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Estimation of Crop Production at Smaller Geographical Level in India

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SUMMARY

Crop production statistics for smaller geographical (or small area) levels like Community Development Block level (Block) or Gram Panchayat (GP) level are in great demand to make area-specific plans for agricultural development programmes in India. The crop production estimates in the country are obtained through scientifically designed Crop Cutting Experiments (CCEs) conducted under the General Crop Estimation Survey. Large number of CCEs are conducted annually for producing reliable estimates of crop production of different crops at the district level. If reasonably precise estimates are required for further smaller geographical levels such as Block or GP level, the number of CCEs is expected to increase enormously. However, conducting requisite number of area specific CCEs is neither operationally feasible nor it is economically viable. In this paper we explore an alternative approach for estimation of crop production at Block level. The proposed approach uses available District level data from CCEs and the auxiliary information from various administrative sources to obtain a reliable estimate of crop production at Block level. An empirical study with wheat production data of Barabanki district of the State of Uttar Pradesh, India shows that approach works well and provides reliable estimates at Block level.

Keywords : Development block, Crop cutting experiments, Crop-production estimates.

1. INTRODUCTION

In recent years, the thrust of planning process has shifted from macro to micro level. There is demand by the administrators and policy planners for reliable estimates of various parameters at the micro level. In view of the demands of modern time the thrust of research efforts has also shifted to development of precise estimators for small domains or areas. An offshoot of this development is that various small area estimation (SAE) techniques are being proposed by the researchers for implementation. The SAE techniques involve using micro level basic information related to study character for scaling down estimates available at the higher level to the lower level.

Agriculture in India is the means of livelihood of almost two thirds of the work force in the country. It is the major source of income for about three-fourths of India's population who live in villages. Agriculture is not only an important occupation of the people, but also way of life, culture and custom. Further, as the Indian economy is mainly based on agriculture, its proper planning is very important. The planning in agriculture is mainly looked after by the Planning Commission of India which operates and executes under the aegis of the Government of India. The sole objective of the Planning Commission in terms of Agriculture Planning in India is to enhance the total output of agriculture and boost the economic growth of the country. However, availability of reliable statistics is a key for success of any planning process and their monitoring. India has a well established National Agricultural Statistics System. The system is very comprehensive providing data on variety of parameters of interest of agricultural production

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system. As a result reliable estimates of various parameters of interest are available at the macro level. In view of the decentralized system of planning in the country, reliable estimates of various parameters are required at the micro level. For example, estimates of yield rates of various crops are available at the district level only. These estimates are obtained by conducting suitable number of scientifically designed Crop Cutting Experiments (CCEs) under the scheme of General Crop Estimation Surveys (GCES). For the purpose of micro level planning estimates of yield rates and production of crops are required at the smaller geographical level, for example, Community Development Block level (Block) or Gram Panchayat (GP) level. In view of larger number of Blocks in the country, the total number of CCEs for various crops is expected to increase enormously for yield or production estimation at Block level if the same methodology of estimation is extended to the micro level estimation as well. Carrying out large number of CCEs is not a viable proposition in view of lack of basic infrastructure and the accumulation of large non-sampling errors that are likely to creep in. See for example, Sud *et al.* (2012), Chandra (2012).

In this paper we describe small area estimation (SAE) approach as an alternative methodology for estimation of crop production at Block level. This approach does not require additional survey or conducting extra CCEs for producing the crop production estimate at Block level. In particular, District level data already available from the present system of CCEs along with the auxiliary information available from various secondary sources are exploited to obtain reliable estimate of crop production at Block level. The remaining paper is organized as follows. In section 2 we review some of the existing methodologies for estimating the crop production at smaller geographical level and describe small area estimators based on regression models. Section 3 set out the empirical results using wheat production data of Barabanki district of the State of Uttar Pradesh, India to examine the various proposed estimators. Finally section 4 is devoted to concluding remarks.

