**Addressing limitation of PROBIT estimators in RAM surveys**

**Introduction**

The estimate of malnutrition made from the SMART survey data using a classic frequentist estimator:

An alternative “PROBIT” estimator may be used. This is a model-based approach proposed by the WHO in 1995 [WHO, 1995]. PROBIT estimators are used in RAM type surveys which are conducted by a number of NGOS and UNOs globally.

The PROBIT function is also known as the inverse cumulative distribution function. This function converts parameters of the distribution of an indicator (e.g. the mean and standard deviation of a normally distributed variable) into cumulative percentiles. This means that it is possible to use the normal PROBIT function with estimates of the mean and standard deviation of indicator values in a survey sample to predict (or estimate) the proportion of the population falling below a given threshold. For example, for data with a mean MUAC of 256 mm and a standard deviation of 28 mm the output of the normal PROBIT function for a threshold of 210 mm is 0.0502 meaning that 5.02% of the population are predicted (or estimated) to fall below the 210 mm threshold. This example uses MUAC but the method can be used for indicators expressed using z-scores. Both the classic and the PROBIT methods can be thought of as estimating area. See Figure 1.

**Figure 1 :** Classic and PROBIT estimators

A close up of a map

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The example here is for GAM by MUAC in a population of adults aged 50 years or older. PROBIT estimators of malnutrition are

currently used in this population [RAM-OP].

Both Classic and PROBIT methods estimate the probability that an individual drawn at random from the population will meet a case-definition based on an anthropometric threshold. If prevalence is 5% then the probability that a child picked at random will be a case is 0.05 (i.e. 5%). PROBIT keeps this equality between prevalence and probability. If the probability of being a case is 0.05 then prevalence is also 5%.

The principal advantage of the PROBIT approach is that the required sample size is usually smaller than that required to estimate prevalence with a given precision using the classic frequentist method [WHO, 1996].

The PROBIT method often assumes that the anthropometric indicator is a normally distributed variable. If this is not the case, then the distribution of can be transformed towards normality or robust (i.e. not sensitive to outliers and asymmetry) estimators of location and dispersion (e.g. median and inter-quartile range) may be used instead of the mean and standard deviation.

**Problems with PROBIT**

The PROBIT estimator used in (e.g.) RAM surveys works well for a single anthropometric variable and can be used, for example, to calculate the probability that a child drawn at random from a population will have a MUAC < 115 mm. This probability is the same as the prevalence of MUAC < 115 mm in the population. There is, however, a problem with case-definitions for malnutrition that use more than one anthropometric variable. For example, severe acute malnutrition (SAM) may be defined as:

MUAC < 115 mm or oedema

Global acute malnutrition (GAM) may be defined as:

MUAC < 125 mm or oedema

These case definitions use two variables (i.e. MUAC and oedema).

There has been recent interest in using "combined" case-definitions [REFERENCE] which use MUAC, WHZ, and oedema. SAM may be defined as:

MUAC < 115 mm or WHZ < -3 or oedema

GAM may be defined as:

MUAC < 125 mm or WHZ < -2 or oedema

These case-definitions use three variables (i.e. MUAC, WHZ, and oedema)

In this article we explore the possibility for extending PROBIT for estimating prevalence using these case definitions.

**Extending PROBIT**

When we extend PROBIT we are combining probabilities (e.g. low MUAC and oedema). If there is no overlap (intersection) between the set of children with low MUAC and the set of children with oedema then there are two separate groups:

(A) Childen with MUAC < 115

(B) Children in which oedema is present

and no child is a member of both groups:

**Figure 2 :** Two groups with no overlap / no intersection.

![A picture containing device

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In this case, we can estimate both probabilities separately and simply add the two probabilities together.

P(SAM) = P(MUAC < 115 mm) + P(oedema is present)

The situation is not so simple when the groups overlap (intersect) with each other:

Figure 3 : Two groups overlap (intersection)

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If we add the two probabilities together, we will overestimate prevalence because we will be counting the children represented in the intersection (labelled “**(X)”** in *Figure 3*) twice. Instead, we should add the two probabilities together and then subtract the probability of the intersection:

P(SAM) = P(MUAC < 115 mm) + P(OEDEMA) - P(MUAC < 115 mm AND OEDEMA)

We can do this using a hybrid PROBIT / classic frequentist approach:

P(MUAC < 115 mm) can be estimated using PROBIT

and:

P(OEDEMA) and the intersection probability P(MUAC < 115 AND OEDEMA) can

be estimated using the classic frequentist approach.

