A Measurement Error Approach to Assess the Association between Dietary Diversity, Nutrient Intake, and Mean Probability of Adequacy1–4

Maria L. Joseph* and Alicia Carriquiry

Department of Statistics, Iowa State University, Ames, IA 50011

Abstract

Collection of dietary intake information requires time-consuming and expensive methods, making it inaccessible to many resource-poor countries. Quantifying the association between simple measures of usual dietary diversity and usual nutrient intake/adequacy would allow inferences to be made about the adequacy of micronutrient intake at the population level for a fraction of the cost. In this study, we used secondary data from a dietary intake study carried out in Bangladesh to assess the association between 3 food group diversity indicators (FGI) and calcium intake; and the association between these same 3 FGI and a composite measure of nutrient adequacy, mean probability of adequacy (MPA). By implementing Fuller’s error-in-the-equation measurement error model (EEM) and simple linear regression (SLR) models, we assessed these associations while accounting for the error in the observed quantities. Significant associations were detected between usual FGI and usual calcium intakes, when the more complex EEM was used. The SLR model detected significant associations between FGI and MPA as well as for variations of these measures, including the best linear unbiased predictor. Through simulation, we support the use of the EEM. In contrast to the EEM, the SLR model does not account for the possible correlation between the measurement errors in the response and predictor. The EEM performs best when the model variables are not complex functions of other variables observed with error (e.g. MPA). When observation days are limited and poor estimates of the within-person variances are obtained, the SLR model tends to be more appropriate. 


Introduction

The main goal in dietary assessment studies is to determine whether consumption of foods by a sample of individuals is sufficient to meet the nutrient requirements of the sample. Methods for estimating the prevalence of nutrient adequacy have been proposed (1,2) and can be implemented when a minimum of 2 daily food intake observations is collected for at least some sample individuals. Although the number of observations needed for each person is low, collecting the information is still costly. Interviewers must be trained to accurately record food and beverage intake and an up-to-date, complete food composition database must be available. In resource-poor countries, all of this can be a challenge. The main objective of this work is to explore whether simple measures of dietary diversity can be used to approximately determine whether a sample of individuals is meeting its intake requirements. We present the statistical methodology that can appropriately be used to carry out this type of analysis.

We used a subset of available data from a quantitative dietary intake survey carried out in Bangladesh among women of the Office of Health, Infectious Disease, and Nutrition, Bureau for Global Health, United States Agency for International Development (USAID), under terms of Cooperative Agreement No. GHN-A-00-08-00001-00, through the Food and Nutritional Technical Assistance II Project (FANTA-II), managed by AED. The opinions expressed herein are those of the authors and do not necessarily reflect the views of USAID or the United States Government. Publication costs for this supplement were defrayed in part by the payment of page charges. This publication must therefore be hereby marked "advertisement" in accordance with 18 USC section 1734 solely to indicate this fact. The opinions expressed in this publication are those of the authors and are not attributable to the sponsors or the publisher, Editor, or Editorial Board of The Journal of Nutrition.

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4 An explicit description of the methods used to obtain estimates of the parameters in the error-in-the-equation measurement error model and standard measurement error model as well as Supplemental Figures 1–4 are available with the online posting of this paper at jn.nutrition.org.

* To whom correspondence should be addressed. E-mail: josepall@iastate.edu.

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reproductive age. The main objective of our analysis was to determine whether simple, individual-level measurements of dietary diversity are good predictors of calcium intake and average nutrient adequacy in this sample of women. To meet the goal of the study and, in general, to describe an analytical framework for similar studies, we propose a regression modeling approach that accounts for potentially correlated measurement error in the response and predictor variable. This modeling approach is often known as Fuller’s error-in-the-equation measurement error model (EEM) approach in the literature (3). To illustrate the performance of the EEM, we carried out a simulation study.

While many dietary intake studies (including the one we discuss in this work) have the type of data required to fit complex models such as the EEM, it is important to recognize that this is not always the case, particularly for studies carried out in resource-poor countries or at a national level. In many instances, all that is available is a 1-d measurement of each sample person’s food consumption. We investigate how much is lost, in terms of inference about mean probability of adequate micronutrient intake (MPA) defined later, when only 1 d of food and nutrient intake is collected for each person in the study.

