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ESTIMATING THE PREVALENCE OF NUTRIENT INADEQUACY FROM HOUSEHOLD CONSUMPTION AND EXPENDITURE SURVEYS

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ESTIMATING THE PREVALENCE OF NUTRIENT INADEQUACY FROM HOUSEHOLD CONSUMPTION AND EXPENDITURE SURVEYS

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Abstract

Malnutrition is pervasive in both low- and middle-income countries. Yet, there is a scarcity of food consumption data collected at the individual level to describe diets, determine the prevalence of inadequate nutrient consumption in populations, and to shed light on how diets contribute to the malnutrition burden. In the absence of nationally representative individual-level food consumption surveys, particularly in low- and middle-income countries, many researchers are using food data collected in household consumption and expenditure surveys (HCES) as a second-best option to make inferences on the food and nutrient consumption of populations.

To assess the prevalence of nutrient inadequacy (PoNI) in a population, it is necessary to have information on the distribution of usual consumption. To that aim, dietary surveys usually collect repeated observations on individual food consumption over short-term reference periods (usually, 24 hours). To estimate usual consumption, data must thus be treated to remove within-person variation (i.e. to adjust for excess day-to-day variability). This is achieved with statistical methods such as the one developed by the National Cancer Institute of the United States (NCI method) (US National Cancer Institute, 2021), which also removes some of the measurement errors.

Household-level food consumption data, on the other hand, are collected with longer reference periods (one week to one month). Daily per capita consumption values, obtained as an average over the number of days in the reference period and the number of people that partakes the households' food, are interpreted as direct estimates of usual consumption. However, estimating the distribution of usual consumption in the population presents a challenge due to presence of various types of measurement errors. Not treating the data to remove excess variation due to measurement errors can induce biases when estimating the prevalence of inadequate consumption.

The aim of this study is two-fold: i) to present an approach for adjusting nutrient consumption data from HCES for excess variability due to measurement error; and ii) to present a method for using those data for estimating the PoNI. Both are inspired from elements of the Food and Agriculture Organization of the United Nations (FAO) methodology to compute the prevalence of undernourishment (PoU).

We demonstrate the effectiveness of the approach for adjusting HCES consumption data for excess variability and estimating the distribution of usual consumption levels by comparing estimates of coefficients of variation (CVs) from the 2015 Bangladesh Integrated Household Survey before and after adjustment. Further, using the same survey, we estimate the prevalence of inadequacy for eight micronutrients (vitamins A, B1, B2, B6, B12 and C, and calcium and zinc) based on the adjusted, household-level, food consumption data and contrast them with estimates obtained from food consumption data at the individual level, collected from the same households through two household-level 24-hour recalls, adjusted to control for day-to-day variability using the NCI method), a standard approach for this type of analysis. We find that the CVs obtained from adjusted household-level data are very similar or only slightly higher than those estimated using individual-level data, with differences that vary depending on the nutrient, ranging from 0.5 percentage point for vitamin A (CV = 36.6 percent against 37.1 percent, with the two methods respectively) to 16.7 percentage points for vitamin B12 (53.0 percent against 36.3 percent). This confirms that our proposed method to treat household-level food consumption data achieves the desired result in terms of controlling excess variability. However, the PoNI for the eight

micronutrients estimated using the adjusted household-level data are always lower than the corresponding estimates obtained from individual-level data. For two micronutrients (calcium and vitamin A), for which we find very high PoNI, the differences are minimal, but for the other six micronutrients, the differences in estimated PoNI range from 14.6 percentage points to 41.6 percentage points, depending on the nutrient considered. Given the closeness of the estimated coefficient of variation, the main reason for the lower PoNI is the invariably higher value for the *average* consumption level obtained from household-level data, compared to that obtained from the individual-level data.

Overall, our results show that (a) estimates of average nutrient consumption based on data collected using modules typically included in HCES are higher than those obtained from food consumption data collected at individual-level; (b) failing to adjust food consumption data from HCES for excess variability would generate biased estimates of PoNI; and (c) when estimating the PoNI with the FAO methodology, for non-episodically consumed nutrients, a reliable CV parameter can be obtained from HCES data. From these, we conclude that the exclusive use of HCES data to estimate the PoNI is indeed a promising avenue to obtain assessment when no large-scale dietary surveys are available. Given the growing importance of food consumed away from home, efforts should be made to increase the reliability of food consumption data collected in HCES, especially with respect to the ability to correctly represent food consumed away from home.

Contents

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1 Introduction

Deficiencies in essential micronutrients contribute greatly to the global burden of disease, affecting children's physical and cognitive development, exacerbating disease and resulting in decreased work capacity and earning potential. Deficiencies most likely occur when people do not have access to micronutrient-rich foods, usually because they are too expensive to buy or are locally unavailable (Bailey, West and Black, 2015).

The sufficiency status of individuals for micronutrients is usually best determined using biomarkers. However, not all micronutrients have a biomarker, and when these are available they are not always practical or feasible for widespread assessment or for use outside the clinical setting (Bailey, West and Black, 2015; Carriquiry, 2017). Individual dietary intake surveys, with all the methodological challenges they carry, represent an inevitable alternative to the estimation of micronutrient consumption (Carriquiry, 2017) and so far represent the best data source for dietary assessment (Gibson, Charrondiere and Bell, 2017). However, individual quantitative dietary data are usually not representative at national level, especially in low- and middle-income countries (Micha *et al.*, 2018), or they do not cover the whole diet, as found in a study of individual-level food consumption surveys from 19 European countries (Rippin *et al.*, 2018). Thus, to make inferences in the food consumption of populations, researchers have been using other data types like food consumption data from household consumption and expenditure surveys (HCES) and food availability data from food balance sheets (FBS).

For the assessment of the inadequacy of nutrient consumption in particular, researchers have used FBS data because it has a wide country and time coverage. To assess the prevalence of nutrient inadequacy (PoNI) in a country, it is important to have information on the average consumption and the inequality in consumption (that is, the variability in the distribution of consumption in the population, measured by the coefficient of variation). Given that FBS data do not provide information on the variability in the distribution of consumption, researchers have proxied the average consumption with FBS data and the variability using coefficients of variation based on small studies conducted in children from low-income countries several decades ago (Arsenault, Hijmans and Brown, 2015; Beal *et al.*, 2017). Using the same coefficient of variation to derive estimates of the PoNI of a nutrient from a large number of countries is less than ideal (Passarelli *et al.*, 2022) because the differences in diet quality (Darmon and Drewnowski, 2008) and nutrient intake (Novaković *et al.*, 2014) between population groups of different socioeconomic status may be highly country-specific (The Independent expert group of the Global Nutrition Report, 2020).

