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District and Social Group-wise Estimation and Spatial Mapping of Food Insecurity in the State of Odisha in India

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SUMMARY

The Sustainable Development Goal of Zero Hunger is a bold commitment towards 795 million undernourished people to end all forms of hunger and malnutrition by 2030 (http://www.undp.org/sustainable-development-goals/goal-2-zero-hunger/). India, sharing a quarter of the global hunger burden, has set a comprehensive action against the food insecurity and hunger issue through microscopic identification of food insecure mass followed by decentralized level planning and effective monitoring. Availability of reliable disaggregate level statistics using Small Area Estimation (SAE) approach for measuring the prevalence of food insecurity can be a potential key to the Governmental organization to take consistent steps towards framing strategic plans eyeing zero hunger. A pragmatic approach in SAE is to consider Hierarchical Bayes (HB) framework, which provide an added flexibility of using complex models without concerning much about known design variance or traditional normality assumption. However, this approach does not incorporate the survey weights that are essential for valid inference given the informative samples that are produced by complex survey designs. In this paper, involving survey design information a number of model specifications are discussed in area level HB version to generate reliable and representative district and district by social groupwise estimates of food insecurity incidence for rural areas of the State of Odisha in India by combining the Household Consumer Expenditure Survey 2011-2012 data of National Sample Survey Office and the Population census 2011. Spatial maps have been produced to observe the inequality in food insecurity distribution among the districts as well as districts cross classified by socio-economic categories. Such maps are definitely useful for policy formulation, fund disbursement purpose and for the Government in taking effective administrative decisions targeting zero hunger.

Keywords: Food insecurity, Hierarchical Bayes, Small area estimation, Spatial map.

1. INTRODUCTION

The Sustainable Development Agenda marked the start of a new era in monitoring progress towards achieving a world without hunger and malnutrition in all its forms. According to Food and Agriculture Organization (FAO) estimates 14.8% of the population is undernourished in India (The State of Food Security and Nutrition in the World, 2018). The Global Hunger Index (GHI), 2018 ranks India at 103 out of 119 countries on the basis of three leading indicators; prevalence of wasting and stunting in children under 5 years, under 5 child mortality rate and the proportion of undernourished in the population (www.globalhungerindex.org/results/). 80% of Indian poor live in rural areas; only 7 low income states namely, Uttar Pradesh, Bihar, Madhya Pradesh, Odisha, Jharkhand, Rajasthan and Chhattisgarh house 62% of India's poor. Another dimension is added in prevalence of food insecurity in India when caste hierarchy is also taken into account. The 'Scheduled Tribe' (ST) and 'Scheduled Caste' (SC) individuals are succumbed to social exclusion and deprivation due to their position in the lowest of caste hierarchy in terms of social and economic status. The category 'Other Backward Caste' (OBC) lies in between the SC/STs and the General category. UN's sustainable agenda for India to reduce the goal on hunger require more attention to lessen food insecurity in poorer states as well as nutrition gap also needed to be reduced amongst regions and also between different social groups

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In India, the nation-wide socio-economic surveys of National Sample Survey Office (NSSO) are designed to represent the macro geographical units or large domain; state and national level estimates produced through these surveys are precise enough and widely acceptable. But these NSSO survey data cannot directly be used to generate reliable estimates at micro or local level i.e., village or district level, because within each district sample size is not large enough to provide district level estimates with adequate precision and reliability. Small Area Estimation (SAE) approach is used to provide estimates based on borrowing strength from related areas or domain through using definite relationship between the values of the response variable(s) and the auxiliary information. Two primary types of mixed model implemented in the SAE literature are based on the level of available auxiliary information: area level models and unit level models. In the former case models are used to smooth out the variability in the unstable area level direct survey estimates, while in the latter case models are for the individual survey measurements and include area effects (Rao and Molina, 2015). Area level modeling is typically used when unit level data are unavailable, or, as is often the case, where model covariates (e.g. census variables) are only available at area-level. The Fay–Herriot (FH) model (Fay and Herriot 1979) is a widely used area level model that assumes area specific survey estimates are available, and that these follow an area level linear mixed model with independent area random effects. Two basic approaches of drawing inferences about the small area parameters of interest (e.g., mean, totals, proportions, count etc.) of mixed models. One is Empirical Best Prediction (EBP) approach which is based on classical or frequentist idea to estimate unknown model parameters (e.g., fixed and random effect parameters in FH model); another is Hierarchical Bayes (HB) approach which assumes particular prior distribution for the unknown hyperparameters to obtain posterior quantities of the parameter of interest. The HB approach is straightforward compared to EBP in the sense that, the posterior distributions, once computed, can be used for all inferential purposes. Additional flexibility is that HB approach can handle complex SAE model without concerning much about known design variances or traditional normality assumption. The application of basic FH model and its various extensions from both frequentist as well as Bayesian perspective are widely available in various real life studies and literatures to solve the small domain estimation problems (Rao, 2003; Jiang and Lahiri, 2006; You, 2008; Liu *et al.* 2014; Pratesi and Salvati 2016; Chandra *et al.* 2018).

When model under consideration is properly specified and auxiliary variables are informative too, small area models tend to provide much more precise estimates than traditional direct estimation technique. But, standard model-based approaches to the analysis often ignore the sampling mechanism. Whereas, incorporation of complex survey design information is crucial in the sense, small area models that do not allow available survey information are subjected to possible model misspecification as well as tend to produce potentially large biases in the resultant estimates. The survey design can be incorporated into small area models in different ways. In the area level case, design based estimators are modeled directly and the survey variance of the associated direct estimator is introduced into the model via the design based errors. In the case of the unit level, the observations can be weighted using the survey weight. Hidiroglou and You (2016) has devised area level direct estimates for small area population mean under informative sampling mechanism basically assuming the Horvitz-Thompson estimator (HT) and the weighted Hájek estimator (HA) in FH model set up. However, their method for continuous data requires extension for binary or count data, as in most of the practical applications e.g., for estimating small area poverty or food insecurity proportions considering Generalized Linear Mixed Model (GLMM) structure. Consequently, our strategic idea here is to modeling survey weighted proportions. Basically we attempt to model area level survey weighted proportions of food insecurity under HB framework through Logistic Normal Mixed Model (LNMM). Two alternative models which are variant of LNMMare also postulated that considers sampling variances are unknown with the later one also drops the normality assumption and replacing with beta distribution.

Rest of the article is organized as follows. Next section describes the study area and empirical data. Section 3 details about methodology including direct sampling variance of the target variable of interest and Design Effect (DEFF) reflecting the effect of complex survey mechanism and then small area models are discussed along with HB inference for small area proportions. Results and discussion section is furnished to the end of this article followed by relevant concluding remarks.

