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Spatial hierarchical Bayes Small Area Model for disaggregated level crop acreage estimation

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ABSTRACT

Crop area statistics in most of the states in India are provided based on complete enumeration or census approach. But, shortage of man power, failure of the primary and revenue staffs to devote adequate time and attention in collection and compilation of data has deteriorated the quality of area statistics as well as increased the time lag in availability of data in hand. In the view of above problem, a well-designed sample survey has the ability to cater the need of accurate and timely crop area information with utilization of limited resources. A pilot study conducted by ICAR- Indian Agricultural Statistics Research Institute attempts to estimate disaggregated level crop yield based on reduced number of Crop Cutting Experiments (CCEs) while crop acreage estimation has been done through sample survey approach. But, traditional sampling theory has also some limitations in providing reliable and valid estimates particularly for districts/areas with few or negligible sample sizes. To tackle this need Small Area Estimation (SAE) approach has been considered in this paper. In particular, using Hierarchical Bayes spatial small area model disaggregated level crop area has been estimated for two major crops, rice and wheat respectively in the state of Uttar Pradesh for Agriculture year 2015-16. Estimates produced using SAE technique has acceptable precision level.

Key words: Crop area statistics, Hierarchical Bayes, Small area estimation

In developing countries, agriculture tends to be the most important segment of the national economy. Agricultural statistics provides the foundation on which policies for development of the country are built. Whereas, for sound policy and planning it is vital that the system of generation of relevant data for the agriculture and allied sector has a high degree of credibility and is able to capture a wide range of parameters. The focus of agricultural policy, worldwide, has shifted from merely increasing production to doing so sustainably, while not losing sight of the goals of equity and development. This has increased the demands on agricultural statistics in terms of scope, reliability and timeliness. There are numerous aspects to agricultural data. These include the structure of agriculture, i.e. agricultural holding by size, operational tenure, input use, annual agricultural activities including crop and livestock yield and production, seasonal information related to cost of cultivation, trade and prices of agricultural products. In particular, crop statistics (i.e. crop area, yield and production) play an important role in the planning and allocation of resources for the development of the agricultural sector. Reliable and timely information on crop area, yield and production acts as a fundamental input to the planners and policymakers responsible for formulating efficient agricultural policies, and for making important decisions with respect to procurement, storage, public distribution, import, export and other related issues. The Crop-cutting experiments (CCEs) conducted under the scheme of General Crop Estimation Surveys (GCES) accurately estimate crop yield during the cultivation cycle. Currently, around 1300000 CCEs are conducted every year covering 52 food and 16 non-food crops in different States/UTs in India. For obtaining crop area statistics, the States and UTs are broadly classified into two groups. States and UTs which have been cadastral surveyed and where area and land use statistics form a part of the land records maintained by the revenue agency are referred as Temporarily Settled States. Such system is followed in 18 States/UTs. Kerala, Odisha and West Bengal are referred as Permanently Settled States, where there is no land revenue agency at the village level and crop area and land use statistics are obtained through a scheme of sample surveys. In part of Assam (hill districts), Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura and the two UTs of Andaman and Nicobar Islands and Lakshadweep, personal assessment approach (from village headman) is followed. Crop production estimates are