HCES represent a good alternative to the use of FBS data for dietary adequacy assessments and have been increasingly used for food and nutrient consumption analyses (e.g. Fiedler, 2014; Álvarez-Sánchez, C. *et al.*, 2021; Troubat and Sharp, 2021). They are typically used by FAO to estimate the variability in the distribution of usual[1] dietary energy consumption, controlling for measurement errors, to assess chronic dietary energy inadequacy (also known as chronic undernourishment) (Borlizzi, Delgrossi and Cafiero, 2017; Wanner *et al.*, 2014). HCES data have also been used, although to a lesser extent, to estimate the PoNI (Bermudez *et al*., 2012; Dop *et al*., 2012; Mekonnen *et al.,* 2020), but – to the best of our knowledge –

[1] By usual consumption we refer to the average consumption of food over a period of a least one year. It is also often referred to as "habitual" consumption (Cafiero, 2014).

this has always been done without controlling for the potential impact of measurement errors in assessing the variability in nutrient consumption.

This paper proposes a method to estimate the PoNI using food data collected at the household level after adjusting them for excess variability. The method builds on the one developed by FAO to estimate the prevalence of undernourishment used in the global monitoring of food insecurity (FAO *et al.*, 2021).

1.1 Concept of usual consumption

Dietary recommendations are intended to be met over a long-term period; therefore, the assessment of nutrient inadequacy using food consumption data requires information on the distribution of usual nutrient consumption, and not short-term consumption. Usually, HCES collect the apparent consumption of food of the entire household (hereafter referred to as "household-level food consumption") during a reference period of 7 or 14 days. Such data, however, are known to be subject to different types of measurement error (FAO and The World Bank, 2018; Friedman *et al.*, 2016), which can inflate estimates of the variability in food consumption across households, even when such errors may be assumed to be non-systematic. Furthermore, when samples are not properly time-stratified, seasonality can induce variation in the recorded nutrient consumption that should also be controlled for when the interest is on usual, rather than seasonal, consumption. As a result, when used to estimate the distribution of usual consumption in a population, data from HCES should be treated to remove excess variation due to measurement errors and seasonal variability.

1.2 Assessing the prevalence of inadequate nutrient consumption

Two methods have been traditionally used to estimate the PoNI (Gibson, 2005). One is the probability approach, which requires comparing the distribution of nutrient intake with the distribution of requirements. The other one is the Estimated Average Requirement (EAR) cut-point method, which uses only the mean of the distribution of requirements as a threshold (Carriquiry, 1999) and has been widely used as an easier alternative to the probability approach. This method consists in a simple count of individuals whose estimated usual consumption is below the average requirements of the population and stands on the assumption that the distribution of intake is statistically independent from the distribution of requirements.

To estimate the PoU, based on the adequacy of dietary energy consumption, the FAO Statistics Division has developed a method that resembles the EAR cut-point method, but is consistent with the assumption that dietary energy intake is highly correlated with dietary energy requirements for those people who are adequately nourished, while the correlation breaks down for the undernourished and the overnourished. The method (hereafter referred to as the "FAO probabilistic cut-point method") is based on defining a parametric model for the distribution of usual, daily dietary energy intake levels for the *average individual* in the population and contrasting it with the range of dietary energy requirements that are consistent with an active and healthy life for the same average individual. In its most recent version, the FAO probabilistic cut-point method assumes a log-normal distribution for the usual daily dietary energy consumption levels, defined by two parameters (the mean and the coefficient of variation). The prevalence of dietary energy consumption inadequacy is then obtained as the cumulative probability that the daily usual consumption of nutrients is below the appropriate threshold, which corresponds to the lower end of the range of requirements for the average individual in the population (Cafiero, 2014).

The reliability of the method depends crucially on the possibility to correctly estimate the distribution of usual dietary energy consumption levels for the average individual in the population. While not a problem to estimate the *average* consumption, using data affected by random errors, such as those collected in HCES, requires statistical treatment to correct for excess variability, which, if untreated, would inflate the estimate of the parameters that represents the spread of the distribution. For that reason, the FAO Statistics Division has devised appropriate methods to treat dietary energy consumption data from HCES, used them since the 1990s (FAO, 1996) and continuously refined them over time (Álvarez-Sánchez *et al.*, forthcoming; Naiken, 2003; Wanner *et al.*, 2014).

1.3 The FAO method extended to nutrients

In this paper, we propose to extend the FAO probabilistic cut-point method to the estimation of the prevalence of inadequacy to a set of nutrients other than dietary energy, using food consumption data collected in HCES. For each nutrient in the set, we estimate the probability that the nutrient's usual consumption level of a randomly selected individual is inadequate to satisfy their nutrient requirements consistent with long-term and good health. As with the traditional FAO probabilistic cut-off method, we assume a log-normal distribution for the usual, daily consumption level as it applies to the average person, meant to represents the whole population. Such an average person is a statistical device used to reflect all sexes, ages and physiological statuses of the individuals in the population under study.[2] Note that the concept of an *average* individual is different from that of a *reference* individual, used for example in defining the adult male equivalent (AME) concept (Weisell and Dop, 2012).

The only difference in applying the method to estimate the PoNI, instead of the PoU, lies in how the appropriate threshold to determine inadequacy is defined. For dietary energy, to the extent that people can adjust their food consumption levels, individuals with higher requirements tend to also have higher intakes, and vice versa (Institute of Medicine, 2000), because regulatory human body mechanisms operate to maintain a balance between energy intake and requirements. As a result, for people who are not chronically undernourished, in the long run energy intake tends to equal energy requirements. Therefore, in the absence of interference factors, dietary energy intake and dietary energy requirements, though variable, are highly correlated within large groups of people (FAO, WHO and United Nations University, 1985). For this reason, the EAR cut-off method (where the estimated average requirement is used as a cut-off point) cannot be applied to estimate energy inadequacy, as it would lead to a significant overestimation (Carriquiry, 1999). To appreciate why, we consider the extreme example of a population where everybody eats according to their energy requirement: there would not be dietary energy consumption inadequacy and there would be perfect correlation between dietary energy intake and requirements. In such a case an EAR cut-off method would incorrectly predict 50 percent inadequacy, as one half of the group would have usual intakes that are less than the EAR of the whole group. This is where the FAO probabilistic cut-off method differs substantially from the EAR cut-point method, as the FAO method recognizes the variability in dietary energy requirements (induced by variations in characteristics such as sex, age, body mass, physical activity levels and physiological status) and uses it to determine a *range* of dietary energy requirements that applies to the average individual. Then, the minimum of that

[2] The concept of an average individual is implicitly used when assessing the PoNI when using only Food Balance Sheets (FBS) data, and with reference to per capita values (Arsenault, Hijmans and Brown, 2015; Beal *et al.*, 2017), and explicitly used to assess the prevalence of undernourishment with both FBS (FAO *et al.*, 2021) and HCES data (Moltedo *et al.*, 2014).

range (Minimum Dietary Energy Requirement, or MDER) rather than the EAR is properly used as a threshold to estimate dietary energy inadequacy.

