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Article

Estimating the burden of child malnutrition across parliamentary constituencies in India: A methodological comparison

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ABSTRACT

In India, data on key developmental indicators used to formulate policies and interventions are routinely available for the administrative unit of districts but not for the political unit of parliamentary constituencies (PC). Recently, Swaminathan et al. proposed two methodologies to generate PC estimates using randomly displaced GPS locations of the sampling clusters ('direct') and by building a crosswalk between districts and PCs using boundary shapefiles ('indirect'). We advance these methodologies by using precision-weighted estimations based on hierarchical logistic regression modeling to account for the complex survey design and sampling variability. We exemplify this application using the latest National Family Health Survey (NFHS, 2016) to generate PC-level estimates for two important indicators of child malnutrition – stunting and low birth weight – that are being monitored by the Government of India for the National Nutrition Mission targets. Overall, we found a substantial variation in child malnutrition across 543 PCs. The different methodologies yielded highly consistent estimates with correlation ranging r = 0.92-0.99 for stunting and r = 0.81-0.98 for low birth weight. For analyses involving data with comparable nature to the NFHS (i.e., complex data structure and possibility to identify a potential PC membership), modeling for precision-weighted estimates and direct methodology are preferable. Further field work and data collection at the PC level are necessary to accurately validate our estimates. An ideal solution to overcome this gap in data for PCs would be to make PC identifiers available in routinely collected surveys and the Census.

1. Introduction

One way to promote greater accountability for population health and well-being is to ensure routine collection of data at, or at least linked in a way to allow aggregation to, the political unit at which public policies get designed, implemented, and monitored (Dowell et al., 2016; Krieger, 2001). Particularly in the context of low- and middle-income countries, where lack of political will is often blamed for poor performances, monitoring the distribution of health and developmental indicators at local political units can be an important step towards ensuring evidence-based political discourse and policy evaluations (Dowell et al., 2016). In India, there is a fundamental disconnection between the administrative unit (i.e., 640 districts) at which data on key developmental indicators are available and the political

Abbreviations: $D_{modeled}$, Direct and Modeled; D_{raw}, Direct and Raw; DLHS, District Level Household & Facility Survey; $I_{modeled}$, Indirect and Modeled; I_{raw}, Indirect and Raw; MP, Member of Parliament; NFHS, National Family Health Survey; NITI Aayog, National Institution for Transforming India; NNM, National Nutrition Mission; PC, Parliamentary Constituency; SD, Standard deviation; WHO, World Health Organization

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unit (i.e., 543 parliamentary constituencies [PC]) at which political actions take place (Swaminathan et al., 2019).

The discussion and decision around policies and programmes concerning health, education, and livelihoods are largely driven by data at the district level, which in part is due to the availability of data in India. For instance, the District Level Household & Facility Survey (DLHS) was designed to specifically focus on providing health care and utilization indicators at the district level (IIPS, 2010). The latest National Family Health Survey (NFHS) also covered all 640 districts and allowed for district-level estimates for many important indicators (IIPS, 2017). Other sources, including the Census (Office of the Registrar General and Census Commissioner of India, 2011), also consistently include identifiers for districts, enabling a plethora of district-level statistics. The National Institution for Transforming India (NITI) Aayog has identified 117 "aspirational districts" based on a composite index of socio-economic caste census, key health and education sector performance, and state of basic infrastructure to encourage greater attention to uplift the lagging districts (Paul et al., 2018). However, there are no political representatives directly accountable for the performance at this administrative level.

At the same time, Members of Parliament (MPs) in the Lok Sabha (Lower House of the Indian Parliament), each representing 543 PCs as per the 2014 India map, are the representatives with the most direct interaction with their constituents (Maheshwari, 1976; Parliament of India Lok Sabha House of the People). The MPs of the Lok Sabha are elected by first-past-the-post universal adult suffrage and serve 5-year terms during which they are accountable for the vision and implementation of public policies at the national and the specific constituency level (Maheshwari, 1976; Parliament of India Lok Sabha House of the People). In order for MPs to efficiently and effectively serve their people, and also for the constituents to understand the performance of their MPs for re-election, it is critical to produce the most accurate and up-to-date evidence on the state of health and well-being at the PC-level (Swaminathan et al., 2019). However, absence of PC identifiers in nationally representative surveys or the Census inhibits such assessment.

While the district and PC boundaries overlap to some extent, they do not form a hierarchical structure where PCs perfectly nest within districts, or vice versa. This discordance between the two units, and the lack of data at the PC level, can be consequential. The latest example concerns the National Nutrition Mission (NNM), launched by the Government of India in 2018, to improve nutritional outcomes for children, adolescents, pregnant women and lactating mothers (NITI Aayog, 2017). Like many other government programmes, the NNM is planned to roll out at the district level in a phased manner with 315 districts covered in 2017-18, followed by additional 235 districts in 2018-19, and the remaining districts in 2019-20 (NITI Aayog, 2017). District-wide statistics on undernutrition indicators are also widely available, but they are less relevant for MPs who need to first understand the burden of child malnutrition amongst the constituents they directly represent and accordingly develop a strategy to make progress.

Recently, two methodologies were developed to enable PC-level estimations from the NFHS data (Swaminathan et al., 2019). The first method ('direct') involved aggregation of individual level data to a potential PC linked via the randomly displaced GPS locations of the sampling clusters in the NFHS. The second method ('indirect') used boundary shapefiles to build a crosswalk between districts and PCs. We advance these proposed methodologies by using precision-weighted estimations based on hierarchical logistic regression modeling to account for complex survey design and sampling variability, a method well-known for small area estimation (Arcaya, Brewster, Zigler, & Subramanian, 2012; Goldstein, 2011; Jones, & Bullen, 1994; Subramanian et al., 2003). We exemplify these methodologies using the latest NFHS data for two important indicators – stunting and low birth weight – that are being monitored by the Government for the NNM targets (NITI Aayog, 2017). We provide a comprehensive overview of the different processes, optimizing the state-of-the-art GIS and statistic techniques, to derive PC estimates when data are available only at the individual or district levels without PC identifiers. After assessing the consistency across different methodologies, we apply the most preferable approach (i.e., direct methodology with modeling for precision-weighting) to present the estimates and the ranking of 543 PCs for additional malnutrition indicators (i.e., underweight, wasting, and anaemia) to provide a broad assessment for inclusive dicussion around child nutrition in India.

2. Material and methods

2.1. Data source

The fourth round of NFHS (2015-16) was used for this analysis. The NFHS, equivalent to the Demographic Health Survey (https://dhsprogram.com/) in India, collects data on key population, health, and nutrition indicators (IIPS, 2017). This is an important source of data used to generate evidence to inform the Ministry of Health and Family Welfare and other agencies for policy and programme purposes. The NFHS-4, for the first time, covered all 640 districts across 36 states and union territories in India (IIPS, 2017). A representative sample of households was selected using a stratified two-stage sample design. First, within each district, primary sampling units (referred to as clusters hereafter) were selected based on a sampling frame of the 2011 Census. For rural areas, clusters corresponded to villages. In urban areas, clusters corresponded to census enumeration blocks. A complete household mapping and listing operation were conducted within each cluster. At the second stage of sampling, households were selected using a systematic sampling with probability proportional to the size. The NFHS-4 had a response rate of 97.6% for household surveys and 96.7% for individual women interviewed within households (IIPS, 2017).

2.2. Study population

A total of 247,743 children aged less than five years were alive at the time of the survey. After excluding 22,741 children (9.2%) who were missing height measures, 225,002 children remained for the stunting analysis. A larger number of children were missing data on birth weight (N = 60,561, 24.4%). The final analytic sample for the low birth weight analysis included 187,182 children (Fig. 1). In our final analytic sample with reported birth weight, 53.2% were from a written card and the remaining 46.8% were based on mother's recall.

2.3. Outcomes

Stunting and low birth weight are two indicators of child malnutrition being monitored for the NNM. One of the NNM targets is to reduce child stunting, a measure of linear growth retardation resulting from chronic undernourishment, by at least 2% per annum and ultimately to as low as 25% by 2022 (NITI Aayog, 2017). In the NFHS, child's standing height was obtained for children older than 24 months. For children less than 24 months, recumbent length was measured with children lying on the board placed on a flat surface (IIPS, 2017). The raw height measures were transformed into age- and sex-specific z-scores based on the World Health Organization (WHO) child growth reference standards, and children with height-for-age z-scores < -2 standard deviation (SD) were classified as being stunted (WHO Multicentre Growth Reference Study Group, 2006). Similarly, the NNM also targets to reduce low birth weight by 2% per annum (NITI Aayog, 2017). Low birth weight was defined as birth weight less than 2,500 grams regardless of gestational age (NITI Aayog, 2017). In addition to these two main outcomes, wasting (i.e., weight-for-height z-score < -2 SD), underweight (i.e., weight-for-age z-score < -2 SD) and anaemia (i.e., hemoglobin level < 11.0g/dl) were also considered for application of one of the selected methodologies.

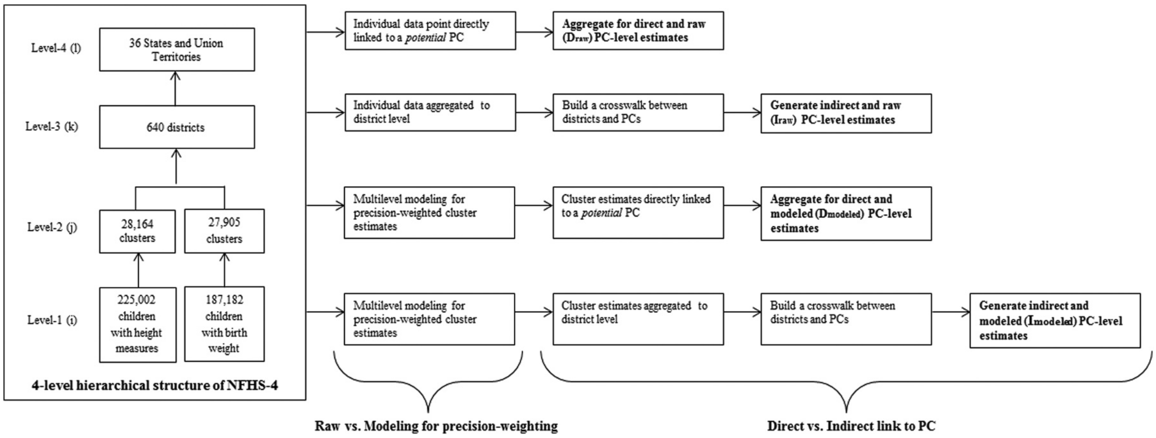


Fig. 1. Hierarchical structure of the final analytic sample from the National Family Health Survey 2016 and an outline of the four different methodologies used to generate estimates of stunting and low birth weight at the level of Parliamentary Constituencies.