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generally portrayed as the product of two components: area harvested and yield per unit area. Therefore, the accurate estimation of both harvested area and yield are equally important in ensuring the accurate determination of their product. Although the yield estimation gets most of the attention, there are many complexities to the estimation of area that might not be readily apparent. Crop area statistics of the temporarily settled areas are comprehensive, being based on the complete enumeration or census method. But, shortage of man power, failure of the primary and revenue staffs to devote adequate time and attention in collection and compilation of data has deteriorated the quality of area statistics as well as increased the time lag in availability of data in hand. In the view of above problem, a well-designed sample survey for catering the need of area information, can provide much cheaper statistics than a census and serve more timely information on current conditions. Sampling procedure has the ability to tailor the accuracy of estimates to specific need and is especially important to developing countries which have very limited resources to apply to the collection of agricultural data. Henceforth, a pilot study was conducted by ICAR-Indian Agricultural Statistics Research Institute, New Delhi in 5 states of India to generate reliable crop production statistics at district level. Attempt has been made to estimate crop yield based on reduced number of CCEs. For area statistics Stratified multi-stage random sampling design has been followed with districts as strata. In this paper, disaggregated level (i.e. district level) area estimates (refer as 'Direct' estimates) are furnished which has been obtained from this pilot study in the state of Uttar Pradesh (UP) for two major crops, i.e. rice (*kharif*) and wheat (*rabi*) of agriculture year 2015-16. Additionally, direct estimates have been compared with the estimates obtained based on Small Area Estimation (SAE) approach. SAE is a model-based technique which utilizes the existing survey data (from pilot study) and auxiliary variable from census or administrative registers without additional budgetary expenses and known to provide much more precise and acceptable estimates than direct. The direct estimates are not satisfactory to represent areas/domains having small or insufficient sample sizes specifically at micro or decentralized level of administration. Therefore, in recent years SAE technique has drawn a great deal of attention from both public and private sectors as lot of emphasis are now given to micro or disaggregate level planning, budget allocation, regional development and target-specific policy formulation. It is the main endeavor of SAE approach to produce sound predictions of a target statistic for small domains to answer the problem of small sample sizes.

MATERIALS AND METHODS

In the planning process of any country the initial requirements normally pertain to estimates of macro-level parameters. However, with the growth in the development process, requirement of statistics at lower level become more and more important. Small area statistics has become a practical necessity in almost every field of application as far as the data needs are concerned. Surveys are normally planned with specific populations in view. Quite often, interest also lies in parts of the population known as subpopulations or domains of interest. Domain parameters may be estimated satisfactorily through usual sample survey approach provided the domains get sufficient representation of sampled units in the main sample (which is domain direct estimates). Sometimes, the subpopulations or domains are too small to provide reliable direct estimates. The term small domain or area typically refers to the part of a population for which reliable statistics of interest cannot be produced due to certain limitations of the data. Contextually model based SAE approaches has continually gained attention to provide acceptable estimates for such small area or small domain.

Sampling methodology

In the state of Uttar Pradesh number of sample villages under Timely Reporting Scheme (TRS) were 20000 and for the pilot survey 10% of TRS villages (i.e. 2000 villages) were selected. For obtaining crop production statistics, the adopted sampling design was Stratified multi-stage random sampling. Districts have been considered as strata, 50% of the Tehsils/Taluks in a district have been selected as First stage Sampling Units (FSUs) by Simple Random Sampling Without Replacement (SRSWOR). Villages within a FSU are taken as Second stage Sampling Units (SSUs), and within each SSU, survey/sub-survey numbers have been taken as Third stage Sampling Units (TSUs). The SSUs and TSUs have been selected using SRSWOR. Further, 100 survey numbers have been selected in the form of 20 clusters of 5 survey numbers within each selected villages. For each major crop, two survey/sub-survey numbers have been selected randomly out of 100 survey numbers for conducting CCEs for estimation of yield rate. For acreage estimation (direct method) crop area was noted in each of the 100 survey numbers selected within villages. In this pilot experiment, thus sample survey approach has been employed for construction of frame in place of complete enumeration of villages to reduce cost and time. But, this resulted in inadequate sample sizes in districts as compared to census approach. Further, there were districts with no data received due to some administrative problems while collection of data. To tackle the problem of insufficient/zero sample sizes and to produce acceptable and representative crop area estimates at district level, SAE approach has been advocated in this paper. In the SAE technique, particularly we have used aggregated level spatial small area model which has the potentiality of accounting spatial associationship between neighboring areas though spatially varying auxiliary variates (Chandra *et al.* 2017, Anjoy *et al.* 2018). Hierarchical Bayes (HB) framework has been implemented to draw needful small domain inference. One of the strategic advantages of using Bayes framework is that here estimations are described by assuming particular probability distributions, which render the opportunities to analyze the uncertainties involved in the decision process (Rao and Molina 2015).