Because the associations of interest are between usual dietary diversity and usual nutrient intake (for any 1 nutrient) and usual dietary diversity and usual MPA, some statistical challenges arose in the analysis. Here, usual (4) is used to denote the long-run average dietary diversity, nutrient intake or MPA for a woman, but usual dietary diversity, usual nutrient intake, and usual MPA are not observable in practice. Thus, we accounted for the measurement error in usual dietary diversity and usual nutrient intake to help ameliorate the bias in the ordinary least squares (OLS) regression coefficient estimate (3).

Methods

Description of data and analysis variables

Study sample. In the analysis presented, we used the 303 nonpregnant, nonlactating (NPNL) women aged 15–49 y from the original Bangladesh study sample. Of the 303 women, 92 were interviewed on 2 nonconsecutive occasions and their 24-h food consumption was recorded on both days. The remaining 211 women were interviewed once and thus their 24-h food consumption was observed for 1 d only. Daily nutrient intake for each woman was estimated using food composition tables appropriate for Bangladesh (5). Nutrients of interest in this study were vitamin A, vitamin C, thiamin, riboflavin, niacin, vitamin B-6, folate, calcium, iron, and zinc. Our analysis of the Bangladesh data focused specifically on calcium intake and MPA.

Nutrient requirements and probability of adequate nutrient intake. To determine the adequacy of daily nutrient intake by a sample individual we compared the individual’s daily nutrient intake to the appropriate distribution of requirements. Given gender, age and pregnancy/lactating status information, the distribution of requirements of a nutrient for a sample is assumed to be normal with the mean equal to the Estimated Average Requirement (EAR) and SD equal to:

\[
SD_{\text{req}} = CV \times \text{EAR}. 
\]

For most nutrients, an EAR has been estimated for the U.S. and Canada populations and the CV set to 10% (6–10). For calcium, an EAR has not yet been determined and thus the distribution of requirements cannot be characterized. The Adequate Intake (AI) can be used to evaluate the adequacy of calcium intake (6). However, because the AI is not an EAR, any inferences about the adequacy of a woman’s calcium intake are approximate at best (6).

In this study, we used the Dietary Reference Intakes for NPNL women 14–50 y identified by Arimond et al. (11) (see Table A2-1). For iron and zinc, we adjusted the EAR proposed by the WHO/FAO (12) for an assumed level of bioavailability of 5 and 34%, respectively (11).

We estimated the probability of adequate daily nutrient intake for a woman by comparing her estimated usual intake to the appropriate distribution of nutrient requirements. Let \( y_i \) denote the usual intake of a nutrient by the \( i \)th woman. If \( r_i \) denotes requirement of the nutrient for the \( i \)th woman and, \( r_i - N(\text{EAR}, (CV \times \text{EAR})^2) \), then the probability of AI of the nutrient for the \( i \)th woman in the sample \( p_i \) can be estimated as:

\[
p_i = \Pr(r_i \leq y_i). 
\]

If intakes of a nutrient have been power-transformed, then the distribution of requirements given in the original scale must also be transformed to calculate \( p_i \). A simple approach to estimating \( p_i \) in the transformed scale can be implemented as follows. Given a nutrient, draw a large number \( M \) of values \( r_1, ..., r_M \) from a normal distribution with mean equal to the EAR of the nutrient and variance equal to \((CV \times \text{EAR})^2\). Transform each draw using the same power used to transform observed intakes of the nutrient. If \( a \) denotes the power that was used to transform intakes, then \( r_i^{(a)} \) is the \( k \)th transformed requirement. Sort the transformed draws in ascending order to obtain the sample order statistics, denoted by \( r_{(1)}^{(a)}, ..., r_{(M)}^{(a)} \). The probability of adequacy of the daily intake of the nutrient for the woman is then:

\[
p_i = 0 \text{ if } y_i < r_{(i)}^{(a)} \\
p_i = k/M \text{ if } r_{(k)}^{(a)} \leq y_i < r_{(k+1)}^{(a)} \\
p_i = 1 \text{ if } y_i \geq r_{(M)}^{(a)}.
\]

where \( p_i \) is the estimated probability that the usual intake of a nutrient for woman \( i \) is adequate.

