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Small Area Estimation Method for District Level Prevalence of Maternal Health Care Indicators in Bangladesh

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Abstract

Small area estimation (SAE) method is commonly used to obtain micro-level estimates of development indicators. The SAE method through Fay-Herriot model is well-known to compute small area level estimates. This study aims to apply Fay-Harriot model to estimate the district level maternal health care indicators (MHCI) viz., antenatal care (ANC), postnatal care (PNC), skilled birth attendance (SBA), and caesarean section (C-section) with their accuracy level. Both Bangladesh Demographic and Health Survey (BDHS) 2011 and Bangladesh Population and Housing Census (BPHC) 2011 datasets are used to perform this study. The results of the study demonstrate that model-based estimates provide a better representation than the direct estimates showing lower coefficient of variations. The map of the various MHCI reveals substantial inequality across the district level estimates of Bangladesh. The study findings indicated that ANC visits (at least one) varies from 28% to 98% and most vulnerable district is appeared as Rangamati. The standard visits of ANC (four or more) differs within 8-51% showing Narail district hold the lowest ranking. The SBA lies within the range 0-55% and Netrokona district is the worst position. Further, PNC deviates within 27-73% and found Netrokona as the most vulnerable condition. Finally, C-section varies within range 5-35% and Bhola district appeared as the worst position. The outcomes of the study could be helpful for policymakers to identify the most vulnerable districts regarding MHCI and taking initiative to strengthen the existing programs relating to MHCI in the vulnerable areas.

Keywords: Small Area Estimation; Fay-Herriot Model; Direct Estimate, Antenatal Care; Postnatal Care; Skilled Birth Attendant; C-section.

1. Introduction

Maternal health means women's health at the time of pregnancy, birth giving, and the postpartum period. Though motherhood is a positive experience and pleasing aspiration, it is related to poor health, which may cause of death for many women. Every day about 810 women die either from pregnancy or childbirth-related complications around the world [1] and it was about 295,000 in 2017 [2]. Almost all maternal deaths (94%) occur in developing countries that are struggling for resources, among which more than fifty percent occur in sub-Saharan Africa and nearly one-third occur in South Asia [1]. The scenario of maternal health services is not at a satisfactory level in low-resource countries like Bangladesh [3].

Though Bangladesh has achieved its Millennium Development (MDG) Goal-4 states about reducing child mortality and MDG-5 indicates about reducing maternal mortality, but the existing ratio of maternal mortality was 173 per 100 thousand live births [1] and the rate of neonatal mortality was 28 per 1000 live births [4] which indicates significantly high rate. Less utilization of maternal healthcare services, viz., ANC, PNC, SBA, and delivery facility could be the main reason for the high mortality rate of mother and children [5]. The Sustainable Development Goal 3 (SDG 3) set the target for Bangladesh to reduce the ratio of maternal mortality from 173 to 105 per 100 thousand live births within 2030 [6]. Thus, to achieve the relevant targets of the SDGs, it is essential to improve maternal health indicators (ANC, SBA, facility delivery, and PNC) by ensuring an integrated maternal healthcare system.

ANC, which is provided by trained medical personnel, is an elementary maternal healthcare (MHC) service. By ensuring a better quality of ANC, maternal and perinatal mortality could be reduced by identifying women those who were suffering from anemia, preterm labor, and pregnancy-induced hypertension [7]. ANC could help to escalation the use of SBA (midwife, nurse, or doctor) at the time of delivery and postnatal care [4]. In Bangladesh, only 31% of pregnant women received 4 or more ANC, however, it varied from division to division [4, 8]. For example, for Sylhet division the percentage of 4 or more ANC was 10 while for the Khulna division, the percentage was 28 [8].

In Bangladesh, midwives, nurses and doctors who have the expertise to do typical deliveries are recognized as skilled birth attendants. Only 42% of births during the period of 2011-2014 was assisted by skilled birth attendants [4]. At the division level, only 25% of deliveries in Sylhet and 29.5% in Barisal were attended by SBA, while in Khulna and Dhaka divisions the rates are 52.4% and 40.3% respectively [9].

Only 37% of all births in the previous 3-year of BDHS-2014 was delivered in a health facility. Among the delivering births in health facilities, 61% (23% of all births) were delivered by C-section [4]. The inequality in the facility delivery is highly significant across the divisions, for example, for Sylhet division the percentage of institutional delivery was 22.6 while for Khulna division the percentage was 54.6.

Among the maternal health care services, PNC is essential to save life for both the newborn and mother. In the three years preceding the BDHS-2014, about 36 % of women received PNC of their last birth from a medically trained worker. The inequality in PNC is also experienced the same trend as C-section, for example, the percentage of PNC for Sylhet is 23.4 and for Khulna, it is 50.9 [4].

