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Self-rated health: Small area large area comparisons amongst older adults at the state, district and sub-district level in India

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Abstract

We compared prevalence estimates of self-rated health (SRH) derived indirectly using four different small area estimation methods for the Vadu (small) area from the national Study on Global AGEing (SAGE) survey with estimates derived directly from the Vadu SAGE survey.

The indirect synthetic estimate for Vadu was 24% whereas the model based estimates were 45.6% and 45.7% with smaller prediction errors and comparable to the direct survey estimate of 50%.

The model based techniques were better suited to estimate the prevalence of SRH than the indirect synthetic method. We conclude that a simplified mixed effects regression model can produce valid small area estimates of SRH.

Keywords

Small area estimation; Self-rated health; Empirical best linear unbiased prediction; Hierarchical Bayes estimation

1. Introduction

Nationally representative large area health surveys are valuable sources of information used by countries for health planning and evaluation. However, logistical and financial constraints limit the application of this information from the aggregated national or sub-national/state (large area) level to smaller sub-national areas as the sample size of such large area surveys is often inadequate to estimate health indicators with any level of precision at the district or sub-district (small area) level. A domain (area) is considered large if the domain-specific survey sample is large enough to yield 'direct estimates' of adequate precision and 'small' if otherwise. Such large area surveys, though rich in detailed health information, are of limited value to local health agencies at the district or sub-district level for purposes of formulation and evaluation of policy and program and resource allocation (Douglas et al., 2001; Paul-Shaheen et al., 1987). On the other hand, the demand for small area statistics has greatly increased in recent years due to decentralized health micro-planning and decision-making in India and elsewhere. Small area estimation (SAE) analysis

are statistical procedures ranging from simple design-based direct estimates to complex model-based estimates that borrow strength by using information about the variable of interest from other similar small areas or from information in the same area collected in the past, and thus increase the effective sample size of the small area. These values are combined into the estimation process through a model which links the related small areas through the use of auxiliary information, most often census information available at the small area level (Ghosh and Rao, 1994).

Many of the SAE methods have been pioneered in the USA (Ericksen, 1974; Fay and Herriot, 1979; Kalton et al., 1993; Levy, 1979; Platek and Singh, 1986) and more recently in the UK (Bajekal et al., 2004; Martuzzi and Elliott, 1996; Twigg et al., 2000). SAE methods are broadly classified according to the data source they borrow information from—whether cross-sectional from other similar areas or from past data in the same area or both. They are further classified by type of inference as ‘design-based’ or ‘model-based’ with further classification based on whether they involve using the ‘frequentist’ or Bayesian approach in estimation (Pfeffermann, 2002). Alternately, these estimators are typically categorized into three groups—(i) direct estimates derived without any modeling from area-level data, (ii) synthetic or indirect estimates derived from the synthesis of survey and auxiliary data by some type of regression modeling and (iii) composite estimate, derived by combining direct and indirect estimates (Raffle, 2008). A number of studies have recently applied SAE methods to estimate disease counts including prevalence of diabetes (Congdon, 2006a), heart disease and stroke (Schwartz et al., 2009), psychiatric illness (Congdon, 2006b; Hudson, 2009), asthma (Mendez-Luck et al., 2007), chlamydial infection (Thomas and Nandram, 2010), dental caries (Leroux et al., 1996), rare outcomes like birth defects (Earnest et al., 2010) and disability (Jia et al., 2004) at the county or small area level. SAE methods have been used to estimate risky health behaviors like smoking (Cui et al., 2012; Li et al., 2009b), and alcohol use (Twigg and Moon, 2002), and obesity (Li et al., 2009a; Xie et al., 2007; Zhang et al., 2011) and prioritize communities with high under-five mortality rates (Asimwe et al., 2011) and breast cancer (Knutson et al., 2008) for targeted public health interventions. Other studies have applied SAE techniques to estimate the unmet need for contraceptive use (Amoako Johnson et al., 2012), institutional births (Amoako Johnson et al., 2010), and monitoring vaccination coverage (Eberth et al., 2013; Jia et al., 2006). Studies have used SAE methods to understand geographical disparities in disease (Hudson and Soskolne, 2012; Schneider et al., 2009), inequities in income, poverty (Elbers et al., 2003), ecological relationship between inequity and illness (Curtis et al., 2006), health insurance coverage (Pickle and Su, 2002; Yu et al., 2007) and homelessness (Hudson and Vissing, 2010).