The number of draws \( M \) must be large enough so that draws from both tails of the distribution are included in the sample. The value of \( M \) is arbitrary and in this study, we set \( M = 1000 \). This is expected to be large enough across all nutrients to capture nutrient intakes at the lower tail of the distributions as they are bounded by zero.

For iron, the distribution of requirements is assumed to be skewed (9). The appropriate probabilities of AI have been computed for several ranges of usual iron intake and by gender, age group, and pregnancy/lactating status, using a bioavailability assumption of 18% for NPNL women (9). We adjusted these iron intake thresholds to correspond to our assumed iron bioavailability of 5% (11).

Nutrients without an EAR present the greatest challenge when calculating the probability of adequate usual intake for an individual. Calcium is the only nutrient under consideration in this study for which only an AI was available. [Values for AI were obtained from Table A2-2 of (11).] To estimate the probability of adequate daily
calcium intake for each woman, we used the approach proposed by Foote et al. (13):

For $y_i \leq 0.25 \text{AI}$, $\bar{p}_i = 0$

For $0.25 \text{AI} < y_i \leq 0.5 \text{AI}$, $\bar{p}_i = 0.25$

For $0.5 \text{AI} < y_i \leq 0.75 \text{AI}$, $\bar{p}_i = 0.5$

For $0.75 \text{AI} < y_i \leq \text{AI}$, $\bar{p}_i = 1.0$.

By averaging the estimated probabilities over the ten aforementioned nutrients, we obtain an estimate for MPA.

**Food group diversity indicators as a measure of dietary diversity**

Several different food group diversity indicators (FGI) were constructed to quantify dietary diversity, varying in level of food group aggregation and minimum consumption required for a food group to count in the FGI score. At the highest level of aggregation, foods were classified into 1 of 6 food groups and at the lowest level of aggregation, foods were classified into 1 of 21 food groups. An intermediate indicator was also constructed by classifying foods into 1 of 13 groups. These 3 levels of aggregation resulted in the FGI known as FGI-6, FGI-13, and FGI-21. The value of each FGI was calculated daily for each woman by counting the number of food groups (in which at least 1 g of food was consumed) included in the woman’s diet. A variant of FGI-6, FGI-13, and FGI-21 was also constructed. These indicators required that at least 15 g of a food be consumed for the food group to count and they are known as FGI-4R, FGI-13R, and FGI-21R (6,14). The results reported here focus on FGI-6R, FGI-13R, and FGI-21R, because these indexes have been identified as more reasonable predictors of nutrient intake and the probability of its adequacy in exploratory analysis.

**Description of statistical models**

Described in decreasing order of complexity are the statistical methods that can be used to explore the association between FGI and nutrient intake, and FGI and MPA when all variables are subject to measurement error. The different modeling approaches require that different amounts of data be collected on sample individuals. In many resource-poor settings, the more data intensive approaches may not be feasible.

First, the EEM will be described (3). The EEM produces approximations of the regression slope when the measurement errors on the response and on the predictor variable are correlated. To fit an EEM, estimates of several variances and covariances are required, and thus the method can result in estimators with large SE except in large samples. Also described are less-complex model formulations, including the standard measurement error model (MEM) and simple linear regression (SLR) models when different combinations of data are available for the response and predictor. The MEM assumes that the predictor is observed with measurement error but that the error is uncorrelated to the error in the predicted usual response variable. The SLR model (in all its observed with measurement error but that the error is uncorrelated to the predictor (BLUP) of the response and o the predictor (3,14). The BLUP is thus the method can result in estimators with large SE except in large settings, the more data intensive approaches may not be feasible.