For micronutrients such as vitamins and minerals, there is no conclusive evidence that intake is correlated with requirements (Murphy and Vorster, 2007; Carriquiry, 1999; Institute of Medicine, 2000). Individuals with higher requirements for a certain vitamin or mineral do not tend to automatically select diets with a higher content in that nutrient and, therefore, the common approach to assess the PoNI through the EAR cut-point method will generate unbiased estimates on the implicit assumption that intake and requirements are statistically independent random variables (Carriquiry, 1999). In those cases, the average of the range of requirements can be safely used as a threshold to estimate the PoNI, irrespective of whether one uses the empirical distribution of usual consumption levels, or – as with the FAO method – refers to the distribution of values as applicable to the *average* individual.

In this paper, applying the FAO probabilistic cut-point method, the PoNI is therefore obtained as the cumulative probability that usual nutrient consumption levels of the average individual (x) is below the mean of the distribution of nutrient requirements, as shown in Equation 1.

$$PoNI = \int_{x<EAR} f(x|\mu; CV)dx \qquad \text{[Equation 1]}$$

where: EAR is the estimated average requirement of the population for the nutrient under analysis; μ and CV are, respectively, the mean and the coefficient of variation that define the log-normal distribution of usual nutrient consumption for the average individual.

2 Methodology

2.1 Data

We used data from the second round of the Bangladesh Integrated Household Survey (BIHS) conducted from January to June 2015, which includes a typical household-level seven-day recall (7DR) module and two 24-hour recall (24HR) modules.[3] As is typical in most HCES, the 7DR collected information on food consumption for the entire household in the previous seven days, with no information regarding the allocation of that food to individual members. The 24HR module collected information on foods consumed in the household in the previous 24 hours and on its allocation among household members. Both modules are designed to also capture food consumed away from home. While the first 24HR recall interview covered the entire sample, the second one was conducted only in ten percent of the households, and the purpose was to collect sufficient information to estimate day-to-day variability in food consumption. Information on households' socioeconomic characteristics, sex, age, pregnant and lactating status, and height of household members was also recorded and used in the analysis. It is worth noting that the amount of food reported as consumed away from home (FAFH) in the 24HR module appears suspiciously low, which we shall return to later in this paper.

The sample is statistically representative at the following levels: (a) nationally representative of rural Bangladesh; (b) representative of rural areas of each of the seven administrative divisions of the country: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur and Sylhet; and (c) representative of the Feed the Future (FTF) zone of influence. Our analysis is conducted on the sample that represents rural Bangladesh. We excluded 124 households with incomplete surveys (refused, migrated or were not at home during survey). We also excluded individual records of children less than 2 years of age because a large number of them were exclusively breastfed. We also excluded individual records with missing data in the 24HR module, which could have happened either because those people were away from home at the time of the survey, or because they did report not consuming any food in the specific 24 hours considered. The final analytical samples consisted of 5 427 households with 22 319 household members for the 7DR module, and 5 424 households with 21 310 individuals for the 24HR module (considering the two rounds).

2.2 Selection of micronutrients

The nutrients selected for the study are vitamin B1 (thiamine), vitamin B2 (riboflavin), vitamin C, vitamin A, vitamin B6, vitamin B12, zinc and calcium. The criteria used in selecting the micronutrients included: public health relevance, wide availability of nutrient data in relevant food composition tables/food composition databases (FCTs/FCDBs) and suitability of the information collected through HCES to analyse the nutrients under consideration. Iron, folate, iodine and sodium were also considered, but not selected. Iron was excluded because the distribution of requirements in some population groups is skewed. In such cases, the methodology to adjust household-level data for excess variability would be very complex and would require a separate study. Folate was excluded because reliable data on folate content in foods are generally not available in FCTs/FCDBs (Olivares *et al.*, 2006). In the case of iodine and sodium, the best

[3] We downloaded the 2015 BIHS database from the Harvard Dataverse data repository (IFPRI, 2016a). Detailed information on the sampling procedures, survey methodology and questionnaires are provided in IFPRI (2016b).

method to assess intake is through the analysis of urinary samples, not dietary assessment, given that results based on the latter are known to be largely underestimated (Carriquiry *et al.*, 2016; McLean, 2014).

2.3 Determination of the threshold

The threshold used to estimate the PoNI of a specific nutrient in a population group corresponds to the EAR of that nutrient. As the FAO probabilistic method is defined in terms of the average individual and is applied to the total population, the threshold used in the model is obtained as the weighted average of the EAR for each sex-age group, using as weights the proportion of each group in the total population. The source of information for the distribution of zinc requirements was the International Zinc Nutrition Consultative Group (IZiNCG, 2004). We accounted for different levels of zinc absorption by comparing consumption to dietary requirements for both unrefined diets[4] and mixed[5]/refined[6] vegetarian diets. US Health and Medicine Division (HMD) values were used for calcium and for vitamin A (expressed in Retinol Activity Equivalents, or RAE) (US National Institutes of Health, 2019). The EAR of vitamin B12 was taken from FAO and WHO (2004). The EARs of vitamins B1, B2, B6 and C were calculated starting from the Recommended Nutrient Intake (RNI) values published by FAO and WHO (2004), using the formula EAR = RNI - 2 standard deviations, assuming a normal distribution of requirements with a CV of ten percent (IOM, 2006).

2.4 Data treatments

Food consumption data collected with both the 24-hour recall modules at the individual level, and the 7-day recall module at the household level needed to be processed to derive the corresponding values of nutrient consumption and to control for measurement error.

2.4.1 Individual-level food consumption from the 24-hour recall data

For the 24-hour recall data, foods were matched with food composition data also considering the way they were reported being consumed (e.g. raw, boiled, fried, etc.). There were five possible pathways involving single-ingredient foods and multi-ingredient dishes: (1) *Single-ingredient food consumed raw* (e.g. apples) were matched with a raw item in the FCTs/FCDBs; raw weights were used; adjustments to control for non-edible portions were made, as necessary. (2) *Single-ingredient food items consumed as cooked* (e.g. rice) were matched with a raw item in the FCTs/FCDBs; retention factors were applied in these cases, to account for alterations in nutrient content during cooking (Vásquez-Caicedo, Bell and Hartmann, 2007); again, raw weights were used; adjustment for non-edible portions was applied as necessary. (3) *Multi-ingredient dishes consumed cooked* with *no list of ingredients* (e.g. a "burger") were matched with cooked mixed dishes in the FCTs/FCDBs; reported cooked weights were used. (4) For *multi-ingredient dishes consumed raw with a list of ingredients* (e.g. a "salad"), each item/ingredient was matched with a raw item in the FCTs/FCDBs; raw weights were used; adjusting for non-edible portions as necessary. (5) For *multi-ingredient dishes consumed cooked, with a list of ingredients* (e.g. "bhuna curry"), each item/ingredient was matched with the corresponding raw item in the FCTs/FCDBs; retention factors were applied to account for alterations in nutrient content during cooking; raw weights were used;

[4] "Cereal-based diets, with > 50% of energy intake from unrefined cereal grains or legumes and negligible intake of animal protein" (IZiNCG, 2004).