2. SMALL AREA ESTIMATION OF CROP PRODUCTION

An early development in SAE for crop-yield can be dated back to 1966 and 1968 when Panse *et al.* (1966) and Singh (1968), respectively, made an attempt to estimate the crop-yields at Block level using double sampling approach. Eye's estimates of crop yield from large number of plots prior to harvest based on crop-cutting experiments on a sub-sample of plots were used as supplementary information to build up estimates of crop-yields at Block level. However, this technique could not succeed due to physical constraints and it could not be pursued further at that time. Within a framework of sampling design conforming to GCES approach, an attempt was made to develop crop-yield estimates at Blocks level using farmers estimates by Sud *et al.* (2001). These estimates were, in fact, direct estimates and were based on usual sample survey techniques for improvement of estimators. The methods did not fit into the SAE approach. Srivastava *et al.* (1999) used a synthetic method for crop-estimation at Block level. The population was classified into two dimensions with small area on one side and post-strata (homogeneous groups) on the other side. For crop-yield, the cell weights were estimated by raking ratio methods using the data collected in the crop-cutting approach. In fact, many auxiliary information collected during crop-cutting experiments were used in conjunction with small area level data for crop-area for estimating the cell-weights. This approach was applied for estimation of crop-yields at Block level for wheat and paddy crops on the basis of data from crop estimation surveys in Haryana State of India during 1987-88. The results were quite consistent and satisfactory. However, the effect of estimating cell-weights could not be taken into account. Moreover, the results were based on certain assumptions and efficiencies were based on variances which did not account for the biases. If assumptions fail, the biases could be serious. These have been major limitation of this approach.

The synthetic approach of estimation was also applied by Singh and Goel (2000) for estimation of crop yields for wheat crop at Tehsil level (level bigger than the Block), using remote sensing data. Post-strata were formed using vegetation index derived from remote sensing satellite data. Wheat crop data from GCES during 1995-96 in Rohtak district of Haryana State in India while the spectral data of IRS-IBLISS-II for February 17, 1996 were taken for vegetation index. The method improved the efficiency of the estimators to some extent in terms of standard error. However, neglecting the bias remains a serious limitation. A National Agricultural Insurance Scheme (NAIS) replacing Comprehensive Crop Insurance Scheme (CCIS) was launched during 1999-2000 in India and area unit level was identified as GP level in place of

Blocks. This necessitated immediate need of crop yield at GP level for finalization of premium, claim for indemnity etc., by the insurance companies. An alternative approach was suggested by Sharma *et al.* (2004) for scaling down Block level crop yields to GP level by developing correction factors based on the information on crop yields on selected fields through enquiries from farmers. This approach has a number of limitations: (i) it is not cost-effective (ii) subjective assessment of crop yields by farmers, which could be underestimation and/or overestimation and, finally may affect correction factors and (iii) at large level, the approach is not physically feasible. A multiple regression model with data obtained on a sample of farms selected purposely from different counties in USA was used to develop small area statistics for wheat production at Country level by Stasny *et al.* (1991). The predictor variables used in the model were acres planted in wheat, acres harvested, previous wheat production estimates at county level, acres of irrigated wheat, acres of non-irrigated wheat and the indicator variables for the District and the region of the State in which the farm is located.

Small Area Estimation using Regression Model

In India, estimates for crop production/ productivity at District level are made available through CCEs. The District level estimates are then aggregated at State and National level. However, there is lack of estimates below this level, e.g., Block level which is an important level for policy planning and fund allocation specially for rural India. We describe a scale down approach using multiple regression models to obtain the Block level estimate from the District level crop-production estimate. To start, we first assume the availability of auxiliary variables (or predictors) that are related to the crop production/productivity at both District and Block level.