Hierarchical Bayes Small Area Estimation

Small area model which utilizes unit specific survey and auxiliary information are called unit level models. In most of the practical applications, availing information on variables at unit level is difficult; hence the alternative is aggregated level small area model. Among the aggregated level small area models, most pioneering is the Fay-Herriot model (Fay and Herriot 1979). Basic structure of the FH model includes a sampling model for the direct survey estimates and a linking model to incorporate auxiliary information as well as area specific random effect which probably explains unstructured variations among areas not countered by fixed effect part (auxiliary variables). We express the sampling and linking model respectively as follows,

$$y_i = \theta_i + e_i,\ i = 1,\ldots,m \text{ and } \theta_i = \mathrm{x}_i'\beta + v_i,\ i = 1,\ldots,m.$$

For estimating small area population quantity (i.e. crop area at district level) θ_i, we assume y_i, be the direct survey estimate; *i* index for districts or small areas. In UP there are total *m*=75 districts. The independent sampling error associated with direct survey estimator is e_i. It is assumed that $E(e_i) = 0$ and $var(e_i) = \sigma_{ie}^2$. Usually the sampling variances σ_{ie}^2 for *i*=1,…,*m* are treated to be known, i.e. estimated based on survey data considering the underlying survey design (You and Zhou 2011). The component $\mathbf{x}_i = (1, x_{i1}, \ldots, x_{ip-1})'$ represents area-specific auxiliary information with intercept and *p-1* auxiliary variables; $\hat{\mathbf{a}} = (\hat{a}, \ldots, \hat{a}_{p-1})'$ is the vector of regression coefficients; v_i being the area specific random effect which is independent and identically distributed (i.i.d) as $E(v_i) = 0$ and $var(v_i) = \sigma_v^2$.

The FH model postulates that fixed-effect parameter or regression coefficient vector β does not vary spatially, i.e. β is spatially invariant, this is the case of spatial stationarity. But, there may be situation where parameter of a model is spatial in nature, i.e. its value varies over space then it is called spatial nonstationarity (Fotheringham *et al.* 2002, Chandra *et al.* 2015, Baldermann *et al.* 2018). Regression coefficients in the FH model therefore may be expressed as explicit functions of the spatial locations of the sample observations instead of defining one single global model with fixed parameter, we denote this model as Spatial FH (SFH). We express the sampling and linking model of such spatial nonstationary SFH model respectively as follows,

$$y_i = \theta_i + e_i,\ i = 1,\ldots,m \text{ and } \theta_i = \mathrm{x}_i'\beta + v_i,\ i = 1,\ldots,m.$$

Here, l_i denotes the coordinates of an arbitrarily defined spatial location (longitude and latitude); generally this will be its centroid. In matrix notation, the HB version of SFH model is expressed as below,

$$\mathrm{y} \mid \theta \sim N(\theta,\Omega) \text{ and } \theta \mid \beta,\eta,\sigma_v^2 \sim N(\mathrm{X}\beta,\ \mathrm{Z}\Sigma_\eta\mathrm{Z}'+\sigma_v^2\mathrm{I}).$$