2.4. Statistical analysis

As outlined in Fig. 1, we used a combination of different statistical estimation (raw *versus* modeling for precision-weighting) and methodologies to link to PC (direct *versus* indirect) to produce four different estimates per outcome: 1) raw individual data point directly linked to a potential PC ('direct and raw' or D_{raw}), 2) raw individual data aggregated to district and indirectly linked to a PC via a cross-walk ('indirect and raw' or I_{raw}), 3) precision-weighted cluster data directly linked to a potential PC ('direct and modeled' or $D_{modeled}$), and 4) precision-weighted cluster data aggregated to district and indirectly linked to a PC via a cross-walk ('indirect and modeled' or $I_{modeled}$). Of note, we use the term 'raw' to refer to procedures that do not involve modeling for precision-weighting but in some occasions the 'raw' data themselves may have been already aggregated, transformed, or weighted before being made available to the users. D_{raw} and I_{raw} stunting estimates for 540 PCs were reported in a prior study in which district estimates from NFHS-4 district fact sheets were used to perform the cross-walk (Swaminathan et al., 2019), and $D_{modeled}$ estimates for stunting and low birth weight were drawn from our working paper (Kim, Xu, Joe, & Subramanian, 2018). We present a comprehensive overview of the four different methodologies and assess the consistency in their estimations.

2.4.1. Modeling for precision-weighted estimates

A hierarchical model, also known as random effects or multilevel models, provides a technically robust and efficient framework to account for complex survey design and to produce precision-weighted estimates for predictions at higher level entities (Bell et al., 2016; Jones & Bullen, 1994; Subramanian et al., 2003). For instance, in a two-level linear regression model with individual observations at level-1 (i) nested within groups at level-2 (j):

$$y_{ij} = \beta + (u_j + e_{ij})$$

$$u_j \sim N(0, \sigma_u^2)$$

$$e_{ij} \sim N(0,\sigma_e^2)$$

The term u_j denotes a group-specific residual with a variance of σ_u^2 and the term e_{ij} denotes an individual-specific residual with a variance of σ_e^2.

In this model, the group-specific average outcome (β_j) is a weighted combination of the fixed group intercept (β_j^*) and the overall multilevel intercept (β):

$$\beta_j = w_j\beta_j^* + (1 - w_j)\beta$$

Where the overall multilevel intercept (β) is a weighted average of all the fixed group intercept (β_j^*):

$$\beta = \left(\sum w_j\beta_j^*\right) / \sum w_j$$

And the weights represent the reliability or precision of the fixed terms that take into account of the ratio of the between-group variance to the total variance and a sampling variance affected by the number of observations within each district (n_j):

$$w_j = \sigma_u^2/[\sigma_u^2 + (\sigma_e^2/n_j)]$$

Hence, compared to raw estimates, multilevel estimates have the following advantages (Arcaya et al., 2012; Jones & Bullen, 1994): (1) pooling information between j groups, with all the information in the data being used in the combined estimation of the fixed and random part, (2) borrowing strength, whereby poorly estimated j group-specific predictions benefit from the information for other groups; and (3) precision-weighted estimation, whereby unreliable j group-specific fixed estimates are differentially down-weighted or shrunken towards the overall mean which is based on all the data.

We extend this approach to the four-level structure of the NFHS with child i (level-1) nested within cluster j (level-2), district k (level-3), and state l (level-4) to calculate cluster-specific probabilities of stunting and low birth weight:

$$logit(\pi_{ijkl}) = \beta + (u_{jkl} + v_{kl} + f_l)$$

$$f_l \sim N(0,\sigma_f^2)$$

$$v_{kl} \sim N(0,\sigma_v^2)$$

$$u_{jkl} \sim N(0, \sigma_u^2)$$

In this model, the state mean is shrunk towards the overall mean, which is a precision-weighted average of all the state means; the district mean is shrunk towards its associated shrunken district mean; and the cluster mean is shrunk towards its associated shrunken cluster mean. In essence, the precision-weighted cluster means pool information and borrow strength from other clusters that share the same district membership. For binary outcome models, the variance at the individual level is approximated using a latent variable method as $\pi^2/3$ (Browne, Subramanian, Jones, & Goldstein, 2005).

Multilevel modeling was performed in the MLwiN 3.0 software program via Monte Carlo Markov Chain (MCMC) methods using Gibbs sampler with non-informative priors, a burn-in of 500 cycles, and monitoring of 5000 iterations of chains (Browne, 2017).

2.4.2. Linking to parliamentary constituency

The direct and indirect methodologies to link data at individual and district levels to PCs were outlined in detail in a recent study (Swaminathan et al., 2019). Their direct methodology used the GPS data on each NFHS cluster location recorded in degrees of latitude and longitude (accurate to ± 15 meters). The survey cluster coordinates were randomly displaced by a maximum of 2 kilometers for urban clusters and 5 kilometers for rural clusters but was contained within the district (DHS, 2018). Swaminathan et al generated a GIS map of these cluster points and combined it with the 2014 PC boundary shapefiles from the Community Created Maps of India (http://projects.datameet.org/maps/) to determine which PC each cluster *potentially* falls into. We utilized this data file with a potential PC identifier assigned to each observation. Their indirect methodology used the boundary shapefiles for PCs and districts to create a cross-walk that assigned weighted average of the population of the segments of district that fall in each PC (Swaminathan et al., 2019). We used this crosswalk to transform and aggregate district-level data to generate estimates of stunting and low birth weight for the PCs. This method can be modified for geographic or land-based indicators by computing the weighted average using the area of district segments instead of population.

We compared the degree of consistency in the PC estimates resulting from these different methods in three ways. First, we computed Pearson correlation and Spearman's rank correlation across the four estimates for each outcome. Second, we further assessed the number and proportion of PCs with less than ± 5, ± 5 to ± 10, and more than ± 10 percentage point difference between each estimate in reference to the D_{raw} estimates. Third, we compared the overlap in the list of 100 PCs with the highest estimates of stunting and low birth weight using the four methodologies.

Finally, the $D_{modeled}$ methodology was selected, for the reasons described later, to be applied to additional indicators of child malnutrition. We provide the $D_{modeled}$ estimates and the ranking of 543 PCs for stunting, low birth weight, wasting, underweight, and anaemia.

3. Results

The exact estimates of stunting and low birth weight from the four different methodologies are provided in Supplementary Tables 1 and 2. For interpretation and identification of the geographical location of PCs, we included index map for 36 Indian States/Union Territories (Supplementary Fig. 1), a map showing the discordance between district and PC boundaries (Supplementary Fig. 2), and index map for PCs (Supplementary Fig. 3). Overall, we found a substantial variation in these two indicators of child malnutrition across 543 PCs. The four different methodologies yielded highly consistent estimates.

3.1. Stunting

The mean and the range in predicted probability of stunting across 543 PCs was 35.8% (10.0% to 65.4%) using D_{raw} approach, 35.8% (15.0% to 62.1%) using I_{raw} approach, 35.2% (15.0% to 63.6%) using $D_{modeled}$ approach, and 35.0% (15.9% to 60.8%) using $I_{modeled}$ approach. The largest difference in the mean and median stunting estimates was between D_{raw} and $I_{modeled}$, with a difference of 0.8 and 1.6 percentage points, respectively. The correlation in PC-level stunting was very strong among all estimates, ranging from r = 0.99 for I_{raw} and $I_{modeled}$ to r = 0.92 for D_{raw} and $I_{modeled}$ methods (Fig. 2**A**). The same was true for spearman rank correlation (Supplementary Table 3). Moreover, 77 PCs were found to consistently rank in the top 100 highest stunting prevalence using all four methods (Supplementary Table 1).

More specifically, in comparing D_{raw} and I_{raw} estimates of stunting, we found that the majority of PCs (N = 461, 85%) had less than 5 percentage point difference while 67 PCs (12%) had a difference of 5-10 percentage point and only 15 PCs (3%) had a difference larger than 10 percentage point (Fig. 3**A**). The PCs with the largest difference were Mumbai North in Maharashtra (D_{raw} = 15.0%; I_{raw} = 31.9%; difference = -16.9%), followed by Jaynagar in West Bengal (D_{raw} = 40.7%; I_{raw} = 25.6%; difference = 15.1%), and Chevella in Telangana (D_{raw} = 37.3%; I_{raw} = 23.9%; difference = 13.4%). A larger proportion of PCs (N = 503, 93%) had less than 5 percentage point difference when comparing D_{raw} and $D_{modeled}$ estimates of stunting. The PCs with the largest difference were Mumbai North-West in Maharashtra (D_{raw} = 10%; $D_{modeled}$ = 22.9%; difference = -12.9%), Biwandi in Maharashtra (D_{raw} = 53.2%; $D_{modeled}$ = 41.8%; difference = 11.4%), and Arambag in West Bengal (D_{raw} = 42.3%; $D_{modeled}$ = 32.1%; difference = 10.2%). Around 81% of PCs (N = 440) had less than 5 percentage point difference in stunting estimates derived from D_{raw} and $I_{modeled}$ methodologies, while 3.9% of PCs (N = 21), including Mumbai North (D_{raw} = 15.0%; $I_{modeled}$ = 31.9%; difference = -16.9%), Mumbai North-West (D_{raw} = 10%; $I_{modeled}$ = 25.2%; difference = -15.2%), and Biwandi (D_{raw} = 53.2%; $I_{modeled}$ = 38.1%; difference = 15.2%) in Maharashtra had more than 10 percentage point difference.

3.2. Low birth weight

Across 543 PCs, the mean predicted probability of low birth weight was estimated as D_{raw} = 17.7% (range: 3.6% to 41.5%), I_{raw} = 17.7% (range: 6.6% to 35.3%), $D_{modeled}$ = 16.6% (range: 4.1% to 35.5%), and $I_{modeled}$ = 16.4% (range: 6.3% to 31.0%) using different methodologies. The largest difference in mean low birth weight was 1.3 percentage points between D_{raw} and $I_{modeled}$ and in median low birth weight was 1.4 percentage points between D_{raw} vs $I_{modeled}$. The correlation in PC-level low birth weight was the strongest between I_{raw} and $I_{modeled}$ estimates (r = 0.98) followed by $D_{modeled}$ and $I_{modeled}$ estimates (r = 0.94), and the weakest between D_{raw} and $I_{modeled}$ (r = 0.81) (Fig. 2**A**). The spearman rank correlation also ranged from r = 0.80 to 0.98 (Supplementary Table 3). In comparing the ranking of PCs with the highest prevalence of low birth weight, we found that 71 PCs were consistently identified to be ranked within 100 PCs with the highest estimates according to all four methodologies (Supplementary Table 2).

