Small-Area Estimation of Child Undernutrition in Bangladesh

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The Bangladesh Bureau of Statistics
in collaboration with
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Summary

Small-area estimates (SAE) of stunting and underweight in children under five years of age in Bangladesh are produced at upazila level by combining survey data from the Child and Mother Nutrition Survey of Bangladesh 2012 (CMNS) and the Health and Morbidity Status Survey 2011 (HMSS) with auxiliary data derived from the Bangladesh Population and Housing Census 2011. A model for predicting standardized height-for-age and weight-for-age have been used for estimating stunting and underweight, respectively, in children under five years using CMNS, supplementary data from HMSS, and contextual variables derived from the census at the level of the clustering used in the two surveys. The models have been applied to child level census data to estimate underweight and stunting at upazila level. The small-area estimation procedure used in this study does not produce *measures* of child undernutrition at the local level. Rather the procedure applied is able to *estimate* nutrition outcomes – based on a statistical model estimated in the relevant household survey. These estimates are measured with error, and the degree of imprecision will vary as a function of a wide variety of factors, most notably the degree of disaggregation at which indicators of wellbeing are being estimated. In this study it was found that estimates at upazila level were sufficiently accurate. Estimates at any finer geographical level are not usable because they are too imprecise.

Executive Summary

1. Small area estimation is a mathematical technique to extract more detailed information from existing data sources by statistical modelling. The methodology is important because it produces finer level information than is possible for a sample survey analysed by standard methods, for poverty related variables that are not collected in the census. The cost of small area studies can be saved many times over by having this better poverty information at a finer level for use in aid allocation.

2. The report, undertaken by staff from Massey University, New Zealand, covers the application of small area estimation techniques to child undernutrition in Bangladesh, using sample survey and census data from 2011 and 2012.

3. The particular aspects of poverty that are considered in this report are stunting and underweight in children under five years of age assessed via statistical models for height-for age (HAZ) and weight-for-age (WAZ), respectively.

4. These indicators reflect the food security and nutrition interests and concerns of the sponsor of the complete undernutrition mapping study, which is the World Food Programme (WFP). This report recognises the importance of both measures to a wide range of international aid agencies. Financial support for this research has been provided by the International Fund for Agricultural Development (IFAD). The Bangladesh Bureau of Statistics (BBS), under the Ministry of Planning, Government of Bangladesh, is a partner to this study.

5. For Bangladesh, the sample survey data sources considered in detail are the Child and Mother Nutrition Survey of Bangladesh 2012 (CMNS) and the Health and Morbidity Status Survey 2011 (HMSS). The census used is the Bangladesh Population and Housing Census 2011. Area coding information and its matching between survey and census at all levels was required as a prerequisite to using the census data and linking it by area code with the survey data to develop statistical models for small area estimation.

6. Although at the initial feasibility assessment stage we were not able to be confident that small area estimation of underweight and stunting would be feasible for Bangladesh using the data sources available, further testing using the census data has clarified the situation. The models for stunting and underweight now show good overall predictive performance at upazila level because of the extensive aggregation, even though the predictive power at child level is very much more limited.

7. The conclusion is that availability of clean survey and census data from the Bangladesh Bureau of Statistics has made it possible to produce estimates of stunting and underweight with acceptable accuracy at upazila level, and maps at that level that provide a coherent national picture across the whole of Bangladesh.

8. The completion of this report follows extensive consultation with BBS and WFP, and more limited discussions with the World Bank, and Economics Research Group (ERG). The authors are grateful for these contributions. Viewpoints and opinions expressed in this report do not however necessarily reflect those of all or any of the organisations consulted.

Scope

The small area estimation at upazila level for prevalence of stunting and underweight (and severe stunting and underweight) in Bangladeshi children under five years of age has been undertaken in four phases.

Phase One:

- Identification and examination of relevant data sources and reports, including of necessity the Bangladesh Population and Housing Census of 2011, to determine which show potential for use in small area estimation of these undernutrition indicators;
- Identification and listing of questions asked in the census and in the selected surveys, particularly the Child and Mother Nutrition Survey 2012 (CMNS) and the Health and Morbidity Status Survey 2011 (HMSS) that *prima facie* are similar enough to be used for small area estimation of stunting and underweight. This investigation is based on the English versions of questionnaires where available;
- Preliminary matching, for those questions in common to census and survey, of the census response categories with those of the corresponding survey question. This matching was re-examined in the light of statistical comparisons before the production of final estimates;

. Investigating the matching of the various data sources via geocodes and/or survey design variables, and correcting the matching where necessary.

Phase Two

- Merging and cleaning the selected survey data to create a child-level dataset containing the variables identified in Phase One, suitably re-coded, together with the relevant survey design variables and area indicators;
- Creating area-based means at an appropriate level from the Population and Housing Census2011 and merging these with the survey data;
- Developing and testing preliminary statistical regression models, including estimation of variance components, for height-for-age (for stunting prevalence) and weight-for-age (for underweight prevalence).

Phase Three:

- Cleaning available census data for compatibility with the final survey dataset used for model development;
- Trial production of preliminary estimates of stunting and underweight using census data;
- Assessment of the quality and precision of the preliminary estimates of stunting and underweight;
- Mapping of preliminary estimates and assessment of results.

Phase Four:

- Further development of statistical models for height-for-age and weight-for-age based on survey data;
- Application of models to census data and aggregation of predictions to small area (upazila) level;
- Estimation of standard errors to assess accuracy of small area estimates;
- Mapping to assess area level variation and patterns;
- Repetition of the four steps above until final models are developed and the small area estimates from them are mapped.

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1. Introduction

1.1 Background

A report in 2013 by the General Economics Division (GED) of the Bangladesh Planning Commission on the country's progress towards the Millennium Development Goals (MDGs) notes that "while Bangladesh has demonstrated its capacity for achieving the goal of poverty reduction within the target timeframe, attaining food security and nutritional wellbeing still remains a challenge" (GED 2013).

Target 1.C of the MDGs is to: "Halve, between 1990 and 2015, the proportion of people who suffer from hunger". Progress towards this goal is monitored using Indicator 1.8: "Prevalence of underweight children under-five years of age". Here underweight is defined as having a body weight more than two standard deviations below the median weight, adjusted for age and gender using an international standard reference population (de Onis et al, 2006). Other indicators used to measure undernutrition are stunting (low height-for-age) and wasting (low weight-for-height). For the efficient distribution of food aid, it is useful to have estimates of these indicators at a fine geographic level so that areas with unusually high levels of undernutrition can be targeted. This can be attempted through the technique of small area estimation.

1.2 Small area estimation - overview

Small area estimation is a mathematical and statistical method that models data collected from one or more data sources, to produce estimates, for example of poverty, that are more accurate at small area level than using only data collected from each small area. The additional accuracy is achieved in many such models by "borrowing strength" for the estimate for a particular small area by using information from areas to which it is similar. Some small area estimation techniques combine data from different sources. For example, census and new survey information may be combined to update estimates from the original census. Alternatively, and this is more usually the case for poverty and undernutrition estimates, a statistical model is fitted to survey data collected around the same time as the census, and this model is used to predict a variable not collected in the census, based on variables that are collected in both survey and census.

In poverty studies, the most usual variable predicted is expenditure (or its logarithm) based on a model which includes education, age of household members, number of people in the household and type of house construction, among other variables. Undernutrition indicators, on the other hand, are derived from anthropometric measurements on children under five years of age. The resultant estimates are often mapped in detail, which is why this technique is sometimes given the generic title, poverty mapping. For undernutrition rather than expenditure poverty measures, the technique can be called undernutrition mapping. The maps can make interpretation simpler, but the central point is not the maps *per* se, but that deprivation indices can be assessed at a much finer level at a much lower cost than by increasing the sample size sufficiently or rerunning the census with additional variables. The statistical modelling has a cost, of course, but this can be saved many times over by having better information at a finer level and maps for use in aid allocation.

The most common methodology for small area estimation of poverty and undernutrition in developing countries is the World Bank method (Elbers, Lanjouw and Lanjouw, 2001, 2003), which is now available as free software (PovMap – Zhao, 2006; PovMap 2 – Zhao and Lanjouw, 2009) from the World Bank website. Variations of the Elbers, Lanjouw and Lanjouw (ELL) method have been implemented for the World Bank in a number of other countries including Thailand (Healy, 2003), South Africa (Alderman et al., 2002), Brazil (Elbers et al. 2001), the Philippines (Haslett and Jones, 2005), and for the World Food Programme in Bangladesh (Jones and Haslett, 2003), Nepal (Jones, Haslett and Parajuli, 2006), and Cambodia (Haslett, Jones, and Sefton 2013).

1.3 Small area estimation in Bangladesh – historical perspective

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 2000 Household Income and Expenditure Survey (HIES) and the 2000 Child Nutrition Survey (CNS). The methodology used was a standard application of the World Bank (ELL) method (Elbers, Lanjouw and Lanjouw, 2001, 2003). Estimates of adequate precision were produced at sub-district (upazila) level for poverty incidence, gap and severity based on a model for log per capita expenditure using HIES. Average kilocalorie intake and proportion below the recommended kilocalorie intake level were also produced at upazila level, using a model for log per capita kilocalorie intake fitted to the HIES data. This model had lower explanatory power, and the estimates were in general less precise, but still useful, at upazila level. Prevalence of stunting and underweight in children under five were derived from models for height-for-age and weight-for-age, respectively, based on the anthropometric data in CNS. Again the models were low in explanatory power but the resulting estimates were nevertheless reasonably precise when aggregated to upazila level, both as estimates and in terms of the probability that underweight or stunting exceeded 50%.

Since the 2003 study, no further small area estimates of stunting and underweight in Bangladesh have been produced. Successive rounds of HIES have however been used to produce poverty statistics for the country and at division level (World Bank, 2008). In 2008 the World Bank carried out an exercise to update Jones and Haslett's upazila-level estimates using the 2005 HIES, by restricting their modelling to variables that were judged not to have changed since the 2000 census (World Bank, 2009).

1.4 More recent developments

A new round of the HIES survey was conducted by the Bangladesh Bureau of Statistics (BBS) in 2010 (Bangladesh Bureau of Statistics, 2010). Poverty estimates were again produced for the country and at division level, using poverty lines updated from the 2005 study using regional price indices. The poverty rate for the country was found to be 31.5% (35.2% rural and 21.3% urban), continuing a decades-long trend in poverty reduction from 48.9% in 2000 and 40.0% in 2005. In a subsequent report by the World Bank (World Bank, 2013) this trend in poverty reduction is discussed and contrasted with the situation in health and nutrition outcomes, which have not improved as substantially.

Following the Population and Housing Census of 2011 (Bangladesh Bureau of Statistics, 2011), a new round of small area estimation of poverty was conducted by the World Bank in conjunction with the BBS and WFP, using the full census data and the HIES 2010 survey data. (World Bank, 2014)

The World Bank analysis provides upazila-level estimates of economic poverty indicators, but not of undernutrition indicators. HIES 2010 did not include anthropometric measures of children under five, so cannot be used for the estimation of stunting and underweight prevalence. Such measures are typically available only in surveys specifically focussing on health and nutrition.

The Bangladesh Household Food Security and Nutrition Assessment Report 2009 (Institute of Public Health Nutrition, UNICEF and World Food Programme, 2009) was produced in response to a rapid increase in food prices during 2008, to investigate the effects on the country's food security and nutritional situation. The data collection included anthropometric measurements on children aged 6 to 59 months, from which estimates of stunting, wasting and underweight were calculated based on the WHO 2006 growth standards (WHO Multicentre Growth Reference Study Group, 2006). The country-level estimates were given as 48.6%, 13.5% and 37.4%, respectively. Rates were higher in the rural areas in comparison to urban areas.

The 2011 Bangladesh Demographic and Health Survey (BDHS) was conducted under the authority of the National Institute of Population Research and Training (NIPORT) of the Ministry of Health and Family Welfare and implemented by Mitra and Associates of Dhaka. The BDHS is part of the worldwide Demographic and Health Surveys program, which is designed to collect data on fertility, family planning, and maternal and child health. The report (National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International, 2013) gives estimates for the prevalence of stunting (41%), wasting (16%) and underweight (36%) for the country and compares these with figures from the 2004 and 2007 BDHS. However BDHS was not administered by the Bangladesh Bureau of Statistics, so in its available unit record datasets BDHS does not have the regional indicators required for matching of primary sampling units in the survey to those in the census data. BDHS was, consequently, not usable for the small area estimation project.

The Child and Mother Nutrition Survey of Bangladesh (CMNS) conducted by the Bangladesh Bureau of Statistics in 2012 also collected anthropometric data on children under five. This was an extension of the Child Nutrition Survey (CNS) series to include data on mothers. It was conducted in a sub-sample of areas of the Health and Mortality Status Survey (HMSS) of 2011. The preliminary report (Bangladesh Bureau of Statistics, 2013) gives prevalences of stunting, wasting and underweight as 41.2%, 13.4% and 34.4%, respectively, so is in broad agreement with those of BDHS 2011.

Other reports of some relevance include the Bangladesh Multiple Indicator Cluster Surveys (MICS) carried out by the BBS and UNICEF. The 2009 report (Bangladesh Bureau of Statistics and UNICEF, 2010) was the first to provide information at the upazila level. It focused on the MDGs indicators related to women and children, but did not include stunting, wasting or underweight. The indicators considered that related to health and nutrition were breastfeeding rates, child mortality and reproductive health. The MICS was also carried out again in 2012-2013, this time including anthropometric measurements for children using a smaller, but still substantial, sample size of 51,895 households (BBS & UNICEF: 2014a, 2014b). However, neither the results of nor the data from MICS 2012-2013 were available at the time the research was undertaken for the current small area estimation study.

The Population and Housing Census 2011 included a Long Form questionnaire administered to a 1% sample of the population to supplement the main census (Bangladesh Bureau of Statistics, 2012). The Long Form questionnaire includes questions on reproductive history and mortality, but there is nothing related directly to child nutrition status.

1.5 Geographic and administrative units

For administrative purposes, Bangladesh is divided into a total of 7 divisions. These in turn are divided into *zila*, *upazila*, *union*, and *mauza*, which is the smallest administrative unit. Table 1.1 shows the total number of each of these units in Bangladesh, and their approximate sizes in terms of average number of households.

Table 1.1 Approximate number of administrative units at different levels.

	division	district	Upazila /thana	Union /ward	mauza
Number	7	64	544	7755	64637
Mean no. households	4540812	496651	58430	4099	492

Source: Bangladesh Population and Housing Census 2011

Some knowledge exists on the general spatial pattern of stunting and underweight in children under five years of age in Bangladesh. Recent surveys (see Section 3) give estimates of nutritional status for the whole country and for each division. However the accuracy of such estimates depends crucially on the effective sample size at that level. At district / zila level and below, the standard errors of survey-based estimates become too large to be useful because each is based on a small number of observations.

Effective targeting of food related development assistance requires a nation-wide overview of nutrition status at sub-division level. Estimates need to be precise, i.e. with small standard errors, so that the areas with the greatest need are identified correctly. Our analysis includes an investigation using small-area estimation methods of how finely the estimates of stunting and underweight in children under five years of age may be disaggregated while still maintaining a reasonable level of precision.

1.6 Mapping of small area estimates of stunting and underweight in children under five years of age

The statistical technique of small-area estimation (Ghosh and Rao, 1994, Rao, 1999; Rao, 2003) provides a way of improving survey estimates at small levels of aggregation, by combining the survey data with information derived from other sources, typically a population census. The variant of small area estimation methodology developed by a research team at the World Bank specifically for the small-area estimation of poverty measures (Elbers, Lanjouw and Lanjouw, 2001, 2003) is described in detail in the next section. Some additional general methodological issues are covered in Haslett and Jones (2005b; 2010), Haslett, Isidro and Jones (2010) and Haslett (2013). Outputs, in the form of estimates at local level together with their standard errors, can be combined with GIS location data to produce a small area estimate map for the whole country, giving a graphical summary of which areas are suffering relatively high deprivation.

1.7 Measures of child undernutrition

Two central measures of undernutrition are considered for small area estimation in this report, both based on measurements of a child's height, weight and age. Stunting or low height-for-age is defined as having a height at least two standard deviations below the median height for a reference population. Underweight or low weight-for-age is similarly defined.

The data used as a reference standard in these definitions was established in 1975 by the National Center for Health Statistics / Centers for Disease Control in the USA (Hamill, Dridz, Johnson, Reed et al., 1979). The update provided in WHO (2006) was used. Implicit in the use of a single international reference standard is the assumption that variations in height and weight for children below five years are caused largely by environmental rather than genetic factors, although even without this assumption it can provide a fixed reference point in international comparisons.

In this report we consider the nutrition status of children below the age of 60 months (i.e. five years). Within a particular area, stunting is defined as the proportion of such children with a standardized height-for-age (HAZ) value below –2. Children with standardized height-for-age below –3 are considered "severely stunted". Similarly underweight is the proportion with a standardized weight-for-age (WAZ) value below –2, and severe underweight below –3. Stunting can be regarded as evidence of chronic undernutrition. Underweight reflects both chronic undernutrition and acute undernutrition: it is a current condition resulting from inadequate food intake, past episodes of undernutrition or poor health conditions. Our original aim in this report was to construct upazila-level maps for these measures.

1.8 The intent and focus of this report

Given our report's focus, some general comments about the relationship between small area estimation and mapping are warranted. Small area estimation of stunting and underweight in children can provide a detailed perspective on the spatial distribution of child undernutrition. Other variables are also important however (e.g. health information, rainfall, and other Geographical Information System (GIS) data), even if these cannot be produced at such a fine level. For most users of this information, an atlas of maps is much more useful than a detailed technical report on small area estimation methodology, even if it also contains finer level tabulated detail. The detailed methodological report is however essential, as it provides a clear indication of the methodological foundation for small area maps (often called poverty maps) that are included in the atlas. Without sound use of small area methodology, and publication of the technical report that outlines that methodology, the utility of the more generally-used atlas must remain in doubt. The intent of our report, and the statistical models it contains, is to provide in more details, in the form of a foundation document for any consequent atlas, the technical basis for the small area estimates and the maps of stunting and underweight at upazila level.

Our main purpose in producing maps of stunting and underweight at upazila level is to aid the planning of development assistance programmes. They could in addition prove useful as a research tool, for example by overlaying geographic, social or economic indicators.

2. Methodology

We present in this section a brief overview of small-area estimation and the extension to the ELL method necessary for modelling stunting and underweight in children. Details of the implementation in Bangladesh are given in Section 4.

2.1 Small-area estimation

Small-area estimation refers to a collection of statistical techniques designed for improving sample survey estimates through the use of auxiliary information. We begin with a target variable, denoted *Y*, for which we require estimates over a range of small subpopulations, usually corresponding to small geographical areas. (In this report *Y* is standardized height-for-age or weight-for-age for stunting and underweight, respectively.) Direct estimates of *Y* for each subpopulation are available from sample survey data, in which *Y* is measured directly on the sampled units (eligible children, i.e. children under five years of age). Because the sample sizes within the subpopulations typically will be very small, these direct estimates will have large standard errors and hence not be reliable. Indeed, some subpopulations may not be sampled at all in the survey. Auxiliary information, denoted *X*, can be used under some circumstances to improve the estimates, giving lower standard errors.

In the situations examined in this report, *X* represents additional variables that have been measured for the whole population, either by a census or via a GIS database. A relationship between *Y* and *X* of the form

$$Y = X\beta + u$$

can be estimated using the survey data, for which both the target variable and the auxiliary variables are available. Here β represents the estimated regression coefficients giving the effect of the *X* variables on *Y*, and *u* is a random error term representing that part of *Y* that cannot be explained using the auxiliary information. If we assume that this relationship holds in the population as a whole, we can use it to predict *Y* for those units (i.e. children under five years of age) for which we have measured *X* but not *Y*. Small-area estimates based on these predicted *Y* values will often have smaller standard errors than the direct estimates, even allowing for the uncertainty in the predicted values, because they are based on much larger samples. Thus the idea is to “borrow strength” from the much more detailed coverage of the census data to supplement the direct measurements of the survey.

2.2 Clustering

The units on which measurements have been made are often not independent, but are grouped naturally into clusters of similar units. Children cluster within households, and households tend to cluster together into small geographic or administrative units, which are themselves relatively homogenous. Put simply, households that are close together tend to be more similar than households far apart, and children within households would also be expected to share characteristics. When such structure exists in the population, the regression model above can be more explicitly written as

$$Y_{ijk} = X_{ijk}\beta + c_i + h_{ij} + e_{ijk} \tag{2.1}$$

where Y_{ijk} represents the measurement on the *k*th child under five in the *j*th household in the *i*th cluster, c_i the error term held in common by the *i*th cluster, h_{ij} the household-level error within the cluster, and e_{ijk} the error within each sampled household. The relative importance of the three sources of error can be measured by their respective variances σ_c^2, σ_h^2 and σ_e^2. In the general explanation given below we focus on equation (2.1) in order to establish general principles useful for distinguishing the characteristics of variation at 'highest', 'middle' and 'lower' levels. The three error terms form a sequence in which the cluster remains the highest level of aggregation, household takes an intermediate status, and individual level variation is at the finest level. There is also the possibility of including a small area level error term at the greatest level of aggregation. Doing so does not affect the small-area estimates themselves, but does have the potential to increase standard error estimates, perhaps markedly. The small area models of Rao (2003) contain such an error term, but those of Elbers, Lanjouw and Lanjouw (2003) do not. In practice however methods based on Elbers, Lanjouw and Lanjouw (2003) instead use contextual effects in survey based models. These contextual variables are based on census means aggregated to the same cluster level as in the survey, but for the whole population. Because these are known for every cluster in the entire country via the census data, and (given the often considerable effort put into identifying each and every cluster in the survey via area code matching) they provide a substitute which is more specific than using prediction of random effects in mixed models. This means that ELL-type models are not simply synthetic estimators, as claimed by Molina and Rao (2010). Nevertheless, despite the considerable merit of using contextual effects in models, checking for the size of the small area-level error variance is strongly recommended, because if it is sufficiently large its omission leads to small-area estimates with understated standard errors and hence overstated accuracy. The issue is addressed for small-area estimation in Jones, Haslett and Parajuli (2006) for example, where in Nepal the effect of the small area variance on the standard error estimates was found to be negligible.

Similarly for Cambodia (Haslett, Jones and Sefton, 2013). Theoretical aspects of this question are discussed in detail in Haslett and Jones (2010).

We note that the auxiliary variables X_{ijk} may be useful primarily in explaining the cluster-level variation, or the household-level variation. The more variation that is explained at a particular level, the smaller the respective error variance, σ_c^2, σ_h^2 or σ_e^2. The estimate for a particular small area will typically be the average of the predicted *Y*s in that area. Because the standard error of a mean gets smaller as the sample size gets bigger, the contribution to the overall standard error of the variation at each level, child, household and cluster, depends on the sample size at that level. The number of households in a small area will typically be much larger than the number of clusters, and the number of children under five larger again, so to get small standard errors for the small area estimates it is of particular importance that, at the highest level, the unexplained cluster-level variance σ_c^2 should be small. Two important diagnostics of the model-fitting stage, in which the relationship between *Y* and *X* is estimated for the survey data, are the R^2 measuring how much of the variability in *Y* is explained by *X*, and the ratio $\sigma_c^2/(\sigma_c^2+\sigma_h^2+\sigma_e^2)$ measuring how much of the unexplained variation is at the cluster level. Other ratios such as $\sigma_c^2/(\sigma_c^2+\sigma_h^2)$ and $\sigma_h^2/(\sigma_h^2+\sigma_e^2)$ can also be useful. Note that although σ_c^2, σ_h^2 and σ_e^2 are parameters, they are different for different models with different regressors. GIS data and cluster-level means can be particularly useful in lowering this ratio. Some care is required when using R^2 as a diagnostic however, because it very much depends on the level of aggregation, and the level of aggregation in the fitted model is very much less than that of the small-area estimates. So, while high R^2 values at child level are good, they are not essential, provided the variances at the finest level are sufficiently larger than those at more aggregated levels. This diminution in both importance and size of R^2 is especially apparent where child level data is being used (as for stunting, underweight and wasting), rather than household level data (as for kilocalories and expenditure modelling, where the variation within household, which may be large, is effectively omitted from the estimation of R^2 from the model due to data aggregation to household level). For small area estimation, what can be a rather better indicator than R^2 at child or household level is a generalised-R^2 for the model assessed at small area level. Generalised-R^2 is defined as the proportion of variation explained by the model once the variation at finer levels is removed. For example, at cluster level we calculated the generalised-R^2 after removing the variation at child and household level. This measure is more relevant and always considerably higher than R^2, owing to the aggregation to small area level for the small area estimates.

Another important aspect of clustering is its effect on the estimation of the model. The survey data used cannot be regarded as a simple random sample, because they have been obtained from a complex survey design which, although it is random, nevertheless involves weighting, stratification and cluster sampling. To account properly for the complexity of the survey design requires the use of specialised statistical routines (Skinner et al., 1989; Chambers and Skinner, 2003; Lehtonen and Pakhinen, 2004; Longford, 2005) in order to get consistent estimates for the regression coefficient vector β and its variance V_β.

2.3 The ELL method and its extensions

The ELL methodology was designed specifically for the small-area estimation of poverty measures based on per capita household expenditure. In this case the target variable Y is log-transformed expenditure, the logarithm being used to make more symmetrical the highly right-skewed distribution of untransformed expenditure. It is assumed that measurements on Y are available from a survey. A similar approach is taken for kilocalories per capita for data at household level, where again a log transform is used.

For stunting and underweight in children under five, the variables modelled are standardised height-for-age and weight-for-age, respectively. These are adjusted for age to form z-scores, which are modelled directly.

The first step for modelling standardised height-for-age and weight-for-age, as for log expenditure or log kilocalories, is to identify a set of auxiliary variables X that are in the survey and are also available for the whole population. It is important that these should be defined and measured in a consistent way in both data sources. The model (2.1) is then estimated for the survey data, by incorporating aspects of the survey design for example through use of the “expansion factors” or inverse sampling probabilities. The residuals $\hat{u}_{ijk}$ from this analysis are used to define cluster-level residuals $\hat{c}_i = \hat{u}_{i\cdot\cdot}$, the dots denoting averaging over j and k, household-level residuals $\hat{h}_{ij} = \hat{u}_{ij\cdot} - \hat{c}_i$, and child level residuals $\hat{e}_{ijk} = \hat{u}_{ijk} - \hat{u}_{ij\cdot}$.

It is usually assumed that the cluster-level effects c_i all come from the same distribution, but that the household-level effects h_{ij} may be heteroscedastic. This can be modelled by allowing the variance σ_e^2 to depend on a subset Z of the auxiliary variables:

$$g(\sigma_h^2) = Z\alpha + r$$

where $g(.)$ is an appropriately chosen link function, α represents the effect of Z on the variance and r is a random error term. Fujii (2004) uses a version of the more general model of ELL involving a logistic-type link function, fitted using the squared household-level residuals. Fujii's model is:

$$\ln\left(\frac{\hat{h}_{ij}^2}{A-\hat{h}_{ij}^2}\right)=Z_{ij}\alpha+r_{ij} \tag{2.2}$$

From this model the fitted variances $\hat{\sigma}_{h,ij}^2$ can be calculated and used to produce standardized household-level residuals $\hat{h}_{ij}^* = \hat{h}_{ij} / \hat{\sigma}_{h,ij}$. These can then be mean-corrected or mean-centred to sum to zero, either across the whole survey data set or separately within each cluster.

