RAM-OP: A rapid assessment method for assessing the nutritional status, vulnerabilities, and needs of older people in emergency and development settings

Experiences from a field trial in an urban setting

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Introduction

Older people are a neglected group in humanitarian responses, even as their numbers are growing as life-expectancy increases in much of the developed and developing world. This neglect is particularly obvious in the nutrition sector where the overwhelming majority of activities target children and / or women of childbearing age. Older people are vulnerable to malnutrition but their nutritional status and needs are very seldom assessed and almost never addressed. There is a need for a simple, cheap, and rapid tool to assess these (and other) needs and to enable humanitarian actors to advocate, plan, and deliver relevant and comprehensive responses for older people.

In January 2014, HelpAge International, Valid International, and Brixton Health funded by the Humanitarian Innovation Fund (HIF) began developing a novel method for assessing the nutritional and other needs of older people in emergency and development settings. The **Rapid Assessment Method for Older People** (RAM-OP) is intended to offer a simple, rapid, low cost, accurate, and reliable survey method for assessing the nutritional status, vulnerabilities, and needs of older people.

The RAM-OP method will use a two-stage spatial sample with a small (e.g. $m = 16$ clusters) and spatially even first-stage sample and a small (i.e. $n < 200$) overall sample. Modern computer-intensive data analysis procedures will be used. Free and open-source data analysis software will be developed. Guidelines, articles, and training material will be produced. The focus of the work developing RAM-OP is on older people but elements of the work will also be applicable for assessing the nutritional status, dietary diversity, IYCF practices, food security and other indicators in other populations.

The first field trial of the RAM-OP method was undertaken in Kolfe Keranyio, a sub-city of Addis Ababa (Ethiopia) in February and March 2014. Testing involved performing two surveys using the SMART method and a prototype RAM-OP method simultaneously in the same population and comparing the two surveys in terms of resource requirements and survey results. This article describes key elements of the RAM-OP method and the results of the first field trial of the method. The field trial reported here is for an urban / peri-urban population. A second trial in a rural setting in sub-Saharan Africa is planned.

Survey Setting

Kolfe Keranyio is a sub-city of Addis Abba with a population of about 430 thousand persons according to the 2007 Ethiopian census. About 7.4% of the population of Kolfe Keranyio are aged fifty years and older. The sub-city hosts a mix of communities (i.e. from the very poor to the very affluent in both Muslim and Christian faith communities). Housing densities and types vary from dense urban and peri-urban shanties, suburban villa and apartment developments, and peri-urban smallholdings.

The sub-city is divided into administrative districts which were called "kebele" in 2007 but are now called "woreda". These administrative districts are further divided into smaller contiguous and non-overlapping areas called "enumeration areas" (EAs). These EAs were used for the 2007 census and form the basis for budget allocation and service planning by national, city, and district governments.

The current population size and the number of households in each EA were estimated from the 2007 census. Detailed large-scale maps of EAs were available. *Figure 1* shows a simplified EA map. The availability of population data and usefully detailed maps led to us choosing census EAs as the primary sampling unit (PSU) for the RAM-OP and SMART surveys reported here.

Sampling

Sample sizes were calculated using standard formulae to achieve a 95% confidence interval of plus or minus two percentage points on a 5% estimate for GAM assuming a design effect of 1.5. The overall sample size required for the RAM-OP survey was $n = 192$. The overall sample size required for the SMART survey was $n = 684$. The difference in the required sample sizes was due to RAM-OP using a more efficient estimator for GAM than the estimator used by SMART (see *Box CP* for details of the different approaches). The required sample size for the RAM-OP survey was increased to $n = 240$ for this field trial because this was the first use of the RAM-OP method (all previous experience with RAM type surveys had been in children aged between six and fifty-nine months and children aged between zero and 23 months) and the first use of RAM in an urban setting.

Both surveys used two-stage cluster sampling :

First stage samples

In first stage sampling for the SMART survey, 30 PSUs (EAs) were selected using population proportionate sampling (PPS) from a complete list of EAs in the survey area.

In first stage sampling for the RAM-OP survey, 20 PSUs (EAs) were selected systematically from a complete list of EAs in the survey area sorted by administrative district. This procedure, known as *implicit stratification*, should select a sample that is reasonably evenly distributed across the survey area. This also tends to spread the sample properly among important sub-groups of the population such as urban / peri-urban, administrative districts, ethnic / religious sub-populations, and socio-economic groups.

Figure 2 shows a map of Kolfe Keranyio with PSUs (EAs) selected for the SMART and the RAM-OP survey marked. Both samples are evenly distributed across the survey area. This is due to the reasonably uniform distribution of the populations of potential PSUs. In settings where potential PSUs had widely varying populations, the SMART sample would have been concentrated in the most populous PSUs (EAs).

Second stage samples

The second stage sample (i.e. for selection of the respondents in each sampled PSU) for both surveys was taken using systematic household sampling. The sampling intervals were calculated before the start of the surveys based on the average EA population size and the target sample size for each survey. Every second household was selected for the SMART survey. Every fourth household was selected for the RAM-OP survey.

