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SMALL AREA ESTIMATION OF POVERTY IN RURAL BANGLADESH

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ABSTRACT

Poverty is a complex phenomenon and most of the developing countries are struggling to overcome the problem. Small area estimation offers help to allocate resources efficiently to address poverty at lower administrative level. This study used data from Census 2011 and Household Income and Expenditure Survey (HIES)-2010. Using ELL and M-Quantile methods, this study identified Rangpur division as the poorest one where Kurigram is the poorest district. Finally, considering both upper and lower poverty lines this study identified the poverty estimates at upazila level of Rangpur division using ELL and M-Quantile methods. The analyses found that 32% of the households were absolute poor and 19% were extremely poor in rural Bangladesh. Among the upazilas under Rangpur division Rajarhat, Ulipur, Char Rajibpur, Phulbari, Chilmari, Kurigram Sadar, Nageshwari, and Fulchhari Upazilas have been identified as the poorest upazilas.

Keywords: Small area, poverty, ELL, M-Quantile methods

I. INTRODUCTION

Bangladesh is a developing country in the south Asia. According to the recent statistics by Bangladesh Bureau of Statistics (BBS, 2017, HIES, 2010) the per capita annual income of Bangladesh is US$1610, estimated Gross Domestic Product (GDP) is 7.28, and the percentage below the poverty line (upper) is 24.30 percent. The population is predominantly rural, with about 70 percent people living in rural areas (HIES, 2016).

In Bangladesh, poverty scenario was first surveyed in 1973-1974. In this study, data were used from the Household Income and Expenditure Survey (HIES, 2010). In HIES (2010), food intake, direct calorie intake and cost of basic needs (CBN) method were used. Daily per capita 2122 kilo-calorie and 1805 kilo-calorie were considered as cut off points for absolute and hardcore poverty respectively. According to HIES (2016), head count ratio of poverty incidence using upper poverty line by CBN method from 50.1% in 1995-96 has been reduced to 24.3% in 2016. Other indices such as poverty gap index (PGI) and squared poverty gap index (SPGI) reduced at national, rural and urban levels. In terms of the upper poverty line based on calorie intake, 41.2 million in rural areas and 14.8 million in urban areas were poor in 2005. The number of hardcore poor was 18.7

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million in rural areas and 8.3 million in urban areas in 2005 (BBS, 2005). With appropriate interventions, Bangladesh could successfully reduce the number of poor people. Using per capita consumption expenditure or CBN approach in 2016 the percentage poor in urban areas based on upper poverty line was 18.9% and that for lower poverty line was 7.6%. In the rural areas these were 26.4% and 14.9% respectively (HIES, 2016). This remarkable achievement lead Bangladesh to fulfill the MDG targets and Bangladesh has been recognized highly for such success. However, despite all efforts, rural areas are lagging behind compared to urban areas with more poor people living in rural areas. Therefore, it is necessary to accurately estimate the poverty in rural areas of Bangladesh. Furthermore, recently government has been planning to implement local area level budget, which will require small area level estimates of poverty for efficient disbursement of resources. This study aims to provide small area estimates of poverty in rural Bangladesh using latest statistical methodologies, which has not yet been practiced in Bangladesh.

Small area estimation is a mathematical and statistical method, which is applied in many areas of research, e.g. environmental statistics, economics, demography, epidemiology, and so on. The estimates from these models 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 (Haslett *et al*. 2014). To estimate poverty direct and indirect estimation and model-based methods are used. In model-based approach, a regression model is developed based on the survey data and known auxiliary variables. These small area estimation methods can be split into two groups according to their use of implicit and explicit models (Das, 2016). Methods that use implicit models related to small areas use supplementary data from census and survey, whereas methods that use explicit models account for variability between small areas and between units in the areas through variation in the auxiliary data (Das, 2016).

Poverty mapping is a method to estimate the welfare level and the degree of inequality at lower aggregation levels such as upazila or village. Geographically disaggregated level indicators provide information about the spatial distribution of inequality and poverty within a country or a large state of a country. A poverty map is a useful technique to capture the heterogeneity in poverty and inequality across different regions in a country. Based on the gradient distributions of poverty indicators and their determinants policy makers may design area-specific interventions. A poverty map also helps to allocate aid during periods of natural disaster such as flood or an earthquake (Das, 2016).

Globally several projects have been conducted to estimate poverty maps based on SAE methods. The first project was conducted by the US Census Bureau to estimate Small Area Income and Poverty (Citro *et al*. 1997), which is the ongoing program of US Census Bureau to estimates the number of poor school-age children within states and counties each year. The World Bank initiated to develop expenditure-based SAE method (Hentschel and Lanjouw, 1996) and applied to poverty mapping (Elbers *et al*. 2002, 2003), which is known as the "World Bank" methodology. More than 60 countries, especially the developing countries, in the world are using this method to map poverty (Elbers and Van der Weide, 2014).

To estimate poverty at a disaggregated level, the Small Area Estimation method developed by Elbers *et al*. (2003) which referred to as ELL, recently has been gaining popularity among development practitioners worldwide. One advantage of the ELL method is that it not only sets out to estimate poverty incidence, but also yields estimates of standard errors on the poverty estimates.

The standard errors are useful about the precision and reliability of the estimates produced with the ELL methodology. Several studies have used this method (Tarozzi and Deaton, 2009; Molina and Rao, 2010; World Bank, 2016).