Self-rated health (SRH) is a widely used measure based on a person’s self-assessment of his status in response to a global health question “In general, how would you rate your health today?” (Fayers and Sprangers, 2002; Lundberg and Manderbacka, 1996; World Health Organization, 1996). SRH, though non-specific in its measurement, is a surprisingly reliable measure that is sensitive to a person’s perception of his health and it complements other more specific measures of health. It has been used in surveys to assess health status of populations, predict health outcome, survival, impending morbidity and death (Blazer, 2008; Hirve et al., 2012; Idler and Benyamini, 1997; Jylha, 2009). A strong association between poor SRH and risk of all-cause and disease-specific mortality independent of age, sex, income, education, social environment, health behaviors and chronic illness has been consistently reported by all studies (Benamins et al., 2004; Benyamini and Idler, 1999; Frankenberg and Jones, 2004; Heidrich et al., 2002; Ishizaki et al., 2006; Kaplan and Camacho, 1983; Mossey and Shapiro, 1982; Ng et al., 2012; Nielsen et al., 2008; Yu et al., 1998). An inherent problem with SRH often overlooked is the concern of interpersonal incomparability. When an individual chooses a discrete response on an ordinal scale, the

response is analyzed with the assumption that it represents a measure of his true health on an underlying latent interval scale. Different individuals use different thresholds to categorize their perception of their true health. This difference in reporting behavior referred to as reporting heterogeneity, unless recognized and corrected for, can lead to misleading and incorrect comparisons (Banks et al., 2007).

The Study on global AGEing and adult health (SAGE) is a multi-country study that includes a nationally representative survey implemented in India 2007–2008 under the aegis of the World Health Organization (WHO) that aims to improve understanding of health and well-being of adults aged 50 years and older, in low to middle income countries (Kowal et al., 2012). The SAGE survey was designed to provide estimates aggregated to the national and sub-national i.e. state level with adequate precision. The SAGE survey design did not allow estimation with adequate precision at the district or lower level. In addition to the national SAGE survey, an identical version was also implemented in a small rural population of about 100,000 under health and demographic surveillance (HDSS) Vadu, spread over 22 villages in Pune district in India in 2007 as part of the collaboration between SAGE and the International Network for the Demographic Evaluations of Populations and their Health (INDEPTH Network). In this paper, we derive SRH estimates for Vadu (small area) from the national WHO-SAGE survey, using different SAE methods and validate these small area level estimates against direct survey estimates derived from the INDEPTH-SAGE survey implemented in Vadu.

2. Methods

2.1. Ethics statement

The WHO SAGE survey was approved by the Ethics Review Committee of the WHO, Geneva and respective Ethics Committees of KEM Hospital Research Center, Pune implementing the Vadu SAGE survey and the International Institute of Population Sciences, Mumbai implementing the national SAGE survey. All individuals participated in the study after having completed an informed written consent.