The government and the policymakers are trying to improve the situation of the poor conditions of maternal health care services that has been observed from the various studies conducted in the last two decades [4; 10]. Consequently, a significant number of development programs have been implementing through government and non-government organizations throughout the nation. Most of the implementation plans are usually implemented at disaggregated levels such as district levels. However, the researchers and policymakers always face difficulty in obtaining accurate estimates of maternal health indicators at the district level. The reason of facing difficulty of not getting accurate estimates at disaggregate level (e.g. district level) is due to inadequate and inconsistent sample sizes at district levels. For example, BDHS 2011 includes all 64 districts but the sizes of district-level samples are not enough to obtain reliable estimates using direct estimation methods. In this situation, a proper indirect statistical technique such as small area estimation (SAE) could be used to estimate any indicators at micro-level administrative units by utilizing a nationwide survey data and contemporary census data.

SAE is an indirect statistical technique to obtain precise estimates with accuracy for the desired disaggregated level of a country's administrative units. The primary concept of the SAE method is combining survey data with a recent census data via a statistical model [11]. It requires both survey data consisting of the response variable and census data consisting of the explanatory variables, specified in the regression model. Availability of auxiliary variables plays an important role to consider an appropriate small area model: when individual and/or household level auxiliary variables are available, the model is known as a unit-level model and when data of area-level are available, the model is known as an area-level model [12]. Since pregnancy status of 15-49 years old married women are unavailable in the Bangladesh Population and Housing Census data (BPHC), unit-level SAE method is not possible in this study. Therefore, this study used area level small area model to obtain desired SAE estimates.

The aim of this study is to estimate the district-level maternal health care indicators (MHCI) with their accuracy by employing the area level Fay-Herriot (FH) SAE model [13] and make a comparison with direct estimates. The study also portrayed the district level maps of the estimated MHC indicators of Bangladesh.

2. Methodology

For performing the analysis, the BDHS 2011 data are combined with the BPHC 2011 data. This study used BDHS 2011 data instead of BDHS 2014 data since the sampling design of BDHS 2011is based on the Census 2011. A two-stage stratified sampling design was used to collect the BDHS 2011 data, incorporating all 64-district and seven-division.

2.1 Bangladesh Population Census 2011

Bangladesh is now divided into a total of 8 divisions for administrative determinations but in 2011 it was 7 divisions. The lower administrative units are Zila (district), Upazila (sub-district), Union/Ward, and Mauza. In the nationwide household survey of Bangladesh, these lower administrative units are not usually considered in sampling design. The lowest unit considered for sampling design in different surveys is the enumeration area (EA), which can be a village, part of the village, or a combination of several villages, consisting of about 100-120 villages.

The area-level census data of Bangladesh is huge and contains aggregated area level information for areas like division, district, sub-district, union, village, mauza, etc. from where we need to extract division, and district information. Table 1 shows the total number of each of the administrative units and their approximate sizes in terms of the average number of households obtained from 2011 Bangladesh Population Census.

Table 1 Approximate number of administrative units and households in 2011 Census.

Division	District	Upazila/ Thana	Union	Mauza	EA
Number of administrative units					
7	64	544	7755	64637	293579
Average number of households					
4540812	496651	58430	4099	492	110

The census data consist of information of socio-demographic characteristics that include employment, education, schooling, age, sex, housing characteristics and disability. Contextual variables at the district level can easily be created from the area level census data and then be utilized in the model specification.

2.2 Bangladesh Demographic and Health Survey 2011

In Bangladesh, the Demographic and Health Surveys (DHS) started four-yearly health-related and demographic data collection from 1993/94 and still continuing this program. The sampling design of BDHS 2011 is based on the 2011 BPHC. The BDHS 2011 data-set were based on two-stage stratified sampling design that covers all divisions and districts including 20 strata, 600 EAs and 30 households for each EAs. Information on maternal health care services were collected covering all ever-married women who have given childbirth within the 3 years earlier of the survey date. The cluster information with geographic location along with approximate latitude and longitude are available in the geographic dataset.