2. STUDY AREA AND DATA DESCRIPTION

The paper attempts to generate efficient estimates of disaggregate level food insecurity incidences in the state of Odisha through appropriate small area HB model based method. In the state of Odisha there is a contiguous zone of acute food insecurity, all the districts of the Eastern Ghats and the adjoining coastal districts. A large proportion of this state is under dense forest cover, hence people has developed forest based economy in many places as agriculture is being hampered by frequent flood or drought situations. Hilly regions of southern Odisha is a hindrance for settling up various infrastructural facilities. These are also areas of high proportion of agricultural labourers and low wage rates. A large proportion of socially marginalized people (SC, ST population) have endorsed social and economic disparity in most of the districts. Women backwardness is another factor come to the front as most of the districts of the state is utterly poverty stricken. Thus, ensuring food security and improving the nutritional status is a challenge for the state of Odisha as a whole. The identification of certain districts and social categories for priority action can be the foremost step towards framing strategic plans in uprooting hunger and malnutrition. Our endeavor remains to obtain fairly precise estimate of food insecurity proportion in the 30 districts of Odisha and as well as districts cross classified social categories.

The country-wide Household Consumer Expenditure Survey (HCES) of NSSO involves stratified multi-stage random sampling with districts as strata, villages as first stage units and households as the second stage units. Hence when the domain in relevance is either districts or social categories within districts, sample size becomes too small even zero in some case. SAE can be a proficient alternative thereof due to limitation of traditional design based method to produce acceptable estimates at every domain. For employing small area models, we require two variables, one is variable of interest or study variable and another is auxiliary variable(s). We expect that auxiliary variable(s) is so selected, having strong association with the study variable. Here, the variable of interest at the unit (household) level in the binary, corresponding to whether a household is food insecure or not. The base for calorie consumption is 2400 calorie per person per day in rural areas. So a person is undernourished or food insecure if per day calorie consumption is less than 2400; however, we do not consider here the case of over nutrition which is likely to be present in urban sectors than rural areas. Such calorie data was calculated from available information on diet of Protein, Carbohydrate, Fat and other nutrients in survey file of HCES 2011-12. The parameter of interest is then the proportion of food insecure households within each district and within social groups (ST, SC, OBC and Others) in each district. In the HCES 2011-12 of NSSO used in this study, total of 2973 households were surveyed from 30 districts of Odisha. District specific sample size ranges from 64 to 160 with a median sample size of 95. Districts has been divided into three groups based on their sample sizes, 10 districts with sample size as 64; 8 districts with sample sizes 95 and 96; 12 districts with sample sizes 126, 128 and 160. District categories based on sample sizes are presented in Table 1.

Table 1. Defining district categories based on sample sizes

District categories	Sample sizes	District name
Small districts (D1)	64	Jharsuguda, Sambalpur, Deogarh, Gajapati, Kandhamal, Boudh, Sonepur, Nuapada, Rayagada and Malkangiri
Medium districts (D2)	95, 96	Jagatsinghpur, Dhenkanal, Angul, Nayagarh, Khurda, Bolangir, Nawrangapur and Koraput
Large districts (D3)	126, 128, 160	Baragarh, Sundargarh, Keonjhar, Mayurbhanja, Balasore, Bhadrak, Kendrapara, Cuttack, Jajpur, Puri, Ganjam and Kalahandi

Table 2 represents summary of sample sizes of different social groups across districts in HCES 2011-12. Categorization into different social groups sample sizes become too small even zero for certain caste and district groups. For example, in ST, SC and Others category the minimum sample size is 0 for some districts, such districts are referred as non-sample districts. Evidently direct survey estimation approach which is based on only domain-specific sample data fails for such districts. SAE technique enables us to obtain precise small area estimates not only for districts with negligible sample sizes but also for non-sample districts, where the direct estimation approach typically incapable. For SAE modeling, there was pool of auxiliary variables to be selected from Population Census 2011. These covariates are only available as counts at district level. Therefore, a preliminary data analysis was carried out to select appropriate covariates for SAE modeling. Methodology section describes the technique of covariates selection through constructing Principal Components (PCs)

Table 2. Social Group-wise summary distribution of sample sizes

Sample Size	Social group				
	All	ST	SC	OBC	Others
Minimum	64	0	0	2	0
Average	99	22	19	38	20
Maximum	160	83	45	79	74
Total	2973	671	565	1151	586

3. METHODOLOGY

3.1 Direct Sampling Variance and Design Effect

Let population U of size N is split into M non-overlapping small areas U_i of known size N_i, such that $U=\bigcup_{i=1}^{M}U_i$ and $N=\sum_{i=1}^{M}N_i$. The units making up the sample in small area i are denoted by s_i of size n_i so that $s=\bigcup_{i=1}^{M}s_i$ and $n=\sum_{i=1}^{M}n_i$. Let y_{ij} denotes the value of the variable of interest for unit j (j=1, …, n_i) in small area i. The variable of interest, with values y_{ij}, is binary (e.g., $y_{ij}=1$ if household j in small area i is food insecure household and 0 otherwise), and the aim is to estimate the small area population proportions, $P_i=\frac{1}{N_i}\sum_{j=1}^{N_i}y_{ij}$ in small area $i(i=1,...,M)$. The usual unweighted direct estimator of small area population proportion is $p_{iuw}=\frac{1}{n_i}\sum_{j=1}^{n_i}y_{ij}$. Considering the given survey design, let w_{ij} denotes the survey weight attached to individual sampling unit $y_{ij}\,(j=1,...,n_i;i=1,...,M)$. Now direct area level estimates can also be obtained for each area using the survey weights and unit observations from the area. The survey weighted design estimator in area $i\ (i=1,...,M)$ is defined as, $p_{iw}=\left(\sum_{j=1}^{n_i}w_{ij}\right)^{-1}\sum_{j=1}^{n_i}w_{ij}y_{ij}$. The estimate of variance of p_{iw} can be expressed as,

$$\hat{var}(p_{iw})=\left(\sum_{j=1}^{n_i}w_{ij}\right)^{-2}\left\{\sum_{j=1}^{n_i}w_{ij}(w_{ij}-1)(y_{ij}-p_{iw})^2\right\}.$$

Let, $\mathrm{var}_{srs}(p_{iw})$ and $\mathrm{var}_{sw}(p_{iw})$ be the true variance of p_{iw} under a simple random sampling (SRS) design and a complex survey design respectively. The true design effect $DEFF_i$ for $_{iw}$ is given by $DEFF_i=\frac{\mathrm{var}_{sw}(p_{iw})}{\mathrm{var}_{srs}(p_{iw})}$, evidently we can write $\mathrm{var}_{sw}(p_{iw})=\frac{P_i(1-P_i)}{n_i}DEFF_i$. Further $DEFF_i$ can be approximate as function of know quantities $deff_i=n_i\left(\sum_{j=1}^{n_i}w_{ij}\right)^{-2}\sum_{j=1}^{n_i}w_{ij}^2$.

