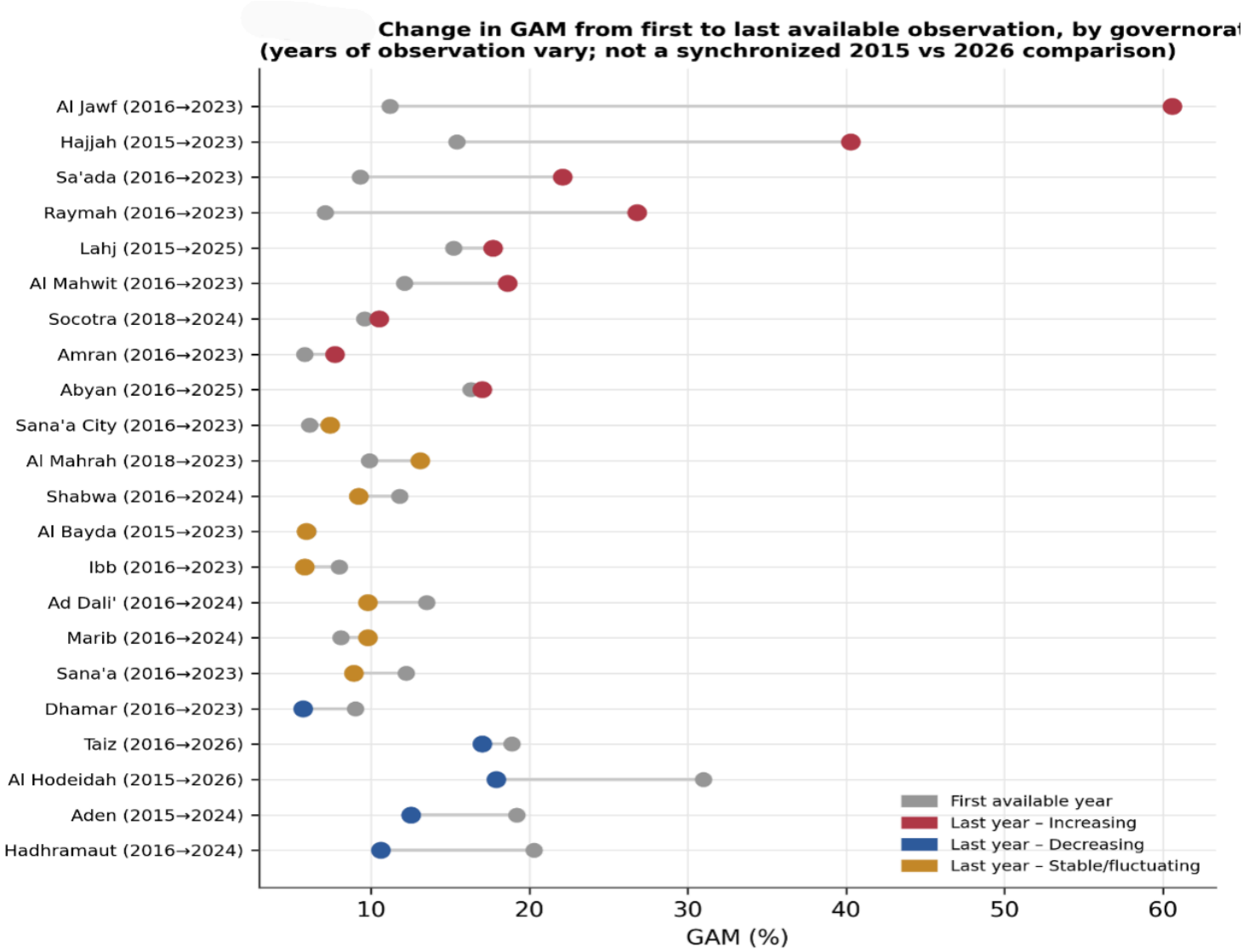


Figure 3

Change in GAM from first to last available observation, by governorate. Years of observation vary substantially by governorate (shown in parentheses); this is not a synchronized 2015 vs. 2026 comparison

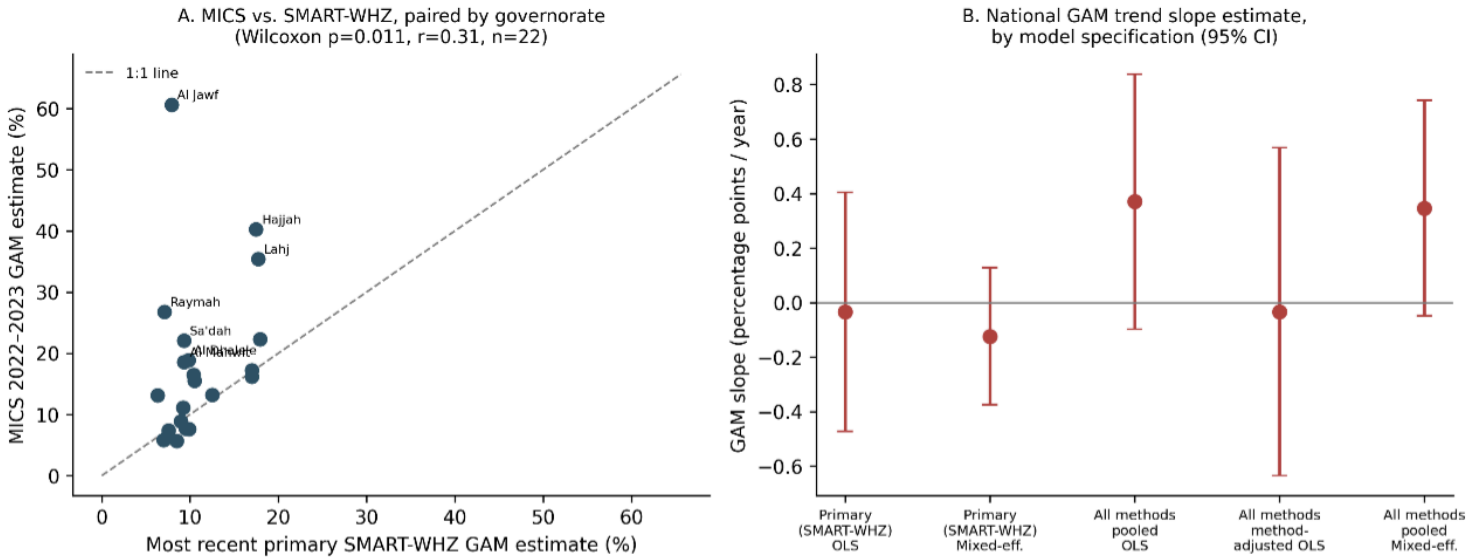


Figure 4

Methodological comparison and sensitivity analysis. **(A)** MICS 2022–2023 GAM estimates plotted against SMART-WHZ estimate **(B)** National GAM trend slope (OLS and mixed-effects), all methods pooled without adjustment (OLS and mixed-effects)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix1Full107dataset.xlsx
- Appendix4Fig.5comparisonWHZvs.MUACGAMsamesurveyround.png
- Appendix3Fig.4governoratetrajectories.png
- Appendix2AdditionalTables.docx