Cost-effectiveness analysis (CEA) is a way of examining the costs and health outcomes of one or more interventions. It compares an intervention to another intervention (or the absence of intervention) by estimating how much it costs to gain a unit of a desired health outcome such as a year of life gained, a case of disease cured, or a life saved. Cost-effectiveness analysis provides information on health impacts and costs of an intervention compared to an alternative intervention (or the absence of intervention). Results are presented as a cost-effectiveness ratio which is the is the cost of an intervention divided by changes in health outcomes. Examples include cost per year of life gained, cost per case cured, and cost per life saved. Interventions can then be compared in terms of cost per unit of effectiveness. This handbook covers the types of outcomes used in CEA analyses, the creation of counterfactuals to model the absence of an intervention, building models of program outcomes and costs, accounting for uncertainty in models using fuzzy numbers and fuzzy arithmetic, the types of costs that need to be considered in cost-effectiveness analyses, detailed methods and tools needed to collect and work with costs data from a variety of sources, and guidance on interpreting cost-effectiveness estimates. A method of cost-effectiveness analysis for community management of acute malnutrition (CMAM) programs is presented including worked examples from Bangladesh, Ethiopia, Kenyam and Nigeria.

Mark Myatt is a consultant epidemiologist. His clients include the governments of the UK, USA, Ethiopia, Zambia, Malawi, Nigeria, and Sudan; the UK National Health Service and Public Health Laboratory Service; the Scottish Centre for Infection and Environmental Health; United Nations Organisations such as WHO, UNICEF, UNHCR, and WFP; ASEAN; and many International NGOs. He has taught at several UK Universities and national schools of public health.He has done cost-effectiveness analyses of nutrition programs in Bangladesh, Nigeria, Pakistan, Ethiopia, Burkina Faso, and Niger.

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and Assaye Bulti

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CONTENTS

INTRODUCTION

Cost-effectiveness analysis is based on a very simple idea. Cost-effectiveness (CE) is just:

$$CE = \frac{cost}{outcome}$$

where *cost* is the amount of money spent on a program over a defined period of time and *outcome* is the number of desired or positive outcomes delivered by the program over the same period of time.

If, for example, a program costed US$119,697 and cured 653 case of severe acute malnutrition (SAM) then the *cost per case recovered* is calculated as:

$$CE = \frac{US\$119{,}697}{653} = US\$183.30$$

The *cost* term always includes *institutional costs*. These are the costs of all inputs used by implementing institutions including personnel, transport, medicines, and therapeutic or supplementary foods. *Societal costs* such as the costs incurred by beneficiaries during their participation in the program may also be included. The *cost* term should cover the majority of resources that were used to make a program function and should include all important cost contributions.

A number of different *outcome* measures may be used. Typical outcomes are:

> **Cases treated :** This is the number of cases treated by a program regardless of outcome. The effectiveness (e.g., the cure rate) of the program is **<u>not</u>** taken into account. Analyses using this outcome are best considered as *cost-efficiency* rather than as *cost-effectiveness* analyses. This type of analysis is only useful for well-proven and highly effective treatments or for primary prevention (e.g., vaccine) programs.
>
> **Cases recovered (case cured) :** This is the number of cases treated by a program that were cured. Analyses using this *positive* outcome are *cost-effectiveness* analyses
>
> **Lives saved (deaths averted):** This is the number of lives saved, which is the same as the number of deaths averted, by a program. This is an

important measure of *cost-effectiveness* for programs treating conditions associated with high mortality such as severe acute malnutrition (SAM). The calculation of the number of lives saved requires the use of a *counterfactual* (i.e. an informed guess about what would have happened in the absence of the program) derived from *cases recovered* and the expected mortality in untreated cases.

Disability Adjusted Life Years (DALY) averted : This is the number of DALYs averted by a program. DALY calculations combine the number of years of life lost (*YLL*) and the number of years living with disability (*YLD*) associated with the condition being treated. The DALY calculation requires the use of a *counterfactual* derived from the duration of illness in treated and untreated cases, the severity of disability associated with illness, *cases recovered*, *lives saved*, and life expectancy. The use of disability and mortality makes the DALY outcome suitable for use with both acute and chronic conditions.

The *cost per life saved* and *cost per DALY averted* measures may be compared between programs addressing different conditions. This makes them useful for health policy and planning purposes.

This handbook concentrates on the $DALY_{Averted}$ outcome because it is a widely applicable measure of program effectiveness and because the *cases treated*, *cases recovered*, and *lives saved* outcomes are components of the $DALY_{Averted}$ outcome. If you calculate the $DALY_{Averted}$ outcome you will have also calculated the other three outcomes. This is illustrated in *Figure 1*.

DISABILITY ADJUSTED LIFE YEARS (DALYS)

Disability Adjusted Life Years (DALY) calculations have two components:

The number of years lived with the disability (YLD) associated with the condition of interest.

The number of years of life lost (YLL) associated with the condition of interest.

DALYs are estimated as the sum of the YLD and YLL components:

$$
\begin{aligned}
YLD &= Duration\ of\ disease\ episode\ \times\ Disability\ Weight \\
YLL &= Expected\ life - Age\ at\ death\ from\ the\ disease \\
DALY &= YLD + YLL
\end{aligned}
$$

In this handbook we will concentrate on DALY calculations related to severe acute malnutrition (SAM). The described method can be easily adapted for use with other conditions. Note that other outcomes that are commonly used in cost-effectiveness analyses (i.e., cases recovered and lives saved) are components of DALY calculations.

Years Living with Disability (YLD)

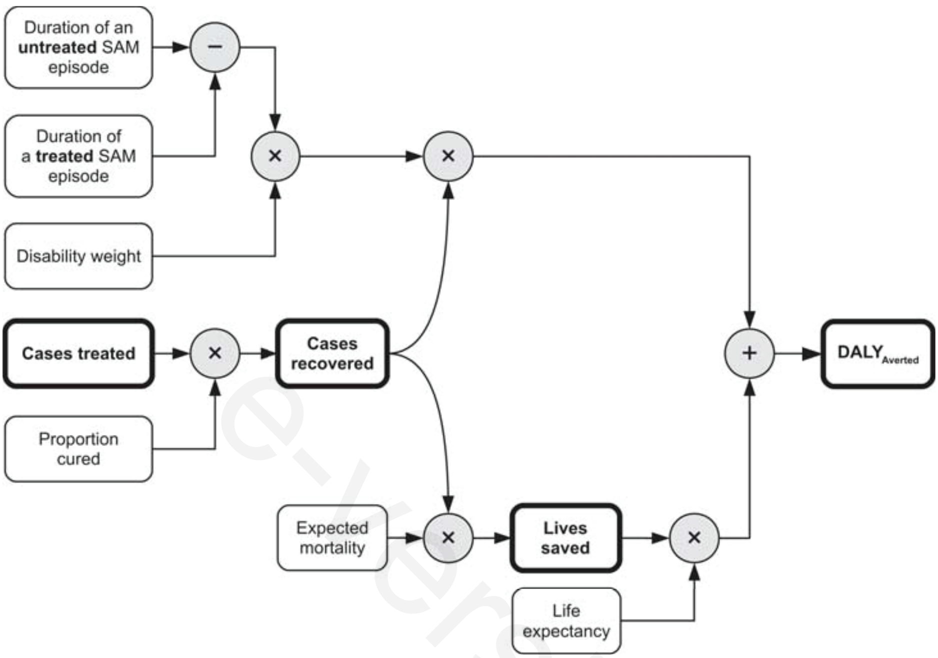
YLD for different diseases are calculated using disease-specific disability weights that range between zero (perfect health) and one (death).

It is common practice to use the disease-specific disability weights used in the most recent Global Burden of Disease (GBD) study or Global Health Estimates (GHE) study. For example:

The disability weight for severe wasting used in the 2010 GBD study and the GHE 2000-2011 study was D = 0.127.

The disability weight for kwashiorkor (nutritional oedema) used in the 2010 GBD study and the GHE 2000-2011 study was D = 0.055.

Figure 1 : Cases treated, cases recovered, and lives saved are Components of $DALY_{Averted}$



Outcomes commonly used in cost-effectiveness analyses are shown in **bold**

This diagram presents the $DALY_{Averted}$ calculation for an acute condition with little or no lasting disability such as SAM. Other conditions may have lasting post treatment disability, and this would need to be accounted for in the $DALY_{Averted}$ calculation.

The only time that you may need to use historical (i.e. older) disability weights is when you want to compare current and past programs.

Severe acute malnutrition (SAM) is defined as:

$$SAM = Severe\ wasting\ \boldsymbol{OR}\ Kwashiorkor$$

Severe wasting is commonly defined using mid-upper arm circumference (MUAC). Kwashiorkor is most commonly defined as the presence of bilateral pitting oedema. SAM is, therefore, commonly defined as:

$$SAM = MUAC < 115\ mm\ \boldsymbol{OR}\ Bilateral\ pitting\ oedema$$

This means that a child with SAM may have severe wasting, kwashiorkor, or both severe wasting and kwashiorkor. A child with both conditions will be more disabled (i.e. sicker) than a child with a single condition.

Disability weights for two co-existing conditions (comorbidities) are combined using:

$$D_{1\ and\ 2} = 1 - (1 - D_1)\ \times\ (1 - D_2)$$

This approach can be extended to include any number of conditions.

The disability weights that are currently used for the three different types of SAM are:

Severe wasting only	$D = 0.127$
Kwashiorkor only	$D = 0.055$
Severe wasting **AND** Kwashiorkor*	$D = 1 - (1 - 0.127)\ \times\ (1 - 0.055)$ $= 0.175$

* This is sometimes referred to as *marasmic kwashiorkor*

DALYs may be used to measure both *burden* and *effectiveness*.

Burden is the quantity of disability associated with a condition. This is estimated in the GBD 2010 study and the GHE 2000-2011 study as:

$$Burden = Prevalence\ \times\ Population\ \times\ Disability\ weight$$

This is consistent with the basic YLD formula:

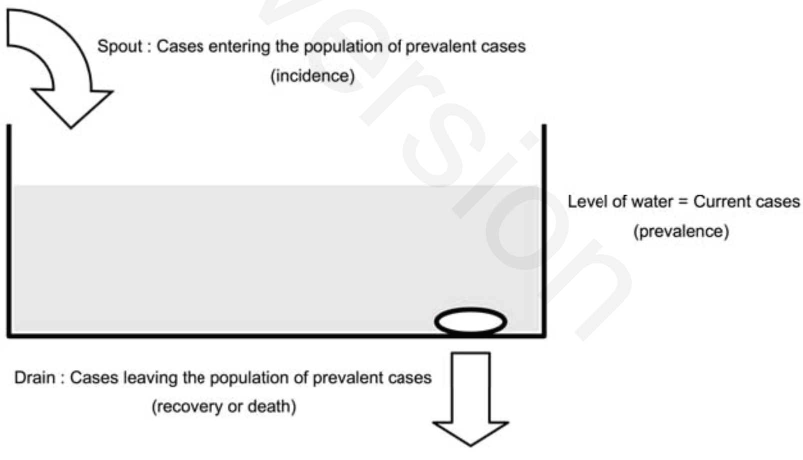
$$YLD = Duration\ of\ disease\ episode\ \times\ Disability\ Weight$$

because of the relationship between incidence, prevalence, and duration of disease.

The relationship between incidence, prevalence, and duration of illness is frequently described using a "bathtub" metaphor (see *Figure 2*). In this model the flow of water into the bathtub represents incidence, the level of the water in the bathtub represents prevalence, and the flow of water out of the bathtub through the drain represents recovery and mortality. Prevalence, therefore, depends, to a large extent, upon incidence and the average duration of illness. This handbook does **not** cover SAM burden estimation using prevalence and YLD. This is because SAM burden is more usefully estimated as the sum of prevalent cases at the start of a planning period and incident cases expected to arise during that planning period. This estimate can be combined with expected coverage to predict program caseload over a planning period.

DALYs may also be used to measure *effectiveness*. Effectiveness is the quantity of disability (including death) that is *averted* (i.e., avoided or prevented) by an intervention against a condition. Estimating effectiveness is more complicated than estimating burden using the method employed by the GBD 2010 study and the GHE 2000-2011 study. Both the YLD and YLL components are used and a *counterfactual* is constructed.

Figure 2 : The "bathtub" metaphor for the relationship between incidence and prevalence



This handbook concentrates on using DALYs to measure program effectiveness.

A counterfactual for YLD

Estimating the number of years living with disability (YLD) averted ($YLD_{Averted}$) by an intervention requires the construction of a *counterfactual*.

The counterfactual is an informed guess at what would have happened in the absence of the intervention.

To use the basic YLD formula:

$$YLD = Duration\ of\ disease\ episode\ \times\ Disability\ Weight$$

we need to calculate the difference between the durations of disease (t) for untreated and treated SAM episodes:

$$\Delta t = t_{Untreated\ SAM} - t_{Treated\ SAM}$$

This is the duration of the SAM episode that is *averted* by treatment.

It is common to use the duration of SAM episodes from treatment to discharge as cured in the program under study for $t_{Treated\ SAM}$. This is calculated for recovered cases only. Treatment episodes resulting in death, transfer, or default are **not** considered.

We usually know the length of a successfully treated episode of SAM. This is the length of stay in the program for SAM cases that are discharged as cured.

We do not usually know the duration of an untreated episode of SAM. It is common practice to use six months. This figure is derived from historical (i.e., from the late twentieth century) cohort studies.

If the length of a successfully treated episode of SAM is two months and the length of an untreated episode of SAM is six months, then:

$$\begin{aligned} \Delta t &= t_{Unreated\ SAM} - t_{Treated\ SAM} \\ &= 6 - 2 \\ &= 4\ months \end{aligned}$$

The effect of treatment is to shorten the duration of the disease episode by four months.

For this episode of severe wasting the program averted:

$$YLD_{Averted} = \frac{4}{12} \times 0.127 = 0.0423$$

We could calculate $YLD_{Averted}$ for every SAM case that was discharged as cured by a program. The sum of these individual $YLD_{Averted}$ figures would be the estimate of the $YLD_{Averted}$ by the program.

Working with individual data can be expensive and time-consuming. It also raises issues of confidentiality and data protection and may be illegal in some settings unless all identifying data is removed.

We usually work with summary measures (e.g., counts of cases and average lengths of treatment episodes) taken from routine program monitoring statistics.

Table 1 shows the relevant routine program monitoring statistics for a CMAM program from Bangladesh.

Table 1 : Routine program monitoring data for the example CMAM program

Number admitted*	711
Number cured**	653
Average length of a cured episode	37.4 days
Average length of an untreated episode	182.5 days (6 months)

* This is the outcome we would use in a cost-efficiency analysis of cost per case treated

** This the outcome we would use in a cost-effectiveness analysis of cost per case recovered

If we assume that all SAM cases were admitted with severe wasting only then the average $YLD_{Averted}$ for each case is:

$$YLD_{Averted} = \frac{182.5 - 37.4}{365} \times 0.127 = 0.0505$$

The $YLD_{Averted}$ by the program was:

$$YLD_{Averted} = 0.0505 \times 653 = 32.9765$$

This analysis assumes that all SAM cases were admitted with severe wasting only. It is usually safe to do this because kwashiorkor is a rare condition and tends to account for only a small proportion of program caseload. In a CMAM program in Bangladesh, for example, there were just six (0.84% of all admissions) cases of kwashiorkor and seven (0.98% of all admissions) cases of concurrent severe wasting with kwashiorkor. Also, the contribution of the $YLD_{Averted}$ component of the DALY calculation:

$$DALY_{Averted} = YLD_{Averted} + YLL_{Averted}$$

will be small compared to the $YLL_{Averted}$ component (i.e., the mortality averted) for an acute condition which is associated with high mortality such as SAM.

If a large proportion of SAM cases are admitted with kwashiorkor, then you may want to calculate $YLD_{Averted}$ for each type of SAM separately and add them together. As a general rule you should try to keep calculations as simple as possible.

This analysis provides only a point estimate of $YLD_{Averted}$. A method that yields a range of values for $YLD_{Averted}$ that accounts for the uncertainty and variability in durations, disability, and the proportion cured would be both more useful and more credible.

Accounting for uncertainty

Uncertainty can be incorporated into estimates using *triangular fuzzy numbers*. Using triangular fuzzy numbers to account for uncertainty is similar to using a *sampling-based approach* to account for uncertainty (see *Box 1*).

A triangular fuzzy number is a *generalization* of a “regular” real number in the sense that it does not refer to a single value but rather to a connected set of possible values. Each possible value has its own weight or *membership function* (μ) which is a measure of the degree of membership in the set of all possible values. The membership function (μ) ranges between zero and one. Impossible values have a weight of zero, the most likely value has a weight of one, and all other possible values have a weight above zero but below one.