For *m* small areas, $\mathrm{y} = (y_1,\ldots,y_m)'$ is the *m* component vector of direct survey estimates; $\grave{e} = (\grave{e}_1,\ldots,\grave{e}_m)'$ is the vector of population level quantities; $\mathrm{X} = (x'_1,\ldots,x'_m)'$ be $m \times p$ matrix of auxiliary variates; $\Omega = \mathrm{diag}\ \{\sigma_{ie}^2;\ 1 \le i \le m\}$ is the matrix of design variances. $\mathrm{Z} = \{\mathrm{diag}\ (\mathrm{x}_1),\ldots,\mathrm{diag}\ (\mathrm{x}_m)\}$ is a $m \times pm$ matrix; $\Sigma_\eta = \mathrm{W} \otimes (\mathrm{cc}')$, where ⊗ denotes the Kronecker product. $\mathrm{W} = \{w_{jk}\} = (1 + d_{j,k})^{-1}$ is a matrix defining spatial distances between sample locations (loc_j, loc_k), **I** be the identity matrix of order *m*. In general, the only constraint on the vector **c** is that $\Sigma_\eta = \mathrm{W} \otimes (\mathrm{cc}')$, is symmetric and non-negative definite. For simplification, **c** is taken as $\mathrm{c} = \sqrt{\eta}\ 1_p$, with 1_p denoting the unit vector of order *p* and $\eta \ge 0$ denotes the strength of spatial heterogeneity being explained by spatially varying covariates and this also distinguishes nonstationary process SFH from other HB models (e.g. FH). For executing HB small area estimation the prior choice for β is usually taken to be $N(0, 10^6)$ and for σ_v^2 it is *Inverse Gamma(0.01, 0.01)*. The prior distribution for η has been taken as *Inverse Gamma (0.01, 0.01)*. A parameter in HB method is estimated by posterior mean and posterior variance is taken as the measure of the variability or uncertainty of the estimate (Anjoy and Chandra 2018). All computations have been carried out using R and JAGS software. R Code has been formulated for analysis purpose.

RESULTS AND DISCUSSION

This section presents the implementation of HB SAE approach in producing small domain estimates of rice and wheat crop acreage for the agriculture year 2015-16 for different districts of the state Uttar Pradesh in India. The auxiliary variable (X) required for implementation of FH and SFH models is TRS reported area for the respective crops in the agriculture year 2014-15. For checking the evidence of spatial nonstationarity in the regression coefficients, Geographic Weighted Regression (GWR) model was fitted (Chandra *et al.* 2017). Table 1 reports the estimated regression coefficients from a GWR fit. This Table confirms that there exists variation in the district specific regression coefficients. Hence, we may expect a better performance of the small area estimates produced by spatial nonstationary SFH model over the non-spatial alternative FH model. Fig 1 shows the comparative percentage coefficient of variation (%CV) for direct estimates as well a small area model based estimates. This figure is reported considering 66 districts in case of rice and 73 districts in case of wheat. For rice and wheat information on 9 districts and 2 districts respectively were not received by the pilot experiment. Hence, direct estimates cannot be produced for such districts. But, SAE technique has the ability to provide representative estimates for such districts too. Estimates with smaller %CV are

Table 1 Summary statistics for GWR parameter estimates

Crop	Rice		Wheat	
values	Intercept	Slope	Intercept	Slope
Minimum	69.73	1.16	89.78	1.65
Q1	77.36	1.61	92.49	1.65
Mean	79.81	1.64	93.44	1.66
Median	80.72	1.70	93.66	1.66
Q3	83.01	1.72	94.39	1.67
Maximum	83.99	1.79	95.63	1.67

Table 2 District wise estimates of rice crop acreage (in '000 ha) along with standard error (SE) and % CV for direct and spatial estimation approach

