Statistical analysis of anthropometric survey data to estimate or predict malnutrition prevalence and trends

Statement of problem

Anthropometric survey data are routinely used to generate population-level estimates of the prevalence of stunting, overweight and wasting among young children in low- and middle-income countries. In the 2019 *Recommendations for data collection, analysis and reporting on anthropometric indicators children under 5 years old*, the World Health Organization (WHO) and the United Nations Children's' Fund (UNICEF) advocated for standard analysis methods to estimate malnutrition prevalence indicators (i.e., proportions of all eligible children with measurements below or above conventional z-score thresholds) and mean anthropometric z-scores, accounting for complex survey designs.[1] Using child-level data from cross-sectional surveys in low- and middle-income countries – typically Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), or SMART surveys – prevalences are estimated for a single point in time nationally and across sub-groups defined by geographic, demographic or socioeconomic variables available within the survey dataset. For geographic sub-groups, surveys are typically representative down to the state/province level, but the availability of geolocation metadata further enables subnational estimation in smaller areas defined by other administrative or geographic criteria.[2]

The 2019 WHO/UNICEF *Recommendations* advised that data quality assessments and exclusion of implausible values be undertaken prior to analyses of survey data.[1] However, as described in more detail in other research briefs, there is a lack of consensus regarding optimal methods for the identification and management of individual child-level data outliers and implausible values (brief 7), and the interpretation of anthropometric data quality assessments (brief 8). Some methods for outlier exclusion may result in the exclusion of substantial proportions of surveyed children (see brief 7), and in rare situations, data quality assessments may lead to the rejection of an entire survey (see brief 8). Therefore, there is interest in statistical modelling methods that would enable retention of outliers and incorporation of data quality metrics to adjust or weight input data.

In addition to prevalences (i.e., proportions of low/high z-scores) and means, other survey-level metrics can be generated by analysing the underlying height-for-age z-score (HAZ), weight-for-age z-score (WAZ), weight-for-height z-score (WHZ), BMI-for-age z-score (BMIz), or raw weight and height measurement distributions.[3] Some alternative statistics (e.g., median, winsorized mean) are robust estimators of central tendency, meaning they are less sensitive to influential outliers compared to a mean. As well, certain mean/median estimation methods could be used to attenuate the influence of extreme outliers (e.g., robust regression, quantile regression).[4] However, these methods are not widely used and there is a lack of evidence to support the adoption of alternative metrics to address inadequate data quality.

Some researchers have used the standard deviation (SD) of the HAZ distribution to quantify the uncertainty[5] in the stunting prevalence, or performed post-hoc adjustment of estimates[6] based on the extent to which the SD exceeds that of the standard distribution (SD=1). Others have used the probit function to estimate prevalence based on the empirical mean z-score and assuming SD=1 rather than the observed SD.[7,8] However, as explained in brief 8, HAZ dispersion may be increased by true between-child variance, not just random measurement error, such that there is a lack of consensus regarding the use of SD as a measure of data quality.

Anthropometric data from population-representative surveys in low- and middle-income countries (e.g., DHS, MICS, SMART) are also commonly used as inputs for multi-survey analyses aimed at global malnutrition burden modelling and progress tracking. Multi-survey models have the advantage of leveraging data from diverse sources across space and time to generate more precise estimates and time trends, and to generate predictions at the country or smaller-area-level even where (or when) empirical estimates are unavailable. Models can incorporate a wide range of covariates from external data sources (e.g., socioeconomic characteristics) to improve predictive accuracy and represent a harmonized approach to the estimation of indicators across countries and over time. However, multi-survey regression models may compromise the granularity of information obtained from a cross-sectional survey, such that a smoothed secular trajectory predicted for a country could mask true short-term or localized upticks in the burden of malnutrition due to humanitarian disasters or other acute health shocks. Because predictions from mixed-effects models tend to be closer to a regional or global 'grand' mean than corresponding empirical estimates,[9] the degree to which a country or district is a true outlier could be under-appreciated. An overarching issue is the increasing complexity of statistical and machine learning methods, which may pose a barrier to independent method validation or between-method comparisons and benchmarking studies.