We do not need to worry about specifying membership functions when using triangular fuzzy numbers. We need only specify the minimum, maximum, and the most likely values for each quantity (See *Box 2*). This is useful because in many situations we can usually estimate the minimum, maximum, and the most likely values even if we do not know the exact shape of the sampling distribution.

Figure 3 expresses the duration of an **untreated** episode of SAM as a triangular fuzzy number.

Triangular fuzzy numbers can be represented using three points:

$$A = (a_1, a_2, a_3)$$

The duration of an untreated episode of SAM shown in *Figure 2* ranges between 3.5 months (a_1) and 7.5 months (a_3) with a central (most likely) value of 6.0 months (a_2):

$$A = (3.5, 6.0, 7.5)$$

Figure 3 : Duration of an untreated episode of SAM expressed as a triangular fuzzy number

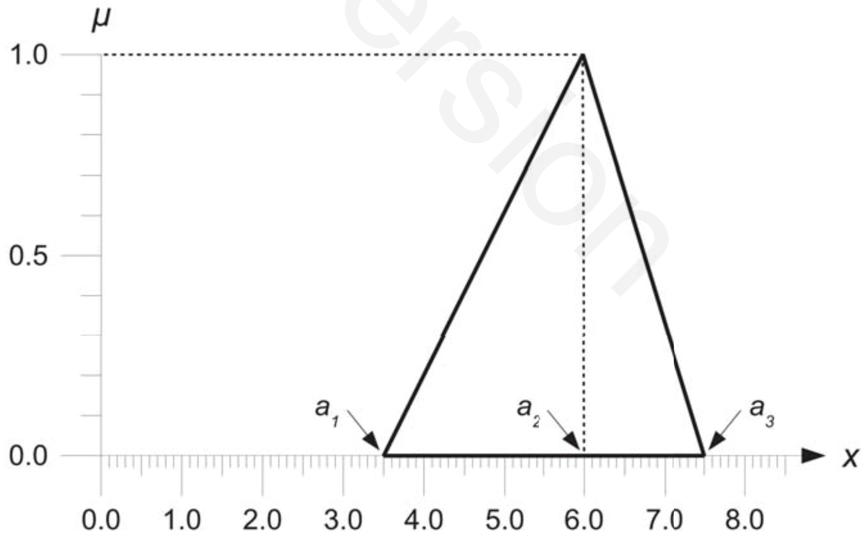


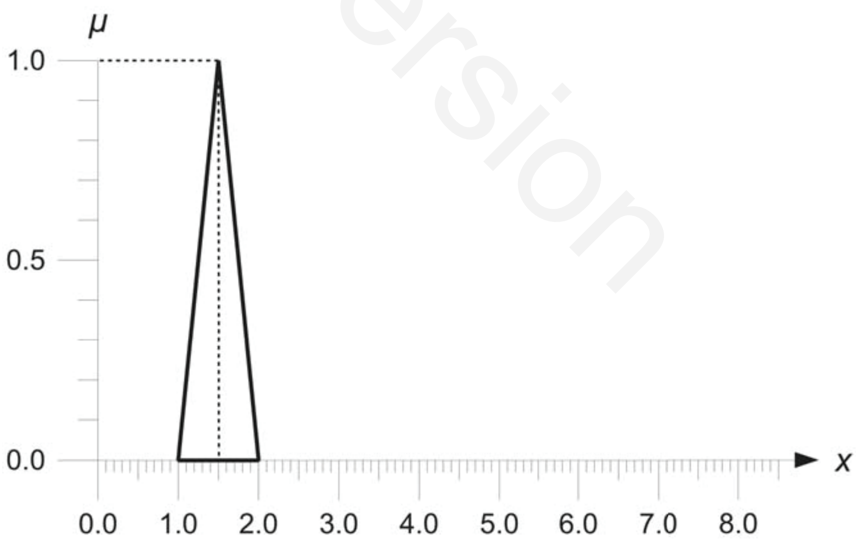
Figure 4 expresses the duration of a **treated** episode of SAM as a triangular fuzzy number.

The duration of a treated episode of SAM as shown in *Figure 3* ranges between 1.0 months (b_1) and 2.0 months (b_3) with a central (most likely) value at 1.5 months (b_2):

$$B = (1.0, 1.5, 2.0)$$

These values approximate program data. The minimum length of stay in the example program (b_1) was 28 days (i.e. four weeks). This was a program rule. All exits before four weeks were transfers to hospital, defaulters, or deaths. Four weeks is approximated as one month. The average length of stay in the example program was 37.4 days. This is approximated as 1.5 months. The maximum length of stay in the example program was 56 days (i.e. eight weeks). This was also a program rule. Beneficiaries that failed to meet discharge criteria for cure after eight weeks were referred to hospital. Eight weeks is approximated as 2.0 months.

Figure 4 : Duration of a treated episode of SAM expressed as a triangular fuzzy number



Using the basic YLD formula:

$$YLD = Duration\ of\ disease\ episode \times Disability\ Weight$$

we need to work out the difference between the durations of untreated and treated SAM episodes. These are the triangular fuzzy numbers expressed in *Figure 3* and *Figure 4* and labelled A and B. We want to find:

$$C = A - B$$

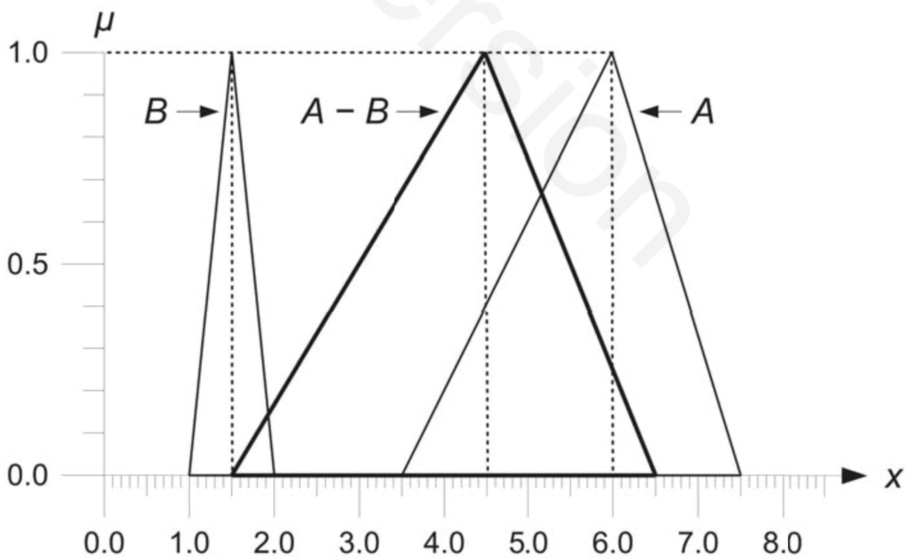
with the result expressed as a triangular fuzzy number.

Operations with triangular fuzzy numbers are shown in *Box 3*. We are dealing with positive numbers only so we may use the simpler procedure:

$$\begin{aligned} A - B &= (a_1 - b_3, a_2 - b_2, a_3 - b_1) \\ &= (3.5 - 2.0, 6 - 1.5, 7.5 - 1.0) \\ &= (1.5, 4.5, 6.5) \end{aligned}$$

This operation is illustrated in *Figure 5*.

Figure 5 : The fuzzy operation C = A – B where A = (3.5, 6.0, 7.5) and B = (1.0, 1.5. 2.0)



The difference between the duration of untreated and treated SAM episodes in months expressed as a triangular fuzzy number is:

$$C = (1.5, 4.5, 6.5)$$

YLD is expressed in years so we should express this in years rather than months:

$$C = \left(\frac{1.5}{12}, \frac{4.5}{12}, \frac{6.5}{12}\right) = (0.1250, 0.3750, 0.5417)$$

The disability weight used for severe wasting in the GBD 2010 study and the GHE 2000 – 2011 study was 0.127 with an uncertainty interval of 0.081 to 0.183. We can express this as a triangular fuzzy number:

$$D = (0.081, 0.127, 0.183)$$

The program admitted 711 SAM cases and cured 653 of these cases. The proportion of SAM admissions that were cured was:

$$Proportion_{Cured} = \frac{653}{711} = 0.9184$$

This is equivalent to the proportion of SAM cases that were cured that is used and reported in routine program monitoring statistics which uses the number of exits from the program as the denominator. This is because all admissions will result in an exit of one kind or another (i.e. cure, death, transfer, non-response, or default). The two methods will yield the same value in cases where all admissions have exited the program. They may yield different values if not all admissions have exited the program at the time of evaluation.

We usually want to generalise our results so we treat $Proportion_{Cured}$ as an estimate of what we might expect from similar programs or from the same program in the future.

The standard error (SE) of this point estimate is:

$$SE = \sqrt{\frac{p(1-p)}{n}} = \sqrt{\frac{0.9184 \times (1 - 0.9184)}{711}} = 0.0103$$

A triangular fuzzy number should cover all possible values of the quantity of interest. Nearly all values (i.e., a little above 95%) of $Proportion_{Cured}$ that are consistent with the data will lie within two standard errors of the point estimate. This enables us to represent the proportion cured as a triangular fuzzy number:

$$\begin{aligned} P &= (p - 2 \times SE, p, p + 2 \times SE) \\ &= (0.9184 - 2 \times 0.0103, 0.9184, 0.9184 + 2 \times 0.0103) \\ &= (0.8978, 0.9184, 0.9390) \end{aligned}$$

We can convert these proportions into numbers of cured cases:

$$\begin{aligned} N &= P \times 711 \\ &= (0.8978, 0.9184, 0.9390) \times 711 \\ &= (638, 653, 668) \end{aligned}$$

We now have everything we need to estimate $YLD_{Averted}$:

$$YLD_{Averted} = C \times D \times N$$

where:

C is the duration (in years) of SAM episodes that is averted by treatment:

$$C = (0.1250, 0.3750, 0.5417)$$

D is the disability weight for severe wasting:

$$D = (0.081, 0.127, 0.183)$$

and N is the numbers of cured cases:

$$N = (638, 653, 668)$$

We split the calculation into two steps. We will calculate $C \times D$ first:

$$\begin{aligned} C \times D &= (0.1250 \times 0.081, 0.3750 \times 0.127, 0.5417 \times 0.183) \\ &= (0.0101, 0.0476, 0.0991) \end{aligned}$$

This is the $YLD_{Averted}$ in each cured case.

We multiply $YLD_{Averted}$ in each cured case by the number of cured cases (N):

$$(C \times D) \times N = (0.0101 \times 638, 0.0476 \times 653, 0.0991 \times 668)$$
$$= (6.4438, 31.0828, 66.1988)$$

to find the $YLD_{Averted}$ by the program.

The best interpretation of this result is that:

The most likely result is:

$$YLD_{Averted} = 31.0828$$

The lowest (worst) possible result consistent with the data is:

$$YLD_{Averted} = 6.4438$$

The highest (best) possible result that is consistent with the data is:

$$YLD_{Averted} = 66.1988$$

We do not usually report the worst and best possible results. We usually present a 95% confidence interval (95% CI) for the most likely result. The procedure for calculating a 95% confidence interval for a triangular fuzzy number is shown in *Box 4*.

When we apply this procedure to our results we find:

$YLD_{Averted}$ = 31.0828 (95% CI = 12.5107 – 58.9559)

This analysis assumes that all SAM cases were admitted with severe wasting only. It is usually safe to do this because oedema tends to account for only a small proportion of program caseloads and the contribution of the $YLD_{Averted}$ component of the DALY calculation is usually small compared to the $YLL_{Averted}$ component for an acute condition associated with high mortality such as SAM.

If a large proportion of cases are admitted with oedema, then you may want to calculate $YLD_{Averted}$ for each type of SAM separately and add them together (see *Box 5*).

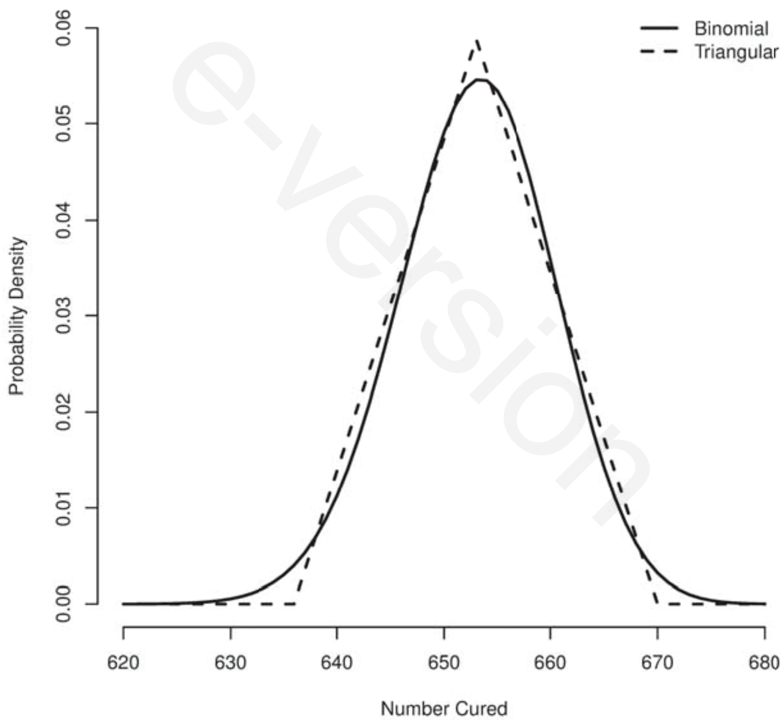
As a general rule you should try to keep calculations as simple as possible (see *Box 6*).

Note that some GBD disability weights may have questionable *face-validity* in the sense that they do not appear to accurately reflect the concept that they purport to represent. For example, urinary incontinence (D = 0.142) is weighted as being a more severe condition than “treated” paraplegia (D = 0.047), which may involve urinary incontinence as well as other disabilities. Such inconsistencies are gradually being resolved.

Box 1 : Triangular fuzzy numbers and sampling-based approaches to uncertainty

With a sampling-based approach we use probability distributions to represent quantities. A binomial distribution might, for example, be used to represent the number of cured cases. When we use triangular fuzzy numbers, we restrict ourselves to using triangular distributions to represent quantities. *Figure 6* shows how the number of cured cases might be represented using a binomial distribution and using a triangular distribution.

Figure 6 : A quantity represented using binomial and triangular distributions



The binomial and triangular distributions shown in *Figure 6* are similar to each other. This will usually be the case with other distributions (e.g., a gamma distribution used to represent durations of disease episodes and a Poisson distribution used to represent mortality rates) that might be used with a sampling-based approach.

Triangular fuzzy numbers originated from set theory. Probability is replaced by a measure of the degree of membership in a set of possible values. Each possible value has a weight or *membership function* (μ) which ranges between zero and one. Impossible values have a weight of zero, the most likely value has a weight of one, and all other possible values have a weight above zero but below one.

Triangular fuzzy numbers and sampling-based approaches are similar ways of accounting for uncertainty and tend to produce similar results. With the example Bangladesh program, the estimate for $DALY_{Averted}$ produced using triangular fuzzy numbers was:

$$\text{DALY}_{\text{Averted}} = 12{,}373 \text{ (95\% CI} = 9{,}207 – 16{,}774)$$

and the estimate for $DALY_{Averted}$ produced using a sampling-based approach with similar inputs was:

$$\text{DALY}_{\text{Averted}} = 12{,}186 \text{ (95\% CI} = 10{,}182 – 14{,}313)$$

The use of triangular fuzzy numbers is simpler than using a sampling-based approach. All calculations can be done by hand (see *Box 3*) or with a simple calculator (see *Box 3* and *Appendix 1*).

Box 2 : Minimum, maximum, and most likely values

We specify triangular fuzzy numbers using the minimum, maximum, and the most likely values for a quantity. This is useful because in many situations we can usually estimate the minimum, maximum, and the most likely values even if we do not know the exact shape of the sampling distribution.

When deciding on the minimum, maximum, and the most likely values to use, it is important give a "typical" value for the most likely value. This is usually a measure of central tendency. The *median* (i.e., the middle value) is a good measure of central tendency to use as it is not overly influenced by extreme values. The *mode* (i.e., the most common value) is also a good measure of central tendency to use.