We then postulate a regression model between the crop production and auxiliary variables at District level of form:

$$Y_i = f(X_{ij} \mid \beta) + \varepsilon_i, \tag{1}$$

where Y_i is the crop production in the year i (i = 1, ..., n), X_{ij} is the value of auxiliary variable j (j = 1, ..., p) in the year i, $\beta = (\beta_0, \beta_1, ..., \beta_p)'$ is vector of unknown parameters and ε_i is error term assumed to follow normal distribution with mean 0 and variance σ^2. We use a "hat" to denote the estimated quantity and then the fitted model is expressed as

$$\hat{Y}_i = f(X_{ij} \mid \hat{\beta}), \tag{2}$$

where $\hat{\beta}$ is a least square estimate of β and $\hat{Y}_i$ is the estimated value of Y_i for corresponding values of X_{ij}'s in the year i. Following Montgomery and Peck (1982) we decompose the sum of squares due to regression, *i.e.* $SS_R(\beta_1, \beta_2, ..., \beta_p|\beta_0)$ to define a weight that determines the relative contribution of each predictor variable included in the model, as follow:

$$w_j = \frac{SS \text{ due to } j\text{-th predictor}}{SS_R(\beta_1, \beta_2, ..., \beta_p \mid \beta_0)} \tag{3}$$

Using these weights, an estimator of crop production Y_q of Block q is constructed as follows:

$$\hat{Y}_q = \left(\sum_{j=1}^{p} w_j x_j\right)\hat{\bar{Y}}; \quad q = 1, ..., Q, \tag{4}$$

where Q is total number of Blocks in a given District, x_j is the value of j-th predictor at Block level in a given year, $\hat{\bar{Y}} = \hat{Y}/A$ and $\hat{Y}$ is obtained through the fitted model (2) and A is the area under the crop in a given year. Note that the weight w_j depends on the set of data on Y and X_{ij} used to fit model (1). To find out a stable value of w_j one can use iteration technique by fitting model (1) first with n years data and then with $(n + 1)$, $(n + 2)$ ... years data till we get a stable value of w_j. Consequently, the estimate $\hat{Y}_q$ would also be stable one. The estimator $\hat{Y}_q$ is an unbiased estimator of Y_q if $\sum_{j=1}^{p} w_j x_j$ is considered to be a constant quantity for a given Block since under model (1) expected value of $\hat{\bar{Y}}$ is $\bar{Y}$. The variance of $\hat{Y}_q$ is given by

$$\text{V}(\hat{Y}_q) = (\delta_q / A)^2 \text{V}(\hat{Y}), \tag{5}$$

where $\delta_q = \sum_{j=1}^{p} w_j x_j$. The variance of $\hat{Y}$ is easily available by fitting model (1), which is equal to $\hat{\sigma}^2$, the estimated error variance. It is obvious that, in general, $\sum_{q=1}^{Q} \hat{Y}_q \neq Y$, where Y is the actual crop production reported at District level through the crop cutting experiment in a given year. The new scaled estimator of Y_q is given as

$$\tilde{Y}_q = a_q \hat{Y}_q, \tag{6}$$

where a_q are constant such that $\sum_{q=1}^{Q} \tilde{Y}_q = \sum_{q=1}^{Q} a_q \hat{Y}_q = Y$. There can be three alternative choices of a_q. First,

$$a = Y / \sum_{q=1}^{Q} \hat{Y}_q, \text{ if } a_q = a \text{ for all } q = 1, ..., Q. \tag{7}$$

Another choice of a_q could be one that minimizes the sum of squared difference between $\tilde{Y}_q$ and $\hat{Y}_q$ subject to condition that $\sum_{q=1}^{Q} a_q \hat{Y}_q = Y$. This leads to

$$a_q = 1 + \left(Y - \sum_{q=1}^{Q} \hat{Y}_q\right) / Q\hat{Y}_q. \tag{8}$$

The third choice of a_q could be one that minimizes the sum of square of relative differences $(\tilde{Y}_q - \hat{Y}_q)/\hat{Y}_q$ subject to condition that $\sum_{q=1}^{Q} a_q \hat{Y}_q = Y$. This gives

$$a_q = 1 + \frac{\hat{Y}_q \left(Y - \sum_{q=1}^{Q} \hat{Y}_q\right)}{\sum_{q=1}^{Q} \hat{Y}_q^2}. \tag{9}$$