The availability of detailed EA maps (see *Figure 1*) facilitated the location of PSUs and PSU boundaries.

The final sample size for the RAM-OP survey was $n = 320$. This is considerably (i.e. one-third) larger than was intended. The final sample size for the SMART survey was $n = 569$. This is somewhat smaller (i.e. about one-sixth) than was intended. Over-sampling is waste of resources. Under-sampling raises both ethical concerns and (potentially) political problems. Problems of over-sampling and under-sampling would not have occurred using a within-PSU quota sample (i.e. taking a fixed number of persons from each PSU). It is envisaged that future field trials of the RAM-OP method will use a within-PSU quota sample as is done in EPI surveys and was done in the original SMART methodology.

It should be noted that the sampling methods used were approved by the SMART Initiative through the medium of anonymous posting of questions on EN-NET which were answered by members of the SMART team who provided direct answers to questions as well as electronic documents related to sampling. We tried posting questions regarding sampling on the SMART Forum but could find no way of posting questions to the SMART Forum.

Survey implementation

Permissions to carry out the surveys were obtained from all relevant national and local bodies. Woreda health departments provided local guides to assist in location of PSUs and to liaise with community leaders and other agency personnel (e.g. the police).

The four-day training for data collectors included training on the objectives of the surveys, the survey questionnaire, survey indicators, sampling methodology, field procedures, MUAC measurement (with standardization), and field testing.

Seven teams of two enumerators were recruited, three teams for RAM, four teams for SMART. The survey teams were supervised by HelpAge International's Humanitarian Health and Nutrition Adviser (PF), assisted by two experienced epidemiologists from Brixton Health (MM) and Valid International (KS). The two surveys were completed in eight days. A total of $n = 889$ people aged between 50 and 102 years (self-reported) were sampled.

The main challenges in the field were related to logistics. Seven teams shared two vehicles and a lot of time was wasted waiting in traffic and dropping each team off at their designated PSU. In addition, the mobile phone network coverage was very poor and once the teams finished, it was often difficult for them to get in touch with drivers to be taken to another PSU. These issues delayed the survey and each team was able to complete, on average, only one PSU per day. If each team had their own vehicles or better communications had been available, then each team would have been able to sample two PSUs per day. This would would have shortened the duration of both surveys by half. Also, the survey questionnaire was in English and wasn't translated into local languages. Translation and making sure that everyone understood the meaning of the questions was extensively practiced during the training, however it is evident from results that there were some issues and inconsistencies in the way questions were translated by different enumerators. For the next pilot, the questionnaires will be translated in the local language in order to ensure data quality and consistency.

Data Entry and Checking

The data for both surveys were entered into identically structured *EpiData v3.10* databases by dedicated data-entry staff. Interactive checks for range and legal values were applied. All data were double-entered and validated (verified) using a record-by-record and variable-by-variable comparison. Errors and discrepancies were resolved by consulting data-collection forms. Any errors that could not be resolved resulted in obviously or potentially erroneous values being censored (i.e. set to missing).

Data Management

Data management consisted of creating indicators from the collected survey data. This was done for both the SMART and RAM-OP data using the same purpose-written scripts. Scripts were written using the *R* Language for Data Analysis and Graphics and managed using the *R-AnalyticFlow* scientific workflow system. This approach allowed for modular development of data-management and data-analysis code and provided tools for the documentation, testing, and debugging of scripts. *Box K6*, for example, shows the contents of a workflow node that was used to calculate the K6 (Kessler six item psychological distress score) indicator [K6].

Data related to survey costs were collected and entered into an OpenOffice Calc spreadsheet.

Data Analysis

Analysis of survey data consisted of estimating proportions and means for a variety of indicators. The SMART survey data were analysed using the *Taylor Linearised Deviation* approach, as implemented in the *CSAMPLE* module of *EpiInfo*, to calculate confidence intervals for proportions and means [TLD]. The RAM-OP survey data were analysed using a *blocked weighted bootstrap* estimator:

> **Blocked :** The block corresponds to the primary sampling unit (PSU) or cluster.

> **Weighted :** The RAM-OP sampling procedure does not use population proportional sampling to weight the sample prior to data collection as is done with SMART type surveys. This means that a posterior weighting procedure is required. We used a "roulette wheel" algorithm (see *Figure BBW*) to weight (i.e. by population) the selection probability of PSUs in bootstrap replicates.

A total of m PSUs are sampled *with-replacement* from the survey dataset where m is the number of PSUs in the survey sample. Individual records within each PSU are then sampled *with-replacement*. A total of n records are sampled *with-replacement* from each of the selected PSUs where n is the number of individual records in a selected PSU. The resulting collection of records *replicates* the original survey in terms of both sample design and sample size. A large number of replicate surveys are taken (the work reported here used $r = 3999$ replicate surveys). The required statistic (e.g. the mean of an indicator value) is applied to each replicate survey. The reported estimate consists of the 50th (point estimate), 2.5^{th} (lower 95% confidence limit), and the 97.5^{th} (upper 95% confidence limit) percentiles of the distribution of the statistic across all replicate surveys. The bootstrap procedure is outlined in *Figure BBW*. The bootstrap approach is computer-intensive but allows estimation of the sampling distribution of almost any statistic using only simple computational methods.