2.2. Data sources

We used four different sources of data for our analysis—(1) the WHO-SAGE survey dataset for India, (2) the INDEPTH-SAGE survey dataset for Vadu, (3) the Census of India 2011, and (4) HDSS, Vadu dataset for 2007. The WHO-SAGE survey in India used a multi-stage, stratified cluster sample design (He et al., 2012). The sample was drawn from 19 of the 28 states and 7 union territories. The 19 states were categorized into six groups based on four indicators of infant mortality, female literacy, per capita income and safe deliveries. One state was randomly selected from each group. The sample was further stratified by urban or rural locality. Individual weights were post-stratified according to 2006 projected population estimates. For our analysis, we included only the sample from the rural strata of one of the six selected states viz. Maharashtra. Maharashtra has a population of about 9 million aged 50 years and above living in about 44,000 villages in 35 districts of the state. The WHO-SAGE survey was administered to a sample of 630 of this population living in rural areas of 21 districts of the state. Five individuals were excluded due to missing information on district of residence. The Vadu demographic surveillance area comprising 22 villages in Pune district of the state had a population of about 9800 aged 50 years and over. The INDEPTH-SAGE survey used a simple random sample design to select 500 individuals from a list of 9801 individuals aged 50 years and older that was generated from the most recent 2006 HDSS dataset. Sampling weights (inverse of the probability of the individual getting selected) were assigned for these individuals. The provisional population counts disaggregated to the district level for Maharashtra state were downloaded from the Census

of India 2011 website. We tabulated population census counts for each district for age groups 50–59y, 60–69y, 70–79y and 80+y separately for men and women who lived in rural areas of Maharashtra. We similarly, tabulated population counts for Vadu from the HDSS dataset stratified by age and sex.

The national and INDEPTH- SAGE survey datasets included variables on demographic and socio-economic characteristics, individual reports of their health status and subjective well-being, and social networking. Wealth quintiles were derived from household ownership of assets, dwelling characteristics and access to safe drinking water and sanitation. The SRH response of very poor/poor/ fair SRH on the original five-category Likert scale was recoded as ‘poor SRH’ while the response good/very good SRH was recoded as ‘good SRH’. We constructed the shortened version of the WHO disability assessment schedule (WHODAS-II) score based on twelve questions that assessed six domains of functioning in daily life (understanding and communicating, getting around, self-care, getting along with others, life activities and participation in society) (World Health Organization, 2001). The weighted mean of responses to the twelve questions was transformed into a final score that ranged from 0 to 100 (where 0 indicated no disability and 100 indicated extreme disability). The WHO quality of life (WHOQOL) score was a mean of eight responses to questions on satisfaction with health, living conditions and other aspects of life. The mean score ranged from 1 to 5 where 1 indicated ‘best’ and 5 indicated ‘worst’ quality of life. The female literacy rate, proportion with house ownership, proportion with access to safe drinking water and sanitation, socio-economic development index for the district were taken from the Census data.

2.3. Data analysis

Our outcome measure for analysis is the prevalence estimate for ‘good SRH’. We used four different SAE approaches to estimate SRH at the district/sub-district level. We used the national SAGE survey and the Census India dataset to generate an indirect synthetic estimate for each district. Similarly we used the Vadu HDSS dataset to generate the estimate for the Vadu demographic surveillance area.

2.3.1. Basic indirect synthetic estimate—We grouped the SAGE survey participants into eight groups ($k=1, \dots, 8$) according to sex and age. We computed the estimated district specific prevalence ($\hat{p}_j$) as:

$$\hat{p}_j = \sum_{k=1}^8 \frac{n_{jk}}{n_j} \hat{p}_{.k}$$

where n_{jk} is the census count in demographic group k in district j , n_j is the total census count in district j , and $\hat{p}_{.k}$ is the estimated prevalence rate for demographic group k at the state level. A 95% credible interval was estimated via Monte Carlo Markov Chain (MCMC) simulation.