District	Direct			Spatial		
	Estimate	SE	%CV	Estimate	SE	%CV
Agra	*	*	*	41.28	6.44	15.61
Aligarh	341.82	88.84	25.99	269.64	26.18	9.71
Prayagraj	431.81	47.54	11.01	429.70	43.09	10.03
Ambedkar Nagar	256.58	47.34	18.45	320.70	31.97	9.97
Amethi	363.66	40.44	11.12	267.68	26.25	9.81
Amroha	61.45	12.87	20.95	62.98	10.38	16.49
Auraiya	106.89	74.55	69.75	115.17	25.28	21.95
Azamgarh	636.43	204.55	32.14	346.28	118.5	34.22
Baghpat	24.91	6.82	27.37	34.29	4.42	12.90
Bahraich	296.05	22.29	7.53	269.95	18.98	7.03
Ballia	139.13	30.82	22.15	206.49	14.11	6.83
Balrampur	217.99	31.96	14.66	252.18	28.38	11.25
Banda	236.35	36.94	15.63	121.44	12.21	10.05
Barabanki	313.63	39.3	12.53	326.42	37.57	11.51
Bareilly	681.02	203.35	29.86	280.19	31.78	11.34
Basti	488.45	97.35	19.93	143.66	24.76	17.24
Bhadrohi	63.27	10.26	16.22	74.38	10.11	13.59
Bijnor	100.72	23.84	23.67	93.65	15.32	16.35
Budaun	119.38	34.92	29.25	127.08	22.68	17.85
Bulandshahr	230.10	20.23	8.79	234.26	18.58	7.93
Chandauli	238.29	44.13	18.52	224.53	17.72	7.89
Chitrakoot	34.52	24.05	69.66	46.86	5.23	11.15
Deoria	257.90	42.84	16.61	255.67	39.24	15.35
Etah	55.02	32.58	59.21	48.31	11.83	24.50
Etawah	74.31	46.48	62.55	92.00	33.34	36.24
Faizabad	463.06	85.9	18.55	277.16	53.29	19.23
Farrukhabad	39.24	11.86	30.22	56.31	7.16	12.72
Fatehpur	524.80	155.02	29.54	148.90	15.27	10.26
Firozabad	*	*	*	69.56	15.51	22.30
Ghaziabad	*	*	*	48.12	7.51	15.60
Ghazipur	235.20	26.79	11.39	235.29	25.67	10.91
Gonda	207.71	77.62	37.37	282.49	58.25	20.62
Gorakhpur	755.69	167.39	22.15	316.58	66.01	20.85
GTB Nagar	*	*	*	60.30	15.62	25.90
Hamirpur	*	*	*	24.58	1.28	5.19
Hapur	89.11	9.71	10.90	62.31	5.89	9.45
Hardoi	173.02	51.37	29.69	280.69	37.73	13.44
Hathras	*	*	*	72.91	14.52	19.91
Jalaun	*	*	*	25.28	1.67	6.60

Cond.

Table 2 (*Concluded*)

District	Direct			Spatial		
	Estimate	SE	%CV	Estimate	SE	%CV
Jaunpur	214.43	61.43	28.65	9.64	47.58	23.72
Jhansi	5.70	3.99	69.93	22.64	3.4	15.03
Kannauj	58.62	18.3	31.22	36.47	6.94	19.04
Kanpur Dehat	31.89	13.15	41.24	44.85	11.63	25.92
Kanpur Nagar	177.85	53.82	30.26	51.13	13.6	26.59
Kasgunj	24.04	10.07	41.91	41.51	8.73	21.04
Kaushambi	201.23	42.28	21.01	120.77	13.64	11.30
Kheri	346.15	55.18	15.94	370.20	48.13	13.00
Kushinagar	200.69	29.74	14.82	201.57	27.93	13.86
Lalitpur	*	*	*	25.95	1.96	7.54
Lucknow	275.35	156.23	56.74	106.08	12.88	12.14
Maharajganj	375.48	52.6	14.01	328.86	46.55	14.15
Mahoba	*	*	*	24.52	1.33	5.41
Mainpuri	102.86	57.65	56.05	159.41	20.6	12.92
Mathura	144.14	61.74	42.83	72.84	14.14	19.41
Mau	92.53	28.59	30.90	113.87	26.01	22.84
Meerut	113.43	14.64	12.91	81.72	10.72	13.12
Mirzapur	352.61	155.04	43.97	343.42	58.76	17.11
Moradabad	239.09	29.07	12.16	245.21	26.84	10.95
Muzaffar-nagar	105.70	15.72	14.87	52.22	4.75	9.10
Pilibhit	192.94	42.29	21.92	98.96	15.92	16.09
Pratapgarh	73.31	16.13	22.00	90.24	14.02	15.54
Rae Bareli	165.17	28.97	17.54	164.79	12.64	7.67
Rampur	189.46	16.96	8.95	191.36	15.02	7.85
Saharanpur	140.82	18.73	13.30	132.65	14.60	11.01
Sambhal	73.96	14.07	19.02	85.26	8.24	9.66
Sant Kabir Nagar	349.73	85.12	24.34	282.71	61.48	21.75
Shahjahanpur	565.05	205.79	36.42	104.14	19.24	18.48
Shamli	34.15	9	26.36	38.09	8.79	23.09
Shrawasti	65.35	9.97	15.26	27.45	3.73	13.60
Siddharth-nagar	271.72	25.13	9.25	236.20	20.9	8.85
Sitapur	311.60	87.9	28.21	475.58	44.65	9.39
Sonbhadra	75.54	26.09	34.54	142.44	24.72	17.35
Sultanpur	130.19	13.08	10.05	46.01	5.19	11.28
Unnao	289.49	65.48	22.62	138.05	26.45	19.16
Varanasi	102.48	35.69	34.83	153.09	29.96	19.57