Comparisons between the results from the SMART and RAM-OP surveys were performed using the *two-sample z-test*. 95% confidence intervals on the difference between indicator levels estimated from the SMART and RAM-OP surveys were also calculated. See *Box ZCI* for details of the methods used.

Data related to survey costs were analysed using an OpenOffice Calc spreadsheet.

Results

Table RC shows the estimates of indicator levels from each survey and between survey comparisons for a selection of indicators for which data were collected. The indicators shown in *Table RC* were selected as examples of:

- Means of a single continuous variable (i.e. age, MUAC).

- Means of a single discrete variable (i.e. household size, meal frequency from 24 hour recall).

- Means of multi-variable discrete scales or scores (i.e. dietary diversity from 24 hour recall, K6 psychological distress scale).

- Proportions for indicators calculated from a single variable (i.e. lives alone, has a source of income).

- Proportions for indicators calculated from multiple variables (i.e. consumes one or more foods rich in vitamin A, previously screened using MUAC or for bilateral pitting oedema).

The final row of *Table RC* shows the results for global acute malnutrition (GAM) based on the case definition MUAC < 210 mm. The SMART result is calculated using a classic prevalence estimator. The RAM-OP result is calculated using a PROBIT estimator. See *Box CP* for details of these two approaches. Estimates from the SMART and RAM-OP surveys were not significantly different from each other. It is likely, however, that the observed difference would have been smaller had we used longer MUAC straps. We used MUAC straps that could not measure MUACs above 350 mm. All MUAC measurements above 350 mm were treated as MUAC = 350 mm. This occurred for approximately 6% of respondents. The likely effect of this truncation of higher MUAC values would be to have created a small negative bias in the PROBIT estimate of GAM. The next RAM-OP pilot will use MUAC straps capable of measuring MUACs up to about 500 mm.

All estimates of indicator levels made from the RAM-OP survey data were made with useful precision. The next RAM-OP pilot will reduce the RAM-OP sample size to $n = 192$ collected from $m = 16$ PSUs taking a fixed size (quota) sample from each PSU.

All of the comparisons presented in *Table RC* were not significant at either the $p < 0.05$ or the corrected $p < 0.0009$ levels (see *Box ZCI*). This was not the case for thirteen of the sixty calculated indicators. All of these thirteen indicators were based on non-validated question sets. For example, low vision and blindness (significant at $p = 0.0105$) was assessed by self-report rather than by a formal assessment of visual acuity. No significant differences were found between the surveys for any indicator calculated in a standard manner from data collected using standardised questions-sets or from purely quantitative measurements. The next RAM-OP pilot will use tested and standardised techniques for all indicators.

Table CC shows the costs for the SMART and RAM-OP surveys reported here. The RAM-OP survey was cheaper than the SMART survey in proportion to the number of clusters sampled. In the work reported here the RAM-OP survey cost about two thirds that of a broadly equivalent SMART survey. It is hoped that the number of PSUs could be reduced further (i.e. from $m = 20$ to $m = 16$ PSUs) which should reduce the costs of a RAM-OP survey to about half that of an equivalent SMART survey. The use of smaller within-PSU samples may bring further savings by allowing data to be collected from more PSUs per day.

Conclusions

The field trial reported here suggested changes to the RAM-OP method which will be piloted in subsequent field trials. These include:

- Taking a fixed size (quota) sample from each PSU.

- Further use of standardised question sets and measure methods.

- Strict forward and backward translation of survey instruments and other survey documents.

- Better logistics and communications.

- Use of MUAC tapes capable of measuring MUACs up to 500 mm.

We will also test a wider range of food-security indicators and make better use of data collected for the purposes of assessing dietary diversity.

In the field trials reported here the RAM-OP survey provided comparable results to the SMART survey at about two-thirds of the cost of the SMART survey. Larger (i.e. up to 50%) cost savings may be possible. We will test whether savings of this magnitude can be made in subsequent field trials of the RAM-OP method.