2.3 Fay-Herriot Model

The basic area-level model proposed by Fay and Herriot [13] is briefly described below:

Suppose design-based direct weighted estimate $(\bar{y}_{wd})$ of true unknown area mean $(\bar{y}_d)$is available for every area$(d = 1,2,..,D)$. It is assumed that the true area mean$\bar{y}_d$ is related to area-specific auxiliary data

$Z_d = (Z_{1d}, Z_{2d}, .., Z_{pd})^{/}$ through a linear model called linking model as $\bar{y}_d = Z_d^{/}\beta + u_d$; $d = 1,2,..,D$ and design unbiased estimator $\bar{y}_{wd}$can be expressed by a sampling model $\bar{y}_{wd} = \bar{y}_d + e_d$; $d = 1,2,..,D$. Combining these two models, a special case of a general linear mixed model consisting of both design-induced random variable e_d and model-based random variable u_d is obtained as

$$\bar{y}_w = Z\beta + u + e$$

where $\bar{y}_w = (\bar{y}_{w1}, \bar{y}_{w2}, \dots, \bar{y}_{wD})^{/}$, Z is a $(D \times p)$ matrix of $Z_d{}'s$, $e = (e_1, e_2, \dots, e_d)^{/}$ and $u = (u_1, u_2, \dots, u_d)^{/}$ are distributed independently as $N(0, R)$ and $N(0, \sigma_u^2 \mathrm{I}_D)$ where $R = Diag(\sigma_{e1}^2, \sigma_{e2}^2, \dots, \sigma_{eD}^2)$ and I_D is an identity matrix of order D. Considering σ_u^2 and σ_{ed}^2 known, the BLUP estimator of $u_d$can be written as $\hat{u}_d^{BLUP} = \sigma_u^2\{\sigma_{ed}^2 + \sigma_u^2\}^{-1}(\bar{y}_{wd} - Z_d^{/}\hat{\beta}^{BLUE})$. And hence the BLUP of $\bar{y}_d$

$$\begin{aligned}\hat{\bar{y}}_d^{BLUP} &= Z_d^{/}\hat{\beta}^{BLUE} + \hat{u}_d^{BLUP} \\ &= Z_d^{/}\hat{\beta}^{BLUE} \\ &\quad + \sigma_u^2\{\sigma_{ed}^2 + \sigma_u^2\}^{-1}(\bar{y}_{wd} \\ &\quad - Z_d^{/}\hat{\beta}^{BLUE}) \\ &= \lambda_d \bar{y}_{wd} + (1 - \lambda_d) Z_d^{/}\hat{\beta}^{BLUE}\end{aligned}$$

where $\lambda_d = \sigma_u^2/(\sigma_u^2 + \sigma_{ed}^2)$, $\hat{\beta}^{BLUE} = (Z^{/}V^{-1}Z)^{-1}(Z^{/}V^{-1}\bar{y}_w)$ with $V = diag(\sigma_u^2 + \sigma_{ed}^2; d = 1,2,..,D)$. Thus $\hat{\bar{y}}_d^{BLUP}$is a weighted average of design-based unbiased estimator $(\bar{y}_{wd})$ and regression-synthetic estimator$(Z_d^{/}\hat{\beta}^{BLUE})$. Also, it is clear that $\hat{\bar{y}}_d^{BLUP}$tends to $\bar{y}_{wd}$if $\lambda_d \to 1$ and to $Z_d^{/}\hat{\beta}^{BLUE}$ if$\lambda_d \to 0$. Under normality, an empirical BLUP (EBLUP) or empirical Bayes (EB) estimator could be found by substituting efficient estimator of σ_u^2 and σ_{ed}^2 in $\hat{\bar{y}}_d^{BLUP}$ as

$$\hat{\bar{y}}_d^{EBLUP} = Z_d^{/}\hat{\beta}^{EBLUE} + \hat{u}_d^{EBLUP} = Z_d^{/}\hat{\beta}^{EBLUE} + \hat{\sigma}_u^2/(\hat{\sigma}_u^2 + \sigma_{ed}^2)\,(\bar{y}_{wd} - Z_d^{/}\hat{\beta}^{EBLUE}).$$

The main problematic issue of Fay-Herriot model is the estimation ofσ_u^2 and σ_{ed}^2. Normally σ_{ed}^2 are assumed known and estimated from survey data or other sources. Asymptotically consistent maximum likelihood (ML) and restricted ML (REML) estimator of σ_u^2 can be utilized to obtain the EBLUP estimator [14].

Mean squared error (MSE) of the estimator $\hat{\bar{y}}_d^{EBLUP}$has been developed by Prasad and Rao [15]. For estimating district-level estimates a spatial FH model can be developed using a distance among the districts and also their geographic location (latitude and longitude). When the direct estimates are not available from the survey data, the indicators for those areas will be estimated using the synthetic estimator $(\hat{\bar{y}}_d^{EBLUP} = Z_d^{/}\hat{\beta}^{EBLUE})$ and its MSE estimator.

This estimator will be used mainly for the districts for which there will be no information in the survey data.

