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# SMALL AREA ESTIMATION OF NUTRITIONAL STATUS OF UNDER-FIVE CHILDREN IN SYLHET DIVISION: AN M-QUANTILE APPROACH

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## ABSTRACT

Under nutrition is one of the severe problems around the globe and finds its place in the global agenda. Sustainable Development Goals (SDGs) highlight the need for special attention to eradicate malnutrition. Bangladesh having high prevalence of malnutrition is committed to fulfill the targets of SDGs. Though Bangladesh achieved remarkable success in improving nutritional status of under-five children at national level, there have been regional variations. Government is planning to target need based resource allocation to small administrative levels. To do that real time, small area level estimates of nutrition will be required. Sylhet division was severely suffering from one or all form of malnutrition (BBS, 2014). This research tried to address these issues for which a primary sample of size 300 was collected from Dharampasha Upazila of Sunamgonj district of Sylhet division for in-depth analysis. M-Quantile estimation method was used to identify small area estimates at Upazila level of Sylhet division. The Upazilas exhibiting poorest nutritional status was identified in maps for comparison. Special care should be given to help these Upazilas to come out of the cycle of malnutrition in addition to the common national programmes. The results are efficient and may be adopted in the future, especially where we have doubted in the distributional assumption of the data.

**Key Words:** Small area estimation, nutritional status, M-quantile approach.

## I. INTRODUCTION

Bangladesh Bureau of Statistics (BBS) published a report on 2014 on small area estimation of child undernutrition in Bangladesh. They used Censsu-2011, Child and Mother Nutrition Survey-2012 and Health and Morbidity Status Survey-2011 data and used Word Bank method (Elbers, Lanjouw and Lanjouw, ELL) to find under-five child nutrition status for stunting and underweight indices. Most of the districts as

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well as Upazilas of Sylhet division were suffering from one or all from of malnutrition (BBS, 2014). They also found that Sunamganj district has the highest prevalence of stunting 46% and underweight 41% compared to all other districts of Bangladesh. Considering the computational identity, we have narrowed down our small area estimation exercise to Sylhet division only. We used M-quantile method of estimation to find the small area estimates of under-five children of rural Bangladesh through three indices stunting, wasting and underweight. Recently, there have been growing interests to use newly developed M-Quantile (MQ) regression introduced by Breckling and Chambers, 1988 that uses the ideas of M-regression (Huber, 1973) to model the relationship between the dependent variable and its predictors for various M-quantiles of the distribution. Depending on the choice of the loss function, M-quantiles may reduce to ordinary quantiles and expectiles. The obtained results have been described in the following sections. We used MQ-Poverty-Lib-package in R programming (Pratesi, 2015) to obtain the estimate of malnutrition prevalence.

Study on nutritional status demands separate researches on children and adults as the measurements of nutritional status are somewhat different in definition and measurement techniques for the two groups. For developing countries child nutrition is given utmost priority over adult health due to resource limitation to address both and child nutrition is the base of future health progression. Like many developing countries prevalence of malnutrition is one of the indicators of child health in Bangladesh. Factors influencing the child malnutrition status may lead to policy formulation for the governments of the country. The term malnutrition generally refers to both undernutrition and overnutrition. Malnutrition is a sustaining problem in many of the developing countries. It is one of the main causes of morbidity and mortality among children under five years of age (Martorell and Haschke, 2001; Semba and Bloem, 2007). In developing countries malnutrition is an important root of infant and young child mortality and reduced life span (Dalzell-Ward, 1972). It is associated with more than half of all deaths of children worldwide. Many factors can cause malnutrition, most of which relate to poor diet or severe and repeated infections, particularly in underprivileged populations. Inadequate diet and disease, in turn, are closely linked to the general standard of living, the environmental conditions, and whether a population is able to meet its basic needs such as food, housing and health care. Malnutrition is thus a health outcome as well as a risk factor for disease and exacerbated malnutrition and it can increase the risk both of morbidity and mortality. Although it is rarely the direct cause of death (except in extreme situations, such as famine), child malnutrition was associated with 54% of child deaths (10.8 million children) in developing countries in 2001 (Blössner and de Onis, 2005). Malnutrition that is the direct cause of death is referred to as “protein-energy malnutrition”.