In standard applications of small-area estimation, the estimated model (2.1) is applied to the known X values in the population to produce predicted Y values, which are then averaged over each small area to produce a point estimate, the standard error of which is inferred from appropriate asymptotic theory. In the case of stunting and underweight, as for poverty mapping based on log expenditure, our interest is not always directly in Y but in various non-linear functions of Y (see Section 1.7). The ELL method obtains unbiased estimates and standard errors for these by using a bootstrap procedure as described below.

2.4 Bootstrapping

Bootstrapping is the name given to a set of statistical procedures that use computer-generated random numbers to simulate the distribution of an estimator (Efron and Tibshirani, 1993). In the case of the extension of poverty mapping based on household level data to child level variables such as stunting and underweight, we construct not just one predicted value

$$\hat{Y}_{ijk} = X_{ijk}\hat{\beta}$$

(where $\hat{\beta}$ represents the estimated coefficients from fitting the model) but a large number of alternative predicted values

$$Y_{ijk}^b = X_{ijk}\beta^b + c_i^b + h_{ij}^b + e_{ijk}^b \ , \quad b = 1,\ldots,B$$

in such a way as to take account of their variability. The statistical analysis of the chosen model for Y yields information on how to appropriately insert variability into the calculation of the predicted values. We know for example that $\hat{\beta}$ is an unbiased estimator of β with variance V_β, so we draw each β^b independently from a multivariate normal distribution with mean $\hat{\beta}$ and variance matrix V_β. The cluster-level effects c_i^b can be taken from the empirical distribution of c_i, i.e. drawn randomly with replacement from the set of cluster-level residuals $\hat{c}_i$, since the appropriate cluster level residual is known only for the clusters in the sample not all the clusters in the census. To take account of unequal variances (heteroscedasticity) in the household-level residuals, we can first draw α^b from a multivariate normal distribution with mean $\hat{\alpha}$ and variance matrix V_α, combine it with Z_{ij} to give a predicted variance and use this to adjust the household-level effect

$$h_{ij}^b = h_{ij}^{*b} \times \sigma_{h,ij}^b$$

where h_{ij}^{*b} can represent a random draw from the empirical distribution of h_{ij}^*, either for the whole data set or just within the cluster chosen for c_i (consistently with the mean-centring of Section 2.3). For height-for-age and weight-for-age a model for heteroscedasticity might also be fitted at child level within household. In practice however, heteroscedasticity is seldom an issue at either level, with the percent of variance explained by the model (2.2) almost invariably being less that 3%. It would be heteroscedasticity at cluster level that would be of more concern, but this is effectively controlled via the contextual variables.

For height-for-age and weight-for-age in children under five years of age, the bootstrap residuals at cluster, household and child level can also be generated parametrically from normal distributions with zero means and variances determined from the estimates of the variance components σ_c^2, σ_h^2 and σ_e^2.

In the current study (as for Cambodia – see Haslett, Jones and Sefton, 2013), for height-for-age and weight-for-age in children under five years of age, a heteroscedasticity model was not used, and all bootstrapping was done parametrically.

Each complete set of bootstrap values Y_{ijk}^b, for a fixed value of *b*, will yield a set of small-area estimates. The mean and standard deviation of a particular small-area estimate, across all *b* values, then yields a point estimate and its standard error for that area. Note that while the small area estimates need to be sufficiently accurate to be useful, this does not require that the bootstrap estimates at child or even household or cluster level are useful, except in aggregate at small area level. This important point is linked to the earlier discussion of why generalised-R^2 (at small area level) is more useful than R^2 (at household or child level) for small area estimation models.

2.5 Interpretation of standard errors

The standard error of a particular small-area estimate is intended to reflect the uncertainty in that estimate. A rough rule of thumb is to take two standard errors on each side of the point estimate as representing the range of values within which we expect the true value to lie. When two or more small-area estimates are being compared, for example when deciding on priority areas for receiving development assistance, the standard errors provide a guide for how accurate each individual estimate is and whether the observed differences in the estimates are indicative of real differences between the areas. They serve as a reminder to users of small area estimate based maps that the information in them represents estimates, which may not always be very precise. A particular way of incorporating the standard errors into a poverty map is suggested in Section 6.

The size of the standard error depends on a number of factors. The poorer the fit of the model (2.1), in terms of small R^2 or generalised-R^2, large σ_c^2 or (to a lesser extent) σ_h^2 or σ_e^2, or a large $\sigma_c^2/(\sigma_c^2+\sigma_h^2+\sigma_e^2)$ or $\sigma_c^2/(\sigma_c^2+\sigma_h^2)$ ratios, the more variation in the target variable will be unexplained and the greater will be the standard errors of the small-area estimates. The population size, in terms of both the number of households and the number of clusters in the area, is also an important factor. Generally speaking, standard errors decrease proportionally as the square root of the population size. Standard errors will be acceptably small at higher geographic levels but not at lower levels. If we decide to create a small area estimate based map at a level for which the standard errors are generally acceptable, there will still be some, smaller, areas for which the standard errors are larger than we would like.

The sample size used in fitting the model is also important. The bootstrapping methodology incorporates the variability in the estimated regression coefficients $\hat{\alpha}$, $\hat{\beta}$. If the sample size is small these estimates will be very uncertain and the standard errors of the small-area estimates will be large. This problem is also affected by the number of explanatory variables included in the auxiliary information, *X* and *Z*. A large number of explanatory variables relative to the sample size increases the uncertainty in the regression coefficients. We can always increase the apparent explanatory power of the model (i.e. increase the R^2 from the survey data) by increasing the number of *X* variables, or by dividing the population into distinct subpopulations and fitting separate models in each, but the increased uncertainty in the estimated coefficients may result in an overall loss of precision when the model is used to predict values for the census data, and sudden changes in level (which are artefacts of the survey data) at the divisional boundaries between different sub-models. We must take care not to “over-fit” the model.

There will be some small uncertainty in the estimates, and indeed the standard errors, due to the bootstrapping methodology, which uses a finite sample of bootstrap estimates to approximate the distribution of the estimator. This could be decreased, at the expense of computing time, by increasing the number of bootstrap simulations B.

Finally, the integrity of the estimates and standard errors depends on the fitted model being correct, in that it applies to the census population in the same way that it applied to the sample. This relies on good matching of survey and census to provide valid auxiliary information. We must also take care to avoid, as much as possible, spurious relationships or artefacts which appear, statistically, to be true in the sample but do not hold in the population. This can be caused by fitting too many variables, but also by choosing variables indiscriminately from a very large set of possibilities. Such a situation could lead to estimates with apparently small, but spurious, standard errors. For this reason the final step in small area based mapping, field verification, is extremely important.

The requirement for variables to match in this way between survey and census is one reason that special care must be taken if survey and census are not from the same period. The changes between periods can be structural changes, i.e. the interpretation of a particular variables has changed, or simply a change in level. Both types of change have the potential to add to standard errors of estimates, and in some cases to produce bias.

3. Data Sources

3.1 Bangladesh Demographic and Health Survey (BDHS) 2011

The 2011 Bangladesh Demographic and Health Survey (BDHS) was not used for the small area estimation, *per se*, but was used for comparison purposes. See Section 5.

As noted in Section 1.4, BDHS 2011 was conducted under the authority of the National Institute of Population Research and Training (NIPORT) of the Ministry of Health and Family Welfare and implemented by Mitra and Associates of Dhaka, as part of the worldwide Demographic and Health Surveys program, designed to collect data on fertility, family planning, and maternal and child health. As also noted in Section 1.4, their report (National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International, 2013) gives estimates for the prevalence of stunting (41%), wasting (16%) and underweight (36%) for the country and compares these with figures from the 2004 and 2007 BDHS. There is a decrease in the prevalence of both stunting and underweight during this time, but it is not as marked as the decrease in economic poverty.

The BDHS 2011 is the sixth DHS survey undertaken in Bangladesh. The earlier surveys were conducted in 1993-94, 1996-97, 1999-2000, 2003-04, and 2007-08. The main objective of DHS is to provide current information on fertility and childhood mortality levels; fertility preferences; awareness, approval, and use of family planning methods; maternal and child health; knowledge and attitudes toward HIV/AIDS and other sexually transmitted infections (STI); and community-level data on accessibility and availability of health and family planning services. All ever-married women aged 12-49 who were usually members of the selected households and those who spent the night before the survey in the selected households are eligible to be interviewed in the survey. The survey design produced representative results for the country as a whole, for the urban and the rural areas, and for each of the seven administrative divisions.

One in three households in the survey was selected for a male survey. In these households, all ever-married men age 15-54 chosen on the same residency criteria as the women were eligible for interview. The survey collected information on their basic demographic status, use of family planning, and knowledge and attitudes toward HIV/AIDS and other sexually transmitted infections.

The sampling frame used for BDHS 2011 was the complete list of enumeration areas (EAs) for the whole of Bangladesh, prepared by the Bangladesh Bureau of Statistics for the 2011 population census. On average, an EA is a geographic area of about 120 households. The sampling frame contains EA location, type of residence (urban or rural), and the estimated number of residential households. Further detail of the sampling frame is provided in National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International (2013).

The 2011 BDHS sample was stratified and selected in two stages. Each division was stratified into urban and rural areas. Urban areas of each division were further stratified into two strata: "city corporations" and "other than city corporations". As noted in National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International (2013), "Samples of EAs were selected independently in each stratum in two stages. Implicit stratification and proportional allocation were achieved at each of the lower administrative levels by sorting the sampling frame within each sampling stratum before sample selection, according to administrative units in different levels, and by using a probability proportional to size selection at the first stage of sampling. In the first stage, 600 EAs were selected, with probability proportional to the EA size and with independent selection in each sampling stratum….. In the second stage of selection, a fixed number—30 households per cluster—were selected with an equal probability systematic selection from the newly created household listing".

The survey selected 600 EAs, 207 urban and 393 rural, and was conducted in 18,000 residential households, 6,210 urban and 11,790 rural.

The household response rate was 96 percent in both urban and rural areas and the women's individual response rate was 98 percent for both urban and rural areas.
Sampling weights are needed for analysis of the 2011 BDHS data.

3.2 Child and Mother Nutrition Survey of Bangladesh (CMNS) 2012

The Child and Mother Nutrition Survey of Bangladesh (CMNS), conducted by the Bangladesh Bureau of Statistics in 2012, also collected anthropometric data on children under five. CMNS was an extension of the Child Nutrition Survey (CNS) series to include data on mothers. It was conducted in a sub-sample of areas of the Health and Mortality Status Survey (HMSS) of 2011. The preliminary report

(Bangladesh Bureau of Statistics 2013) gives prevalence of stunting, wasting and underweight as 41.2%, 13.4% and 34.4%, respectively, so is in broad agreement with those of BDHS 2011.

The CMNS 2012 was a nationally representative sample of rural and urban children aged zero to-59 months, and their mothers. The field work was undertaken on four consecutive days: 7 to 10 March 2012. Information of mother and children was collected from 350 PSUs, in 63 districts and 7 divisions. The CMNS 2012 was conducted among a subsample of clusters and hence households surveyed by the Health and Mortality Status Survey (HMSS 2011).

The CMNS 2012 surveyed 4112 children aged 0-59 months and 3521 mothers living in 3484 households in urban and rural Bangladesh. Data for the CMNS 2012 was collected from a sub-sample of 350 primary sampling units (PSUs), selected from 1000 PSUs of HMSS-2011. The HMSS 2011 surveyed 30 households in each selected primary sampling unit (PSUs), as did CMNS 2012. The 30 households for each sampled PSU were selected from a newly completed household listing by systematic sampling to provide reliable estimates of key demographic and nutrition variables for Bangladesh as a whole, as well as for each of the seven divisions, and for urban and rural areas. The survey selected 10,500 households in total from 350 PSUs selected from the 1000 PSUs in HMSS. Table 3.1 shows the distribution of CMNS 2012 sample PSUs and Table 3.2 shows the distribution of sample households by division and area of residence.

Table 3.1: Distribution of PSU for the CMNS 2012 and HMSS 2011 by division and area of residence, Bangladesh, 2012

Division	CMNS 2012			HMSS 2011		
	Rural	Urban	Total	Rural	Urban	Total
Barisal	33	17	50	55	25	80
Chittagong	33	17	50	116	63	179
Dhaka	32	18	50	172	117	289
Khulna	31	19	50	89	57	146
Rajshahi	35	15	50	88	46	134
Rangpur	33	17	50	82	35	117
Sylhet	36	14	50	38	17	55
Total	233	117	350	640	360	1000

Key: PSU=primary sampling unit
Source: Bangladesh Bureau of Statistics (2013)

Table 3.2: Division and rural-urban sample allocation for CMNS 2012

	SL No	Number of Sample PSU			Number of sample SSU (HH)		
		Urban	Rural	Total	Urban	Rural	Total
1	Barisal	17	33	50	510	990	1500
2	Chittagong	17	33	50	510	990	1500
3	Dhaka	18	32	50	540	960	1500
4	Khulna	19	31	50	570	930	1500
5	Rajshahi	15	35	50	450	1050	1500
6	Rangpur	17	33	50	510	990	1500
7	Sylhet	14	36	50	420	1080	1500
	Total	117	233	350	3510	6990	10500

Key: PSU=primary sampling unit; SSU=secondary sampling unit
Source: Bangladesh Bureau of Statistics (2013)

The CMNS questionnaire collected information on household socio-economic and socio-demographic status, access to health services and health environment, household food security, caring practices and anthropometry (length/height, weight and mid upper arm circumference - MUAC) of children and their mothers.

The UNISCALE (Seca, Hamburg, Germany) was used to measure the weight of children and mothers to the nearest 100 gm. Height scales were used to measure the length of children aged less than two years, and the height of mothers and children aged two years and older, to the nearest 1 mm. MUAC for children, and women (both pregnant and non-pregnant) was measured to the nearest .2 mm.

As noted in Bangladesh Bureau of Statistics (2013), for CMNS 2012, information was collected by a three-member team, one male member from the upazila statistical office, one male member from head office and one female member. The survey teams were supervised and coordinated by a supervising officer from both head office and field offices responsible for a district. District supervising officers had two days' training at headquarters, and there was a two day training programme at district level for enumerators. A separate three-day anthropometric measurement training programme was conducted in head office, that included sessions on how to administer the questionnaires, take anthropometric measurement, and address problems in the field. There were role play and practical sessions on filling out the questionnaires and on taking anthropometric measurements.

Because the sample size at a particular level has an important bearing on the precision of estimates at that level, we present in Table 3.3 a summary of the coverage of CMNS 2012 at various levels and the mean and minimum number of households and PSUs at each level. For CMNS 2012, Table 3.4 gives the number of children under five years of age for households with children under five years of age. The number of divisions, zila, upazila, unions and mauza sampled in CMNS 2012 can be compared with the numbers in Bangladesh as a whole via Table 3.5. The number of children under five years of age in households with children under five years of age for Bangladesh as a whole is given in Table 3.6.

There are 4112 eligible children in total in CMNS 2012; most are in separate households, although 16.4% of households have two or more eligible children. This has implications for our ability to separate household and within-household variation in the target variables (weight-for-age, height-for-age). There is an average of 17 eligible children per upazila, and only 247 upazila (out of 544 in Bangladesh) are sampled: so it is clear that direct survey estimates are not possible at this level. One out of 64 districts is not sampled, and some of the other districts have very small samples, so direct district-level estimates are also not possible.

Table 3.3 Structure of CMNS 2012 at various levels

	division	district	upazila	union	mauza
Contains	7	63	247	350	350
Mean children	587	65	17	11.7	11.7
Min children	513	7	3	2	2
Mean households	498	55	14	9.95	9.95
Min households	453	6	3	2	2
Mean PSU	50	5.6	1.42	1	1
Min PSU	50	1	1	1	1

Key: PSU=primary sampling unit

Table 3.4 Number of children under five years of age in households with children under five years of age for CMNS 2012

No. of children	1	2	3	4	>4	Total
%. of households	83.58	14.95	1.32	0.14	0	100

The target variables available through CMNS 2012 and used in this study are height-for-age and weight-for-age for children under five years of age, which are then converted to stunting and underweight (plus severe stunting and underweight) based on WHO Multicentre Growth Reference Study Group (2006). The target variables height-for-age, and weight-for-age (see also Section 1.4) were calculated using the WHO's Stata programme. See de Onis et al. (2006) for further comment on this methodology.

3.3 Bangladesh Population and Housing Census 2011 (Census 2011)

Bangladesh has conducted population census on decennial basis since 1872. The fifth Population and Housing Census of Bangladesh, and the fifteenth in the region, was conducted 15-19 March 2011. The main objective was to collect information on housing, households and population for development planning and human resource development programmes, and for economic management.

The Bangladesh Bureau of Statistics (BBS) conducted the fifth Population and Housing Census of Bangladesh in 2011 under the United Nations conceptual framework. BBS started preparatory activity at the beginning of 2009 with updating of maps and area geo-codes. Following this, there were three phases:

- Basic data for all households and individual members of the households were gathered 15-19 March 2011
- Quality and coverage were verified through a Post Enumeration Check (PEC) survey 10-14 April 2011.
- Detailed socio-economic information was collected using a census "long form" questionnaire via a sample survey to supplement the main census, 15-25 October 2011.

The questionnaire was designed in a machine readable format with technical assistance from US Census Bureau and was printed abroad with financial assistance from European Union (EU) through the United Nations Population Fund (UNFPA).

In the census there were 293,579 enumeration areas (EAs). On average, an EA comprised around 120 households. For the enumeration, 3,360 enumerators were employed from among the local educated unemployed females (Bangladesh Bureau of Statistics, 2012).

Training of master trainers (census zila coordinators) was undertaken in Dhaka and training of supervisors and enumerators at the zila (i.e. district) level.

Table 3.5 Structure of Bangladesh Census 2011 at various levels

	division	district	upazila	union	mauza
Contains	7	64	544	7755	64637
Mean children	2166992	237014	27884	1956	235
Min children	867366	52265	535	19	1
Mean households	1751841	191607	22542	1581	190
Min households	723093	37424	467	16	1
Mean PSU	9233	599	119	8.3	1
Min PSU	3522	199	3	1	1

Key: PSU=primary sampling unit

Table 3.6 Number of children under five years of age in households with children under five years of age from Bangladesh Census 2011

No. of children	1	2	3	4	>4	Total
%. of households	79.229	18.349	2.030	0.309	0.083	100

4. Implementation

4.1 Selection of auxiliary data

The auxiliary data *X* used to predict the target variable *Y* can be classified into two types: the survey variables, obtainable or derivable from the survey at household or individual level, and area-level variables applying to particular geographic units that can be merged from other sources into the survey data using area codes (e.g. division, zila, upazila, union, mauza enumeration area codes). The latter includes means of census variables calculated at mauza level from the census data.

As noted earlier, it is important that any auxiliary variables used in modelling and predicting should be comparable in the estimation (survey) data set and the prediction (census) data set. In the case of survey variables, we begin by examining the survey and census questionnaires to find out which questions in each elicit equivalent information. In some cases equivalence may be achieved by collapsing some categories of answers. For example, in the 2011 census there are three sources of drinking water (tap; tube-well; and other), while in CMNS 2012 there are six categories (tap; tube well / deep tube well; ring well / dug well; pond; river /ditch / canal; others) so that on a preliminary assessment the first two categories match, and the remaining categories should be classified as “other” for both survey and census. A preliminary identification and matching of common survey and census variables, in consultation with BBS staff, was reported by Haslett, Jones and Isidro (2014). Common variables were then subjected to statistical checks to ensure that the corresponding survey and census variables matched statistically as well as conceptually. In the case of categorical data we compare proportions in each category: for numerical data, such as household proportion of females, we compare the means and standard deviations. For this purpose confidence intervals were calculated for the relevant statistics in the survey data set, taking account of the stratification and clustering in the sample design. The equivalent statistic for the census data should be within the confidence interval for the survey. Failures in statistical matching can sometimes be resolved by further collapsing categorical variables. A list of matching variables for CMNS 2012 and the 2011 census (i.e. variables with sufficiently similar statistical properties) occurring in both datasets is given in Appendices A, Table A.1.

For modelling purposes the first level of each categorical variable was dropped so that the first category becomes the reference category with which others are compared. We also created some new variables from this basic list, for example the approximately mean-corrected squared household size defined as hhsz2=(hhsize-6)^2 –

see Figure 4.1, and interactions between basic variables such as nstoiletXu which modifies the effect of having a non-sanitary toilet depending on whether the area is urban or rural.

Geocodes for Bangladesh consist of 12 digits, corresponding to the hierarchy of geographical and administrative units in the country:

1 to 2	Division code
3 to 4	District code
5 to 6	Sub-district or upazila code
7 to 8	Union or ward code
9 to 11	Mahala or mauza code
12	RMO – rural (1), urban (2) or other (3); “other” has the characteristics of “urban”

EAs are parts of, or sometimes entire, mauzas. The World Bank poverty mapping exercise used mauza in the census predictions as equivalent to survey PSUs. The survey strata for HMSS were the urban and rural parts of divisions. Because PSUs were systematically sampled from lists of EAs within each stratum, at most one PSU per mauza was selected. Thus each PSU in HMSS has a unique geocode. The HMSS dataset contains the geocodes for the sampled PSUs, but these are based on the 2001 census. In order to merge with the 2011 census means, the geocodes need to be checked for matching, and any discrepancies resolved. BBS staff investigated this and created a translation table between the 2001 and 2011 geocodes for the 1000 PSUs in HMSS. All the PSUs from HMSS that were selected for CMNS have been successfully matched with mauza in the 2011 Census.

Generally, variables which are in either census dataset, but are either not in the survey or do not match properly, can still be used by forming regional averages and merging them with the survey data using regional indicators. The inclusion of these census means should be straightforward since they can be merged with the survey and census data using indicators for the geographical unit to which each household or individual belongs. This can be problematic in practice however, because of changing boundaries and the creation of new units or codes. Most of these problems were solved in collaboration with BBS.

Appendix A, Table A.2 gives a list of all the census means considered in the modelling process. These variables have all been averaged at mauza level.

4.2 First stage regressions

The fitting of models for weight-for-age and height-for-age using the CMNS data requires the design variables from the survey in order to produce unbiased estimates with the correct standard errors. Survey weights for CMNS are different from those of HMSS, since the PSUs were sub-sampled within each stratum, and only households with eligible children (below five years) were surveyed. The survey weights were not provided originally, but have been calculated in conjunction with BBS staff. There are 14 strata, with the number of PSUs per stratum ranging from 15 to 35.

The selection of an appropriate model for (2.1) is a difficult problem. We have a large number of possible predictor variables (26 + 18 = 44 for CMNS2014 - see Appendix A) to choose from, with inevitably a good deal of interrelationship between them in the form of multicollinearity. If we also include two-way interactions there are nearly a thousand. (A "two-way interaction" is the product of two basic or "main-effect" variables). Squares or other transformations of numerical variables, which would add to this number, could also be considered. As noted in Section 2.5, we must be careful not to over-fit, so the number of predictors included in the model should be small compared to the number of observations in the survey, but there is also the problem of selecting a few variables from the large number available which appear to be useful, only to find (or even worse, not find) that an apparently strong statistical relationship in the survey data does not hold for the population as a whole. We return to this important issue below when detailing models for height-for-age and weight-for-age, and whether explicit division-level effects should be included in these models.

The search for significant relationships over such a large collection of variables must inevitably be automated to a certain extent, but we have chosen not to rely entirely on automatic variable selection methods such as stepwise or best-subsets regression. See Miller (2002) for a general discussion of subset selection. We have generally adopted the principle of hierarchical modelling in which higher-order terms such as two-way interactions are included in the model only if their corresponding main-effects are also included. Thus we begin with main-effects only, and add interaction and nonlinear terms carefully and judiciously. We look not just for statistical significance but also for a plausible relationship. For example, the effect of household size (hhsize) on height-for-age and weight-for-age was investigated by first fitting hhsize as a categorical variable, and then choosing a parsimonious functional form that produces the correct approximate shape. This principle is illustrated in Figure 4.1 for weight-for-age.

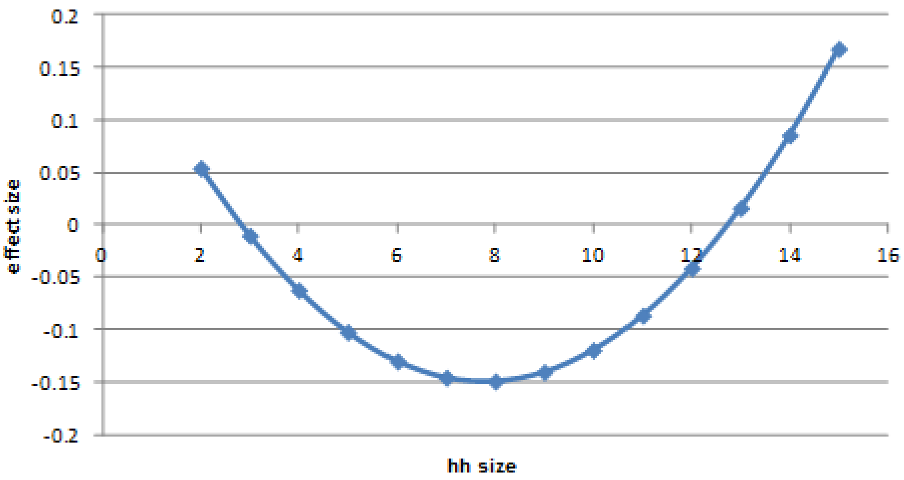


Figure 4.1: Modelled effect of household size on weight-for-age

This process was repeated for all numerical variables to give in each case a parsimonious functional representation of the effect of each numerical auxiliary variable on the target variable. Following the initial fit, some categorical variables were collapsed further to give smaller numbers of distinct categories when there was no significant difference between the estimated effects of similar categories.

Other implementations of ELL methodology have fitted separate models for each stratum defined by the survey design. This has the advantage of tailoring the model to account for the different characteristics of each stratum, but it can increase the problem of over-fitting if some strata are small. We chose initially to try for one model across the whole country, and then to use regional interaction terms as necessary to allow for modelling differences between regions. This has the advantage of more stable parameter estimates and a better chance of finding genuine relationships that apply outside of the estimation data. The fitting of separate models to different strata, or areas such as divisions, is related (but not identical) to the intermediate option of including explicit division-level effects in an overall model.