3.2 Hierarchical Bayes Inference

In order to estimate small area proportion P_i, we explore three HB small area models with known and unknown sampling variance structures. The first model is LNMM model with known sampling variance of the survey weighted small area proportions, provided that both the sampling and linking models has normal distributions (denoted by LN1). However, normality may not be a reasonable assumption if the sample sizes n_i is small or if P_i is near 0 or 1. The assumption of known sampling variances is problematic as well. In an effort to overcome these problems, we examine two alternative models for small area proportions. The second model (denoted by LN2) assumes that sampling variance is unknown in the sampling model and replace with unknown variance function . The third model is a variant of LN2 which postulates non-normality of the sampling distributions and here, sampling model postulates beta type (beta-I) distribution having the desirable property of range (0, 1). We denote third model as LNN (Logistic Non-Nomal). All the three models are expressed as below.

(i) LN1: Sampling model: $p_{iw}\,|P_i\sim N(P_i,\sigma_{ei}^2)$ and Linking model: $logit(P_i)\,|\boldsymbol{\beta},\sigma_v^2\sim N(\mathbf{x}_i'\boldsymbol{\beta},\sigma_v^2)$,

where σ_{ei}^2 is the sampling variance term which is assumed to be known, generally replaced by direct variance estimate $\hat{var}(p_{iw})$ calculated using available survey data.

(ii) LN2: Sampling model: $p_{iw}\,|P_i\sim N(P_i,\psi_i)$ and Linking model: $logit(P_i)\,|\boldsymbol{\beta},\sigma_v^2\sim N(\mathbf{x}_i'\boldsymbol{\beta},\sigma_v^2)$.

Here, in the sampling model instead of known σ_{ei}^2, an unknown variance function ψ_i is used involving model parameter P_i. For estimating proportion ψ_i can be approximated as $ø_i=\frac{P_i(1\text{-}P_i)}{n_i}deff_i$

(iii) LNN: Sampling model: $p_{iw}\,|P_i\sim beta(a_i,b_i)$, and Linking model: $logit(P_i)\,|\boldsymbol{\beta},\sigma_v^2\sim N(\mathbf{x}_i'\boldsymbol{\beta},\sigma_v^2)$.

Following Liu *et al.* (2014), the choice for parameters a_i and b_i are given as,

$$a_i = P_i\left(\frac{P_i(1-P_i)}{\psi_i}-1\right) = P_i\left(\frac{n_i}{deff_i}-1\right) \text{ and}$$

$$b_i = (1-P_i)\left(\frac{P_i(1-P_i)}{\psi_i}-1\right) = (1-P_i)\left(\frac{n_i}{deff_i}-1\right).$$

HB method is implemented employing Gibbs sampling approach, here a parameter is estimated by posterior mean and posterior variance is taken as the measure of the error or uncertainty of the estimates. HB approach can effectively deal with complex small area models using Monte Carlo Markov Chain (MCMC), which overcomes the computational difficulties of high-dimensional integrations of posterior densities (You, 2008). Choice of prior distributions plays a crucial role in Bayesian analysis, because inferences drawn from posterior densities depend on wide range of prior distributions. Various non-informative prior distributions for σ_v^2 have been suggested in Bayesian literature including a uniform density on σ_v^2 and Inverse Gamma prior of σ_v^2, i.e., $(1/\sigma_v^2) \sim G(0.001, 0.001)$ (Gelman, 2006; Souza *et al.*, 2009). Non-informative prior distributions are intended to allow Bayesian inference for parameters about which not much is known beyond the data included in the analysis.

In selection of auxiliary variables for HB small area models, we first examined the correlation between different covariates available from Population Census-2011 and the target variable (direct survey estimates), then selected eight covariates namely proportion of SC population, proportion of ST population, female literacy rate, gender ratio, main working population ratio, marginal working population ratio, proportion of main female agricultural labourer and female cultivator and proportion of marginal female agricultural labourer and female cultivator. These are the variables showing maximum association with the variable of interest. So, the potential reason for food insecurity in rural Odisha can be traced to group of causes, like dominance of SC and ST (tribal) people in most of the districts; agrarian issues; women backwardness. Next we use Principal Component Analysis (PCA) to derive a composite score for selected group of variables namely female literacy rate, gender ratio, proportion of main female agricultural labourer and female cultivator and proportion of marginal female agricultural labourer and female cultivator. We have taken these four variables for constructing PCs because these are the variables which correlate women backwardness with food insecurity. The first principal component (denoted by P1) explained 84.90 per cent of the variability in the selected group of variables, while adding the second component (denoted by P2) explained 94.72 per cent.

HB small area proportion estimates are computed for all the three small area models using Metropolis-Hastings algorithm, drawing random samples from full conditional distributions of posterior quantities. Finally, Posterior mean $E(P_i | p_{iw})$ is taken as point estimate of P_i and posterior variance $V(P_i | p_{iw})$ is taken as measure of variability. Next section portrays the empirical results obtained in analysis using R and WINBUG software. Purpose of using WINBUG software is that the software uses MCMC technique efficiently to implement various HB models.

4. RESULTS

This study uses the HB based SAE method to generate the model-based small area estimates of food insecurity proportion across the districts of Odisha, additionally estimates have been developed covering different districts by social groups in the caste hierarchy. The study variable has been obtained from HCES of NSSO which is basically complex survey scheme implementing stratified multi-stage design. Table 2 represent summary of design effect ($deff_i$) in HCES 2011-12. Average values of $deff_i$ in all categories were 2 or more. This is strong evidence that sampling design used in the HCES is informative. Hence, modeling of survey-weighted food insecurity proportions are expected to produce better result as compared to modeling of survey-unweighted direct estimates. The district-wise survey weighted and unweighted direct estimates of proportion are shown in Fig. 1. It is evident from Fig. 1 that the unweighted direct estimates underestimate the proportion of food insecurity.