This method can be extended to include any number of variables. The "combined" SAM case-definition for SAM:

MUAC < 115 mm or WHZ < -3 or oedema

is illustrate in Figure 3.

**Figure 3 :** Combined SAM

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The prevalence of "combined" SAM is:

P(SAM) = P(A) + P(B) + P(X) - P(W) - P(X) - P(Y) - P(Z)

where:

A = P(MUAC < 115 mm)

B = P(WHZ < -3)

C = P(OEDEMA)

W = P(MUAC < 115 mm & OEDEMA)

X = P(MUAC < 115 mm & WHZ = -3)

Y = P(WHZ < -3 & OEDEMA)

Z = P(MUAC < 115 & WHZ < -3 & OEDEMA)

P(A), P(B), and P(C) can be estimated using PROBIT and P(W), P(X), P(Y), and P(Z) would need to be estimated using classical frequentist methods.

**Methods**

The approaches outlined above were tested using computer-based simulations.

Simulated populations were created from a database of existing surveys. Then surveys describing these populations were simulated by sampling from populations created from these original survey data sets.

**Database**

The database used in the analysis consisted of 2436 nutritional surveys involving children aged between 6 and 59 months from fifty-one different countries, totalling 1,796,991 children. The surveys were carried out by fourteen different organisations involved in nutrition programs throughout the world. The surveys included measurements of weight, height, MUAC and assessment of oedema. WHZ was calculated using the WHO growth standards [WGS, 2006]. Table 1 describes the database used in the analyses reported here.

**Creation of simulated populations**

Each of the 2,436 surveys in the database was used to create a simulated population of 17,000 children by sampling with replacement from the survey data set. This size of population was chosen as being typical of the population of children aged between 6 and 59 months in which nutritional anthropometry surveys are commonly performed. Highly improbable values of the selected indicator were censored before the population was created (i.e. records in which weight-for-height z-score (WHZ) was < -5 SD or > 5 SD from the WHO growth standard median or MUAC was < 80mm or > 240mm) and appropriate case definitions (Table 2) were applied to the remaining records.

Each of the 2,436 simulated populations was sampled using simple random sampling without replacement using a sample size of n = 384. This sample size was chosen because it would be sufficient to estimate a prevalence of 10% with a precision of ±3% using a classic frequentist estimator. This was done for the four case-definitions in Table 2. ### surveys were simulated from each population. This process resulting in a total of ### (i.e. 2,436 \* ### \* 4 = ###) simulated surveys being performed.

**Calculation of true prevalence in the simulated populations**

We calculated the true prevalence in each simulated population by counting the number of children meeting each of the case-definitions shown in Table 2 in the population and calculating the ratio of this number to the total population.

**Estimation of prevalence with classical and PROBIT methods in the simulated surveys**

First, we calculated the prevalence using the classic frequentist method, by counting the number of children meeting the case definitions shown in Table 2 and calculating the ratio of this number to the total sample size. Second, we estimated the prevalence with the hybrid PROBIT / classic frequentist approaches outlined above. PROBIT estimates were made using the normal PROBIT function using the median and the interquartile range (IQR) divided by 1.34898 as the parameters of location and dispersion which is the method most commonly used in RAM surveys.

**Investigation of bias and precision**

Bias was investigated for the PROBIT method by the estimation of mean error (true prevalence minus estimated prevalence). Precision was investigated by the 95 % limits of agreement (mean (error) ± 1.96 × SD(error) [Bland & Altman, 1986]. Figure EP.BA illustrated the method graphically for combined GAM prevalence using the hybrid PROBIT / classic frequentist approach (a small number of replicates (i.e. r = XXX) was used for illustrative purposes).

The method used to test the hybrid PROBIT / classical frequentist approach that follows that used previously to test the PROBIT method with nutritional anthropometry survey data [Dale, 2012; Blanton, 2013].