The process of finding a suitable model for height-for-age and weight-for-age was not straightforward. Initially the focus was on weight-for-age, and a number of strategies were used in addition to that of building a model from first principles. The initial complication was that preliminary models contained a number of effects related to interactions with division, suggesting that the underlying models may be different in different parts of Bangladesh. As an exploratory strategy only, to assess the extent of these apparent differences, separate models were fitted to different survey strata both to find variables that were common across strata and those that appeared important only in particular strata. While this effort was informative, the complication was that the strata based models seemed to overfit. For example, in the Bangladesh Demographic and Health Survey, BDHS2011, estimated underweight was more marked in Rangpur Division than Rajshahi Division, while in CMNS 2012 the opposite was true. These surveys were conducted in consecutive years, so the differences are most likely attributable to the fact that division based estimates and hence small area models based on division level data are not sufficiently accurate for this purpose. We consequently focused on more global models, ones that (while they contained some division level effects) were not separate models for separate divisions. The advantage became obvious after small area estimates were calculated and mapped: there were no sudden changes in estimates of the level of underweight at division boundaries, or divisions that seemed markedly higher or lower than expected in comparison with others.

This raises a wider issue of adequacy of models fitted to survey data for small area estimation. There are a number of available diagnostics including F-tests of the overall model. Use of R^2, the coefficient of variation (or percentage of variance explained) is also popular, even though it applies only for a model at a much finer level than small area. For household-level data used in models for log expenditure and kilocalories, R^2 also does not need to account for variation within household, so direct comparison with other models fitted at child level is not possible. In any event, it is not the fit at household or child level that is important, but how useful the model is at the small area level which is considerably more aggregated (commonly consisting of 15,000 households or more). The consequence is that R^2 at child or even household level can be rather low (though obviously not zero) without models being inadequate at small area level. Even at PSU or cluster level in the survey, which is not as aggregated as small area level, R^2 at this level can be substantial even for models where R^2 is low at household or child level. Much hinges on the relative sizes of the variance components at cluster, household and child level. High relative variation at child or even household level is much less important than high variation at cluster level, because there are many more children and households than clusters (or small areas). A useful diagnostic then is R^2 adjusted or generalised to cluster level, i.e. putting aside household (and child) level variation. Even this is an underestimate of R^2 at small area level.

Appendix B contains the relevant statistics for the final models for height-for-age and weight-for-age. For both, although R^2 is low, suggesting caution, generalised R^2 is high (very high in the case of weight-for-age) even at cluster level, suggesting (when taken with other diagnostics such as F statistics and variance component ratios) that the survey-based models for weight-for-age and height-for-age provide useful and sufficiently accurate estimates when used via census predictions and aggregated to small area level.

We departed from the usual ELL implementation in our use of a single-stage, robust regression procedure for estimating model (2.1). This has the advantages of accounting for the survey design and obtaining consistent estimates of the covariance matrices in a single step. These covariance matrices were saved, along with the parameter estimates and both household- and cluster-level residuals (as defined in Section 2.3), for implementation of the prediction step.

4.3 Variance modelling

For modelling height-for-age and weight-for-age we found it necessary to depart from the usual methodology, in order to account for the expected correlation in these measures between children in the same household. We now have a three-level model, in which the regression residuals can be decomposed into three components

$$u_{ijk} = c_i + h_{ij} + e_{ijk} \tag{4.1}$$

for child k in household j of cluster (PSU) i. The variances σ_c^2, σ_h^2, σ_e^2 of the respective components can be estimated by maximum likelihood (ML) or restricted maximum likelihood (REML), and the cluster- and household-level residuals (or random effects) derived as empirical best linear unbiased predictors (EBLUPs). For methodological details see Laird and Ware (1982) and Robinson (1991). The alternative of defining household-level residuals to be the average of the regression residuals for each respective household is not appropriate here, as most households had only one child. Our previous implementation of this method in Nepal (Jones, Haslett and Parajuli, 2006) adjusted the three sets of residuals for shrinkage and used these in a nonparametric bootstrap procedure, as described in the next section. Here we use the much simpler parametric bootstrap approach, sampling from normal distributions with variances set to the estimated variance components. There should be little difference in practice as estimation with this many levels tends to encourage approximate normality in the residuals.

4.4 Simulation of predicted values

Simulated values for the model parameters β were obtained by parametric bootstrap, i.e. drawn from their respective sampling distributions as estimated by the survey regressions. As noted earlier, simulation of the cluster, household,-and child level effects, c_i , h_{ij} and e_{ijk} presents several possible choices. A parametric bootstrap could be used by fitting suitable distributions (e.g. Normal, *t*) to the residuals and drawing randomly from these, or they can be generated parametrically from the distribution determined by the estimates of the variance components σ_c^2 , σ_h^2 and σ_e^2 .

A total of 100 bootstrap predicted values Y_{ij}^b were produced for each child in the census for each target variable, as described in Section 2.4. For the three-level models for height-for-age and weight-for-age, this was

$$Y_{ijk}^b = X_{ijk}\beta^b + c_i^b + h_{ij}^b + e_{ijk}^b \ , \quad b = 1,\ldots,B$$

with the residuals at each level $c_i^b, h_{ij}^b, e_{ijk}^b$ drawn independently from normal distributions with mean zero and variances equal to the estimated variance components from the regression analysis.

4.5 Production of final estimates

The predicted values of height-for-age and weight-for-age for each child from the census can then be assessed as being stunted, severely stunted, underweight or severely underweight, and each of these measures separately grouped at the appropriate geographic level. Our main target is upazila-level small-area estimates, but we have also considered higher levels of aggregation (division, and district), for comparison with the direct survey estimates. Once the predicted values have been produced and stored it is easy to investigate alternative levels of aggregation, using the standard errors at each level as a guide to what is the finest possible area level for which estimates are acceptably accurate.

For stunting, severe stunting, underweight, and severe underweight, the census units are children within households. Hence the census units for height-for-age and weight-for-age are individual children, so no weighting is required. For example the estimated prevalence of stunting for small area *R* is:

$$S_R^b = \sum_{ij \in R} I(HAZ_{ij}^b < -2.00) / N_R$$

where N_R is the number of eligible children in *R*.

The 100 bootstrap estimates for each small area, e.g. $S_R^1,\ldots,S_R^{100}$ were summarized by their mean and standard deviation, giving a point estimate and a standard error for each small area. For height-for-age and weight-for-age we give two measures: prevalence below two standard deviations (stunting and underweight, respectively) and prevalence below three standard deviations (severe stunting and severe underweight, respectively).

5. Results for Child Undernutrition Measures

The results for the child undernutrition measures, stunting and underweight, were first accumulated to high levels of aggregation for comparison with the direct estimates available from the CMNS 2012. Table 5.1 shows both sets of estimates together with their standard errors (se). These estimates are for comparison purposes only. The standard errors for the direct survey estimates have been calculated using a robust variance technique which controls for the survey design. The standard errors for the small-area estimates (SAE) are the standard deviations of the 100 bootstrap estimates. We have added a standardized difference between the sets of estimates, defined as

$$Z = \frac{\text{Small area estimate - direct estimate}}{\sqrt{(\text{small area se})^2 + (\text{direct estimate se})^2}}$$

If both methods are correctly estimating the same quantities, then Z should approximate a standard normal distribution.

We note that, although in all cases the SAEs are more precise (i.e. smaller standard errors) than the direct estimates, there is little reduction in standard error from the small-area methodology at the largest levels of aggregation. This is because the uncertainty in the direct estimates due to sampling variability is replaced by uncertainty in the estimated model for the SAEs. At the lower levels however the improvement in precision is much more dramatic.

As an important aside, had the Multiple Indicator Cluster Survey 2012-2013 results been available before the final SAE results were completed, the MICS results might have been incorporated at district level by inverse variance weighting of the MICS and SAE results at that level, with the SAE upazila estimates being adjusted to sum to the amended district level estimates. However, the benefit would have been small because the standard error for the SAE estimates at district level is markedly smaller than that for the direct estimates from MICS, i.e. even at district level, despite the national sample of over 50,000 households for MICS, the SAE estimates are at least four times more accurate (in terms of variance) than the MICS ones. Inverse variance weighting would consequently have only marginally improved the accuracy of the SAE results. The conclusion follows from noting that, even if the design effect for MICS was one, and it is almost certainly more, MICS results where available at upazila level would have an average standard error (SE) of 10% or more, while the SAE estimates generally have an SE under 5%. Using inverse variance weighting would only improve the accuracy in terms of SE of the composite estimate, when compared with the SAE result, from 5% to $(10^{-2}+5^{-2})^{-0.5}$ = 4.5%. An interesting corollary is that SAE, when undertaken by sufficiently expert statisticians, can provide considerably more accurate estimates at a fine geographical level than can direct estimates even from very large sample surveys, and at much lower cost.

5.1 Small area estimation results for stunting

Table 5.1 Comparison of estimates of stunting prevalence (S2) from CMNS 2012

Division	CMNS		SAE		Standard Difference	BDHS
	S2	se	S2	se	(Z)	S2
Barisal	0.310	0.023	0.397	0.011	3.447	0.451
Chittagong	0.459	0.025	0.421	0.010	-1.433	0.413
Dhaka	0.426	0.029	0.404	0.008	-0.711	0.433
Khulna	0.349	0.030	0.395	0.009	1.458	0.341
Rajshahi	0.393	0.023	0.410	0.009	0.679	0.337
Rangpur	0.362	0.026	0.421	0.011	2.127	0.429
Sylhet	0.513	0.024	0.446	0.012	-2.532	0.493

Key: se=standard error

These Z scores show that the small-area estimates except Barisal are all within three standard errors of the direct estimates, indicating a reasonable level of agreement between the two methods especially since there are seven tests of significance. The comparison is however complicated by estimates at division level from CMNS 2012 being different both in level and in their ordering from the BDHS 2011 estimates. In particular, the biggest disagreement between CMNS and SAE is in Barisal, where there is an even bigger disagreement between CMNS and BDHS; the SAE can in fact be seen as a compromise between these two, suggesting that both direct survey estimates are unreliable. This issue has been discussed in Section 3. In essence, stunting estimates from CMNS 2012 and BDHS 2011 are not sufficiently reliable at division level. Small area estimation is also intended to provide estimates at a lower level than division where its standard errors are not dominated by the standard error of parameter estimates in the underlying regression model.

The first stage regression models for height-for-age at individual child level were poor in terms of predictive power, with R^2 values of around 5% (see Appendix B.1), although predictive power improves dramatically at higher levels of aggregation which are still less aggregated than small area (i.e. upazila) level (R^2_{adj} at cluster level is 34%). Table 5.1 indicates that the small-area estimates of stunting have smaller standard errors than the direct estimates from the surveys at high aggregation levels. This is because very little of the residual variation from the regression model used for small area estimation of height-for-age is at PSU-level, so that this unexplained variation, though considerable, is mostly averaged over a large number of households and children.

Turning to the district-level estimates, summarized in Table 5.2, we find that the standard errors are quite small, with an average of only 1.2%. The estimates of stunting prevalence range from 34% to 48%. The standard errors for severe stunting are also quite small, also averaging 1.2% in comparison with the standard deviation of 2.8%, so should provide a reasonably accurate comparisons of severe stunting between areas. A complete listing of the estimates is given in Appendix C.

Table 5.2 Summary of district-level estimates of stunting prevalence (S2, S3)

District	Stunting		Severe stunting	
	S2	se2	S3	se3
Mean	0.4122	0.0123	0.2338	0.0125
Standard deviation	0.0261	0.0016	0.0276	0.0025
Minimum	0.3416	0.0099	0.1794	0.0089
Maximum	0.4771	0.0167	0.3116	0.0199

Key: se2=standard error of S2
se3=standard error of S3

Even at upazila level, where standard errors would be expected to be higher, as shown in Table 5.3 the estimates of both S2 and S3 have reasonably small standard errors in comparison with the variability of the small area estimates between the upazila, indicating that upazila level estimates can generally be distinguished from one another even allowing for modelling errors. Stunting prevalence S2 has an average standard error of 1.9%. Estimates at upazila level range from 28% to 51%. Standard errors for severe stunting S3 average 1.8%, in comparison with the standard deviation of 3.6% between the upazila. Thus, although the models used to derive the estimates have low predictive power for individual children, for the reasons outlined previously, they seem to be capturing a considerable amount of variability in undernutrition between upazila.

Table 5.3 Summary of upazila-level estimates of stunting prevalence (S2, S3)

Upazila	Stunting		Severe stunting	
	S2	se2	S3	se3
Mean	0.4069	0.0194	0.2306	0.0175
Standard deviation	0.0391	0.0075	0.0361	0.0054
Minimum	0.2788	0.0110	0.1299	0.0103
Maximum	0.5099	0.0636	0.3419	0.0415

Key: se2=standard error of S2
se3=standard error of S3

5.2 Small area estimation results for underweight

As for stunting, estimates of underweight (U2) from CMNS 2012 were compared with the direct survey-only estimates. The comparison is presented in Table 5.4.

Table 5.4 Comparison of prevalence of underweight (U2) from CMNS 2012

Division	CMNS		SAE		Standard Difference	BDHS
	U2	se	U2	se	(Z)	U2
Barisal	0.267	0.021	0.334	0.009	2.947	0.400
Chittagong	0.394	0.025	0.368	0.021	-0.811	0.374
Dhaka	0.335	0.026	0.323	0.009	-0.455	0.366
Khulna	0.262	0.024	0.320	0.008	2.317	0.291
Rajshahi	0.373	0.024	0.340	0.008	-1.291	0.342
Rangpur	0.327	0.024	0.357	0.009	1.165	0.345
Sylhet	0.395	0.019	0.385	0.015	-0.424	0.449

Key: se=standard error

None of the Z-scores for the difference between direct estimates and small area estimates at division level exceed three, indicating reasonable general agreement. Again however, there are discrepancies between the CMNS 2012 and the BDHS 2011 estimates at division level. Interestingly, the small area estimates are often intermediate, suggesting that, as for stunting, the small area modelling while picking up on underlying structure and relationships of other variables with underweight, is not overly influenced by anomalies in the surveys at district level.

The district-level estimates for underweight, described in Table 5.5, have standard errors similar to those for stunting, having an average of only 1.3%. The underweight estimates themselves range from 23% to 41%. The standard errors for severe underweight are also quite small, with a standard error of 0.5% in contrast to the district-level standard deviation of 2%. A complete listing of the estimates is given in Appendix C.

Table 5.5 Summary of district-level estimates of underweight prevalence (U2, U3)

District	Underweight		Severe underweight	
	U2	se2	U3	se3
Mean	0.3450	0.0134	0.0810	0.0052
Standard deviation	0.0350	0.0071	0.0132	0.0029
Minimum	0.2278	0.0076	0.0424	0.0027
Maximum	0.4086	0.0389	0.1064	0.0165

Key: se2=standard error of U2
se3=standard error of U3

Again at upazila level the standard errors for underweight prevalence are reasonably small, as shown in Table 5.6 with an average of 1.8%. Estimated prevalence of underweight ranges from 17% to 45%. Thus the models for weight-for-age, although similarly low in predictive power to those of height-for-age, for similar reasons seem to be capturing a considerable amount of the variability in prevalence of underweight between upazila.

Table 5.6. Summary of upazila-level estimates of underweight prevalence

Upazila	Underweight		Severe underweight	
	U2	se2	U3	se3
Mean	0.3384	0.0182	0.0792	0.0069
Standard deviation	0.0546	0.0089	0.0193	0.0037
Minimum	0.1678	0.0086	0.0258	0.0029
Maximum	0.4467	0.0687	0.1289	0.0278

Key: se2=standard error of U2
se3=standard error of U3

5.3 Child undernutrition maps

Maps of the stunting prevalence estimates, including severe stunting are given in Appendix D.2. Maps for underweight and severe underweight are in Appendix D.3.

6. Conclusions and Discussion

We have produced small-area estimates of stunting, underweight, severe stunting and severe underweight in Bangladesh at upazila level by combining survey data from the Child and Mother Nutrition Survey (CMNS 2012) with auxiliary data derived from the 2011 Population and Housing Census. A single model for height-for-age, albeit with some division level effects and interactions, was found to be adequate for predicting stunting and severe stunting. Similarly, a single model for weight-for-age was found adequate for predicting underweight and severe underweight. The upazila-level estimates obtained have acceptably low standard errors.

It is interesting to note that the estimates derived from height-for-age, weight-for-age had acceptably small standard errors down to upazila level, even though our predictive models for these variables had comparatively low R^2 values at child level. The lower R^2 values for these regression models in comparison with models fitted to household level data (such as for log expenditure and kilocalories) in part reflects the additional level of variation (children within households), and is acceptable because of the very high proportion of residual variation that is at child level within household. This variation within household does not reflect differential feeding practices within household, but rather that the effect of undernutrition is cumulative, so that older children tend to have lower z-scores relative to the reference population. This is reflected in the significance of age in the regression models for height-for-age and weight-for-age even after use of the reference population to adjust directly for age.

Smaller R^2 is also more acceptable if the large unexplained variation is truly random across households or individuals, with little or no cluster-level variation. Since the methodology incorporates in the standard errors any remaining cluster-level variation, this would appear to be the case. It is nevertheless likely that some of this variation represents missing variables in the model which would give better prediction if they were available. If important factors are missing then the small-area estimates obtained will not reflect the true variability in these undernutrition indicators and, even if not biased because the model includes random effects, will tend to have larger standard errors than would otherwise be the case. There are other factors, particularly health-related ones, that would be useful predictors of undernutrition, but these variables were not available for the population from the census data, which has an essentially economic focus, and so could not be included in the small-area models.

Geographic Information System (GIS) variables were not used directly in the regression models. GIS variables are necessarily at aggregate level and, as for census means, because they are aggregated they are not able to provide household level information. Like all regressor variables, they are to be included in models only where they explain variation *in addition* to that explained by the other variables in the model.

As noted earlier, we have departed from previous implementations of ELL methodology in a few important ways. More detailed discussion can be found in Haslett and Jones (2005b, 2010) and Haslett (2013). For example, the strategy for choosing appropriate regression models for the target variable is not usually made explicit, but Miller (2002) sounds a number of cautions. Using separate survey based models for subgroups such as geographical strata, especially where there are a large number of such subgroups, and selecting variables from a very large pool of possibilities including all interaction terms, cannot be recommended. Model-fitting criteria such as generalised- R^2 or Akaike information criterion (*AIC*) adjusted for the survey design will penalize for fitting too many variables, but do not account for the number of variables that are being selected from. Cross-validation (i.e. dividing the sample, fitting a model to one part, and testing its utility on the other) might be useful here. We have tried where possible to fit a single model for the whole population, including interaction terms only when the corresponding main effects are also included and looking carefully at the interpretability of the estimated effects, i.e. whether the model makes sense. This is a time-consuming procedure but can lead to more stable parameter estimation and more reliable prediction. This does not preclude fitting subgroup or area effects in models when required, or combining area based models into an essentially equivalent single model containing appropriate interactions to improve stability of regression parameter estimates. When the effects of most factors on the target variable are similar in all areas, with modulation only between rural and non-rural areas, an urban/rural covariate possibly with some interactions with other variables will suffice. Even a single model can produce marked discrimination between small areas when appropriate, as the results in Appendix C attest. Furthermore if there is prior knowledge on which factors are likely to affect the target variable, this can be incorporated into the model selection. A more formal way of doing this would be through a Bayesian analysis, but this is beyond the scope of the present research.

The use of specialised survey regression routines, such as those available in Stata, Sudaan and WesVar, in the initial model fitting to the survey data has distinct advantages, since it incorporates the entire survey design and gives a consistent estimate of the covariance matrix. These specialized routines use a robust estimation methodology, essentially collapsing the covariance matrix within clusters, and such methods are consequently more stable than ones which estimate a covariance within each cluster. A perceived disadvantage is that such robust methods may give poor estimates if used for small subpopulations with few clusters. However this is a real effect, not an artefact of the fitting procedure. Note that such routines require *all* survey data to be included in any analysis (even of a subpopulation) in order to give unbiased standard errors, so that analysis of sub-setted survey data is not recommended, even if different models are being fitted to different subgroups. The weighting of the survey observations is complex not only because of the survey design but also because the target variable is often a per capita average. Alternatively, if individual data are used, these will be correlated when from the same family, although the robust variance estimate is still valid even there because it only assumes independence between clusters, not of observations within clusters.

To allow for non-independence between children in the same household at the prediction stage, we have extended the ELL approach to incorporate three levels of variation. Whilst the estimation of variance components in such a hierarchical model is now well-understood, the use of estimated random effects in a non-parametric bootstrap raises some theoretical issues, such as adjustment for degrees of freedom, which might provide fruitful areas for further research. We have also tested, to the extent possible given that many sampled upazila contain only one sampled primary sampling unit (PSU), whether (through the use of contextual effects, i.e. census means) small area (i.e. upazila) level random effects are negligible for estimating standard errors.

The benefits of the ELL methodology accrue when interest is in several nonlinear functions of the same target variable, as in the case of poverty measures defined on household per capita expenditure. If only a single measure were of interest, it might be worthwhile considering direct modelling. For example small-area estimates of stunting prevalence could be derived by estimating a logistic regression model for prevalence in the survey data. This would however ignore information on how stunted individual children are, and would require a separate model for severe stunting. Similar considerations apply to underweight. Ghosh and Rao (1994) consider this situation within the framework of generalized linear models. If on the other hand there are several target variables which might be expected to be highly correlated, it might increase efficiency to use a multivariate model rather than separate univariate regressions. However, such techniques tend to shrink estimates of each component toward one another, and it is sometimes the contrast, rather than the combination of variables such as height-for age and weight-for-age, that is important.

From a theoretical perspective, the best (i.e. most efficient) small-area estimator uses the actual observed *Y* when these values are known, i.e. for the units sampled in the survey, and the predicted *Y* values otherwise. The resulting estimator can be thought of as a weighted mean of the direct estimator from the survey only, and an indirect estimator derived from the auxiliary data, the weights being related to the standard errors of the two estimates. In practice it may be impossible for confidentiality reasons to identify individual households in the survey and match them to the census, but there is a theoretical basis for using a weighted mean of the two estimates and thereby increasing precision. Further it is not necessary to resample unconditionally from the empirical distribution of the cluster-level residuals for those clusters which are present in the survey. An alternative would be to resample each of these parametrically from an estimated conditional distribution, i.e. for clusters present in the survey we would calculate the bootstrap predictions using the known value rather than a draw from a random distribution. This would however not have a major effect where the number of clusters in the sample is small relative to the number of clusters defined over the whole population. See also Valliant, Dorfman and Royall (2000). Further, in small area estimation using ELL, many of the small areas are unsampled, so it is only through the census data for each particular small area (e.g. contextual effects) that adjustments can be made to what is otherwise essentially a synthetic estimator.

The provision of standard errors with the small-area estimates is very important, because it gives the user an indication of how much accuracy is being claimed, conditional on the model being correct. Ultimately decisions are to be made on which areas should receive the most development assistance, so it is important that this information be given to users in a way that is most useful for this purpose. It is not clear exactly how the standard error information should be incorporated, but this is at least in part because the answer will depend on the nature of the decision problem. We have explored a possible way of incorporating the standard errors into a poverty map, first calculating standardized departures from a pre-specified prevalence level, say 40%, as

$$Z = \frac{\text{estimate} - 0.40}{\text{standard error}}$$

and then transforming this into a probability assuming a normal distribution. This value can then be mapped and interpreted as the probability that the corresponding area has a poverty incidence at least as high as the pre-chosen level. Thus when targeting assistance we could focus on those areas which we believe have the greatest chance of exceeding a threshold poverty incidence, although as with any single map some caution is required if the population sizes in the areas differ markedly. The probabilities here are calculated on the assumption that the sampling distributions of the small-area estimates of incidence (or of prevalence) are approximately normal. A nonparametric alternative would be to take the proportion of bootstrap estimates above the cut-off value. See for example, the earlier implementation of small area estimation methods for Bangladesh in Jones and Haslett (2003). Such methods however, while useful, tend not to convey as much information as mapping of the estimates themselves, as in this report. In the case of Bangladesh, the increased precision of the undernutrition estimates in 2011 as compared with 2001 reflects that fact that only a 5% sample from the 2001 census was available for small area estimation, while complete information was available from the 2011 census. It is also of consequence that the census means used to provide contextual effects in 2001 were only available at upazila level due to difficulties with geocoding, while for the 2011 census geocode matching of CMNS 2012 with the census was possible at the rather finer mauza level, giving much more scope for modelling the cluster-level variation.

From a technical perspective, the statistical methods used in this report would benefit from further theoretical development and justification. The range of models possible using small-area estimation is very broad, and while the ELL methodology has a number of theoretical and practical advantages, sensitivity of estimates to different small-area estimation models remains an only partially explored issue. This question relates both to the choice of the ELL method, *vis-à-vis* others, and to the choice of explanatory variables within models (e.g. submodels for different areas, cross-validation of variables selected from a large pool including higher level interactions, consistency of sign and magnitude of parameter estimates with likely influence on poverty in the presence of correlated variables). These questions need theoretical work and extend beyond the present study.

Ground truthing or validation of small-area estimates by visits to selected small areas after models have been fitted and small-area estimates derived from them can be a useful exercise. Some cautions are however warranted. The first is that small-area estimation is a technique that works best in aggregate - not every small-area estimate can be expected to give precise information, so that choosing areas to visit on the basis of possible anomalies can give a biased picture of the utility of the estimates as a whole. It is also difficult to ask participants in a validation exercise to differentiate various types of poverty and undernutrition, or not to include aspects (such as health or water quality) which because they are not included in the census variables cannot be part of the small-area estimates themselves. Validation exercises are also usually limited by funds, so that formal testing of the accuracy of the small-area estimates is not possible by this method. Nevertheless, validation can provide useful qualitative insights and even more importantly a forum for discussion of results of poverty and undernutrition mapping with local communities.

Small-area models are not perfect, and standard errors derived from them depend on the model being at least approximately correct, or at least correct enough to make sound predictions. Despite these caveats, from a practical point of view the explicit small-area estimates of stunting, severe stunting, underweight and severe underweight for children under five years of age in Bangladesh that have been presented in this report are at a much finer geographical level than has previously been possible and consequently should be of considerable benefit when a mechanism for allocation of development assistance is required.

Bibliography

Alderman H., Babita M., Demombynes G., Makhata N. and Ozler B. (2002) How low can you go? Combining census and survey data for mapping poverty in South Africa, *Journal of African Economics*, 11, 169-200.

Bangladesh Bureau of Statistics (2010) *Report of the Household Income & Expenditure Survey 2010*, Bangladesh Bureau of Statistics, 2010.

Bangladesh Bureau of Statistics (2011) *2011 Population & Housing Census: Preliminary Results*, Bangladesh Bureau of Statistics, 2011.

Bangladesh Bureau of Statistics (2012) *Bangladesh Population and Housing Census 2011: National Report, Volume – 4 Socio-Economic And Demographic Report*, Bangladesh Bureau of Statistics, December 2012.

Bangladesh Bureau of Statistics (2013) *Child and Mother Nutrition Survey of Bangladesh 2012*, Bangladesh Bureau of Statistics, April 2013.

Bangladesh Bureau of Statistics & UNICEF (2010) *Bangladesh Multiple Indicator Cluster Survey 2009*, Volume 1: Technical Report, UNICEF, June 2010.