[5] "Mixed diets, and lacto-ovo-vegetarian diets that are not based on unrefined cereal grains or high extraction rate (> 90%) flours" (IZiNCG, 2004).

[6] "Refined diets low in cereal fiber, and where animal foods provide the principal source of protein" (IZiNCG, 2004).

adjustments for non-edible portions were applied as necessary. The sum of nutrient content in the raw ingredients' quantities adjusted for retention factor yielded the total content of the nutrient in the multi-ingredient dish. The sizes of non-edible portions and the contents of vitamins A, B1, B2, B6 and C, calcium and zinc in the foods were mostly obtained from the *Food Composition Table for Bangladesh* (Shaheen *et al.*, 2013). When necessary to fill gaps, values from the Indian FCT (Longvah *et al.*, 2017), the Association of Southeast Asian Nations (ASEAN) Food Composition Database (Mahidol University Institute of Nutrition, 2014), and the US Department of Agriculture (USDA) Food Data Central database (US Department of Agriculture, 2019) were sourced, in the listed order of preference. The content of vitamin B12 in foods was obtained from the USDA database. Once values of individual's daily nutrient consumption level were computed, values laying outside the central interquartile range of the log-transformed series were considered outliers and substituted by the closest quartile.

To adjust short-term individuals' nutrient consumption for excess variability (i.e. to control for within-person day-to-day variation), we applied the method validated by the National Cancer Institute (NCI) as implemented in the MIXTRAN and DISTRIB macros, version 2.1, developed by the Center for Disease Control (US National Cancer Institute, 2021). The NCI method produces estimates of usual consumption based on non-linear mixed regression models assuming that the 24-hour intake is an unbiased estimator of individuals' usual consumption on the original scale. This means that biases such as underreporting, implicit in self-reported dietary data, or other systematic biases are not removed when estimates of usual consumption are obtained (Ahluwalia *et al.*, 2016). There are two variants of the MIXTRAN macros. The "one-part" (or amount-only) macro-model (US National Cancer Institute, 2022) is appropriate when the distribution of consumption is defined over strictly positive values and was applied to the pooled samples for all nutrients except for vitamin B12. Estimates of consumption are adjusted for sex, age, region and income decile group, and for "sequence" (i.e. sequence number of an individual's records) and "weekend" (i.e. weekend or weekday record) effects. As the percentage of individuals with zero consumption was above 10 percent, for vitamin B12 we applied the MIXTRAN "two-parts" macro-model with correlated and with independent random effects (US National Cancer Institute, 2022). Once again, the models were applied to the pooled sample, adjusting for sex, age, "sequence" and "weekend" effects.[7] The sex-age groups were defined according to each nutrient's requirement groups and sampling weights were used to infer the estimates at the population level. Finally, the potential effect of seasonality in nutrient consumption was removed by adjusting daily per capita nutrient consumption for each nutrient using a seasonal factor.[8]

2.4.2 Household-level food consumption from the 7-day recall data

For the 7-day recall data, single-ingredient foods consumed raw were matched as described for the 24-hour data. In the absence of information on the non-edible portion for a given food (e.g. for some types of fish), we used the value available for similar items. In the case of multi-ingredient dishes prepared and consumed away from home, the 7DR module did not collect information on quantities consumed, but only on the associated expenditures. Therefore, the contribution of each nutrient from these items was estimated from the corresponding expenditures, based on the median (at the region-income quintile

[7] Adjustment for region and income decile group was not conducted due to the amount of time needed to process the data.

[8] The seasonal factor corresponds to the ratio of the nutrient yearly weighted average by the nutrient monthly weighted average for each region. These factors indicate by how much the monthly regional average nutrient deviates from the yearly regional average.

level) of the ratio between the expenditure and quantity of each nutrient from the item's at-home consumption (Moltedo *et al.*, 2018). Outliers and seasonal effects were treated in the same way as described for individual-level data. The procedure followed to control for excess variability due to measurement error is described in section 3.2.

2.4.3 Other data

In addition to food consumption data, aggregate households' consumption expenditures, as computed by the International Food Policy Research Institute (IFPRI), were used as a proxy of households' incomes. Consumer and food price indices (FAO, 2019) were used to deflate households' income and food expenditure respectively.

3 Estimating the prevalence of nutrient inadequacy

3.1 Individual-level food consumption from the 24-hour recall data

Using 24HR data, PoNI estimates were computed using two alternative approaches, depending on whether the NCI method to control excess variability is applied to each sex-age group separately, or to the whole sample.

In the *stratified analysis*, the NCI method is applied to each sex-age group separately, meaning that a distribution of usual nutrient consumption is estimated for each sex-age group separately, a PoNI value is estimated for each group, and the prevalence for the entire population is obtained as the weighted average of the PoNI in the different groups, using group sizes as weights. We refer to this as the disaggregate framework (24HR-NCI-Disag model).

In the *pooled* analysis[9] (24HR-NCI-Agg model) the NCI method is applied only once to the entire sample; one overall distribution of usual consumption is obtained; and the PoNI value is obtained as the percentage of cases for which usual consumption is below the EAR of the whole population. We refer to this as the aggregated framework. In this framework, it was also possible to estimate a CV of the usual nutrient consumption distribution of the average individual in the population, as the weighted standard deviation divided by the weighted average of the distribution, using the distribution produced by the NCI method, to be compared with the values obtained from the 7DR data.

3.2 Household-level food consumption from the 7-day recall data

To estimate the PoNI using 7DR data we use the probabilistic EAR cut-point method, assuming a log-normal distribution for usual nutrient consumption. We derive both the mean and the CV from the 7DR data. The CV is estimated both before and after adjusting for seasonality and for excess variability, to determine the extent of excess variability that is removed from the series. In practice, we followed five main steps.

Step 1. Transform households' total consumption into per capita consumption

The total consumption of each nutrient is divided by the number of household members to obtain an estimate of the average, per capita, daily consumption in each household. In this way, variability in nutrient consumption of people of different sex, age and physiological status within a household is neglected. This is not a problem for nutrients whose consumption is assumed to be independent of requirements, the average requirement in the population could be used as a threshold (contrary to the case with dietary energy), and no further adjustment is necessary when computing the usual consumption distribution of the average individual.[10] Furthermore, possible economies of scale linked to efficiency in

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[9] Before performing the analysis on the whole sample (i.e. without disaggregating by sex-age groups) we verified that the ratios of the variance's components (i.e corresponding to within-person and between-person variation) were similar between the sex-age groups (Davis *et al.*, 2019).

[10] Many studies based on methods designed to be applied to individual consumption data have been conducted using data collected in HCES. In those cases, to "individualize" food consumption starting from household-level data, some have applied modelling approaches where the total household food consumption is assigned to different household members based on age and sex (Naska, Vasdekis and Trichopoulou, 2001; Vasdekis, Stylianou and Naska,

managing bulk quantities of food by larger households are not considered here, as we make no attempt to control for household level waste.[11]

Step 2. Estimate the mean of the distribution of usual nutrient consumption

The mean of the distribution of usual nutrient consumption levels for the average individual was simply estimated as the weighted[12] average of daily per capita households' apparent nutrient consumption from the 7DR data. As measurement errors are assumed to be random, there is no need to adjust the data to estimate the mean.