The ELL method assumes that the only significant source of higher-level variation is between-cluster variation, which is equivalent to the assumption that it is possible to incorporate a large enough number of explanatory variables in the two-level regression model to ensure between-area variation. Therefore, the ELL method will fail to provide efficient estimates when there is non-negligible between-area variation in the distribution of the response variable (Das, 2016). Though this method is robust to departures from the assumption of normal errors and is not computationally intensive, it is not robust to the presence of outliers and is not robust to model misspecification. However, it does have the advantage that since the model is fitted at household (unit) level and then simulated, the same predicted model is used to estimate poverty indicators at any level of the population (Guadarrama *et al*. 2015). Tzavidis *et al.* (2008) proposed an M-quantile (MQ) approach to poverty mapping as an alternative to the ELL and EBP methods. Several studies have used this method (Giusti *et al.* 2012; Fabrizi *et al.* 2012).

More specifically, in the study we have used a novel linear M-quantile model (Chambers and Tzavidis, 2007) for poverty estimation at small area levels and provided a poverty map for rural Bangladesh. The poverty maps provide a graphical summary of areas, which are suffering from a relatively high deprivation. The main purpose in producing such maps is to aid the planning of social interventions. Furthermore, the commonly used ELL estimates (Elbers *et al*. 2003) will be produced using same set of data to compare the efficiency between ELL and M-quantile estimates. Therefore, this study intends to answer the research questions; what are the reliable estimates of poverty at small area levels in rural Bangladesh? Which areas in rural Bangladesh are performing poorly in terms of poverty? To address the questions the study attempted to estimate poverty at small area levels using M-quantile method and compared with the poverty estimates by ELL method and map poverty estimates at small area levels.

II. DATA AND METHODS

Data

This study was based on secondary data, e.g., Household Income and Expenditure Survey (HIES)-2010 and Census-2011. It can be noted that though HIES 2016 report has been published, the complete set of data has not been released yet. Household Income and Expenditure Survey (HIES) 2010 conducted by Bangladesh Bureau of Statistics (BBS) was a two-stage stratified random sample. In the HIES 2010, a total of 12240 households were randomly selected from 7 divisions, 64 districts, and 384 sub-districts. In this study, we have used 7840 rural households in Bangladesh to identify the important factors associated with poverty in rural Bangladesh.

This study used 5% Census-2011 data for small area estimation practice collected from BBS. The census was a nationwide operation counting all the population of the country. In order to conduct the Population and Housing Census 2011 efficiently, the unit of enumeration was considered as the Enumeration Area (EA) constituted with around one hundred households. Usually, Population and Housing Census collects a wide range of data on household and individual characteristics, including employment, housing conditions, educational attainment, sources of drinking water, access to sanitation, electricity, etc. However, as a global practice, population census does not include consumption and income data, which are supplemented from HIES for small area estimation practices. Like the HIES 2010 data, similar variables were created from census data. In addition, data checking has been done for consistency and reliability.

Methods

ELL method

In order to develop a regression model let $\mathrm{E}_{\mathrm{ijk}}$ be per capita expenditure and its log-transformed response variable, $\mathrm{Y}_{\mathrm{ijk}} = \log(\mathrm{E}_{\mathrm{ijk}})$ and X_{ijk} is the explanatory variables for k^{th} HH lives in j^{th} cluster of i^{th} area available in a sample data of recent Household Income and Expenditure Survey (HIES) 2010. The standard methods of fitting regression model cannot be used here due to the hierarchical nature in the HIES data. Hence, a nested-error linear regression model (Battese *et al.* 1988) is built up considering HHs at level 1 and clusters at level 2 as follows:

$$y_{ijk} = x_{ijk}^T \beta + u_{ij} + \varepsilon_{ijk} \; ; i = 1,\ldots,D \;\; j = 1,2,\ldots,C_i \;\;\; k = 1,2,\ldots,N_{ij}$$

$$u_{ij} \sim N\left(0,\sigma_u^2\right); \; \varepsilon_{ijk} \sim N(0,\sigma_\varepsilon^2) \qquad (1)$$

where cluster-specific and HH-specific errors u_{ij} and $\varepsilon_{\mathrm{ijk}}$ are assumed to follow approximately normal distribution with constant variance.

To obtain unbiased estimates of poverty indicators with their standard errors the ELL method uses a parametric bootstrap procedure. There involve some steps in estimation procedure (see for details, Das, 2016). In ELL methodology, the basic idea is to increase the predictive power of the fitted regression model (high R-squared value) and to reduce as much as possible the ratio of between-cluster variation to total variation $\hat{\sigma}_u^2\left(\hat{\sigma}_u^2 + \hat{\sigma}_\varepsilon^2\right)^{-1}$. For these reasons, more explanatory variables at different hierarchical levels such as HH, cluster and area are considered in the regression model.

M-quantile method (MQ method)

M-quantile models, an approach to small area estimation based on the quantiles of the conditional distribution of the variable of study Y given the covariates (Chambers and Tzavidis, 2007 and Tzavidis *et al.* 2007) were considered.