The nutritional status of women and children is particularly important, because it is through women and their off-spring that the pernicious effects of malnutrition are propagated to future generations. A malnourished mother is likely to give birth to a low-birth-weight (LBW) baby susceptible to disease and premature death, which only further undermines the economic development of the family and society, and continues the cycle of poverty and malnutrition. Although child malnutrition declined globally during the 1990s, with the prevalence of underweight children falling from 27% to 22% (de Onis et al., 2004a), national levels of malnutrition still vary considerably (0% in Australia; 49% in Afghanistan) (WHO, 2003). The largest decline in the level of child malnutrition was in eastern Asia where underweight levels decreased by one half between 1990 and 2000.Underweight rates also declined in south-eastern Asia (from 35% to 27%), and in Latin America and the Caribbean the rate of underweight children decreased by one third (from 9% to 6%) over the last 10 years. In contrast, south-central Asia still has high levels of child malnutrition, even though the rate of underweight children declined from 50% to 41% during the 1990s. In Africa, the number of underweight children actually increased between 1990 and 2000 (from 26 million to 32 million), and 25% of all children under five years old are underweight, which signals that little changed from a decade earlier. The projection for 2005 was that the prevalence of child malnutrition will continue to decline in all regions but Africa, which is dominated by the trend in sub-Saharan Africa (de Onis et al., 2004b).

Many factors can contribute to high rates of child malnutrition, ranging from those as fundamental, as political instability and slow economic growth, to highly specific ones such as the frequency of infectious diseases and the lack of education. These factors can vary across countries. A cross-country analysis found that the determinants of stunting in preschool children varied considerably between nations, and among provinces within nations (Frongillo *et al.*, 1997). Important determinants of child malnutrition, such as the prevalence of intra-uterine growth retardation (IUGR), also differ considerably across geographical regions (de Onis, Blössner & Villar, 1998). Whether or not children are undernourished, therefore seems to be as much a consequence of national and provincial factors, as of individual and household circumstances. According to BDHS 2009, in Bangladesh among the under five children, 43 percent were stunted (chronic malnutrition), and 16 percent were severely stunted. About 17 percent of children under five were wasted (acute malnutrition), and 3 percent were severely wasted. About 41 percent of children under five were underweight (under nutrition), and another 12 percent were severely underweight. Combating the problem of poor nutritional status is an ongoing process and frequent survey on the prevalence of the malnutrition is a pre-requisite in this process. Furthermore, with the presence of differences in regional settings and other contextual differences the study of child malnutrition becomes complicated which requires sophisticated statistical modeling practices (Alom, 2012).For the developing countries like Bangladesh, prevalence of malnutrition is one of the indicators of child health. Factors influencing the malnutrition status may lead to policy formulation for the governments in these countries.

Small area estimation methods were used in this study which is basically a mathematical and statistical method that models data collected from one or more sources, to produce estimates, for example, poverty, nutrition status, etc., that are more accurate at small area level than using only data collected from each small area. The most common methodology for small area estimation of poverty and undernutrition in developing countries is the World Bank method (Elberset *et al.*, 2001, 2003), which is now available as free software (PovMap–Zhao, 2006; PovMap2–Zhao and Lanjouw, 2009) from the World Bank website. In Bangladesh, few studies have been conducted through small area estimation. Haslett et al, published a report in 2014 on small area estimation of child undernutrition in Bangladesh. They produced Upazila level stunting and underweight status of children under five years of age in Bangladesh by combining survey data from the Child and Mother Nutrition Survey of Bangladesh 2012 (CMNS 2012) and the Health and Morbidity Status Survey 2011 (HMSS 2011) with auxiliary data derived from the Bangladesh Population and Housing Census 2011.The initial, national, small area estimation of poverty and undernutrition in Bangladesh was undertaken in 2003 by Jones and Haslett (2004) for the UN World Food Programme, using a 5% clustered sample from the 2001 population census, the Household Income and Expenditure Survey 2000 (HIES 2000) and the Child Nutrition Survey (CNS 2000). Since the 2003 study, no further small area estimates of stunting and underweight in Bangladesh have been produced. In 2008 the World Bank carried out an exercise to update Jones and Haslett’s Upazila-level estimates using the HIES-2005, by restricting their modelling to variables that were judged not to have changed since the 2000 census (Jones, G., and Haslett, S.J. 2004).