2.4 Design-based Direct Estimator

Design-based direct estimates of target parameters for small areas can be obtained by Horvitz-Thompson estimator, using the response variable available in the survey data. The design-based direct estimator (DIR) for area i for the target proportion P_i is

$$\hat{P}_i^{DIR} = \sum_{j \in s_i} w_{ij} Z_{ij},\ i = 1,2,\dots\dots D;$$

$$j = 1,2,\dots\dots K$$

where $w_{ij} = w_{ij}^* / \sum_{j \in s_i} w_{ij}^*$ is known as survey weights for unit j within area (say, district) i where $\sum_{j \in s_i} w_{ij} = 1$ and w_{ij}^* is survey weight (transpose of the inclusion probability) for unit j within area i. The variance of the design-based DIR estimator could be obtained by,

$$var(\hat{P}_i^{DIR}) \approx \sum_{j \in s_i} w_{ij}(w_{ij} - 1)(z_{ij} - \hat{P}_i^{DIR})^2$$

The variance estimator of the direct estimator is obtained from [14], with the simplifications$w_{ij} = 1/\pi_{ij}$, $\pi_{ij,ij} = \pi_{ij}$ and $\pi_{ij,ik} = \pi_{ij}\pi_{ik},\ j \neq k$, where π_{ij} is the first order inclusion probability of unit j in area i and $\pi_{ij,ik}$ is the second order inclusion probability of units j and k in area i. In particular, this approximation avoids the use of second order inclusion probabilities and uses $\pi_{ij,ik} \approx \pi_{ij}\pi_{ik}$. Under simple random sampling $w_{ij}^* = N_i n_i^{-1}$ and the direct estimator is $\hat{P}_i^{DIR} = n_i^{-1} \sum_{j \in s_i} Z_{ij}$ with

$$var(\hat{P}_i^{DIR}) \approx n_i^{-1}(n_i^{-1} - 1)\sum_{j \in s_i}(z_{ij} - \hat{P}_i^{DIR})^2$$

The DIR survey estimator is unbiased, and it based on area-wise sample data. Consequently, the DIR estimator becomes inefficient for area-wise small sample size. When the sampling variability is high; these estimates show huge confidence interval. In addition, for areas without sample data, it is not possible to use DIR estimates. Henceforth, DIR estimates are not encouraged to use for SAEs. For example, direct survey estimates computed from the BDHS 2011 data in Bangladesh have large standard errors at the district level and they cannot even be computed for districts with no sample data. In this situation, model-based SAE methods that 'borrow strength' through statistical models could be utilized to get precise small area estimates. These approaches involve indirect estimators based on the appropriate linking model [16].

2.5 Explanatory Variables Used in Model

Explanatory variables used to develop Fay-Herriot models are presented in Table 2.

Table 2: Description of explanatory variables used in model development

Name	Description	Type
Delv_Place	Place of Delivery	Indicator
Literacy.F	Proportion of Female Literacy	Indicator
Pop.Women	Total Population (Women)	Continuous
Dep.Ratio	Dependent Ratio	Continuous
Pop. dens	Population Density	Continuous

3. Results and Discussion

The five-number summary and mean of the estimated prevalence of ANC visits, coverage of at least 4 ANC visits which is known as standard ANC visits, SBA, C-section and PNC across the districts and their coefficient of variations (CVs) are shown in Table 3 to Table 7. The direct estimates of the indicators shows larger CVs than SAE. It may be due to the calculation of these estimates from small sample sizes by direct method, while the SAE estimator overcomes these problems (though it comes from small sample sizes) and providing lower CVs. It is clear that the median estimated CVs of the FH estimators are smaller than those estimated from direct method. It indicates that CV's of FH is functioning much better than that obtained by the direct method when sample sizes are small.

Table 3: Summary statistics of ANC visits at district level with CV using direct (DIR) and SAE (FH) methods

Statistics	Estimates		CV (%)	
	DIR	FH	DIR	FH
Minimum	8.33	29.79	5.64	5.53
Q1	57.11	58.40	14.58	13.89
Mean	65.21	65.94	22.47	18.78
Median	67.56	67.82	18.94	17.01
Q3	77.46	77.12	25.33	21.01
Maximum	97.74	96.77	100	49.91

Table 4: Summary statistics of ANC above 4 visit (Standard ANC) at district level with CV using direct (DIR) and SAE (FH) methods

Statistics	Estimates		CV (%)	
	DIR	FH	DIR	FH
Minimum	4.76	8.67	5.64	5.62
Q1	14.93	15.20	14.58	13.89
Mean	24.94	24.67	22.47	18.71
Median	22.86	23.30	18.94	17.18
Q3	31.25	30.12	25.33	21.10
Maximum	53.44	50.85	100	49.91