Let x_i be a known vector of auxiliary variables for each population unit i in small area j, with N_j denoting the number of population units in area j. Assume that information for the variable of interest y_{ij}, the household consumption expenditure for unit i in small area j, is available only for the n_j sampled units in area j, denoted as s_j. The target is to use these data to estimate the cumulative distribution function of the household consumption expenditure. For this purpose, the y_{ij} values of the $N_j - n_j$ not sampled units in areas j, denoted as r_j, need to be predicted under a given small area model. The M-Quantile small area model is

$$y_{ij} = x_{ij}^T \beta_\varphi(\theta_i) + \varepsilon_{ij} \qquad (2)$$

where,

y_{ij} : is the study variable for the unit i in the area j

x_{ij}^T : is the vector of the p auxiliary variables for the unit i in the area j (Both survey and census)

β : is the unknown regression vector

θ_i : is the unknown area specific coefficient

ε_{ij} : is an individual disturbance or ε_{ij} has a non-specified distribution

The predictor for the target variable of the non-sampled unit *k* in area is

$$\hat{y}_{ki} = x_{kj}^T \hat{\beta}_{\varphi}(\hat{\theta}_j) \quad (3)$$

The estimating equations can be solved with a straightforward application of an iterative weighted least squares (IWLS) algorithm. In the MQ model the conditional distribution of *y* given **x** is independent on the pre-defined hierarchical structure. In addition, it is assumed that since MQ coefficients are determined at population level, population units within a small area have almost similar to MQ coefficients. The MQ coefficient q_k for the sample unit *k* with values y_k and x_k is obtained such that $Q_{q_k}(x_{ik};\Psi) = y_{ik}$. Here ψ is an appropriately chosen influence function such as Huber Proposal 2 influence functions (Das, 2016).

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

$$\hat{F}_{\alpha i}^{MQ} = N_d^{-1}\left[\sum_{k\in s_i} F_{\alpha ik} + \sum_{k^1\in r_i} \hat{F}_{\alpha ik^1}\right] \quad i = 1,2,..., D \ \alpha = 0,1,2 \quad (4)$$

Marchetti *et al*. (2012) proposed an alternative procedure to calculate (4) following a MC simulation approach parallel to the EBP approach. The basic steps are as follows:

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

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

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

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

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

$$mse\left(\hat{F}_{\alpha i}^{MQ}\right) = \mathrm{var}\left(\hat{F}_{\alpha i}^{MQ}\right) + bias\left(\hat{F}_{\alpha i}^{MQ}\right)^2 \quad (5)$$

where, the estimated bias and variance of the estimated parameter $\hat{F}_{\alpha i}^{MQ}$ are $bias\left(\hat{F}_{\alpha i}^{MQ}\right) = B^{-1}R^{-1}\sum_{b,r}\left(\hat{F}_{\alpha i}^{*(br)} - F_{\alpha i}^{*(b)}\right)$ and

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

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

Poverty Mapping

Poverty map usually is a visual presentation technique where poverty related information are present in the area maps to better identify the poor performing localities and finally to efficiently plan the resource allocation (Figure 1). Governments around the globe use this exercise to set their poverty eradication strategies and so far, these tools have been found successful. One prime advantage of poverty mapping is that it reduces the likelihood of under coverage of the actual poor communities (Das, 2016).

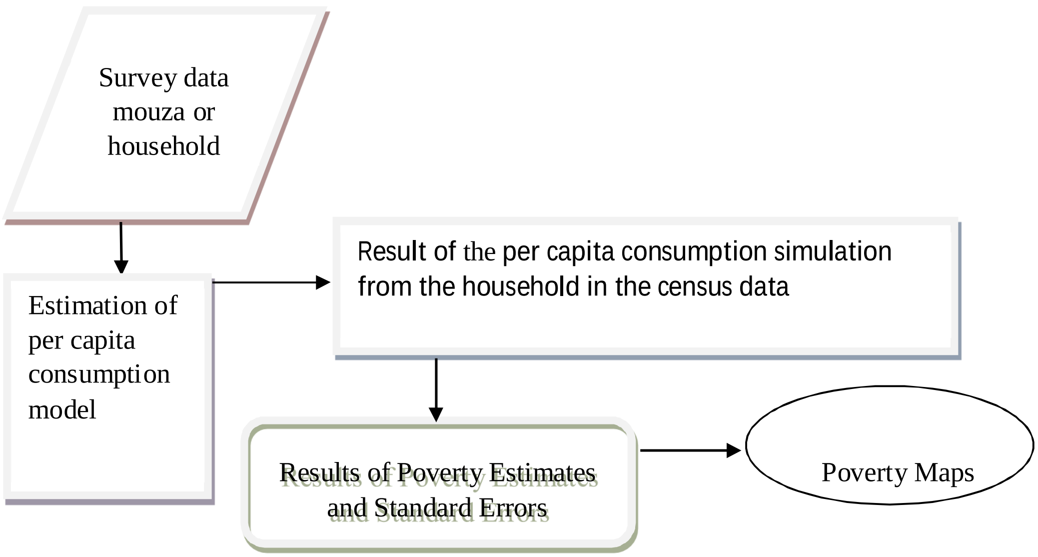


Figure 1: Flowchart for Poverty Mapping

Outputs obtained using ELL and M-quantile method, in the form of estimates at local level together with their standard errors, can be combined with Geographical Information System (GIS) data to produce a "poverty map" for the whole country, giving a graphical summary of which areas are suffering relatively high deprivation.

III. RESULTS AND DISCUSSION

According to the World Bank (2015), Rangpur division exhibits the highest poverty level (upper poverty line 42.0). Hence, we have selected rural Rangpur division for in-depth study.