Using these choices of a_q, we define three improved scaled estimators of Y_q as:

$$\tilde{Y}_q^{(1)} = \hat{Y}_q \left(\frac{Y}{\sum_{q=1}^{Q} \hat{Y}_q} \right) \tag{10}$$

$$\tilde{Y}_q^{(2)} = \hat{Y}_q + \left(Y - \sum_{q=1}^{Q} \hat{Y}_q\right) / Q \tag{11}$$

$$\tilde{Y}_q^{(3)} = \hat{Y}_q + \frac{\hat{Y}_q^2 \left(Y - \sum_{q=1}^{Q} \hat{Y}_q\right)}{\sum_{q=1}^{Q} \hat{Y}_q^2}. \tag{12}$$

Here the estimators $\tilde{Y}_q^{(1)}$ and $\tilde{Y}_q^{(3)}$ are biased while $\tilde{Y}_q^{(2)}$ is unbiased. The variance and MSE are given as follows:

$$\text{MSE}(\tilde{Y}_q^{(1)}) = \frac{\left(Y - \sum_{q=1}^{Q} \hat{Y}_q\right)^2 Y_q^2}{\left(\sum_{q=1}^{Q} \hat{Y}_q\right)^2} + \frac{Y^2}{\left(\sum_{q=1}^{Q} \hat{Y}_q\right)^2} \text{Var}\left(\hat{Y}_q\right) \tag{13}$$

$$\text{V}(\tilde{Y}_q^{(2)}) = \frac{Q-2}{Q} \text{Var}\left(\hat{Y}_q\right) + \frac{1}{Q^2} \sum_{q=1}^{Q} \text{Var}\left(\hat{Y}_q\right) \tag{14}$$

$$\text{MSE}(\tilde{Y}_q^{(3)}) \cong \left[1 + \frac{Y - \sum_{q=1}^{Q} \hat{Y}_q}{\sum_{q=1}^{Q} \hat{Y}_q^2} \hat{Y}_q \right]^2 \left(\delta_q / A\right)^2 \text{Var}\left(\hat{Y}\right). \tag{15}$$

3. EMPIRICAL EVALUATIONS

An empirical investigation is carried out to illustrate the relative efficiencies of the various estimators described in Section 2. To illustrate the methodologies we propose to estimate wheat production at Block level in Barabanki district of State of Uttar Pradesh in India. We consider the following model at District level, of the form

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \varepsilon_i, \tag{16}$$

where y_i is the wheat production, x_{i1} is the irrigated area under wheat crop, x_{i2} is the fertilizer consumption (kg/ha) for wheat crop and x_{i3} is the relative area under wheat crop as per cent to gross cropped area of Barabanki district in the i^{th} year. Here β_j (j = 0, 1, 2, 3) are unknown parameters and ε_i is random error component distributed normally with mean 0 and variance σ^2. The time series data on production of wheat, area under wheat, irrigated area under wheat, gross cropped area and fertilizer consumption (N, P, K) pertaining to the period 1980-81 to 2003-04 for Barabanki district of the State of Uttar Pradesh are obtained from the Bulletin of Agricultural Statistics, published by Directorate of Agricultural Statistics and Crop Insurance, Govt. of Uttar Pradesh, India. Since most of the area under wheat is irrigated, the area under wheat is not included in the model. It may be noted that the fertilizer consumption (N, P, K) is not being reported crop wise, hence the total fertilizer consumption in a year was apportioned for the wheat crop. Approximately 40 per cent of the total fertilizer consumption in a year is considered to have been used for wheat crop. The Block wise data on the predictors, x_1, x_2 and x_3 in Barabanki district are also obtained for some of the recent years from District Statistical Bulletins, published by Directorate of Economics and Statistics, Govt. of Uttar Pradesh, India. The Block wise actual data of wheat production based on crop cutting experiments in Barabanki district during the year 1996-97 are also available in District Statistical Bulletins.