Table 5: Summary statistics of SBA at district level with CV using direct (DIR) and SAE (FH) methods

Statistics	Estimates		CV (%)	
	DIR	FH	DIR	FH
Minimum	8.96	9.72	4.94	4.95
Q1	17.20	18.81	12.96	11.00
Mean	27.54	27.28	19.95	15.81
Median	24.69	24.89	17.41	14.68
Q3	33.33	32.62	25.60	19.91
Maximum	71.43	54.76	54.92	36.99

Table 6: Summary statistics of C-section at district level with CV using direct (DIR) and SAE (FH) methods

Statistics	Estimates		CV (%)	
	DIR	FH	DIR	FH
Minimum	4.55	5.03	7.50	7.46
Q1	8.89	10.41	19.29	15.29
Mean	15.56	14.92	29.10	10.18
Median	14.29	14.24	26.10	19.81
Q3	21.21	19.31	37.70	24.56
Maximum	34.85	34.69	100	43.94

Table 7: Summary statistics of PNC at district level with CV using direct (DIR) and SAE (FH) methods

Statistics	Estimates		CV (%)	
	DIR	FH	DIR	FH
Minimum	20.00	28.58	3.35	3.33
Q1	35.18	39.09	8.57	7.89
Mean	48.08	48.75	13.92	10.51
Median	49.43	47.75	10.85	9.83
Q3	58.60	56.96	15.60	13.15
Maximum	80.00	72.68	66.67	25.10

The direct and FH estimates of the indicators along with their CVs are plotted against district-specific sample sizes in Figure 1 to Figure 5 respectively. In all of these figures, the FH estimates go through the direct estimates (Panels (a)) which indicates the FH estimator provides approximately unbiased estimates. District-level estimates obtained from both direct and FH methods differ from district to district (Panels (a)). Direct estimates show high variability for districts those have small (less than 100) sample size. In contrast, districts that have large (more than 100) sample size, the DIR estimates are remained stable and very near to the FH estimates (Panels (a)).

The pattern of the estimated CVs of the indicators (Panels (b)) support the above-mentioned statement that is shown in Figure 1 to Figure 5. For small sample sizes, the CVs of the DIR estimators are higher than those of FH estimators for all indicators, however increasing sample size reduces the differences of CVs between DIR and FH estimators (Panels (b)). In Figure 1, for ANC, CVs (Panel (b)) of FH estimators are smaller than direct estimators for small sample size (?100) while CV's are almost the same for direct and FH methods for large sample size (for example when the sample size is greater than 200) which indicates that FH estimators are more precise than the direct estimators for the small sample size. The similar patterns of CVs are also obtained for the rest of the four indicators (Figure 2 to Figure 5).

The district level maps of Bangladesh for the prevalence of ANC (Figure 6), ANC above 4 visits (Figure 7), SBA (Figure 8), C-section (Figure 9) and PNC (Figure 10) are depicted. In Bangladesh national level proportion of ANC above 4, SBA, C-section and SBA are estimated as 31%, 42%, 23% and 39% respectively [4], while district-level SAE estimates vary from district to district. Figure 6 indicates that 11 districts (viz. Mymonsingh, Netrokona, Sunamganj, Kishoreganj, Habiganj, Narsingdi, Khagrachhari, Rangamati, Bandarban, Sirajganj, Jamalpur) have had the lowest ANC prevalence within the range of 28%-55%. More specifically, the highest ANC prevalence is found at the Joypurhat district (98%) in the Rajshahi division and lowest at the Rangamati district (28%) in the Chittagong division. Figure 7 shows that 13 districts (namely Sirajganj, Jamalpur, Kishoreganj, Habiganj, Sunamganj, Narsingdi, Comilla, Magura, Narail, Lakshmipur, Noakhali, Cox's Bazar and Madaripur) have had the lowest prevalence of ANC above 4 within the range of 8%-15%. The highest ANC above 4 prevalence is found in Khulna district (50.84%) and the lowest in Narail district (8.67%).

Figure 8 shows that 12 districts (viz., Jamalpur, Mymensingh, Netrokona, Kishoreganj, Sunamganj, Narsingdi, Noakhali, Khagrachhari, Rangamati, Bandarban, Cox's Bazar, Shariatpur) have experienced the lowest prevalence of SBA within the range of 0-16.3%. For SBA, the highest prevalence is found in Dhaka district (55%) and the lowest in Netrokona district (9.72%). The scenario of C-section is revealed in Figure 9, indicating that 13 districts (viz., Dhaka, Narayanganj, Gazipur, Khulna, Jessore, Jhenaidaha, Chuadanga, Meherpur, Kushtia, Rajshahi, Naogaon, Joypurhat, and Dinajpur) have the highest prevalence of C-section (20%-35%) and the lowest is found in Bhola district (5%). There are 13 districts viz., Cox's Bazar, Bandarban, Noakhali, Lakshmipur, Narsingdi, Kishoreganj, Netrokona, Sunamganj, Habiganj, Sirajganj, Jamalpur, Gaibandha and Gopalganj have had the lowest prevalence of PNC (Figure 10) contained the range of 27%-37%. The maximum prevalence of PNC have been found in Meherpur (73%) and the minimum is in Netrokona (29%).