Based on fitting generalized linear model using direct survey estimates of proportions of food insecure households as the response variable and the six variables i.e. proportion of SC population, proportion of ST population, main working population ratio, marginal working population ratio, P1 and P2 as

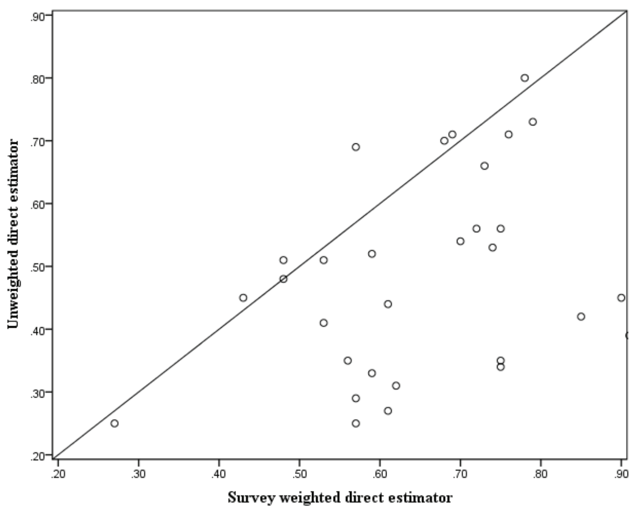

Fig. 1. District-wise survey weighted direct estimates versus unweighted direct estimates of proportion

potential covariates we obtained the final auxiliary variables to be used in discussed HB SAE technique. The final model consisted of two variables P1 and main working population ratio. We also fitted generalized linear model for each social categories within districts (ST, SC, OBC and Others), we found that P1 as the selected variable in all cases with least value of AIC and residual deviance.

Table 3. Summary of design effect (deffi) in HCES 2011-12 in Odisha

*deff*i	Social group				
	All	**ST**	**SC**	**OBC**	**Others**
Minimum	1.68	0.23	0.01	2.08	0.71
Q1	2.27	0.66	0.66	3.28	1.40
Average	3.04	2.39	1.98	4.68	4.07
Median	2.59	1.06	1.45	4.39	2.73
Q3	3.31	2.89	2.67	6.75	6.82
Maximum	6.88	10.99	9.32	8.73	12.55

Table 4 represents the social group-wise summary of percentage coefficient of variation (%CV) across the districts for direct survey estimates (DIR) as well as model-based small area estimates generated by LN1, LN2 and LNN methods of SAE. For all the HB models, prior distribution of $\boldsymbol{\beta}$ has been taken to be N(0, 10^6) and Inverse Gamma prior for σ_v^2, i.e., $(1/\sigma_v^2) \sim G(0.001, 0.001)$. In annexure (Table 6) additionally we represents how the discussed HB small area models perform under different prior set up basically different forms of uniform priors for variance. Table 4 show that model-based estimates have a higher degree of reliability as compared to the direct survey estimates, particularly the relative performance of model-based estimates improves when sample size decreases. In combined (All) class, the performance of model-based estimates over the direct estimate is slightly better, however when we move to individual categories (ST, SC, OBC and Others) the performance of model-based estimates over traditional direct estimate is reasonably quite high. The reason behind is, in combined (All) category, the sample size distribution across the districts is comparatively better than individual categories. This indicates HB small area models are highly acceptable even when the sample sizes in domain are too less even zero in some case. The sharp reduction in maximum CV% compared to those of direct estimates is noticeable in this table. Further, comparing between the models in combined class, we find that here all the three HB small area models (LN1, LN2, LNN) are performing quite similar. Performance of LN1 is good where known sampling variances are quite agreeable in precision due to sufficient sample size. In all other caste categories (ST, SC, OBC and Others), LN2 outperforms the LN1 method. Which reflects that, postulation of unknown sampling variance term in LN2 has the potentiality to yield comparatively more stable estimates. The LN1 method is based on the assumption of known sampling variances obtained using direct survey approach, so may result in less precise estimates relative to the LN2, when the domain specific sample sizes are small. However, the performance of LNN is exploratory in the discussed social classes. In majority of cases, LNN performs better over LN1 but poorer than LN2, which may be due to the complexity of the full conditional distribution for the beta model. In case of small domain, the assumption of normality as well as known sampling variance is questionable. In this regard, we found LN2 and LNN is a better competitor over LN1. Finally, the district and social group-wise estimates of food insecurity incidence along with 95% confidence interval (lower and upper) and %CV for the direct (DIR) and the model-based SAE method based on LN2 are reported in Table 5 in annexure. It is to be noted that the 95% CI's for the LN2 estimates are more precise. In few districts direct estimate has unacceptable and invalid confidence limit. SAE has tackled this situation precisely.

5. DISCUSSIONS

This paper focuses on the estimation of undernourished households across the districts and caste categories in the state of Odisha. The values of model based estimates of food insecurity proportions at the small domain level have been furnished in table 6 along with 95% CI of such estimates and reasonably precise CV%. The implication and implementation of our effort is at policy level in supporting the Governmental organization for formulating consistent and stable actions towards upliftment of food insecure mass. The spatial mapping of the incidence of food insecurity among social groups (ST, SC, OBC and Others) and also for their combined category is shown in Fig 2. Such mapping is useful in microscopic identification of location as well as extent of food in security in socially marginalized categories. Considering ST category, the model-based estimate of undernourished households within districts ranges between 39 to 94 %, whereas for 7 districts Keonjhar, Malkangiri, Kalahandi, Gajapati, Rayagada, Nuapada and Nawrangapur such incidence of food insecurity is above 80%. In SC category, incidence of food insecure households within districts ranges between 27 to 86 %, whereas for Nawrangapur, Kalahandi, Rayagada and Jajpur such prevalence of malnutrition is above 80%. In OBC and Others category incidence of undernourished households ranges between 38 to 84% and 39 to 80% respectively. The regional and social dimensions of food insecurity manifest themselves in the fact that undernourished households are highest in the southern region and most prevalent among the STs. Further, this spatial map of the regional patterns reveals that development has not been evenly spread and there have been pockets of underdevelopment in Odisha. Model-based estimates produced for each social category also connect women backwardness with food insecurity as discussed in section 2. So another strategy to combat the hunger issue is women empowerment at gross level. Similarly, poverty proportion across the districts is also assumed to be associated with hunger and malnutrition. Cross linking all this facts, institutional actions eying zero hunger should be framed. Specifically, priority intervention is required for the districts most beset by hunger and food insecurity as revealed from our study.