## II. DATA AND METHODOLOGY

Bangladesh Bureau of Statistics (BBS, 2014) with the help of the staff from Massey University, New Zealand, estimated child undernutrition in Bangladesh by the application of small area estimation techniques, using sample survey and census data from 2011 and 2012. They used stunting and underweight indices to measure the child nutrition status and found that Sylhet division has the highest prevalence of malnutrition and among Sylhet division, Sunamgonj (Map 3.2) is the most malnourished district. Sylhet division has 4 districts and 38 Upazilas. The districts are Habiganj, Maulvibazar, Sunamgonj and Sylhet. Due to unavailability of sampling frame and resource limitations the research adopted purposive sampling techniqueto collect necessary information with a structured questioner from 300 families of Dharampasha Upazila of Sunamgonj district who have at least one under-five child. To collect the data, we have taken help from Upazila agricultural extension officer (AEO) of Dharampasha Upazila. Out of 300 families 45 had twin babies of under-five age, so finally have been got 345 cases to analyse the data. We used M-quantile method of estimation to find the small area estimates of under-five children of rural Bangladesh through three indices stunting, wasting and underweight. The obtained results have been described in the following sections. We used MQ-Poverty-Lib-package in R programming (Pratesi, 2015) to obtain the estimate of malnutrition prevalence.

**Small Area Estimation Method**

The estimation of nutritional status of under-five children in rural Bangladesh assessed in terms of stunting, wasting and underweight is crucial to achieving targeted implementation of welfare policies. During the last decade there has been a rising interest for what concern malnutrition measures. The measures of malnutrition at small area level (or Upazila) play a central role to identify malnourished areas with greater accuracy. In Bangladesh, there is a growing demand from policy makers, planners, and researchers to produce reliable estimates of malnutrition at local level for the allocation of government funds and in regional planning. However, the data availability at the local level (small area) from a survey is often very limited by cost and hence direct estimators produce inefficient estimates or large variances and might be very unreliable. In addition, they do not provide estimates for zero samples or out sample areas. In this case, increasing sample size can be an alternative but it is extremely expensive and, in general, there are no resources in terms of time and money to undertake this solution. In such a situation, one possible solution for obtaining efficient estimates at local level is the use of small area estimation (SAE) methodologies. The SAE techniques aim at producing reliable efficient estimates for such small areas (Upazilas) with small (or even no) sample sizes by borrowing strength from related small areas through linking models based on auxiliary data such as census data. This leads to model-based indirect estimators. The model-based estimates are based on an explicit statistical regression models in which the individual areas are linked in some way and combines the direct estimates based on survey data and information from auxiliary data on small areas obtained from a census. For a comprehensive overview of SAE techniques, see Rao (2003).

The SAE models can be divided broadly two types: (1) Area level models and (2) Unit level models. Area level models are used to obtain small area estimates if auxiliary data are available only at the area level. The basic area level model is the Fay-Herriot (FH) model (Fay and Herriot, 1979). On the contrary, the nested error linear regression model proposed originally by Battese *et al.* (1988) called hereafter BHF model which is used to obtain small area estimates when auxiliary data are available at the unit level. In recent decades, the most widely used robust unit-level SAE method is the M-Quantile (MQ) method (Tzavidis *et al.*, 2008). In the M-Quantile (MQ) method, the between-area variations are captured by calculating area-specific M-quantile coefficients instead of random effects. The distinguishing features of this method are distribution free assumptions on the model errors and the area effects, and this also allows outlier robust inference.