Table 1 shows the comparison of the direct estimate with ELL and MQ result obtained for Rangpur division. Further analysis was carried out to find out the estimates at district and upazila levels within Rangpur division using ELL and MQ method. Table 2 reveals that Kurigram district has the highest poverty incidence with 50.2% poor in that region (Lower poverty line) using ELL method. Panchagarh district has the lowest poverty level (18.1%) within the Rangpur division. MQ method reveals the same with Kurigram district having the highest poverty incidence (50.7 %) and Panchagarh district having the lowest (13.7%) among the districts.

Table 1: Comparison of poverty estimates (Direct) from 2010 HIES and SAE method in rural Rangpur division

2010 HIES and Census 2011 based poverty estimates of Rangpur rural		
Methods of Estimates	Headcount poverty rate (percent) of Rangpur rural	
	Upper poverty line	Lower poverty line
Direct	47.20	30.80
ELL	45.04	29.59
MQ	46.77	29.81

In terms of the poverty gap and severity of poverty, these two districts show the same order. The poverty gap estimated by ELL for Kurigram was 13.4% and the severity was 5%, while these percentages for Panchagarh district were 3.4% and 1% respectively (Table 2). Furthermore, Table 2 shows that Kurigram and Panchagarh had the highest and lowest poverty incidences respectively, estimated using MQ method. The MQ estimates of poverty (lower poverty line) gap and severity for Kurigram were 11.9% and 3.9%respectively. Whereas, these three estimates for Panchagarh district were 13.6%, 2.1% and 0.5% respectively (Table 2).

Table 2: Estimates of poverty incidence (HCR) at the district level based on mouza of rural Rangpur division using LPL by ELL and MQ method

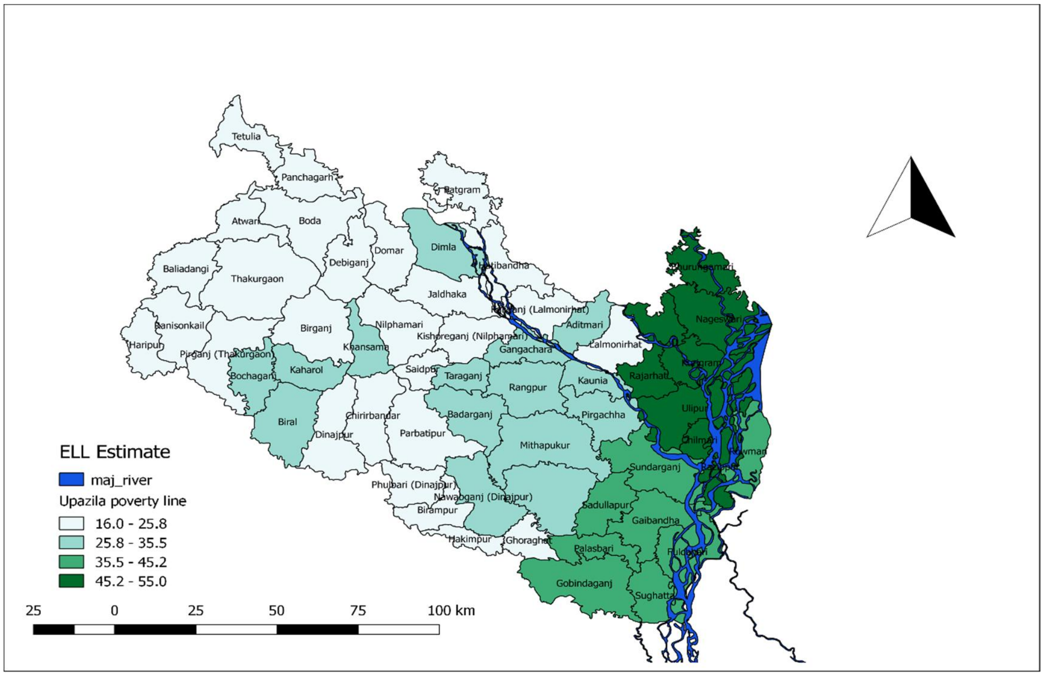
District	Lower poverty line (LPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Dinajpur	24.1	5.0	1.5	25.8	4.9	1.4
Gaibandha	41.5	10.2	3.6	43.8	9.7	3.1
Kurigram	50.2	13.4	5.0	50.7	11.9	3.9
Lalmonirhat	21.6	4.3	1.3	17.7	2.8	0.7
Nilphamari	22.4	4.4	1.3	18.8	3.1	0.8
Panchagarh	18.1	3.4	1.0	13.7	2.1	0.5
Rangpur	27.9	6.0	1.9	29.4	5.6	1.6
Thakurgaon	19.7	3.8	1.1	14.6	2.3	0.6

Similar exercise using the upper poverty line identified the same districts having the highest and lowest poverty incidence. The ELL estimates of poverty incidence for Kurigram was 66.1% (Table 3), while the poverty gap and severity were 20.9% and 8.7% respectively (Table A3 in Appendix A). For Panchagarh the ELL estimate of poverty incidence was 31.7% (Table 3) and the poverty gap and severity were 7.0% and 2.3% respectively (Table 3). The MQ estimates of poverty incidence, gap and severity (Upper poverty line) for Kurigram district were 68.7%, 20.0% and 7.7% respectively (Table 3). The MQ estimates suggest that Panchagarh district has the lowest poverty incidence, gap and severity with 27.8%, 5.2%, 1.4% respectively (Table 3)