Bangladesh Bureau of Statistics & UNICEF (2014a) *Multiple Indicator Cluster Survey, Progotir Pathey: Key Findings,* Bangladesh Bureau of Statistics, UNICEF, May 2014.

Bangladesh Bureau of Statistics & UNICEF (2014b) *Multiple Indicator Cluster Survey, Progotir Pathey: Key District Level Findings*, Bangladesh Bureau of Statistics, UNICEF, May 2014.

Chambers R.L and Skinner C.J. (eds.) (2003) *Analysis of Survey Data*. Wiley.

Efron B. and Tibshirani R.J. (1993) *An Introduction to the Bootstrap*. Chapman and Hall.

Elbers C., Lanjouw J.O. and Lanjouw P. (2001) *Welfare in villages and towns: micro-level estimation of poverty and inequality*, unpublished manuscript, The World Bank.

Elbers C., Lanjouw J. and Lanjouw P. (2003) Micro-level estimation of poverty and inequality, *Econometrica*, 71, 355-364.

Elbers C., Lanjouw J.O., Lanjouw P. and Leite P.G. (2001) *Poverty and Inequality in Brazil: new estimates from combined PPV-PNAD data*, unpublished manuscript, The World Bank.

Food and Agriculture Organization/ World Health Organization/ United Nations University (1985) *Energy and Protein Requirements*, WHO Technical Report Series 724. Geneva, WHO.

Fujii T. (2004) Commune-level estimation of poverty measures and its application in Cambodia, In *Spatial Disparities in Human Development: Perspectives from Asia*, edited by Kanbur R., Venables A.J., & G. Wan. United Nations University Press.

Ghosh M. and Rao J.N.K. (1994) Small area estimation: an appraisal, *Statistical Science*, **9**, 55-93.

Hamill P.V.V., Dridz T.A., Johnson C.Z., Reed R.B. et al. (1979) Physical growth: National Center for Health Statistics percentile. *American Journal of Clinical Nutrition*, 32, 607-621.

Haslett. S. (2013) Small area estimation of poverty using the ELL/PovMap method, and its alternatives, Chapter 12 in *Poverty and Social Exclusion: New Methods of Analysis*, ed. G. Betti and A Lemmi, Routledge, 2013.

Haslett, S. Isidro, M. and Jones, G. (2010) Comparison of survey regression techniques in the context of small-area estimation of poverty, *Survey Methodology*, 36, 2, 157-170.

Haslett, S. and Jones, G. (2005a) *Estimation of Local Poverty in the Philippines*, Philippines National Statistics Co-ordination Board / World Bank, November 2005.

Haslett, S. and Jones, G. (2005b) Small-area estimation using surveys and censuses: some practical and statistical issues, *Statistics in Transition*, 7 (3), 541-555

Haslett, S. and Jones, G. (2010) Small-area estimation of poverty: the aid industry standard and its alternatives, *Australian and New Zealand Journal of Statistics*, 52 (4), 341-362.

Haslett, S., Jones, G., and Sefton. A. (2013) *Small-area Estimation of Poverty and Malnutrition in Cambodia*, National Institute of Statistics, Ministry of Planning, Royal Government of Cambodia and the United Nations World Food Programme, Cambodia, April 2013, ISBN 9789996375507.

Haslett, S., Jones, G. and Isidro, M. (2014) *Potential for Small Area Estimation of Under-nutrition at sub-District Level in Bangladesh: Interim Feasibility Report to UN World Food Programme*, Massey University, New Zealand, February 2014.

Healy A.J., Jitsuchon S. and Vajaragupta, Y. (2003) *Spatially Disaggregated Estimation of Poverty and Inequality in Thailand*, preprint.

Institute of Public Health Nutrition, UNICEF and UN World Food Programme (2009) *Bangladesh Household Food Security and Nutrition Assessment Report 2009*, World Food Programme, 2009.

Isidro. M. (2010) *Intercensal Updating of Small-Area Estimates*, Thesis in partial fulfilment of PhD degree requirements, Massey University, New Zealand.

Isidro, M., Haslett, S. and Jones, G. (2010a) Comparison of intercensal updating techniques for local level poverty statistics, *Proceedings of Statistics Canada Symposium 2010*, 10B-4, http://www.statcan.gc.ca/conferences/symposium2010/abs-res-eng.htm

Isidro, M, Haslett, S. and Jones, G. (2010b) Extended structure-preserving estimation method for updating small-area estimates of poverty, *Joint Statistical Meetings, Proceedings of the American Statistical Association 2010*, Vancouver, Canada, http://www.amstat.org/meetings/jsm/2010/onlineprogram

Jones, G. and Haslett, S. (2003) *Local Estimation of Poverty and Malnutrition in Bangladesh*. Bangladesh Bureau of Statistics and UN World Food Programme.

Jones G., and Haslett, S. (2006) *Small-Area Estimation of Poverty, Caloric Intake and Malnutrition in Nepal*, Published: Nepal Central Bureau of Statistics / UN World Food Programme / World Bank, September 2006, 184pp, ISBN 999337018-5.

Jones, G., Haslett, S. and Parajuli, D. (2006) *Local Estimation of Poverty, Undernourishment and Malnutrition in Nepal*, The Central Bureau of Statistics of His Majesty's Government of Nepal / United Nations World Food Programme.

Laird, N.M. and Ware, J.H. (1982). Random-effects models for longitudinal data, *Biometrics*, 38, 963 - 974.

Lehtonen, R. and Pakhinen, E. (2004) *Practical Methods for Design and Analysis of Complex Sample Surveys*, 2nd Edition, Wiley.

Longford, N. T. (2005) *Missing Data and Small-area estimation*, Springer Verlag.

Miller, A. (2002) *Subset Selection in Regression*, 2nd edition, Chapman and Hall / CRC

Molina, I. and Rao, J. N. K. (2010) Small area estimation of poverty indicators, *Canadian Journal of Statistics*, 38, 369–385.

National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International (2013) *Bangladesh Demographic and Health Survey 2011*. Dhaka, Bangladesh and Calverton, Maryland, USA: NIPORT, Mitra and Associates, and ICF International, January 2013.

de Onis, M., Onyango, A. W. , Borghi, E., Garza, C. and Yang, H. (2006). Comparison of the World Health Organization (WHO) Child Growth Standards and the National Center for Health Statistics/WHO international growth reference: implications for child health programmes, *Public Health Nutrition*, 9 (7), 942–947, DOI: 10.1017/PHN20062005

Rao J.N.K. (1999) Some recent advances in model-based small-area estimation, *Survey Methodology*, 23, 175-186.

Rao, J.N.K. (2003) *Small-Area Estimation*. Wiley.

Robinson, G.K. (1991) That BLUP is a good thing: the estimation of random effects, *Statistical Science*, 6, 15-51.

Skinner C.J., Holt D. and Smith T.M.F. (eds) (1989) *Analysis of Complex Survey Data*. Wiley.

Swindale A. and Ohri-Vachaspati, P. (2004) *Measuring Household Food Consumption: A Technical Guide. Washington DC: Food and Nutrition Technical Assistance (FANTA) Project*, Academy for Educational Development (AED).

UNDP (2013) *Human Development Report, 2013*, United Nations Development Programme, New York.

Valliant, R., Dorfman, A. H., and Royall, R. M. (2000) *Finite Population Sampling and Inference: A Prediction Approach*, John Wiley, New York.

WHO Multicentre Growth Reference Study Group (2006) *WHO Child Growth Standards: Length/Height-for-Age, Weight-for-Age, Weight-for-Length, Weight-for-Height and Body Mass Index-for-Age: Methods and Development*. Geneva: World Health Organization; pp 312. : http://www.who.int/childgrowth/publications/en/

World Bank (2008), *Poverty Assessment for Bangladesh: Creating Opportunities and Bridging the East-West Divide*, Bangladesh Development Series Paper No. 26, World Bank, October 2008.

World Bank (2009). *Bangladesh - Updating Poverty Maps: Bangladesh Poverty Maps for 2005* : Technical report. Washington, DC: World Bank, August 2009.

World Bank (2013) *Bangladesh Poverty Assessment-2000-2010 Key Messages*, World Bank, June 2013.

World Bank (2014) *2010 Poverty Maps of Bangladesh: Key Findings*, World Bank, Dhaka, 2014.

World Food Programme, United Nations Children's Fund & Institute of Public Health Nutrition (2009) *Bangladesh Household Food Security and Nutrition Assessment Report 2009*, World Food Programme, 2009.

World Health Organisation (2011) *WHO Anthro: Version 3.2.2, January 2011, and Macros*. http://www.who.int/childgrowth/software/en/

Zhao, Q. (2006) *User Manual for PovMap*, World Bank. http://siteresources.worldbank.org/INTPGI/Resources/342674-1092157888460/Zhao_ManualPovMap.pdf

Zhou, Q. and Lanjouw. P. (2009) *PovMap2: A User's Guide*, The World Bank. http://go.worldbank.org/QG9L6V7P20

Appendices

Appendix A. Potential auxiliary variables

Table A.1: Child- and household-level variables in CMNS 2012 and Census 2011

Name	Label
sex	sex of child (0=male; 1=female)
age	age in completed years
urban	urban area
hfem	hh head is female
pafem	propn of adults who are female
hage	age of hh head
afseced	hh has adult female with secondary edn
pademp	propn of adults who are employed
pempag	propn of adults employed in agriculture
hhsz	household size
pkids06	propn of hh under 7 years of age
pkids714	propn of hh 7 to 14 years of age
pelder	propn of hh aged 65+
pfem	propn of hh who are female
pdisab	propn of hh who are disabled
seph	separate house
electric	house has electricity
dwater	source of drinking water 1 "tap" 2 "tube-well" 3 "other"
toilet	type of toilet 1 "sanitary with water seal" 2 "sanitary w\o water seal" 3 "non-sanitary" 4 "none"
htype	type of house 1 "pucka" 2 "semi-pucka" 3 "kutcha" 4 "jhupri"
hmstat	hh head marital status 1 "unmarried" 2 "married" 3 "widowed" 4 "divorced separated"
hedlev	hh head education level 0 "no school" 1 "primary" 2 "secondary" 3 "tertiary"
hdistype	hh head disability type 0 "none" 1 "visual" 2 "hearing" 3 "mobility" 4 "cognition" 5 "self care" 6 "speech"
hocctype	hh head occupation type 0 "none" 1 "agriculture" 2 "service" 3 "other"
ownrent	tenancy of house 1 "owner" 2 "rented" 3 "rentfree"
hhrelig	religion of hh head 1 "moslem" 2 "hindu" 3 "christian" 4 "buddhist" 5 "other"

Table A.2: Census means mauza level) from Census2011 (Short Form)

Name	**Label**
nhh	number of hh in mauza
npp	number of people in mauza
rmo	rural, municipal, other
name_m	name of mauza
ppucka_m	propn of pucka hh in mauza
pspuck_m	propn of semi-pucka hh in mauza
pjhupri_m	propn of jhupri hh in mauza
ptap_m	propn hh with tapwater in mauza
ptube_m	propn of hh with tube-well in mauza
psan_m	propn of hh with sanitary toilet in mauza
punsan_m	propn of hh with unsanitary toilet in mauza
pelec_m	propn of hh with electricty in mauza
pfem_m	propn of females in mauza
pemp15_m	propn of 15+ persons employed in mauza
pempag_m	propn of 15+ persons employed in agriculture
plit_m	propn of 7+ persons who can write a letter
pmidsec_m	propn persons 15+ with middle secondary eduation
phisec_m	propn persons 15+ with higher secondary eduation

Appendix B. Survey-Based Regression Results

B.1 Model for height-for-age in CMNS 2012

n	n_{psu}	p	R^2	R^2_{adj}	σ_c^2	σ_h^2	σ_e^2
4112	350	16	0.054	0.322	0.132	0.289	2.401

where n = sample size, n_{psu} = PSU sample size, p = number of variables, R^2 = coefficient of determination; R^2_{adj} = coefficient of determination adjusted or generalised to cluster level; σ_c^2 = cluster-level variance, σ_h^2 = household-level variance, σ_e^2 = residual variance.

For model overall: $F(16,321)=10.75$, probability that model not significant<0.0001.

Variable	Coef.	Std. Err.	t	P>t	Label
age0	0.6145	0.0899	6.84	0.000	age 0
lnhhsz	-0.2539	0.0989	-2.57	0.011	natural log of hh size
electric	0.1488	0.0879	1.69	0.091	has electricity
hedsec	0.2228	0.0745	2.99	0.003	hh head has secondary education
hunmarr	-0.8137	0.3627	-2.24	0.025	hh head unmarried
pafem	0.5187	0.2427	2.14	0.033	propn of adult in hh who are female
pkids714	0.4767	0.2197	2.17	0.031	propn of children 7 to 14 years in hh
seph	-0.2969	0.0944	-3.14	0.002	separate house
electricXu	0.3439	0.1935	1.78	0.076	has electricity, urban area
hunmarrXu	1.6365	0.5284	3.10	0.002	hh head unmarried, urban
hwsdXu	0.8173	0.2360	3.46	0.001	hh head widowed, separated or divorced, urban area
pafemXu	-0.7704	0.3667	-2.10	0.036	propn of adult in hh who are female, urban area
pempag_m	0.8280	0.1959	4.23	0.000	propn adults in mauza employed in agric
pnotoilet_m	-0.2919	0.1938	-1.51	0.133	propn hh in mauza without toilet
plit_m	0.9636	0.3637	2.65	0.008	propn literate in mauza
pspuck_mXu	0.8233	0.4098	2.01	0.045	propn hh pucka or semi-pucka in mauza, urban
_cons	-2.5614	0.3943	-6.50	0.000	constant term

B.2 Model for weight-for-age in CMNS 2012

n	n_{psu}	p	R^2	R^2_{adj}	σ_c^2	σ_h^2	σ_e^2
4112	350	21	0.071	0.8239	0.0343	0.0714	1.2935

where n = sample size, n_{psu} = PSU sample size, p = number of variables, R^2 = coefficient of determination; R^2_{adj} = coefficient of determination adjusted or generalised to cluster level; σ_c^2 = cluster-level variance, σ_h^2 = household-level variance, σ_e^2 = residual variance.

For model overall: $F(21,316)=10.26$, probability that model not significant<0.0001.

Variable	Coef.	Std. Err.	t	P>t	Label
age0	0.3612	0.0741	4.87	0.000	age 0
age1	0.2760	0.0670	4.12	0.000	age 1
age2	0.2171	0.0664	3.27	0.001	age 2
age3	0.1700	0.0579	2.94	0.004	age 3
afseced	0.1220	0.0499	2.45	0.015	hh has female with secondary education or higher
hedpri	0.1102	0.0594	1.85	0.065	hh head has primary education
hedsec	0.1512	0.0573	2.64	0.009	hh head has secondary education
electric	0.1353	0.0533	2.54	0.012	has electricity
hhsz	-0.0231	0.0130	-1.78	0.076	hh size
hhsz2	0.0062	0.0025	2.50	0.013	(hhsz-6)^2
hwsd	0.3513	0.1173	2.99	0.003	hh head widowed, separated or divorced
seph	-0.1646	0.0636	-2.59	0.010	separate house
plit_m	0.6287	0.1682	3.74	0.000	propn literate in mauza
hfemXr	-0.4726	0.1138	-4.15	0.000	hh head is female, rural area
nstoiletXu	-0.3272	0.1206	-2.71	0.007	non-sanitary toilet, urban area
div_60	-0.1789	0.0763	-2.35	0.020	Sylhet division
s_60_pempag	0.3845	0.1825	2.11	0.036	propn of adults employed in agriculture, Sylhet divn
s200	5.2703	1.7747	2.97	0.003	rural Chittagong
s_20_pdem	-0.9893	0.1389	-7.13	0.000	propn of adults who are employed, Chittagong
s_201_nmoslem	0.7071	0.2235	3.16	0.002	hh head non-moslem, urban Chittagong
s_200_pfem	-9.5383	3.3818	-2.82	0.005	propn of females in mauza, rural Chittagong
_cons	-1.8790	0.1199	-15.68	0.000	constant term

Appendix C. Summary of Small-Area Estimates

District-level stunting and underweight measures

S2 = prevalence of stunting, seS2 = standard error of S2,
S3 = prevalence of severe stunting, seS3 = standard error of S3
U2 = prevalence of underweight, seU2 = standard error of U2,
U3 = prevalence of severe underweight, seU3 = standard error of U3
Nch=number of children under 5 years
DisGeoCode=district geocode

divn	zila	Division	District	DisGeoCode	U2	seU2	U3	seU3	S2	seS2	S3	seS3
10	4	Barisal	Barguna	1004	0.323110	0.011363	0.071754	0.004127	0.38501	0.013111	0.218256	0.012828
10	6	Barisal	Barisal	1006	0.316631	0.009479	0.070218	0.003577	0.382527	0.011895	0.215109	0.011219
10	9	Barisal	Bhola	1009	0.380962	0.011525	0.093518	0.004863	0.429425	0.012874	0.250598	0.011590
10	42	Barisal	Jhalokati	1042	0.288435	0.010523	0.060831	0.003693	0.369967	0.015625	0.206478	0.012840
10	78	Barisal	Patuakhali	1078	0.343280	0.010554	0.079127	0.004147	0.404524	0.011576	0.232533	0.010936
10	79	Barisal	Pirojpur	1079	0.296687	0.011217	0.062810	0.003832	0.381483	0.014191	0.215810	0.013502
20	3	Chittagong	Bandarban	2003	0.395769	0.038947	0.106388	0.016460	0.477122	0.016357	0.290515	0.017711
20	12	Chittagong	Brahamanbaria	2012	0.388284	0.023328	0.099635	0.009547	0.424193	0.011761	0.242280	0.009638
20	13	Chittagong	Chandpur	2013	0.378757	0.024557	0.095488	0.010082	0.401014	0.010949	0.228794	0.010444
20	15	Chittagong	Chittagong	2015	0.335368	0.018496	0.081024	0.006547	0.40769	0.011944	0.230157	0.011366
20	19	Chittagong	Comilla	2019	0.372979	0.024098	0.093481	0.009722	0.403161	0.010373	0.227111	0.009653
20	22	Chittagong	Cox'S Bazar	2022	0.371071	0.031195	0.094079	0.011917	0.466218	0.014573	0.278738	0.014305
20	30	Chittagong	Feni	2030	0.341042	0.021806	0.081908	0.008283	0.413541	0.012022	0.234884	0.012258

20	46	Chittagong	Khagrachhari	2046	0.375875	0.030296	0.095760	0.011955	0.446580	0.016138	0.266936	0.017113
20	51	Chittagong	Lakshmipur	2051	0.396794	0.024674	0.102514	0.010144	0.424144	0.012646	0.245743	0.010788
20	75	Chittagong	Noakhali	2075	0.391312	0.023760	0.101666	0.009887	0.435422	0.011212	0.254168	0.011454
20	84	Chittagong	Rangamati	2084	0.328068	0.037897	0.078241	0.013736	0.427935	0.014211	0.251373	0.015556
30	26	Dhaka	Dhaka	3026	0.227829	0.014597	0.042406	0.003907	0.341587	0.016734	0.179449	0.012740
30	29	Dhaka	Faridpur	3029	0.345564	0.009117	0.079928	0.003577	0.402092	0.012371	0.229184	0.010921
30	33	Dhaka	Gazipur	3033	0.269905	0.010687	0.054827	0.003239	0.384974	0.012664	0.214116	0.011984
30	35	Dhaka	Gopalganj	3035	0.320850	0.010246	0.071218	0.00374	0.370247	0.013516	0.206107	0.012336
30	39	Dhaka	Jamalpur	3039	0.390050	0.012178	0.097064	0.005222	0.433773	0.012288	0.253142	0.011640
30	48	Dhaka	Kishoreganj	3048	0.376753	0.011402	0.092055	0.004725	0.443115	0.011585	0.260482	0.011655
30	54	Dhaka	Madaripur	3054	0.347535	0.010543	0.080781	0.004201	0.410284	0.010973	0.234494	0.010300
30	56	Dhaka	Manikganj	3056	0.350399	0.009984	0.082209	0.004058	0.408142	0.010787	0.232671	0.009463
30	59	Dhaka	Munshiganj	3059	0.304189	0.011193	0.065426	0.003906	0.398097	0.011686	0.223413	0.012300
30	61	Dhaka	Mymensingh	3061	0.370625	0.009779	0.089531	0.004080	0.440434	0.01105	0.259206	0.011200
30	67	Dhaka	Narayanganj	3067	0.277878	0.012111	0.057403	0.003722	0.413474	0.013676	0.233862	0.014816
30	68	Dhaka	Narsingdi	3068	0.337502	0.010967	0.077886	0.004290	0.434201	0.010087	0.252370	0.010715
30	72	Dhaka	Netrakona	3072	0.391357	0.011524	0.097506	0.004921	0.436401	0.012764	0.256320	0.012730
30	82	Dhaka	Rajbari	3082	0.337815	0.009287	0.076842	0.003486	0.399703	0.011314	0.228048	0.010890
30	86	Dhaka	Shariatpur	3086	0.363339	0.011206	0.086687	0.004685	0.410399	0.013531	0.234816	0.013387
30	89	Dhaka	Sherpur	3089	0.380171	0.011989	0.092558	0.004987	0.431519	0.013071	0.252150	0.011698
30	93	Dhaka	Tangail	3093	0.351799	0.009859	0.082511	0.004003	0.419811	0.010387	0.242926	0.009346
40	1	Khulna	Bagerhat	4001	0.313895	0.009874	0.068438	0.003569	0.384495	0.01252	0.218439	0.012287
40	18	Khulna	Chuadanga	4018	0.341535	0.009905	0.078457	0.003637	0.411450	0.012182	0.236955	0.011846
40	41	Khulna	Jessore	4041	0.304627	0.008154	0.065367	0.002832	0.392005	0.009932	0.222237	0.010991
40	44	Khulna	Jhenaidah	4044	0.331546	0.008764	0.074603	0.003320	0.398641	0.010758	0.226236	0.010014
40	47	Khulna	Khulna	4047	0.290833	0.008259	0.061467	0.002732	0.382251	0.010080	0.213774	0.010455
40	50	Khulna	Kushtia	4050	0.336656	0.010088	0.076490	0.003852	0.417213	0.010694	0.239947	0.009986

40	55	Khulna	Magura	4055	0.335347	0.008405	0.075945	0.003245	0.388572	0.011728	0.218668	0.010511
40	57	Khulna	Meherpur	4057	0.337890	0.011701	0.076673	0.004376	0.402523	0.013639	0.230532	0.012249
40	65	Khulna	Narail	4065	0.316948	0.010455	0.069773	0.003826	0.367416	0.013799	0.205771	0.012986
40	87	Khulna	Satkhira	4087	0.329972	0.008411	0.074133	0.003162	0.398241	0.011649	0.227140	0.011464
50	10	Rajshahi	Bogra	5010	0.328276	0.008787	0.074226	0.003251	0.391054	0.009938	0.220601	0.008884
50	38	Rajshahi	Joypurhat	5038	0.301249	0.008256	0.064386	0.002829	0.368486	0.012972	0.206109	0.012880
50	64	Rajshahi	Naogaon	5064	0.334993	0.008201	0.075908	0.003103	0.405989	0.011966	0.234177	0.013100
50	69	Rajshahi	Natore	5069	0.333090	0.008561	0.075272	0.003233	0.385068	0.011904	0.216801	0.010629
50	70	Rajshahi	Nawabganj	5070	0.358142	0.010318	0.084990	0.004079	0.433217	0.013364	0.252223	0.013727
50	76	Rajshahi	Pabna	5076	0.345876	0.009754	0.080143	0.003776	0.417915	0.010823	0.240451	0.010124
50	81	Rajshahi	Rajshahi	5081	0.313892	0.007645	0.069284	0.002737	0.382433	0.010684	0.215127	0.010961
50	88	Rajshahi	Sirajganj	5088	0.367016	0.010439	0.087962	0.004168	0.450737	0.011444	0.267638	0.010939
55	27	Rangpur	Dinajpur	5527	0.329938	0.008184	0.074163	0.003092	0.408237	0.011210	0.191420	0.011770
55	32	Rangpur	Gaibandha	5532	0.372969	0.010634	0.090212	0.004354	0.430689	0.013396	0.206346	0.012932
55	49	Rangpur	Kurigram	5549	0.386578	0.010759	0.09576	0.004651	0.423308	0.013028	0.201389	0.016172
55	52	Rangpur	Lalmonirhat	5552	0.365209	0.011041	0.08683	0.004409	0.417064	0.012846	0.196426	0.015737
55	73	Rangpur	Nilphamari	5573	0.367535	0.009494	0.088047	0.003946	0.433638	0.013236	0.208809	0.012847
55	77	Rangpur	Panchagarh	5577	0.33844	0.009901	0.076838	0.003761	0.406442	0.011908	0.189608	0.014931
55	85	Rangpur	Rangpur	5585	0.347438	0.009342	0.080623	0.003598	0.419823	0.010421	0.198946	0.012333
55	94	Rangpur	Thakurgaon	5594	0.344857	0.008802	0.079336	0.003280	0.425884	0.013868	0.202960	0.012504
60	36	Sylhet	Habiganj	6036	0.393853	0.015101	0.099743	0.006297	0.443020	0.012166	0.295296	0.018013
60	58	Sylhet	Maulvibazar	6058	0.366606	0.016499	0.088828	0.006576	0.437458	0.011247	0.292898	0.019922
60	90	Sylhet	Sunamganj	6090	0.408595	0.015822	0.105343	0.006720	0.460588	0.014723	0.311577	0.019266
60	91	Sylhet	Sylhet	6091	0.368631	0.016550	0.090170	0.006572	0.439713	0.012191	0.292083	0.019028

Upazila level stunting and underweight measures

S2 = prevalence of stunting, seS2 = standard error of S2,
S3 = prevalence of severe stunting, seS3 = standard error of S3
U2 = prevalence of underweight, seU2 = standard error of U2,
U3 = prevalence of severe underweight, seU3 = standard error of U3
Nch=number of children under 5 years
UpzCode=Upazila geocode