**EEM.** The objective was to assess the association between usual response $y_i$ and usual FGI $x_i$. If the pair $(y_i, x_i)$ for the $r$th woman were observable, the SLR model $y_i = \beta_0 + \beta_1 x_i + q_i$ could be fit, where $q_i \sim N(0, \sigma_{qq})$ for $i = 1, \ldots, N$ and $\beta_1$ is the slope of the regression of $y_i$ on $x_i$. The unobservable usual response for an individual is defined as the long run average of daily responses (at least in some transformed scale); hence, $E(Y_i) = y_i$ for $i = 1, \ldots, n_i$. Likewise, $E(X_j|x) = x_j$, where $X_j$ is the FGI score for individual $i$ on day $j$. Under these assumptions, now model daily response (or daily FGI score) as the usual response (or usual FGI score) plus a measurement error for that individual on that day, so that

$$Y_i = y_i + \epsilon_i$$

and

$$X_i = x_i + u_i,$$

where $\epsilon_i$ and $u_i$ represent the errors in measuring the usual response and usual FGI score, respectively. Use $\sigma_{yy}$ and $\sigma_{xx}$ to denote the between-person variances in usual response and usual FGI, the methods focus on estimating $\beta_1$ and its variance. Methods used in estimating the slope and variance components of the EEM can be found in the Supplemental Materials.

**Standard MEM.** When it is assumed there are uncorrelated measurement errors between the predictor and response, one can obtain an unbiased estimate of $\beta_1$ with the MEM given that $\sigma_{yy}$ can be estimated. Given observations $(Y_0, X_0)$, the MEM is

$$\hat{Y}_i = \beta_0 + \beta_1 X_i + q_i$$

and

$$\hat{X}_i = x_i + u_i,$$

where $(x_i, q_i, u_i) \sim N(0, 0, 0, \text{diag}(\sigma_{xx}, \sigma_{qq}, \sigma_{uu}))$. Estimation of these model parameters is similar to that of the EEM. Details of this estimation can be found in the Supplemental Materials.

**SLR model when at least 2 d of data are available for the predictor and response.** Assuming that the predictor is observed with measurement error that is uncorrelated with the usual response (either usual nutrient intake or usual MPA) and usual FGI. Thus, to assess the association between usual response and usual FGI, the methods focus on estimating $\beta_1$ and its variance. Methods used in estimating the slope and variance components of the EEM can be found in the Supplemental Materials.

**SLR model when only 1 d of data is available for the predictor.** When 2 d of data are not available for both the predictor and response for at least a subsample of individuals, a different SLR approach must be used. If only 1 observation day is available on the predictor, but a reliable estimate of $y_i$ from multiple observation days (perhaps the BLUP) is available, the BLUP of the usual response $\hat{Y}_i$ can be regressed on the
observed predictor on d 1 X_{i1}. If, on the other hand, only 1 observation is available for both the predictor and response for each individual in the sample, then it is only possible to regress the response from d 1 Y_{i1} on its corresponding predictor variable from d 1 X_{i1}.

If it is known that the predictor is observed with measurement error, one must accept that in these 2 SLR approaches, the OLS estimate of the slope will be biased toward 0 or attenuated. An estimate of the attenuation coefficient \( \kappa_s \) might be available from a different study, and if so the OLS estimate of the slope can be adjusted. An unbiased estimate of the true slope \( \beta_1 \) of the usual response and usual predictor is given by

\[
\hat{\beta}_1 = \frac{\hat{\beta}_1}{\kappa_s},
\]

where \( \hat{\beta}_1 \) is the OLS estimate for the slope and \( \kappa_s = \frac{\sigma_{uu}}{\sigma_{uu} + \sigma_{xx}} \).

To estimate the attenuation coefficient, assume that \( \sigma_{xx} \) and \( \sigma_{uu} \) are known. By using both days of data, one can obtain estimates for these variances: \( \hat{\sigma}_{xx} = m_{xx} \) and \( \hat{\sigma}_{uu} \) can be estimated from Eq. 2 in the Supplemental Materials. To test the hypothesis that \( \beta_1 \neq 0 \), we need to estimate the variance of the adjusted estimate of the slope:

\[
\hat{V}(\hat{\beta}_1) = \frac{s^2}{\hat{\sigma}_{uu}} \frac{1}{N} \frac{1}{\sum_{i=1}^{N} x_i^2} \frac{1}{\sum_{i=1}^{N} 1},
\]

where \( s \) is the mean squared error (MSE) of the SLR model.