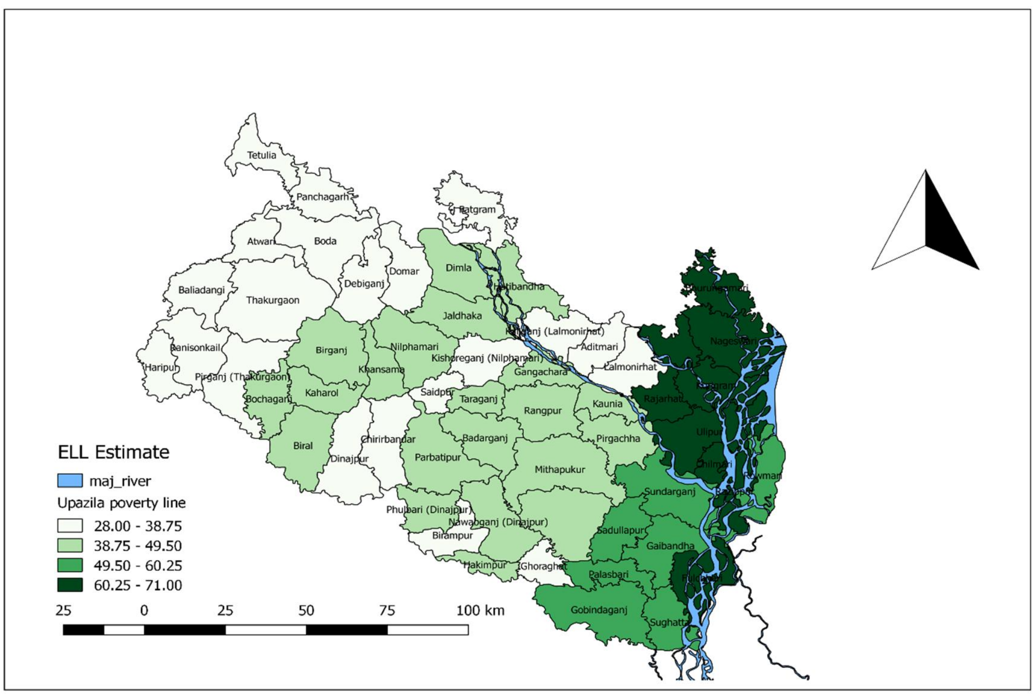
Table 3: Estimates of poverty incidence (HCR) at the district level based on mouza of Rural Rangpur division using UPL by ELL and MQ method

District	Upper poverty line (UPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Dinajpur	39.3	9.6	3.3	42.9	10.1	3.3
Gaibandha	58.0	17.0	6.7	62.0	17.1	6.3
Kurigram	66.1	20.9	8.7	68.7	20.1	7.7
Lalmonirhat	36.4	8.4	2.8	34.3	6.7	1.9
Nilphamari	37.5	8.8	2.9	35.8	7.1	2.1
Panchagarh	31.7	7.0	2.3	27.8	5.2	1.5
Rangpur	43.5	10.9	3.9	47.6	11.2	3.7
Thakurgaon	33.7	7.7	2.6	29.6	5.6	1.6

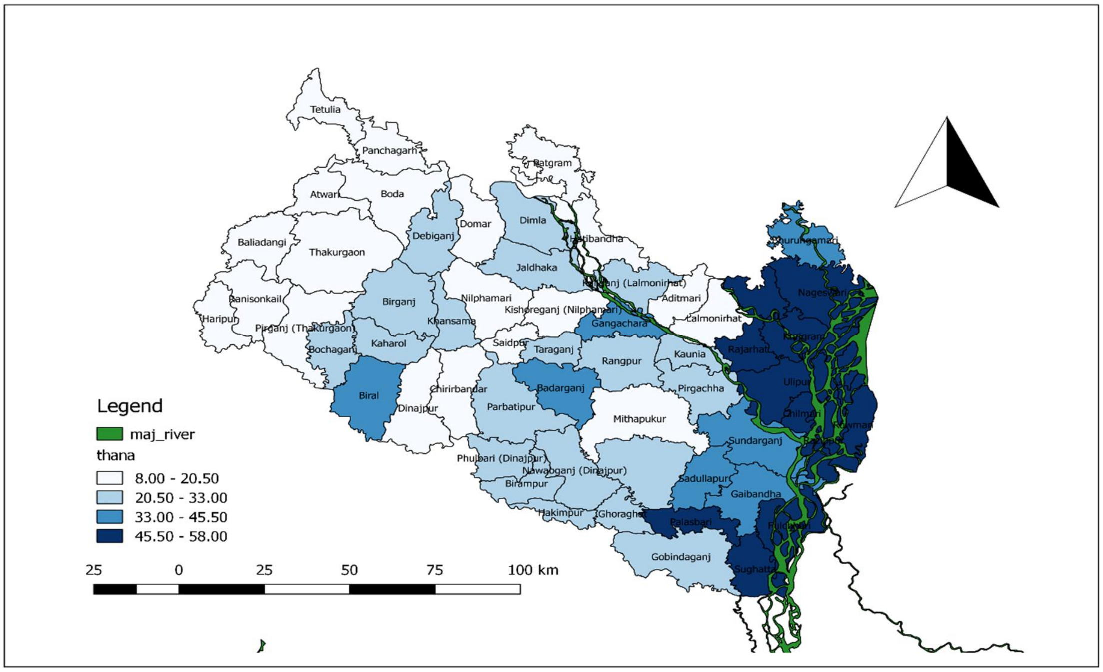
At the final stage of the analysis, we have estimated the poverty estimates at upazila level using both ELL and MQ methods. Appendix 1 reveals both the ELL and MQ estimates of poverty incidence, poverty gap and severity using lower poverty line. Appendix 2 reveals the ELL and MQ estimates of poverty incidence (HCR), poverty gap and severity using upper poverty line. These estimates have been presented in maps (Map 1, Map 2, Map 3 and Map 4). From these Maps, it revealed that Rajarhat, Ulipur, Char Rajibpur, Phulbari, Chilmari, Kurigram Sadar, Nageshwari, and Fulchhari Upazilas have been identified as the poorest Upazilas. Almost similar upazilas were identified to have the highest level of poverty incidences by World Bank (2015) though results were presented at the overall upazila level. These areas are located near the Brahmaputra, Teesta and Dharla rivers and suffer from flood and river erosion and often by seasonal droughts. These are some obvious reasons that explain the highest poverty incidences in these upazila.