6. CONCLUDING REMARKS

In the context of meeting the SDG goal, one of the key approach in which one could go about addressing food insecurity, is to target the most

Table 4. Social group-wise summary of percentage coefficient of variation (%CV) for the Direct (DIR) and HB small area models

Social Group	Method	Minimum	Q1	Average	Median	Q3	Maximum
All	DIR	3.68	7.98	10.97	10.59	13.11	20.79
	LN1	3.26	7.31	9.65	9.30	11.86	17.75
	LN2	4.49	7.73	9.85	9.27	11.44	20.84
	LNN	4.01	7.66	9.89	9.52	11.99	20.12
ST	DIR	0.96	8.58	21.55	11.69	24.89	97.89
	LN1	0.76	6.73	14.96	12.55	20.79	42.7
	LN2	2.97	5.05	11.01	13.55	14.09	32.4
	LNN	1.65	4.67	11.37	14.55	14.9	33.53
SC	DIR	6.82	15.38	25.82	22.94	34.84	61.9
	LN1	5.69	12.18	17.85	17.66	23.22	32.92
	LN2	5.57	12.85	17.44	19.11	20.57	32.74
	LNN	4.98	13.52	17.83	20.34	22.37	28.68
OBC	DIR	3.01	13.11	19.95	20.48	24.43	44.59
	LN1	2.63	11.85	16.47	17.01	19.91	28.23
	LN2	8	11.3	15.57	15.44	20.75	25.9
	LNN	5.3	11.35	15.89	15.8	21.72	26.23
Others	DIR	4.93	15.18	29.92	22.36	36.08	108.14
	LN1	3.76	13.61	21.69	21.21	29.69	40.45
	LN2	5.93	16.09	18.46	19.43	21.97	30.82
	LNN	5.06	16.7	18.97	19.62	22.87	33.86

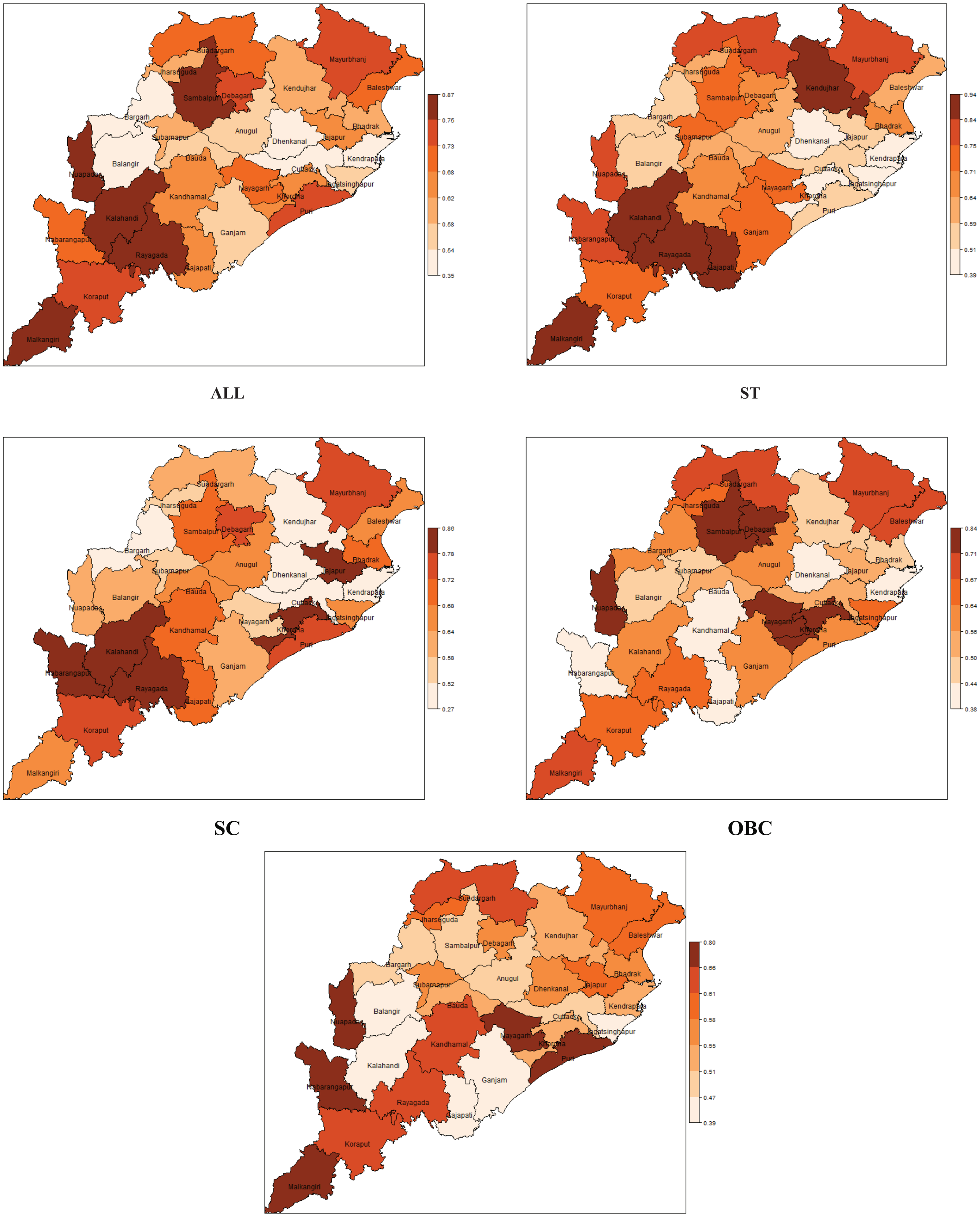

Fig. 2. Social group-wise maps of food insecurity incidence across the districts of Odisha

severely undernourished populations, both by region and by social class including gender characteristics. This would be amply justified on moral grounds that those who are the most deprived should receive the most attention in any use of public money. It would also be justified on economic grounds that at the lowest levels of nourishment, the very ability of adults to work and of children to learn, are most adversely affected. An improvement in nutritional status would increase the productivity of working adults, thus yielding an immediate economic benefit. An improvement in the nutritional status of school-going children would increase their learning capacity and thus be an investment in the future. Finally, an improvement in the nutritional status of the most under-nourished mothers is a gain not only for them but would also have inter-generational benefits in reducing the incidence of low-weight births. The analysis in this paper shows that ensuring food security and improving nutritional status is a challenge for the state, as in most of the districts of Odisha and in certain social categories the food insecurity proportion is at critical level. However, the identification of certain districts for priority action does not mean that either resources or efforts to bring up all districts can slacken; but only draws attention to the need for more inclusive growth efforts for aspirational districts.