Division	District	Upazila	UpzCode	U2	seU2	U3	seU3	S2	seS2	S3	seS3
Barisal	Barguna	Amtali	100409	0.34520	0.01405	0.07963	0.00532	0.39397	0.01675	0.22360	0.01490
Barisal	Barguna	Bamna	100419	0.31137	0.01684	0.06709	0.00560	0.38454	0.02018	0.21685	0.01785
Barisal	Barguna	Barguna Sadar	100428	0.31719	0.01283	0.06980	0.00479	0.38878	0.01606	0.22114	0.01463
Barisal	Barguna	Betagi	100447	0.31844	0.01501	0.06993	0.00560	0.37722	0.01821	0.21417	0.01579
Barisal	Barguna	Patharghata	100485	0.30280	0.01383	0.06460	0.00482	0.36901	0.01625	0.20785	0.01586
Barisal	Barisal	Agailjhara	100602	0.30400	0.01355	0.06493	0.00496	0.36842	0.01816	0.20485	0.01656
Barisal	Barisal	Babuganj	100603	0.28947	0.01443	0.06069	0.00513	0.36076	0.01981	0.19851	0.01531
Barisal	Barisal	Bakerganj	100607	0.31628	0.01379	0.06965	0.00515	0.38904	0.01565	0.22108	0.01344
Barisal	Barisal	Banari Para	100610	0.29566	0.01434	0.06255	0.00510	0.37267	0.02123	0.20792	0.01977
Barisal	Barisal	Gaurnadi	100632	0.31043	0.01158	0.06778	0.00454	0.37183	0.01494	0.20777	0.01355
Barisal	Barisal	Hizla	100636	0.37822	0.01642	0.09196	0.00633	0.40730	0.02069	0.23280	0.01902
Barisal	Barisal	Barisal Sadar (Kotwali)	100651	0.27289	0.01058	0.05607	0.00326	0.38528	0.01491	0.21708	0.01264
Barisal	Barisal	Mehendiganj	100662	0.36150	0.01248	0.08568	0.00507	0.40243	0.01575	0.22969	0.01376
Barisal	Barisal	Muladi	100669	0.34074	0.01345	0.07852	0.00540	0.36897	0.01918	0.20502	0.01459
Barisal	Barisal	Wazirpur	100694	0.31071	0.01254	0.06765	0.00476	0.36479	0.01803	0.20094	0.01468
Barisal	Bhola	Bhola Sadar	100918	0.36651	0.01178	0.08815	0.00461	0.43713	0.01521	0.25392	0.01241
Barisal	Bhola	Burhanuddin	100921	0.37444	0.01571	0.09088	0.00659	0.41637	0.02155	0.24108	0.01792
Barisal	Bhola	Char Fasson	100925	0.38260	0.01457	0.09409	0.00631	0.42788	0.01469	0.25146	0.01507
Barisal	Bhola	Daulatkhan	100929	0.38340	0.01571	0.09440	0.00637	0.43553	0.02242	0.25186	0.01703
Barisal	Bhola	Lalmohan	100954	0.39486	0.01550	0.09908	0.00683	0.41998	0.01851	0.24289	0.01610

Barisal	Bhola	Manpura	100965	0.40638	0.02602	0.10343	0.01116	0.46067	0.02623	0.27691	0.02252
Barisal	Bhola	Tazumuddin	100991	0.38303	0.01909	0.09359	0.00806	0.42548	0.02399	0.25182	0.02439
Barisal	Jhalokati	Jhalokati Sadar	104240	0.27494	0.01104	0.05646	0.00366	0.35738	0.01663	0.19695	0.01378
Barisal	Jhalokati	Kanthalia	104243	0.28939	0.01495	0.06081	0.00493	0.35627	0.02399	0.19687	0.01717
Barisal	Jhalokati	Nalchity	104273	0.29647	0.01246	0.06361	0.00485	0.38464	0.01819	0.21884	0.01552
Barisal	Jhalokati	Rajapur	104284	0.29454	0.01411	0.06286	0.00499	0.37856	0.01829	0.21092	0.01577
Barisal	Patuakhali	Bauphal	107838	0.33927	0.01334	0.07787	0.00519	0.40492	0.01500	0.23275	0.01306
Barisal	Patuakhali	Dashmina	107852	0.36136	0.01630	0.08517	0.00671	0.41636	0.02214	0.24333	0.01597
Barisal	Patuakhali	Dumki	107855	0.31665	0.01939	0.06958	0.00715	0.38249	0.02405	0.21547	0.02033
Barisal	Patuakhali	Galachipa	107857	0.36584	0.01095	0.08704	0.00454	0.41240	0.01362	0.23832	0.01335
Barisal	Patuakhali	Kala Para	107866	0.34429	0.01476	0.07910	0.00575	0.40340	0.01765	0.23278	0.01555
Barisal	Patuakhali	Mirzaganj	107876	0.31630	0.01438	0.06936	0.00552	0.38737	0.01842	0.21923	0.01528
Barisal	Patuakhali	Patuakhali Sadar	107895	0.32476	0.01195	0.07308	0.00444	0.40085	0.01343	0.22854	0.01274
Barisal	Pirojpur	Bhandaria	107914	0.29253	0.01469	0.06160	0.00519	0.36960	0.02024	0.20462	0.01836
Barisal	Pirojpur	Kawkhali	107947	0.28537	0.01373	0.05856	0.00455	0.39939	0.02093	0.23245	0.02143
Barisal	Pirojpur	Mathbaria	107958	0.30840	0.01515	0.06668	0.00517	0.38635	0.01573	0.21937	0.01552
Barisal	Pirojpur	Nazirpur	107976	0.31663	0.01387	0.06918	0.00500	0.37209	0.02073	0.20798	0.01712
Barisal	Pirojpur	Pirojpur Sadar	107980	0.27322	0.01323	0.05556	0.00443	0.36616	0.01836	0.20563	0.01518
Barisal	Pirojpur	Nesarabad (Swarupkati)	107987	0.27758	0.01533	0.05643	0.00526	0.39389	0.01995	0.22478	0.01867
Barisal	Pirojpur	Zianagar	107990	0.32036	0.01776	0.07040	0.00680	0.39460	0.02822	0.22777	0.02062
Chittagong	Bandarban	Alikadam	200304	0.44537	0.04318	0.12713	0.02069	0.48085	0.04068	0.28913	0.03379
Chittagong	Bandarban	Bandarban Sadar	200314	0.34859	0.03465	0.08712	0.01368	0.43830	0.01776	0.25941	0.01804
Chittagong	Bandarban	Lama	200351	0.35768	0.04452	0.08937	0.01702	0.48562	0.02356	0.29763	0.02506
Chittagong	Bandarban	Naikhongchhari	200373	0.44668	0.03855	0.12886	0.01941	0.49211	0.03357	0.30956	0.03508
Chittagong	Bandarban	Rowangchhari	200389	0.40940	0.05073	0.11028	0.02262	0.45876	0.02931	0.27674	0.02931
Chittagong	Bandarban	Ruma	200391	0.39138	0.05637	0.10466	0.02410	0.48213	0.02954	0.28668	0.02809
Chittagong	Bandarban	Thanchi	200395	0.43567	0.04879	0.12473	0.02219	0.50556	0.03081	0.30965	0.02796
Chittagong	Brahamanbaria	Akhaura	201202	0.35946	0.02307	0.08757	0.00861	0.40793	0.01559	0.23089	0.01226
Chittagong	Brahamanbaria	Banchharampur	201204	0.43230	0.03310	0.11705	0.01505	0.43255	0.01748	0.24759	0.01492
Chittagong	Brahamanbaria	Bijoynagar	201207	0.37714	0.02787	0.09388	0.01099	0.43154	0.01409	0.24822	0.01293
Chittagong	Brahamanbaria	Brahmanbaria Sadar	201213	0.34004	0.01997	0.08157	0.00712	0.42313	0.01420	0.24142	0.01170
Chittagong	Brahamanbaria	Ashuganj	201233	0.36859	0.02642	0.09222	0.01013	0.43151	0.02181	0.24598	0.02021
Chittagong	Brahamanbaria	Kasba	201263	0.37507	0.02480	0.09404	0.01003	0.39752	0.01372	0.22149	0.01109
Chittagong	Brahamanbaria	Nabinagar	201285	0.42170	0.03050	0.11313	0.01345	0.41152	0.01599	0.23391	0.01182

Chittagong	Brahamanbaria	Nasirnagar	201290	0.40766	0.02909	0.10679	0.01214	0.44915	0.01761	0.26365	0.01620
Chittagong	Brahamanbaria	Sarail	201294	0.39905	0.02681	0.10388	0.01150	0.43213	0.01869	0.24585	0.01608
Chittagong	Chandpur	Chandpur Sadar	201322	0.36894	0.01919	0.09252	0.00788	0.40569	0.01305	0.23127	0.01169
Chittagong	Chandpur	Faridganj	201345	0.39468	0.03395	0.10149	0.01456	0.38385	0.01428	0.21502	0.01275
Chittagong	Chandpur	Haim Char	201347	0.38069	0.03267	0.09519	0.01257	0.41660	0.02432	0.24179	0.01819
Chittagong	Chandpur	Hajiganj	201349	0.36626	0.02529	0.09042	0.01007	0.40217	0.01596	0.22945	0.01520
Chittagong	Chandpur	Kachua	201358	0.38458	0.02720	0.09708	0.01127	0.41028	0.01237	0.23593	0.01264
Chittagong	Chandpur	Matlab Dakshin	201376	0.39644	0.02486	0.10333	0.01116	0.40300	0.01596	0.23023	0.01534
Chittagong	Chandpur	Matlab Uttar	201379	0.36567	0.02616	0.08993	0.00986	0.40238	0.01662	0.23067	0.01393
Chittagong	Chandpur	Shahrasti	201395	0.37645	0.03035	0.09489	0.01269	0.39250	0.01541	0.22438	0.01504
Chittagong	Chittagong	Anowara	201504	0.32931	0.02931	0.07685	0.01067	0.42746	0.01676	0.24808	0.01665
Chittagong	Chittagong	Bayejid Bostami	201506	0.38326	0.02279	0.09974	0.00996	0.35714	0.02417	0.19099	0.01906
Chittagong	Chittagong	Banshkhali	201508	0.38911	0.02981	0.10012	0.01187	0.45090	0.01663	0.26475	0.01509
Chittagong	Chittagong	Bakalia	201510	0.41146	0.02944	0.11179	0.01375	0.36244	0.03332	0.18744	0.02190
Chittagong	Chittagong	Boalkhali	201512	0.29124	0.02737	0.06363	0.00900	0.43180	0.02195	0.24556	0.02119
Chittagong	Chittagong	Chandanaish	201518	0.28971	0.02993	0.06410	0.00943	0.43321	0.01902	0.24864	0.01749
Chittagong	Chittagong	Chandgaon	201519	0.35045	0.02770	0.08611	0.01077	0.34589	0.03321	0.18190	0.02370
Chittagong	Chittagong	Chittagong Port	201520	0.34831	0.03705	0.08443	0.01467	0.32141	0.03661	0.16924	0.02897
Chittagong	Chittagong	Double Mooring	201528	0.36314	0.02327	0.09104	0.00988	0.33854	0.02348	0.17635	0.01522
Chittagong	Chittagong	Fatikchhari	201533	0.33429	0.02743	0.08087	0.00988	0.45431	0.01514	0.26839	0.01655
Chittagong	Chittagong	Halishahar	201535	0.35662	0.02636	0.08834	0.01075	0.33847	0.02562	0.17661	0.02107
Chittagong	Chittagong	Hathazari	201537	0.25743	0.02933	0.05295	0.00883	0.43074	0.02387	0.24396	0.02382
Chittagong	Chittagong	Kotwali	201541	0.28168	0.02715	0.06358	0.00914	0.33409	0.03213	0.17824	0.02292
Chittagong	Chittagong	Khulshi	201543	0.39628	0.02688	0.10570	0.01233	0.36010	0.02282	0.19203	0.01779
Chittagong	Chittagong	Lohagara	201547	0.34498	0.02664	0.08320	0.00975	0.44984	0.02335	0.25999	0.01964
Chittagong	Chittagong	Mirsharai	201553	0.36474	0.02887	0.08980	0.01134	0.40955	0.01593	0.23271	0.01407
Chittagong	Chittagong	Pahartali	201555	0.37035	0.02994	0.09467	0.01296	0.33782	0.03041	0.17570	0.02562
Chittagong	Chittagong	Panchlaish	201557	0.36335	0.03217	0.09220	0.01334	0.33043	0.03568	0.17008	0.02651
Chittagong	Chittagong	Patiya	201561	0.27859	0.02833	0.05970	0.00849	0.44158	0.01667	0.25433	0.01921
Chittagong	Chittagong	Patenga	201565	0.37177	0.03576	0.09402	0.01460	0.33806	0.04355	0.18391	0.03148
Chittagong	Chittagong	Rangunia	201570	0.32633	0.02544	0.07738	0.00896	0.43460	0.01656	0.24982	0.01755
Chittagong	Chittagong	Raozan	201574	0.29899	0.02355	0.06666	0.00793	0.41072	0.01904	0.23184	0.01656
Chittagong	Chittagong	Sandwip	201578	0.41419	0.03597	0.11062	0.01550	0.42377	0.02225	0.24701	0.02023
Chittagong	Chittagong	Satkania	201582	0.32475	0.02487	0.07532	0.00867	0.42895	0.01698	0.24777	0.01410

Chittagong	Chittagong	Sitakunda	201586	0.24513	0.03172	0.05234	0.00861	0.42666	0.01843	0.24456	0.02089
Chittagong	Comilla	Barura	201909	0.39449	0.02848	0.10110	0.01199	0.38072	0.01538	0.21102	0.01164
Chittagong	Comilla	Brahman Para	201915	0.35731	0.02840	0.08598	0.01077	0.39001	0.01771	0.21618	0.01590
Chittagong	Comilla	Burichang	201918	0.31491	0.02594	0.07057	0.00903	0.39213	0.01537	0.21792	0.01393
Chittagong	Comilla	Chandina	201927	0.38943	0.02583	0.09906	0.01056	0.39496	0.01569	0.22207	0.01160
Chittagong	Comilla	Chauddagram	201931	0.36714	0.02903	0.09138	0.01161	0.40686	0.01153	0.23053	0.01156
Chittagong	Comilla	Comilla Sadar Dakshin	201933	0.35902	0.02179	0.08806	0.00841	0.39000	0.01173	0.21815	0.01055
Chittagong	Comilla	Daudkandi	201936	0.35402	0.02346	0.08578	0.00867	0.40799	0.01280	0.23121	0.01230
Chittagong	Comilla	Debidwar	201940	0.37680	0.02522	0.09437	0.01015	0.40578	0.01359	0.22988	0.01209
Chittagong	Comilla	Homna	201954	0.38770	0.02531	0.09993	0.01051	0.43700	0.02061	0.24997	0.01716
Chittagong	Comilla	Comilla Adarsha Sadar	201967	0.32138	0.01733	0.07512	0.00617	0.38955	0.01498	0.21621	0.01300
Chittagong	Comilla	Laksam	201972	0.38306	0.02350	0.09725	0.00960	0.41596	0.01333	0.23712	0.01225
Chittagong	Comilla	Manoharganj	201974	0.39256	0.03826	0.10150	0.01629	0.39951	0.01442	0.22375	0.01423
Chittagong	Comilla	Meghna	201975	0.32758	0.03372	0.07574	0.01203	0.42249	0.02257	0.23999	0.01840
Chittagong	Comilla	Muradnagar	201981	0.39582	0.02745	0.10239	0.01144	0.41621	0.01316	0.23671	0.01179
Chittagong	Comilla	Nangalkot	201987	0.42386	0.03597	0.11466	0.01630	0.41395	0.01319	0.23700	0.01115
Chittagong	Comilla	Titas	201994	0.39275	0.02988	0.10004	0.01275	0.41023	0.02376	0.22759	0.01772
Chittagong	Cox'S Bazar	Chakaria	202216	0.33223	0.03020	0.07813	0.01053	0.43500	0.01666	0.25173	0.01662
Chittagong	Cox'S Bazar	Cox'S Bazar Sadar	202224	0.37981	0.02566	0.10035	0.01015	0.46241	0.02156	0.27701	0.01967
Chittagong	Cox'S Bazar	Kutubdia	202245	0.35869	0.03959	0.08933	0.01518	0.46269	0.03806	0.27597	0.03128
Chittagong	Cox'S Bazar	Maheshkhali	202249	0.34270	0.04572	0.08183	0.01715	0.46134	0.02187	0.27472	0.02302
Chittagong	Cox'S Bazar	Pekua	202256	0.38537	0.03605	0.09888	0.01472	0.43111	0.02806	0.24953	0.02448
Chittagong	Cox'S Bazar	Ramu	202266	0.37561	0.03692	0.09470	0.01466	0.47726	0.02092	0.28583	0.01793
Chittagong	Cox'S Bazar	Teknaf	202290	0.42677	0.03591	0.11622	0.01537	0.50370	0.02836	0.30727	0.02889
Chittagong	Cox'S Bazar	Ukhia	202294	0.38856	0.03589	0.10025	0.01435	0.50987	0.02720	0.32056	0.02936
Chittagong	Feni	Chhagalnaiya	203014	0.33181	0.02217	0.07790	0.00832	0.40162	0.01694	0.22707	0.01524
Chittagong	Feni	Daganbhuiyan	203025	0.36248	0.03110	0.08935	0.01265	0.41844	0.01652	0.23491	0.01528
Chittagong	Feni	Feni Sadar	203029	0.31582	0.01900	0.07297	0.00657	0.41370	0.01488	0.23465	0.01418
Chittagong	Feni	Fulgazi	203041	0.28197	0.02641	0.06186	0.00808	0.40200	0.01396	0.22836	0.01521
Chittagong	Feni	Parshuram	203051	0.37412	0.02224	0.09517	0.00892	0.39546	0.01630	0.22542	0.01500
Chittagong	Feni	Sonagazi	203094	0.38543	0.02952	0.09732	0.01206	0.42848	0.01945	0.24695	0.01745
Chittagong	Khagrachhari	Dighinala	204643	0.33656	0.04155	0.07953	0.01542	0.43319	0.03054	0.25109	0.02590
Chittagong	Khagrachhari	Khagrachhari Sadar	204649	0.34650	0.02694	0.08528	0.01035	0.41387	0.02108	0.24148	0.01844
Chittagong	Khagrachhari	Lakshmichhari	204661	0.40505	0.04734	0.10696	0.02054	0.45506	0.02569	0.26807	0.02242

Chittagong	Khagrachhari	Mahalchhari	204665	0.35241	0.04513	0.08467	0.01683	0.43455	0.02740	0.26026	0.02611
Chittagong	Khagrachhari	Manikchhari	204667	0.43611	0.03535	0.12293	0.01649	0.47236	0.03823	0.29821	0.03532
Chittagong	Khagrachhari	Matiranga	204670	0.37687	0.03403	0.09390	0.01345	0.45454	0.02296	0.26967	0.02046
Chittagong	Khagrachhari	Panchhari	204677	0.39190	0.04109	0.10191	0.01719	0.45814	0.03760	0.28068	0.03763
Chittagong	Khagrachhari	Ramgarh	204680	0.39848	0.03317	0.10629	0.01419	0.46378	0.02245	0.27961	0.02335
Chittagong	Lakshmipur	Kamalnagar	205133	0.40112	0.03645	0.10403	0.01438	0.45758	0.02200	0.27143	0.02057
Chittagong	Lakshmipur	Lakshmipur Sadar	205143	0.39124	0.02687	0.10028	0.01118	0.41352	0.01374	0.23604	0.01236
Chittagong	Lakshmipur	Roypur	205158	0.37486	0.02717	0.09287	0.01103	0.41684	0.02059	0.23909	0.01687
Chittagong	Lakshmipur	Ramganj	205165	0.38838	0.03623	0.09926	0.01529	0.37891	0.01442	0.21128	0.01499
Chittagong	Lakshmipur	Ramgati	205173	0.43080	0.02760	0.11694	0.01196	0.46511	0.02185	0.28118	0.01784
Chittagong	Noakhali	Begumganj	207507	0.36745	0.02556	0.09134	0.01025	0.42319	0.01578	0.24389	0.01533
Chittagong	Noakhali	Chatkhil	207510	0.34682	0.03265	0.08275	0.01249	0.38364	0.01797	0.21453	0.01446
Chittagong	Noakhali	Companiganj	207521	0.36734	0.02900	0.08989	0.01122	0.42292	0.02276	0.24593	0.01910
Chittagong	Noakhali	Hatiya	207536	0.42415	0.02965	0.11465	0.01283	0.46706	0.02127	0.28204	0.02013
Chittagong	Noakhali	Kabirhat	207547	0.40780	0.02888	0.10797	0.01241	0.45914	0.01624	0.27160	0.01649
Chittagong	Noakhali	Senbagh	207580	0.35640	0.02863	0.08758	0.01182	0.42065	0.01389	0.23964	0.01554
Chittagong	Noakhali	Sonaimuri	207583	0.37553	0.03658	0.09529	0.01571	0.39745	0.01629	0.22242	0.01466
Chittagong	Noakhali	Subarnachar	207585	0.40282	0.03280	0.10479	0.01330	0.46863	0.01914	0.27977	0.02051
Chittagong	Noakhali	Noakhali Sadar (Sudharam)	207587	0.41990	0.02573	0.11660	0.01290	0.43758	0.01428	0.25556	0.01381
Chittagong	Rangamati	Baghai Chhari	208407	0.34712	0.04593	0.08531	0.01731	0.44371	0.02786	0.26572	0.02324
Chittagong	Rangamati	Barkal	208421	0.28250	0.05485	0.06436	0.01873	0.44062	0.02604	0.26034	0.02717
Chittagong	Rangamati	Kawkhali (Betbunia)	208425	0.33490	0.03682	0.07929	0.01314	0.44238	0.03177	0.25173	0.02990
Chittagong	Rangamati	Belai Chhari	208429	0.34593	0.06872	0.08355	0.02778	0.47211	0.05204	0.29101	0.04043
Chittagong	Rangamati	Kaptai	208436	0.32496	0.04142	0.07911	0.01539	0.39764	0.02999	0.23389	0.02810
Chittagong	Rangamati	Jurai Chhari	208447	0.34911	0.05394	0.08682	0.02145	0.43052	0.03960	0.25715	0.03427
Chittagong	Rangamati	Langadu	208458	0.33973	0.04288	0.08224	0.01603	0.44258	0.02333	0.26310	0.02678
Chittagong	Rangamati	Naniarchar	208475	0.31809	0.04238	0.07188	0.01545	0.42222	0.02695	0.24822	0.02775
Chittagong	Rangamati	Rajasthali	208478	0.32181	0.04673	0.07523	0.01708	0.43764	0.04201	0.25846	0.03093
Chittagong	Rangamati	Rangamati Sadar	208487	0.31253	0.02395	0.07267	0.00827	0.38320	0.01876	0.21522	0.01501
Dhaka	Dhaka	Adabor	302602	0.23093	0.02321	0.04327	0.00670	0.33919	0.02813	0.17493	0.01965
Dhaka	Dhaka	Badda	302604	0.20931	0.02325	0.03658	0.00602	0.29814	0.03550	0.14770	0.02328
Dhaka	Dhaka	Bangshal	302605	0.19259	0.01845	0.03206	0.00471	0.34618	0.02985	0.18514	0.02691
Dhaka	Dhaka	Biman Bandar	302606	0.20491	0.03393	0.03729	0.00965	0.34795	0.06358	0.19350	0.03971
Dhaka	Dhaka	Cantonment	302608	0.17685	0.02414	0.02830	0.00566	0.30431	0.04630	0.15039	0.02961

Dhaka	Dhaka	Chak Bazar	302609	0.20707	0.02304	0.03632	0.00624	0.34429	0.03027	0.17968	0.02270
Dhaka	Dhaka	Dakshinkhan	302610	0.20010	0.03437	0.03388	0.00903	0.27882	0.05241	0.12994	0.03055
Dhaka	Dhaka	Darus Salam	302611	0.22454	0.02039	0.04096	0.00586	0.31768	0.02801	0.15993	0.02015
Dhaka	Dhaka	Demra	302612	0.21031	0.02308	0.03714	0.00606	0.29542	0.03550	0.14873	0.02178
Dhaka	Dhaka	Dhamrai	302614	0.31581	0.01213	0.06946	0.00440	0.40524	0.01100	0.22876	0.01175
Dhaka	Dhaka	Dhanmondi	302616	0.17766	0.02367	0.02860	0.00621	0.31447	0.04028	0.16306	0.03091
Dhaka	Dhaka	Dohar	302618	0.31507	0.01391	0.06956	0.00517	0.39839	0.01580	0.22297	0.01426
Dhaka	Dhaka	Gendaria	302624	0.19118	0.02058	0.03203	0.00509	0.32440	0.03483	0.16447	0.02330
Dhaka	Dhaka	Gulshan	302626	0.21649	0.02227	0.03928	0.00630	0.33505	0.03161	0.17439	0.02290
Dhaka	Dhaka	Hazaribagh	302628	0.23264	0.01713	0.04392	0.00499	0.35920	0.02477	0.19432	0.01881
Dhaka	Dhaka	Jatrabari	302629	0.20840	0.02732	0.03633	0.00718	0.31930	0.03403	0.16055	0.02707
Dhaka	Dhaka	Kafrul	302630	0.21168	0.02117	0.03761	0.00554	0.31175	0.02684	0.15700	0.02074
Dhaka	Dhaka	Kadamtali	302632	0.20942	0.02729	0.03653	0.00703	0.31210	0.03523	0.15434	0.02519
Dhaka	Dhaka	Kalabagan	302633	0.18214	0.02316	0.02950	0.00573	0.31901	0.04222	0.16782	0.02891
Dhaka	Dhaka	Kamrangir Char	302634	0.24708	0.03233	0.04663	0.00959	0.33847	0.04648	0.17186	0.02939
Dhaka	Dhaka	Khilgaon	302636	0.22430	0.01911	0.04120	0.00539	0.33240	0.02977	0.16871	0.01818
Dhaka	Dhaka	Khilkhet	302637	0.21862	0.01911	0.03978	0.00490	0.29465	0.02620	0.14890	0.01834
Dhaka	Dhaka	Keraniganj	302638	0.26629	0.01659	0.05316	0.00506	0.40938	0.02456	0.22840	0.02467
Dhaka	Dhaka	Kotwali	302640	0.18677	0.02092	0.03084	0.00553	0.34868	0.03318	0.18736	0.02722
Dhaka	Dhaka	Lalbagh	302642	0.23995	0.01947	0.04557	0.00559	0.34756	0.02267	0.18534	0.01610
Dhaka	Dhaka	Mirpur	302648	0.18522	0.01863	0.03017	0.00452	0.29971	0.02989	0.14975	0.01943
Dhaka	Dhaka	Mohammadpur	302650	0.21839	0.01939	0.03980	0.00523	0.34615	0.02874	0.18261	0.02252
Dhaka	Dhaka	Motijheel	302654	0.19113	0.01895	0.03214	0.00475	0.32512	0.03159	0.16877	0.02502
Dhaka	Dhaka	Nawabganj	302662	0.30887	0.01364	0.06723	0.00506	0.39049	0.01595	0.21674	0.01298
Dhaka	Dhaka	New Market	302663	0.16782	0.03119	0.02583	0.00783	0.31484	0.05851	0.16433	0.04149
Dhaka	Dhaka	Pallabi	302664	0.22268	0.01843	0.04084	0.00498	0.32107	0.02671	0.16507	0.01585
Dhaka	Dhaka	Paltan	302665	0.16988	0.02543	0.02658	0.00653	0.32815	0.04721	0.17589	0.03568
Dhaka	Dhaka	Ramna	302666	0.19315	0.02081	0.03262	0.00550	0.33140	0.03397	0.17225	0.02570
Dhaka	Dhaka	Rampura	302667	0.19375	0.02306	0.03245	0.00573	0.31804	0.03579	0.16112	0.02275
Dhaka	Dhaka	Sabujbagh	302668	0.21388	0.01921	0.03794	0.00513	0.33057	0.02757	0.16870	0.02028
Dhaka	Dhaka	Savar	302672	0.23553	0.01450	0.04433	0.00403	0.37046	0.02082	0.20247	0.01787
Dhaka	Dhaka	Shah Ali	302674	0.22273	0.01997	0.04156	0.00577	0.32211	0.02884	0.16594	0.01895
Dhaka	Dhaka	Shahbagh	302675	0.18020	0.02727	0.02933	0.00713	0.32205	0.04331	0.16400	0.03184
Dhaka	Dhaka	Shyampur	302676	0.21805	0.02145	0.03879	0.00607	0.33124	0.02849	0.16809	0.02218