Figure 1 : Simplified EA map for census EA 03-004-40 (RAM-OP Cluster 209)
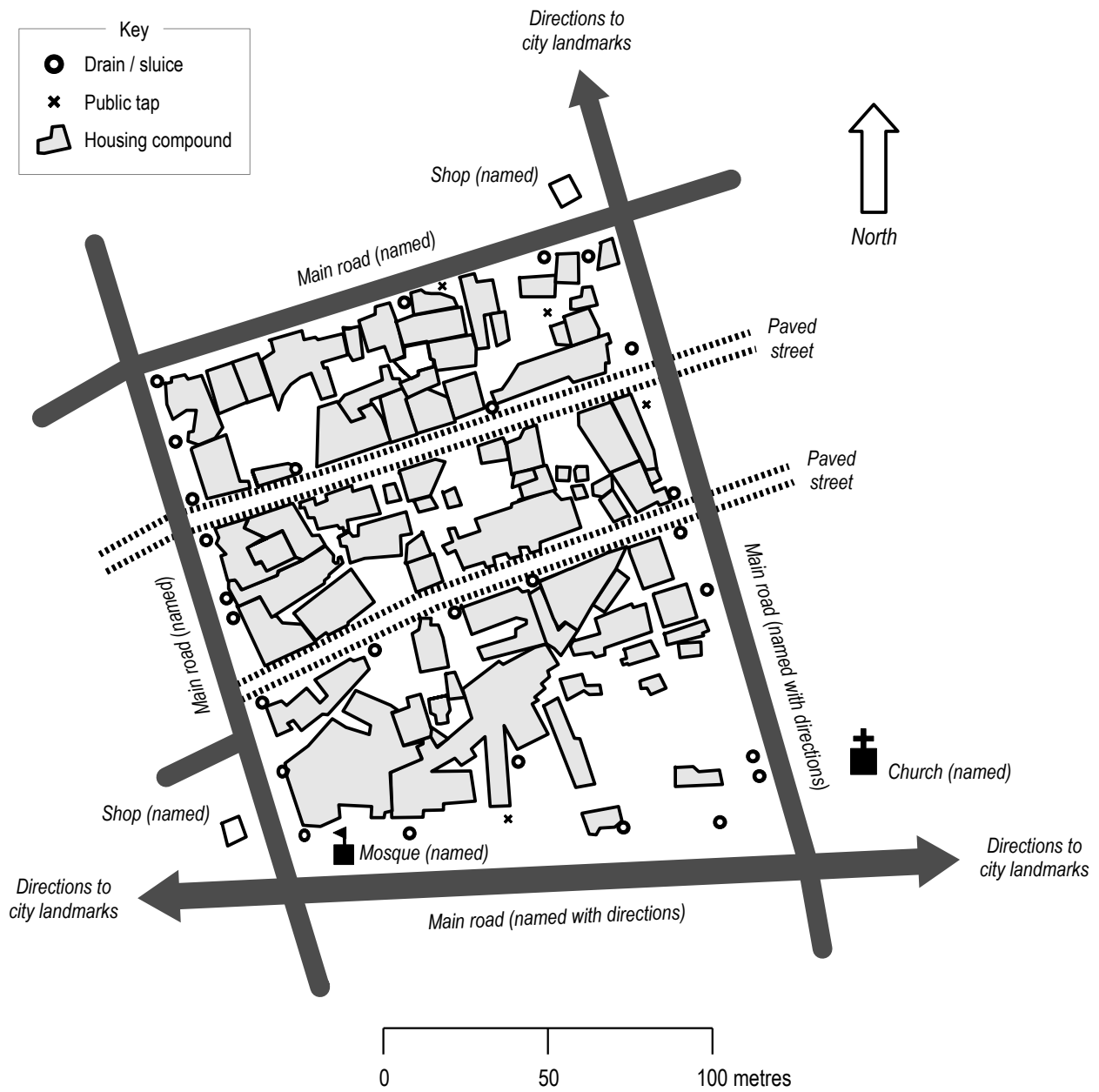
This map shows equivalent detail to the official EA map. The map has been redrawn and labelled in English to illustrate the type of map that was available to survey staff.