**M-Quantile (MQ) Method**

The linear MQ regression model for $y_k$ given $x_k$ is one where we assume that the $q^{th}$ M-quantile satisfies $Q_q(x_k;\Psi) = x_k^T\beta_\Psi(q)$. For a specified *q* and continuous ψ, the MQ regression parameters $\beta_\Psi(q)$ are estimated by solving the estimating equations $\sum_{k=1}^{n}\Psi_q\left[\varphi^{-1}\left\{y_k - x_k^1\hat{\beta}_{\Psi(q)}\right\}\right]x_k = 0.$ Here ψ is an appropriately chosen influence function such as Huber Proposal 2 influence function. The estimating equations can be solved with a straightforward application of an iterative weighted least squares (IWLS) algorithm. In the MQ model the conditional distribution of *y* given **x** is independent on the pre-defined hierarchical structure. Also it is assumed that since MQ coefficients are determined at population level, population units within a small area have almost similar MQ coefficients. The MQ coefficient $q_k$ for the population unit *k* with values $y_k$ and $x_k$ is obtained such that $Q_{q_k}(x_{ik};\Psi) = y_{ik}$.

The MQ estimator of FGT poverty indicators and quantiles can be written as

$$\hat{F}_{\alpha i}^{MQ} = N_d^{-1}\left[\sum_{k\in s_i}F_{\alpha ik} + \sum_{k^1\in r_i}\hat{F}_{\alpha ik^1}\right] i = 1, 2,...,D \ \alpha = 0,1,2 \qquad (3.1)$$

Marchetti *et al.* (2012) proposed an alternative procedure to calculate (3.1) following a MC simulation approach parallel to the EBP approach. The basic steps are as follows:

**Step 1**: Fit the MQ small area models to the survey data $(y_s, x_s)$ and obtain estimates of MQ parameters $\theta_i$ and $\beta_\psi(\theta_i)$ for i = 1,2,...,D.

**Step 2**: Generate an out of sample vector of size $(N_i - n_i)$ using the estimated model parameters $\hat{\theta}_i$ and $\hat{\beta}_\psi(\hat{\theta}_i)$ in the MQ model $y_k^* = x_k^T\hat{\beta}_\psi(\hat{\theta}_i) + e_k^*; k \in r_i$ *where*, $e_k^*$ is drawn from the empirical distribution function of the model residuals.

**Step 3**: Repeat step 2 a large number of times *L* (say, *L* =1000) to calculate *L* estimate of $F_{\alpha i}\ (F_{\alpha i}^{*(l)}; l = 1,2,..,L)$ combining sample $(y_{s_1})$ and non-sample observations $(y_{r_i}^*)$ in each process.

**Step 4:** Average the *L* estimates of $F_{\alpha i}$ to obtain ultimate MQ estimate as $\hat{F}_{\alpha i}^{MQ} = \sum_{l=1}^{L} F_{\alpha i}^{*(l)}$.

A non-parametric bootstrap procedure is proposed by Marchetti *et al.* (2012) to estimate the MSE for not only small area mean but also poverty indicators and quantiles. The bootstrap MSE estimator of $\hat{F}_{\alpha i}^{MQ}$ can be calculated as follows:

$$mse\left(\hat{F}_{\alpha i}^{MQ}\right) = \operatorname{var}\left(\hat{F}_{\alpha i}^{MQ}\right) + bias\left(\hat{F}_{\alpha i}^{MQ}\right)^2 \qquad (3.2)$$

where, the estimated bias and variance of the estimated parameter $\hat{F}_{\alpha i}^{MQ}$ are