The estimates of regression coefficient, their standard errors and value of coefficient of determinations (R^2) obtained by the fitting regression model (16) from the data described above, are presented in Table 1. The effects of irrigated area under wheat and fertilizer consumption have shown positive and significant effect on wheat production in the district. Further, the coefficient of determination (R^2) was quite high, *i.e.,* 91.25 per cent which is indicative of the fact that these variables included in the model are quite sufficient to explain the variability in the data of wheat production at District level. The analysis of variance for regression analysis of the aforesaid model is presented in Table 2. This also shows the overall significance of the model fitted. Using the analysis of variance Table 2, the contribution of individual variables towards sum of squares due to regression was calculated. In order to find out the contribution of individual regressor variable, the first variable namely irrigated area under wheat (x_1) was included in the model followed by fertilizer consumption in kg/ha (x_2) and per cent relative area under wheat to the gross cropped area (x_3). On the basis of their contribution, the stable values of weights w_j as defined in previous section, were calculated through iteration technique. In this technique, the model was fitted initially with 15 year data starting from 1980-81 to 1995-96. The process is continued with data increasing year by year and the stable value of w_j were found at 19th year starting from 1980-81 to 2000-01, which is presented in Table 3.

Table 1. The estimate of model parameters.

Variable	Estimate	SE	R^2 (%)
Intercept	–1277636		91.25**
Irrigated area (x_1)	41.615135**	12.91245	
Fertilizer (x_2)	10710.849*	1591.633	
Relative area (x_3)	–77598.92	43723.51	

*$p < 0.05$, **$p < 0.01$

Table 2. Analysis of variance for regression analysis.

Source	d.f.	Sum of square	Mean square	F ratio	Prob.
Regression	3	10.30×10^{12}	3.42×10^{12}	62.57	1.02×10^{-9}
Residual	18	0.984×10^{12}	0.055×10^{12}		
Total	21	11.30×10^{12}			

Table 3. Contribution of individual variable towards sum of squares due to regression and the stable value of weights (w_j).

Variables	Contribution of variable	w_j
X_1	SSR $(\beta_1\vert\beta_0) = 4.242 \times 10^{12}$	0.66
X_2	SSR $(\beta_2\vert\beta_0, \beta_1) = 2.028 \times 10^{12}$	0.32
X_3	SSR $(\beta_3\vert\beta_0, \beta_1, \beta_2) = 0.164 \times 10^{12}$	0.02
Total	SSR $(\beta_1, \beta_2, \beta_3\vert\beta_0) = 6.434 \times 10^{12}$	1.00

Using the weights and Block wise data on x_1, x_2 and x_3, the Block level estimates of wheat production based on four estimators, their per cent standard error and an overall average error (E_i) were computed for the year 1996-97 and are presented in Table 4.

The per cent standard error (% SE) of the estimates is calculated as

$$\%SE = \sqrt{\frac{\text{Variance/MSE of estimator}}{\text{Estimate of } Y_q}} \times 100.$$

The overall average error in $\tilde{Y}_q^{(i)}$ as compared to $\hat{Y}_q$ is calculated as

$$E_i = \sqrt{\frac{\sum_{q=1}^{Q}\left(\hat{Y}_q - \tilde{Y}^{(i)}\right)^2}{Q}}, \ (i = 1, 2, 3).$$