Step 3. Estimate the CV

An empirical CV could be computed as the ratio between the weighted standard deviation and the weighted mean of the series of average daily usual consumption values of all households. Such a value, however, will be affected by the presence of random measurement errors and could not be deemed an unbiased estimate of the actual CV of usual nutrient consumption in the population. To obtain the needed adjustment for excess variability due to measurement errors, we use the same approach used by FAO in treating dietary energy consumption when estimating the PoU (see Álvarez-Sánchez *et al.*, forthcoming). To that aim, values of per capita nutrient consumption in each household are modelled as the dependent variable in a regression against relevant household characteristics[13] (see Equation 2).

$$NC_h = \ln(Income_h) + \ln(Income_h)^2 + Region_h + Region_h * \ln(Income_h) + Region_h * \ln(Income_h)^2 + \varepsilon_h \qquad \text{[Equation } 2\text{]}$$

where: NC is the daily per capita nutrient apparent consumption; $Income$ is the daily per capita income; $Region$ is a set of dummy variables indicating the region in which the household is located; ε is the error term.

The needed estimate of the CV would be obtained as the ratio between the weighted standard deviation and the weighted mean of the series of predicted values from the regression. The rationale is that all other sources of variability will be captured by the regression residual and thus eliminated. It is important to note that, before applying Equation 3, both per capita nutrient consumption and household incomes were adjusted for seasonality using a different seasonal factor for each nutrient (see footnote 8), so that the CV will not be influenced by seasonality in food consumption.

Step 4. Estimate the PoNI

The final step is the estimation of the PoNI, obtained as

$$PoNI = \phi(\ln(EAR), \mu, sd) \qquad \text{[Equation 3]}$$

2001). Others have assumed an allocation of food according to household members' energy requirements using adult male equivalent (AME) factors (Coates *et al.*, 2017).

[11] Neglecting economies of scale would be a rather strong limiting assumption in analyses of food expenditures, rather than consumption, since purchasing larger quantities, as usually done by larger families, usually implies non-negligible savings.

[12] Using population weights defined as household weight times household members.

[13] Due to the high correlation between income and other socioeconomic characteristics, only income is used as independent variable in the regression.

where EAR is the Estimated Average Requirement; $sd = \sqrt{ln(CV^2 + 1)}$, $\mu = \ln(mean) - 0.5 * sd^2$, and $mean$ is the inferred average daily per capita apparent consumption; *CV* is the coefficient of variation and *ϕ()* is the normal probability density function.

4 Results

In this section, for each of the analysed nutrients, we compare estimates of the average consumption; of the coefficient of variation of usual consumption; and of the prevalence of nutrient inadequacy obtained from 24HR data and 7DR data respectively. All the results refer to the total population of rural Bangladesh. Table 1 presents the estimates of average consumption and requirements of each nutrient as obtained from the two data sets (24HR and 7DR).

Table 1. Average consumption and average requirements for the total population in rural Bangladesh (2015) estimated from 24HR and 7DR data

	Average consumption (person/day) from 24HR data	Average consumption (person/day) from 7DR data[a]	EAR (person/day) from 24HR data	EAR (person/day) from 7DR data
Calcium, mg	336	471	1 084	1 077
Zinc, mg, refined diet[b]	8.9	11.8	6.6	6.6
Zinc, mg, unrefined diet[b]	8.9	11.8	9.0	8.9
Vitamin A, μg RAE	196	277	495	491
Vitamin B1, mg	0.62	0.88	0.89	0.88
Vitamin B2, mg	0.60	0.84	0.91	0.91
Vitamin C, mg	55	94	35	35
Vitamin B6, mg	1.11	1.50	1.03	1.03
Vitamin B12,[b] μg	1.37	1.76	1.84	1.84

Notes: EAR = estimated average requirements; RAE = retinol activity equivalents.

[a] HCES collect food quantities at the household level, not at the individual level and households' consumption was divided by the number of people present in the household.

[b] In the case of zinc, assuming an unrefined diet implies a higher daily per person average dietary requirements (9.0 mg) than assuming a mixed/refined diet (6.6 mg), due to a lower bioavailability of zinc in an unrefined diet.

[c] The two-part model with correlated and with independent random effects (see section 2.4.1 above) produced the same average consumption estimate.

Source: Author's own elaboration.

Not surprisingly, estimates of the EAR for the entire population, derived from the two sets of data, are very similar. Notably, though, the average consumption estimates from 7DR were higher than those from 24HR, for all nutrients. This result is consistent with similar findings in the literature (see, for example, Karageorgou *et al.*, 2018), confirming that household surveys that use the food consumption modules typically found in HCES data, tend to generate estimates of consumption that are higher than those obtained from individual-level data.

Possible reasons why 7DR modules may overestimate consumption includes: (a) the methodology used to estimate the nutrient content in food prepared and consumed away from home based on monetary values may results in too high energy values, as part of the expenditure on FAFH covers services provided the caterers (Moltedo *et al.*, 2018); (b) the fact that households may be misreporting the total quantities of food obtained from own production rather than the share that is actually consumed (based on the authors' experience in processing data from many HCES, this is a problem commonly encountered in surveys conducted in rural areas); and (c) the fact that quantities for foods that are actually consumed as cooked but reported in quantities acquired in their raw form (e.g. chicken), may be incorrectly matched with the nutrient contained in the raw form of the food, due to lack of information on the preparation method (e.g. roasted, fried, boiled, etc.) (Moltedo *et al.*, 2021b).

In general, individual dietary surveys are considered superior tools for the assessment of food consumption. However, studies have found that these surveys underestimate the consumption of foods due to recall errors, particularly by children and adolescents (Kerr *et al.*, 2015), and/or to under reporting the quantity of main staples included in a portion (Alemayehu, Abebe and Gibson, 2011; Arsenault *et al.*, 2020) and consequently leading to underestimating micronutrient consumption (Poslusna *et al.*, 2009). It must also be noted that the 24HR module used in the survey we analyze was not compiled by each person in the household, rather the information on each member was provided only by one person, who reported on the food consumed individually by all others too. It is likely that, for example, the food consumed away from home by other members of the households was underreported, which may contribute to underestimating the average.

This study presents empirical estimates of the levels of inequality in usual nutrient consumption for the whole referenced population, based on individual quantitative dietary data. The dataset analyzed in this study allows for the comparison of the CVs obtained from 24HR data with CVs obtained from 7DR data. Table 2 presents three different estimates of the coefficient of variation of the distribution of usual nutrient consumption. The first one (column A) obtained from 7DR data without adjusting them for excess variability; the second one (column B) from 7DR data adjusted for excess variability, and the third one (column C) with the 24HR data after having adjusted for excess variability using the NCI method. As expected, for all nutrients, adjusting the 7DR data for excess variability using the 7DR-FAO-CV model (column B), produced lower CV estimates compared to the CV obtained from the unadjusted 7DR data (column A).