$$bias\left(\hat{F}_{\alpha i}^{MQ}\right) = B^{-1}R^{-1}\sum_{b,r}\left(\hat{F}_{\alpha i}^{*(br)} - F_{\alpha i}^{*(b)}\right)$$

and

$$\operatorname{var}\left(\hat{F}_{\alpha i}^{MQ}\right) = B^{-1}R^{-1}\sum_{b,r}\left(\hat{F}_{\alpha i}^{*(br)} - \hat{F}_{\alpha i}^{*(br)}\right)^2 \text{ where } \overline{\hat{F}}_{\alpha i}^{*(br)} = R^{-1}\sum_{r=1}^{R}\hat{F}_{\alpha i}^{*(br)}$$

$with\ b = 1,2,..,B\ and\ r = 1,2,..,R$ (For details, see Das, 2016).

## III. RESULTS AND DISCUSSION

### District-wise Estimation of Under-five Child Nutritional Status at Sylhet Division

Sylhet division has four districts which are Habiganj, Maulvibazar, Sunamganj and Sylhet. The M-quantile estimates corresponding to these districts are demonstrated in Table1.

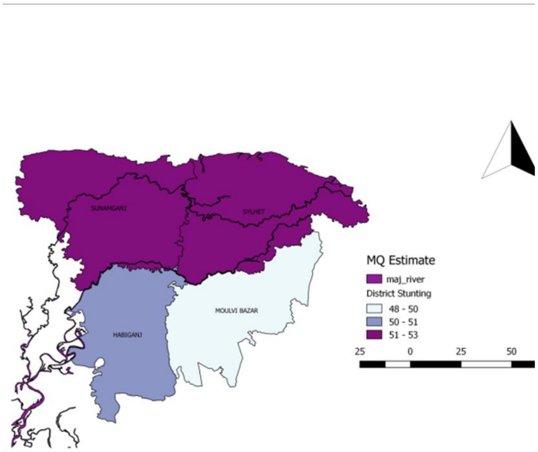
**Table 1: District-wise M-quantile estimates of nutritional status of Sylhet division**

| District | Stunting | | Wasting | | Underweight | |
|---|---|---|---|---|---|---|
| | Prevalence | SE | Prevalence | SE | Prevalence | SE |
| Habiganj | 0.507 | 0.020 | 0.224 | 0.022 | 0.515 | 0.024 |
| Maulvibazar | 0.475 | 0.024 | 0.198 | 0.016 | 0.452 | 0.026 |
| Sunamganj | 0.526 | 0.022 | 0.176 | 0.015 | 0.483 | 0.021 |
| Sylhet | 0.518 | 0.017 | 0.179 | 0.014 | 0.477 | 0.018 |

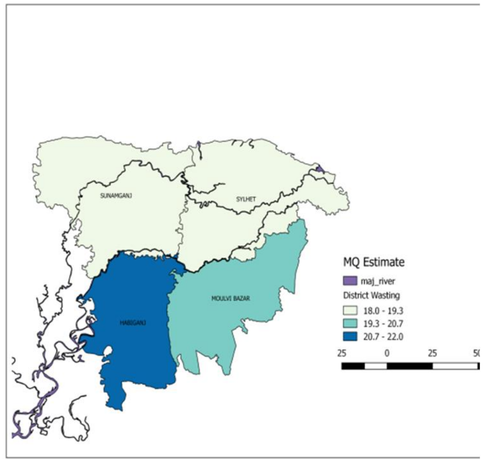
*SE = Standard Error

Table 1 shows that highest prevalence (53%) of stunting is in Sunamganj district followed by Sylhet (52%), Habiganj (51%) and lowest in Maulvibazar (48%). The results have the similarity with the findings of BBS (2014). BBS (2014) showed that Sunamganj district had highest prevalence (46%) of stunted child followed by Habiganj (44%), Sylhet (44%) and lowest in Maulvibazar (43%). However, we found maximum prevalence of underweight (52%) in Habiganj and minimum (47%) in Sylhet sadar district respectively. However, BBS (2014) explained that maximum