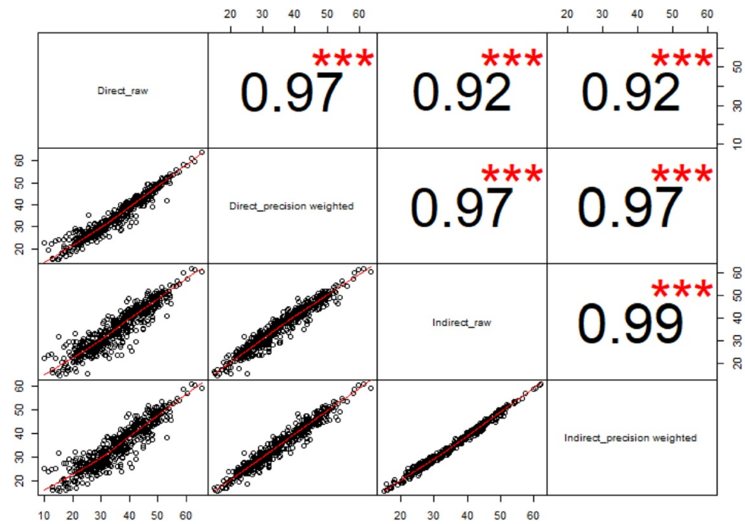
Compared to the simplest approach (D_{raw}), I_{raw} yielded very similar estimates of low birth weight (i.e., less than 5 percentage point difference for the majority of PCs (N = 489, 90.1%)) (Fig. 3**B**). A total of 7 PCs in Andhra Pradesh, Maharashtra, and West Bengal had a difference larger than 10 percentage point between D_{raw} and I_{raw} estimates of low birth weight. Similarly, only 4 PCs, including Narsapuram in Andhra Pradesh (D_{raw} = 41.5%; $D_{modeled}$ = 25.7%; difference = 15.8%), Barasat in West Bengal (D_{raw} = 30%; $D_{modeled}$ = 15.5%; difference = 14.5%), Pune in Maharashtra (D_{raw} = 32.5%; $D_{modeled}$ = 19.5%; difference = 13%), and Barddhaman-Durgapur in West Bengal (D_{raw} = 35%; $D_{modeled}$ = 22.1%; difference = 12.9%) had a difference larger than 10 percentage point between D_{raw} and $D_{modeled}$ estimates of low birth weight. A larger difference was found between D_{raw} and $I_{modeled}$ estimates, with 10.7% (N = 58) and 1.8% (N = 10) of PCs having 5-10 and more than 10 percentage point differences, respectively.

For the purpose of substantive and empirical discussion around patterning of malnutrition, in terms of other commonly used indicators, we present the $D_{modeled}$ estimates and the rankings of 543 PCs for wasting, underweight, and anaemia in addition to stunting and low birth weight (Table 1). The corresponding maps illustrating geographic distribution of each indicator are presented in Supplementary Fig. 4.

4. Discussion

Using two examples of child malnutrition indicators that are highly relevant for the current policy discussion around NNM in India, we demonstrated four possible methodologies to derive PC level estimates. Based on our findings of substantial variation in stunting and low birth weight across 543 PCs in India and high consistency in the PC estimates using different methodologies, we make the following

A. Stunting



B. Low birth weight

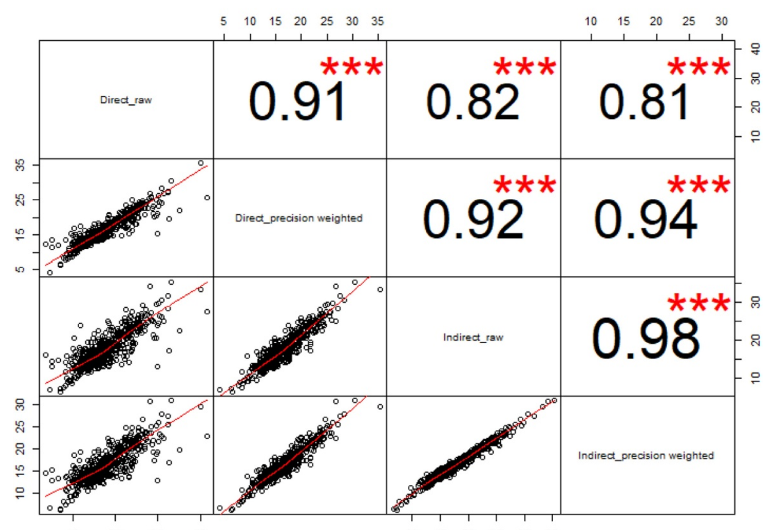
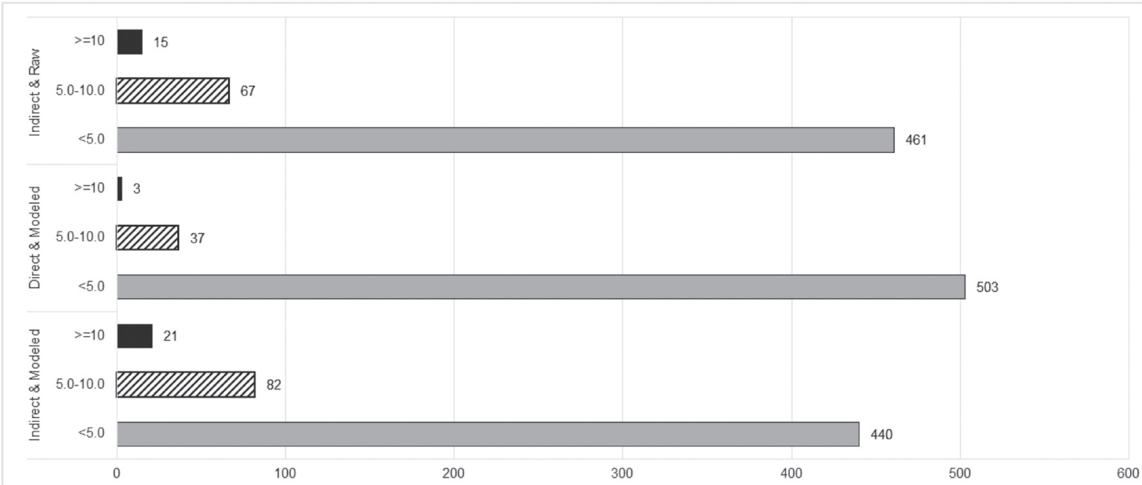


Fig. 2. Pearson correlation comparing estimates for 543 Parliamentary Constituencies derived from four different methodologies for A) stunting and B) low birth weight. ***p < 0.001. Results from Spearman Rank correlation remained virtually the same (Supplementary Table 3).

recommendations. First, for surveys with complex sampling design like NFHS, precision-weighted estimations are recommended to account for sampling variability and to produce smoothed estimates. In general, the largest differences in stunting and low birth weight estimates across different methodologies were found in a few PCs in the states of Andhra Pradesh, Maharashtra, and West Bengal. These PCs had a relatively small sample size (< 100 observations), which resulted in multilevel modeling to down-weight their estimates more towards the overall mean. Second, when GPS coordinates for survey clusters are available to be linked to PC boundaries, even if they are displaced to certain degree, direct methodology is preferable given that creating the indirect cross-walk between districts and PCs is less straightforward. However, in the absence of geographic location of survey clusters and/or when the data available are aggregated at the district level, indirect methodology produces highly consistent PC estimates. Third, an ideal solution to overcome this gap in data for PCs would be to make PC identifiers available in routinely collected surveys and the Census.

Lok Sabha, the Lower House of the Indian Parliament, is referred as “the repository of power and authority” with the MPs playing critical roles in ordering the affairs of the state and in shaping the allocation of public goods and larger social structures and processes (Maheshwari, 1976). MPs work with public authorities to achieve demands from their constituents and also mobilize themselves for the purpose of promoting interests of his state at the level of the central government (Kapur & Mehta, 2006; Maheshwari, 1976). In the absence of standard inventory for compiling community problems, the panchayati raj leadership or influential persons of an area often articulate the development needs of the locality (Maheshwari, 1976). Indeed, evidence supports that among PCs with the historically disadvantaged social groups, those that mobilized themselves politically gained more relative to others during 1970s and 1980s in rural India (Banerjee & Somanathan, 2007). Despite Parliament being an agent of accountability, minimum effort has been made to date to link existing data to PCs (Banerjee & Somanathan, 2007).

A. Stunting



B. Low birth weight

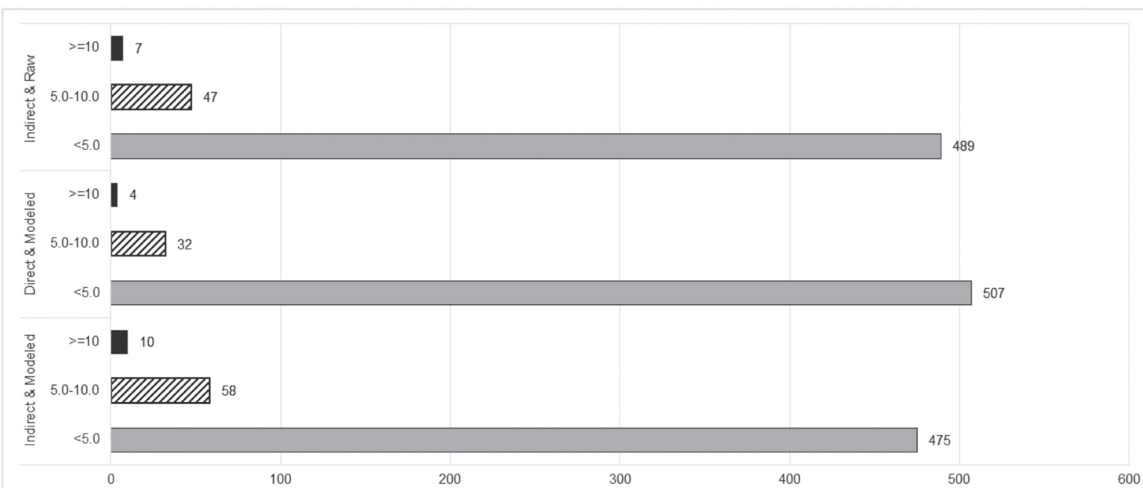


Fig. 3. Difference in estimates (in percentage point) between 'direct and raw' (D_{raw}) method versus other approaches for A) stunting and B) low birth weight across 543 Parliamentary Constituencies. The exact estimates using the four different methodologies and the differences between them are presented in Supplementary Table 1 for stunting and Supplementary Table 2 for low birth weight.