2.3.2. Model based regression estimate—We used two routines (xtmelogit) and generalized linear and latent mixed model (GLLAMM) in STATA v11 to develop a random effects model as:

$$\text{logit}(p_{ij}) = X_{ij}B + u_j$$

where X was a vector of age, sex, disability, quality of life and social networking as significant individual level covariates, B was a vector of corresponding fixed effects, and u_j was a vector of district specific residuals. From the model, we predicted p_{ij} for each individual, computed the expected prevalence estimate (p_{jk}), for each demographic group in each district and then the expected district specific prevalence estimate (p_j). We included the random effect term in the model but excluded individual values of the random effects while computing the expected prevalence estimates. Both routines provided empirical best linear unbiased predictions (EBLUP) post-estimation of the random parameters (estimates and their prediction and standard error) given the observed data.

2.3.3. Hierarchical Bayesian (HB) estimate (random effects logistic regression model)—We developed a random effects logistic regression model in WinBUGS software as follows:

$$Y_{ij} \sim \text{Be}(p_{ij}) \quad \text{logit}(p_{ij}) = X_{ij}B + u_j \quad u_j \sim N(0, \sigma_u^2)$$

We assumed a Bernoulli distribution with probability p_{ij} for the outcome. We defined a logistic regression model with random effect (u_j) for each district to be distributed normally with mean 0 and variance (σ_u^2). We used the likelihood function in conjunction with non-informative priors to estimate the posterior distributions for the β coefficients and random effect and their prediction error parameters. We used the mean of the posterior distributions of the parameters to compute the district-specific prevalence estimates in the same way as for the other approaches.

2.4. Validation

We cross-validated the prevalence estimates generated by the different SAE approaches with the prevalence directly estimated from the WHO-SAGE survey data for each district and from the INDEPTH-SAGE survey data for the Vadu demographic surveillance area.

3. Results

The INDEPTH-SAGE survey was administered to 321 out of a randomly generated list of 500 individuals from the HDSS dataset (response rate 64%) after excluding 54 (11%) individuals who refused and 125 (25%) who had migrated or could not be traced. The non-responders did not differ significantly in terms of age, sex, education and socioeconomic status.

The age (mean 62 years) and sex (51% men) composition of the SAGE survey participants from Vadu was not significantly different from that for Maharashtra (Table 1). Individuals from Vadu were significantly better educated (20% had secondary education or more), had a higher proportion currently working (68%) as compared to those from the state. A significantly higher proportion (31%) from the state reported disability as a reason for not currently working as compared to 6% from Vadu. The individuals from the state reported significantly greater disability (DAS score 28.4) and lower quality of life (QOL score 57.0) compared to the Vadu group (DAS score 20.8, QOL score 72.2). A significantly higher proportion of individuals from Vadu reported good SRH (50%) compared to 23% from the state.

Only three of the 21 districts sampled in the WHO-SAGE survey had more than fifty individuals generally considered as a minimum sample required estimating prevalence (median sample size was 30 individuals per district, range: 14 to 81 individuals). The regression coefficient estimates for the fixed and random effects parameters as estimated by