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ANNEXURE

Table 5. District and social group-wise estimates of food insecurity incidence (Estimate) along with lower (Lower) and upper (Upper) 95% confidence interval and percentage coefficient of variation (%CV) generated by the direct (DIR) and the model-based small area estimation using LN2 (SAE) method

Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Baragarh	128	0.68	0.55	0.81	9.87	0.68	0.56	0.78	8.66
Jharsuguda	64	0.61	0.45	0.78	13.75	0.61	0.50	0.71	9.22
Sambalpur	64	0.91	0.84	0.97	3.68	0.83	0.73	0.91	5.76
Deogarh	64	0.75	0.59	0.91	11.04	0.73	0.63	0.82	6.75
Sundargarh	128	0.73	0.62	0.85	8.18	0.72	0.60	0.81	7.68
Keonjhar	128	0.59	0.46	0.72	11.45	0.61	0.48	0.72	9.98
Mayurbhanja	128	0.76	0.66	0.86	6.97	0.74	0.64	0.83	6.62
Balasore	128	0.48	0.33	0.62	15.51	0.51	0.38	0.63	12.58
Bhadrak	128	0.53	0.42	0.65	11.13	0.53	0.42	0.63	10.34
Kendrapara	126	0.43	0.30	0.55	15.06	0.44	0.33	0.56	13.11
Jagatsinghpur	96	0.61	0.48	0.75	11.15	0.58	0.45	0.72	11.45
Cuttack	128	0.48	0.36	0.60	13.05	0.48	0.38	0.60	11.43
Jajpur	128	0.69	0.58	0.80	7.92	0.66	0.56	0.76	7.66
Dhenkanal	96	0.27	0.16	0.39	20.79	0.35	0.22	0.50	20.84
Angul	95	0.56	0.43	0.69	11.55	0.57	0.43	0.69	11.78
Nayagarh	96	0.75	0.64	0.86	7.58	0.70	0.57	0.82	9.31
Khurda	96	0.74	0.61	0.86	8.47	0.67	0.52	0.79	10.73
Puri	128	0.79	0.69	0.89	6.46	0.73	0.62	0.84	7.51
Ganjam	160	0.57	0.46	0.68	10.13	0.58	0.49	0.67	7.88
Gajapati	64	0.62	0.46	0.78	12.94	0.67	0.51	0.80	11.41
Kandhamal	64	0.59	0.41	0.76	15.48	0.63	0.45	0.78	13.41
Boudh	64	0.57	0.42	0.72	13.14	0.61	0.43	0.76	13.28
Sonepur	64	0.57	0.35	0.80	19.97	0.59	0.48	0.69	9.23
Bolangir	96	0.53	0.38	0.69	14.78	0.58	0.44	0.71	12.35
Nuapada	64	0.75	0.61	0.90	9.79	0.75	0.59	0.87	10.18
Kalahandi	128	0.78	0.67	0.89	7.18	0.77	0.67	0.86	6.51
Rayagada	64	0.85	0.75	0.96	6.30	0.81	0.66	0.92	8.38
Nawrangapur	96	0.70	0.57	0.83	9.31	0.72	0.60	0.82	8.32
Koraput	96	0.72	0.58	0.86	9.96	0.73	0.60	0.85	8.49
Malkangiri	64	0.90	0.79	1.02	6.68	0.87	0.78	0.93	4.49

ST									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Baragarh	11	0.50	0.11	0.90	39.69	0.64	0.39	0.82	17.63
Jharsuguda	25	0.61	0.38	0.85	19.77	0.61	0.46	0.75	11.81
Sambalpur	16	0.94	0.85	1.03	5.03	0.74	0.53	0.92	14.30
Deogarh	19	0.60	0.27	0.92	27.91	0.65	0.47	0.80	13.43
Sundargarh	74	0.77	0.64	0.90	8.73	0.77	0.71	0.82	3.57
Keonjhar	36	0.87	0.70	1.03	9.67	0.84	0.74	0.92	5.63
Mayurbhanja	83	0.76	0.63	0.89	8.53	0.76	0.72	0.80	2.97
Balasore	6	0.28	-0.15	0.72	78.15	0.59	0.27	0.83	23.36
Bhadrak	0	**	**	**	**	0.52	0.39	0.78	24.73

ST									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Kendrapara	1	1.00	*	*	*	0.50	0.39	0.71	21.64
Jagatsinghpur	1	0.00	*	*	*	0.49	0.37	0.73	24.34
Cuttack	2	1.00	*	*	*	0.51	0.38	0.75	25.67
Jajpur	4	1.00	*	*	*	0.54	0.40	0.80	25.35
Dhenkanal	11	0.09	-0.08	0.25	97.89	0.39	0.12	0.62	32.40
Angul	8	0.50	0.10	0.91	40.97	0.60	0.34	0.81	20.27
Nayagarh	16	0.82	0.63	1.01	11.83	0.71	0.52	0.88	13.09
Khurda	6	1.00	*	*	*	0.45	0.35	0.65	21.67
Puri	0	**	**	**	**	0.51	0.40	0.71	21.56
Ganjam	2	1.00	*	*	*	0.74	0.63	0.94	14.43
Gajapati	23	0.90	0.74	1.07	9.19	0.88	0.78	0.95	5.05
Kandhamal	40	0.67	0.43	0.91	18.23	0.68	0.57	0.78	7.94
Boudh	17	0.66	0.44	0.88	16.96	0.69	0.52	0.82	11.13
Sonepur	5	0.97	0.89	1.04	3.88	0.74	0.49	0.94	16.38
Bolangir	21	0.57	0.27	0.87	26.59	0.64	0.47	0.78	12.93
Nuapada	16	0.79	0.58	1.01	13.71	0.81	0.64	0.92	9.19
Kalahandi	23	0.91	0.80	1.03	6.46	0.88	0.76	0.95	5.63
Rayagada	51	0.85	0.74	0.97	7.05	0.85	0.80	0.90	3.13
Nawrangapur	32	0.82	0.63	1.00	11.55	0.83	0.74	0.90	5.05
Koraput	80	0.70	0.54	0.85	11.33	0.71	0.65	0.76	3.84
Malkangiri	42	0.99	0.97	1.01	0.96	0.94	0.86	0.99	3.49

* Standard error of DIR could not be computed because food insecurity proportion is either 0 or 1.
** Out of sample areas.