The methodologies proposed to link NFHS data with PC boundary are not without limitations (Swaminathan et al., 2019). Directly linking survey cluster to a potential PC may have measurement errors due to random displacement of GPS coordinates in the NFHS. The accuracy of indirect methodology depends on the validity of cross-walk. The cross-walk methodology assumes that sampled observations are uniformly distributed across districts, when in reality certain areas of a district may have a higher sampling cluster density than others. This could lead to biased PC estimates when one district is split between multiple PCs. Additionally, small boundary discrepancies between the district and PC shapefiles, for example along state borders, can lead to low levels of noise when calculating PC estimates. While our estimates of stunting and low birth weight based on both direct linkage and indirect cross-walk were highly consistent, further field work and data collection at the PC level are necessary to accurately validate our estimates.

Our empirical exemplification focused on stunting and low birth weight in order to illustrate the range of consistency in D_{raw}, I_{raw}, $D_{modeled}$, and $I_{modeled}$ methodologies for indicators with different sample sizes and potential measurement errors. While children's height in the NFHS was comprehensively and objectively measured by field investigators, birth weight was self-reported by mothers based on written card (53.2%) or from recall (46.8%) and was missing for a larger fraction of the surveyed children. The geographical distribution of children who were excluded due to missing measures of height and birth weight was of particular concern. However, when 22,741 children who were excluded from the analysis for stunting were each linked to a potential PC using the direct method, we found no evidence of clustering. Less than 1% of the excluded children for stunting estimation were nested within each of the 538 PC, with the largest proportion of excluded children being in Nagaland (2.6%) and Arunachal East (3.3%). Similarly, among 60,561 children who were excluded from the analysis for low birth weight, 4.5% were located in Nagaland and 2.5% in Outer Manipur and the remaining were randomly distributed across the remaining PCs (< 1% for 536 PCs). We found no evidence of systematic bias affecting the estimation of stunting and low birth weight for the few PCs with a larger proportion of children with missing data. While the correlation in PC estimates for low birth weight in general was lower than the correlation for stunting, they were still very strong

Table 1
Application of 'direct and modeled' ($D_{modeled}$) methodology to compute estimates and ranking for 543 Parliamentary Constituencies by five indicators of child malnutrition (Note: Ranked from the highest (1) to the lowest (543) prevalence).

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
1	Jammu & Kashmir	1	Leh (Ladakh)	28.9	380	9.5	533	17.9	510	10.1	536	45.9	450
		2	Baramulla	26.6	435	14.1	389	12.8	538	8.4	539	51.9	374
		3	Srinagar	24.8	477	12.9	456	13.5	534	11.1	522	43.5	468
		4	Anantnag	22.2	509	12.1	501	11.1	543	7.8	540	38.5	492
		5	Udhampur	31.8	320	13	454	19.6	500	13.7	468	44	464
		6	Jammu	26.4	439	14.6	358	16.4	518	11	524	41.9	478
2	Himachal Pradesh	7	Hamirpur	26	446	19.5	125	18.8	505	11.7	515	41.5	481
		8	Kangra	25.9	449	15.5	298	20.6	485	11.9	512	46.6	440
		9	Shimla	25.5	461	18.8	150	25.2	421	16.2	388	57.2	282
		10	Mandi	22.1	514	14.7	350	16.3	520	13.4	479	39.9	487
3	Punjab	11	Jalandhar	28	406	11.8	510	22.7	453	15.9	399	58.6	257
		12	Hoshiarpur	24.1	493	17.4	200	19.6	498	15.2	428	61.4	225
		13	Fatehgarh Sahib	21.7	517	19.3	132	19.8	492	14.6	445	61.6	222
		14	Firozpur	26.9	430	14.7	352	26.5	393	19.3	270	54.3	337
		15	Patiala	21.9	515	19.9	113	16.9	514	12.5	501	54	345
		16	Bathinda	26.2	442	16.7	238	20.6	486	13.5	472	51.9	375
		17	Gurdaspur	22.2	511	13.5	420	19.7	497	14.4	452	71.3	74
		18	Amritsar	21.8	516	12.2	497	13.9	530	11.6	518	44.3	463
		19	Khadoor Sahib	23	504	12.5	484	16.7	516	12.1	511	55.9	307
		20	Anandpur Sahib	21.5	518	15.7	280	21.6	468	13.4	480	70.5	85
		21	Sangrur	24.7	479	18.7	152	18	509	13.8	466	50.5	394
		22	Ludhiana	25.3	467	16	271	24.8	425	17.3	344	57.4	278
		23	Faridkot	28.9	383	15.3	309	23.5	441	16.8	367	54.7	331
4	Chandigarh	24	Chandigarh	29.7	357	20	103	24.2	432	10.6	532	71.3	73
5	Uttarakhand	25	Almora	28.9	382	23.6	30	21.8	467	19.1	276	37.9	496
		26	Hardwar	34.8	264	23.5	31	26.5	395	17.2	351	65.3	163
		27	Tehri Garhwal	30.4	347	21.2	78	36	216	36.1	4	47.3	435
		28	Garhwal	29	377	19.6	118	25.3	417	21.1	211	46.6	441
		29	Nainital - Udhamsingh Nagar	33.1	293	23.4	32	22.3	461	11	526	60.1	244
6	Haryana	30	Ambala	24.6	481	13.8	402	30.2	324	31.7	13	72.2	66
		31	Krukshetra	31.8	321	16.6	249	31.9	289	23.7	144	64.7	175
		32	Sirsa	30.4	348	18.7	153	29.3	340	21	216	72.8	57
		33	Karnal	39.9	187	17.9	173	34.9	238	21.4	199	69.8	93
		34	Sonipat	35.1	257	21.9	57	29.7	333	22.6	168	65.4	157
		35	Hisar	27.2	420	14.3	374	25.5	414	22.4	171	71.3	72
		36	Rohtak	28.9	379	17.8	178	22.4	459	15	434	74.8	32
		37	Bhiwani - Mahendragarh	29.1	375	17.7	184	25.2	419	16.5	380	74.9	29
		38	Gurgaon	39.4	195	22	55	31.4	301	18.2	312	77.8	9
		39	Faridabad	33.4	290	22.8	43	26.7	388	20.8	219	75	28
7	NCT of Delhi	40	West Delhi	29.4	367	20.8	87	22.6	455	15.4	422	67.9	122
		41	North West Delhi	34.9	263	26.8	6	29.6	335	17.1	357	69.4	100
		42	Chandni Chowk	30.2	349	19.9	110	28.1	365	18.3	305	68.3	115
		43	North East Delhi	27.2	419	20	101	23.5	440	13.5	475	63.5	199
		44	South Delhi	28.7	388	17.8	176	26.9	382	21.1	209	63.3	202
		45	East Delhi	25.6	457	22.5	48	22.8	452	19.8	256	52.6	361
		46	New Delhi	28.1	402	20.4	95	26.5	394	18.9	286	66.6	140
8	Rajasthan	47	Churu	31.4	328	14.5	362	26.5	392	20.8	222	43	470
		48	Bikaner	32.3	309	12.6	475	31.1	311	22.9	158	49.9	407
		49	Jhunjhunun	31.8	319	15.3	305	20.7	482	14	464	47.9	426
		50	Alwar	40.8	165	19.6	119	34.2	254	17.7	326	54.1	343
		51	Jodhpur	39.6	192	19.4	131	37.1	195	21.7	192	56.2	300
		52	Sikar	29.2	372	18.7	151	21.2	474	12.2	507	48.6	418
		53	Nagaur	38.4	205	18.3	162	31.2	308	18.3	303	69.8	92