the GLLAMM and the xtmelogit routine were almost identical (Table 2). The corresponding parameters estimated by the Bayesian approach were similar to those estimated by the GLLAMM and xtmelogit routines. The posterior variance of the district specific prevalence estimates was smaller (.089) with tighter intervals compared to those estimated by the two routines. Table 3 compares the district (small area) level prevalence estimates for good SRH derived using different SAE methods with the prevalence estimated directly from the survey. None of the district level variables (female literacy rate, proportion with house ownership, access to safe drinking water and sanitation, socio-economic development index for the district) were statistically significant and were excluded from the SAE models. The direct survey prevalence at the state level was 23.3% (95% credible intervals 20.0–26.7%). At the district level, the estimate varied from 4.8% to 47.1% with very wide 95% credible intervals reflecting the small sample size for each district. The indirect synthetic estimate for the state was 23.5% (similar to the direct estimate), however with minimal variation amongst the districts. The 95% credible intervals were less wide compared to those for the direct prevalence estimates at the district level. The regression model based prevalence estimates from both routines (xtmelogit and GLLAMM) were similar both at the state (18.7% and 19%) and district level. The 95% confidence intervals derived from both routines were also very similar, yet tighter than the 95% credible intervals derived by either the direct survey estimation or the indirect synthetic method. The district level estimates derived from the hierarchical Bayesian model were closer to the district level direct survey estimates albeit with wider 95% credible intervals reflecting the uncertainty around the estimates. Fig. 1 ranks each district by the amount of its district-specific random effect i.e. by the amount by which the log odds of the mean district-specific prevalence estimate differs from the log odds of the overall mean state level prevalence. Districts with a positive random intercept had a higher likelihood of reporting good SRH as compared to districts with a negative random intercept despite controlling for individual level covariates. This difference in district-specific prevalence however was not significant as was seen by the overlap of their 95% confidence intervals. Fig. 2a shows the Bayesian model based HB estimate and indirect synthetic prevalence estimates plotted against the direct survey estimate for each district. There is minimal variation in the indirect synthetic estimate between districts compared to the between-district variation of the model-based estimate. For most districts, the model based estimate was far lower than the estimate derived directly from the SAGE survey. Fig. 2b shows the Bayesian model based HB estimate and GLLAMM prevalence estimates plotted against the direct survey estimate for each district. For most districts, the HB estimates show closer approximation to the direct survey estimates than the GLLAMM estimates. The correlation between the different model-based estimates (xtmelogit, GLLAMM and HB) was high (greater than 0.95). The correlation between the model-based estimates and the direct survey and indirect synthetic estimate and the direct survey estimate was 0.75 and –0.56, respectively (detailed results not shown). Fig. 3 show the geographical disparity in the distribution of prevalence of good SRH derived using the xtmelogit model-based SAE method. A lower prevalence of good SRH was seen in the economically better developed western region of Maharashtra (exception the coastal district of Sindhudurg) as compared to a higher prevalence of good SRH seen in the economically backward Vidarbha region in Eastern Maharashtra. This difference however was not significant.

The prevalence of good SRH in the Vadu demographic surveillance area was 50.1% as estimated directly from the INDEPTH-SAGE survey. The model-based estimates (xtmelogit-45.6%, GLLAMM-45.7%, HB-45.2%) for Vadu were similar with tighter 95% credible intervals and not substantially different from the direct survey estimate. The indirect synthetic estimate for Vadu (23.2%) was a poor approximation to the direct survey or model-based estimate (Table 4).

4. Discussion

Our paper describes district and sub-district level disparities in prevalence of good SRH using different SAE methods. The direct survey estimate of prevalence for good SRH for the Vadu area was about 50%. No clear significant pattern was seen between economic development and SRH prevalence at the district level. A lower prevalence of good SRH seen in some of the economically better districts of Western Maharashtra may reflect the higher expectations of people living in better-developed areas. It may also reflect the inadequacies of district level economic indices to capture or reflect the economic reality of rural areas of the district.

Our paper provides evidence that the random effects regression models were better suited to estimate the prevalence of SRH than the fixed effects model (indirect synthetic method). We chose the fixed effects model (indirect synthetic) estimate as it is historically the most commonly used SAE method in public health due to its intuitive approach and ease of implementation (Levy, 1979). However the method is imprecise as it assumes that the difference in health outcome measures is solely due to differences in their demographic composition (Schaible, 1996). This assumption is incorrect as individual health outcomes are known to vary by contextual factors operating at the area level (Macintyre et al., 2002). On the other hand, the multilevel random effect logistic regression model allows contextual factors to influence the model estimates and provides increased accuracy of standard errors. We used the GLLAMM and xtlogit routines to perform comparative mixed model analysis for logistic response families. The models fitted by the two routines overlap with some differences in syntax, data organization, output, computational speed, accuracy, predictions and post-estimation statistics. GLLAMM uses numerical integration to evaluate the marginal likelihood and numerical derivatives to maximize it. This can make the model computationally intensive and the program slow as the number of latent variables, parameters, quadrature or free-mass points and observations increase in the model. Both routines use best linear unbiased prediction (BLUP) to estimate the random effects (Robinson, 1991). However, by simply plugging in the estimated parameters into the predictor does not account for the additional variability, leading to overly optimistic variances for the EBLUP. The EBLUP estimate is relatively robust to variations in the sample size of each small area as the model estimates based on fewer observations are 'shrunk' towards the global mean for the data (Twigg and Moon, 2002). BLUPs are a useful smoothing tool. The shrinkage property keeps them from over fitting the data. On the other hand, the HB approach treats both the fixed effects and random effects parameters as random and assumes a joint distribution for these parameters. Modeling is carried out in several stages that are easier to understand even if the model fitting process is complicated. HB estimates have smaller mean square errors and account for the uncertainty in the prediction error than corresponding EBLUP estimates. However, the HB estimates are computationally complex and are sensitive to the specification of their priors and use MCMC simulations to approximate the posterior distributions of the parameter estimates.