Figure 2 : Map of Kolfe Keraniyo showing PSUs selected for the RAM-OP and SMART surveys
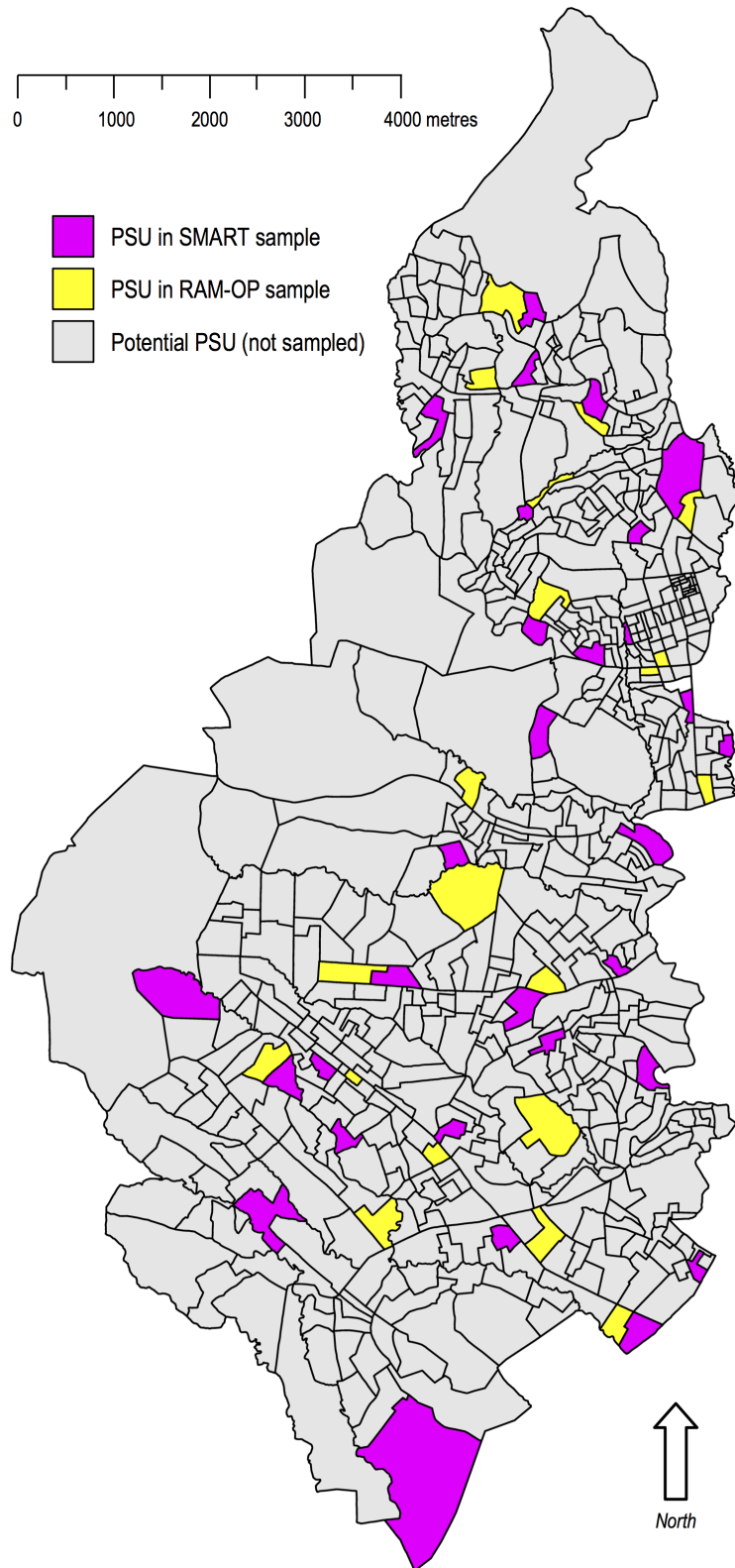
Box K6 : Example of indicator creation script (K6 short form psychological distress score)

```
###############################################################################
#                                                                             #
#   K6 : Short form psychological distress score                              #
#                                                                             #
#   The K6 (and K10) score is described in :                                  #
#                                                                             #
#     Kessler RC, Andrews G, Colpe LJ, Hiripi E, Mroczek, DK, Normand SLT,    #
#     et al. (2002). "Short screening scales to monitor population prevalences #
#     and trends in non-specific psychological distress". Psychological       #
#     Medicine, 32(6), 959-976                                                #
#                                                                             #
###############################################################################

###############################################################################
#
#   Recode data to account for DON'T KNOW, REFUSED, NA, and MISSING VALUES
#
#   NOTE : This will score DON'T KNOW, REFUSED, NA, and MISSING as 5 (NONE)
#
svy$wb2 <- recode(svy$wb2, "6:9=5")
svy$wb3 <- recode(svy$wb3, "6:9=5")
svy$wb4 <- recode(svy$wb4, "6:9=5")
svy$wb5 <- recode(svy$wb5, "6:9=5")
svy$wb6 <- recode(svy$wb6, "6:9=5")
svy$wb7 <- recode(svy$wb7, "6:9=5")

###############################################################################
#
#   Reverse the coding scheme used on survey questionnaire
#
svy$wb2 <- 5 - svy$wb2     # Nervous
svy$wb3 <- 5 - svy$wb3     # Hopeless
svy$wb4 <- 5 - svy$wb4     # Restless
svy$wb5 <- 5 - svy$wb5     # Depressed
svy$wb6 <- 5 - svy$wb6     # Everything too much effort
svy$wb7 <- 5 - svy$wb7     # Worthless

###############################################################################
#
# Create K6 score as the sum of individual item scores
#
K6 <- svy$wb2 + svy$wb3 + svy$wb4 + svy$wb5 + svy$wb6 + svy$wb7

###############################################################################
#
#   Apply case-definition for serious psychological distress(i.e. K6 > 12)
#
K6Case <- recode(K6, "0:12=0; 13:hi=1")
```
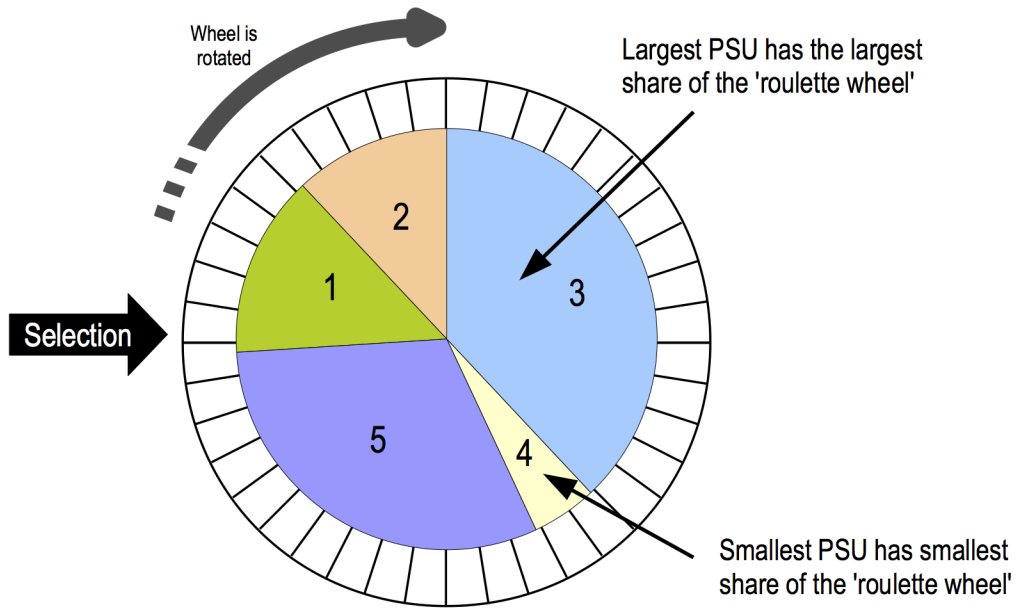
Figure BBW : The blocked weighted bootstrap used to make estimates from RAM-OP data