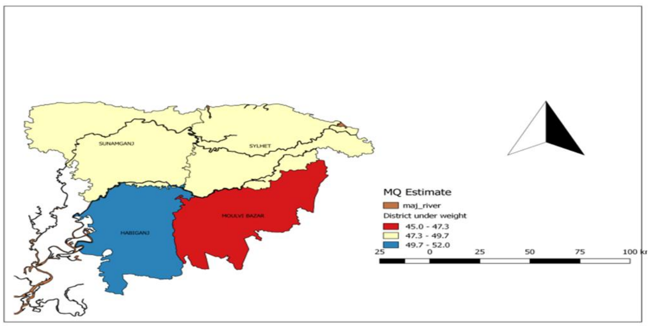
(41%) was in Sunamganj district and minimum (36%) was observed in Maulvibazar district. We obtained highest prevalence (22%) of wasting in Habiganj district followed by Maulvibazar (20%), Sylhet (18%) and Sunamganj (17.6%) respectively. District-wise MQ estimates of stunting, wasting and underweight of under-five children of rural area of Sylhet division are given in Map 1, Map 2 and Map 3 respectively.




**Map 1: District-wise Stunting of Sylhet division**




**Map 2: District-wise Wasting of Sylhet division**




**Map 3: District-wise Underweight of Sylhet division**

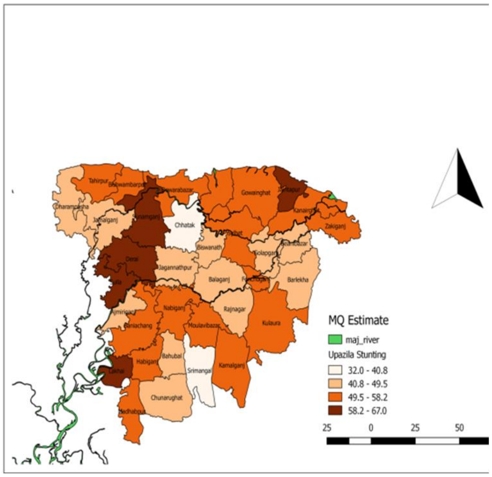
## Upazila-wise M-quantile Estimation of under-five child nutritional status at Sylhet division

Sylhet division has 38 Upazilas, but BDHS-2011 collected data from 36 Upazilas. Table 2 shows that Sunamganj Sadar Upazila of Sunamganj district has the highest prevalence of stunting (67%) whereas for wasting Gowainghat Upazila (32%) of Sylhet district and for underweight Baniachong Upazila (72%) of Habiganj district are the most malnourished areas. Chhatak Upazila (32%) in Sunamganj district is the lowest stunted area and for both wasting and underweight Barlekha Upazila in

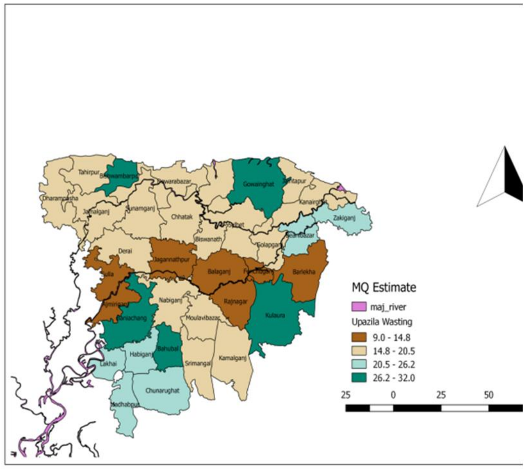
Maulvibazar district is the least malnourished area (8% and 30% respectively). The results of BBS (2014) revealed that most of the Upazilas of Sunamganj district have the highest prevalence of stunting and underweight. Tahirpur Upazila has the highest prevalence of stunting (49%) followed by Bishwambarpur and Dharampasha (47%) and Jamalganj (46%). The lowest stunted Upazila in Sunamganj district was found to be Jagannathpur and among the Sylhet division the least malnourished Upazila was Kulaura (41%). On the other hand, the highest prevalence of underweight children was found in Dharampasha Upazila (43%) in Sunamganj district which was also the most stunted area among the Sylhet division. The lowest prevalent underweight Upazila in Sylhet district was found Sylhet Sadar and that of in Sunamganj district was Sunamganj Sadar Upazila respectively. Upazila wise small area MQ estimates of stunting, wasting and underweight of Sylhet division are presented in Map 4, Map 5 and Map 6 respectively for better understanding.