A major limitation of any model-based SAE method is that if substantively important individual or area level covariates are excluded due to their unavailability, then the estimates will be imprecise. Another limitation of this and any other model-based SAE approach is that it is restricted by the availability of covariates common to both the survey and the auxiliary data. Furthermore, to avoid computational complexity in our model, we did not allow the effect of covariates on the outcome to vary across districts (random slope).

There is no consensus on which SAE method provides the best estimates. The two main challenges of SAE are calculating the estimate with any level of precision given the small sample size at the small area level and estimating its standard or prediction error. The

general framework used for SAE includes pooling data over time or geographical space, modeling complex structural relationships between the outcome variable and domain-specific covariates, and/or exploiting spatial correlation by modeling a spatial component (Srebotnjak et al., 2010). SAE methods borrow strength from related small areas sampled in a survey to find more precise estimates for a given small area or even for areas not sampled in the survey. This has led to the development of methods such as EBLUP, empirical Bayes (EB) and hierarchical Bayes (HB) estimation. These methods have a distinct edge over indirect synthetic methods in estimating more precise estimates (Ghosh and Rao, 1994). The EB approach is similar to EBLUP except that the prior distributions are estimated from the data, and then used in conjunction with the likelihood to obtain the posterior distributions of the random parameters. The main shortcoming of the EB estimates is that the variance does not take into account the uncertainty of the parameters, which are treated as known and derived from the data. The HB approach overcomes this shortcoming by using non-informative prior distributions of parameters in conjunction with the likelihood to obtain the posterior distributions of the random parameters. In recent years there has been an increased interest in the application of conditional autoregressive spatial models (that borrow strength from neighboring areas) and shared component spatial models (that models two outcomes simultaneously to overcome the problem of mean square error of sparse counts) to analyze areal-level data for mapping rare diseases or where many small areas have zero or very low expected disease counts (Earnest et al., 2010).

Our paper demonstrates that a simplified mixed effects regression model can produce valid small area estimates of SRH and prediction errors. More generally, these methods can be applied for other health outcome measures such as prevalence of chronic conditions, disability etc. that will help improve planning and evaluating intervention strategies for healthy aging by local health agencies with limited resources.

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Fig. 1.
Small area (district) level effects (with 95% confidence intervals) for prevalence of good SRH, Maharashtra ($n=625$).

Fig. 2. Comparison of HB and indirect synthetic estimate (panel A), and HB and GLLAMM estimate (panel B) of prevalence of good SRH with direct survey estimate for districts in Maharashtra, India. Districts are labelled by their codes. Solid line indicates perfect correlation with direct survey estimate.

Fig. 3.
District (small area) level model based estimate of prevalence of good SRH, Maharashtra
($n=625$).

Table 1

Selected demographic and socio-economic characteristics of SAGE participants.