Data are collected using a two-stage cluster design:
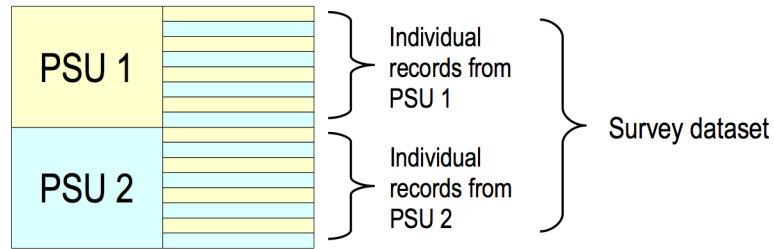
PSUs are selected from the survey dataset *with-replacement* and with probability proportional to population size using a *roulette wheel* algorithm :


PSUs are selected *with-replacement* and proportional to population size :

Individual records are selected *with-replacement* from within each PSU to create a *replicate* survey. The estimator is applied to the replicate survey and the result recorded. This process is repeated many times. The estimate of the indicator value is made from the distribution of the results from each replicate survey which is the *empirical sampling distribution* of the indicator :
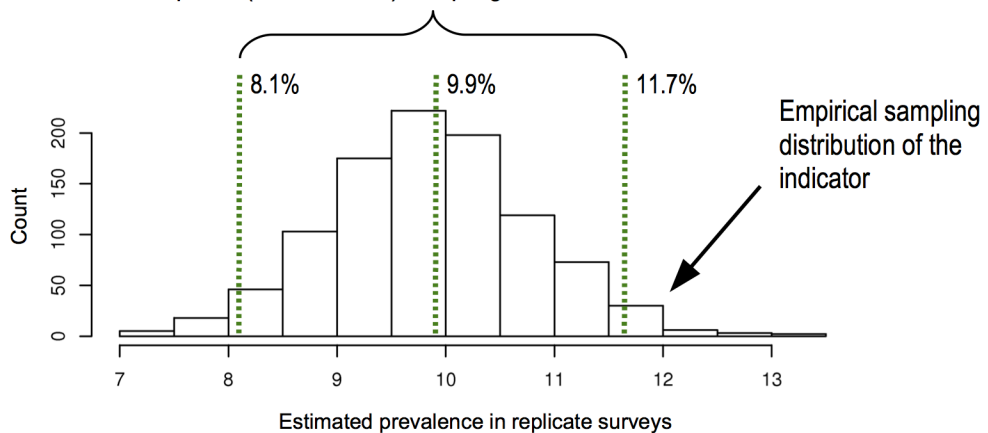
Box ZCI : Methods used for between survey comparisons of estimates of indicator levels

Comparisons between the results from both surveys were performed using a *two-sample z-test*.

The *z-test* was calculated using the standard errors (SE) reported by the *CSAMPLE* module of *EpiInfo* for the SMART survey data and calculated from estimates of indicator levels for the RAM-OP survey data:

$$SE = \frac{UCL - LCL}{2 \times 1.96}$$

where *LCL* and *UCL* are the 95% upper and lower confidence limits of the bootstrap estimates made from the RAM-OP survey data. Standard errors were pooled:

$$SE_{Pooled} = \sqrt{SE^2_{SMART} + SE^2_{RAM\text{-}OP}}$$

and the *z-test* calculated as:

$$z = \frac{|p_{SMART} - p_{RAM\text{-}OP}|}{SE_{Pooled}}$$

Where p_{SMART} and $p_{RAM\text{-}OP}$ are the point estimates from the SMART and RAM-OP survey data.

95% confidence intervals on the differences between indicator levels the SMART and RAM-OP surveys were also calculated:

$$95\% \, CI = |p_{SMART} - p_{RAM\text{-}OP}| \pm 1.96 \times SE_{Pooled}$$

Sixty between survey comparisons were performed in the work described here.

Without *correction for multiple comparisons* the probability of finding at least one significant test at the *p* < 0.05 significance level is approximately:

$$p_{Positive\,test} = 1 - (1 - 0.05)^{60} = 0.9539$$

even when all of the differences are actually non-significant.