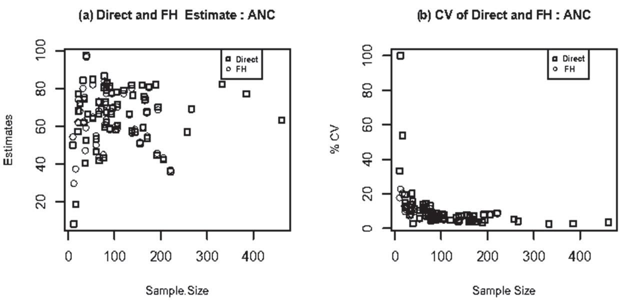

Figure 1: Estimates of average ANC visits at district level with CV's using direct (DIR) and SAE (FH) estimators against the district-specific sample size.

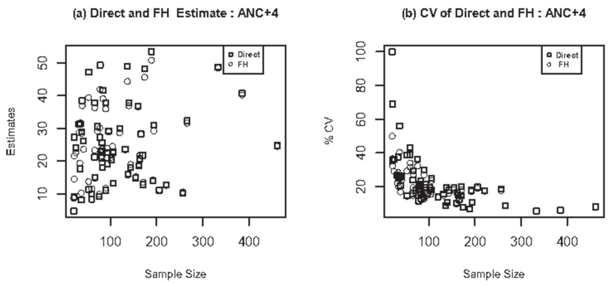

Figure 2: Estimates of prevalence of ANC above 4 at district level with CV's using direct (DIR) and SAE (FH) estimators against the district-specific sample size.

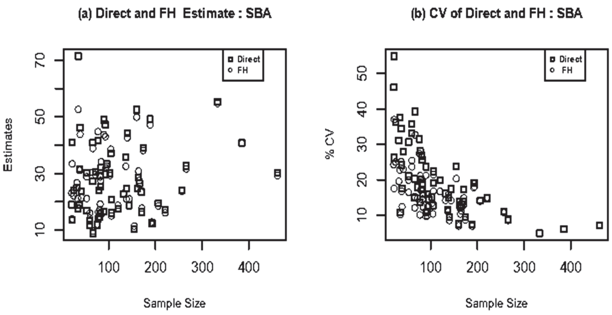

Figure 3: Estimates of the prevalence of SBA at district level with CV's using direct (DIR) and SAE (FH) estimators against the district-specific sample size.

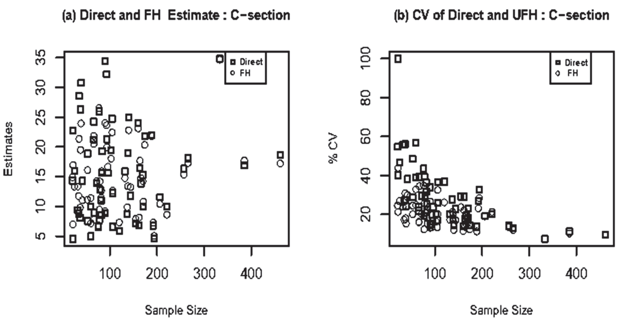

Figure 4: Estimates of the prevalence of C-section at district level with CV's using direct (DIR) and SAE (FH) estimators against the district-specific sample size.

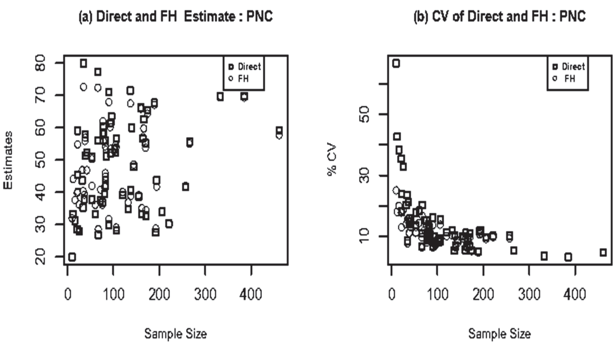

Figure 5: Estimates of the prevalence of PNC at district level with CV's using direct (DIR) and SAE (FH) estimators against the district-specific sample size.