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		54	Tonk - Sawai Madhopur	34.9	262	24.7	15	34.5	245	19.5	262	63.5	197
		55	Bharatpur	44	104	21.1	79	31.5	296	16.1	392	56.1	302
		56	Barmer	35.6	247	12.5	481	37.8	186	24.1	136	54.5	333
		57	Ajmer	32.5	307	19.2	138	36	219	28.1	57	67.2	134
		58	Karauli - Dhaulpur	47.8	54	28.3	3	36.8	201	16.5	378	51.7	378
		59	Jhalawar - Baran	38.1	209	21.6	63	42.5	97	28.5	50	76	22
		60	Rajsamand	37.5	224	19.4	129	36.8	204	25.1	112	69.6	94
		61	Jalore	42.1	142	14.8	343	44.9	64	29.9	32	68.4	112
		62	Bhilwara	34.8	267	17.9	174	40.6	137	31.5	15	74.1	37
		63	Kota	32.8	299	18.6	155	38.6	175	25.9	97	76.4	18
		64	Pali	40.3	178	17.7	187	39.4	165	21.7	191	58.1	262
		65	Ganganagar	31.4	327	14.9	340	26.3	397	19.3	269	45.8	452
		66	Dausa	34	279	24.3	19	28.3	363	15.7	403	48.6	419
		67	Chittaurgarh	40.5	171	22.3	51	45.4	57	27.3	70	72.9	56
		68	Jaipur	32.5	306	20.4	94	24	434	12.8	490	50.3	398
		69	Banswara	47.3	63	21.6	64	50.1	12	31.7	12	80.3	3
		70	Udaipur	44.7	91	21.9	59	49.7	13	31	23	77.9	8
		71	Jaipur Rural	35.7	246	22.7	45	25.1	423	12.4	504	48	425
9	Uttar Pradesh	72	Saharanpur	35.2	256	22.9	41	34.1	255	16.4	383	76.5	15
		73	Kairana	39.4	194	23.9	25	37.1	197	17.3	345	76.2	21
		74	Nagina	42.5	136	24.1	21	40.5	139	23.8	142	72.6	61
		75	Muzaffarnagar	38.3	207	24.5	16	35.5	227	18.8	288	77.6	10
		76	Baghpat	34.7	269	21.3	74	32.6	278	14.3	456	75.9	23
		77	Amroha	41.1	160	23.4	33	37.8	184	18.4	302	73.2	49
		78	Sambhal	44.2	101	27.1	5	42.1	109	15.7	405	76.3	20
		79	Meerut	34.9	261	22.4	50	33.1	269	17.7	325	73.3	44
		80	Lalganj	40.8	167	15	325	34.1	258	17.3	348	60.2	242
		81	Jalaun	43.4	119	21.8	61	43.7	83	26.3	88	78.8	6
		82	Rampur	44.6	93	27.5	4	42.7	92	19.4	265	77.1	13
		83	Ghaziabad	35.5	250	21.9	58	28.7	352	12.4	503	62	218
		84	Pilibhit	49.6	32	19.2	139	42.6	95	20.1	245	76.7	14
		85	Bulandshahr	43	127	19.4	128	33.2	267	15.2	429	64.9	171
		86	Kheri	52.1	17	24.4	18	39.7	160	17.7	327	50.4	396
		87	Bareilly	43.7	111	23	38	39.7	157	17.4	342	74	39
		88	Aonla	48.8	39	21.5	69	45	62	18.7	293	69.4	99
		89	Budaun	54	9	19.9	111	52.7	3	18.9	283	64	191
		90	Shahjahanpur	48.7	44	20	105	51.9	5	22.4	173	77.1	12
		91	Bahraich	63.6	1	25.2	13	42.2	105	12.9	489	73.2	50
		92	Aligarh	46.1	81	22.1	53	36.4	209	14.9	437	67.9	124
		93	Dhaurahra	54.9	7	23.6	29	42.6	96	15.7	404	51.4	380
		94	Etah	50.2	27	21.4	70	32.7	275	11.2	520	40.4	485
		95	Mathura	40.3	179	18.8	149	27.1	379	11.8	514	56.1	304
		96	Farrukhabad	48.1	48	21.3	72	31.4	300	9.1	538	41.6	480
		97	Hardoi	50.4	23	24	23	40.2	146	15.2	425	46.4	442
		98	Hathras	45.6	84	23.6	28	34.9	236	12.3	505	57.2	283
		99	Domriaganj	56	6	17.7	190	42.1	110	13.3	483	65.4	158
		100	Sitapur	54.6	8	26.2	8	46.6	47	13.1	487	56.1	301
		101	Firozabad	43.5	115	24.5	17	27.2	377	10.7	531	48.4	421
		102	Maharajganj	53.3	11	16.6	241	37.4	192	12.2	506	58	263
		103	Mainpuri	47.7	56	20	104	33	270	10.9	527	42.8	472
		104	Kaisarganj	59.7	3	23.8	26	41	130	10.3	533	72.3	64
		105	Gonda	58.3	4	21.6	66	40.4	143	10.2	535	73.3	45
		106	Misrikh	49.2	37	21.3	73	41.9	113	17.5	333	55.6	312
		107	Barabanki	50.2	25	22.7	44	39.4	166	12.1	510	45.5	454
		108	Kushi Nagar	46.4	77	15.2	317	35.4	230	14.2	457	60.7	233
		109	Fatehpur Sikri	45.8	83	23	40	34.9	237	13.5	473	52.3	368
		110	Azamgarh	40.1	185	17.1	213	31.8	291	16.1	391	63.3	203
		111	Bansgaon	40.8	166	15	324	31.7	292	14.9	435	68.4	114
		112	Amethi	43.6	113	14.5	366	40.6	135	22	185	65.3	161
		113	Akbarpur	43.5	116	17.1	212	41	129	21.4	200	69.9	91
		114	Rae Bareli	37.7	220	17.9	172	40.4	142	28.9	43	61.7	220
		115	Mohanlalganj	41	163	19.4	127	44.4	72	28.7	45	72.7	60
		116	Deoria	43.8	106	13.6	410	34.5	244	13.9	465	67.6	129
		117	Sant Kabir Nagar	48.7	42	14.5	364	37	198	13.2	486	68	120
		118	Faizabad	50.4	22	15.1	320	44.8	65	17.6	328	62.9	210
		119	Etawah	47.3	62	19.9	108	37.8	187	17.6	329	59.9	248
		120	Sultanpur	43.8	105	14.9	334	36.5	206	17	361	67.4	131

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		121	Salempur	40.2	183	14	391	32.7	277	15.2	427	64.4	178
		122	Ghosi	40.3	177	13.2	448	34.2	253	18.7	297	61	228
		123	Chandauli	44.2	98	16.4	255	39.5	164	19.4	266	64.3	181
		124	Allahabad	43.7	109	14.8	346	44.3	76	18.7	294	62.1	215
		125	Mirzapur	49.5	33	13.4	428	46.4	48	18.9	282	63.4	200
		126	Robertsganj	44.8	90	14.8	341	43.2	87	20.8	224	60.3	241
		127	Fatehpur	51.6	19	21.2	75	39.8	156	14.5	446	45.5	457
		128	Jaunpur	47.1	69	14.8	348	51.8	7	26.1	93	60.2	243
		129	Pratapgarh	40.8	168	11.3	517	42	111	22.8	159	64.4	179
		130	Hamirpur	42.3	138	16.8	227	42.2	107	24.9	114	65.4	160
		131	Kaushambi	47.2	66	13.2	444	48.7	20	26.5	84	64.6	176
		132	Ballia	41.5	153	14.1	388	31.9	290	15.5	415	63	208
		133	Jhansi	38	213	18.3	161	42.3	103	29.6	34	75.7	24
		134	Ghazipur	41.4	155	12.8	462	32	285	17.2	349	69.5	96
		135	Machhlishahr	47.6	58	15.7	281	49.2	16	24.7	121	57.1	287
		136	Phulpur	43.3	121	13.9	397	41.1	128	18.7	296	60.5	239
		137	Sant Ravi Das Nagar (Bhadohi)	49.8	28	17	219	47.6	33	20.7	226	64.2	183
		138	Ambedkar Nagar	43.3	120	15.7	283	40.1	150	20.8	225	61.6	221
		139	Banda	48	51	15.6	289	47.1	41	25.6	102	68.4	113
		140	Kanpur	43.5	117	15.4	303	39.6	162	20.7	228	72.7	59
		141	Unnao	46.1	80	21	82	34.4	248	12.6	496	45.5	455
		142	Kannauj	47	70	18	170	35.9	220	15.4	423	54.3	335
		143	Lucknow	40.3	176	17.8	177	43.3	86	29.9	33	72.8	58
		144	Varanasi	43.1	124	17.4	203	45.9	52	24.2	134	59.5	250
		145	Gorakhpur	42.7	131	14.2	381	34.8	241	17.9	317	58.8	255
		146	Basti	48.6	45	15.9	277	33.8	260	13.5	474	71.2	77
		147	Shrawasti	61.3	2	20	107	39.8	155	10.2	534	71.2	76
		148	Agra	44.2	99	23	39	33.6	263	12.7	495	49.1	414
		149	Gautam Buddha Nagar	33	295	24	22	27.7	373	13.8	467	66.4	143
		150	Bijnor	38.6	203	23.9	24	36.4	207	18.8	290	75.3	27
		151	Moradabad	41.9	149	24.9	14	39.2	168	15.5	414	73	53
10	Bihar	152	Muzaffarpur	46.7	73	17.5	198	41.8	117	16.9	364	59.4	253
		153	Valmiki Nagar	43.7	108	10.4	526	40	154	20.6	235	63.9	193
		154	Araria	48	52	12.5	480	45.3	58	21.7	190	60.7	235
		155	Gopalganj	37.6	223	15.2	311	32.2	283	16.3	387	64.9	169
		156	Siwan	38.1	210	11.1	518	31.4	298	14.5	447	64.2	184
		157	Vaishali	47.6	57	16.3	257	40.8	133	16.9	363	60.7	234
		158	Jhanjharpur	52.5	15	12	505	45.8	54	18.3	304	64.4	180
		159	Supaul	47.6	59	12.9	461	44.5	68	22.1	180	70.8	81
		160	Pashchim Champaran	44.3	97	11.7	511	39.1	169	18.2	309	63.1	207
		161	Madhubani	49.3	36	13.1	452	41.3	127	16.9	366	64.1	187
		162	Kishanganj	48.7	43	10.5	523	46.8	45	22.2	177	66.3	146
		163	Darbhanga	48.1	49	17.8	182	41	131	15.5	416	68.9	103
		164	Purnia	51.8	18	14.4	368	45.5	56	19.9	247	65.7	154
		165	Maharajganj	42.1	141	13.5	421	37.6	189	16.3	384	62.4	213
		166	Madhepura	48.3	47	11.3	516	45.7	55	22.7	165	63.5	198
		167	Begusarai	44.7	92	15.6	294	38.4	179	18	316	63.5	196
		168	Arrah	43.7	112	8.3	538	48.3	23	26.5	85	71.4	71
		169	Sasaram	52.2	16	12.3	491	47.7	31	21.1	214	61.3	226
		170	Nawada	48.4	46	14.7	351	47.3	38	22.4	174	59.9	249
		171	Banka	49.3	34	9.7	531	47.4	37	24.7	120	71.4	70
		172	Nalanda	52.7	12	17.2	206	47.1	42	22.2	178	58.8	256
		173	Katihar	48.7	41	10.8	521	44.6	66	19.9	252	63.3	201
		174	Samastipur	50.2	26	14	393	41.6	122	17.4	339	68.6	109
		175	Khagaria	47.4	61	13.7	404	42.3	104	19.2	273	66	150
		176	Pataliputra	45.2	88	13.3	438	44.6	67	27.1	72	54.3	336
		177	Buxar	46	82	10.9	520	42.2	106	18.9	287	62.1	216
		178	Patna Sahib	41.2	158	14.1	385	42.4	102	27	74	50.8	391
		179	Bhagalpur	47.3	65	9.4	534	41.9	115	23	154	70.4	86
		180	Munger	46.5	75	13.8	401	44.4	74	20.6	230	63.7	194
		181	Purba Champaran	48	50	13.3	435	40.3	144	17.1	359	64.9	170
		182	Sheohar	52.6	13	15.7	286	43.1	89	14.7	443	65.3	162
		183	Sitamarhi	57.9	5	14.9	335	48.5	22	15.5	411	69.4	98
		184	Ujiapur	49	38	12.2	500	41.7	121	17.1	354	65.9	151