Depending on the nutrient, the CVs estimated from 7DR data and adjusted for excess variability (column B), were similar or higher than those estimated using 24HR data (column C). The difference varies with the nutrient. For vitamin A the CV estimates were similar (37.1 percent with 24HR data and 36.6 percent with 7DR data (a negligible difference of only 0.5 percentage points). For vitamin B12, which was the only episodically consumed nutrient, the 7DR data produced a higher CV than the 24HR data (53.0 percent vs. 36.3 percent, respectively, that is a difference of 16.7 percentage points). The inequality in usual nutrient consumption differs between sex-age groups within and between countries (Passarelli *et al.*, 2022). This confirms the importance of producing up-to-date estimates of inequality levels in nutrient consumption for the whole population and the relevance of publishing the PoNI estimates with clear and detailed metadata including information on the data sources used in the analysis.

Table 2. Coefficients of variation in usual consumption of various nutrients estimated from 24-hours recall, individual-level data, and from 7-days recall, household-level data

	(A)	(B)		(C)	
	7DR Empirical (percent)	7DR FAO method (percent)	Difference (B - A) [percentage change (B - A) * 100 / A]	24HR (percent)	Difference (C - B) [percentage change (C - B) * 100 / B]
Calcium	62.2	42.3	-19.9 [-32.0%]	34.0	-8.3 [-19.6%]
Zinc	34.5	23.5	-11 [-31.9%]	22.2	-1.3 [-5.5%]
Vitamin A	81.9	36.6	-45.3 [-55.3%]	37.1	0.5 [1.4%]
Vitamin B1	45.7	31.8	-13.9 [-30.4%]	24.4	-7.4 [-23.3%]
Vitamin B2	46.5	33.1	-13.4 [-28.8%]	25.1	-8.0 [-24.2%]
Vitamin C	59.8	34.4	-25.4 [-42.5%]	30.4	-4.0 [-11.6%]
Vitamin B6	38.7	26.1	-12.6 [-32.6%]	22.5	-3.6 [-13.8%]
Vitamin B12	83.1	53.0	-30.1 [-36.2%]	36.3	-16.7 [-31.5%]

Notes: All values refer to the total population in rural Bangladesh in 2015.
(A): CV computed from 7DR data without adjustment to control for excess variability.
(B): CV computed from 7DR data after adjusting for excess variability, as per the FAO method.
(C): CV estimated from 24HR data, applying the pooled analysis, as the weighted standard deviation divided by the weighted mean of the distribution of usual nutrient consumption, derived with the NCI macros after having adjusted for within-person variation.
Source: Author's own elaboration.

Table 3 shows the PoNI values for the whole population in rural areas, computed using the NCI method for both the disaggregated (24HR-NCI-Disag) and the aggregated (24HR-NCI-Agg) models. We would have expected the two models to produce similar estimates of the prevalence of nutrient inadequacy; however, this was not always the case. When comparing the PoNI estimates from the two 24HR models, the larger differences are found for zinc within a refined diet (5.1 percentage points, equivalent to 33.1 percent of the value in column B) and for vitamin C (2.3 percentage points, that is a difference of 13.5 percent). In both cases, using the model based on the aggregated analysis produced higher nutrient inadequacy estimates than the analysis conducted separately by stratified sex-age groups. Even though we considered the appropriateness of performing a pooling analysis by comparing the similarity of the within-person ratios to between-person variance components of the sex-age groups (Davis *et al.*, 2019), it might be possible that the equal variance assumption may not hold for vitamin C.

Table 3. PoNI estimates using 24HR data, for the whole population in rural areas

	(A)	(B)	
	PoNI 24HR-NCI-Disag (percent)[a]	**PoNI 24HR-NCI-Agg (percent)[b]**	**Difference (B - A) [percentage change (B - A) * 100 / B]**
Calcium, mg	99.8	99.9	0.1 [0.1%]
Zinc, mg, refined diet	15.4	20.5	5.1 [33.1%]
Zinc, mg, unrefined diet	55.4	51.4	-4.0 [-7.2%]
Vitamin A, μg RAE	98.0	98.4	0.4 [0.4%]
Vitamin B1, mg	91.2	89.0	-2.2 [-2.4%]
Vitamin B2, mg	92.0	91.8	-0.2 [-0.2%]
Vitamin C, mg	17.1	19.4	2.3 [13.5%]
Vitamin B6, mg	40.5	41.2	0.7 [1.7%]
Vitamin B12,[c] μg	77.8	78.1	0.3 [0.4%]

Notes: RAE = retinol activity equivalents.

[a] PoNI model 24HR-NCI-Disag, using 24HR data, corresponds to disaggregate framework, adjusted for excess variability, and sex-age groups' PoNI values estimated with the NCI macros.

[b] PoNI model 24HR-NCI-Agg, using 24HR data, corresponds to aggregate framework, adjusted for excess variability, and computed with the NCI macros.

[c] The two-part model with correlated and with independent random effects produced the same PoNI estimates.

Source: Author's own elaboration.

Given that nutrient requirements are defined separately for different sex-age groups, the PoNI at the national level computed from sex-age groups' prevalence values produced by the NCI method was selected as the reference value for a comparison with the estimates obtained from 7DR data. Table 4 presents the PoNI values for the whole population in rural areas for the reference model (24HR-NCI-Disag) and the 7DR-FAO-CV.

Table 4. PoNI estimates for the whole population in rural areas, derived using models 24HR-NCI-Disag and 7DR-FAO-CV

	(A)	(B)	
	PoNI 24HR-NCI-Disag[a]	**PoNI 7DR-FAO-CV**[b]	**Difference (B - A) [percentage change (B - A) * 100 / B]**
Calcium	99.8	98.8	-1.0 [-1.0%]
Zinc, refined diet	15.4	0.8	-14.6 [-94.8%]
Zinc, unrefined diet	55.4	13.8	-41.6 [-75.1%]
Vitamin A	98.0	96.4	-1.6 [-1.6%]
Vitamin B1, mg	91.2	57.2	-34.0 [-37.3%]
Vitamin B2, mg	92.0	64.8	-27.2 [-29.6%]
Vitamin C	17.1	0.3	-16.8 [-98.2%]
Vitamin B6	40.5	9.0	-31.5 [-77.8%]
Vitamin B12	77.8	62.9	-14.9 [-19.2%]

Notes:
[a] PoNI model 24HR-NCI-Disag, using 24HR data, corresponds to the disaggregated framework, adjusted for excess variability, and sex-age groups' PoNI values estimated with the NCI macros.
[b] PoNI model 7DR-FAO-CV, using 7DR data, adjusted for excess variability and PoNI values computed with the FAO probabilistic EAR cut-point method.
Source: Author's own elaboration.