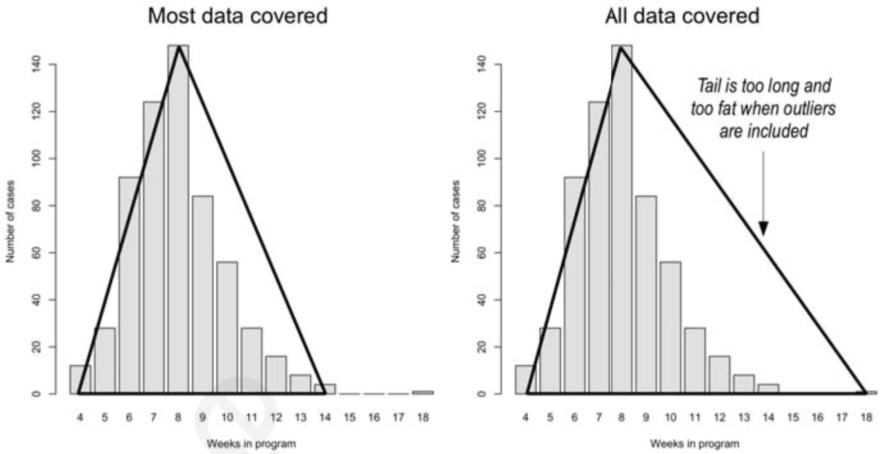
The minimum and maximum values need only cover the most likely range of values. This is the case when we use the 95% uncertainly limits for disability weights and the approximate 95% confidence limits for proportions. It is usually a good idea to ignore extreme or "outlying" observations when specifying minimum and maximum values. Including outliers may seriously (and spuriously) degrade the precision of final results in DALY calculations (see *Figure 7*).

Figure 7 shows two different triangular fuzzy numbers defined using the same program data for the duration of treatment in weeks seen in a CMAM program in Kenya.

The triangular fuzzy number that covers *most* of the data in *Figure 7* fits the distribution of treatment durations reasonably well. This triangular fuzzy number, or a slightly narrower triangular fuzzy number with an upper limit of 12 or 13 weeks, could be used to represent durations of treatment.

The triangular fuzzy number that covers *all* of the data in *Figure 7* is strongly influenced by a single and atypical outlier case at 18 weeks. The triangular fuzzy number that covers *all* of the data does **not** fit the distribution of treatment durations well and its use could seriously (and spuriously) degrade precision.

Figure 7 : Two different triangular fuzzy numbers defined using the same program data



The visual approach to defining a fuzzy triangular number shown in *Figure 7* usually works well but it requires judgment. Different people may, therefore, make different decisions based on the same data. A more objective and repeatable approach to defining a fuzzy triangular number from data is to use the 2.5th, 50th, and 97.5th percentiles of the variable of interest. The data plotted in *Figure 7* represented as a table is:

Weeks	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Count	12	28	92	124	148	84	56	28	16	8	4	0	0	0	1

It is useful to calculate *cumulative counts*:

Weeks	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Count	12	28	92	124	148	84	56	28	16	8	4	0	0	0	1
Cumulative counts*	12	40	132	256	404	488	544	572	588	596	600	600	600	600	601

* This is the sum of the previous and current counts. For example, the cumulative count for six weeks is 12 + 28 + 92 = 132

There are data for 601 cases. The 2.5th percentile is located at position:

$$601 \times \frac{2.5}{100} = 15$$

This lies in cumulative count for five (5) weeks.

The 50th percentile is located at position:

$$601 \times \frac{50}{100} = 300$$

This lies in cumulative count for eight (8) weeks.

The 2.5th percentile is located at position:

$$601 \times \frac{97.5}{100} = 586$$

This lies in cumulative count for twelve (12) weeks.

The length of stay in weeks for the Kenya program could reasonably be represented as:

$$C = (5, 8, 12)$$

The approach of using the 2.5th, 50th, and 97.5th percentiles of the variable of interest is a *robust method* and can be used when the distribution of values is symmetrical or asymmetrical about a central value. This can be very useful when dealing with data related to costs.

Box 3 : Operations between triangular fuzzy numbers

The simpler operations given here work for positive real numbers.

Given two triangular fuzzy numbers:

$$A = (3, 6, 8)$$

and:

$$B = (1, 2, 3)$$

The fuzzy triangular number A has three parts (i.e. a_1 = 3, a_2 = 6, and a_3 = 8). The fuzzy triangular number B also has three parts (i.e. b_1 = 1, b_2 = 2, and b_3 = 3).

The basic arithmetic operations are:

$$\begin{aligned} A + B &= (a_1 + b_1, a_2 + b_2, a_3 + b_3) \\ &= (3 + 1, 6 + 2, 8 + 3) \\ &= (4, 8, 11) \end{aligned}$$

$$\begin{aligned} A - B &= (a_1 - b_3, a_2 - b_2, a_3 - b_1) \\ &= (3 - 3, 6 - 2, 8 - 1) \\ &= (0, 4, 7) \end{aligned}$$

$$\begin{aligned} A \times B &= (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3) \\ &= (3 \times 1, 6 \times 2, 8 \times 3) \\ &= (3, 12, 24) \end{aligned}$$

$$\begin{aligned} A \div B &= (a_1 \div b_3, a_2 \div b_2, a_3 \div b_1) \\ &= (3 \div 3, 6 \div 2, 8 \div 1) \\ &= (1, 3, 8) \end{aligned}$$

Operations involving constants (or non-fuzzy numbers) are simple. For example:

$$\begin{aligned} A + 12 &= (a_1 + 12, a_2 + 12, a_3 + 12) \\ &= (3 + 12, 6 + 12, 8 + 12) \\ &= (15, 18, 20) \end{aligned}$$

The approach is the same for all operations involving constants (or non-fuzzy numbers). For example:

$$\begin{aligned} A \div 12 &= (a_1 \div 12, a_2 \div 12, a_3 \div 12) \\ &= (3 \div 12, 6 \div 12, 8 \div 12) \\ &= (0.2500, 0.5000, 0.6667) \end{aligned}$$

Fuzzy arithmetic operations are a little more complicated when dealing with zero and / or negative numbers. In this case a 'minimum / maximum rule' is used:

$$A \odot B = (\min(a_1 \odot b_1, a_1 \odot b_3, a_3 \odot b_1, a_3 \odot b_3),\\ a_2 \odot b_2, \max(a_1 \odot b_1, a_1 \odot b_3, a_3 \odot b_1, a_3 \odot b_3))$$

where $\odot$ is the operation (i.e., addition, subtraction, multiplication, or division) required, *min* represents the minimum (i.e., smallest value) of a set of numbers, and *max* represents the maximum (i.e., largest value) of a set of numbers.

Care needs to be taken to avoid divisions by zero.

It is unlikely that the more complicated 'minimum / maximum rule' method will be needed in DALY calculations.

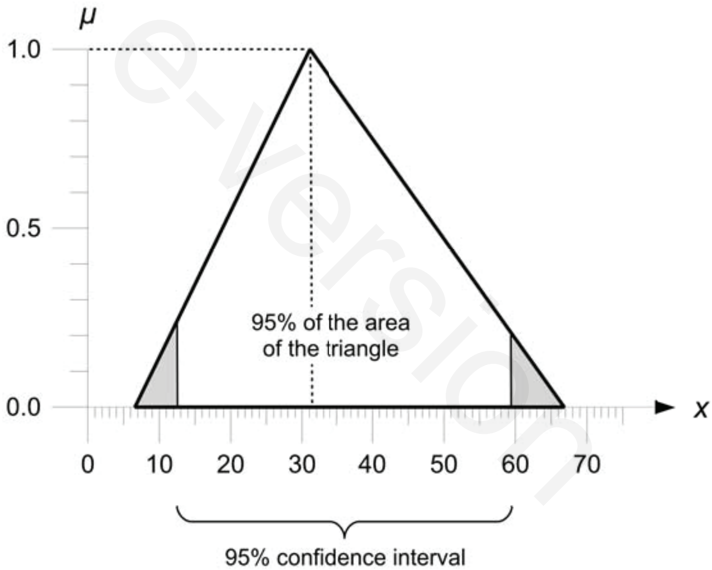
The rules of arithmetic with triangular fuzzy numbers are simple but tedious to perform. The large number of operations required for even simple calculations can make mistakes quite common. It is usually best to use a fuzzy arithmetic calculator (see *Appendix 1*).

Box 4 : Confidence limits for a triangular fuzzy number

A triangular fuzzy number expresses the most likely value and the range of possible values for a quantity. We can think of the upper and lower limits of a triangular fuzzy number as an approximate 100% confidence interval since it should contain all, or very nearly all, possible values of the quantity of interest. We usually want to present 95% confidence intervals.

Figure 8 shows a 95% confidence interval (95% CI) for a triangular fuzzy number.

Figure 8 : A 95% confidence interval for A = (6.4, 31.1, 66.9)



The 95% CI contains the central 95% of the area of the triangle.

Given a triangular fuzzy number $A = (a_1, a_2, a_3)$, the point estimate is a_2. The 95% confidence limits for a_2 are:

$$Lower\ 95\%\ confidence\ limit = a_1 + \sqrt{(a_3 - a_1)\ \times\ (a_2 - a_1)\ \times\ 0.025}$$

$$Upper\ 95\%\ confidence\ limit = a_3 - \sqrt{(a_3 - a_1)\ \times\ (a_3 - a_2)\ \times\ 0.025}$$

If we calculate $YLD_{Averted}$ using triangular fuzzy numbers and find:

$$YLD_{Averted} = (6.4, 31.1, 66.9)$$

then the 95% confidence limits on $YLD_{Averted}$ are:

$$\begin{aligned} Lower\ confidence\ limit &= 6.4 + \sqrt{(66.9 - 6.4)\ \times\ (31.1 - 6.4)\ \times\ 0.025} \\ &= 12.5 \end{aligned}$$

$$\begin{aligned} Upper\ confidence\ limit &= 66.9 - \sqrt{(66.9 - 6.4)\ \times\ (66.9 - 31.1)\ \times\ 0.025} \\ &= 59.5 \end{aligned}$$

We would report our findings as "$YLD_{Averted}$ = 31.1 (95% CI = 12.5 – 59.5)".

Box 5 : A more complicated $YLD_{Averted}$ calculation

If a large proportion of cases are admitted with oedema (kwashiorkor) then you may want to calculate $YLD_{Averted}$ separately for each category of admission and add the results together. We will do this for the Bangladesh CMAM program.

The data for admissions and cured cases are:

Admission criteria	Number admitted	Number cured	Proportion cured (SE)	Proportion cured*,**	Number of cured cases**
Severe wasting	698	645	0.9241 (0.0100)	(0.9041, 0.9241, 0.9441)	(631, 645, 659)
Kwashiorkor	6	4	0.6667 (0.1924)	(0.2819, 0.6667, 1.0000)	(2, 4, 6)
Both***	7	4	0.5714 (0.1870)	(0.1974, 0.5714, 0.9454)	(1, 4, 7)

* Calculated as the proportion cured ± 2 standards errors (truncated at zero and one)

** Expressed as triangular fuzzy numbers

*** Admissions with both severe wasting AND kwashiorkor

In this example we will assume that the duration of a SAM episode that is averted by treatment is the same for all categories of admission and is (0.1250, 0.3750, 0.5417) years.

The $YLD_{Averted}$ calculations using triangular fuzzy numbers are:

	Term*	Severe wasting	Kwashiorkor	Both**
Duration of a SAM episode averted by treatment	C	(0.1250, 0.3750, 0.5417)		
Disability weights***, ****	D	(0.081, 0.127, 0.183)	(0.033, 0.055, 0.082)	(0.111,0.175, 0.250)
$YLD_{Averted}$ per case	C × D	(0.0101, 0.0476, 0.0991)	(0.0041, 0.0206, 0.0444)	(0.0139, 0.0656, 0.1354)
Number of cured cases	N	(631, 645, 659)	(2, 4, 6)	(1, 4, 7)
$YLD_{Averted}$ in each admission category	(C × D) × N	(6.3731, 30.7020, 65.3069)	(0.0082, 0.0824, 0.2664)	(0.0139, 0.2624, 0.9478)
$YLD_{Averted}$ by The program	SUM	(6.3952, 31.0468, 66.5211)		

* Naming of terms follows that used in the main text

** Admissions with both severe wasting AND kwashiorkor

*** Disability weights used in the GBD 2010 study and the GHE 2000 - 2011 study

, ** Disability weights for both were calculated by combining disability weights for severe wasting and kwashiorkor

In this example, the $YLD_{Averted}$ by the program calculated for each admission category is:

$$YLD_{Averted} = (6.3952, 31.0468, 66.5211)$$

and the $YLD_{Averted}$ by the program calculated assuming all cases were admitted with severe wasting is:

$$YLD_{Averted} = (6.4438, 31.0828, 66.1988)$$

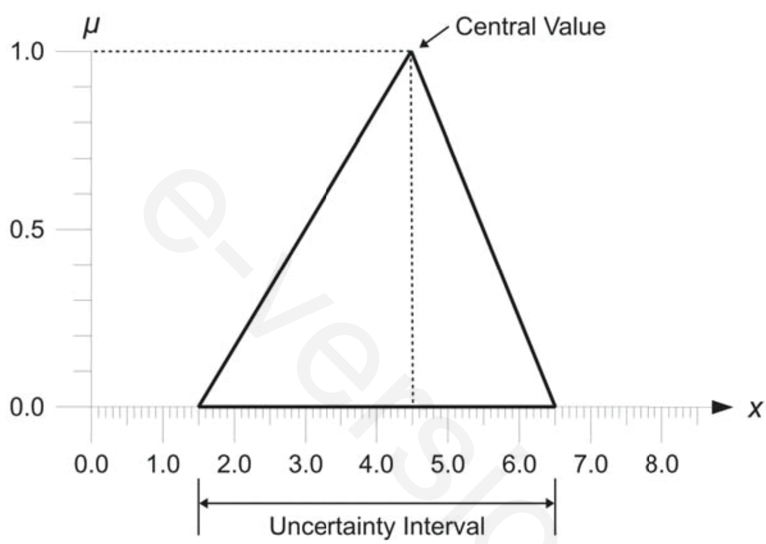
A little accuracy has been gained but a little precision has been lost by using the more complicated approach.

It is usually safe to use the simpler approach because kwashiorkor is a rare condition and tends to account for only a small proportion of program caseloads. Also, the contribution of the $YLD_{Averted}$ component of the DALY calculation will be small compared to the $YLL_{Averted}$ component for an acute (i.e. short duration) condition which is associated with high mortality such as SAM.

Box 6 : Accuracy, uncertainty, and simplicity

Almost all quantities in a DALY model will have a central value with an interval of some sort attached. The interval reflects uncertainty about the value of the quantity being represented Triangular fuzzy numbers are one way of representing quantities in this way (See *Figure 9*).

Figure 9 : A triangular fuzzy number and the associated uncertainty interval



When we do calculations involving intervals, we do not lose any uncertainty. No valid operation involving intervals can ever reduce uncertainty. Instead, uncertainty accumulates, and each operation tends to increase uncertainty. This means that elaborate models (i.e., models with very many parameters) may give more accurate results than simpler models but the results will often be more uncertain (i.e., less precise) than simpler models.

Many people instinctively feel that we should improve accuracy even if this is at the expense of increasing uncertainty. They feel that a lack of accuracy means that something must be very wrong with a model. They acknowledge that uncertainty is not a good thing but that an accurate model with a lot of uncertainty will do well on average and is not fundamentally flawed. This view can be mistaken. It is true that a high uncertainty and low bias model will do well in terms of long-run averages, but we most often work with a single instance and the long-run average is not particularly relevant. With DALY calculations, for example, we often want to demonstrate effectiveness and cost-effectiveness of a single intervention. For such applications, reducing uncertainty at the cost of reducing accuracy a little is an acceptable strategy. There are two main approaches to reducing uncertainty. We can try to reduce uncertainty by using larger sample sizes to estimate quantities or we can simplify models. Reducing uncertainty by increasing sample sizes is often not possible. Simplifying models is easy to do but we need to be careful that we do not oversimplify and end up with a grossly inaccurate model.

A COUNTERFACTUAL FOR YEARS OF LIFE LOST ($YLL_{AVERTED}$)

The counterfactual for years of life lost ($YLL_{Averted}$) is similar to the counterfactual for years living with disability ($YLD_{Averted}$). It is an informed guess about what would have happened in the absence of the intervention.

The simplest form of $YLL_{Averted}$ counterfactual is the number of lives saved by the intervention multiplied by life expectancy.

This requires us to estimate the number of lives saved by the intervention. We can do this by estimating mortality in an imagined cohort of untreated cases with a similar severity of disease as the cases successfully treated by the program and correcting this for background mortality:

$$Expected\ mortality = Case\ fatality\ rate_{Untreated\ SAM} - Background\ mortality$$

We can find the expected case fatality rate in untreated SAM cases using historical cohort data.