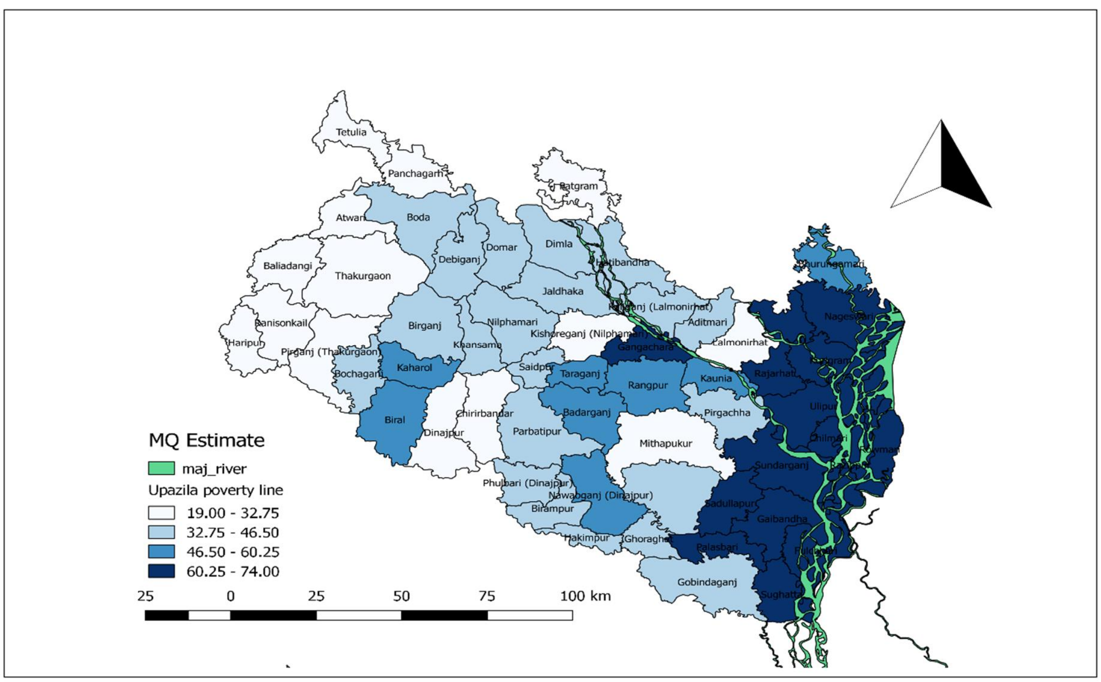
Map 1: Poverty map of rural Rangpur division at upazilla level (ELL method) using lower poverty line



Map 2: Poverty map of rural Rangpur division at upazila level (ELL method) using upper poverty line



Map 3: Poverty map of rural Rangpur division at upazilla level (MQ method) using lower poverty line



Map 4: Poverty map of rural Rangpur division at upazila level (MQ method) using upper poverty line

IV. CONCLUSION AND POLICY IMPLICATIONS

Considering the vastness of the task and time limitation the execution of small area estimation techniques has been limited to the most severely poverty prone division. Using both ELL and MQ estimates rural Rangpur division was identified as the poorest division in rural Bangladesh. This study devoted to identify the district and upazila level estimates of poverty under rural Rangpur using both ELL and MQ methods. The results reveal that Kurigram district has the highest poverty incidence with 50.2% poor in that region (Lower poverty line) using ELL method. Panchagarh district has the lowest poverty level within the Rangpur division. MQ method reveals the same with Kurigram district having the highest poverty incidence and Panchagarh district having the lowest among the districts. In terms of the poverty gap and severity of poverty, these two districts show the same order. The poverty gap estimated by ELL for Kurigram was 13.4% and the severity was 5%, while these percentages for Panchagarh district were 3.4% and 1% respectively. Furthermore, Kurigram and Panchagarh had the highest and lowest poverty incidences respectively, estimated using MQ method. According to upper poverty line, the ELL estimates of poverty incidence for Kurigram was 66.1%, while the poverty gap and severity were 20.9% and 8.7% respectively. For Panchagarh the ELL estimate of poverty incidence was 31.7% and the poverty gap and severity were 7.00% and 2.3% respectively. The MQ estimates of poverty incidence, gap and severity (Upper poverty line) for Kurigram district were 68.71%, 20.09% and 7.70% respectively. The MQ estimates suggest that Panchagarh district has the lowest poverty incidence, gap and severity. Upazila wise estimates of poverty incidence were presented in maps. Upazilas suffering most from poverty considering both upper and lower poverty lines have been confirmed by both ELL and MQ methods. Some upazilas of Kurigram and Gaibanda districts are performing badly. Both ELL and MQ estimates identified more or less the same list of upazilas to be extremely poor. Appropriate interventions should be taken to address these areas taking the environmental hazards and other socio-economic aspects into account. Among the upazilas under Rangpur division Rajarhat, Ulipur, Char Rajibpur, Phulbari, Chilmari, Kurigram Sadar, Nageshwari, and Fulchhari Upazilas have been identified as the poorest upazilas. These upazilas have underlying causes, which may be somewhat different from other upazilas, for such poor condition. Specific interventions should be taken to address the poverty issue in the region.