SC									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Baragarh	18	0.64	0.29	0.38	28.15	0.64	0.39	0.85	19.11
Jharsuguda	13	0.51	0.17	0.38	34.41	0.55	0.27	0.81	25.41
Sambalpur	12	0.82	0.58	0.26	15.38	0.71	0.46	0.9	16.55
Deogarh	11	0.84	0.62	0.24	13.87	0.76	0.51	0.93	14.32
Sundargarh	19	0.57	0.18	0.43	35.15	0.61	0.35	0.82	20.24
Keonjhar	26	0.42	0.09	0.35	39.84	0.48	0.29	0.67	20.40
Mayurbhanja	7	0.83	0.57	0.28	16.15	0.72	0.41	0.94	19.30
Balasore	33	0.57	0.32	0.26	22.36	0.58	0.42	0.72	12.85
Bhadrak	45	0.52	0.33	0.20	18.54	0.52	0.39	0.66	13.26
Kendrapara	19	0.36	0.11	0.27	36.21	0.40	0.23	0.59	23.21
Jagatsinghpur	13	0.79	0.55	0.25	15.44	0.67	0.42	0.87	17.86
Cuttack	24	0.37	0.13	0.26	33.58	0.39	0.24	0.56	21.54
Jajpur	38	0.88	0.74	0.14	8.01	0.82	0.68	0.92	7.74
Dhenkanal	22	0.17	-0.02	0.20	56.95	0.27	0.12	0.46	32.74
Angul	13	0.66	0.37	0.32	22.94	0.64	0.36	0.85	20.41
Nayagarh	18	0.56	0.27	0.31	26.64	0.54	0.33	0.76	20.35
Khurda	22	0.89	0.76	0.13	7.38	0.78	0.6	0.92	10.60
Puri	22	0.85	0.67	0.19	10.84	0.76	0.59	0.9	10.86
Ganjam	38	0.57	0.34	0.24	20.09	0.58	0.43	0.72	12.71

SC									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Gajapati	17	0.69	0.40	0.31	21.54	0.71	0.48	0.87	14.55
Kandhamal	0	**	**	**	**	0.68	0.53	0.98	22.77
Boudh	9	0.69	0.37	0.35	23.86	0.68	0.37	0.9	20.57
Sonepur	13	0.49	0.05	0.48	45.37	0.56	0.28	0.78	23.44
Bolangir	9	0.63	0.20	0.48	34.84	0.67	0.38	0.88	19.75
Nuapada	18	0.50	0.11	0.43	40.22	0.61	0.32	0.82	21.33
Kalahandi	45	0.89	0.77	0.12	6.82	0.86	0.76	0.94	5.57
Rayagada	6	0.92	0.75	0.18	9.39	0.83	0.59	0.97	12.49
Nawrangapur	19	0.83	0.60	0.24	14.02	0.80	0.61	0.93	10.28
Koraput	9	0.75	0.32	0.47	28.96	0.76	0.48	0.93	15.77
Malkangiri	7	0.45	-0.10	0.63	61.90	0.64	0.32	0.86	22.65

** Out of sample area.

OBC									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Baragarh	79	0.73	0.57	0.88	10.96	0.70	0.55	0.82	9.99
Jharsuguda	19	0.69	0.39	0.99	22.12	0.65	0.47	0.81	13.45
Sambalpur	33	0.94	0.88	0.99	3.01	0.84	0.69	0.94	8.00
Deogarh	34	0.82	0.65	1.00	10.79	0.77	0.63	0.88	8.56
Sundargarh	28	0.70	0.42	0.98	20.25	0.68	0.51	0.81	11.30
Keonjhar	50	0.46	0.23	0.68	24.99	0.48	0.35	0.6	13.55
Mayurbhanja	32	0.72	0.50	0.95	15.95	0.69	0.54	0.82	11.05
Balasore	56	0.49	0.27	0.72	22.92	0.50	0.39	0.62	12.08
Bhadrak	53	0.57	0.39	0.75	15.90	0.56	0.38	0.73	16.89
Kendrapara	79	0.39	0.23	0.55	20.80	0.41	0.28	0.56	17.87
Jagatsinghpur	50	0.72	0.56	0.88	11.53	0.65	0.47	0.81	13.99
Cuttack	50	0.52	0.34	0.70	17.59	0.51	0.34	0.69	18.08
Jajpur	38	0.51	0.31	0.71	19.80	0.52	0.31	0.72	20.75
Dhenkanal	51	0.34	0.18	0.50	24.43	0.39	0.23	0.59	23.87
Angul	40	0.58	0.38	0.79	17.58	0.58	0.43	0.7	12.16
Nayagarh	33	0.85	0.69	1.01	9.48	0.78	0.62	0.9	9.02
Khurda	31	0.78	0.58	0.98	13.11	0.71	0.56	0.84	10.17
Puri	32	0.63	0.37	0.88	20.80	0.56	0.3	0.8	23.31
Ganjam	79	0.62	0.47	0.77	12.67	0.61	0.47	0.74	11.58
Gajapati	17	0.28	0.03	0.52	44.59	0.38	0.21	0.57	25.90
Kandhamal	18	0.38	0.11	0.66	36.71	0.44	0.26	0.62	21.80
Boudh	35	0.42	0.22	0.63	24.91	0.45	0.3	0.6	16.97
Sonepur	43	0.48	0.20	0.77	30.19	0.50	0.37	0.63	13.84
Bolangir	60	0.50	0.30	0.70	20.72	0.51	0.39	0.62	11.82
Nuapada	25	0.84	0.63	1.05	12.55	0.78	0.63	0.91	9.52
Kalahandi	48	0.66	0.46	0.86	15.64	0.63	0.34	0.86	21.40
Rayagada	4	0.76	0.33	1.19	28.67	0.66	0.35	0.92	23.07
Nawrangapur	29	0.39	0.17	0.61	29.14	0.44	0.29	0.6	18.69
Koraput	2	1.00	*	*	*	0.64	0.48	0.95	25.78
Malkangiri	3	0.83	0.49	1.17	20.80	0.67	0.36	0.91	22.95

* Standard error of DIR could not be computed because food insecurity proportion is 1.