Figure 10 shows the case fatality rates (in deaths / 1,000 cases / year) at different levels of MUAC reported by four historical cohort studies. There is little between-study variation in the observed relationships between MUAC and mortality despite the fact that these studies were undertaken by different teams in different locations at different times with varying lengths of follow-up and inconsistent censoring of accidental and violent deaths. This suggests that each study is estimating the same underlying rates and the observed differences were due to varying lengths of follow-up, inconsistent censoring of accidental and violent deaths, measurement error, and sampling variation. *Table 2* shows the same data as *Figure 10* for different levels of MUAC less than or equal to 125 mm.

Figure 10 : Case fatality rates at different levels of MUAC reported by four historical cohort studies in deaths / 1,000 cases / year

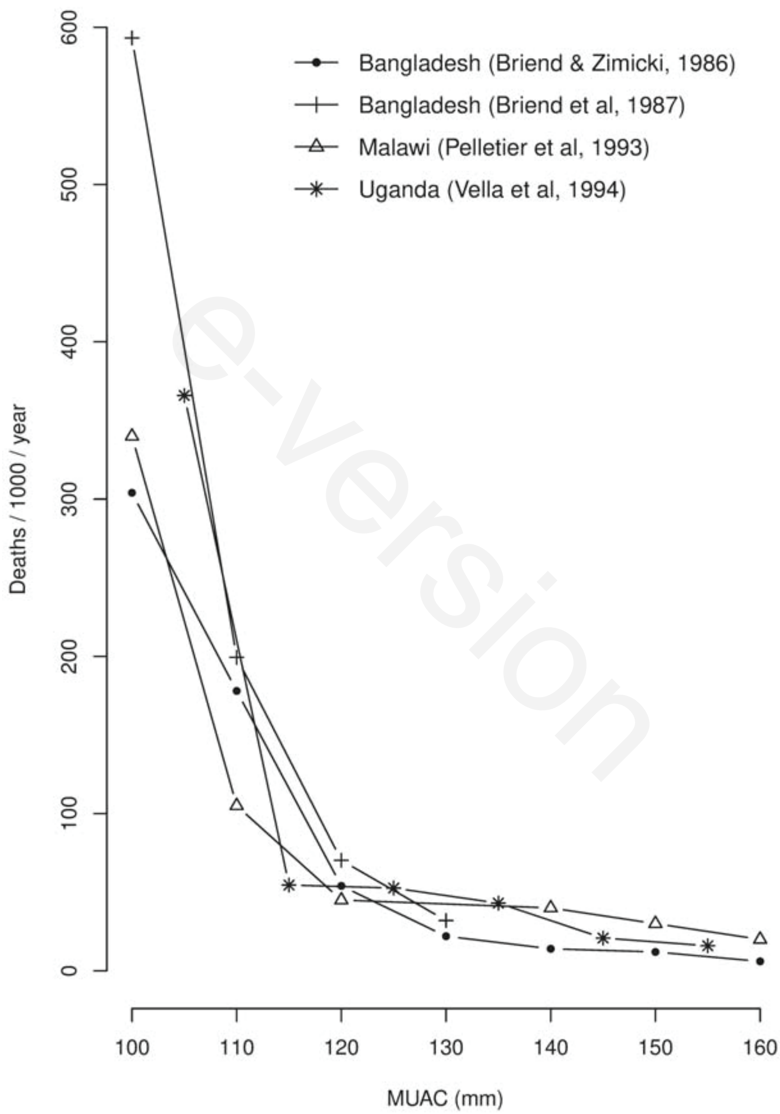


Table 2 : *Case fatality rates for different levels of MUAC reported by four historical cohort studies in deaths / 1,000 cases / year for different levels of MUAC less than or equal to 125 mm*

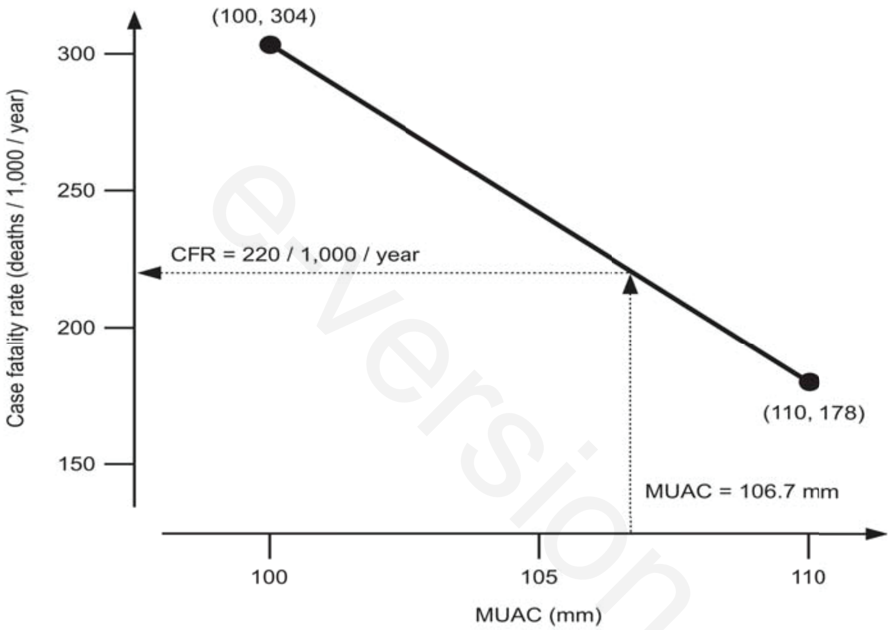
		MUAC (mm)					
Country	**Study**	**100**	**105**	**110**	**115**	**120**	**125**
Bangladesh	Briend & Zimicki (1986)	304		178		54	
	Briend, el al (1987)	593		199		70	
Malawi	Pelletier et al (1993)	340		105		45	
Uganda	Vella et al (1994)		366		55		53

The average MUAC at admission in the cured cases in the example program from Bangladesh was 106.7 mm. There is no column in *Table 2* that exactly matches 106.7 mm. We can, however, use a *linear interpolation* procedure to estimate mortality in children with MUAC = 106.7 mm.

The Linear Interpolation Procedure

Figure 11 shows an example of graphical linear interpolation using the Briend & Zimicki (1986) results to estimate the case fatality rate for children with MUAC = 106.7 mm.

Figure 11 : Linear interpolation using the Briend & Zimicki (1986) results to estimate the case fatality rate for children with MUAC = 106.7 mm



Using the Briend & Zimicki (1986) results to estimate the case fatality rate for children with MUAC = 106.7 mm arithmetically, we have (x_1, y_1) = (100, 304) and (x_2, y_2) = (110, 178). The case fatality rate associated with MUAC = 106.7 mm cam be estimated:

$$
\begin{aligned}
CFR &= y_1 - \frac{y_2 - y_1}{x_2 - x_1} \times (x_1 - MUAC) \\
&= 304 - \frac{178 - 304}{110 - 100} \times (100 - 106.7) \\
&= 219.58
\end{aligned}
$$

Figure 11 shows this procedure done graphically.

We should repeat this calculation for the reported case fatality rates from each of the four historical cohort studies. The calculations and results for MUAC = 106.7 mm are shown in *Table 3*.

Table 3 : *Case fatality rates for MUAC = 106.7 mm from four cohort studies*

Study	x_1	y_1	x_2	y_2	Case fatality rate
Briend & Zimicki (1986)	100	304	110	178	$304 - \frac{178 - 304}{110 - 100} \times (100 - 106.7) = 219.58$
Briend, el al (1987)	100	593	110	199	$593 - \frac{199 - 593}{110 - 100} \times (100 - 106.7) = 329.02$
Pelletier et al (1993)	100	340	110	105	$340 - \frac{105 - 340}{110 - 100} \times (100 - 106.7) = 182.55$
Vella et al (1994)	105	366	115	55	$366 - \frac{55 - 366}{115 - 105} \times (105 - 106.7) = 313.13$

It seems reasonable (i.e. from an inspection of *Figure 10*) to assume that each study is estimating the same underlying rate and the observed differences were due to varying lengths of follow-up, inconsistent censoring of accidental and violent deaths, measurement error, and sampling variation. This means that an average of the four case fatality rates is likely to provide a better estimate than is available from a single study. A good average to use when working with rates is the harmonic mean:

$$Harmonic\ mean = \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \cdots + \frac{1}{x_n}}$$

With the case fatality rates calculated in *Table 3* the harmonic mean is:

$$\overline{CFR} = \frac{4}{\frac{1}{219.58} + \frac{1}{329.02} + \frac{1}{182.55} + \frac{1}{313.13}} = 245.93$$

We can represent this as a triangular fuzzy number:

$$\begin{aligned} CFR &= (lowest\ CFR, harmonic\ mean\ CFR, highest\ CFR) \\ &= (182.55, 245.93, 329.02) \end{aligned}$$

This estimate of expected mortality will include baseline or background mortality and may cause us to overestimate the number of lives saved by the intervention and the $YLL_{Averted}$ component of $DALY_{Averted}$ estimates. Some adjustment to account for baseline mortality is required.

The average under five-years mortality rate (U5MR) for the locations (i.e. countries) and times of the four cohort studies was about 1 death per 10,000 children per day. This is same as 36.5 deaths per 1,000 children per year. Applying this adjustment yields:

$$\begin{aligned} Expected\ mortality &= (182.55, 245.93, 329.02) - 36.5 \\ &= (146.05, 209.43, 292.52) \end{aligned}$$

It is convenient to express expected mortality as a proportion:

$$\begin{aligned} Expected\ mortality_{proportion} &= (146.05, 209.43, 292.52)\ /\ 1000 \\ &= (0.1461, 0.2094, 0.2925) \end{aligned}$$

The number of lives saved (or deaths averted) can be estimated as:

$$Lives\ saved = \ Expected\ Moratality_{Proportion} \times \ Number_{Cured}$$

The number of lives saved (or deaths averted) is an important program outcome and may be used in cost-effectiveness analyses. For the Bangladesh example program, we have:

$$Expected\ mortality_{Proportion} = (0.1461, 0.2094, 0.2925)$$

$$Number_{Cured} = (638, 653, 668)$$

$$\begin{aligned} Lives\ saved &= (0.1461, 0.2094, 0.2925) \ \times\ (638, 653, 668) \\ &= (93.2118, 136.7382, 195.3900) \end{aligned}$$

This is the outcome we would use in a cost-effectiveness analysis of *cost per life saved*. We can convert the number of lives saved to $YLL_{Averted}$ by multiplying it by the life expectancy at the time of death. A standard life expectancy known as the 'standard expected years of life lost' (SEYLL) may be used (see *Box 7* for alternative measures of life expectancy). The SEYLL values for children aged birth to five years is shown in *Table 4*.

Table 4 : Standard Expected Years of Life Lost (SEYLL)

Age at death (years)	Standard expected years of life lost (SEYLL)*
0	91.94
1	91.00
2	90.01
3	89.01
4	88.02
5	87.02

* The SEYLL standard may be subject to revision over time.

The age at admission to the program ranged between 6 and 42 months with an average of 19 months. We need this expressed in years:

$$\begin{aligned} Age\ at\ admission &= (6, 19, 42)\ \div 12 \\ &= (0.5000, 1.5833, 3.5000) \end{aligned}$$

Time to death can only be guessed at. A sensible guess is that some deaths occur quite quickly (i.e. about half of all deaths occur after only two months) and all deaths that are reasonably attributable to SAM occur before about 7.5 months. Expressed in years this is:

$$\begin{aligned} Time\ to\ death &= (0.0, 2.0, 7.5)\ \div 12 \\ &= (0.0000, 0.1667, 0.6250) \end{aligned}$$

The expected age at death is calculated as:

$$\begin{aligned} Expected\ age\ at\ death &= Age\ at\ admisison + Time\ to\ death \\ &= (0.5000,1.5833, 3.5000) + (0.0000, 0.1667, 0.6250) \\ &= (0.5000, 1.7500, 4.1250) \end{aligned}$$

The expected YLL is calculated from the SEYLL life table using linear interpolation:

$$YLL = SEYLL_1 + [(Expected\ age\ at\ death - Age_1) \times (SEYLL_2 - SEYLL_1)]$$

For a child aged 0.5000 years this is:

$$\begin{aligned} YLL &= 91.94 + [(0.5000 - 0) \times (91.00 - 91.94)] \\ &= 91.4700 \end{aligned}$$

For a child aged 1.7500 years this is:

$$\begin{aligned} YLL &= 91.00 + [(1.7500 - 1) \times (90.01 - 91.00)] \\ &= 90.2575 \end{aligned}$$

For a child aged 4.1250 years this is:

$$\begin{aligned} YLL &= 88.02 + [(4.1250 - 4) \times (87.02 - 88.02)] \\ &= 87.8950 \end{aligned}$$

These three values can be expressed as a single triangular fuzzy number:

$$SEYLL = (87.8950, 90.2575, 91.4700)$$

$YLL_{Averted}$ can now be calculated:

$$\begin{aligned} YLL_{Averted} &= Lives\ saved \times SEYLL \\ &= (93.2118, 136.7382, 195.3900) \times (87.8950, 90.2575, 91.4700) \\ &= (8192.8512, 12341.6481, 17872.3233) \end{aligned}$$

Some complications with calculating the YLD and YLL components are discussed in *Box 7*.

Note : The use of SEYLL may be simplified by using life-expectancy at birth (91.94 years) and expected age at death. For example:

$$\begin{aligned} SEYLL &= (91.94 - 4.1250, 91.94 - 1.7500, 91.94 - 0.5000) \\ &= (87.8150, 90.1900, 91.4400) \end{aligned}$$

Using this approach, we would estimate $YLL_{Averted}$ as:

$$\begin{aligned} YLL_{Averted} &= Lives\ saved\ \times\ SEYLL \\ &= (93.2118, 136.7382, 195.3900) \times (87.8150, 90.1900, 91.4400) \\ &= (8185.3942, 12332.4183, 17866.4616) \end{aligned}$$

The size of the error introduced using this simplification is small (i.e. < 1%).

Putting $YLD_{Averted}$ and $YLL_{Averted}$ together to find $DALY_{Averted}$

$YLD_{Averted}$ and $YLL_{Averted}$ are added together to give DALYs averted.

For the Bangladesh program:

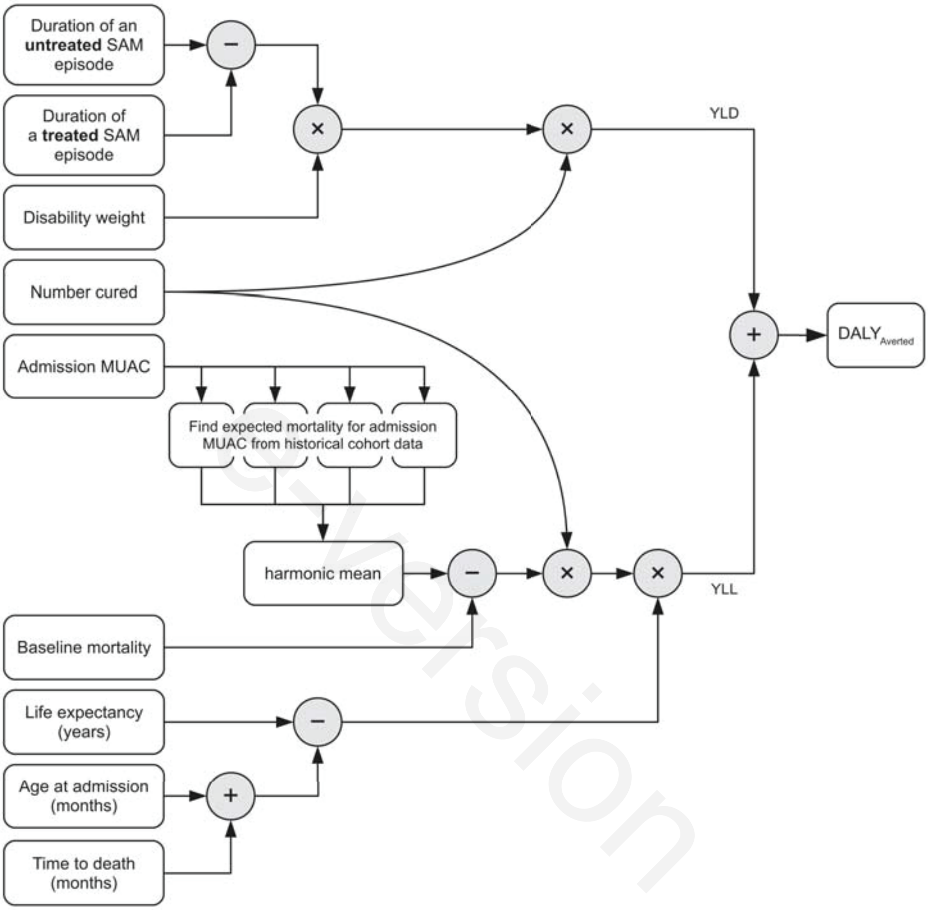
$$\begin{aligned} DALY_{Averted} &= YLD_{Averted} + YLL_{Averted} \\ &= (6.4438, 31.0828, 66.1988) + (8192.8512, 12341.6481, 17872.3233) \\ &= (8199.2950, 12372.7309, 17938.5221) \end{aligned}$$

The estimate for DALYs averted by the Bangladesh program is:

$DALY_{Averted}$ = 12,372.73 (95% CI = 9,207.34 – 16,774.41)

The process for the calculation of DALYs averted is summarised as an *influence diagram* in *Figure 12* which is an expanded version of *Figure 1*.