At the *p* < 0.05 significance level we would expect to find three significant results in sixty tests even when all of the differences are actually non-significant.

To avoid these *false positives* results whilst maintaining the *p* < 0.05 significance level the critical value for *p* should be reduced from *p* < 0.05 to:

$$p < 1 - (1 - 0.05)^{1/60} = 0.0009$$

This is known as the *Šidák Correction* [SC]. This corrected critical value for *p* should be treated with caution as the correction is intended only to reduce the number of *false positive* results and does so at the cost of increasing the number of *false negative* results with a consequent reduction in statistical power.

Table RC : Estimates of indicator levels from each survey and between survey comparisons for a selection of indicators

Indicator	Units	Type*	SMART				RAM-OP				Difference	Pooled SE	LCL	UCL	z^{**}	p^{**}
			Estimate	LCL	UCL	SE	Estimate	LCL	UCL	SE						
Age	years	C1	63.0810	62.1590	64.0040	0.4707	63.4900	62.3373	64.4793	0.5464	-0.4090	0.7212	-1.8225	1.0045	0.5671	0.5706
MUAC	mm	C1	269.9610	265.0940	274.8270	2.4829	267.6719	264.4384	270.6311	1.5798	2.2891	2.9429	-3.4789	8.0571	0.7778	0.4367
HH size	count	D1	5.4490	5.2090	5.6890	0.1224	5.6303	5.3459	5.9086	0.1435	-0.1813	0.1887	-0.5511	0.1885	0.9609	0.3366
Meal frequency	count	D1	2.7100	2.6350	2.7850	0.0383	2.7791	2.6557	2.9174	0.0668	-0.0691	0.0769	-0.2199	0.0817	0.8980	0.3692
Dietary diversity	score	D2	5.9810	5.7950	6.1660	0.0946	6.1792	5.9815	6.3754	0.1005	-0.1982	0.1380	-0.4688	0.0724	1.4358	0.1510
K6	score	D2	6.1880	5.1890	7.1870	0.5097	6.0924	5.5803	6.5725	0.2531	0.0956	0.5691	-1.0198	1.2110	0.1680	0.8666
Living alone***	Y/N	P1	0.0316	0.0218	0.0415	0.0050	0.0364	0.0189	0.0570	0.0097	-0.0048	0.0109	-0.0262	0.0167	0.4358	0.6630
Personal income***	Y/N	P1	0.8383	0.7658	0.9108	0.0370	0.9060	0.8518	0.9470	0.0243	-0.0677	0.0442	-0.1544	0.0190	1.5298	0.1261
Vitamin A rich foods***	Y/N	P2	0.6362	0.5660	0.7064	0.0358	0.6607	0.5728	0.7382	0.0422	-0.0245	0.0553	-0.1330	0.0840	0.4427	0.6580
Screened***	Y/N	P2	0.0018	-0.0017	0.0052	0.0017	0.0030	0.0000	0.0101	0.0026	-0.0012	0.0031	-0.0073	0.0049	0.3983	0.6904
GAM***, ****	Y/N	MIX	0.0439	0.0274	0.0605	0.0084	0.0209	0.0051	0.0434	0.0098	0.0230	0.0129	-0.0022	0.0483	1.7858	0.0741

* Type of indicator : C1 for the mean of single continuous variable, D1 for the mean of a single discrete variable, D2 for the mean of a multi-variable discrete scale or score, P1 for a proportion calculated from a single variable, P2 for a proportion calculated from multiple variables, MIX for mixed methods (see text).