The results presented in Table 4 shows that the Block estimates obtained from four different estimators are subject to maximum of almost 5 per cent standard error. The per cent standard error for Block estimates varied between 2.88 to 5.10 per cent in case $\hat{Y}_q$ followed by 3.12 to 5.32 per cent for $\tilde{Y}_q^{(1)}$, 2.94 to 5.06 per cent for $\tilde{Y}_q^{(2)}$ and 2.88 to 5.10 per cent for $\tilde{Y}_q^{(3)}$. It shows that the range of per cent standard error for Block estimates is smaller for $\tilde{Y}_q^{(2)}$ as compared to other estimators. An overall average error is also found to be 3219.18 in case of which is smaller as compared to that of other estimators. Therefore, it can be concluded that the $\tilde{Y}_q^{(2)}$ is best scaled improved estimator for estimating the Block estimates as compared to other estimators. It may also be observed from Table 4 that the Block estimates obtained from the estimators $\tilde{Y}_q^{(1)}$, $\tilde{Y}_q^{(2)}$ and $\tilde{Y}_q^{(3)}$ are much closer to the actual value of the block production except in few blocks.

Table 4. Block estimates of wheat production based on different estimators and their overall average error during the year 1996-97.

Block	*Actual production Y	Estimates				% SE			
		$\hat{Y}_q$	$\tilde{Y}_q^{(1)}$	$\tilde{Y}_q^{(2)}$	$\tilde{Y}_q^{(3)}$	$\hat{Y}_q$	$\tilde{Y}_q^{(1)}$	$\tilde{Y}_q^{(2)}$	$\tilde{Y}_q^{(3)}$
Dewan	262653	287459	283684	284240	283104	3.67	3.86	3.59	3.67
Harakh	257177	271468	267903	268249	267584	3.82	4.02	3.74	3.82
Barabanki	180724	225148	222191	221929	222476	3.65	3.80	3.65	3.65
Masauli	182515	201456	198810	198237	199317	4.13	4.31	4.14	4.13
Dariyabad	258617	235698	232603	232479	232770	4.27	4.51	4.20	4.27
Banikodar	289730	278453	274796	275234	274366	3.81	4.05	3.73	3.81
Pure Dalai	212968	236587	233480	233368	233637	2.88	3.12	2.94	2.88
Mavai	217740	245838	242610	242619	242653	3.52	3.71	3.50	3.52
Fatehpur	238394	257824	254438	254605	254321	3.94	4.13	3.87	3.94
Nindura	265905	275486	271868	272267	271486	4.90	5.06	4.74	4.90
Ramnagar	228755	201458	198812	198239	199319	4.45	4.70	4.42	4.45
Suratganj	313909	285467	281718	282248	281172	4.17	4.42	4.06	4.17
Haidargarh	241654	265483	261997	262264	261768	4.62	4.77	4.49	4.62
Siddhaur	226005	245682	242456	242463	242501	4.24	4.41	4.16	4.24
Trivediganj	209903	186594	184144	183375	184759	5.10	5.32	5.06	5.10
Sirauli	233011	201658	199010	198439	199515	3.79	4.09	3.82	3.79
Rudauli	292860	265487	262001	262268	261772	4.41	4.65	4.30	4.41
Total	4112520	4167246	4112522	4112520	4112520				
Overall average error (E_i)							3245.48	3219.18	3315.41

**Based on crop cutting experiments*

4. CONCLUSION

The SAE approach described in Section 2 was applied to wheat production data of Barabanki district of the State of Uttar Pradesh, India. The empirical results show that the Block level estimates of crop production obtained by use of proposed approach are reasonably good. It is noteworthy that the percentage standard errors (or coefficient of variations) are below 6 per cent for all the areas or Blocks. This approach can be adapted widely to other data sets from different Districts and for several crops for generating the production estimate at Block level.

There are various other issues that need to future research attention. We can use random effect model to capture dissimilarities between the areas (see Chandra *et al.* 2011*a*, *b*) and spatial association between the area can be accounted by using spatial models. See Chandra *et al.* (2012).

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