Figure 12 : Influence diagram summarising the calculation of DALYAverted



A baseline mortality of 1 / 10,000 / day (i.e., 36.5 / 1000 / year) is a sensible choice.

Box 7 : Complications with calculating $YLD_{Averted}$ and $YLL_{Averted}$ components

The *YLL* component calculated in the text used 'standard expected years of life lost' (SEYLL). This approach is currently recommended by the WHO for estimating burden.

Prior to 2010, it was common practice to use local life expectancies. Moving from using local life expectancy to SEYLL will usually increase estimates of $YLL_{Averted}$ because the SEYLL is based on projections to the year 2050 using data from developed countries with long life expectancies. This SEYLL may not be appropriate for estimating $YLL_{Averted}$ for CMAM programs which are often run in low- and middle-income countries (LMIC) which have considerably shorter life-expectancies than SEYLL. It is be more realistic to use local life-expectancies.

The WHO Global Health Observatory figure for life expectancy at birth for Bangladesh for males and females combined is 66.6 years for the time the program was running. This means that a shift from using local life expectancy to SEYLL will increase the estimate of $YLL_{Averted}$ by a factor of:

$$\frac{91.94}{66.6} \approx 1.38$$

If you need to compare $DALY_{Averted}$ between your program and programs that reported DALYs calculated using local life-expectancies, then you will need to use an estimate of local life expectancy to calculate $YLL_{Averted}$. In this case $YLL_{Averted}$ is calculated as:

$$YLL_{Averted} = Lives\ saved\ \times\ (Life\ expectancy - Average\ age\ at\ death)$$

Both of these methods treat all years as being the same. Prior to 2010 it was common practice to apply age-weighting and discounting:

Age-weighting : More weight is given to years of life in early adulthood. Earlier and later years of life are given less weight.

Discounting : Progressively less weight is placed on years in the future.

Applying age-weighting and discounting requires the use of the following formula to calculate both $YLL_{Averted}$ and $YLD_{Averted}$:

$$YLL\ or\ YLD = D\frac{KCe^{ra}}{(r+\beta)^2}\{e^{-(r+\beta)(L+a)}[-(r+\beta)(L+a)-1] - e^{-(r+\beta)a}[-(r+\beta)a-1]\} + \frac{1-K}{r}(1-r^{-rL})$$

a = age at death (for YLL) or age at onset of illness (for YLD); β = age-weighting parameter (β = 0.04);

C = constant (C = 0.1658); D = disability weight; e = base of natural the logarithm (Euler's Number, 2.71828);

K = age-weighting modulation factor (K = 1); L = life expectancy at specified age (for YLL) or duration of disease (for YLD); r = discount rate (fixed at r = 0.03).

You will only have to use age-weighting and discounting if you want to compare $DALY_{Averted}$ between your program and programs that reported $DALY_{Averted}$ calculated using age-weighting and discounting.

If data are available (only summary data are required) then it may be easier to recalculate $DALY_{Averted}$ for historic programs using the simpler "no frills" method.

Note that when comparing $DALY_{Averted}$ between programs make sure you use the same disability weights for all programs.

In most cases you will want to use the simpler "no frills" method (i.e. use either SEYLL or local life expectancies, the most current disability weights, and **<u>not</u>** use age-weighting and discounting). This will mean, however, that your estimates cannot be directly compared with estimates made using earlier methods.

DATA REQUIREMENTS FOR DALY CALCULATIONS

Table 5 shows the data required to calculate $YLD_{Averted}$ and $YLL_{Averted}$.

Table 5 : Data required to calculate $YLD_{Averted}$ and $YLL_{Averted}$

Quantity		Used to calculate ...	Default value	Notes
Disability Weights*	Severe wasting only	$YLD_{Averted}$	(0.081, 0.127, 0.183)	Default values are from the GBD 2010 study and the GHE 2000-2011 study. Historical values may be used for comparison with older reports.
	Kwashiorkor only	$YLD_{Averted}$	(0.033, 0.055, 0.082)	
	Severe wasting **AND** kwashiorkor	$YLD_{Averted}$	(0.111, 0.175, 0.250)	
Number of SAM cases admitted		$YLD_{Averted}$	NO DEFAULT	Value taken from program data
Number of SAM cases cured		$YLD_{Averted}$ $YLL_{Averted}$	NO DEFAULT	Value taken from program data
Length of a **cured** episode of SAM		$YLD_{Averted}$	NO DEFAULT	Value taken from program data
Length of an **untreated** episode of SAM		$YLD_{Averted}$	(3.5, 6.0, 7.5)	Default value is given in months and taken from historical cohort studies.
MUAC at admission of **cured** cases		$YLL_{Averted}$	NO DEFAULT	Value taken from program data. Possible to use average MUAC at admission for all cases if data are not available for cured cases only.
Case fatality rate for **untreated** SAM		$YLL_{Averted}$	NO DEFAULT	Value will depend on average MUAC at admission.
Background mortality		$YLL_{Averted}$	36.5 / 1,000 / year	See text.
Life expectancy		$YLL_{Averted}$	SEYLL for age at admission	Local life-expectancy may be used instead of SEYLL.
Age at admission**		$YLD_{Averted}$ $YLL_{Averted}$	NO DEFAULT	Value taken from program data
Time to death		$YLL_{Averted}$	(0.0, 2.0, 7.5)	Default value is an informed guess and given in months.

* Usually sensible to use only the disability weights for severe wasting

** Used to calculate $YLD_{Averted}$ only when age-weighting and discounting are used

WORKED EXAMPLE : THE NIGERIAN NATIONAL CMAM PROGRAM

In this worked example we will estimate DALYs averted by a large national CMAM program delivered at primary healthcare facilities by the Nigerian Ministry of Health with the support of UNICEF using program data from September 2009 through to October 2014. The data supporting the analysis is shown in *Table 6*.

Table 6 : Data used to calculate $YLD_{Averted}$ and $YLL_{Averted}$

Quantity		**Value**
Disability weights	Severe wasting only	(0.081, 0.127, 0.183)
Number of SAM cases admitted		919,876
Number of SAM cases cured		691,747
Length of a **cured** episode of SAM*		(0.5, 1.6, 2.8) months
Length of an **untreated** episode of SAM		(3.5, 6.0, 7.5) months
Average MUAC at admission of **cured** cases*		106.1 mm
Case fatality rate for **untreated** SAM**		(172, 234, 328) deaths / 1,000 / year
Background mortality		36.5 / 1,000 / year
Life expectancy***		54.48 years
Age at admission*		(6, 16, 30) months
Time to death		(0.0, 2.0, 7.5) months

* Calculated from an analysis of 102,245 beneficiary records.

** Calculated using admission MUAC and historical cohort data using the following linear interpolation:

Study	**Case fatality rate (CFR)**	**Harmonic mean CFR**
Briend & Zimicki (1986)	202 / 1,000 / year	234 / 1,000 / year
Briend, el al (1987)	328 / 1,000 / year	
Pelletier et al (1993)	307 / 1,000 / year	
Vella et al (1994)	172 / 1,000 / year	

*** Local life expectancy was used. Male life expectancy = 53.4 years, female life expectancy = 55.6 years, and 49% of cases were female. Using a weighted average:

$$\text{Life expectancy} = 53.4 \times 0.51 + 55.6 \times 0.49 = 54.48 \; years$$

We will calculate DALYs averted using the "no frills" approach and local life-expectancy.

$YLD_{Averted}$ for the Nigerian national CMAM program

We start by calculating the difference in the durations of untreated and treated SAM episodes:

$$
\begin{aligned}
Duration_{Averted} &= \text{Duration}_{\text{Untreated SAM episode}} - \text{Duration}_{\text{Treated SAM episode}} \\
&= (3.5, 6.0, 7.5) - (0.5, 1.6, 2.8) \\
&= (0.7, 4.4, 7.0)
\end{aligned}
$$

YLD is expressed in years so we should express this result in years:

$$
\begin{aligned}
Duration_{Averted} &= (0.7, 4.4, 7.0) \div 12 \\
&= (0.0583, 0.3667, 0.5833)
\end{aligned}
$$

We now calculate the number of cured cases. This calculation takes a few steps:

The proportion cured is:

$$Proportion_{Cured} = \frac{691747}{919876} = 0.7520$$

The standard error of this proportion is:

$$SE = \sqrt{\frac{p(1-p)}{n}} = \sqrt{\frac{0.7520 \times (1 - 0.7520)}{919876}} = 0.0005$$

The proportion cured expressed as a triangular fuzzy number is:

$$
\begin{aligned}
P &= (p - 2 \times SE, p, p + 2 \times SE) \\
&= (0.7520 - 2 \times 0.0005, 0.7520, 0.7520 + 2 \times 0.0005) \\
&= (0.7510, 0.7520, 0.7530)
\end{aligned}
$$

We convert this into numbers of cured cases:

$$
\begin{aligned}
Number_{Cured} &= (0.7510, 0.7520, 0.7530) \times 919876 \\
&= (690827, 691747, 692667)
\end{aligned}
$$

We can now calculate $YLD_{Averted}$:

$$YLD_{Averted} = Duration_{Averted} \times Disability\ weight \times Number_{Cured}$$

We split this calculation into two steps:

$$\begin{aligned} &Duration_{Averted} \times Disability\ weight \\ &\quad = (0.0583, 0.3776, 0.5833) \times (0.081, 0.127, 0.183) \\ &\quad = (0.0047, 0.0480, 0.1067) \end{aligned}$$

Multiplying this result by the number of cured cases gives:

$$\begin{aligned} YLD_{Averted} &= (0.0047, 0.0466, 0.1067) \times (690827, 691747, 692667) \\ &= (3247, 33204, 73908) \end{aligned}$$

***YLL**$_{Averted}$* **for the Nigerian national CMAM program**

First, we calculate expected mortality:

$$\begin{aligned} &Expected\ mortality \\ &\quad = Case\ fatality\ rate_{Untreated\ SAM} - Background\ mortality \\ &\quad = (172, 234, 328) - 36.5 \\ &\quad = (135.5, 197.5, 291.5) \end{aligned}$$

and express the result as a proportion:

$$\begin{aligned} Expected\ mortality &= (135.5, 197.5, 291.5) \div 1000 \\ &= (0.1355, 0.1975, 0.2915) \end{aligned}$$

The number of lives saved is:

$$\begin{aligned} Lives\ saved &= Expected\ mortality \times Number_{Cured} \\ &= (0.1355, 0.1975, 0.2915) \times (690827, 691747, 692667) \\ &= (93607, 136620, 201912) \end{aligned}$$

We need to calculate age at death:

$$
\begin{aligned}
Age\ at\ death &= Age\ at\ admission + Time\ to\ death \\
&= (6, 16, 30) + (0.0, 2.0, 7.5) \\
&= (6, 18, 37.5)
\end{aligned}
$$

We want this result in years:

$$
\begin{aligned}
Age\ at\ death &= (6, 18, 37.5) \div 12 \\
&= (0.5, 1.5, 3.125)
\end{aligned}
$$

The expected YLL using local life expectancy is:

$$
\begin{aligned}
Expected\ YLL &= Life\ expectancy - Age\ at\ death \\
&= 54.48 - (0.5, 1.5, 3.125) \\
&= (51.355, 52.98, 53.98)
\end{aligned}
$$

We can now calculate $YLL_{Averted}$:

$$
\begin{aligned}
YLL_{Averted} &= Lives\ saved \times Expected\ YLL \\
&= (93607, 136620, 201912) \times (51.355, 52.98, 53.98) \\
&= (4807187, 7238128, 10899210)
\end{aligned}
$$

$DALY_{Averted}$ for the Nigerian national CMAM program

$YLD_{Averted}$ and $YLL_{Averted}$ are added together to give DALYs averted:

$$
\begin{aligned}
DALY_{Averted} &= YLD_{Averted} + YLL_{Averted} \\
&= (3247, 33204, 73908) + (4807187, 7238128, 10899210) \\
&= (4810434, 7271332, 10973118)
\end{aligned}
$$

The estimate for DALYs averted by the Nigerian CMAM program is:

$DALY_{Averted}$ = 7,271,332 (95% CI = 5,426,180 – 10,217,920)

This was calculated using the “no frills” approach and local life-expectancy.

COST-EFFECTIVENESS

Cost-effectiveness (CE) is calculated as:

$$CE = \frac{cost}{outcome}$$

where *cost* is the amount of money spent on a program over a defined period of time and *outcome* is the number of desired (positive) outcomes delivered by the program over the same period of time.

If, for example, a program spends US$47,416,818 to treat 919,876 children with severe acute malnutrition (SAM) and achieves a cure rate of 83.3% we can estimate cost effectiveness as:

$$CE = \frac{cost}{outcome} = \frac{US\$47{,}416{,}818}{919{,}876 \times \frac{83.3}{100}} = US\$61.88 \; per\ SAM\ case\ recovered$$

Cost-effectiveness analyses of health interventions are usually performed for desired (positive) outcomes only (e.g. cases recovered, deaths averted, disability-adjusted life years (DALYs) averted).

Costs

The cost term always includes *institutional costs* but may also include *societal costs*:

> **Institutional costs** are the costs of inputs used by implementing institutions including personnel, transport, medicines, and foods.
>
> **Societal costs** are the costs incurred by beneficiaries or beneficiary households due to their participation in the program as well as costs incurred by (e.g.) community-based volunteers.

Cost-effectiveness analyses investigating and using only societal costs are seldom done. Such analyses are more often undertaken as part of coverage assessments that aim to identify barriers to access and coverage.

The cost term in the cost-effectiveness calculation should cover the majority of resources that were used to make a program function and efforts should be made to include all important cost contributions.

The scope of costs is always limited. For example:

> The inputs required to develop and test therapeutic feeding products, treatment protocols, and CMAM delivery models are all essential for the delivery of CMAM programming but they are not usually included in cost-effectiveness analyses of CMAM programs.
>
> Organisations such as UNICEF play important local and global roles in CMAM delivery, but global and regional headquarters' costs are also not usually included in cost-effectiveness analyses of CMAM programs.

We are usually most interested in costs that are directly associated with service delivery.

For a program delivering CMAM services at government health facilities you may only be interested in the institutional cost of adding CMAM to an existing primary healthcare program which provides many of the resources essential to delivering CMAM services.

Using restricted sets of costs will always produce lower cost estimates (and seemingly better cost-effectiveness results) than methods that capture and use a more complete set of costs. This can make it difficult to compare the results of different analyses. It is important, therefore, that the scope of costs used in a cost-effectiveness analysis are included in reports. This will usually be a list of what was and what was not included in the reported costs. This allows fair comparisons of results between studies using different methods to be made.

Table 7, for example, shows the costs included in two cost-effectiveness studies from Bangladesh and Nigeria. The Bangladesh study collected a more comprehensive set of costs than the Nigeria study. Comparisons can be made between the results of the two studies by using a common set of costs or by estimating the extent of the "missing" costs for the Nigeria program.

It is often useful to present results for different sets of costs. For example:

$$CE = \frac{institutional\ costs}{outcome}$$

and:

$$CE = \frac{institutional\ costs + societal\ costs}{outcome}$$

This can facilitate comparisons between different studies.

Different sets of costs may be of interest to different stakeholders. For example, the Ministry of Health (MoH) may be most interested in the cost-effectiveness of their contribution to institutional costs:

$$CE = \frac{MoH\ institutional\ costs}{outcome}$$

Using different sets of costs can help inform health policy and planning decisions.