* No data Received

Table 3 District wise estimates of wheat crop acreage (in '000 ha) along with standard error (SE) and %CV for direct and spatial estimation approach

Districts	Direct			Spatial		
	Estimate	SE	%CV	Estimate	SE	%CV
Agra	214.86	21.66	10.08	245.08	31.01	9.65
Aligarh	637.58	92.51	14.51	437.53	56.71	12.96
Prayagraj	432.36	70.21	16.24	421.66	54.29	12.88
Ambedkar Nagar	282.10	43.61	15.46	278.60	35.89	12.88
Amethi	365.47	46.78	12.80	237.72	28.57	12.02
Amroha	184.77	39.26	21.25	209.61	29.33	13.99
Auraiya	237.91	85.98	36.14	227.56	33.4	14.68
Azamgarh	475.03	155.67	32.77	355.58	62.07	17.46
Baghpat	91.38	23.52	25.74	138.09	13.24	9.58
Bahraich	364.21	30.52	8.38	315.95	34.72	10.99
Ballia	217.94	43.33	19.88	281.76	29.69	10.54
Balrampur	567.98	104.57	18.41	250.17	41.7	16.67
Banda	748.47	240.63	32.15	366.67	70.17	19.14
Barabanki	256.15	27.69	10.81	297.20	33.81	11.38
Bareilly	486.45	95.49	19.63	359.04	43.4	12.09
Basti	564.77	78.28	13.86	276.05	38.9	14.09
Bhadrohi	83.46	15.79	18.92	158.44	15.67	9.89
Bijnor	226.20	23.32	10.31	253.71	28.07	11.06
Budaun	673.24	126.91	18.85	461.21	61.64	13.36
Bulandshahr	416.95	28.98	6.95	390.83	44.71	11.44
Chandauli	272.65	37.05	13.59	231.82	21.93	9.46
Chitrakoot	166.79	30.15	18.08	161.02	18.15	11.27
Deoria	324.72	81.7	25.16	310.38	51.46	16.58
Etah	165.47	65.26	39.44	236.59	33.28	14.07
Etawah	228.00	33.83	14.84	193.83	24.02	12.39
Faizabad	528.94	97.59	18.45	279.57	45.51	16.28
Farrukhabad	143.26	55.24	38.56	218.93	31.62	14.44
Fatehpur	801.27	212.34	26.50	296.12	46.64	15.75
Firozabad	90.84	23.71	26.10	201.12	26.18	13.02
Ghaziabad	232.49	64.56	27.77	139.05	15.53	11.17
Ghazipur	164.70	26.85	16.30	119.30	10.4	8.71
Gonda	372.75	90.13	24.18	272.64	42.47	15.58
Gorakhpur	143.86	32.38	22.51	250.63	37.53	14.98
GTB Nagar	608.76	146.83	24.12	366.68	55.75	15.20
Hamirpur	136.57	54.25	39.72	250.41	33.22	13.27
Hapur	141.67	14.76	10.42	137.66	8.08	5.87
Hardoi	516.70	49.86	9.65	504.26	57.93	11.49
Hathras	475.73	93.15	19.58	205.55	18.92	9.20

Cond.