Dhaka	Dhaka	Sher-e-bangla Nagar	302680	0.21358	0.02591	0.03939	0.00712	0.33949	0.03751	0.17596	0.03092
Dhaka	Dhaka	Sutrapur	302688	0.18183	0.01922	0.02953	0.00453	0.33088	0.02943	0.17219	0.02546
Dhaka	Dhaka	Tejgaon	302690	0.19583	0.02456	0.03310	0.00630	0.31372	0.03808	0.16308	0.03100
Dhaka	Dhaka	Tejgaon Ind. Area	302692	0.22597	0.02698	0.04195	0.00786	0.34545	0.03991	0.18249	0.02909
Dhaka	Dhaka	Turag	302693	0.24661	0.02418	0.04782	0.00704	0.31773	0.03732	0.15877	0.02356
Dhaka	Dhaka	Uttara	302695	0.20074	0.01928	0.03536	0.00489	0.35502	0.03892	0.19127	0.02741
Dhaka	Dhaka	Uttar Khan	302696	0.23332	0.04155	0.04353	0.01206	0.30121	0.05885	0.15527	0.03876
Dhaka	Faridpur	Alfadanga	302903	0.34083	0.01291	0.07789	0.00503	0.37935	0.01776	0.21006	0.01527
Dhaka	Faridpur	Bhanga	302910	0.35372	0.01141	0.08304	0.00458	0.40078	0.01535	0.22853	0.01279
Dhaka	Faridpur	Boalmari	302918	0.35556	0.01104	0.08327	0.00445	0.41162	0.01360	0.23648	0.01208
Dhaka	Faridpur	Char Bhadrasan	302921	0.37542	0.02615	0.09078	0.01070	0.42068	0.03632	0.24771	0.03333
Dhaka	Faridpur	Faridpur Sadar	302947	0.31461	0.00984	0.06933	0.00361	0.40940	0.01177	0.23497	0.01069
Dhaka	Faridpur	Madhukhali	302956	0.32940	0.01157	0.07368	0.00449	0.39163	0.01660	0.22030	0.01579
Dhaka	Faridpur	Nagarkanda	302962	0.34677	0.01149	0.07996	0.00431	0.39234	0.01527	0.22092	0.01416
Dhaka	Faridpur	Sadarpur	302984	0.36754	0.01338	0.08777	0.00555	0.40249	0.01944	0.23031	0.01507
Dhaka	Faridpur	Saltha	302990	0.37667	0.01331	0.09112	0.00540	0.40221	0.01974	0.22879	0.01741
Dhaka	Gazipur	Gazipur Sadar	303330	0.24216	0.01420	0.04610	0.00398	0.37556	0.01872	0.20572	0.01607
Dhaka	Gazipur	Kaliakair	303332	0.27679	0.01355	0.05723	0.00409	0.38254	0.01482	0.21096	0.01251
Dhaka	Gazipur	Kaliganj	303334	0.29878	0.01122	0.06332	0.00401	0.39657	0.01436	0.22388	0.01388
Dhaka	Gazipur	Kapasia	303336	0.31999	0.01107	0.07083	0.00431	0.38589	0.01463	0.21739	0.01517
Dhaka	Gazipur	Sreepur	303386	0.30480	0.01189	0.06573	0.00425	0.41102	0.01546	0.23680	0.01414
Dhaka	Gopalganj	Gopalganj Sadar	303532	0.30438	0.01055	0.06567	0.00376	0.36317	0.01560	0.20032	0.01302
Dhaka	Gopalganj	Kashiani	303543	0.31978	0.01271	0.07051	0.00458	0.36973	0.01664	0.20646	0.01363
Dhaka	Gopalganj	Kotali Para	303551	0.32308	0.01326	0.07184	0.00494	0.36875	0.01739	0.20557	0.01598
Dhaka	Gopalganj	Muksudpur	303558	0.34015	0.01111	0.07815	0.00431	0.38226	0.01361	0.21315	0.01282
Dhaka	Gopalganj	Tungi Para	303591	0.31837	0.01674	0.07019	0.00597	0.36468	0.02085	0.20606	0.02164
Dhaka	Jamalpur	Bakshiganj	303907	0.40822	0.02232	0.10402	0.00945	0.43744	0.02351	0.25462	0.02076
Dhaka	Jamalpur	Dewanganj	303915	0.42041	0.01930	0.10927	0.00834	0.46930	0.02001	0.27827	0.02245
Dhaka	Jamalpur	Islampur	303929	0.41478	0.01848	0.10681	0.00814	0.44445	0.02037	0.26288	0.01687
Dhaka	Jamalpur	Jamalpur Sadar	303936	0.35582	0.01020	0.08382	0.00429	0.42139	0.01170	0.24396	0.01035
Dhaka	Jamalpur	Madarganj	303958	0.41018	0.01539	0.10468	0.00666	0.43955	0.01659	0.25742	0.01527
Dhaka	Jamalpur	Melandaha	303961	0.39267	0.01470	0.09761	0.00632	0.42080	0.01814	0.24476	0.01534
Dhaka	Jamalpur	Sarishabari	303985	0.36064	0.01162	0.08578	0.00484	0.41695	0.01266	0.23952	0.01396
Dhaka	Kishoreganj	Austagram	304802	0.40519	0.01949	0.10311	0.00825	0.44803	0.02166	0.26311	0.02232

Dhaka	Kishoreganj	Bajitpur	304806	0.38020	0.01536	0.09345	0.00672	0.44841	0.01740	0.26387	0.01569
Dhaka	Kishoreganj	Bhairab	304811	0.35048	0.01618	0.08260	0.00639	0.45844	0.02098	0.26911	0.01700
Dhaka	Kishoreganj	Hossainpur	304827	0.37730	0.01280	0.09169	0.00529	0.44512	0.01688	0.26424	0.01624
Dhaka	Kishoreganj	Itna	304833	0.41404	0.01768	0.10671	0.00742	0.45500	0.02165	0.26869	0.02075
Dhaka	Kishoreganj	Karimganj	304842	0.37761	0.01615	0.09175	0.00665	0.42691	0.01623	0.24666	0.01519
Dhaka	Kishoreganj	Katiadi	304845	0.38508	0.01362	0.09496	0.00576	0.44569	0.01623	0.26474	0.01497
Dhaka	Kishoreganj	Kishoreganj Sadar	304849	0.35114	0.01263	0.08306	0.00494	0.44569	0.01496	0.26282	0.01349
Dhaka	Kishoreganj	Kuliar Char	304854	0.36990	0.01781	0.08913	0.00717	0.44189	0.02286	0.26250	0.01985
Dhaka	Kishoreganj	Mithamain	304859	0.40521	0.01849	0.10312	0.00794	0.46530	0.02073	0.28015	0.02252
Dhaka	Kishoreganj	Nikli	304876	0.40302	0.02241	0.10177	0.00925	0.44793	0.02269	0.26286	0.02288
Dhaka	Kishoreganj	Pakundia	304879	0.34666	0.01405	0.08018	0.00568	0.41037	0.01559	0.23502	0.01517
Dhaka	Kishoreganj	Tarail	304892	0.38457	0.01588	0.09458	0.00668	0.42337	0.01953	0.24541	0.01729
Dhaka	Madaripur	Kalkini	305440	0.35120	0.01196	0.08235	0.00494	0.39323	0.01478	0.22336	0.01331
Dhaka	Madaripur	Madaripur Sadar	305454	0.32949	0.01030	0.07427	0.00390	0.41564	0.01159	0.23762	0.01094
Dhaka	Madaripur	Rajoir	305480	0.34328	0.01429	0.07890	0.00560	0.41077	0.01618	0.23488	0.01289
Dhaka	Madaripur	Shib Char	305487	0.36615	0.01340	0.08753	0.00527	0.41883	0.01530	0.24040	0.01454
Dhaka	Manikganj	Daulatpur	305610	0.41348	0.01733	0.10742	0.00797	0.43741	0.02036	0.25521	0.01714
Dhaka	Manikganj	Ghior	305622	0.32949	0.01421	0.07362	0.00528	0.39986	0.01466	0.22701	0.01355
Dhaka	Manikganj	Harirampur	305628	0.35466	0.01450	0.08371	0.00553	0.41149	0.01525	0.23547	0.01347
Dhaka	Manikganj	Manikganj Sadar	305646	0.32009	0.01077	0.07130	0.00385	0.40052	0.01239	0.22634	0.01076
Dhaka	Manikganj	Saturia	305670	0.34732	0.01423	0.08006	0.00562	0.41040	0.01663	0.23330	0.01371
Dhaka	Manikganj	Shibalaya	305678	0.33877	0.01220	0.07753	0.00477	0.40241	0.01559	0.23017	0.01243
Dhaka	Manikganj	Singair	305682	0.35285	0.01203	0.08271	0.00480	0.39983	0.01500	0.22582	0.01313
Dhaka	Munshiganj	Gazaria	305924	0.29735	0.01263	0.06331	0.00438	0.38922	0.01657	0.21495	0.01474
Dhaka	Munshiganj	Lohajang	305944	0.31118	0.01382	0.06767	0.00509	0.41317	0.01641	0.23558	0.01421
Dhaka	Munshiganj	Munshiganj Sadar	305956	0.30227	0.01296	0.06509	0.00460	0.40141	0.01563	0.22594	0.01516
Dhaka	Munshiganj	Serajdikhan	305974	0.30985	0.01366	0.06711	0.00488	0.39475	0.01485	0.21963	0.01386
Dhaka	Munshiganj	Sreenagar	305984	0.30407	0.01432	0.06509	0.00500	0.40324	0.01799	0.22706	0.01663
Dhaka	Munshiganj	Tongibari	305994	0.29952	0.01515	0.06391	0.00529	0.38494	0.01725	0.21655	0.01492
Dhaka	Mymensingh	Bhaluka	306113	0.33540	0.01279	0.07664	0.00464	0.42434	0.01474	0.24555	0.01381
Dhaka	Mymensingh	Dhobaura	306116	0.42235	0.01753	0.11014	0.00794	0.45511	0.01809	0.27112	0.01571
Dhaka	Mymensingh	Fulbaria	306120	0.36881	0.01220	0.08855	0.00476	0.43707	0.01546	0.25772	0.01622
Dhaka	Mymensingh	Gaffargaon	306122	0.35207	0.00958	0.08250	0.00397	0.41575	0.01366	0.23994	0.01326
Dhaka	Mymensingh	Gauripur	306123	0.37129	0.01199	0.08933	0.00487	0.43465	0.01330	0.25517	0.01205

Dhaka	Mymensingh	Haluaghat	306124	0.38678	0.01309	0.09532	0.00563	0.43739	0.01585	0.25623	0.01367
Dhaka	Mymensingh	Ishwarganj	306131	0.38293	0.01209	0.09379	0.00502	0.44096	0.01492	0.26083	0.01456
Dhaka	Mymensingh	Mymensingh Sadar	306152	0.34353	0.01148	0.08060	0.00452	0.43909	0.01548	0.25648	0.01354
Dhaka	Mymensingh	Muktagachha	306165	0.36528	0.01176	0.08714	0.00487	0.45172	0.01272	0.26823	0.01234
Dhaka	Mymensingh	Nandail	306172	0.38841	0.01224	0.09584	0.00514	0.45491	0.01686	0.27231	0.01856
Dhaka	Mymensingh	Phulpur	306181	0.38791	0.01234	0.09554	0.00520	0.44890	0.01342	0.26525	0.01302
Dhaka	Mymensingh	Trishal	306194	0.37644	0.01479	0.09147	0.00578	0.44406	0.01773	0.26211	0.01472
Dhaka	Narayanganj	Araihazar	306702	0.34866	0.01586	0.08123	0.00589	0.48999	0.01957	0.29465	0.02175
Dhaka	Narayanganj	Sonargaon	306704	0.29384	0.01334	0.06209	0.00446	0.43075	0.01527	0.24821	0.01604
Dhaka	Narayanganj	Bandar	306706	0.27368	0.01372	0.05551	0.00439	0.39830	0.01675	0.22219	0.01438
Dhaka	Narayanganj	Narayanganj Sadar	306758	0.24379	0.01535	0.04653	0.00440	0.38198	0.01808	0.20773	0.01870
Dhaka	Narayanganj	Rupganj	306768	0.29130	0.01354	0.06130	0.00441	0.42153	0.01654	0.24219	0.01534
Dhaka	Narsingdi	Belabo	306807	0.34568	0.01701	0.07947	0.00658	0.42182	0.01796	0.24413	0.01595
Dhaka	Narsingdi	Manohardi	306852	0.33970	0.01212	0.07770	0.00488	0.40868	0.01378	0.23120	0.01326
Dhaka	Narsingdi	Narsingdi Sadar	306860	0.31479	0.01232	0.07022	0.00440	0.43908	0.01448	0.25647	0.01550
Dhaka	Narsingdi	Palash	306863	0.29273	0.01356	0.06225	0.00471	0.41948	0.01488	0.24012	0.01468
Dhaka	Narsingdi	Roypura	306864	0.38116	0.01653	0.09416	0.00707	0.45405	0.01651	0.26796	0.01462
Dhaka	Narsingdi	Shibpur	306876	0.31403	0.01180	0.06839	0.00414	0.41735	0.01398	0.23895	0.01484
Dhaka	Netrakona	Atpara	307204	0.39395	0.01279	0.09789	0.00563	0.43560	0.01596	0.25522	0.01461
Dhaka	Netrakona	Barhatta	307209	0.39357	0.01458	0.09792	0.00614	0.44234	0.01552	0.25970	0.01577
Dhaka	Netrakona	Durgapur	307218	0.39194	0.01293	0.09736	0.00524	0.43630	0.01514	0.25668	0.01460
Dhaka	Netrakona	Khaliajuri	307238	0.40667	0.01862	0.10307	0.00784	0.46108	0.02165	0.27451	0.02166
Dhaka	Netrakona	Kalmakanda	307240	0.40556	0.01471	0.10317	0.00644	0.44507	0.01693	0.26326	0.01569
Dhaka	Netrakona	Kendua	307247	0.39470	0.01353	0.09866	0.00607	0.43322	0.01396	0.25520	0.01315
Dhaka	Netrakona	Madan	307256	0.41103	0.01674	0.10503	0.00719	0.45189	0.01846	0.26750	0.01883
Dhaka	Netrakona	Mohanganj	307263	0.38355	0.01216	0.09474	0.00506	0.42805	0.01697	0.24935	0.01566
Dhaka	Netrakona	Netrokona Sadar	307274	0.36943	0.01089	0.08996	0.00454	0.42105	0.01230	0.24374	0.01168
Dhaka	Netrakona	Purbadhala	307283	0.38276	0.01207	0.09402	0.00507	0.43138	0.01443	0.25332	0.01389
Dhaka	Rajbari	Balia Kandi	308207	0.32453	0.01118	0.07153	0.00414	0.36941	0.01660	0.20605	0.01542
Dhaka	Rajbari	Goalandaghat	308229	0.37479	0.01519	0.09096	0.00657	0.46396	0.02247	0.27750	0.02034
Dhaka	Rajbari	Kalukhali	308247	0.33969	0.01135	0.07689	0.00440	0.38511	0.01593	0.21760	0.01429
Dhaka	Rajbari	Pangsha	308273	0.35395	0.01183	0.08272	0.00463	0.40349	0.01282	0.23002	0.01287
Dhaka	Rajbari	Rajbari Sadar	308276	0.31898	0.01113	0.07033	0.00412	0.39885	0.01299	0.22694	0.01088
Dhaka	Shariatpur	Bhedarganj	308614	0.37676	0.01530	0.09137	0.00632	0.41531	0.02110	0.23985	0.01937

Dhaka	Shariatpur	Damudya	308625	0.35174	0.01476	0.08259	0.00588	0.40316	0.01738	0.22739	0.01769
Dhaka	Shariatpur	Gosairhat	308636	0.38844	0.01606	0.09656	0.00721	0.40620	0.02077	0.23238	0.01830
Dhaka	Shariatpur	Naria	308665	0.34700	0.01215	0.08084	0.00503	0.42138	0.01327	0.24242	0.01341
Dhaka	Shariatpur	Shariatpur Sadar	308669	0.34204	0.01336	0.07861	0.00526	0.40329	0.01526	0.22941	0.01404
Dhaka	Shariatpur	Zanjira	308694	0.36732	0.01390	0.08789	0.00570	0.40657	0.01918	0.23127	0.01682
Dhaka	Sherpur	Jhenaigati	308937	0.36955	0.01282	0.08818	0.00520	0.42150	0.01735	0.24191	0.01640
Dhaka	Sherpur	Nakla	308967	0.37333	0.01324	0.09004	0.00578	0.41440	0.01828	0.23899	0.01550
Dhaka	Sherpur	Nalitabari	308970	0.37660	0.01540	0.09099	0.00614	0.41253	0.01605	0.23752	0.01392
Dhaka	Sherpur	Sherpur Sadar	308988	0.38466	0.01397	0.09448	0.00593	0.45159	0.01625	0.26886	0.01478
Dhaka	Sherpur	Sreebardi	308990	0.38641	0.01552	0.09487	0.00646	0.43049	0.01776	0.25056	0.01473
Dhaka	Tangail	Basail	309309	0.32738	0.01396	0.07290	0.00529	0.38595	0.02145	0.21390	0.01454
Dhaka	Tangail	Bhuapur	309319	0.37395	0.01489	0.09170	0.00687	0.42690	0.01579	0.24485	0.01284
Dhaka	Tangail	Delduar	309323	0.33189	0.01173	0.07473	0.00440	0.41469	0.01539	0.23847	0.01356
Dhaka	Tangail	Dhanbari	309325	0.36727	0.01413	0.08778	0.00564	0.43925	0.01621	0.26086	0.01720
Dhaka	Tangail	Ghatail	309328	0.35153	0.01283	0.08236	0.00501	0.39868	0.01534	0.22404	0.01032
Dhaka	Tangail	Gopalpur	309338	0.36241	0.01172	0.08609	0.00474	0.40654	0.01542	0.23604	0.01338
Dhaka	Tangail	Kalihati	309347	0.35460	0.01234	0.08295	0.00511	0.43881	0.01325	0.25695	0.01278
Dhaka	Tangail	Madhupur	309357	0.37119	0.01236	0.08910	0.00517	0.42109	0.01524	0.24542	0.01492
Dhaka	Tangail	Mirzapur	309366	0.31939	0.01109	0.07088	0.00402	0.39917	0.01208	0.22749	0.01227
Dhaka	Tangail	Nagarpur	309376	0.38096	0.01278	0.09338	0.00523	0.44137	0.01397	0.26026	0.01287
Dhaka	Tangail	Sakhipur	309385	0.36208	0.01560	0.08622	0.00647	0.40194	0.01908	0.22746	0.01284
Dhaka	Tangail	Tangail Sadar	309395	0.33386	0.00926	0.07672	0.00359	0.44262	0.01374	0.26231	0.01310
Khulna	Bagerhat	Bagerhat Sadar	400108	0.28409	0.01006	0.05843	0.00332	0.37865	0.01378	0.21250	0.01349
Khulna	Bagerhat	Chitalmari	400114	0.33226	0.01444	0.07444	0.00555	0.37366	0.02411	0.20992	0.01805
Khulna	Bagerhat	Fakirhat	400134	0.29403	0.01451	0.06169	0.00503	0.37024	0.01874	0.20879	0.01488
Khulna	Bagerhat	Kachua	400138	0.32111	0.01561	0.07076	0.00547	0.39576	0.01875	0.22650	0.01933
Khulna	Bagerhat	Mollahat	400156	0.33995	0.01555	0.07733	0.00605	0.37214	0.02221	0.20930	0.02018
Khulna	Bagerhat	Mongla	400158	0.31213	0.01269	0.06855	0.00456	0.42722	0.02067	0.25074	0.01728
Khulna	Bagerhat	Morrelganj	400160	0.31800	0.01323	0.06985	0.00490	0.37885	0.01633	0.21437	0.01428
Khulna	Bagerhat	Rampal	400173	0.31326	0.01325	0.06772	0.00491	0.38864	0.01556	0.22090	0.01597
Khulna	Bagerhat	Sarankhola	400177	0.32375	0.02294	0.07176	0.00812	0.40118	0.02816	0.23358	0.02482
Khulna	Chuadanga	Alamdanga	401807	0.34424	0.01089	0.07939	0.00409	0.40840	0.01498	0.23379	0.01479
Khulna	Chuadanga	Chuadanga Sadar	401823	0.33587	0.01149	0.07679	0.00442	0.41358	0.01480	0.23910	0.01262
Khulna	Chuadanga	Damurhuda	401831	0.34382	0.01172	0.07906	0.00428	0.41096	0.01424	0.23692	0.01432

Khulna	Chuadanga	Jiban Nagar	401855	0.34247	0.01385	0.07859	0.00525	0.41427	0.01836	0.23924	0.01325
Khulna	Jessore	Abhaynagar	404104	0.28867	0.01089	0.05998	0.00371	0.38278	0.01524	0.21388	0.01260
Khulna	Jessore	Bagher Para	404109	0.32063	0.01080	0.07062	0.00408	0.39923	0.01300	0.22737	0.01324
Khulna	Jessore	Chaugachha	404111	0.31742	0.01015	0.06930	0.00362	0.38859	0.01381	0.22164	0.01521
Khulna	Jessore	Jhikargachha	404123	0.31633	0.01024	0.06891	0.00361	0.38898	0.01331	0.21970	0.01266
Khulna	Jessore	Keshabpur	404138	0.31401	0.01066	0.06811	0.00388	0.38137	0.01242	0.21596	0.01287
Khulna	Jessore	Kotwali	404147	0.27623	0.00942	0.05662	0.00292	0.39872	0.01476	0.22708	0.01376
Khulna	Jessore	Manirampur	404161	0.31714	0.00996	0.06935	0.00363	0.38760	0.01207	0.21852	0.01225
Khulna	Jessore	Sharsha	404190	0.32391	0.01039	0.07146	0.00392	0.39805	0.01256	0.22661	0.01271
Khulna	Jhenaidah	Harinakunda	404414	0.35401	0.01306	0.08236	0.00489	0.39117	0.01715	0.22067	0.01491
Khulna	Jhenaidah	Jhenaidah Sadar	404419	0.32083	0.00958	0.07129	0.00366	0.39943	0.01114	0.22708	0.01040
Khulna	Jhenaidah	Kaliganj	404433	0.31912	0.00994	0.07018	0.00363	0.39982	0.01307	0.22762	0.01171
Khulna	Jhenaidah	Kotchandpur	404442	0.31054	0.01161	0.06745	0.00412	0.37835	0.01490	0.20934	0.01261
Khulna	Jhenaidah	Maheshpur	404471	0.33598	0.01118	0.07576	0.00426	0.39720	0.01432	0.22482	0.01225
Khulna	Jhenaidah	Shailkupa	404480	0.34596	0.01104	0.07952	0.00428	0.40957	0.01289	0.23464	0.01188
Khulna	Khulna	Batiaghata	404712	0.31697	0.01232	0.06915	0.00441	0.39444	0.01628	0.22475	0.01607
Khulna	Khulna	Dacope	404717	0.31660	0.01581	0.06880	0.00601	0.39443	0.02050	0.22492	0.01898
Khulna	Khulna	Daulatpur	404721	0.24614	0.01738	0.04758	0.00542	0.35029	0.02361	0.19146	0.01689
Khulna	Khulna	Dumuria	404730	0.31230	0.00912	0.06750	0.00349	0.38244	0.01504	0.21432	0.01305
Khulna	Khulna	Dighalia	404740	0.30326	0.01571	0.06488	0.00570	0.41843	0.02485	0.23831	0.02286
Khulna	Khulna	Khalishpur	404745	0.22618	0.01825	0.04185	0.00513	0.33367	0.02513	0.17284	0.01724
Khulna	Khulna	Khan Jahan Ali	404748	0.24371	0.02095	0.04580	0.00621	0.39891	0.03765	0.23043	0.03345
Khulna	Khulna	Khulna Sadar	404751	0.22514	0.01579	0.04180	0.00452	0.34197	0.02522	0.18256	0.01814
Khulna	Khulna	Koyra	404753	0.34747	0.01565	0.08065	0.00595	0.39452	0.02037	0.22382	0.01744
Khulna	Khulna	Paikgachha	404764	0.32330	0.01010	0.07144	0.00390	0.39884	0.01472	0.22720	0.01456
Khulna	Khulna	Phultala	404769	0.27981	0.01897	0.05698	0.00595	0.38952	0.02643	0.21660	0.02100
Khulna	Khulna	Rupsa	404775	0.28736	0.01364	0.05945	0.00441	0.42657	0.01794	0.24510	0.02283
Khulna	Khulna	Sonadanga	404785	0.21521	0.01678	0.03864	0.00442	0.32256	0.02098	0.16895	0.01463
Khulna	Khulna	Terokhada	404794	0.34661	0.01658	0.07971	0.00620	0.39922	0.01961	0.22763	0.01734
Khulna	Kushtia	Bheramara	405015	0.32788	0.01656	0.07351	0.00615	0.39890	0.01645	0.22718	0.01441
Khulna	Kushtia	Daulatpur	405039	0.35432	0.01282	0.08248	0.00494	0.42419	0.01506	0.24412	0.01613
Khulna	Kushtia	Khoksa	405063	0.35215	0.01259	0.08215	0.00513	0.42487	0.01599	0.24504	0.01561
Khulna	Kushtia	Kumarkhali	405071	0.34480	0.01116	0.07919	0.00437	0.43598	0.01371	0.25416	0.01269
Khulna	Kushtia	Kushtia Sadar	405079	0.30549	0.01207	0.06607	0.00410	0.40987	0.01349	0.23571	0.01284