Table 7 : The sets of costs used in the Bangladesh and Nigeria studies

		Study	
Costs	**Detail**	**Bangladesh**	**Nigeria**
Institutional	Purchase of ready to use therapeutic food (RUTF)	●	●
	Port handling and warehousing fees for RUTF	●	●
	Purchase and supply of F75 and F100 therapeutic milks	●	○
	Transport for RUTF from ports to regional centres	●	●
	Storage of RUTF at regions	●	○
	Transport of RUTF to districts	●	○
	Storage of RUTF at districts	●	○
	Transport of RUTF / therapeutic milks to health facilities	●	○
	Storage of RUTF / therapeutic milks at health facilities	●	○
	Training of staff to deliver CMAM services	●	●
	Program monitoring and evaluation (M&E)	●	●
	Coverage assessments	●	○
	Purchase and supply of medicines	●	○
	CMAM program management	●	○
	Staff salaries, wages, and allowances	●	○
	Supervision of staff	●	○
	Community mobilisation and sensitisation	●	○
	Purchase and supply of clinical equipment	●	○
	Maintenance of health centres / health posts	○	○
Societal	Allowances and incentives for community-based volunteers	●	○
	"Shadow" labour costs for community-based volunteers	●	○
	Direct and indirect costs to beneficiary households	●	○

Collecting data on institutional costs

Institutional costs are the costs of inputs used by implementing institutions and usually include personnel, transport, medicines, medical / laboratory tests, and therapeutic foods and milks.

Figure 13 shows a spreadsheet detailing the monthly institutional costs for an international non-governmental organisation (INGO) supporting district ministries of health (MoH) to establish and deliver CMAM programming in two administrative districts in Ethiopia.

Figure 13 : Example institutional costs for an INGO supporting the Ministry of Health to deliver CMAM programming

	A	B	C	D	E	F	P	O	P
1				2017	2018				
2	Category	Code	Description	Dec	Jan	Feb	Oct	Nov	Total
3	International Staff	1.1.1	Country director	314.25	906.71	137.	364.14	447.86	4964.08
4		1.1.2	Program director	460.60	295.83	227.	313.76	330.57	3409.30
5		1.1.3	CMAM expert	1392.38	180.75				1898.89
6	National Staff	1.2.1	Field-based	1139.38	1185.77	209.	282.32	308.79	7149.06
7		1.2.2	Coordination office	173.64	174.10	273.	472.56	505.77	5404.52
8		1.2.3	Head office	258.16	228.21	338.	322.13	329.44	4037.78
9	Fringe benefits	1.3.1	International staff	1204.05		827.	547.83	522.59	6432.60
10		1.3.2	National staff	409.70	576.14	579.	473.88	460.98	5972.76
11	In-country travel	2.1.1	Travel	98.86				324.66	797.69
12		2.1.2	Per-diems		543.29	64.	218.98	305.37	3558.40
13		2.1.3	Vehicle hire			534.	98.97	104.85	1412.90
14		2.1.4	Fuel	127.06			474.56	778.27	5503.48
15	Supplies	3.1.1	Computer / stationery		28.09		9.02		1002.23
16	Consultants	4.1.1	Adapt CMAM guidelines	204.83					416.79
17	M&E	5.1.1	Coverage surveys						12332.41
18	Other	6.1.1	Set-up workshops			95.5			2050.41
19		6.1.2	District planning	145.87	33.59				1104.92
20		6.1.3	Regional planning						465.94
21		6.1.4	National planning	46.69					714.43
22		6.1.5	Mobilisation						333.17
23		6.1.6	Supervision	22.27	11.01	13.73		11.19	230.93
24		6.1.7	Field office costs	436.00	372.00	400.00	19.61	408.00	5022.35
25		6.1.8	Head office costs	154.73	37.31	1984.32	412.00	217.64	6615.33
26		6.1.9	Head office transport	4.68	53.84	688.66	27.13		1989.02
27			Totals :	6592.77	5750.91	6375.72	4327.51	5127.77	**82819.40**

Amounts are recorded in United States dollars

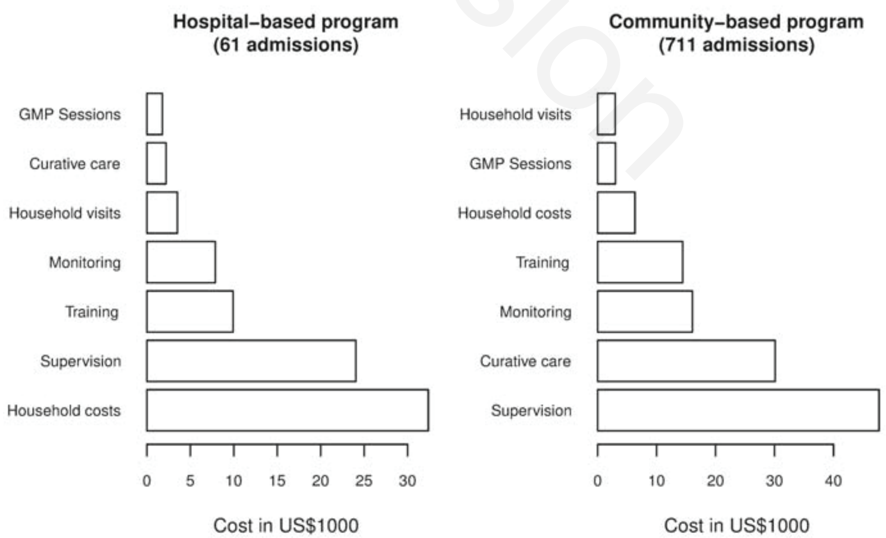
Note that the cost categories, codes, and descriptions shown in *Figure 13* are the same as those used in the INGO's accounting system. Doing this makes it easier to collect costs data and to communicate results. Collecting, recording, and reviewing data on a monthly basis is useful in ensuring that the data are both sensible and complete.

NGO contributions to CMAM programs vary. The NGO may, in some cases, carry most or all of the administration, staff, training, and other costs of a CMAM program. This is likely to be the case in emergency contexts. In other contexts, the NGO may provide considerably less support. In these cases, it may be possible to collect costs data in a similar manner to district level MoH costs (see below).

A cost-effectiveness analysis usually needs only overall (total) costs, but category-specific totals are often used to describe the composition of program costs and to identify potential *cost-efficiencies*. *Figure 14*, for example, shows the distribution of program costs in two programs from Bangladesh. The distribution of costs differs considerably between the two programs. The community-based program may, for example, benefit from increased efficiency in supervising community health workers.

It should be noted that *Figure 14* presents a type of *cost-efficiency* analysis. This is different from a *cost-effectiveness* analysis. In this case, the hospital-based program had many fewer admissions and achieved a much lower cure rate than the community-based program. The community-based program was highly cost-effective. The hospital-based program was not cost-effective. This is not clear from *Figure 14*.

Figure 14 : Composition of costs for two different programs



There is usually more than one source of institutional costs. The costs presented in *Figure 13*, for example, do not include the cost of therapeutic feeding products such as ready to use therapeutic food (RUTF) and medical supplies which were provided by UNICEF. The costs presented in *Figure 13* also do not include costs such as medicines, staff at the district level, staff at health facilities, other health facility costs, and within-district transport of supplies which were provided by the local MoH.

Costs data from organisations such as UNICEF can usually be collected from their accounting systems. It is usually possible to get UNICEF cost data on CMAM supplies. *Figure 15*, for example, shows a spreadsheet created by UNICEF's accounting system detailing CMAM supply costs for a specific program.

Figure 15 : Example institutional costs for UNICEF to deliver CMAM supplies

	A	B	C	D	E	F
1	Order Number	Date	Material	Material	Qty	Value(USD)
2	542366144	30/10/18	SL000465	Printed matter	300	307.35
3	542366144	30/10/18	ST680201	Printed Matter	3811	3904.38
4	543266155	23/02/19	S0531014	Multiple Mn Sachet	14880	9197.00
5	543266221	15/02/12	S0003581	Amoxicillin 250mg PAC	14	28.40
6	[illegible]	[illegible]	[illegible]	[illegible]	2	6.76
7	543266321	15/02/18	SL110735	RUTF 92g Sach.	91	4539.82
8	543271635	26/03/18	S0000240	Syringe 5ml BOX/100	2	4.56
9	543271635	26/03/18	S1559301	Soap bar 180g PAC/30	3	21.12
25	542663923	22/11/18	S003851	Zinc Oxide Ointment 10%	14	15.50
26	542663923	22/11/18	S000240	Tube, feeding, CH08	38	3.24
27					Total :	199544.45

These costs include an overhead for delivery and warehouse costs

It may be difficult to collect an exhaustive set of UNICEF staff costs. It is probably most useful to limit this to the fraction of time and other resources spent supporting CMAM programs by UNICEF health and nutrition staff. This can, if needed, be collected in a similar manner to district level MoH costs (see below).

It will usually be sufficient to limit UNICEF costs to CMAM supply costs as these will be the main part of UNICEF costs. This was the approach taken for both the Bangladesh and Nigeria studies (see *Table 7*).

It may be possible to collect costs data from MoH accounting systems. This will not usually be possible because resources used to deliver CMAM services are also used to deliver other services.

For example, we may know (e.g.) that the nurse-in-charge of a health facility has responsibilities for delivering CMAM services and know their salary, but we also need to know how much of their time is spent delivering CMAM services in order to get an accurate estimate of CMAM delivery costs:

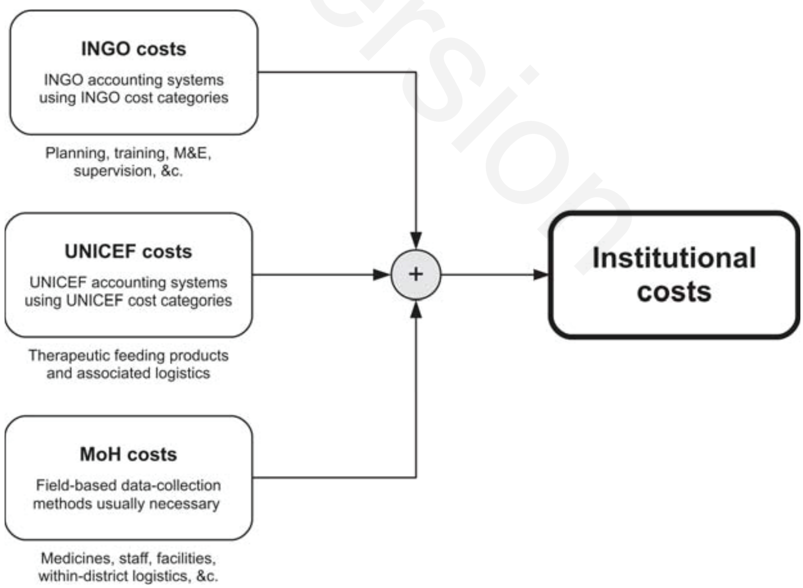
$$Cost_{Nurse-in-charge} = salary \times \frac{hours\ spent\ delivering\ CMAM}{contract\ hours}$$

The time spent by staff, either individually or collectively, that is specifically devoted to delivering CMAM services is very unlikely to be recorded in MoH accounting systems. This means that field-based methods must be employed to collect accurate MoH costs data.

Sources of institutional costs

Figure 16 shows how an INGO, UNICEF, and the MoH (the "institutions") provide resources in a typical CMAM program and how costs data may be collected.

Figure 16 : Multiple sources of institutional costs



It is important to avoid double-counting when dealing with multiple sources of institutional costs. If, for example, an INGO received funding from UNICEF to support MoH activities then there is a risk that this funding will appear as a

UNICEF cost and as an INGO cost in their accounting data. Some of the same money may also appear in MoH costs as (e.g.) training allowances for staff. There is a risk of double-counting or triple-counting. This would result in costs being overestimated. Only one instance of these costs should ever be included in a cost-effectiveness analysis.

Collecting data on societal costs

Societal costs such as the costs incurred by beneficiaries (or by their households) during their participation in the program and the time spent by community-based volunteers on essential program activities such a case-finding, referral, and defaulter follow-up are not covered by institutional accounting systems and will need to be collected using field-based methods.

Field-based methods for collecting costs data

The simplest field-based method to use is questionnaire surveys. A number of simple example questionnaires are presented below. These can be adapted for use in different settings.

There will usually be only one district MoH office and a small number of health facilities with responsibility for delivering CMAM services. Data can and should be collected from **all** of these offices and facilities. *Form 1* shows a questionnaire that could be used to collect data about district level costs. This is intended to be completed with the help of the district nutrition focal point. Calculations based on the data collected using *Form 1* are shown in *Figure 17*. This approach may also be useful for collecting some UNICEF costs.

Form 1 : District costs

CMAM/CEA : District nutrition focal point

Name of respondent: ____

District staff employed in CMAM activities

Name	Grade	CMAM hours per week
		|__|__|
		|__|__|
		|__|__|
		|__|__|
		|__|__|

Supervision and community visits by district staff

How many CMAM supervision / community visits take place each month?

Average number of visits per month: |__|__|

What costs were associated with the last visit?

Transportation: |__|__|__|

Accommodation, per diems, food & drink: |__|__|__|

Communications: |__|__|__|

Other coats: |__|__|__|

CMAM supply and delivery

Who pays for the supply and delivery costs to bring CMAM consumables to the district?

The district |__|
Higher level or NGO / UNICEF |__| -> skip next

What is the average monthly cost to bring CMAM consumables from a higher level to the district?

|__|__|__|__|__|

Who pays for the logistics and delivery costs to bring CMAM consumables to health centres and health posts?

The district |__|
Higher level or NGO / UNICEF |__| -> skip next

What is the average monthly cost to bring CMAM consumables to health centres and health posts?

|__|__|__|__|__|

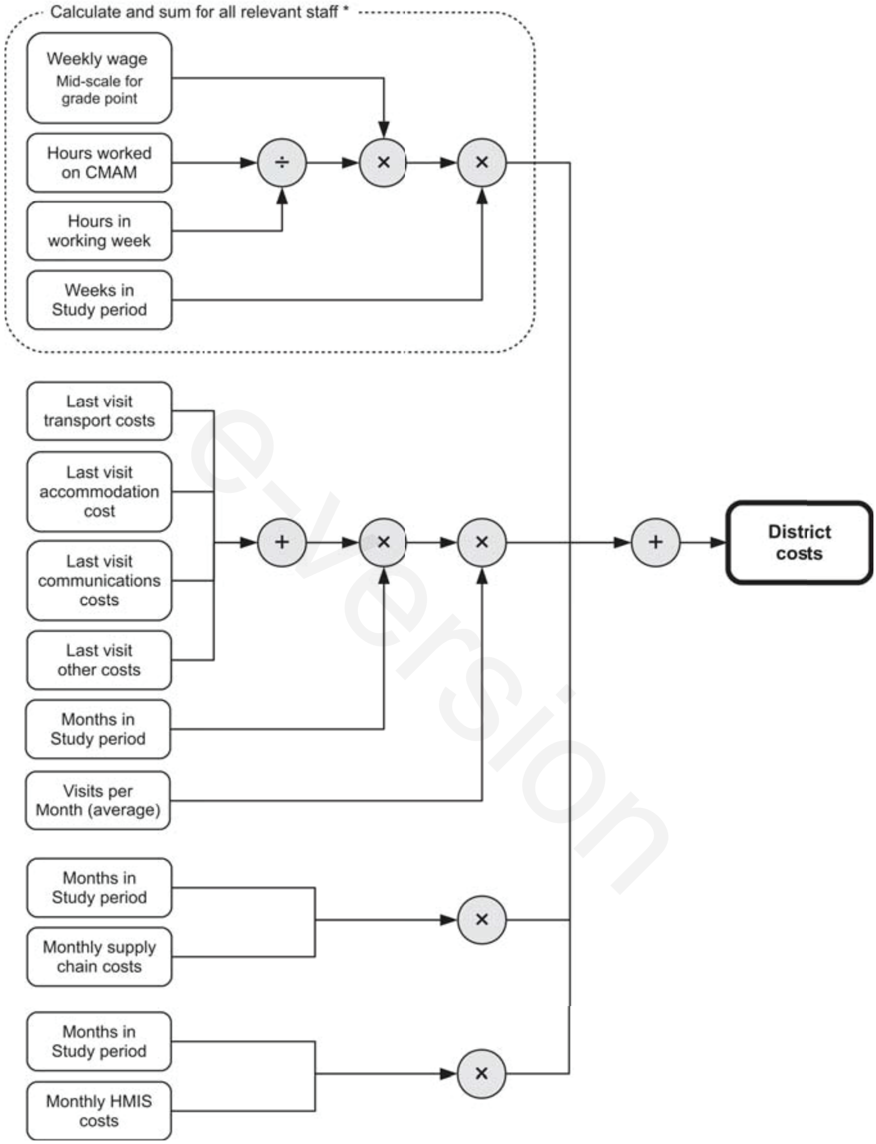
Health management information system (HMIS) costs

What is the average monthly cost to the district for collecting and sending information about the CMAM program?