### Results

#### Model assessment via simulation

In what follows, the results of a simulation assessing the validity of the SLR model in capturing the linear association between 2 variables where both are observed with error are described. Here, only the EEM and the SLR are compared, but a larger comparison that includes the MEM and the SLR using BLUP could also be implemented if space were not limited. First, pairs \((y_{ij}, x_i)\) are simulated and then correlated measurement errors are added to obtain “observed” pairs \((Y_{ij}, X_{ij})\). By simulating data from a model where measurement error is present and the true association is known, one can evaluate the appropriateness of using the OLS estimator of the slope in this type of problem.

Values of the parameters of the measurement error model were fixed: \( \beta_0, \sigma_{uu}, \sigma_{xx}, \sigma_{xy}, \sigma_{uu}, \sigma_{xy}, \mu_u, \) and \( \sigma_{xx} \), where \( \mu_u \) is the mean of \( x_i \) across all individuals. Parameter values were chosen to be similar to the estimates obtained from the EEM fit to calcium intake and FGI in the Bangladesh data.

To generate \( n_i \) simulated daily responses and daily FGI scores for \( N \) individuals, the following steps were implemented: 1) generate model errors \( e_i \) from \( \text{N}(0, \sigma_{e}) \) for \( i = 1, \ldots, N \); 2) generate usual FGI values \( x_i \) from \( \text{N}(\mu_u, \sigma_{xx}) \) for \( i = 1, \ldots, N \); 3) calculate the usual response values \( y_i \), where \( y_i = \beta_0 + \beta_1 x_i + e_i \), for \( i = 1, \ldots, N \); and 4) generate the “observed” values \( X_{ij} \) from \( \text{N}(\text{N}^2[\{X_{ij}\}_{ij=1}^{N}, \{x_i\}_{i=1}^{N}], \{\sigma_{uu}\}_{ij=1}^{N}, \{\sigma_{uu}\}_{ij=1}^{N}) \) for \( i = 1, \ldots, N \) and \( j = 1, \ldots, n_i \).

Once the daily responses and predictors were simulated for a given set of initial conditions, both the SLR model and the EEM were fit to the data. This process was repeated 500 times always using the same set of parameter values to generate the simulated data. The means of the 500 slopes \( \beta_1 \) and \( \hat{\beta}_1 \) are the estimates of the true slope obtained by the SLR model and EEM, respectively. In each case, the 95% CI for the true slope also can be computed (empirically) from the 500 estimates. If these CI cover the true value of the slope \( \beta_1 \), then with 95% probability, the model produces plausible estimates of the slope. If not, the slope estimate is significantly different from the true slope, suggesting that the model is not appropriate for the data.

![FIGURE 1 Empirical means and 95% CI for the slope \( \beta_1 = 0.1 \) based on 500 simulations for the SLR model and the EEM.](https://academic.oup.com/jn/article-abstract/140/11/2094S/4630582)

#### Varying the within-person measurement error variance in the predictor

First, \( \sigma_{uu} \) was varied and the model error variance and response measurement error variance at \( \sigma_{uu} = 0.05 \) and \( \sigma_{uu} = 0.3 \) respectively, were fixed. Fixing the correlation between the measurement errors in the response and the predictor at 0.5 causes the covariance of the measurement errors to vary with the measurement error variances, because \( \sigma_{uu} = 0.5 \sqrt{\sigma_{uu} \sigma_{uu}} \).

Fixing \( \beta_1 = 0.1 \) and \( \beta_0 = 30 \) and choosing several values for the measurement error variance of interest \( \sigma_{uu} = 0.0, 0.6, 1.2, 1.8, 2.4, \) and \( 3.0 \), 500 datasets were simulated with 200 individuals each with \( n_i = 2 \) observations using each of the 6 sets of parameter values.

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When measurement error in the predictor is absent (i.e. \( \sigma_{uu} = 0 \)), the SLR model and EEM produce similar estimates of \( \beta_1 \) (Fig. 1). Although there is still measurement error in the response variable, it is absorbed by the model error \( \sigma_{qq} \) under the assumptions of the SLR model. As the variance in the measurement error of the predictor increases, the mean of the OLS slope estimate begins to deviate from the true value of 0.1. For lower measurement error variances of the predictor, this model tends to overestimate the true slope. However, the bias of the OLS estimate decreases as the variance of the predictor increases; eventually, the bias becomes negative and the slope is underestimated. The EEM performs differently. As the variance component increases, the error-adjusted estimates appear unbiased regardless of the size of the within-person variance in the predictor.