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		185	Hajipur	52.6	14	10.7	522	40.1	153	14.1	462	67.8	125
		186	Karakat	47.1	67	14	392	46	50	22.2	179	57.8	271
		187	Saran (Chhapra)	46.5	76	13.6	414	40.2	145	17.3	343	63.2	204
		188	Jamui	46.7	72	13.4	424	47.3	39	26.1	91	63.2	205
		189	Aurangabad	50.9	20	16.7	239	49.7	14	24.7	117	52.2	369
		190	Gaya	49.3	35	15	327	49.2	17	22.3	176	60.9	231
		191	Jahanabad	50.4	24	12.7	473	49.5	15	24.2	135	65.2	164
11	Sikkim	192	Sikkim	28.7	386	6.6	541	14.3	528	14.3	454	42.1	477
12	Arunachal Pradesh	193	Arunachal West	26.6	437	9.5	532	18.1	507	17.4	338	51.5	379
		194	Arunachal East	29.6	363	9.9	529	16	521	14.2	458	44.8	459
13	Nagaland	195	Nagaland	27.1	426	6.5	542	15.6	523	10.7	530	20	541
14	Manipur	196	Inner Manipur	24.1	494	8.1	539	12.5	541	5.9	543	23.5	534
		197	Outer Manipur	32.4	308	7.7	540	13.6	533	6.8	542	21	539
15	Mizoram	198	Mizoram	28.2	401	4.1	543	12.7	539	7.3	541	20.9	540
16	Tripura	199	Tripura East	26.8	431	15	326	25.8	407	17.5	332	46.2	447
		200	Tripura West	19.9	525	15.5	297	20.7	483	15.5	412	52	372
17	Meghalaya	201	Tura	27.3	417	12.2	496	24.5	429	21.5	198	65.4	159
		202	Shillong	47.9	53	9.9	528	29.8	330	12.6	498	30.6	519
18	Assam	203	Lakhimpur	32.5	305	12.5	479	22.3	460	10.1	537	37.1	501
		204	Dibrugarh	32.8	300	17.1	216	30.2	325	17.2	352	47.4	433
		205	Jorhat	31.4	330	12.4	487	21.3	473	11	525	35.3	508
		206	Tezpur	29.6	365	11.9	508	25.2	418	17.1	355	29.2	523
		207	Kaliabor	33.3	291	12.6	476	23.4	444	13	488	34	511
		208	Mangaldoi	36	239	14	395	29.6	336	16.6	377	41.1	484
		209	Nagaon	35	259	12.7	472	25.7	409	11	523	36.3	504
		210	Autonomous District	31.2	334	9.7	530	21.4	472	12.4	502	26.3	528
		211	Dhubri	42.6	132	15.2	310	36.2	210	19.3	267	39.3	489
		212	Karimganj	38.2	208	11.7	513	32.5	281	17.5	336	26.6	527
		213	Silchar	34.5	271	13.9	398	34.3	251	27.7	63	30	522
		214	Kokrajhar	33.5	288	12.8	464	24	433	12.1	508	36.3	505
		215	Guwahati	29.4	370	15.7	287	24.5	428	14.1	460	35.8	506
		216	Barpeta	37.2	228	14.8	342	28.6	355	16.6	374	32.9	514
19	West Bengal	217	Darjiling	31	340	13.2	446	27.1	378	12.8	492	47.9	427
		218	Arambag	32.1	312	20.3	97	31.4	299	19.1	277	57.9	268
		219	Barasat	24.1	492	15.5	299	21.1	477	14.9	438	54.1	342
		220	Medinipur	26.7	434	15.6	295	37.1	196	25.5	103	50.4	395
		221	Tamluk	27.9	407	13.7	405	32	286	22.1	182	42.7	473
		222	Murshidabad	35.1	258	14	396	30.7	319	14.5	449	44.7	460
		223	Krishnanagar	24.3	485	13.4	432	21.1	478	12.5	499	37	502
		224	Birbhum	38.8	201	12.7	468	41.3	126	28.1	58	58	264
		225	Bolpur	36.5	233	14.9	337	36.8	202	22.8	160	53.4	355
		226	Barddhaman - Durgapur	31.9	316	22.1	54	31.7	294	22.7	163	46.2	446
		227	Puruliya	40.9	164	18.3	158	54.1	2	32.5	10	66.9	137
		228	Barddhaman Purba	29.8	356	19.8	114	30.7	320	22.4	172	46.3	445
		229	Bankura	33.7	285	15.8	278	38.9	172	24.7	119	48.3	423
		230	Asansol	30.6	346	18.3	160	32.9	272	25.2	109	50	405
		231	Ranaghat	24.2	488	11.3	515	19.5	501	11.6	517	35.5	507
		232	Bishnupur	32.5	304	18.1	168	39.7	161	26.8	80	51	387
		233	Jangipur	41.7	151	13.3	436	35.5	226	17.9	319	46.7	439
		234	Balurghat	34.2	275	13.2	439	27.9	367	16.5	379	68.9	105
		235	Maldah Uttar	37.9	218	19.2	135	36.9	200	22	183	57.9	269
		236	Kolkata Uttar	27.1	424	13.1	449	23	451	17.9	318	60	246
		237	Jhargram	32.9	297	16.4	252	42.9	90	27.1	73	57.4	279
		238	Kolkata Dakshin	28.2	400	12.4	486	23.5	443	18.7	295	55.9	309
		239	Uluberiya	32.1	311	15.2	313	28.6	356	16	398	59.4	251

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		240	Mathurapur	27.6	410	12.3	492	28.9	349	18.6	299	66.7	139
		241	Jaynagar	32	314	12.7	471	30.8	317	20.9	218	68.2	116
		242	Diamond Harbour	27.2	421	13.1	450	24.7	427	18.5	300	59.4	252
		243	Kanthi	29.9	355	13.4	429	32.6	279	22.7	164	44.7	461
		244	Basirhat	25.6	455	13.5	422	20.7	484	14.9	436	50	404
		245	Bangaon	24.7	480	12.7	469	20.3	489	12.8	493	49.1	415
		246	Koch Bihar	30.9	342	13.6	412	28.1	366	18.8	289	57.5	277
		247	Alipurduars	32.2	310	16.3	256	27.7	370	18.3	306	68.6	107
		248	Jalpaiguri	31.3	331	16.6	243	26.3	398	17.7	322	65.8	152
		249	Barakpur	25.2	468	12.2	495	19.6	499	13.5	476	54.7	330
		250	Haora	31.5	326	13.7	403	25.1	422	14.4	453	64.2	182
		251	Jadavpur	25.5	459	12.5	477	26.2	400	17.8	321	60.5	237
		252	Hugli	27.7	409	19.3	133	26.9	385	17.5	330	50.9	388
		253	Shrirampur	30.7	344	16.8	226	28.3	362	16.3	386	62	217
		254	Baharampur	38.4	206	14.2	378	31.3	305	14.8	441	43.8	465
		255	Maldah Dakshin	36.7	230	17.4	201	37.7	188	23.1	152	50.9	389
		256	Raiganj	38	215	14.4	369	33.5	264	14.8	442	64.2	186
		257	Ghatal	29.1	376	15.6	290	36.7	205	25.1	110	53.8	347
		258	Dum Dum	23.8	496	13.6	415	18.1	508	12.7	494	53.6	349
20	Jharkhand	259	Jamshedpur	41	162	11.9	509	50.7	10	39.6	1	68	121
		260	Singhbhum	53.4	10	12.4	489	60.9	1	32	11	82.7	2
		261	Rajmahal	49.7	30	11	519	47.9	28	25.4	106	73.8	40
		262	Dumka	43.5	118	14.3	373	48.7	19	31.2	21	73.7	41
		263	Godda	47.7	55	14.5	367	46.7	46	26	94	74.5	35
		264	Palamu	45.3	87	13.6	409	48	25	27.2	71	63.7	195
		265	Hazaribagh	40.2	181	12.2	498	46.3	49	28.6	47	70.8	80
		266	Dhanbad	38.1	212	13.9	399	44.4	69	30.9	25	72.2	67
		267	Kodarma	45.6	85	12	504	42.8	91	21.5	197	73.2	48
		268	Lohardaga	43.7	107	15.1	321	47.4	35	28.4	52	70.4	87
		269	Khunti	42.2	139	13.2	445	51.8	6	36.7	3	74.1	38
		270	Chatra	46.8	71	13.2	443	46.8	44	27.5	66	57.8	270
		271	Ranchi	39.7	191	14.2	380	44	77	26	95	67.9	123
		272	Giridih	41.3	156	13.2	442	47.4	36	32.5	9	74.8	31
21	Odisha	273	Bhadrak	34	278	20.3	98	28.8	350	14.8	439	24.1	532
		274	Jajapur	30	353	19.4	130	29.8	328	16.1	394	30.5	520
		275	Sambalpur	34.1	276	16.7	232	38.5	176	22.8	161	47.3	434
		276	Baleshwar	33.6	287	20.9	85	34.3	252	17.1	358	29	524
		277	Kendujhar	42.3	137	21.5	68	42.7	93	18.8	291	32.1	518
		278	Mayurbhanj	40.4	174	25.6	11	40.4	141	16.2	389	34.8	509
		279	Sundargarh	35.4	251	16.2	264	40.6	138	28.3	54	72.4	62
		280	Bargarh	34.2	274	18.2	163	35.7	223	23.3	150	66.3	147
		281	Dhenkanal	27.3	416	16.9	223	31	314	19.5	264	39.3	490
		282	Bolangir	42.1	144	19.1	140	41.8	116	22.7	166	69.9	90
		283	Kalahandi	35.9	243	16.8	225	39	171	23.9	139	65	167
		284	Kandhamal	36.2	238	18.1	166	38.3	180	20.4	239	42.4	474
		285	Kendrapara	25.1	471	17.1	214	23.5	442	12.6	497	28.4	525
		286	Cuttack	20.2	523	14.9	332	20.9	480	12.1	509	22.7	538
		287	Bhubaneswar	22.7	507	14.5	365	19.2	503	13.3	481	20	542
		288	Aska	29.5	366	17.8	181	23.4	445	17	360	38	495
		289	Jagatsinghpur	20.1	524	17.6	192	18.5	506	12.5	500	25.9	530
		290	Nabarangapur	42.5	134	24.2	20	47.7	32	31.1	22	70.8	79
		291	Koraput	40.4	173	20.4	93	41.6	123	24.4	127	57.9	265
		292	Puri	23.1	503	18.3	157	22	466	14.5	451	25.9	531
		293	Berhampur	31.1	339	14.7	349	29.2	344	17.4	340	51.2	385
22	Chhattisgarh	294	Janjgir-Champa	35.3	254	10.4	525	35.2	234	21.1	208	37.3	499
		295	Raipur	37.4	225	8.7	536	35.1	235	16.7	373	46.9	438
		296	Surguja	31.6	324	15.5	302	34.6	242	21.8	188	37.7	498
		297	Bilaspur	34.4	272	8.8	535	33.9	259	26	96	32.2	517
		298	Rajnandgaon	43.7	110	8.5	537	37.4	193	17.4	341	33.6	512
		299	Durg	33.2	292	11.7	512	34.3	250	19.6	260	44.7	462
		300	Mahasamund	39	199	12.4	488	38.8	173	21.8	189	45.5	456
		301	Raigarh	36.3	235	14.1	386	35.6	224	18.2	310	34.6	510
		302	Kanker	35.5	249	13.2	447	44.4	70	28	59	56.4	295
		303	Bastar	44.3	96	10.2	527	47.9	26	28.2	55	56.8	291