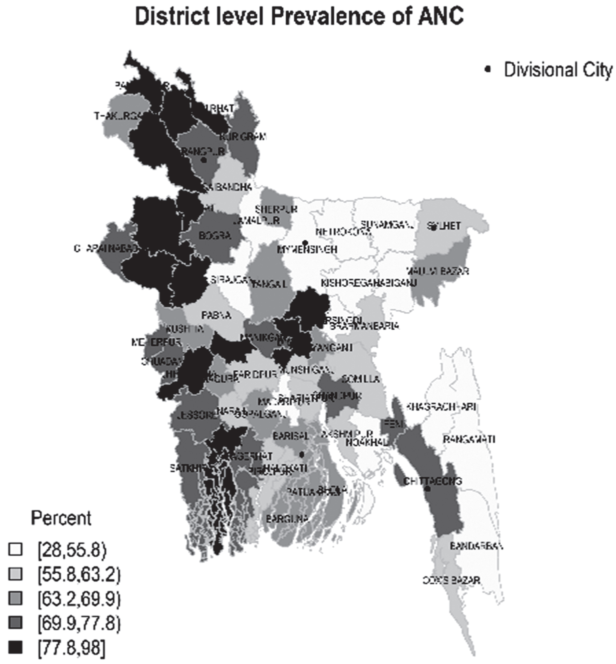

Figure 6: Spatial distribution of the estimated prevalence of ANC at district level using SAE (FH) estimators

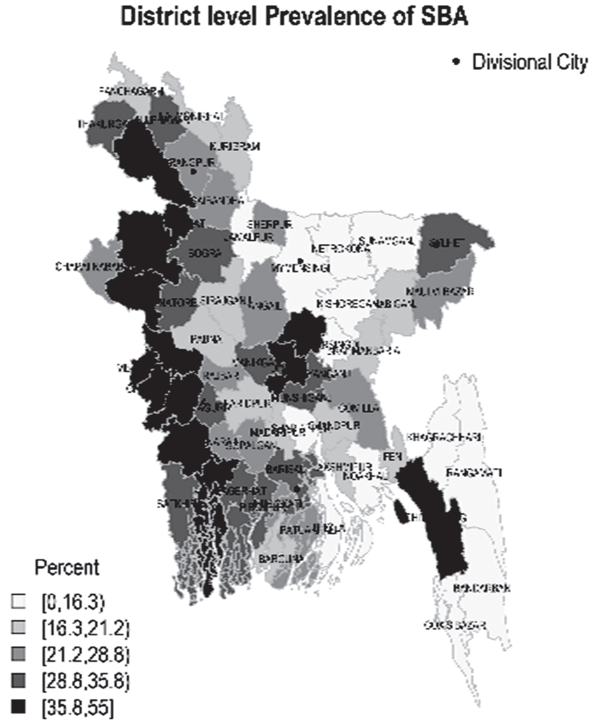

Figure 8: Spatial distribution of the estimated prevalence SBA at district level using SAE (FH) estimators.

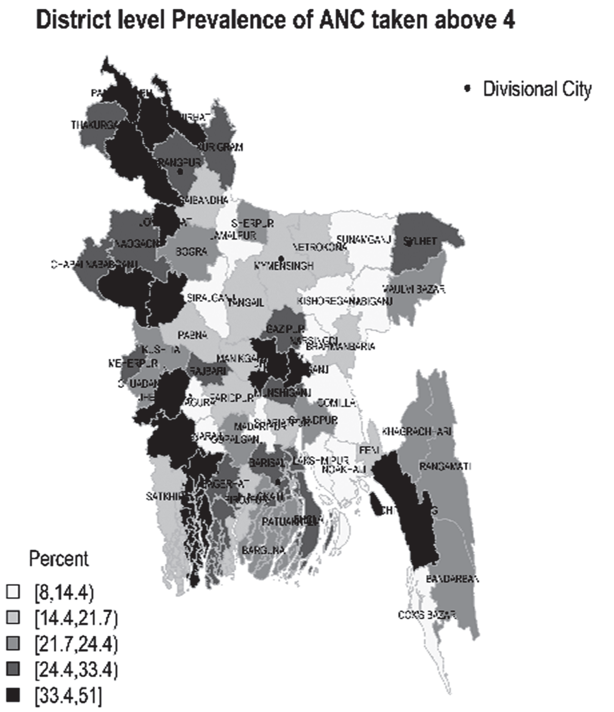

Figure 7: Spatial distribution of the estimated prevalence of ANC above 4 at district level using SAE (FH) estimators.