Khulna	Kushtia	Mirpur	405094	0.34677	0.01301	0.07961	0.00515	0.40561	0.01458	0.23044	0.01209
Khulna	Magura	Magura Sadar	405557	0.32775	0.00867	0.07361	0.00330	0.39010	0.01208	0.21936	0.01044
Khulna	Magura	Mohammadpur	405566	0.35016	0.01169	0.08103	0.00486	0.39350	0.01596	0.22151	0.01360
Khulna	Magura	Shalikha	405585	0.33537	0.01159	0.07553	0.00427	0.37401	0.01747	0.20814	0.01534
Khulna	Magura	Sreepur	405595	0.33216	0.01234	0.07462	0.00496	0.39212	0.01658	0.22321	0.01278
Khulna	Meherpur	Gangni	405747	0.35015	0.01306	0.08113	0.00520	0.41186	0.01809	0.23762	0.01503
Khulna	Meherpur	Mujib Nagar	405760	0.32563	0.01600	0.07189	0.00604	0.38210	0.02070	0.21471	0.02091
Khulna	Meherpur	Meherpur Sadar	405787	0.32749	0.01389	0.07302	0.00496	0.39897	0.01372	0.22796	0.01211
Khulna	Narail	Kalia	406528	0.33543	0.01233	0.07626	0.00494	0.37743	0.01552	0.21323	0.01353
Khulna	Narail	Lohagara	406552	0.31892	0.01269	0.07051	0.00448	0.36062	0.01811	0.20041	0.01527
Khulna	Narail	Narail Sadar	406576	0.29774	0.01216	0.06299	0.00420	0.36475	0.01618	0.20409	0.01623
Khulna	Satkhira	Assasuni	408704	0.33998	0.01118	0.07744	0.00437	0.39402	0.01564	0.22352	0.01399
Khulna	Satkhira	Debhata	408725	0.30956	0.02005	0.06659	0.00678	0.38807	0.02522	0.21604	0.02087
Khulna	Satkhira	Kalaroa	408743	0.32810	0.01083	0.07308	0.00412	0.38814	0.01598	0.22007	0.01336
Khulna	Satkhira	Kaliganj	408747	0.33775	0.01019	0.07701	0.00409	0.41349	0.01412	0.23997	0.01419
Khulna	Satkhira	Satkhira Sadar	408782	0.30903	0.01012	0.06706	0.00365	0.39850	0.01419	0.22661	0.01260
Khulna	Satkhira	Shyamnagar	408786	0.35547	0.01362	0.08352	0.00532	0.39848	0.01563	0.22910	0.01532
Khulna	Satkhira	Tala	408790	0.32489	0.00903	0.07191	0.00323	0.39925	0.01541	0.22704	0.01553
Rajshahi	Bogra	Adamdighi	501006	0.28936	0.01178	0.06047	0.00389	0.37860	0.01305	0.21066	0.01335
Rajshahi	Bogra	Bogra Sadar	501020	0.26293	0.00972	0.05257	0.00289	0.36597	0.01545	0.19995	0.01175
Rajshahi	Bogra	Dhunat	501027	0.38737	0.01521	0.09521	0.00632	0.42260	0.01806	0.24514	0.01634
Rajshahi	Bogra	Dhupchanchia	501033	0.30517	0.01203	0.06598	0.00403	0.36641	0.01295	0.20102	0.01294
Rajshahi	Bogra	Gabtali	501040	0.34103	0.01203	0.07781	0.00454	0.39717	0.01588	0.22652	0.01217
Rajshahi	Bogra	Kahaloo	501054	0.29859	0.01159	0.06316	0.00375	0.36335	0.01591	0.19945	0.01327
Rajshahi	Bogra	Nandigram	501067	0.32654	0.01059	0.07277	0.00394	0.36916	0.01641	0.20529	0.01223
Rajshahi	Bogra	Sariakandi	501081	0.38415	0.01625	0.09402	0.00669	0.41696	0.01699	0.24120	0.01797
Rajshahi	Bogra	Shajahanpur	501085	0.28584	0.01066	0.05975	0.00347	0.36882	0.01470	0.20304	0.01299
Rajshahi	Bogra	Sherpur	501088	0.34888	0.01086	0.08121	0.00397	0.40621	0.01401	0.23133	0.01133
Rajshahi	Bogra	Shibganj	501094	0.34023	0.00984	0.07759	0.00385	0.40381	0.01286	0.23131	0.01212
Rajshahi	Bogra	Sonatola	501095	0.37252	0.01282	0.09033	0.00561	0.41190	0.01533	0.23641	0.01269
Rajshahi	Joypurhat	Akkelpur	503813	0.30631	0.01092	0.06652	0.00407	0.37346	0.01520	0.20990	0.01721
Rajshahi	Joypurhat	Joypurhat Sadar	503847	0.27782	0.01018	0.05675	0.00339	0.35899	0.01557	0.19960	0.01420
Rajshahi	Joypurhat	Kalai	503858	0.31532	0.01097	0.06896	0.00404	0.36952	0.01602	0.20660	0.01464
Rajshahi	Joypurhat	Khetlal	503861	0.30602	0.01358	0.06564	0.00464	0.37170	0.01990	0.20824	0.01879

Rajshahi	Joypurhat	Panchbibi	503874	0.31536	0.00905	0.06884	0.00320	0.37473	0.01403	0.21033	0.01235
Rajshahi	Naogaon	Atrai	506403	0.35029	0.01098	0.08121	0.00445	0.40163	0.01344	0.22750	0.01255
Rajshahi	Naogaon	Badalgachhi	506406	0.32895	0.00983	0.07338	0.00372	0.41036	0.01559	0.23987	0.01594
Rajshahi	Naogaon	Dhamoirhat	506428	0.33414	0.01154	0.07527	0.00454	0.39808	0.01711	0.22953	0.01695
Rajshahi	Naogaon	Manda	506447	0.34248	0.01067	0.07824	0.00393	0.40372	0.01539	0.23266	0.01483
Rajshahi	Naogaon	Mahadebpur	506450	0.31848	0.01002	0.06998	0.00389	0.38771	0.01498	0.21981	0.01670
Rajshahi	Naogaon	Naogaon Sadar	506460	0.31086	0.00959	0.06816	0.00335	0.40722	0.01256	0.23322	0.01115
Rajshahi	Naogaon	Niamatpur	506469	0.34902	0.01135	0.08058	0.00439	0.41645	0.01415	0.24415	0.01544
Rajshahi	Naogaon	Patnitala	506475	0.32700	0.00979	0.07278	0.00394	0.40152	0.01591	0.23189	0.01849
Rajshahi	Naogaon	Porsha	506479	0.36916	0.01420	0.08879	0.00568	0.43826	0.01864	0.25903	0.01741
Rajshahi	Naogaon	Raninagar	506485	0.33112	0.01174	0.07433	0.00412	0.38801	0.01442	0.22036	0.01261
Rajshahi	Naogaon	Sapahar	506486	0.35680	0.01307	0.08391	0.00503	0.42847	0.01820	0.25114	0.01890
Rajshahi	Natore	Bagati Para	506909	0.30993	0.01364	0.06691	0.00484	0.36676	0.01682	0.20455	0.01525
Rajshahi	Natore	Baraigram	506915	0.33395	0.01043	0.07511	0.00386	0.37702	0.01600	0.21221	0.01285
Rajshahi	Natore	Gurudaspur	506941	0.35271	0.01280	0.08217	0.00505	0.39606	0.01677	0.22359	0.01357
Rajshahi	Natore	Lalpur	506944	0.32775	0.01044	0.07331	0.00399	0.39405	0.01287	0.22372	0.01171
Rajshahi	Natore	Natore Sadar	506963	0.31035	0.00940	0.06757	0.00351	0.37453	0.01190	0.20865	0.01092
Rajshahi	Natore	Singra	506991	0.35628	0.01047	0.08359	0.00420	0.39503	0.01407	0.22370	0.01279
Rajshahi	Nawabganj	Bholahat	507018	0.34209	0.01559	0.07866	0.00590	0.40191	0.02033	0.22883	0.01843
Rajshahi	Nawabganj	Gomastapur	507037	0.36000	0.01331	0.08552	0.00513	0.43788	0.01611	0.25659	0.01732
Rajshahi	Nawabganj	Nachole	507056	0.34220	0.01086	0.07853	0.00397	0.40600	0.01561	0.23457	0.01754
Rajshahi	Nawabganj	Nawabganj Sadar	507066	0.35639	0.01190	0.08535	0.00498	0.43436	0.01552	0.25086	0.01531
Rajshahi	Nawabganj	Shibganj	507088	0.36538	0.01316	0.08701	0.00511	0.44176	0.01689	0.25960	0.01626
Rajshahi	Pabna	Atgharia	507605	0.35265	0.01402	0.08166	0.00536	0.40407	0.01669	0.22939	0.01496
Rajshahi	Pabna	Bera	507616	0.37773	0.01401	0.09254	0.00560	0.47718	0.01809	0.28760	0.01625
Rajshahi	Pabna	Bhangura	507619	0.35480	0.01365	0.08314	0.00536	0.39928	0.02034	0.22669	0.01527
Rajshahi	Pabna	Chatmohar	507622	0.35229	0.01231	0.08209	0.00503	0.39295	0.01737	0.22401	0.01434
Rajshahi	Pabna	Faridpur	507633	0.34876	0.01507	0.08067	0.00558	0.39392	0.01878	0.22070	0.01740
Rajshahi	Pabna	Ishwardi	507639	0.30983	0.01211	0.06735	0.00434	0.41235	0.01415	0.23491	0.01248
Rajshahi	Pabna	Pabna Sadar	507655	0.32617	0.01122	0.07364	0.00420	0.41998	0.01355	0.24152	0.01139
Rajshahi	Pabna	Santhia	507672	0.35226	0.01067	0.08178	0.00419	0.41345	0.01508	0.23528	0.01289
Rajshahi	Pabna	Sujanagar	507683	0.36202	0.01269	0.08586	0.00516	0.42051	0.01269	0.24315	0.01185
Rajshahi	Rajshahi	Bagha	508110	0.34044	0.01138	0.07808	0.00467	0.40336	0.01493	0.23279	0.01661
Rajshahi	Rajshahi	Baghmara	508112	0.33379	0.00858	0.07528	0.00332	0.37746	0.01427	0.21118	0.01249

Rajshahi	Rajshahi	Boalia	508122	0.21655	0.01456	0.03965	0.00382	0.32020	0.01980	0.16722	0.01457
Rajshahi	Rajshahi	Charghat	508125	0.33236	0.01022	0.07477	0.00403	0.41115	0.01410	0.23565	0.01287
Rajshahi	Rajshahi	Durgapur	508131	0.31327	0.01149	0.06828	0.00434	0.35920	0.01719	0.19718	0.01482
Rajshahi	Rajshahi	Godagari	508134	0.34529	0.00976	0.08023	0.00395	0.42168	0.01568	0.24622	0.01739
Rajshahi	Rajshahi	Matihar	508140	0.27076	0.01946	0.05589	0.00661	0.36533	0.02882	0.19591	0.02175
Rajshahi	Rajshahi	Mohanpur	508153	0.29664	0.01082	0.06268	0.00379	0.34270	0.01514	0.18544	0.01425
Rajshahi	Rajshahi	Paba	508172	0.32086	0.01047	0.07135	0.00374	0.39769	0.01294	0.22649	0.01368
Rajshahi	Rajshahi	Puthia	508182	0.31750	0.01096	0.06926	0.00365	0.38318	0.01413	0.21580	0.01253
Rajshahi	Rajshahi	Rajpara	508185	0.23385	0.01531	0.04497	0.00449	0.34601	0.02505	0.18657	0.01597
Rajshahi	Rajshahi	Shah Makhdum	508190	0.26785	0.01891	0.05591	0.00663	0.35537	0.02877	0.19474	0.02366
Rajshahi	Rajshahi	Tanore	508194	0.32085	0.01074	0.07109	0.00419	0.37081	0.01693	0.20643	0.01702
Rajshahi	Sirajganj	Belkuchi	508811	0.35574	0.01125	0.08367	0.00423	0.49739	0.01729	0.30646	0.01866
Rajshahi	Sirajganj	Chauhali	508827	0.40155	0.01578	0.10199	0.00695	0.46301	0.01783	0.27999	0.01626
Rajshahi	Sirajganj	Kamarkhanda	508844	0.34886	0.01593	0.08075	0.00603	0.43877	0.01780	0.25567	0.01725
Rajshahi	Sirajganj	Kazipur	508850	0.38553	0.01361	0.09444	0.00572	0.42932	0.01949	0.25127	0.01718
Rajshahi	Sirajganj	Royganj	508861	0.37931	0.01357	0.09236	0.00570	0.43944	0.01402	0.25775	0.01234
Rajshahi	Sirajganj	Shahjadpur	508867	0.37478	0.01376	0.09103	0.00549	0.47361	0.01472	0.28531	0.01443
Rajshahi	Sirajganj	Sirajganj Sadar	508878	0.34544	0.01039	0.08009	0.00395	0.45125	0.01445	0.26760	0.01257
Rajshahi	Sirajganj	Tarash	508889	0.37154	0.01366	0.08929	0.00545	0.39739	0.01827	0.22567	0.01383
Rajshahi	Sirajganj	Ullah Para	508894	0.36179	0.01089	0.08587	0.00429	0.42792	0.01310	0.24901	0.01127
Rangpur	Dinajpur	Birampur	552710	0.33429	0.01198	0.07574	0.00465	0.39676	0.01401	0.18183	0.01411
Rangpur	Dinajpur	Birganj	552712	0.34326	0.00969	0.07901	0.00410	0.41116	0.01336	0.19362	0.01318
Rangpur	Dinajpur	Biral	552717	0.34350	0.01067	0.07845	0.00412	0.42648	0.01397	0.20430	0.01342
Rangpur	Dinajpur	Bochaganj	552721	0.33509	0.01114	0.07578	0.00423	0.39937	0.01357	0.18572	0.01433
Rangpur	Dinajpur	Chirirbandar	552730	0.32974	0.01131	0.07379	0.00420	0.41533	0.01743	0.19603	0.01606
Rangpur	Dinajpur	Fulbari	552738	0.32711	0.01069	0.07299	0.00397	0.39759	0.01389	0.18402	0.01343
Rangpur	Dinajpur	Ghoraghat	552743	0.35136	0.01190	0.08218	0.00478	0.41272	0.01253	0.19295	0.01620
Rangpur	Dinajpur	Hakimpur	552747	0.31657	0.01379	0.06937	0.00497	0.38814	0.01523	0.17769	0.01522
Rangpur	Dinajpur	Kaharole	552756	0.33370	0.01079	0.07516	0.00411	0.41099	0.01474	0.19287	0.01397
Rangpur	Dinajpur	Khansama	552760	0.35043	0.01318	0.08055	0.00531	0.41782	0.01944	0.19834	0.01681
Rangpur	Dinajpur	Dinajpur Sadar	552764	0.28404	0.00916	0.05931	0.00313	0.39195	0.01474	0.18108	0.01228
Rangpur	Dinajpur	Nawabganj	552769	0.35782	0.01179	0.08364	0.00453	0.41526	0.01463	0.19539	0.01519
Rangpur	Dinajpur	Parbatipur	552777	0.32701	0.01066	0.07285	0.00392	0.41178	0.01550	0.19420	0.01326
Rangpur	Gaibandha	Fulchhari	553221	0.41132	0.01824	0.10515	0.00801	0.44501	0.02050	0.21599	0.02139

Rangpur	Gaibandha	Gaibandha Sadar	553224	0.36446	0.01197	0.08766	0.00496	0.44115	0.01733	0.21489	0.01473
Rangpur	Gaibandha	Gobindaganj	553230	0.36160	0.01158	0.08551	0.00459	0.42820	0.01438	0.20390	0.01308
Rangpur	Gaibandha	Palashbari	553267	0.35515	0.01145	0.08348	0.00453	0.42348	0.01467	0.20238	0.01377
Rangpur	Gaibandha	Sadullapur	553282	0.36570	0.01334	0.08720	0.00505	0.41732	0.01481	0.19656	0.01411
Rangpur	Gaibandha	Saghatta	553288	0.38077	0.01265	0.09310	0.00515	0.42989	0.01466	0.20571	0.01438
Rangpur	Gaibandha	Sundarganj	553291	0.38580	0.01287	0.09489	0.00536	0.42975	0.01678	0.20521	0.01508
Rangpur	Kurigram	Bhurungamari	554906	0.38638	0.01575	0.09516	0.00641	0.40703	0.02145	0.18982	0.02243
Rangpur	Kurigram	Char Rajibpur	554908	0.41074	0.02557	0.10569	0.01094	0.42062	0.02709	0.20066	0.02662
Rangpur	Kurigram	Chilmari	554909	0.40258	0.01699	0.10244	0.00750	0.44466	0.02531	0.21525	0.02261
Rangpur	Kurigram	Phulbari	554918	0.37172	0.01627	0.08918	0.00680	0.40699	0.02102	0.19157	0.02095
Rangpur	Kurigram	Kurigram Sadar	554952	0.38127	0.01240	0.09450	0.00551	0.44925	0.01683	0.22060	0.01627
Rangpur	Kurigram	Nageshwari	554961	0.40173	0.01373	0.10190	0.00598	0.42641	0.01606	0.20209	0.01921
Rangpur	Kurigram	Rajarhat	554977	0.34468	0.01254	0.07909	0.00494	0.41204	0.01618	0.19380	0.01460
Rangpur	Kurigram	Raumari	554979	0.40888	0.01613	0.10434	0.00717	0.42561	0.02270	0.20384	0.02148
Rangpur	Kurigram	Ulipur	554994	0.37576	0.01182	0.09118	0.00501	0.41156	0.01500	0.19307	0.01506
Rangpur	Lalmonirhat	Aditmari	555202	0.36656	0.01432	0.08678	0.00568	0.40128	0.02159	0.18406	0.01966
Rangpur	Lalmonirhat	Hatibandha	555233	0.36759	0.01565	0.08777	0.00611	0.40837	0.01718	0.19103	0.01735
Rangpur	Lalmonirhat	Kaliganj	555239	0.36491	0.01342	0.08647	0.00553	0.39648	0.01742	0.18307	0.02104
Rangpur	Lalmonirhat	Lalmonirhat Sadar	555255	0.36229	0.01261	0.08639	0.00539	0.42994	0.01302	0.20677	0.01660
Rangpur	Lalmonirhat	Patgram	555270	0.36575	0.01490	0.08686	0.00563	0.44341	0.01932	0.21259	0.01632
Rangpur	Nilphamari	Dimla	557312	0.38094	0.01465	0.09296	0.00600	0.43173	0.01805	0.20878	0.01662
Rangpur	Nilphamari	Domar	557315	0.35803	0.01251	0.08403	0.00496	0.42343	0.01607	0.20099	0.01551
Rangpur	Nilphamari	Jaldhaka	557336	0.39293	0.01343	0.09793	0.00582	0.44144	0.01730	0.21571	0.01675
Rangpur	Nilphamari	Kishoreganj	557345	0.37972	0.01570	0.09199	0.00629	0.44793	0.02296	0.21851	0.01699
Rangpur	Nilphamari	Nilphamari Sadar	557364	0.36158	0.01080	0.08541	0.00416	0.43913	0.01601	0.21247	0.01346
Rangpur	Nilphamari	Saidpur	557385	0.31771	0.01125	0.07088	0.00399	0.40906	0.01605	0.18903	0.01499
Rangpur	Panchagarh	Atwari	557704	0.31132	0.01409	0.06733	0.00510	0.37911	0.01615	0.17273	0.01658
Rangpur	Panchagarh	Boda	557725	0.33933	0.01235	0.07702	0.00458	0.40122	0.01478	0.18793	0.01562
Rangpur	Panchagarh	Debiganj	557734	0.35563	0.01277	0.08283	0.00487	0.41449	0.01790	0.19528	0.01558
Rangpur	Panchagarh	Panchagarh Sadar	557773	0.33330	0.01070	0.07537	0.00419	0.40560	0.01567	0.18834	0.01867
Rangpur	Panchagarh	Tentulia	557790	0.34504	0.01364	0.07875	0.00525	0.43033	0.01658	0.20207	0.01949
Rangpur	Rangpur	Badarganj	558503	0.36545	0.01238	0.08665	0.00494	0.42383	0.01708	0.19984	0.01487
Rangpur	Rangpur	Gangachara	558527	0.36719	0.01346	0.08751	0.00547	0.43058	0.01601	0.20648	0.01601
Rangpur	Rangpur	Kaunia	558542	0.37211	0.01361	0.09065	0.00536	0.43777	0.01419	0.21323	0.01763

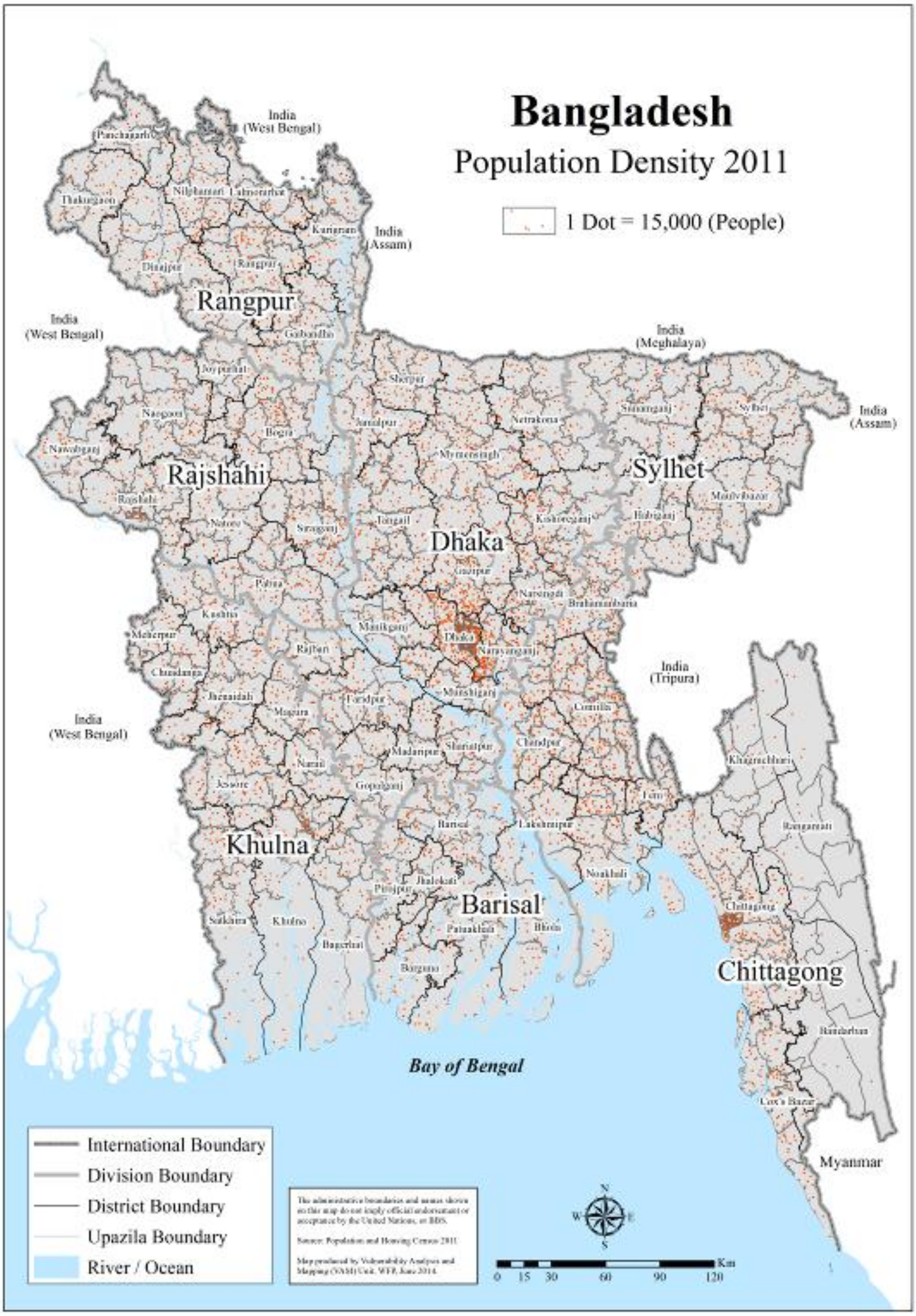
Rangpur	Rangpur	Rangpur Sadar	558549	0.30494	0.00978	0.06631	0.00343	0.41001	0.01256	0.19276	0.01413
Rangpur	Rangpur	Mitha Pukur	558558	0.35035	0.01029	0.08107	0.00390	0.42594	0.01539	0.20323	0.01263
Rangpur	Rangpur	Pirgachha	558573	0.35975	0.01317	0.08455	0.00536	0.41097	0.01335	0.19123	0.01449
Rangpur	Rangpur	Pirganj	558576	0.35366	0.01113	0.08250	0.00424	0.41265	0.01142	0.19434	0.01227
Rangpur	Rangpur	Taraganj	558592	0.36123	0.01614	0.08500	0.00636	0.41984	0.01892	0.19923	0.01674
Rangpur	Thakurgaon	Baliadangi	559408	0.36461	0.01388	0.08656	0.00528	0.43625	0.02105	0.21040	0.01679
Rangpur	Thakurgaon	Haripur	559451	0.37272	0.01274	0.08945	0.00520	0.41817	0.01758	0.19598	0.01507
Rangpur	Thakurgaon	Pirganj	559482	0.34799	0.01069	0.08015	0.00405	0.42490	0.01476	0.20335	0.01265
Rangpur	Thakurgaon	Ranisankail	559486	0.35336	0.01195	0.08234	0.00447	0.42504	0.01526	0.20239	0.01465
Rangpur	Thakurgaon	Thakurgaon Sadar	559494	0.32455	0.00938	0.07212	0.00343	0.42505	0.01641	0.20229	0.01395
Sylhet	Habiganj	Ajmiriganj	603602	0.40882	0.01975	0.10626	0.00882	0.45799	0.02124	0.31118	0.02491
Sylhet	Habiganj	Bahubal	603605	0.39435	0.01565	0.09975	0.00674	0.43970	0.01490	0.29057	0.01976
Sylhet	Habiganj	Baniachong	603611	0.39892	0.01593	0.10158	0.00666	0.44339	0.01727	0.29498	0.01967
Sylhet	Habiganj	Chunarughat	603626	0.39203	0.01726	0.09880	0.00714	0.43388	0.01267	0.28837	0.01964
Sylhet	Habiganj	Habiganj Sadar	603644	0.35987	0.01693	0.08646	0.00672	0.41404	0.01351	0.27018	0.01834
Sylhet	Habiganj	Lakhai	603668	0.42897	0.02044	0.11489	0.00946	0.46622	0.02058	0.31534	0.02178
Sylhet	Habiganj	Madhabpur	603671	0.39870	0.01667	0.10146	0.00702	0.45938	0.01371	0.31060	0.02045
Sylhet	Habiganj	Nabiganj	603677	0.39087	0.01671	0.09818	0.00678	0.44484	0.01317	0.29573	0.01895
Sylhet	Maulvibazar	Barlekha	605814	0.37337	0.01817	0.09204	0.00739	0.45332	0.01495	0.30642	0.02438
Sylhet	Maulvibazar	Juri	605835	0.36855	0.01983	0.08945	0.00811	0.45287	0.02130	0.30720	0.02687
Sylhet	Maulvibazar	Kamalganj	605856	0.38318	0.01769	0.09488	0.00758	0.46107	0.01676	0.31359	0.02107
Sylhet	Maulvibazar	Kulaura	605865	0.35606	0.01793	0.08487	0.00672	0.41315	0.01505	0.27277	0.02175
Sylhet	Maulvibazar	Maulvi Bazar Sadar	605874	0.35393	0.01739	0.08390	0.00690	0.42667	0.01246	0.28117	0.02010
Sylhet	Maulvibazar	Rajnagar	605880	0.37317	0.01881	0.09156	0.00752	0.43099	0.01344	0.29038	0.02054
Sylhet	Maulvibazar	Sreemangal	605883	0.36756	0.01759	0.08871	0.00696	0.44261	0.01418	0.29582	0.02192
Sylhet	Sunamganj	Bishwambarpur	609018	0.41823	0.02119	0.10847	0.00918	0.47231	0.02309	0.32501	0.02562
Sylhet	Sunamganj	Chhatak	609023	0.39741	0.01715	0.10164	0.00717	0.45718	0.01519	0.30643	0.01983
Sylhet	Sunamganj	Dakshin Sunamganj	609027	0.40755	0.01487	0.10486	0.00644	0.45544	0.01833	0.30522	0.02232
Sylhet	Sunamganj	Derai	609029	0.40099	0.01641	0.10214	0.00709	0.44929	0.01618	0.30298	0.01986
Sylhet	Sunamganj	Dharampasha	609032	0.42538	0.01903	0.11157	0.00849	0.46665	0.01780	0.31714	0.02129
Sylhet	Sunamganj	Dowarabazar	609033	0.42349	0.01848	0.11194	0.00817	0.45107	0.01748	0.30369	0.02126
Sylhet	Sunamganj	Jagannathpur	609047	0.39786	0.01678	0.10137	0.00683	0.45069	0.01543	0.30406	0.01888
Sylhet	Sunamganj	Jamalganj	609050	0.41138	0.01799	0.10578	0.00762	0.46153	0.01942	0.31394	0.02064
Sylhet	Sunamganj	Sulla	609086	0.39307	0.02000	0.09846	0.00865	0.45470	0.02065	0.30556	0.02689