**Table 2: Upazila-wise M-quantile estimates of nutritional status of Sylhet division**

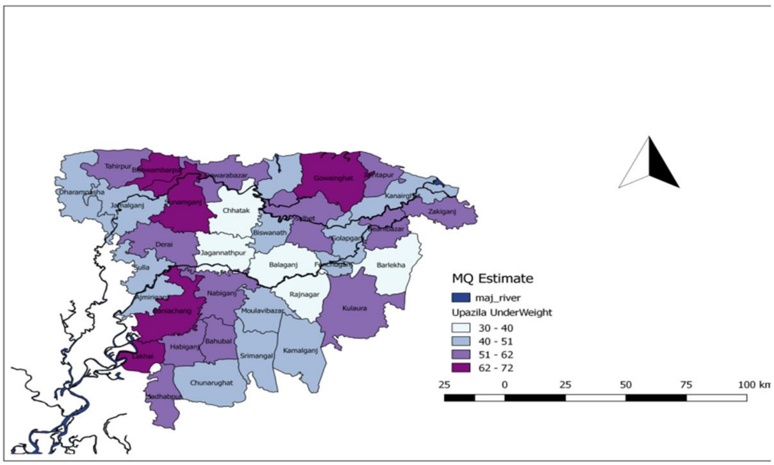
| District | Upazila | Stunting | | Wasting | | Underweight | |
|---|---|---|---|---|---|---|---|
| | | Prevalence | SE | Prevalence | SE | Prevalence | SE |
| Habiganj | Ajmirganj | 0.469 | 0.045 | 0.132 | 0.030 | 0.421 | 0.052 |
| Habiganj | Bahubal | 0.454 | 0.058 | 0.298 | 0.073 | 0.550 | 0.063 |
| Habiganj | Baniachong | 0.583 | 0.073 | 0.307 | 0.078 | 0.718 | 0.110 |
| Habiganj | Chunarughat | 0.443 | 0.046 | 0.226 | 0.035 | 0.462 | 0.043 |
| Habiganj | HabiganjSadar | 0.521 | 0.050 | 0.245 | 0.047 | 0.533 | 0.054 |
| Habiganj | Lakhai | 0.620 | 0.064 | 0.240 | 0.046 | 0.651 | 0.078 |
| Habiganj | Madhabpur | 0.500 | 0.041 | 0.216 | 0.031 | 0.515 | 0.043 |
| Habiganj | Nabiganj | 0.526 | 0.045 | 0.185 | 0.029 | 0.524 | 0.046 |
| Maulvibazar | Barlekha | 0.426 | 0.111 | 0.087 | 0.062 | 0.303 | 0.125 |
| Maulvibazar | Juri | 0.414 | 0.077 | 0.254 | 0.061 | 0.434 | 0.073 |
| Maulvibazar | Kamalganj | 0.507 | 0.052 | 0.159 | 0.033 | 0.438 | 0.060 |
| Maulvibazar | Kulaura | 0.542 | 0.055 | 0.304 | 0.075 | 0.582 | 0.067 |
| Maulvibazar | Maulvibazar Sadar | 0.496 | 0.043 | 0.183 | 0.028 | 0.462 | 0.043 |
| Maulvibazar | Rajnagar | 0.439 | 0.072 | 0.139 | 0.044 | 0.402 | 0.077 |
| Maulvibazar | Sreemangal | 0.399 | 0.058 | 0.181 | 0.027 | 0.412 | 0.052 |
| Sunamganj | Bishwambarpur | 0.559 | 0.058 | 0.278 | 0.063 | 0.622 | 0.072 |
| Sunamganj | Chhatak | 0.322 | 0.086 | 0.150 | 0.031 | 0.325 | 0.077 |
| Sunamganj | DakshinSunamganj | 0.598 | 0.066 | 0.097 | 0.038 | 0.435 | 0.055 |
| Sunamganj | Derai | 0.587 | 0.063 | 0.159 | 0.034 | 0.551 | 0.058 |
| Sunamganj | Dharampasha | 0.473 | 0.078 | 0.181 | 0.048 | 0.432 | 0.085 |
| Sunamganj | Dowarabazar | 0.542 | 0.037 | 0.185 | 0.024 | 0.549 | 0.040 |
| Sunamganj | Jagannathpur | 0.407 | 0.073 | 0.129 | 0.041 | 0.383 | 0.075 |
| Sunamganj | Jamalganj | 0.485 | 0.045 | 0.169 | 0.027 | 0.449 | 0.048 |