When the SLR model was fit to the simulated data with measurement error, the narrowing width of the 95% CI indicated the variance of the OLS estimate slightly decreased as the \( \sigma_{uu} \) of the predictor increased. In contrast, and as expected, the width of the CI for the error-corrected estimates of the slope increased appropriately with the increase in measurement error variance.

**Varying the within-person measurement error variance in the response.** To further investigate the bias of the OLS estimator for the linear association between 2 variables observed with measurement error, more data were simulated, varying \( \sigma_{uu} \) the variance of the measurement error in the response variable. Fixing \( \sigma_{uu} = 1 \) and allowing \( \sigma_{uu} \) to take on several values (0.0, 0.2, 0.4, 0.6, 0.8, and 1.0), the same values for all other parameters were used as in the previous case and 500 datasets for each of these sets of parameters were simulated.

When there is no measurement error in the response, \( \sigma_{uu} = 0 \), the SLR model and EEM perform similarly well in estimating the true slope (Fig. 1). As the \( \sigma_{uu} \) increases, the bias in the OLS estimator also increases. If the variability in the response increases while the predictor variance remains fixed, the SLR model will produce a slope estimate with a bias that increases (in absolute value) as the response error variance increases. Whether the bias is positive or negative depends on the sign of the estimated slope. Again, the EEM appears to produce unbiased estimates of the true slope for each value of \( \sigma_{uu} \).

When using the SLR model on data observed with measurement error, the measurement error in the response now contributes to the overall model error. Thus, the model error variance in the SLR model \( \sigma_{qq} \) increases with \( \sigma_{uu} \), producing wider CI for larger response error variances. In the EEM, the increase in the CI width is attributable to an increasing \( \sigma_{uu} \), which results in increased variance of the error-corrected estimate of the slope.

**Varying the value of the covariance.** To assess how the magnitude of the covariance affects the OLS estimator, the measurement error variances were fixed and only their covariance varied. For simulation, we used \( \beta_0 = 30, \beta_1 = 0.1, \sigma_{qq} = 0.3, \sigma_{uu} = 0.1, \sigma_{dq} = 0.05, \sigma_{uu} = 0.3, \) and \( \sigma_{uu} = 1 \). In particular, the measurement error variances chosen are akin to those identified in exploratory analysis. Covariance values that yield measurement error correlations \( \rho_{uu} \) between \(-1\) and \(1\) were chosen. Hence, \( \sigma_{uu} = \sigma_{uu} \sqrt{\sigma_{uu} \sigma_{uu}} \) results in covariance values ranging from \(-\sqrt{0.3}\) and \(\sqrt{0.3}\). It can be seen that the OLS estimator is biased for the true slope when measurement error present (Fig. 1). The bias of \( \beta_1 \) increases as the absolute value of the correlation between the measurement errors increases. In contrast, the EEM estimator \( \hat{\beta}_1 \) is approximately unbiased.

Although the simulated predictor variables were truly observed with error, by assumption, the SLR model treated them as if they were not. Because predictor error variance was ignored here (i.e. assume \( \sigma_{uu} = 0 \)), the covariance between the “nonexistent” errors must be treated in same way (i.e. assume \( \sigma_{uu} = 0 \)). Therefore, varying \( \sigma_{uu} \) did not affect the variance of the OLS estimate of the slope, as indicated by the constant width of the CI obtained from the SLR model. In contrast, the CI obtained from the EEM estimates of the slope appeared to decrease slightly in width with increasing covariance. This can be attributed to the quadratic nature of the variance estimate of the error-corrected slope estimate in \( \sigma_{uu} \).

**Fitting the models to the Bangladesh data**

The results obtained from fitting the models to the Bangladesh data are presented here. First, the results from fitting the EEM to calcium intakes are summarized. The MEM and different forms of the SLR model were fit to MPA; however, only results obtained from the SLR model fits are presented.

Because the assumption of normality underlies all of the methods implemented, it is first verified that the response and, where necessary, the predictor were normally distributed, at least after transformation. By visual inspection, FGI tended to be approximately normally distributed across sample individuals. Calcium intakes were skewed to the right in the original scale; therefore, the Box-Cox (16) approach suggests a log transformation, which resulted in an approximately normal distribution of intakes.