Collecting data |__|__|__|__|

Sending data |__|__|__|__|

Figure 17 : Influence diagram (calculations) for Form 1 (district costs)

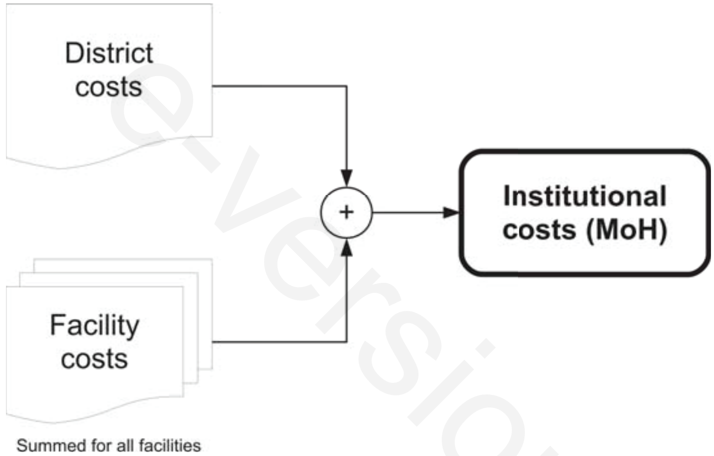


* Usually staff specifically committed to the CMAM program

A similar questionnaire could be used to collect data about facility costs (see *Form 2*). This is intended to be completed with the help of the person in charge of the health facility. Calculations based on the data collected by *Form 2* are similar to those used with *Form 1*.

There will be multiple facilities with a separate copy of *Form 2* for each facility. Costs should be calculated for each facility and then summed to give total facility costs. This sum is added to district costs giving the local MoH contribution to institutional costs (see *Figure 18*).

Figure 18 : MoH contribution to institutional costs



Facilities include all locations at which CMAM clinical services are delivered and may include health posts, health centres, clinics at hospitals, and stabilisation centres. Facilities are not restricted to “bricks and mortar” infrastructure. For example, community health workers in CMAM programs that use community health workers to deliver CMAM clinical services should be treated as separate facilities with data collected using an adapted version of *Form 2*.

Form 2 : Facility costs

CMAM/CEA : Person in charge of health centre / health post / stabilisation centre

Name of facility: ____

Name of respondent: ____

Health facility staff employed in CMAM activities

Name	Grade	CMAM hours per week
		|__|__|
		|__|__|
		|__|__|
		|__|__|
		|__|__|

Supervision and community visits by facility staff

How many CMAM supervision / community visits have taken place each month?

Average number of visits per month: |__|__|

What costs were associated with the last visit?

Transportation: |__|__|__|

Accommodation, per diems, food & drink: |__|__|__|

Communications: |__|__|__|

Other coats: |__|__|__|

CMAM supply and delivery

Who pays for the supply and delivery costs to bring CMAM consumables to this health centre / health post?

The health centre / health post |__|
Higher level or NGO / UNICEF |__| -> skip next

What is the average monthly cost to bring CMAM consumables from the higher level to this health centre / health post?

|__|__|__|__|__|__|

Who pays for the logistics and delivery costs to bring CMAM consumables to this health centre / health posts?

The health centre / health post |__|
Higher level or NGO / UNICEF |__| -> skip next

What is the average monthly cost to bring CMAM consumables from the higher level to the health centre / health post?

|__|__|__|__|__|__|

Health management information system (HMIS) costs

What is the average monthly cost to the health centre / health post for collecting and sending information about the CMAM program?

Collecting data |__|__|__|__|__|

Sending data |__|__|__|__|__|

Sampling

When there are a large number of potential data sources (e.g. beneficiaries and community-based volunteers) then a sample of potential data sources can be collected. This will often be needed when collecting data for estimating societal costs.

A two-stage sample can be used. We start with a sample of health facilities and then take a sample of beneficiaries attending each of the sampled facilities and a sample of community-based volunteers associated with each facility:

> **First stage sample :** The simplest and most representative first stage sample is to sample **<u>all</u>** health facilities (if this is possible). This can be done when you visit health facilities to collect institutional costs data. It is important never to use a "convenience sample" of health facilities (e.g. facilities closest to district offices or located on major roads) because these facilities are likely to be better supervised than less accessible facilities and your sample may be biased.
>
> **Second stage sample :** It is usually sufficient to collect data from about 60 outpatient therapeutic program (OTP) beneficiaries, 30 stabilisation centre (SC) beneficiaries (if possible), and 60 community-based volunteers. These are the smallest sample sizes needed to estimate mean values with useful precision. If it is feasible to collect larger samples, then you should.

OTP beneficiaries may be sampled at health facilities on any CMAM clinic day. Data should be collected after the beneficiary has been processed by the clinic and is ready to leave the facility. OTP beneficiaries may be sampled as they become available for sampling. All facilities should be represented in the sample. If there are (e.g.) 15 health facilities in the program, then you would sample four OTP beneficiaries from each facility to collect an overall sample of 60 OTP beneficiaries.

Stabilisation centre (SC) beneficiaries can be sampled from the pool of patients at the SC on any day that the SC is visited. SC beneficiaries tend to make up less than 5% of program admissions and treatment in SC usually lasts for just a few days. This means that there are usually only a few SC beneficiaries at any given time. You should try to sample as many SC beneficiaries as you can. You may need to return to stabilisation centres several times in order to collect a large enough sample. Thirty SC beneficiaries is a useful minimum number. All stabilisation centres should be represented in the second stage sample. If there are (e.g.) 3 stabilisation centres in the program, then you would sample 10 SC beneficiaries from each SC to collect an overall sample of 30 SC beneficiaries.

Community-based volunteers (CBVs) can be sampled from a list of CBVs associated with each health facility. A simple random sample or a systematic sampling method should be used. You may need to visit CBVs in their home communities to collect data. All facilities should be represented in the second stage sample. If there are (e.g.) 15 health facilities in the program, then you would sample four community-based volunteers associated with each facility to collect an overall sample of 60 CBVs.

Form 3 shows a questionnaire that could be used to collect data from the carers of OTP beneficiaries. Calculations based on the data collected by *Form 3* are shown in *Figure 19*. The calculations in *Figure 19* contain an item labelled "Hourly shadow wage". This places a monetary value on a carer's time. This is usually set to the local hourly minimum wage, the local median hourly wage for women in public works, or the local hourly wage for cash-based relief programs.

Data on lengths of stay and attendance rates should be collected from all health facilities. Data for all closed treatment episodes in the previous three months should be collected. You may also want to collect MUAC at admission and other data used in $DALY_{Averted}$ calculations at the same time.

Attendance rates are calculated as:

$$attendance\ rate = \frac{number\ of\ visits\ recorded}{length\ of\ stay\ (weeks)}$$

The *length of stay (weeks)* in the denominator is calculated as:

$$length\ of\ stay\ (weeks) = \frac{date\ of\ last\ visit - date\ of\ first\ visit}{7}$$

Only data for closed treatment episodes should be used in these calculations.

A similar approach is used for SC beneficiary costs. *Form 4* shows a questionnaire that could be used to collect data from the carers of SC beneficiaries. The calculations for *Form 4* are shown in *Figure 20*.

Form 5 shows a questionnaire that could be used to collect data from community-based volunteers. Calculations based on the data collected by *Form 5* are shown in *Figure 21*. Costs are calculated for each CBV and the average (i.e. mean) cost per CBV calculated. This is multiplied by the number of active CBVs attached to the program to give total CBV costs.

Form 3 : OTP beneficiary costs

CMAM/CEA : Carer of OTP beneficiary

Name of facility : ____

OTP beneficiary costs

From the time you arrived to the time you received all services, RUTF, drugs, &c. and could leave, how long did you spend in this health facility today?

Hours : |__|__|

Minutes : |__|__|

How long was the trip from your house to arrival at this health facility?

Hours : |__|__|

Minutes : |__|__|

Did you or a household member pay anything for the trip or during the trip from your home to the health facility or while waiting to be seen today?

|__|

If YES ... how much money was spent for your trip from home to this health facility today?

|__|__|__|

Did you or a household members pay for any services at this health facility?

|__|

If Yes, how much was spent on these services?

Consultation fees |__|__|__|

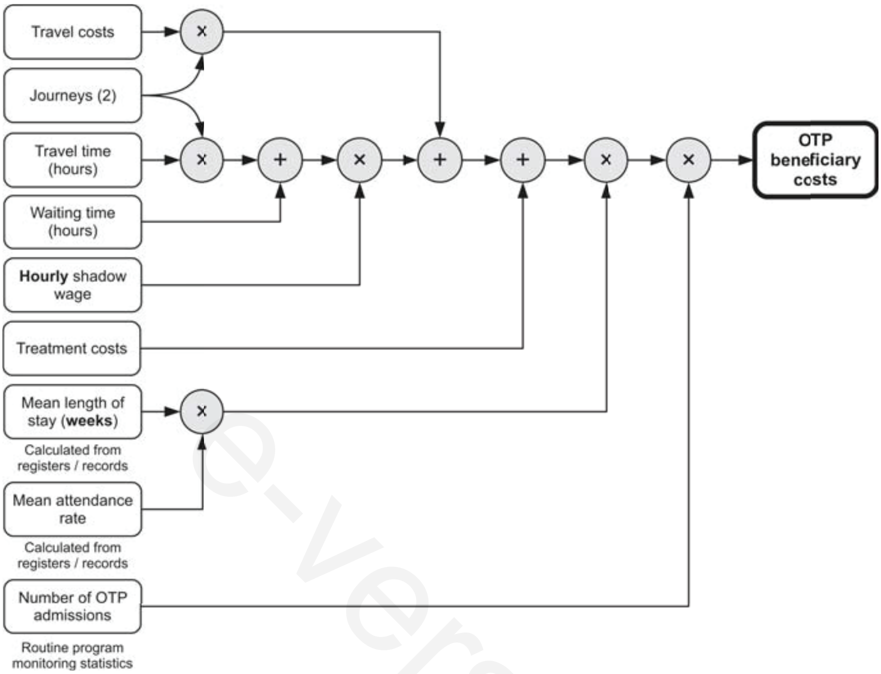
Medicine / drugs |__|__|__|

Laboratory tests |__|__|__|

RUTF |__|__|__|

Other |__|__|__|

Figure 19 : Calculations for Form 3 (OTP beneficiary costs)



Form 4 : SC beneficiary costs

CMAM/CEA : Carer of SC beneficiary

Name of facility : ____

SC beneficiary costs

How long was the trip from your house to arrival at this health facility?

Hours : |__|__|

Minutes : |__|__|

Did you or a household member pay anything for the trip or during the trip from your home to the health facility?

|__|

If YES ... how much money was spent for your trip from home to this health facility?

|__|__|__|

Did you or a household members pay for any healthcare services at this health facility since this time yesterday?

|__|

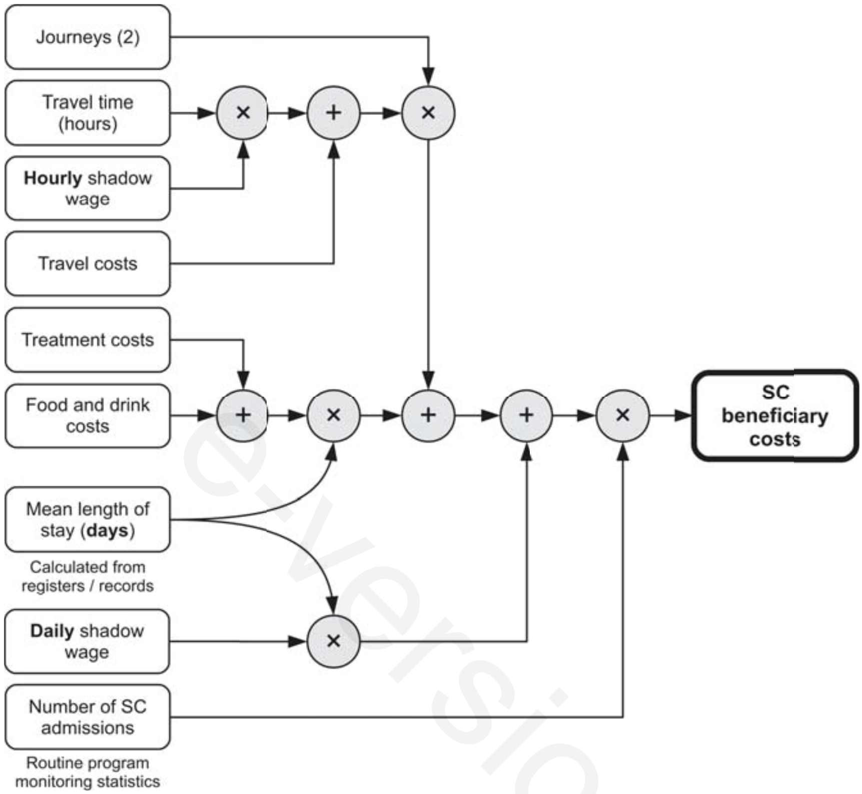
If Yes, how much was spent on these services?

Registration	|__|__|__|
Rent for bed and / or bedding	|__|__|__|
Consultation fees	|__|__|__|
Medicine / drugs	|__|__|__|
Laboratory tests	|__|__|__|
X-Rays	|__|__|__|
Therapeutic milk /RUTF	|__|__|__|
Other	|__|__|__|

What is the approximate value of food, drink, and other items that you and / or your child have consumed at this health facility since this time yesterday?

|__|__|__|

Figure 20 : Calculations for Form 4 (SC beneficiary costs)



Form 5 : Community-based volunteer costs

CMAM/CEA : Community-based volunteer

Name of facility CBV is attached to : ____________________________________

Name of respondent : ____

Time and money

In the last seven days ...

How much time did you spend each day on all **CMAM activities**, both in the communities you serve and at health facilities?

How much did you spend each day on transport including trips to and from the communities you serve and to and from health facilities?

Day	Time	Transport costs
Yesterday [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|
Day before [name day]	Hours : |__|__| Minutes : |__|__|	|__|__|__|

Training

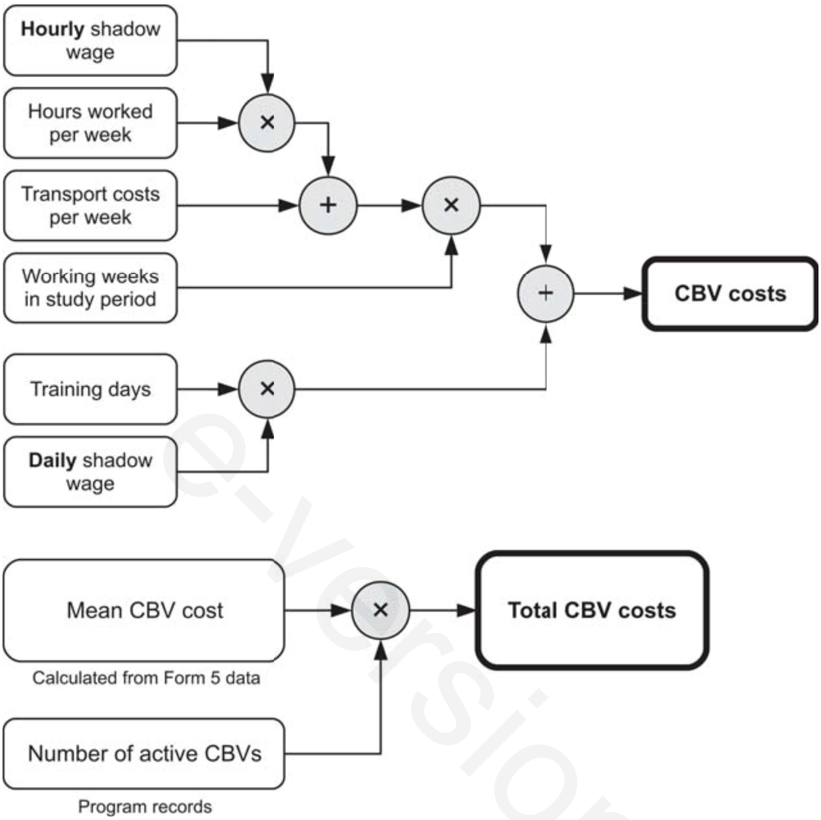
In the **last 12 months**, have you attended any training related to the CMAM program?

|__|

If YES ... How many training days in total (including days travelling) did you have in the last 12 months?

|__|__|

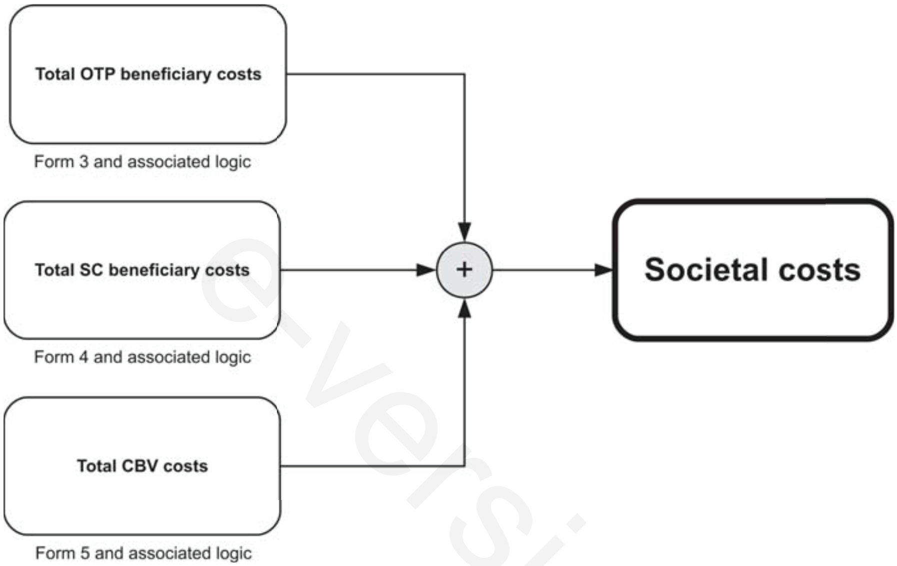
Figure 21 : Influence diagram (calculations) for Form 5 data (CBV costs)



Summing societal costs

Adding OTP beneficiary costs, SC beneficiary costs and CBV costs gives total societal costs (see *Figure 22*).