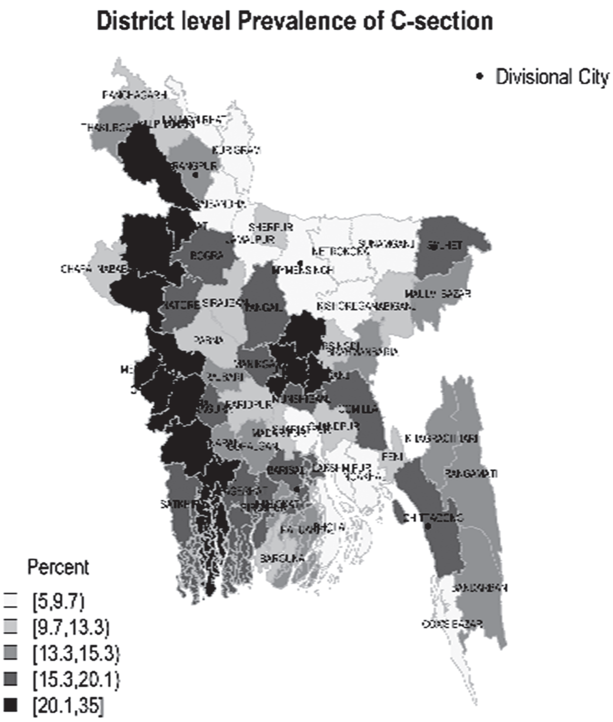

Figure 9: Spatial distribution of the estimated prevalence of C-section at district level using SAE (FH) estimators.

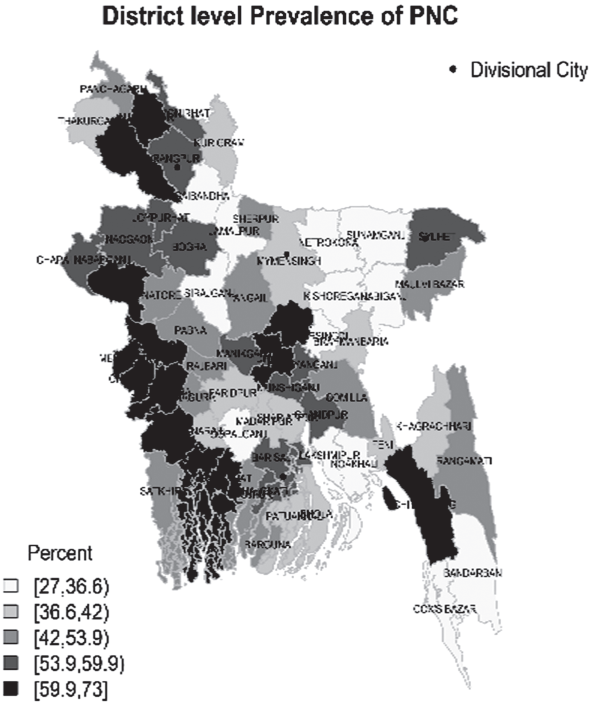

Figure 10: Spatial distribution of the estimated prevalence of PNC at district level using SAE (FH) estimators.

4. Conclusion

In this study, Fay-Herriot small area estimation method is applied to estimate district-level maternal health care indicators with accuracy measures. The investigation found that the SAE method provides unbiased and more accurate estimates when comparing with direct estimators for small sample sizes. The distributions of the estimated coefficient of variation reveal the grater improvement of FH estimators over direct estimators for all of the indicators. FH estimates show better efficiency particularly for the areas with small samples for the investigated variables considered in this study. Future research could consider more areas or more auxiliary variables from different source of data to examine the more likelihood of FH estimates.

The district-level map reveals the inequality of maternal health care indicators among the districts. In terms of taking ANC, Rangamati district is the most vulnerable followed by Khagrachhari district. However, for taking 4+ ANC, scenario is not good throughout the country where Narail district is the most susceptible. In case of SBA and PNC, Netrokona is found the most vulnerable district. Bhola district experienced the least C-section services. The inequality would be higher when the target parameters will be estimated at lower administrative units (say, sub-district). The study findings could help the national and international strategic planner and policymakers for taking initiative to improve the maternal health care services to the vulnerable region.

Small area estimation has more scope for future research. In this study, the random effects and sampling errors in the FH models are considered as identically and independently normally distributed with zero mean and constant variance. However, random effects can be distributed as temporally auto-correlated, spatially-temporally auto-correlated or can be non-normal. Univariate SAE methods considering random effects as spatially-temporally auto-correlated was studied by Marhuenda and Morales [17]. A multivariate Fay-Herriot model with spatial-temporal random effect could be considered in future research in order to obtain more accurate estimates at a more disaggregated level such as sub-district level.

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