To estimate the probability of AI of each nutrient and consequently the MPA for each woman, a log transformation of each micronutrient intake into the (approximately) normal scale was done. Then the BLUP of usual nutrient intake for each woman and each nutrient were obtained and used to compute the probability of AI for each nutrient. The probabilities of adequacy were averaged across the 10 micronutrients of interest to obtain the MPA for each individual in the sample (17). To verify the assumption of normality for MPA, 0.80 was identified as the best power transformation to achieve near normality for MPA given that MPA is a proportion and takes on values between 0 and 1 (Supplemental Fig. 1).

**EEM for calcium intakes.** To assess the association between usual FGI and usual calcium intake, the EEM was fit using transformed calcium intake as the response and FGI as the predictor variable. Using Eq. 1, 2, and 3 in the Supplemental Information, which resulted in an approximately normal distribution of intakes.

To estimate the probability of AI of each nutrient and consequently the MPA for each woman, a log transformation of each micronutrient intake into the (approximately) normal scale was done. Then the BLUP of usual nutrient intake for each woman and each nutrient were obtained and used to compute the probability of AI for each nutrient. The probabilities of adequacy were averaged across the 10 micronutrients of interest to obtain the MPA for each individual in the sample (17). To verify the assumption of normality for MPA, 0.80 was identified as the best power transformation to achieve near normality for MPA given that MPA is a proportion and takes on values between 0 and 1 (Supplemental Fig. 1).
measurement error in the variable \( (s_e) \). The error in the model attributable to measurement error slightly exceeded the MSE of the model, resulting in a negative estimate of the model error variance. In such cases, set the negative estimates of \( \sigma_{qq} \) to 0, the closest value to the actual estimate contained in the parameter space.

The variance and covariance estimates can be used to adjust the OLS estimates and variances of the slope \( \beta_1 \). After accounting for the measurement error in both the response and the predictor, a positive association was observed between calcium intakes and most FGI at a predictor, a positive association was observed between calcium intake and estimated variables. First, the regression of the BLUP of each nutrient intake, not the observed intakes.) A significant positive linear association was demonstrated between BLUP of MPA on FGI and the error-adjusted estimates.

Next, a SLR model was fit that regressed the BLUP of MPA on FGI calculated using only d 1 of food consumption. The OLS estimate of the slope was positive and significant for all FGI (Table 2). Again, the less aggregated FGI resulted in a lower estimate of the slope. The residual variance \( \sigma_{qq} \) was very similar for FGI-13R, FGI-21, and FGI-21R. The residual plots for each FGI suggest that the SLR model fit these data well (Supplemental Fig. 4). However, using a 1-d FGI to predict usual MPA via a SLR model resulted in an attenuated estimate of the slope. If an estimate of the attenuation coefficient \( \kappa_{xx} \) is available, perhaps from other similar studies, it is possible to adjust the OLS estimate of the slope to reduce the bias. The attenuation coefficient estimate for the Bangladesh data varied by FGI, ranging from 0.554 to 0.653 (Table 2). Smaller values of \( \kappa_{xx} \) resulted in greater adjustments. The slope for each FGI was more significant after adjusting for attenuation.

### TABLE 2

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<thead>
<tr>
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<th>BLUP MPA 1</th>
<th>Observed MPA 2</th>
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<tbody>
<tr>
<td></td>
<td>( \sigma_{qq} )</td>
<td>( \beta_1 )</td>
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<tr>
<td>BLUP</td>
<td></td>
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</tr>
<tr>
<td>FGI-13R</td>
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</tr>
<tr>
<td>FGI-21</td>
<td>0.025</td>
<td>0.080</td>
</tr>
<tr>
<td>FGI-21R</td>
<td>0.024</td>
<td>0.082</td>
</tr>
<tr>
<td>Observed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FGI-13R</td>
<td>0.024</td>
<td>0.075</td>
</tr>
<tr>
<td>FGI-21</td>
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<td>0.052</td>
</tr>
<tr>
<td>FGI-21R</td>
<td>0.025</td>
<td>0.058</td>
</tr>
</tbody>
</table>

1 Normal-scaled BLUP of MPA obtained using power transformation of 0.80.
2 Normal-scaled observed MPA; no power transformation necessary.
Discussion

The main contribution of this article is methodological; we argue that via simulation, naive regression modeling and estimation can be inappropriate when both the response and the predictor variable are measured with correlated error. In these cases, it is important to design studies that permit fitting an EEM or at least a MEM. This said, in resource-poor countries, the funds to carry out multiple 24-h recalls with large, representative samples are not always available and consumption information might be limited. Thus, also discussed are approaches to fit less complex models and interpret results appropriately under these simpler models.