Table 3 (*Concluded*)

Districts	Direct			Spatial		
	Estimate	SE	%CV	Estimate	SE	%CV
Jalaun	*	*	*	337.85	60.49	17.90
Jaunpur	368.48	39.13	10.62	400.68	48.14	12.01
Jhansi	289.87	61.05	21.06	236.88	38.38	16.20
Kannauj	100.82	20.41	20.24	157.65	18.95	12.02
Kanpur Dehat	226.17	92.39	40.85	244.15	35.8	14.66
Kanpur Nagar	392.57	74	18.85	218.52	30.18	13.81
Kasgunj	136.00	19.46	14.31	192.57	27.52	14.29
Kaushambi	363.85	64.66	17.77	160.59	19.79	12.32
Kheri	331.32	35.85	10.82	346.13	41.42	11.97
Kushinagar	287.79	74.83	26.00	246.84	25.99	10.53
Lalitpur	105.09	29.34	27.92	226.92	49.46	21.79
Lucknow	303.60	139.66	46.00	147.28	22.54	15.30
Maharajganj	384.65	54.47	14.16	239.48	36.93	15.42
Mahoba	50.48	15.63	30.96	152.55	16.88	11.07
Mainpuri	197.52	70.87	35.88	228.60	40.86	17.88
Mathura	201.10	91.9	45.70	272.87	52.93	19.40
Mau	51.18	14.25	27.85	161.40	27.43	17.00
Meerut	275.34	38.93	14.14	145.23	21.88	15.07
Mirzapur	446.12	102.38	22.95	214.19	24.87	11.61
Moradabad	220.31	26.68	12.11	246.68	30.87	12.52
Muzaffar-nagar	304.59	32.23	10.58	177.59	18.89	10.64
Pilibhit	186.80	32.76	17.54	259.18	34.63	13.36
Pratapgarh	758.67	416.74	54.93	230.24	30.73	13.35
Rae Bareli	214.53	23.45	10.93	261.78	37.04	14.15
Rampur	218.82	22.14	10.12	236.86	33.44	14.12
Saharanpur	206.20	47.67	23.12	205.75	27.02	13.13
Sambhal	129.89	22.35	17.21	216.76	37.25	17.18
SantKabir Nagar	316.45	58.45	18.47	166.41	23.48	14.11
Shahjahanpur	728.37	220.4	30.26	567.89	103.55	18.23
Shamli	437.02	203.74	46.62	172.16	19.72	11.45
Shrawasti	100.76	22.14	21.97	159.63	15.87	9.94
Siddharth-nagar	264.10	24.69	9.35	268.94	37.63	13.99
Sitapur	335.61	57.86	17.24	318.94	49.80	15.62
Sonbhadra	59.89	22.66	37.83	145.99	13.84	9.48
Sultanpur	121.39	14.52	11.96	211.20	20.62	9.76
Unnao	603.22	111.53	18.49	386.26	48.20	12.48
Varanasi	*	*	*	203.16	25.80	12.70