The most widely-known multi-survey anthropometric indicator prediction models have been implemented by the Institute for Health Metrics and Evaluation (IHME) in support of the Global Burden of Disease (GBD) project,[10-12] and the Joint Malnutrition Estimates (JME) initiative,[13,14] which is a collaborative effort of WHO, UNICEF and World Bank that has supported progress tracking related to the World Health Assembly 2025 Global Nutrition Targets. Data inputs into multi-survey models may be country/year-level estimates of malnutrition prevalence from each survey,[15,16] or they may be based on subsets of child-level measurements grouped into small-scale local units (e.g., clusters, villages).[10] Models include covariates for which data are available for each time/space unit of analysis, such as environmental factors (e.g., average rainfall) or sociodemographic indicators (e.g., urban versus rural), which are extracted or modelled based on sources that are often separate from the surveys from which anthropometric outcome data were derived.* The most common application of such models is to generate discrete predictions of malnutrition prevalence that are intended to guide health policy and programming. Where small-area estimation or geostatistical modelling is performed, area-level predictions can be plotted on pixel maps or aggregated to estimate average prevalence at higher administrative or political levels (e.g., subnational district, national).

According to the JME method, stunting and overweight prevalence estimates are annual country-level predictions from a penalized cubic spline linear mixed model.[15] Model predictions, rather than empirical single-survey estimates, are reported as the official indicators for all countries with at least one data point in the model; however, estimates are generated for all countries so that they can be aggregated to calculate regional and global prevalences.[13] The JME uses a different method for wasting and severe wasting: country prevalences are estimated empirically from single surveys, such that they are only reported for years in which surveys were conducted. Regional/global wasting indicator estimates are based on a subregional modelling approach developed by WHO.[16-17] The burden of moderate and severe acute malnutrition may be expressed as wasting prevalence or incidence, but the latter metric may be preferred for programme and policymaking due to the seasonality of wasting as a form of malnutrition.[18] Incidence rates require longitudinal cohorts or correction factors applied to prevalence estimates;[19] however, there is a lack of consensus about the importance of distinguishing between wasting prevalence and incidence when estimating the number of deaths attributable to severe acute malnutrition.[20,21]

In summary, conventional single-survey analysis continues to be widely used to produce malnutrition prevalence estimates in the global nutrition literature.[22] The standard method relies on upstream data cleaning (e.g., exclusion

* ME and IHME methods rely on similar anthropometric data sources and may also have some overlap in covariate data sources; for example, the JME model incorporates a sociodemographic index (SDI) as a covariate. The SDI is a composite measure generated by IHME/GBD, which incorporates total fertility rate under the age of 25, mean education for those aged 15 and older, and lag distributed income per capita. Recent IHME/GBD models do not include the SDI as a covariate but include fertility and educational attainment in women aged 15–49 years.

of individual children with implausible values or outliers) and survey quality assessments, and mandates the use of survey weights, but does not routinely involve the use of statistical models to address random errors, excess skewness or dispersion of parameter distributions, or systematic biases due to low-quality raw data or inadequate population representativeness. Survey-specific estimates serve as inputs into multi-survey models that are used to generate predicted prevalences for global tracking of progress towards Global Nutrition Targets.[14] Other methods, such as the modelling developed by IHME/GBD, use cluster-level estimates of prevalence and geospatial covariates as model inputs, and geostatistical modelling to generate small-area predictions; however, raw input data are still affected by the same considerations of quality and representativeness that pertain to survey-level estimation.

The relative advantages and limitations of the various modelling methods have not been widely discussed in the literature. Moreover, published comparisons of corresponding predictions are lacking and there is no standard framework for model validation. Several specific issues warrant further research: the robustness of available approaches when outliers or implausible anthropometric measurements are retained in the dataset; whether predictive accuracy can be improved by incorporating survey quality metrics as covariates or weightings; the extent to which the modelling method should be customized to each indicator type (e.g., wasting versus stunting or overweight); and, the advantages of small-area estimation, which is becoming increasingly popular but for which the impact on policymaking remains to be established. Furthermore, current conventional malnutrition indicators are based on the proportions (or risks/probabilities) of measurements in the lower/upper tail of the anthropometric z-score distributions, as recommended by WHO/UNICEF. Further research should explore alternative representations of height distributions, particularly when making comparisons of linear growth deficits across age subgroups, for which mean HAZ or stunting prevalence estimates are not well-suited.[3]

This brief describes a research agenda for the development and validation of methods used in the statistical analysis of single anthropometric surveys and multi-survey models for estimation and prediction of malnutrition indicators.

Research questions

1	**What criteria should be used to assess and compare the validity of malnutrition indicator prediction models?**
2	**How are malnutrition prevalence predictions based on current JME and IHME/GBD models influenced by model specifications, assumptions and analytical decisions?**
3	**How can the statistical models used to estimate or predict anthropometric indicators be adapted or extended to: a) enable inclusion of individual child outliers and implausible values in analysed datasets; and to b) incorporate information from survey data quality assessments?**
4	**How are small-area estimates of malnutrition indicators used to guide public health policymaking and programming in low- and middle-income countries?**
5	**What are the advantages and limitations of alternative expressions of population height distributions to describe and track linear growth faltering in low- and middle-income countries?**

Research topic 1

What criteria should be used to assess and compare the validity of malnutrition indicator prediction models?