** Two-sample *z-test* (see *Box ZCI* for details of calculations of the *z-test*, 95% CIs, and the corrected p-value).

*** These results are presented as proportions (multiply by 100 to convert these results to percentages).

**** Results are for a classic estimator (SMART) and a PROBIT estimator (RAM-OP). *See Box CP*.
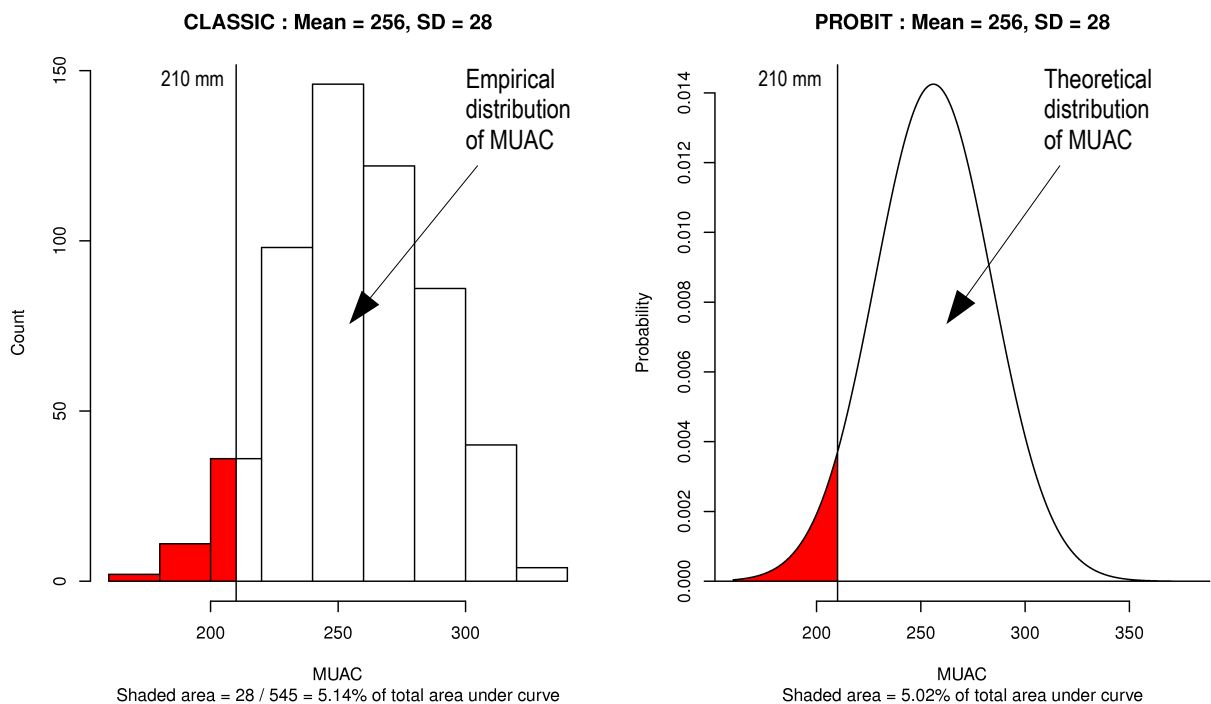
Box CP : Classic and PROBIT estimators of GAM prevalence

The estimate of GAM made from the SMART survey data used the classic estimator:

$$prevalence = \frac{number\ of\ respondents\ with\ MUAC < 210\ mm}{total\ number\ of\ respondents}$$

The estimate of GAM made from the RAM-OP survey data used a PROBIT estimator. This is a *model-based* approach. 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.

Both the classic and the PROBIT methods can be thought of as estimating area:

CLASSIC : Mean = 256, SD = 28 — Shaded area = 28 / 545 = 5.14% of total area under curve

PROBIT : Mean = 256, SD = 28 — Shaded area = 5.02% of total area under curve

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 method.

The PROBIT method assumes that MUAC is a normally distributed variable. If this is not the case then the distribution of MUAC can be transformed towards normality. This was done with data from the RAM-OP survey reported here.

Table CC : Estimated costs for SMART and RAM-OP surveys

Activity	Item	Unit	Cost / Unit	RAM-OP Units	RAM-OP Cost	SMART Units	SMART Cost	Difference[*] RAM-OP − SMART
Training	person-days (survey team & data entry staff)	person-day	$18.00	36	$648.00	44	$792.00	-$144.00
	person-days (national assistant supervisor)	person-day	$36.00	4	$144.00	4	$144.00	$0.00
	person-days (international survey manager)	person-day	$582.00	4	$2328	4	$2328	$0.00
	Venue hire	days	$117.00	4	$468.00	4	$468.00	$0.00
	Refreshments	person-day	$5.00	44	$220.00	52	$260.00	-$40.00
	Handouts, manual, &c.	sheets	$0.10	200	$20.00	240	$24.00	-$4.00
	Stationery (notepads, pens, &c.)	lump sum			$40.00		$50.00	-$10.00
Survey	Survey enumerators	person-day	$21.00	40	$840.00	80	$1,680.00	-$840.00
	Data-entry staff	person-day	$21.00	5	$105.00	9	$189.00	-$84.00
	National assistant supervisor	person-day	$42.00	5	$210.00	10	$420.00	-$210.00
	International survey manager	person-day	$582.00	6	$3,492.00	11	$6,402.00	-$2,910.00
	Translators & local guides	person-days	$21.00	10	$210.00	16	$336.00	-$126.00
	Vehicles with drivers (survey teams)	vehicle-day	$70.00	5	$350.00	16	$1,120.00	-$770.00
	Vehicles with drivers (supervisory staff)	vehicle-day	$70.00	6	$420.00	10	$700.00	-$280.00
	Fuel purchased	lump sum			$400.00		$600.00	-$200.00
	Photocopying of questionnaires	sheet	$0.10	2560	$256.00	4800	$480.00	-$224.00
	Purchase of population data / maps	enumeration area	$67.30	20	$1,346.00	30	$2,019.00	-$673.00
	MUAC tapes	tape	$0.25	16	$4.00	20	$5.00	-$1.00
Other	Communications	lump sum			$20.00		$30.00	-$10.00
	Flights	flight	$900.00	1	$900.00	1	$900.00	$0.00
				Totals	**$12,420.00**		**$18,947.00**	**-$6,526.00**

[*] Negative values indicate that RAM-OP was less expensive then SMART, zero value indicate no difference in cost between RAM-OP and SMART, positive values (not present in this study) indicate RAM-OP was more expensive than SMART.

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