For all the nutrients, the PoNI estimates from 7DR data were lower than those estimated using 24HR data. Differences were very small for calcium and vitamin A, for which both models estimate prevalence values higher than 95 percent. Large differences are found instead for vitamin C (for which 7DR data point to no inadequacy, as opposed to a PoNI of 17.1 percent estimated from 24HR data) and for zinc, when assuming a refined diet (PoNI of 0.8 percent and 15.4 percent respectively). Clearly, these differences are due to the different level of estimated average consumption generated by the two models, as shown in Table 1; the average nutrient consumption from 7DR data was higher (almost double, in the case of vitamin C) than the correspondent estimate obtained using 24HR data.

Overall, most differences in PoNI estimates between 24HR and 7DR data come from differences in *average* consumption estimates. In the probabilistic EAR cut-point method, the mean of the distribution could be proxied with an average consumption estimate derived from different types of data (i.e. individual quantitative intake surveys, HCES or Food Balance Sheets). Therefore, to separate the effect of the different average consumption estimates, we computed the PoNI using the probabilistic EAR cut-point method, using the average consumption estimates obtained from the 24HR and the CV obtained from the 7DR data. Table 5 presents alternative sets of PoNI estimates and demonstrates how, once controlled for the level of average consumption, virtually no difference is found between alternative data sources for calcium and vitamin B2. A small difference is still found for vitamin C (5.3 percentage points), suggesting that, in this case, different sources of data imply some difference also in the extent of measured usual consumption inequality.

Table 5. PoNI estimates for the whole population in rural areas, derived using models 24HR-NCI-Disag and 7DR-FAO-CV using average consumption estimates from 24HR data

	(A)	(B)	
	PoNI 24HR-NCI-Disag[a]	**PoNI 7DR-FAO-CV using 24HR average consumption[b]**	**Difference (B - A) [percentage change (B - A) * 100 / B]**
Calcium	99.8	99.9	0.1 [0.1%]
Zinc, refined diet	15.4	12.0	-3.4 [-22.1%]
Zinc, unrefined diet	55.4	54.6	-0.8 [-1.4%]
Vitamin A	98.0	99.7	1.7 [1.7%]
Vitamin B1, mg	91.2	90.0	-1.2 [-1.3%]
Vitamin B2, mg	92.0	92.7	0.7 [0.8%]
Vitamin C	17.1	11.8	-5.3 [-31.0%]
Vitamin B6	40.5	43.5	3.0 [7.4%]
Vitamin B12	77.8	80.0	2.2 [2.8%]

Notes:

[a] PoNI model 24HR-NCI-Disag, using 24HR data, corresponds to disaggregate framework, adjusted for excess variability, and sex-age groups' PoNI values estimated with the NCI macros.

[b] PoNI model 7DR-FAO-CV, using the average consumption from 24HR data, CV from 7DR data adjusted for excess variability, and PoNI values computed with the FAO probabilistic EAR cut-point method.

Source: Author's own elaboration.

5 Discussion

5.1 Vitamin A

When measured as the prevalence of serum retinol <0.7 mmol/l, the prevalence of subclinical vitamin A deficiency in (i) preschool-age children, (ii) school-age children, and (iii) non-pregnant non-lactating women of reproductive age in the rural population of Bangladesh in 2011 had been estimated at 19.4 percent (i), 20.2 percent (ii) and 5.4 percent (iii), respectively by a previous study (ICDDR *et al.*, 2013). Rural children received vitamin A supplementation between 2011 (ICDDR *et al.*, 2013) and 2014 (National Institute of Population Research and Training (NIPORT), Mitra and Associates and ICF International, 2016); moreover, vitamin A fortification of soybean and palm oil was decreed in 2013 (Raghavan *et al.*, 2019).

This evidence raises concerns regarding the results found in this study where, irrespective of which data are used, we would estimate that more than 95 percent of the rural population in 2015 would be considered without an adequate level of dietary vitamin A consumption.

The estimated values of average usual consumption from the data we used would be half of the average requirements. This analysis confirms that vitamin A estimates obtained from serum retinol analysis and dietary analysis are not comparable, and that assessments of vitamin A intake from food consumption data are likely underestimated. The reasons include the fact that most HCES, like the BIHS 7DR module, do not collect information on food fortification or supplements, and the different criteria to assess the level of vitamin A inadequacy (a biomarker analysis evaluates the risk of suffering from xerophthalmia, while the dietary analysis performed in this study is related to the adequate levels of vitamin A stored in liver). Therefore, when reporting estimated vitamin A inadequacy levels, it is of the utmost importance to clearly state the method used, the criteria assumed to define requirements, and the source of data on the vitamin A content of foods (Moltedo *et al.*, 2021a).

5.2 Vitamin B12

Based on the analysis of the 24HR data, vitamin B12 would be classified as an episodically consumed nutrient, with more than 10.7 percent of individuals having zero consumption over the reference period, and 37.8 percent with some consumption, but with daily consumption less 1 µg/person. Using the 7DR data, on the other hand, only 0.5 percent of households would be found having zero consumption and 28.1 percent would have daily per capita consumption greater than zero but less than 1 µg. Using the 24HR and 7DR data, 77.8 percent (based on 1.37 µg/person/day and an EAR of 1.84 µg/person/day), or 62.9 percent (based on 1.76 µg/person/day and an EAR of 1.84 µg/person/day) of the rural population, respectively, would be estimated as having an inadequate level of dietary vitamin B12 consumption. We note that this level of inadequacy is much higher than the level reported in other studies for rural, non-pregnant, non-lactating women of reproductive age (with an average consumption of 1.98 µg/person/day) in 2011 (21.5 percent), considering two cut-off points of 200 pg/ml and 300 pg/ml for serum level of vitamin B12[14] (ICDDR *et al.*, 2013).

[14] The acceptable range of serum level of vitamin B12 is 200–900 pg/ml (Hanna, Lachover, and Rajarethinam, 2009); however, people with normal serum vitamin B12 levels could be deficient on the vitamin (Lindenbaum *et al.,* 1995).

5.3 Zinc

A previous study based on the 2011–12 National Micronutrient Status Survey estimated that 48.6 percent of preschool-age children and 57.5 percent of non-pregnant non-lactating women of reproductive age had inadequate levels of zinc consumption (ICDDR *et al.*, 2013). However, those estimates are wrongly based on a comparison of zinc consumption adjusted for bioavailability with the recommended dietary allowance (RDA). The appropriate comparison would have been between dietary (i.e. not adjusted for bioavailability) zinc consumption with dietary average requirements (i.e. not RDA) defined for the level of bioavailability, or dietary zinc consumption adjusted for bioavailability with physiological (i.e. not dietary) average requirements.