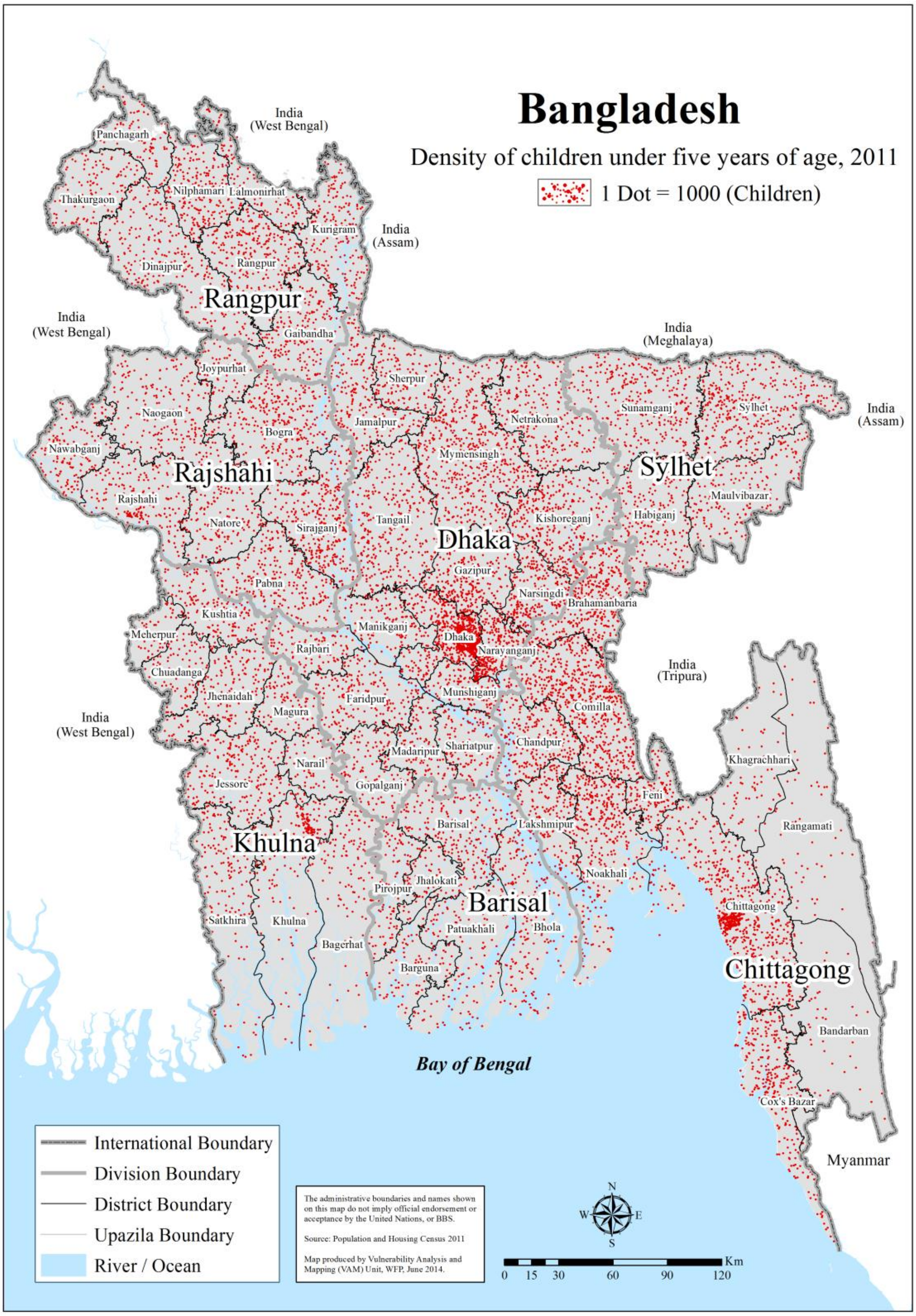
Sylhet	Sunamganj	Sunamganj Sadar	609089	0.40446	0.01652	0.10419	0.00706	0.46021	0.01879	0.31078	0.02059
Sylhet	Sunamganj	Tahirpur	609092	0.41723	0.02065	0.10816	0.00874	0.48780	0.01861	0.33474	0.02362
Sylhet	Sylhet	Balaganj	609108	0.35695	0.01706	0.08486	0.00657	0.43073	0.01300	0.28425	0.02050
Sylhet	Sylhet	Beani Bazar	609117	0.33760	0.01947	0.07842	0.00717	0.41359	0.01530	0.26819	0.02146
Sylhet	Sylhet	Bishwanath	609120	0.37036	0.01899	0.09046	0.00751	0.43491	0.01540	0.28763	0.02154
Sylhet	Sylhet	Companiganj	609127	0.42803	0.01885	0.11316	0.00867	0.49862	0.02217	0.34190	0.02450
Sylhet	Sylhet	Dakshin Surma	609131	0.34710	0.01983	0.08129	0.00749	0.43194	0.01762	0.28489	0.02419
Sylhet	Sylhet	Fenchuganj	609135	0.37414	0.02703	0.09212	0.01140	0.43026	0.02448	0.28416	0.02878
Sylhet	Sylhet	Golabganj	609138	0.34804	0.02088	0.08243	0.00804	0.42070	0.01470	0.27351	0.02189
Sylhet	Sylhet	Gowainghat	609141	0.42611	0.01740	0.11264	0.00783	0.49229	0.01903	0.34118	0.02368
Sylhet	Sylhet	Jaintiapur	609153	0.39756	0.01807	0.10151	0.00746	0.47040	0.01613	0.31746	0.02228
Sylhet	Sylhet	Kanaighat	609159	0.39737	0.01693	0.10153	0.00738	0.44782	0.01475	0.30074	0.02020
Sylhet	Sylhet	Sylhet Sadar	609162	0.32776	0.01944	0.07478	0.00704	0.40106	0.01737	0.25794	0.02026
Sylhet	Sylhet	Zakiganj	609194	0.37526	0.01961	0.09215	0.00807	0.46057	0.01669	0.31142	0.02152

Appendix D. Maps at Small Area Level

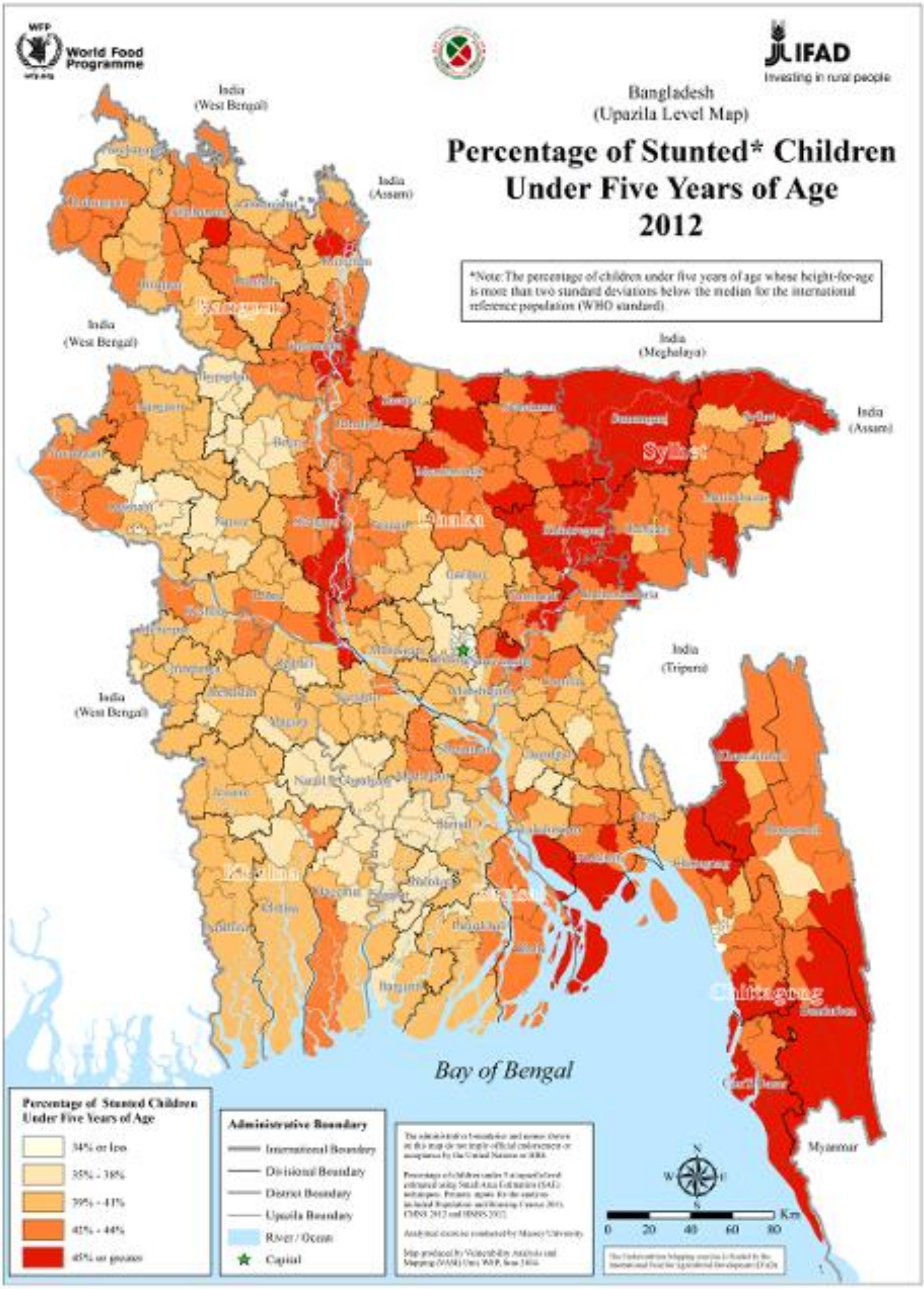
Appendix D.1.

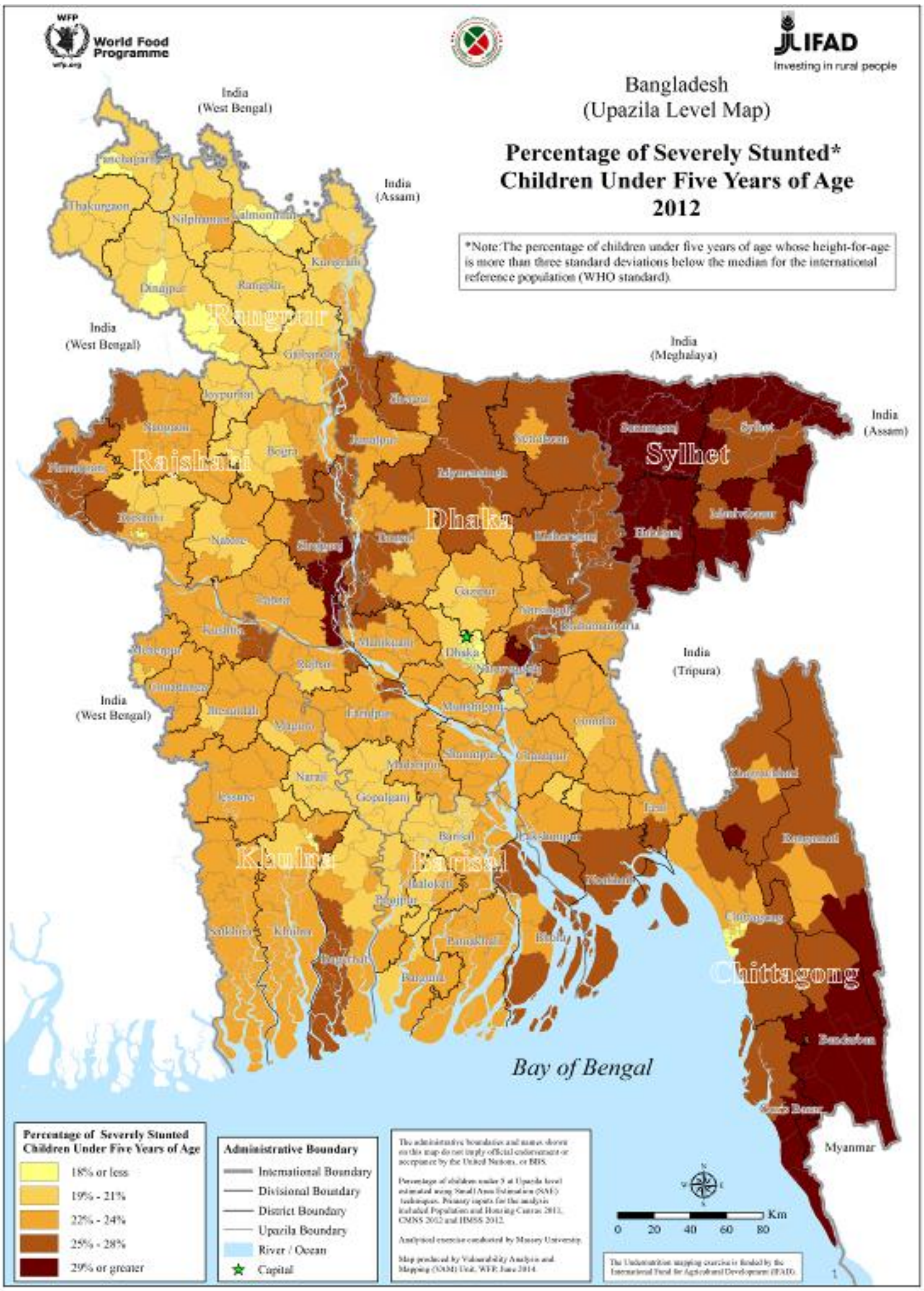
Map of the administrative units including upazila boundaries, and maps of population density and density of children under five years of age.


Bangladesh
Population Density 2011
1 Dot = 15,000 (People)
India (West Bengal)
India (Assam)
India (Meghalaya)
India (Tripura)
Rangpur
Rajshahi
Dhaka
Sylhet
Khulna
Barisal
Chittagong
Bay of Bengal
Myanmar
International Boundary
Division Boundary
District Boundary
Upazila Boundary
River / Ocean
Km
0 15 30 60 90 120
N
S
E
W

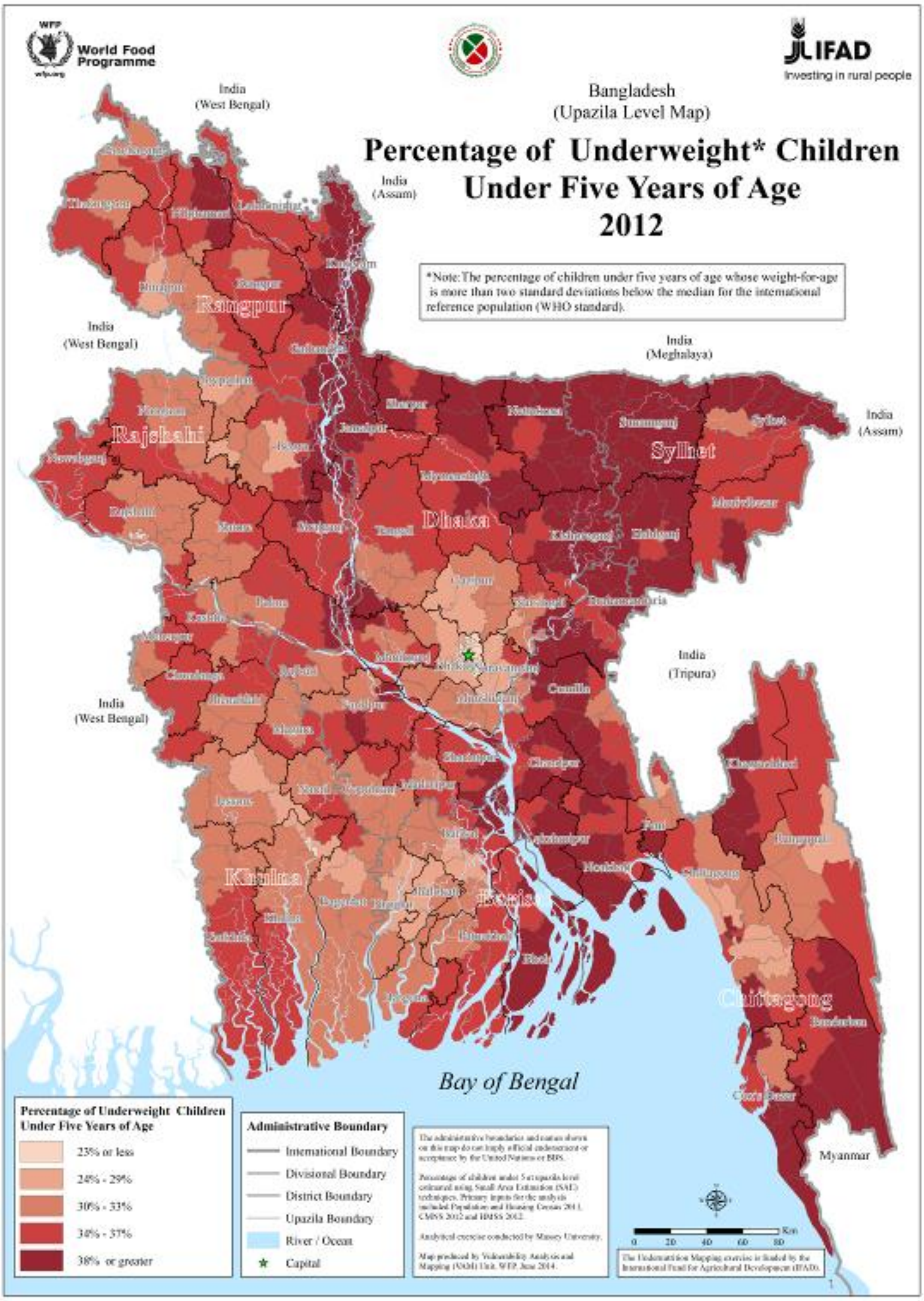

Bangladesh
Density of children under five years of age, 2011
1 Dot = 1000 (Children)
India (West Bengal)
India (Assam)
India (Meghalaya)
India (Tripura)
Myanmar
Bay of Bengal
Rangpur
Rajshahi
Dhaka
Sylhet
Khulna
Barisal
Chittagong
Panchagarh
Thakurgaon
Nilphamari
Lalmonirhat
Kurigram
Dinajpur
Rangpur
Gaibandha
Joypurhat
Naogaon
Bogra
Nawabganj
Rajshahi
Natore
Sirajganj
Pabna
Sherpur
Jamalpur
Netrakona
Mymensingh
Sunamganj
Sylhet
Maulvibazar
Habiganj
Kishoreganj
Tangail
Gazipur
Narsingdi
Brahamanbaria
Kushtia
Meherpur
Chuadanga
Manikganj
Dhaka
Narayanganj
Rajbari
Jhenaidah
Magura
Faridpur
Munshiganj
Comilla
Chandpur
Shariatpur
Madaripur
Narail
Jessore
Gopalganj
Khagrachhari
Feni
Lakshmipur
Barisal
Rangamati
Noakhali
Jhalokati
Pirojpur
Satkhira
Khulna
Bagerhat
Patuakhali
Bhola
Barguna
Chittagong
Bandarban
Cox's Bazar
International Boundary
Division Boundary
District Boundary
Upazila Boundary
River / Ocean
The administrative boundaries and names shown on this map do not imply official endorsement or acceptance by the United Nations, or BBS.
Source: Population and Housing Census 2011
Map produced by Vulnerability Analysis and Mapping (VAM) Unit, WFP, June 2014.
N
W
E
S
Km
0 15 30 60 90 120

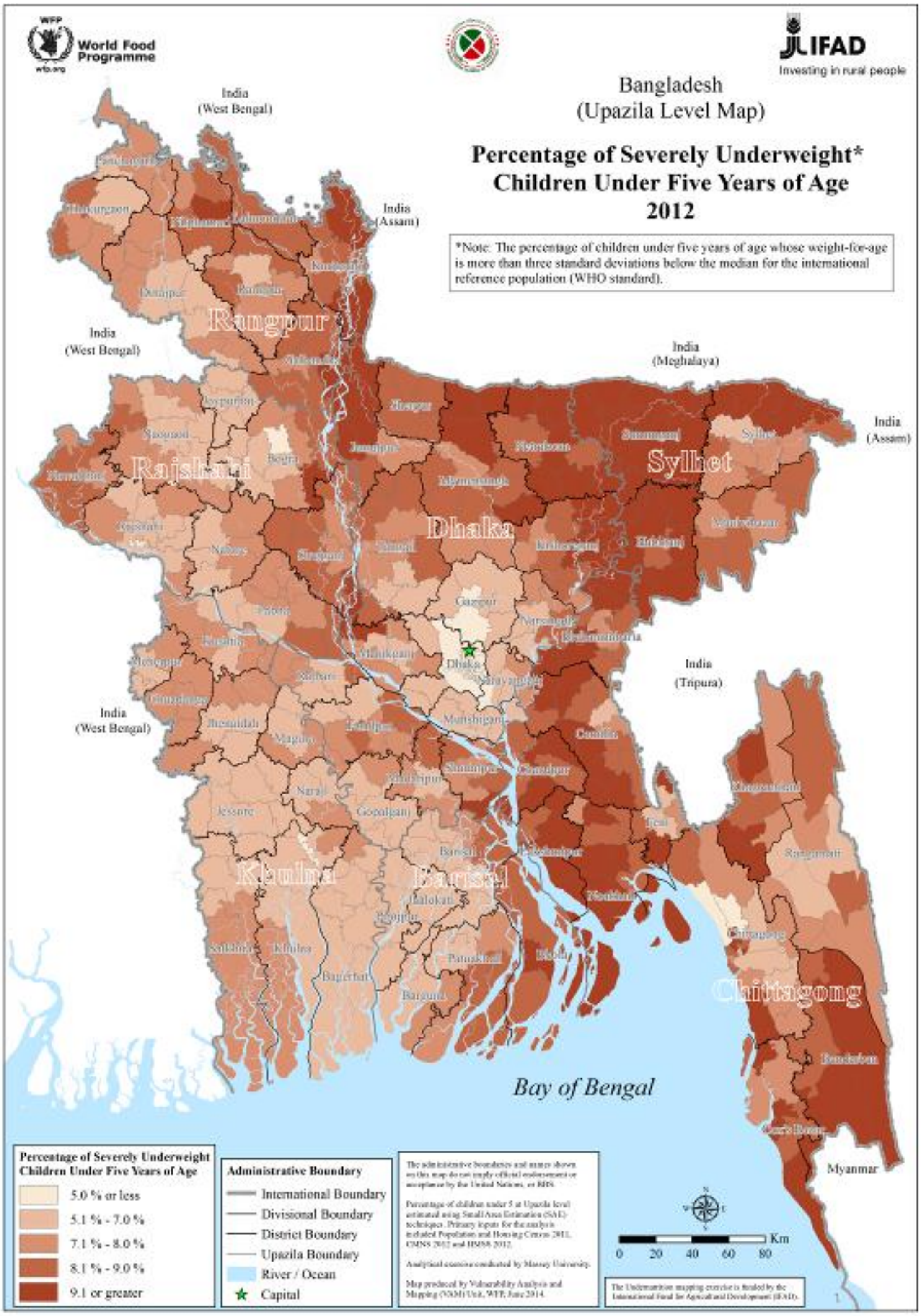
Appendix D.2.
Maps of stunting prevalence and severe stunting prevalence.




World Food Programme
IFAD
Investing in rural people
Bangladesh
(Upazila Level Map)
Percentage of Severely Stunted* Children Under Five Years of Age 2012
*Note:The percentage of children under five years of age whose height-for-age is more than three standard deviations below the median for the international reference population (WHO standard).
India (West Bengal)
India (Assam)
India (Meghalaya)
India (Tripura)
Rangpur
Rajshahi
Dhaka
Sylhet
Khulna
Barisal
Chittagong
Bay of Bengal
Myanmar
Percentage of Severely Stunted Children Under Five Years of Age
18% or less
19% - 21%
22% - 24%
25% - 28%
29% or greater
Administrative Boundary
International Boundary
Divisional Boundary
District Boundary
Upazila Boundary
River / Ocean
Capital
Km
0 20 40 60 80

Appendix D.3.
Maps of underweight prevalence and severe underweight prevalence.




World Food Programme
wfp.org
IFAD
Investing in rural people
Bangladesh
(Upazila Level Map)
Percentage of Severely Underweight* Children Under Five Years of Age
2012
*Note: The percentage of children under five years of age whose weight-for-age is more than three standard deviations below the median for the international reference population (WHO standard).
India (West Bengal)
India (Assam)
India (Meghalaya)
India (Tripura)
Myanmar
Rangpur
Rajshahi
Dhaka
Sylhet
Khulna
Barisal
Chittagong
Bay of Bengal
Percentage of Severely Underweight Children Under Five Years of Age
5.0 % or less
5.1 % - 7.0 %
7.1 % - 8.0 %
8.1 % - 9.0 %
9.1 or greater
Administrative Boundary
International Boundary
Divisional Boundary
District Boundary
Upazila Boundary
River / Ocean
Capital
Km
0 20 40 60 80