APPROACH 1

Type of research	Outcomes	Data source(s)
Mixed methods review: Conduct a landscape review of published literature to identify criteria that should be used to guide the assessment and validation of statistical models used to predict malnutrition burden.	**Primary:** Summary of available evidence that supports the use of specific criteria related to model validation and selection. **Secondary**: Summary of published reports of model validation or between-method comparisons.	Peer-reviewed literature, including relevant validation studies, review papers and commentaries. Technical documents from international agencies that describe methods used to select or justify the implementation of statistical models.

APPROACH 2

Type of research	Outcomes	Data source(s)
Qualitative: Use the Delphi method or another consensus-oriented process to convene experts and stakeholders to review the evidence from the mixed methods review (approach 1) and develop a model validation framework. Consider how criteria should be customized for different indicators (e.g., wasting versus stunting/overweight).	**Primary:** Standard framework and list of criteria to guide the comparative assessment and validation of statistical models used to predict malnutrition burden indicators.	Questionnaires administered to a panel of technical experts and other stakeholders, combined with virtual or in-person discussions.

Research topic 2

How are malnutrition prevalence predictions based on current JME and IHME/GBD models influenced by model specifications, assumptions and analytical decisions?

APPROACH 1

Type of research	Outcomes	Data source(s)
Secondary analyses: Conduct a comparative analysis of published prevalence estimates from JME and IHME/GBD. Conduct new analyses using JME and IHME/GBD methods to assess how modifications of model parameters or specifications contribute to improved correlation and agreement between outputs from JME and IHME/GBD models.	**Primary:** Model specifications or assumptions that influence predictions based on JME and IHME/GBD models. **Secondary**: Correlation and absolute agreement between paired predictions at country/year- level, overall and in subgroups defined by world region, calendar year or other country-level classifiers.	Published malnutrition indicator estimates from JME and IHME/GBD. Raw datasets (model inputs) and statistical code files used by JME and IHME/GBD.

Research topic 3

How can statistical models used to estimate or predict anthropometric indicators be adapted or extended to: a) enable inclusion of outliers and implausible values in analysed datasets; and to b) incorporate information from survey data quality assessments?

APPROACH 1

Type of research	Outcomes	Data source(s)
Mixed methods review: Conduct a systematic literature review and consult technical experts to identify relevant statistical modelling methods that may enable values identified as outliers/implausible to be appropriately included in analysed datasets.	**Primary**: Listing and description of candidate modelling approaches that would be suitable for datasets that include values usually considered to be outliers or implausible.	Peer-reviewed literature; interviews with statisticians and other content experts.

APPROACH 2

Type of research	Outcomes	Data source(s)
Secondary analyses: Examine the impact of including outliers or implausible values on estimates or predictions of malnutrition indicators in analyses of anthropometric survey datasets using: a) conventional methods for single- or multi-survey analyses; and b) candidate statistical or machine learning methods that have not been commonly used for anthropometric data analyses (per approach 1).	**Primary:** Differences in prevalence estimates/predictions generated using datasets that include versus exclude outliers/implausible values, for each method.	Population-representative anthropometric surveys from low- and middle-income countries.

APPROACH 3

Type of research	Outcomes	Data source(s)
Secondary analyses: Examine the impact of incorporating quantitative metrics of survey data quality as covariates or weightings in analyses of anthropometric survey datasets using existing methods for multi-survey analyses.	**Primary:** Differences in prevalence estimates/predictions generated when including versus excluding metrics of survey data quality as model covariates.	Population-representative anthropometric surveys from low- and middle-income countries.

Research topic 4

How are small-area estimates of malnutrition indicators used to guide public health policymaking and programming in low- and middle-income countries?

APPROACH 1

Type of research	Outcomes	Data source(s)
Mixed methods review: Conduct a review of published literature to identify studies or reports regarding the policy-relevant applications of small-area estimates of malnutrition indicators.	**Primary:** Examples of the applications of small-area estimates to improve population health through policy and programming.	Peer-reviewed literature. Technical documents from agencies involved in conducting or disseminating anthropometric survey results, or those that use the outputs of such surveys to guide policy or programming.