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		304	Korba	29.4	368	10.5	524	33	271	25.6	101	33.4	513
23	Madhya Pradesh	305	Bhind	46.6	74	23.7	27	47.8	29	27.3	69	72.9	54
		306	Balaghat	33.6	286	16.1	270	42.5	98	31.2	20	69.4	97
		307	Hoshangabad	36.7	232	17.7	189	38	183	26.8	79	68.2	118
		308	Dhar	43.1	125	22.6	46	47.1	43	29.2	37	77.2	11
		309	Indore	37.6	222	19.9	109	31.1	310	19.2	272	73.5	42
		310	Gwalior	43	126	26	9	47.8	30	27.4	67	68.1	119
		311	Sidhi	40.2	180	15.5	296	40.4	140	27.9	60	65.6	155
		312	Rajgarh	41.3	157	19.7	116	47.9	27	30.9	24	65.6	156
		313	Sagar	40.5	172	19.1	141	36	215	19.1	275	69.6	95
		314	Damoh	42	146	16.6	246	35.8	221	19.3	271	74.4	36
		315	Shahdol	37.6	221	13.6	417	41.9	114	26.8	81	68.6	108
		316	Dewas	42.6	133	20	102	43.5	84	25.7	99	72.1	68
		317	Ujjain	36.7	231	26.8	7	33.2	268	19	281	71.3	75
		318	Bhopal	43.1	123	19.6	121	39.7	158	21.8	187	74.9	30
		319	Vidisha	40.4	175	19.4	126	42.1	108	24.5	126	67.1	135
		320	Ratlam	46.2	78	30.5	2	47.2	40	27	76	74.6	34
		321	Rewa	40.6	170	21	83	36.4	208	18	315	55	328
		322	Satna	41.1	161	17.7	183	39.3	167	26.5	87	72.3	63
		323	Mandsaur	35.8	245	35.5	1	36.1	211	22.1	181	70.6	84
		324	Guna	43.2	122	21.2	76	47.5	34	29.2	38	64.1	189
		325	Chhindwara	34	280	12.7	467	40.1	152	28.9	41	66.3	148
		326	Betul	37.2	227	19.6	117	42.4	100	27.4	68	66.4	144
		327	Khargone	49.7	29	17.4	202	50.3	11	24.4	128	80.1	4
		328	Jabalpur	35.9	242	15.8	279	43.8	79	30.3	29	60.5	238
		329	Mandla	39.1	197	16.3	263	45.3	59	29.1	40	67.4	130
		330	Morena	47.5	60	25.5	12	52.5	4	28.5	49	71.4	69
		331	Tikamgarh	47.1	68	22.8	42	43.3	85	19.6	259	67.6	128
		332	Khajuraho	41.9	148	17.7	188	42.4	101	23.6	145	67.7	127
		333	Khandwa	45.6	86	19.1	143	43.8	81	19.9	251	78.7	7
24	Gujarat	334	Bardoli	35.5	248	16.5	250	41.7	120	32.9	7	50.8	390
		335	Junagadh	31.1	337	15.2	316	28.7	354	26.5	86	76.5	17
		336	Surat	27.8	408	17.6	191	33.7	261	25.7	100	41.4	482
		337	Kheda	42.8	129	21.8	60	43.8	82	25.1	111	58.5	259
		338	Ahmadabad (West)	28.8	384	16	272	31.1	309	26.1	92	74.7	33
		339	Jamnagar	29.7	358	14.7	353	30.3	323	30.3	27	76.5	16
		340	Sabar Kantha	48.7	40	17	217	46	51	24	138	72.2	65
		341	Banas Kantha	39.9	188	17.6	193	42.7	94	20.6	233	56.9	289
		342	Patan	37.9	216	16.3	258	39.7	159	24.4	130	66.1	149
		343	Panch Mahals	41.4	154	22.5	47	43.9	78	31.5	14	52.5	365
		344	Dohad	42	147	21.7	62	48.7	21	25.4	107	57	288
		345	Vadodara	40.2	182	20.1	100	38.6	174	18.3	307	55	325
		346	Anand	44.3	95	17.9	175	38.5	177	21.3	201	58.2	260
		347	Amreli	38.1	211	16.4	254	33.3	266	23.5	147	73	52
		348	Ahmadabad (East)	35	260	16.7	237	40.9	132	27.6	65	69.9	89
		349	Rajkot	31.4	329	13.3	434	31.2	306	23	155	61.5	223
		350	Surendranagar	43.6	114	16.2	268	44.3	75	25.5	104	75.6	26
		351	Navsari	35.3	253	17	218	34.1	256	22.7	162	52.9	358
		352	Bharuch	42.5	135	20.6	90	45.8	53	28.8	44	55.8	310
		353	Chhota Udaipur	44.1	102	22.1	52	45.1	60	27	75	56.2	298
		354	Porbandar	27.1	425	13.4	426	28.8	351	24.9	115	70.2	88
		355	Valsad	42.1	145	19.9	112	48.1	24	34.8	5	61	229
		356	Gandhinagar	31.2	335	17.1	211	38.1	182	28.2	56	73.3	47
		357	Mahesana	40.1	184	17.1	209	42.4	99	25	113	76.4	19
		358	Bhavnagar	46.1	79	17.4	199	43.1	88	24.6	123	68.9	106
		359	Kachchh	37.9	217	13.7	406	37.5	190	31.4	17	79.3	5
25	Daman & Diu	360	Daman & Diu	27.4	414	16.2	267	26.9	384	20.2	242	73.1	51
26	Dadra & Nagar Haveli	361	Dadra & Nagar Haveli	40.6	169	20.3	96	37	199	25.4	105	83.6	1
27	Maharashtra	362	Buldana	41.6	152	20.6	91	40.2	147	21.1	213	43.7	467
		363	Madha	25.9	450	16.8	224	29.8	329	22.4	175	51.4	381
		364	Satara	24	495	16.9	221	28.4	359	22.6	167	56.5	293
		365	Jalgaon	32.6	302	16.9	222	34.8	239	31.4	18	57.6	276
		366	Akola	35.9	241	15	330	37.5	191	24.4	129	57.1	286

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Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		367	Sangli	26.4	440	17.7	186	26.6	391	16.6	376	48.7	417
		368	Solapur	28.6	391	16.6	247	32.6	280	23	156	51.3	384
		369	Amravati	37	229	14.6	360	31.6	295	21.7	193	53.4	354
		370	Ramtek	31.5	325	23.4	35	33.3	265	23.9	140	49.9	408
		371	Nandurbar	42.7	130	18	169	50.7	9	33.6	6	61	230
		372	Bhandara - Gondiya	34.8	268	19.3	134	34.4	249	22.6	169	49.2	412
		373	Wardha	32.9	298	14.4	371	37.2	194	24.2	133	48.9	416
		374	Shirur	25.1	472	16.7	233	26.1	402	19.5	263	55.2	322
		375	Beed	36	240	16.4	253	36.8	203	28.4	51	58.6	258
		376	Maval	32	315	16.7	235	36	217	24.8	116	55.2	320
		377	Parbhani	43	128	17.8	179	40.2	149	19.7	258	50.5	393
		378	Raigarh	31.1	338	16.8	228	35.4	231	23.4	149	54.1	344
		379	Osmanabad	38.7	202	14.9	338	40.1	151	20.6	229	42.1	476
		380	Hatkanangle	26.1	445	18.2	164	28.2	364	20.1	246	49.2	413
		381	Dhule	36.3	236	18.3	159	42	112	29.3	36	60.8	232
		382	Garhchiroli - Chimur	33.5	289	19.8	115	41.7	119	39	2	59.1	254
		383	Raver	32.6	303	21	80	35.3	232	28.6	46	54.9	329
		384	Biwandi	41.8	150	20.8	89	44.4	73	26.8	82	55.5	314
		385	Dindori	39.1	198	16.9	220	44.4	71	30.8	26	52.9	359
		386	Jalna	39.2	196	21.6	67	37.8	185	21.3	202	43.4	469
		387	Aurangabad	35.8	244	23.3	36	36	213	21.1	210	38.9	491
		388	Chandrapur	33.7	284	18.9	145	40.2	148	27.7	64	61.9	219
		389	Nashik	39.9	189	16.8	230	39.5	163	28.4	53	53.5	351
		390	Shirdi	35.4	252	23.2	37	32	288	21.6	195	46.3	444
		391	Hingoli	38	214	15	323	36	214	23	153	52.6	363
		392	Ahmadnagar	34	277	21.6	65	31.7	293	21.9	186	45.6	453
		393	Palghar	39.5	193	21	84	41.3	125	30.3	28	57.9	266
		394	Latur	33.9	281	13.6	413	33.7	262	20.6	232	53	357
		395	Baramati	24.3	486	16.3	261	26.6	390	21	215	52.9	360
		396	Ratnagiri - Sindhudurg	29.7	362	21.2	77	30.7	321	21.7	194	45.2	458
		397	Kolhapur	27.3	418	22.5	49	29.7	332	20.7	227	47	437
		398	Thane	35.3	255	19.5	124	38.5	178	26.7	83	55.1	324
		399	Mumbai North	24.2	487	16.2	265	30.8	318	23.4	148	66.9	138
		400	Mumbai North-West	22.9	506	13.6	411	27.7	371	26.9	77	64.7	173
		401	Mumbai North-East	23.7	497	15	328	25.7	411	20.8	223	60.4	240
		402	Mumbai North-Central	26.5	438	15	331	30	327	21.2	206	64.9	172
		403	Mumbai South	28.9	381	20.4	92	27.7	372	24.7	118	62.4	214
		404	Mumbai South-Central	29.7	361	17.2	207	30	326	23.3	151	64.2	185
		405	Kalyan	36.4	234	20.2	99	35.7	222	23.6	146	55.9	308
		406	Pune	24.1	491	19.5	122	27.8	369	23.7	143	55.3	318
		407	Nanded	39.7	190	13.3	437	34.6	243	19.9	248	53.7	348
		408	Yavatmal - Washim	41.2	159	17.1	215	43.8	80	28.9	42	62.7	212
		409	Nagpur	28.3	398	20.8	88	28.9	348	22	184	47.8	428
28	Andhra Pradesh	410	Araku	31.9	318	14.4	370	32.2	282	17.3	346	71.1	78
		411	Anakapalli	30.9	341	17.5	197	32	287	15.6	408	65.1	166
		412	Srikakulam	28.6	392	12.9	460	29.5	337	15	433	68.6	111
		413	Eluru	27.1	427	20	106	29	346	15.6	409	52.6	362
		414	Rajahmundry	27.6	411	21.4	71	26.9	383	15.3	424	61.1	227
		415	Narsapuram	28.7	390	25.7	10	30.9	315	15.4	420	55	327
		416	Amlapuram	26.7	433	17.5	196	27.3	375	13.2	484	64.7	174
		417	Narasaraopet	25.4	465	16.8	229	29.5	338	15.8	401	62.7	211
		418	Machilipatnam	23.7	498	14.3	372	26.8	387	17.5	335	57.2	284
		419	Guntur	22.2	510	15.2	314	27	380	17.3	347	60.1	245
		420	Ongole	28	405	13.1	451	31	312	15.5	413	58.1	261
		421	Bapatla	25.2	470	14.5	361	29.3	339	15.4	418	57.3	280
		422	Kurnool	42.1	143	13.5	419	35.2	233	17.5	337	53.6	350
		423	Vizianagaram	33.8	282	12.5	485	32.1	284	15.5	417	75.7	25
		424	Kakinada	30	352	21	81	27.9	368	14.1	461	66.5	142
		425	Rajampet	31.3	333	14.9	339	32.9	274	16.1	396	52.3	367
		426	Nellore	27.6	412	17.5	195	28.4	360	16.4	382	52.1	370
		427	Anantapur	39	200	16	274	39.1	170	15.6	410	50.2	401
		428	Kadapa	33	296	13.3	433	32.9	273	16.7	369	55.4	317
		429	Nandyal	40	186	12.6	474	34.4	247	16.2	390	56.2	299