In our study, the daily average zinc consumption was estimated at 11.8 and 8.9 mg/capita from household- and individual-level data respectively. Assuming levels of zinc absorption based on a mixed/refined diet, these consumption levels are higher than the daily requirements (6.6 mg/capita). In this case the corresponding PoNI values would be relatively low: 0.8 percent and 15.4 percent, for 7DR and 24HR data respectively. However, if we assumed lower levels of zinc absorption, as typical when people rely on unrefined diets, the same levels of consumptions would imply higher levels of nutrient inadequacy (13.8 percent from 7DR data and 55.4 percent from 24HR data). These results highlight the relevance of the assumption made in terms of absorption for estimating the prevalence of zinc inadequacy.

5.4 Calcium

Irrespective of the model and dataset used in this study, the level of calcium inadequacy in the rural population on Bangladesh in 2015 would be considered extremely high (greater than 98 percent). This is consistent with results by Bromage and colleagues (2016), who surveyed online databases and several reports related to calcium levels of consumption in the Bangladesh, suggesting widespread dietary calcium inadequacy.

5.5 Vitamin C

Using the 7DR data, we estimate practically zero vitamin C inadequacy in the studied population; however, using the 24HR data, the prevalence of vitamin C inadequacy reaches 17 percent of the population. The difference is easily explained by comparing the average consumption estimates between the two types of data: 93.6 mg/capita with household-level data and 54.9 mg/capita with individual-level data, possibly due to difficulty in capturing all relevant consumption with only two 24-hour recall rounds.

A relatively low level of dietary vitamin C inadequacy might be expected in rural areas, as low levels of vitamin C intake are usually found only in populations consuming diets with very low diversity, such as refugees (WHO, 1999).

5.6 Vitamin B1 (thiamine) and Vitamin B2 (riboflavin)

For vitamins B1 and B2, using either type of data, we estimate a relatively high PoNI: 57.2 percent for vitamin B1 and 64.8 percent for vitamin B2 from 7DR data, and more than 90 percent for both vitamins with 24HR data. As for other nutrients, the different levels of average usual consumption estimates are the reason for different estimated PoNI values.

5.7 Vitamin B6

Discrepancies also appear for vitamin B6: the average vitamin B6 consumption from household-level data is higher than requirements, while from individual-level data it is similar, though higher, to requirements. Using 24HR data the level of vitamin B6 inadequacy at the rural level is 40.5 percent, while the prevalence level using 7DR data is 9.0 percent.

6 Strengths and limitations

The main objective of this study was to demonstrate the possibility to obtain reliable estimates of the prevalence of inadequacy in the reference population for several micronutrients, starting from data typically collected in household consumption and expenditure surveys. The positive result we present is important, as it opens the way to revisiting a large number of existing HCES datasets to conduct retrospective nutrition assessments, and to increase the value of future food consumption data collection.

One distinctive strength of the analysis is the possibility of comparing assessments based on 7DR household-level food consumption data with those conducted on individual 24HR dietary intake modules applied to the same set of households, thanks to the unique characteristics of the 2015 Bangladesh Integrated Household Survey.

However, the data used do have some limitations. Though the 24HR dietary intake module was applied in two rounds for ten percent of the households, thus allowing to estimate the distribution of usual consumption by treating short-term individual dietary consumption data for excess variability, the limitation is that only one person in the households was responsible for reporting the 24-hour food consumption of all members. It may be reasonable to suspect that individuals' consumption of food when away from home might have been underreported, as the respondent might not have been aware of all the food consumption occurrences away from home of other family members. This may be one of the main reasons why the total consumption of virtually all the nutrients considered appears to be lower when estimated from 24HR data, as opposed to 7DR, adding to the known problem of underreporting in 24HR data.

On the other hand, nutrient consumption away from home obtained from 7DR data may also be overestimated due to the lack of information on the actual quantities and variety of foods consumed away from home in the household-level module, which only collects information on the amount of money spent on food prepared and consumed away from home. The nutrient contribution of these foods to the habitual diets could only be indirectly estimated, based on median unit values for each nutrient derived from at-home consumption and expenditures. To the extent that expenditures on food away from home also cover services associated with the provision of food, it is possible that such a procedure might overestimate the nutrient consumption contribution from food consumed away from home, one aspect that deserves further investigation.

Additional studies or country cases would be needed to confirm the results, ideally also using data from an individual food consumption survey (instead of an individualized survey), and by conducting parallel surveys on the average cost and composition of foods typically consumed away from home in each study context.

7 Conclusions

This paper presents estimates of the prevalence of nutrient inadequacy for vitamins A, B1, B2, B6, B12 and C, calcium and zinc, obtained with data collected using the typical food consumption module included in household surveys and compares them with estimates obtained from individual-level data. For most of the nutrients, the values obtained from household-level data are lower than the corresponding estimates obtained from the individual-level data, because of higher estimates of the average consumption, a result often found in other studies.

Once the difference in average consumption is controlled for, PoNI estimates from household-level data, based on the FAO methods to control for measurement error and to compute prevalence rates, are very close to those obtained by applying the standard NCI method on individual-level data collected in the same survey. This finding is promising in terms of confirming the possibility to use household-level data, considering that the two types of data were based on different reference periods, were collected using different tools, were prone to measurement errors, and were analysed using different techniques.

This study also confirms the importance that household-level food consumption data be adjusted for excess variability to avoid overestimating the extent of inequality in usual nutrient consumption and hence biasing PoNI estimates. While questions remain on how to best estimate the average nutrient consumption (whether from household-level data, or from individual-level data), this study shows how to obtain reliable estimates of inequality in usual nutrient consumption for the whole population based on household-level data. We can conclude that, for non-episodically consumed nutrients, the coefficient of variation estimated from 7DR data can safely be used as a proxy for the actual level of inequality in the distribution of usual consumption in a population, once the data are properly treated to remove the effect of seasonality and excess variability associated with measurement error.

Our results demonstrate that obtaining estimates of nutrient inadequacy based on household-level data, as collected in HCES, is a complex, yet feasible task. The comparison of estimates based on data collected on the same population using different methods confirmed known general challenges regarding the precision of the data and the need to invest in standardized methods for food consumption data collection in HCES based on best practices.

One corollary from the results presented here is that, given the residual uncertainty regarding the reliability of estimates of average consumption from different data sources (i.e. individual dietary intake surveys, HCES and FBS), it is important to always publish PoNI estimates with clear and detailed metadata, including information on the methods and data sources used in the analysis.

To summarize, our results confirm that (a) average estimates of nutrient consumption based on food data collected in modules typically found in HCES are higher than those obtained with individual-level data; (b) food consumption data from HCES should be adjusted for seasonality and excess variability before producing estimates of the coefficient of variation of usual consumption; and (c) when estimating the PoNI for non-episodically consumed nutrients with the FAO probabilistic cut-point method, the CV parameter could be obtained from HCES data.

An exclusive use of HCES data to estimate the PoNI is promising; however, questions remain on the reliability of HCES data especially regarding the capture of food prepared and consumed away from home. Additional studies are needed to confirm our results in other contexts.

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