	Census 2011 (Maharashtra)	WHO-SAGE (Maharashtra)	INDEPTH-SAGE (Vadu)	
Population above 50y age (rural)	9170,271	9055,965	9801	
No. of districts	35	21	1	
No. of villages	43,943	46	22	
Female literacy (rural) in age 6pyrs	75%	74%	79%	
SAGE respondent profile		(n = 625)	(n=319)	p-Value^a
Mean age (SD)		62.0 (8.4)	62.2 (8.5)	0.672
Age				
50–59y		44%	38%	0.305
60–69y		37%	41%	
70–79y		16%	17%	
80+y		3%	4%	
Males		51%	51%	0.877
No spousal support		22%	24%	0.541
Education				
<i>None</i>		54%	60%	0.001
<i>Primary</i>		32%	20%	
<i>Secondary</i>		9%	12%	
<i>Higher secondary/college</i>		5%	8%	
Wealth quintiles				
<i>Poorest quintile</i>		25%	16%	<0.001
2nd		21%	24%	
3rd		16%	27%	
4th		25%	19%	
<i>Richest quintile</i>		13%	15%	
Work status				
<i>Currently working</i>		57%	68%	0.002
<i>Not working, disabled</i>		31%	6%	
<i>Not working, retired</i>		44%	37%	
<i>Not working, other reasons</i>		25%	57%	
Disability adjusted score ^b (SD)		28.4 (0.8)	20.8 (0.8)	<0.001
Quality of life score (SD) ^c		57.0 (0.6)	72.2 (0.9)	<0.001
Networking score (SD) ^d		2.3 (0.6)	2.5 (0.6)	<0.001
Self-rated health				<0.001
<i>Very good</i>		1%	6%	
<i>Good</i>		22%	44%	
<i>Fair</i>		58%	43%	
<i>Poor</i>		18 %	6%	
<i>Very poor</i>		1%	1%	

^a *p*-Value for difference between SAGE Maharashtra and SAGE Vadu.

^b Range:0–100; higher score indicates greater disability.

^c Range:0–100; higher score indicates better quality of life.

^d Range: 1–5; higher score indicates higher level of social networking.

Table 2

Multilevel random effects logistic regression model coefficient estimates. The HB coefficients are the posterior means of the coefficients (standard deviation in brackets) estimated by the HB model.

	Xtmelogit Coefficient (SE)	GLLAMM coefficient (SE)	HB coefficient (SD)
Intercept	-5.47*** (.868)	-5.47*** (.868)	-5.01 (.947)
Age (centered on mean)	-.03* (.016)	-.03* (.016)	-.03 (.017)
Sex	-.33 (.246)	-.33 (.246)	-.34 (.249)
Disability score	-.03** (.009)	-.03** (.009)	-.03 (.009)
QOL score	.06*** (.011)	.06*** (.011)	.06 (.011)
Social networking score	.56** (.213)	.56** (.213)	.58 (.216)
Random effect parameters			
District level intercept variance	.214 (.166)	.214 (.166)	.089 (.039)

* Indicates significance level <.05.

** Indicates significance level <.01.

*** Indicates significance level <.001.

Table 3

Comparing small area (district) level estimates for prevalence of good SRH based on direct survey, indirect synthetic approach, multilevel regression analysis, generalized linear latent and mixed model (GLLAMM), and hierarchical Bayesian model, Maharashtra State.