| Sunamganj | SunamganjSadar | 0.673 | 0.081 | 0.193 | 0.035 | 0.629 | 0.074 |
| Sunamganj | Tahirpur | 0.572 | 0.054 | 0.195 | 0.035 | 0.527 | 0.053 |
| Sylhet | Balaganj | 0.456 | 0.040 | 0.123 | 0.029 | 0.387 | 0.050 |
| Sylhet | Beani Bazar | 0.494 | 0.055 | 0.233 | 0.048 | 0.535 | 0.064 |
| Sylhet | Bishwanath | 0.466 | 0.053 | 0.151 | 0.032 | 0.413 | 0.056 |
| Sylhet | Companiganj | 0.542 | 0.048 | 0.147 | 0.032 | 0.455 | 0.057 |
| Sylhet | DakshinSurma | 0.506 | 0.041 | 0.138 | 0.026 | 0.423 | 0.042 |
| Sylhet | Golabganj | 0.432 | 0.040 | 0.188 | 0.025 | 0.423 | 0.037 |
| Sylhet | Gowainghat | 0.583 | 0.055 | 0.322 | 0.080 | 0.661 | 0.082 |
| Sylhet | Jaintiapur | 0.594 | 0.063 | 0.160 | 0.037 | 0.549 | 0.062 |
| Sylhet | Kanaighat | 0.578 | 0.056 | 0.161 | 0.035 | 0.505 | 0.055 |
| Sylhet | Sylhet Sadar | 0.546 | 0.038 | 0.177 | 0.023 | 0.518 | 0.038 |
| Sylhet | Zakiganj | 0.582 | 0.053 | 0.210 | 0.036 | 0.583 | 0.059 |




**Map 4: Upazila-wise Stunting of Sylhet division**




**Map 5: Upazila-wise Wasting of Sylhet division**




**Map 6: Upazila-wise Underweight of Sylhet division.**

## IV. CONCLUSION AND POLICY IMPLICATION

M-Quantile estimation methods are used for the first time for small area estimation of child malnutrition in Bangladesh. The results appeared consistent with the previous results of Haslett et al, (2014) though it was based on different data sets and separate estimation technique (ELL). The Upazilas exhibiting poorest nutritional status demand special attention. There are some Upazilas which are suffering from all the three forms of malnutrition. This suggests devising integrated programme intervention addressing the three forms of malnutrition. MQ estimation being a distributional assumption free method may be adopted in Bangladesh for small area estimation purposes, where there may be confusing regarding distribution pattern of the data. In a sense this attempt may be regarded as piloting of MQ method in Bangladesh.

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