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Appendix 1: Estimates of poverty incidence (HCR) at the upazila level based on mouza of rural Rangpur division using LPL by ELL and MQ method

District/Upazila	Lower poverty line (LPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Dinajpur						
Birampur	22.7	4.6	1.4	29.5	8.1	2.4
Birganj	25.2	5.2	1.6	25.9	4.6	1.2
Biral	25.7	5.4	1.7	35.1	7.0	2.1
Bochaganj	25.8	5.4	1.7	26.7	4.9	1.4
Chirirbandar	22.9	4.7	1.4	14.6	2.3	0.6
Fulbari	23.9	5.0	1.5	24.5	4.4	1.2
Ghoraghat	23.4	4.9	1.5	23.9	4.4	1.2
Hakimpur	23.7	4.9	1.5	24.0	4.4	1.2
Kaharole	27.1	5.7	1.8	30.4	5.7	1.6
Khansama	26.4	5.5	1.7	27.6	5.0	1.4
Dinajpur Sadar	21.7	4.4	1.4	16.6	2.7	0.7
Nawabganj	25.8	5.5	1.7	31.0	6.0	1.7
Parbatipur	24.5	5.1	1.6	25.1	4.5	1.2
Gaibanda						
Fulchhari	43.5	10.9	3.8	46.3	10.3	3.3
Gaibandha Sadar	39.7	9.7	3.4	44.4	9.8	3.1
Gobindaganj	40	9.8	3.4	27.6	5.1	1.4
Palashbari	41.1	10.2	3.6	48.4	11.3	3.7
Sadullapur	43	10.8	3.8	45.8	10.3	3.3
Saghatta	43.3	10.8	3.8	50.4	11.7	3.8
Sundarganj	40.2	9.8	3.4	43.7	9.6	3.0
Kurigram						
Bhurungamari	45.5	11.4	4.0	36.2	7.1	2.0
Char Rajibpur	48	12.1	4.3	49.2	10.8	3.4
Chilmari	46.9	12.3	4.5	47.7	11.0	3.6
Phulbari	53	14.5	5.5	53.5	12.8	4.2
Kurigram Sadar	49.7	13.2	4.9	51.7	12.2	4.0
Nageshwari	49.3	13.0	4.8	55.5	13.6	4.6
Rajarhat	55.3	15.6	6.1	58.6	15.1	5.3
Raumari	40.2	9.6	3.3	46.7	10.4	3.3
Ulipur	52.2	14.2	5.4	57.3	14.4	5.0
Lalmonirhat						
Aditmari	22.9	4.6	1.4	14.3	2.2	0.5
Hatibandha	23.5	4.7	1.4	19.2	3.1	0.8
Kaliganj	22.3	4.4	1.3	23.1	3.9	1.0

District/Upazila	Lower poverty line (LPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Lalmonirhat Sadar	20.3	3.9	1.2	16.6	2.6	0.6
Patgram	19.7	3.8	1.1	15.3	2.4	0.6
Nilphamari						
Dimla	22.9	4.6	1.4	21.3	3.6	0.9
Domar	20	3.9	1.1	19.7	3.2	0.8
Jaldhaka	24.2	4.9	1.5	23.6	4.0	1.1
Kishoreganj	22	4.4	1.3	12.2	1.8	0.4
Nilphamari Sadar	23.1	4.6	1.4	18.2	2.9	0.7
Saidpur	22.2	4.5	1.4	18.0	2.9	0.8
Panchagarh						
Atwari	18.3	3.5	1.0	11.5	1.7	0.4
Boda	18.6	3.5	1.0	17.2	2.7	0.7
Debiganj	21.1	4.1	1.2	23.3	4.0	1.1
Panchagarh Sadar	16.7	3.1	0.9	8.0	1.1	0.2
Tentulia	15.6	2.9	0.8	8.5	1.2	0.3
Rangpur						
Badarganj	27.9	5.9	1.9	37.7	7.7	2.3
Gangachara	29.4	6.4	2.0	44.7	9.7	3.0
Kaunia	27.8	6.0	1.9	28.7	5.4	1.5
Rangpur Sadar	26.8	5.7	1.8	28.5	5.3	1.5
Mitha Pukur	27.5	5.8	1.8	11.9	1.8	0.4
Pirgachha	26.5	5.6	1.8	26.7	4.9	1.3
Pirganj	28.6	6.2	2.0	23.4	4.1	1.1
Taraganj	26.9	5.7	1.8	33.2	6.4	1.8
Thakurgaon						
Baliadangi	20.4	4.0	1.2	16.0	2.5	0.6
Haripur	22.8	4.6	1.4	16.4	2.6	0.7
Pirganj	20.3	4.0	1.2	14.7	2.3	0.6
Ranisankail	21.5	4.2	1.3	14.5	2.2	0.5
Thakurgaon Sadar	18.1	3.5	1.0	11.5	1.7	0.4

*LPL = Lower poverty line.