* No data Received

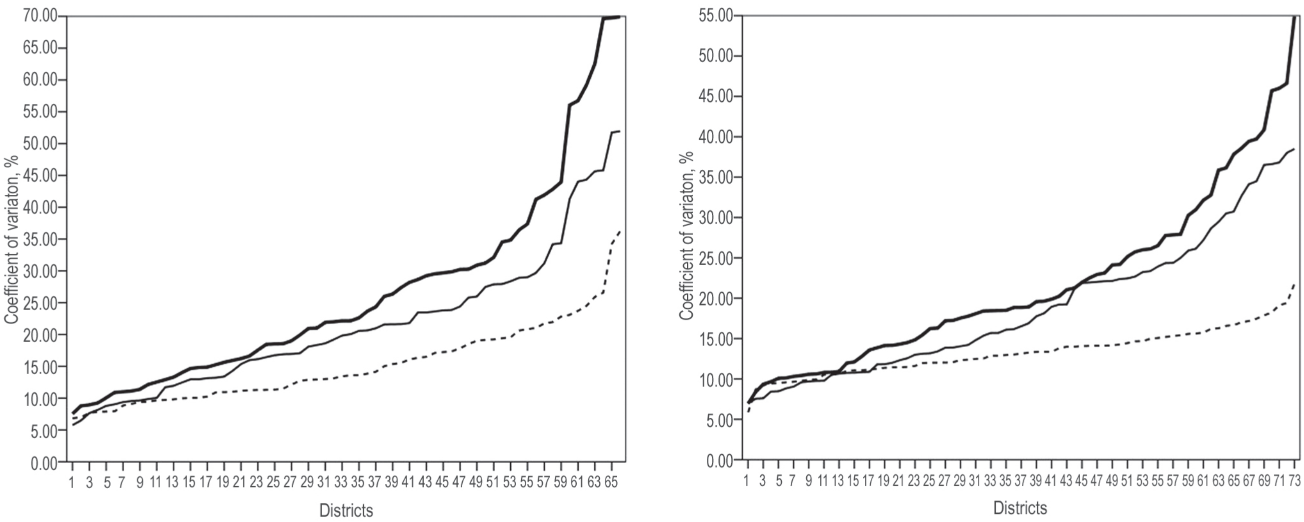

Fig 1 District wise CV % for direct (solid, thick line), non-spatial (solid, thin line) and spatial (dash line) method of SAE.

preferred or more reliable than others. Comparing the direct and all the HB models, it is to be noted small area HB models are far better than the direct method of area estimation. For rice crop, in direct estimation approach %CV was ranging from 7.53-69.93, whereas, in SFH the range of %CV is 6.83-36.24. For wheat similarly, in direct estimation approach %CV was ranging from 6.95- 54.93, whereas, in SFH the range of %CV is 5.87-21.79. Average %CV of direct, FH and SFH estimation approach were respectively 26.63, 21.56 and 15.16 for rice. For wheat average %CV of direct, FH and SFH estimation approach were respectively 21.82, 18.89 and 13.31. Evidently, spatial model has turned out to be better than non-spatial alternative FH. This proves that incorporating spatial information in FH model via spatial nonstationarity approach has the potentiality to yield improved estimates. Therefore, finally SFH model has been advocated to provide acreage estimates for all districts under wheat and rice crop. Table 2 presents district wise estimates of rice acreage along with standard error and %CV for direct and SFH estimation approach. Table 3 presents district wise estimates of wheat acreage in UP along with standard error and % CV for direct and SFH estimation method.

The topic of small area estimation has gained importance in view of growing needs of micro level planning. Demands for reliable small area statistics are increasing both from public and private sectors with growing concerns of governments relating to issues of distribution, equity and disparity. The need for statistics at lower levels has been felt for a long time and but efforts have been made to meet such requirements through traditional approaches. Traditional sampling theory fails to provide reliable and valid estimates in catering the need for decentralized level statistics, while SAE technique has the potentiality of generating micro or disaggregated level statistics with acceptable precision. To strengthen the micro level planning, disaggregate level estimates are often required and small area models serve this purpose both adequately and efficiently. In this context, the current study also reflects a suitable example of why small area model based methods should be preferred. Along with this, the relative proficiency of using spatial information particularly via nonstationary process in aggregated level small area model is also established than the non-spatial alternative. In India there have been sporadic attempts for applications of SAE technique. As a profound application, the suitability of this study can be found in schemes like Pradhan Mantri Fasal Bima Yojana (PMFBY) to generate the micro level estimates of crop area or yield from existing survey data and in extending insurance support to the needy farmers.

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