Provided is a blueprint for parameter estimation and result interpretation in a wide range of data scenarios. Because the type of intake data and the nature of the underlying research question in this work arise often in nutrition epidemiology and public health, it is anticipated that this contribution will be valuable beyond our particular application.

Assessing the relationship between usual FGI and usual calcium intake and between usual FGI and usual MPA was also an objective of this work. An EEM that accommodates the correlated measurement errors in the daily value of the response and of the predictor is, in principle, the optimal approach. This approach was used to investigate the association between usual FGI and usual calcium intake. When the response variable is in itself a complex function of unobservable quantities, correctly implementing the errors-in-the-equation approach is difficult. This is the case with, e.g., MPA.

An intermediate approach based on a MEM was also described. The MEM accounts for the measurement error in observed FGI but assumes no correlation between this error and the usual noise with which the response variable is observed. When fitting a MEM to MPA, slope estimates were positive but had large SE and were thus not significant (results not shown). This is attributable at least in part to the complex form of the response variable. It appears that for the Bangladeshi data, the MEM produces more reliable results even if they are less attractive than the SLR approach.

To explore the association between a complex function of nutrient intakes (such as MPA) and FGI, a more simple methodology is proposed that can approximate the results that would be obtained from the measurement error approach. The approximate methodology carries out the analysis in 2 steps. First, obtain the BLUP of usual nutrient intake and of the usual FGI for each individual. Second, compute the person-level usual MPA using the predicted usual intakes. Finally, a SLR is carried out, using the BLUP of FGI as the predictor and the BLUP of MPA as the response.

The difference between this 2-step approach and the EEM approach is the 2-step analysis ignores the correlation between the 2 measurement errors (in the response and the predictor). Thus, the inferences drawn from the EEM approach and the approximation we propose here will be similar when the correlation between measurement errors is low and less similar when the correlation is strong.

If data are not available on the response and the predictor for \( \geq 2 \) d, the 2-step approach above cannot be implemented. However, if an attenuation coefficient is available from another study, the slope estimated from a SLR model can be corrected. These results show that after correcting the OLS slope with the attenuation coefficient estimated with the Bangladesh data, the results for the SLR model begin to approach those obtained from fitting the MEM. This suggests that it might be possible to improve on SLR results in studies where only 1 observation per person may be available if a suitable reliability coefficient \( k_{xx} \) can be “borrowed” from a different study. This approach is similar to what was proposed by Jahns et al. (18).

Significant associations between usual FGI and usual calcium intake were detected by the EEM. It was argued earlier that when the response is a complex function of unobservable variables, as is the case of MPA, uncovering significant associations is more difficult for various reasons. First, measurement error is present in the estimation of each probability of adequacy for the various nutrients. By averaging these probabilities across all 10 nutrients to estimate MPA, we are using a complex function of already-noisy estimates of the probability of adequate nutrient intake, thus decreasing the likelihood of detecting an association between usual FGI and usual MPA. Second, the Bangladesh sample was small and 2 d of information were available for only a small proportion of women. This adds to the uncertainty with which we can estimate variances and covariances and thus the uncertainty in the reliability of the various adjustments that comprise the EEM approach. When one is not confident that good estimates of variances and covariances can be obtained, it might be better to implement a simpler approach.

Considering that FGI are simple in that they tell little about which foods were consumed by an individual and provide limited information about the quantity of food consumed, some EEM performed reasonably well at identifying linear associations with calcium intake. Adjusting the consumption criterion and food group definitions may lead to even more encouraging results. For MPA and FGI, much larger samples might be required to uncover an association using the EEM approach.

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Literature Cited