APPROACH 2

Type of research	Outcomes	Data source(s)
Qualitative: Use the Delphi method or another consensus-oriented process to convene experts and stakeholders to consider the value and applicability of small-area estimates of malnutrition prevalence in public health priority-setting, policymaking and programming.	**Primary:** Summary of conclusions and recommendations of the expert and stakeholder panel.	Questionnaires administered to a panel of technical experts and other stakeholders, combined with virtual or in-person discussions.

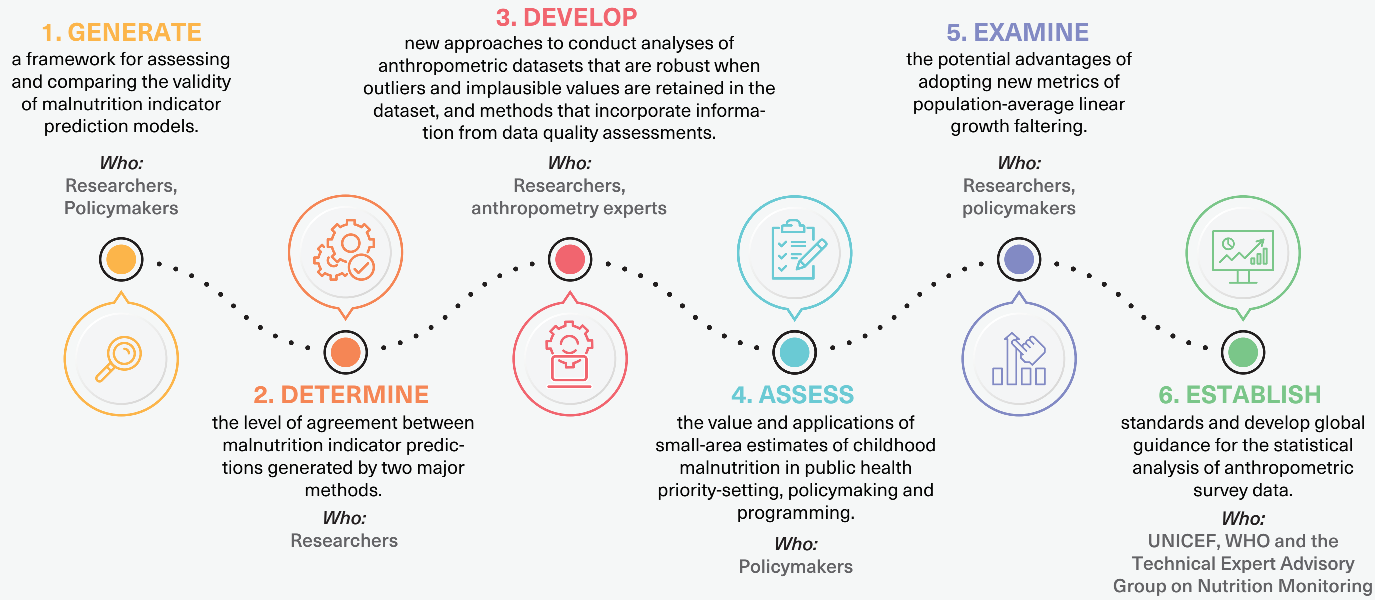
Research topic 5

What are the advantages and limitations of alternative expressions of population height distributions to describe and track linear growth faltering in low- and middle-income countries?

Type of research	Outcomes	Data source(s)
APPROACH 1		
Secondary analyses: Adapt existing statistical approaches for modelling stunting prevalence to generate estimates of alternative metrics of height distributions, such as height-for-age difference and height-age/growth delay.	**Primary:** Descriptions and summaries of alternative metric distributions and patterns.	Population-representative anthropometric surveys from low- and middle-income countries.
APPROACH 2		
Qualitative: Use questionnaires, interviews and focus groups to assess the effect of using alternative metrics on respondents' perceptions of the burden of linear growth faltering, including between-country differences, secular trends and age-related growth trajectories.	**Primary:** Summary and analysis of stakeholder responses.	Questionnaire responses and transcripts of interviews and focus groups involving technical experts and other stakeholders.

Research roadmap

The proposed research agenda aims to address technical issues and areas of uncertainty related to the statistical analyses of anthropometric survey datasets in the context of single-survey analysis that may be relevant to one country, as well as larger-scale multi-survey analyses and prediction modelling used for global burden assessments and progress tracking. The overarching goal is to promote the development and adoption of statistical models that produce valid estimates and predictions and, where possible, to facilitate the harmonization of methods across technical and end-user groups to ensure consistency in the generation, interpretation and application of childhood malnutrition indicators worldwide.



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If interested in joining this effort

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