District	N	Direct survey			Synthetic			Xtmelogit			GLLAMM			HB		
		Estimate (%)	95% credible interval (%)		Estimate (%)	95% credible interval (%)		Estimate (%)	95% credible interval (%)		Estimate (%)	95% credible interval (%)		Estimate (%)	95% credible interval (%)	
AH	19	33.2	15.4	54.3	23.5	20.3	26.8	31.8	27.7	35.9	31.6	28.2	35.1	32.4	18.7	48.2
AK	39	29.4	16.6	44.0	23.5	20.3	26.8	21.5	10.7	32.2	21.5	10.9	32.1	27.0	16.7	39.6
AU	30	21.9	9.7	37.4	23.5	20.4	26.8	17.8	10.6	25.0	17.8	10.6	25.0	19.7	10.4	31.5
BH	13	39.9	17.6	65.1	23.4	20.3	26.7	16.8	3.5	30.1	17.3	3.4	31.2	23.8	12.0	41.4
BU	66	14.7	7.5	24.0	23.5	20.3	26.8	11.8	5.6	18.0	12.1	6.0	18.2	17.4	9.6	26.6
DH	23	24.0	9.8	42.0	23.5	20.3	26.8	19.0	6.2	31.8	19.0	6.4	31.6	20.1	10.9	32.1
JG	31	27.3	13.7	43.6	23.5	20.3	26.8	19.3	7.5	31.0	19.1	7.4	30.9	23.9	14.7	35.3
KO	33	34.3	19.7	50.6	23.4	20.3	26.8	24.5	6.0	43.0	24.8	6.4	43.1	38.8	26.4	50.9
NG	13	20.1	4.8	43.0	23.5	20.3	26.8	8.5	1.8	15.2	9.0	2.1	15.9	11.8	4.7	23.4
ND	35	24.4	12.1	39.3	23.5	20.3	26.8	16.2	7.0	25.3	16.2	7.1	25.3	20.3	10.9	32.9
OS	21	21.7	7.7	40.4	23.5	20.4	26.8	13.5	4.7	22.2	13.7	5.4	22.1	19.1	9.7	31.4
PA	25	25.8	11.6	43.5	23.5	20.3	26.8	18.2	7.8	28.5	18.1	7.9	28.4	24.2	13.4	37.5
PU	70	22.3	13.5	32.5	23.5	20.3	26.8	16.4	6.2	26.6	16.9	7.0	26.7	22.5	13.5	33.0
RG	43	20.1	9.8	32.8	23.4	20.3	26.7	16.9	10.3	23.5	17.8	11.2	24.4	23.4	12.3	35.8
RT	21	39.2	21.0	59.9	23.2	20.0	26.5	19.7	10.4	29.0	20.1	12.2	28.1	23.7	12.0	40.4
SN	15	41.0	19.8	64.7	23.4	20.3	26.8	29.3	14.4	44.2	31.3	16.2	46.5	34.1	20.8	50.4
ST	33	31.5	17.4	47.6	23.4	20.2	26.7	19.4	9.4	29.5	19.5	10.3	28.8	24.2	13.6	38.3
SI	15	47.1	25.0	70.0	23.3	20.2	26.6	36.5	14.9	58.2	36.2	14.6	57.8	49.1	35.5	62.7
SO	14	31.2	11.7	55.2	23.5	20.4	26.8	15.2	3.3	27.1	14.9	3.5	26.3	17.7	9.6	30.7
TH	47	14.3	6.1	25.3	23.4	20.3	26.8	13.8	8.7	18.9	13.9	8.6	19.3	18.0	8.7	28.8
YA	19	4.8	0.1	17.1	23.5	20.3	26.8	7.8	2.1	13.4	8.0	2.4	13.6	10.2	3.2	19.3
Overall	625	23.3	20.0	26.7	23.5	20.3	26.8	18.7	16.1	21.3	19.0	16.4	21.5	23.2	13.3	35.3

Table 4

Comparison of prevalence estimates for Vadu (small area) derived indirectly from WHO-SAGE (large area) survey in India using different small area estimation methods with direct survey estimates for Vadu from INDEPTH-SAGE survey ($n=319$).

	Good SRH prevalence estimate	95% Confidence/ credible interval
Direct survey weighted	50.1	44.5%–55.6%
Indirect synthetic	24.2	19.7%–29.2%
Xtmelogit	45.6	42.8%–48.3%
GLLAMM	45.7	43.0%–48.4%
Hierarchical Bayesian	45.2	42.5%–48.0%