Figure 22 : Societal costs



Adding Institutional to societal costs gives total costs.

Accounting for uncertainty

We can incorporate uncertainty in costs estimates using triangular fuzzy numbers in the same way that is used to incorporate uncertainty in DALY calculations.

Institutional costs taken from institutions' accounting systems may be treated as certain. The INGO costs shown in *Figure 13*, for example, would be expressed as:

$$INGO\ costs = (82819.40, 82819.40, 82819.40)$$

UNICEF costs for supply of therapeutic foods and milks to the district MoH were US$45159.57. This may also be treated as certain and would be expressed as:

$$UNICEF\ costs = (45159.57, 45159.57, 45159.57)$$

Institutional costs collected using simple field-based methods, such as those outlined above, will be uncertain. It is difficult to assess the degree of uncertainty present in this data. A 10% margin of error can be assumed.

MoH costs were estimated to be US$81262.52. With a 10% margin of error this would be expressed as:

$$\begin{aligned} MoH\ costs &= (0.9 \times 81262.52, 1.0 \times 81262.52, 1.1 \times 81262.52) \\ &= (73136.27, 81262.52, 89388.77) \end{aligned}$$

Adding the INGO Costs, UNICEF costs, and MoH costs using triangular fuzzy numbers gives:

$$Institutional\ costs = (201115.24, 209241.49, 217367.74)$$

Societal costs will also be uncertain.

We can use triangular fuzzy numbers to account for this uncertainty. If, for example, we found that OTP beneficiary cost per visit in US$ could be represented using the fuzzy triangular number:

$$A = (0.98, 1.04, 1.10)$$

The length of stay (duration) in weeks for all closed episodes could be represented using the fuzzy triangular number:

$$\mathrm{B} = (5, 6, 8)$$

and the attendance rate could be represented using the fuzzy triangular number:

$$C = (0.82, 0.88, 1.00)$$

and there were 722 admissions:

$$D = (722, 722, 722)$$

We can estimate total OTP beneficiary costs:

$$A \times B = (4.90, 6.24, 8.80)$$
$$(A \times B) \times C = (4.0180, 5.4912, 8.8000)$$
$$[(A \times B) \times C] \times D = (2900.9960, 3964.6464, 6353.6000)$$

A similar approach can be used to estimate SC beneficiary costs and CBV costs. This was done for the example program and the results are shown in *Table 8*.

Table 8 : Costs for the example Ethiopian two district CMAM program

Costs	Source	Amount (US$)	Sum (US$)
Institutional	INGO	(82819.40,82819.40,82819.40)	(201115.24,209241.49,217367.74)
	UNICEF	(45159.57,45159.57,45159.57)	
	MoH	(73136.27,81262.52,89388.77)	
Societal	OTP	(2901.00,3964.65,6353.60)	(12693.04,16522.90,21670.62)
	SC	(349.60,374.40,399.60)	
	CBV	(9442.44,12183.85,14920.42)	
			(213808.28,225764.39,239038.36)

Institutional costs are estimated to be:

$$Institutional\ costs = (201115.24, 209241.49, 217367.74)$$

Societal costs are estimated to be:

$$Societal\ costs = (12693.04, 16522.90, 2167.62)$$

Total costs are estimated to be:

$$Total\ costs = (213808.28, 225764.39, 239038.36)$$

Cost-effectiveness of the example Ethiopian two district CMAM program

Cost-effectiveness (CE) is calculated as:

$$CE = \frac{cost}{outcome}$$

We will work with total costs:

$$Total\ costs = (213808.28, 225764.39, 239038.36)$$

and use triangular fuzzy numbers to account for uncertainty in calculations.

Positive outcomes achieved by the program were estimated to be:

$$Recovered\ cases = (624, 644, 664)$$

$$Deaths\ averted = (128, 174, 260)$$

$$DALYs\ averted = (8044, 10429, 14613)$$

We can calculate the cost-effectiveness of the program for cases recovered:

$$CE = \frac{(213808.28, 225764.39, 239038.36)}{(624, 644, 664)}$$
$$= US\$350.57\ (95\%\ CI = US\$328.60 - US\$376.03)\ per\ case\ recovered$$

We can calculate the cost-effectiveness of the program for deaths averted:

$$CE = \frac{(213808.28, 225764.39, 239038.36)}{(128, 174, 260)}$$
$$= US1297.50 \ \ (95\%\ CI = US\$743.58 - \ US\$1732.77)\ per\ death\ averted$$

We can calculate the cost-effectiveness of the program for DALYs averted:

$$CE = \frac{(213808.28, 225764.39, 239038.36)}{(8044, 10429, 14613)}$$
$$= US\$21.65 \ \ (95\%\ CI = US\$16.26 - \ US\$27.97)\ per\ DALY\ averted$$

Interpreting cost-effectiveness estimates

Cost-effectiveness estimates are usually interpreted by comparison with other programs or against commonly used standard or threshold values.

Table 9, for example, shows the *cost per death averted* for a variety of child survival interventions.

Table 9 : Cost per death averted for a range of child survival interventions

Intervention	Context(s)	Cost per death averted*
CMAM delivered by community health workers**	Bangladesh	US$869.00
Standard EPI package***	Africa / South Asia	US$313.00
Intermittent Preventive Treatment for malaria****	Mozambique	US$232.00
Breastfeeding support (range of models)	Sub-Saharan Africa	US$114.00 - US$342.00
Universal vitamin A distribution****	Philippines	US$76.30
Mass chemoprophylaxis for malaria***	Gambia	US$163.00
Social marketing of insecticide treated nets (ITN)***	Tanzania	US$1780.00

* All dollar values have been standardised to 2012 values.

** The quoted cost is for all staff salaries and allowances, site rental, all logistics costs, all community mobilisation costs, training, supervision, monitoring and evaluation including SQUEAC coverage assessments, case-finding and "watch-list" follow-up in the community, curative care, and costs to households. Note that this is a much broader range of costs than is used in the analysis for the Nigerian CMAM program (see Table 7).

*** The quoted cost is for implementing the program as a semi-vertical addition to existing healthcare package.

**** The quoted cost is for delivering the intervention within an existing EPI program.

The example Ethiopian two district CMAM program (US$1297.50 per death averted) appears to be quite expensive compared to many other child survival interventions including a CMAM program from Bangladesh. It is cost-effective compared to social marketing of insecticide treated bednets in Tanzania.

Cost-effectiveness thresholds

A similar procedure could be used for cost per DALY averted. It is, however, more common to use standard or threshold values. Two standards are commonly used:

> **A single fixed threshold for cost per DALY averted :** Interventions achieving a cost per DALY averted of less than US$100 are classified as being *very cost-effective*. The cost per DALY averted achieved by the example Ethiopian two district CMAM program was US$21.65. This program would, therefore, be classified as being *very cost-effective*.
>
> **Variable thresholds per DALY averted :** The most commonly-used thresholds in the public health nutrition field is one proposed by the WHO. This compares the cost per DALY averted by an intervention with the per capita GDP of the country in which the intervention is implemented:
>
> - Highly cost-effective interventions avert a DALY for less than a country's GDP per capita.
>
> - Cost-effective interventions avert a DALY for between one and three times a country's GDP per capita.
>
> - Intervention that are **<u>not</u>** cost-effective avert a DALY for more than three times a country's GDP per capita.
>
> The cost per DALY averted achieved by the example Ethiopian two district CMAM program was US$21.65. The per-capita GDP for Ethiopia in 2017 was US$549.80. The example Ethiopian two district CMAM program can, therefore, be considered to be *highly cost-effective*.

Classifications like these are useful but when you make classifications using thresholds you are throwing away information. A program costing US$25 per DALY averted and a program costing US$75 per DALY averted would both be classified as "good value" (i.e. cost-effective) using the US$100 threshold. The first program represents "better value" (i.e. is more cost-effective) than the second program. To aid decision making, reports should present both qualitative results (classifications) and quantitative results in terms of the estimated cost per DALY averted.

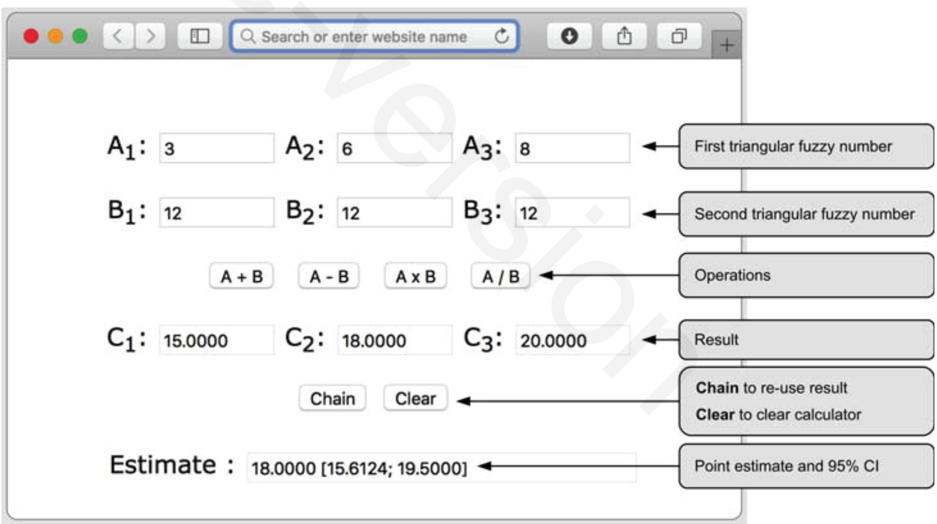
APPENDIX 1 : A CALCULATOR FOR TRIANGULAR FUZZY NUMBERS

The rules of arithmetic with triangular fuzzy numbers are simple but tedious to perform. The large number of operations required for even simple calculations make mistakes quite common. It is usually best to use a fuzzy arithmetic calculator. A fuzzy arithmetic calculator has been developed to accompany this handbook. This is available from:

`http://www.brixtonhealth.com/fuzzy.html`

The calculator is a web-based application and can be run over the Internet or the HTML file can be downloaded and run in a web browser without access to the Internet and looks like this:

Figure A1 : Fuzzy arithmetic calculator



The example shows the addition of fuzzy number A = (3, 6, 8) and the constant 12 which is specified by entering B = (12, 12, 12)

The calculator works with two fuzzy numbers at a time. These are labelled **A** and **B.**

The arithmetic operations allowed are:

Calculator button	Operation
A + B	Add **A** and **B.**
A − B	Subtract **B** from **A.**
A x B	Multiply **A** by **B.**
A / B	Divide **A** by **B.**

Results are displayed as **C.**

Inputs for **A** and **B** are checked to see if they are valid triangular fuzzy numbers before calculations are performed. Warnings are given if either **A** or **B** is not a valid triangular fuzzy number. A warning is also given if a division by zero is attempted.

Other operations provided by the calculator are:

Calculator button	Operation
Chain	Copy the result in **C** to input **A.** This enables the result of one calculation to be the starting point for the next calculation. A number of calculations can be "chained" together. This is demonstrated in the example calculation (see below) and in *Figure A2*.
Clear	Clear the calculator to start a new calculation.

A 95% confidence interval for **C** is calculated automatically using the method described in *Box 4* and displayed as **`Estimate`**. This will usually only be useful at the end of a calculation.

An example calculation

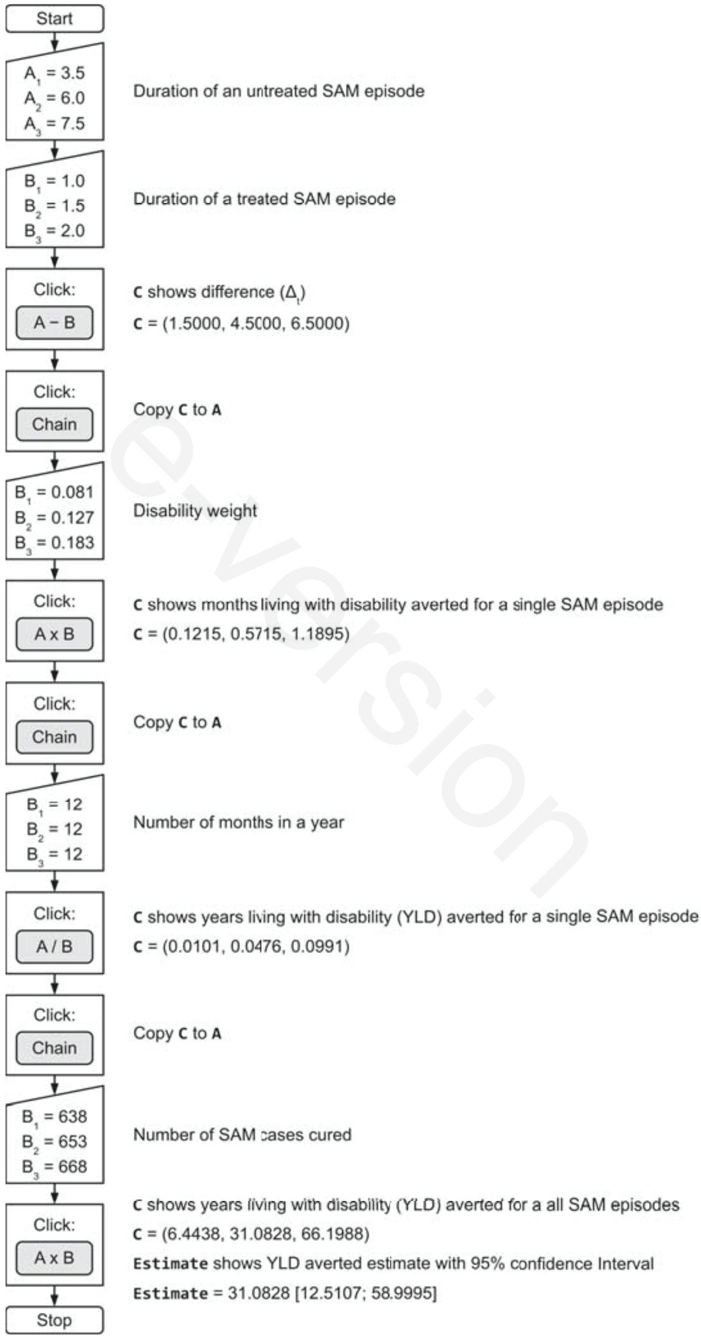
This calculation follows the YLD calculation for the Bangladesh program.

The inputs are:

$$Duration\ of\ an\ untreated\ SAM\ episode = (3.5, 6.0, 7.5)$$
$$Duration\ of\ a\ treated\ SAM\ episode = (1, 1.5, 2)$$
$$Disability\ weight = (0.081, 0.127, 0.183)$$
$$Number\ of\ SAM\ cases\ cured = (638, 653, 668)$$

The process of the YLD calculation is shown in *Figure A1*.

Figure A2 : Example calculation using the fuzzy arithmetic calculator



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