Others									
Districts	Sample size	DIR				SAE			
		Estimate	Lower	Upper	CV	Estimate	Lower	Upper	CV
Baragarh	20	0.62	0.36	0.88	21.23	0.59	0.40	0.77	16.11
Jharsuguda	7	0.69	0.25	1.13	32.66	0.59	0.37	0.81	19.33
Sambalpur	3	0.42	-0.16	1.01	71.00	0.51	0.42	0.85	24.61
Deogarh	0	**	**	**	**	0.56	0.28	0.76	25.70
Sundargarh	7	0.83	0.58	1.08	15.30	0.61	0.36	0.88	22.36
Keonjhar	16	0.48	0.12	0.84	38.50	0.54	0.30	0.76	21.83
Mayurbhanja	6	0.77	0.46	1.09	20.98	0.59	0.31	0.87	23.58
Balasore	33	0.37	0.05	0.69	44.03	0.45	0.26	0.63	21.65
Bhadrak	30	0.46	0.23	0.70	26.24	0.48	0.33	0.64	16.96
Kendrapara	27	0.57	0.31	0.83	23.37	0.54	0.36	0.72	16.60
Jagatsinghpur	32	0.36	0.11	0.60	34.73	0.40	0.25	0.55	19.81
Cuttack	52	0.49	0.28	0.69	21.58	0.49	0.37	0.60	11.64
Jajpur	48	0.62	0.44	0.80	15.14	0.60	0.49	0.70	8.89
Dhenkanal	12	0.65	0.36	0.94	22.59	0.57	0.35	0.80	20.22
Angul	34	0.48	0.27	0.69	22.10	0.50	0.36	0.64	14.23
Nayagarh	29	0.76	0.54	0.97	14.37	0.67	0.49	0.83	13.02
Khurda	37	0.53	0.31	0.76	21.53	0.52	0.38	0.66	13.59
Puri	74	0.84	0.74	0.95	6.56	0.80	0.70	0.88	5.93
Ganjam	41	0.42	0.19	0.64	27.58	0.45	0.32	0.59	16.08
Gajapati	7	0.04	-0.05	0.13	108.14	0.39	0.14	0.62	30.82
Kandhamal	6	0.68	0.19	1.16	36.53	0.61	0.43	0.84	19.53
Boudh	3	1.00	*	*	*	0.57	0.41	0.84	24.59
Sonepur	3	1.00	*	*	*	0.56	0.38	0.83	25.74
Bolangir	6	0.45	-0.06	0.96	57.35	0.53	0.29	0.75	22.11
Nuapada	5	0.94	0.80	1.07	7.39	0.69	0.45	0.91	18.37
Kalahandi	12	0.36	-0.08	0.80	61.54	0.47	0.41	0.84	22.08
Rayagada	3	1.00	*	*	*	0.61	0.25	0.66	24.28
Nawrangapur	16	0.76	0.54	0.98	14.87	0.66	0.42	0.88	18.34
Koraput	5	0.94	0.80	1.08	7.73	0.65	0.35	0.89	22.02
Malkangiri	12	0.96	0.86	1.05	4.93	0.67	0.41	0.90	20.17

* Standard error of DIR could not be computed because food insecurity proportion is either 0 or 1.

** Out of sample areas.

Table 6. Social group-wise summary of percentage coefficient of variation (%CV) for the HB small area models under different prior set up

Prior	Method	Minimum	Q1	Average	Median	Q3	Maximum
	DIR	**3.68**	**7.98**	**10.97**	**10.59**	**13.11**	**20.79**
Uniform (0, 10)	LN1	3.26	7.51	9.64	9.23	11.54	17.21
	LN2	4.54	7.66	9.75	9.09	11.52	19.53
	LNN	6.16	7.87	9.84	9.94	11.63	16.34
Uniform (0, 100)	LN1	3.38	7.51	9.68	9.34	11.80	17.66
	LN2	4.66	7.97	9.80	9.34	11.45	20.26
	LNN	6.01	7.85	9.75	9.48	11.39	17.14
Uniform (0, 1000)	LN1	3.30	7.22	9.63	9.34	11.70	17.49
	LN2	4.62	7.79	9.80	9.08	11.31	19.99
	LNN	6.16	8.31	9.81	9.71	11.57	17.37

Prior	**Method**	**Minimum**	**Q1**	**Average**	**Median**	**Q3**	**Maximum**
	DIR	**3.68**	**7.98**	**10.97**	**10.59**	**13.11**	**20.79**
ST							
Prior	Method	Minimum	Q1	Average	Median	Q3	Maximum
	DIR	0.96	8.58	21.55	11.69	24.89	97.89
Uniform (0, 10)	LN1	0.77	6.91	15.06	11.18	20.40	43.00
	LN2	2.91	5.17	10.81	9.98	14.40	30.66
	LNN	1.55	4.81	11.30	10.55	14.85	32.22
Uniform (0, 100)	LN1	0.78	6.91	15.06	10.99	20.99	43.58
	LN2	2.79	5.31	11.03	9.75	14.12	33.23
	LNN	1.68	4.79	11.37	10.45	14.91	33.91
Uniform (0, 1000)	LN1	0.76	6.76	15.02	11.18	20.68	43.20
	LN2	2.88	5.20	11.00	9.98	14.77	32.50
	LNN	1.62	4.73	11.39	10.55	15.28	33.69
SC							
Prior	Method	Minimum	Q1	Average	Median	Q3	Maximum
	DIR	6.82	15.38	25.82	22.94	34.84	61.90
Uniform (0, 10)	LN1	5.56	12.20	17.96	17.46	23.44	32.98
	LN2	5.70	13.32	17.37	18.67	20.41	31.82
	LNN	5.15	13.56	17.62	20.03	22.11	28.33
Uniform (0, 100)	LN1	5.67	11.68	17.99	17.56	24.01	32.46
	LN2	6.01	12.87	17.49	18.55	20.85	31.78
	LNN	5.11	13.07	17.89	19.88	22.46	29.14
Uniform (0, 1000)	LN1	5.71	12.34	17.82	17.65	23.19	33.44
	LN2	5.85	12.79	17.53	18.97	20.39	33.23
	LNN	5.06	13.57	17.77	20.53	21.73	28.85
OBC							
Prior	Method	Minimum	Q1	Average	Median	Q3	Maximum
	DIR	3.01	13.11	19.95	20.48	24.43	44.59
Uniform (0, 10)	LN1	2.67	12.00	16.51	17.51	19.52	28.69
	LN2	7.84	10.98	15.56	15.15	21.04	26.96
	LNN	5.04	11.49	15.79	15.42	22.21	26.35
Uniform (0, 100)	LN1	2.71	12.15	16.42	17.15	19.51	27.41
	LN2	7.94	11.16	15.67	15.54	20.36	26.35
	LNN	5.33	11.50	16.01	15.91	22.61	26.28
Uniform (0, 1000)	LN1	2.66	12.30	16.48	17.49	19.69	27.71
	LN2	7.83	11.57	15.61	15.36	20.84	25.65
	LNN	5.23	11.58	15.85	15.70	21.85	25.65
Others							
Prior	Method	Minimum	Q1	Average	Median	Q3	Maximum
	DIR	4.93	15.18	29.92	22.36	36.08	108.14
Uniform (0, 10)	LN1	3.91	13.53	21.22	20.58	28.58	39.16
	LN2	5.48	15.98	18.51	19.09	21.97	30.99
	LNN	4.51	16.76	19.02	19.88	22.87	33.94
Uniform (0, 100)	LN1	3.70	13.29	21.45	21.45	28.33	39.44
	LN2	5.73	16.21	18.48	19.36	22.10	31.50
	LNN	4.75	16.57	18.87	19.44	23.10	32.62
Uniform (0, 1000)	LN1	3.68	13.41	21.57	20.94	28.86	39.40
	LN2	5.75	15.82	18.53	19.17	22.15	31.28
	LNN	4.78	16.42	18.95	19.73	22.82	32.05