Appendix 2: Estimates of poverty incidence (HCR) at the upazila level based on mouza of rural Rangpur division using UPL by ELL and MQ method

District/Upazila	Upper poverty line (UPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Dinajpur						
Birampur	37.4	8.9	3.1	39.1	15.2	5.3
Birganj	40.7	9.9	3.5	44.5	9.8	3.1
Biral	40.9	10.1	3.6	54.4	13.5	4.6
Bochaganj	41.1	10.2	3.6	45.1	10.1	3.2
Chirirbandar	37.7	9.0	3.1	29.0	5.5	1.6
Fulbari	38.9	9.4	3.3	42.4	9.3	2.9
Ghoraghat	38.2	9.4	3.3	40.9	9.1	2.9
Hakimpur	38.6	9.4	3.3	41.5	9.2	2.9
Kaharole	43.2	10.8	3.8	49.9	11.6	3.8
Khansama	42.4	10.5	3.7	46.3	10.4	3.3
Dinajpur Sadar	36.1	8.6	3.0	31.8	6.3	1.9
Nawabganj	41.4	10.3	3.6	49.9	11.9	3.9
Parbatipur	39.7	9.7	3.4	43.2	9.5	3.0
Gaibanda						
Fulchhari	60.6	18.1	7.2	64.6	18.0	6.6
Gaibandha Sadar	56.7	16.4	6.4	62.9	17.3	6.4
Gobindaganj	56.9	16.5	6.5	45.7	10.4	3.4
Palashbari	58	17.1	6.8	66.3	19.1	7.3
Sadullapur	60	17.9	7.2	64.1	17.9	6.6
Saghatta	60.4	17.9	7.2	68.4	19.9	7.5
Sundarganj	57.3	16.7	6.6	62.1	17.0	6.2
Kurigram						
Bhurungamari	63	18.8	7.5	55.9	13.7	4.6
Char Rajibpur	65.6	19.8	8.0	68.3	19.0	7.0
Chilmari	63.5	19.6	8.1	65.8	18.9	7.1
Phulbari	69.7	22.7	9.7	71.4	21.3	8.3
Kurigram Sadar	66.5	21.0	8.8	69.5	20.5	7.9
Nageshwari	66.3	20.8	8.6	72.8	22.2	8.8
Rajarhat	71.3	24.0	10.5	74.9	23.9	9.8
Raumari	58.1	16.7	6.5	65.9	18.2	6.7
Ulipur	68.7	22.3	9.5	73.9	23.2	9.3
Lalmonirhat						
Aditmari	38.1	9.0	3.1	29.4	5.5	1.5
Hatibandha	38.9	9.2	3.1	36.7	7.3	2.1
Kaliganj	37.5	8.7	2.9	41.7	8.7	2.6

District/Upazila	Upper poverty line (UPL)					
	ELL method			MQ method		
	Head count rate (%)	Poverty gap (%)	Poverty severity (%)	Head count rate (%)	Poverty gap (%)	Poverty severity (%)
Lalmonirhat Sadar	34.7	7.9	2.6	32.9	6.3	1.8
Patgram	34.2	7.7	2.5	30.7	5.8	1.6
Nilphamari						
Dimla	38.5	9.0	3.1	39.4	8.1	2.4
Domar	34.2	7.8	2.6	37.1	7.5	2.2
Jaldhaka	39.9	9.5	3.2	42.3	8.9	2.7
Kishoreganj	36.9	8.6	2.9	26.2	4.7	1.3
Nilphamari Sadar	38.5	9.0	3.0	35.4	6.9	2.0
Saidpur	37.3	8.8	3.0	34.5	6.9	2.0
Panchagarh						
Atwari	32.2	7.1	2.3	25.0	4.4	1.2
Boda	32.4	7.2	2.4	33.7	6.6	1.9
Debiganj	35.7	8.2	2.7	41.8	8.8	2.7
Panchagarh Sadar	29.8	6.5	2.1	19.0	3.1	0.8
Tentulia	28.4	6.1	2.0	19.6	3.3	0.9
Rangpur						
Badarganj	44.1	11.1	4.0	57.2	14.4	5.0
Gangachara	45.8	11.7	4.2	64.1	17.4	6.3
Kaunia	43.6	11.1	4.0	47.3	10.9	3.6
Rangpur Sadar	42.9	10.7	3.8	47.5	10.8	3.5
Mitha Pukur	43.4	10.9	3.9	25.5	4.6	1.2
Pirgachha	42	10.5	3.7	44.9	10.1	3.2
Pirganj	44.6	11.3	4.1	41.0	8.8	2.7
Taraganj	42.9	10.6	3.7	52.9	12.6	4.2
Thakurgaon						
Baliadangi	34.6	7.9	2.6	31.9	6.1	1.7
Haripur	37.7	9.0	3.1	32.3	6.2	1.8
Pirganj	34.2	7.9	2.6	29.5	5.6	1.6
Ranisankail	36	8.4	2.8	29.7	5.6	1.6
Thakurgaon Sadar	31.6	7.1	2.3	24.6	4.4	1.2

*UPL = Upper poverty line.