(*continued on next page*)

Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		430	Chittoor	30.7	343	13.2	440	31.3	303	16.7	372	49.9	406
		431	Tirupati	29.7	360	15.6	293	28.7	353	15.7	406	50.1	403
		432	Hindupur	36.2	237	15.7	285	36	218	15.1	430	52.5	364
		433	Vijayawada	23.4	500	13.2	441	24.7	426	16.1	393	53.5	352
		434	Visakhapatna-m	29.2	373	15.3	306	31.2	307	16.7	370	63.1	206
29	Karnataka	435	Gulbarga	49.7	31	14.9	336	51.7	8	31.5	16	73.4	43
		436	Bijapur	42.2	140	14.5	363	35.6	225	26.9	78	67.3	133
		437	Chikkodi	34.8	266	19.1	142	36.1	212	29.1	39	67	136
		438	Raichur	44.2	100	12.2	493	45.1	61	32.8	8	73.3	46
		439	Koppal	50.8	21	15	329	45	63	25.3	108	68.6	110
		440	Haveri	37.7	219	14.6	354	34.8	240	27.7	62	65.8	153
		441	Davanagere	45	89	15.5	301	40.7	134	21	217	65.1	165
		442	Chikballapur	33.1	294	13.7	408	29.2	343	21.1	212	56	305
		443	Udupi Chikmagalur	24.4	483	19.5	123	25.2	420	20.3	240	57.1	285
		444	Tumkur	28.2	399	13.6	416	25.5	413	24.5	125	55.9	306
		445	Kolar	32.7	301	12.9	458	28.6	357	17.7	323	57.7	275
		446	Bangalore Rural	24.3	484	14.2	379	23.7	439	20.4	238	55.4	316
		447	Dharwad	38.5	204	13	455	41.6	124	31.2	19	54.2	340
		448	Bangalore North	29.6	364	16.6	244	25.7	410	27.9	61	56.3	297
		449	Dakshina Kannada	25.1	473	15.3	304	23.3	446	17.8	320	55.5	313
		450	Mysore	29.2	374	18.1	167	25.8	408	16.6	375	50.2	400
		451	Chamrajnagar	30.6	345	14.8	345	31	313	19.3	268	55.2	321
		452	Mandya	24.2	489	16.8	231	22.6	456	21.3	203	56.7	292
		453	Bellary	47.3	64	18	171	48.9	18	24.3	131	72.9	55
		454	Chitradurga	30.2	350	12.5	483	30.8	316	29.4	35	62.9	209
		455	Bidar	44.1	103	16.3	260	40.6	136	23.9	141	70.8	82
		456	Uttara Kannada	37.3	226	15.9	276	31.3	304	19.9	253	51.8	376
		457	Shimoga	31.8	322	17.8	180	28.4	361	15.8	400	53.2	356
		458	Hassan	26.7	432	15.6	292	25.9	404	19	280	56.9	290
		459	Belgaum	34.3	273	16.3	259	38.2	181	30.1	30	67.8	126
		460	Bangalore South	28	404	16.1	269	26.1	401	25.8	98	56.3	296
		461	Bangalore Central	28.4	396	16.6	242	27.2	376	24.6	124	57.9	267
		462	Bagalkot	44.5	94	12.7	470	41.8	118	26.3	90	64.9	168
30	Goa	463	South Goa	17.8	535	23.4	34	21	479	22.4	170	46.1	448
		464	North Goa	22.5	508	21.9	56	23.3	447	15.4	419	48.3	422
31	Lakshadweep	465	Lakshadweep	26.3	441	16.6	245	21.5	470	12.8	491	52.1	371
32	Kerala	466	Malappuram	24.5	482	14.3	375	16.9	515	18.7	298	50.4	397
		467	Pathanamthitt-a	16.7	538	17.3	205	13	537	14.5	450	23.3	535
		468	Mavelikkara	15.4	541	14.6	357	15.5	524	17.2	350	24	533
		469	Thiruvananth-apuram	18.5	534	16.6	248	19.7	495	14.1	459	22.8	537
		470	Palakkad	19.8	526	19	144	17.7	511	11.1	521	41.2	483
		471	Thrissur	18.9	531	13.7	407	13.1	535	13.6	471	37	503
		472	Alathur	19.7	527	16	273	15.8	522	11.8	513	38	494
		473	Kasaragod	18.7	532	13.4	430	14.3	527	10.8	528	37.8	497
		474	Attingal	19	530	16.7	236	19.7	496	13.4	477	23	536
		475	Vadakara	20.6	521	12.7	466	14.4	526	11.5	519	40.2	486
		476	Kozhikode	17.5	536	12.5	478	17.5	513	13.4	478	37.3	500
		477	Kannur	22.9	505	12.9	457	12.6	540	11.7	516	42.3	475
		478	Chalakudy	17.3	537	15.2	312	13.7	532	13.3	482	32.9	515
		479	Idukki	16.1	539	13.1	453	14	529	19.8	254	30.3	521
		480	Alappuzha	15.4	542	14.9	333	16.3	519	15.7	402	26.1	529
		481	Kottayam	18.6	533	12.2	494	12.3	542	14.7	444	32.5	516
		482	Kollam	15	543	14.1	387	13	536	16.3	385	17.8	543
		483	Ernakulam	15.8	540	13.5	418	13.8	531	14.5	448	28	526
		484	Wayanad	23.4	501	16.7	234	20.9	481	18.8	292	42.9	471

(*continued on next page*)

Table 1 (*continued*)

Census State ID	State	PC ID	PC	Stunting		Low birth weight		Underweight		Wasting		Anaemia	
				%	Rank	%	Rank	%	Rank	%	Rank	%	Rank
		485	Ponnani	21.1	520	15.1	319	16.4	517	20.5	237	47.6	430
33	Tamil Nadu	486	Erode	28.1	403	13.4	427	20.1	491	16.7	371	54.2	338
		487	Tenkasi	28.5	394	15.2	315	23.3	448	14.3	455	55.7	311
		488	Tirunelveli	28.6	393	14	390	22.5	458	13.7	469	61.4	224
		489	Kanniyakumari	19.3	528	15.7	284	15	525	10.8	529	38.3	493
		490	Coimbatore	25.9	448	14.8	347	23.9	436	20.8	220	45.9	451
		491	Mayiladuthur-ai	24.2	490	15.3	308	22.6	457	18	313	47.1	436
		492	Perambalur	26.1	444	16.5	251	23.9	435	18.9	284	57.7	273
		493	Dindigul	28.7	389	13.5	423	26.8	386	22.9	157	41.8	479
		494	Arakkonam	28.7	387	13.4	425	29.7	334	24	137	52.4	366
		495	Chennai South	29.3	371	12.8	465	21.2	476	18.2	308	51.3	383
		496	Krishnagiri	23.2	502	15	322	21.5	469	18.9	285	54.6	332
		497	Arani	25.2	469	15.3	307	29	347	24.7	122	57.7	274
		498	Tiruvannamal-ai	25.4	464	14.6	356	31.4	297	30	31	55.1	323
		499	Sriperumbudur	25.7	454	18.8	148	19.7	494	17.5	334	46.3	443
		500	Vellore	28.5	395	12.5	482	30.5	322	26.3	89	47.8	429
		501	Kancheepuram	25.3	466	19.6	120	17.7	512	15	432	47.4	432
		502	Kallakurichi	27.4	415	14.6	359	24.9	424	19.5	261	51.8	377
		503	Nilgiris	29.4	369	17.7	185	25.9	405	24.3	132	39.8	488
		504	Chidambaram	29.9	354	18.6	154	25.5	415	18.2	311	52	373
		505	Chennai North	31.3	332	12.3	490	23.2	450	20.2	243	47.5	431
		506	Chennai Central	29.7	359	11.5	514	22.1	464	20.6	236	53.9	346
		507	Thoothukkudi	21.5	519	16.3	262	19.1	504	13.2	485	56.5	294
		508	Nagappattina-m	25.5	462	17.4	204	25.9	406	19.8	255	48.2	424
		509	Tiruvallur	31.2	336	14.2	382	29.2	341	21.6	196	51.2	386
		510	Viluppuram	30.1	351	14.3	376	27	381	16	397	57.3	281
		511	Cuddalore	29	378	17.2	208	25.6	412	17	362	54.4	334
		512	Shivaganga	22.1	513	12.9	459	22.2	462	18.5	301	49.4	411
		513	Theni	27	428	15.5	300	23.7	438	14.8	440	54.1	341
		514	Ramanathapu-ram	23.7	499	15.6	288	22.2	463	16.7	368	48.4	420
		515	Namakkal	25.9	451	15.9	275	19.8	493	15.6	407	49.5	410
		516	Thanjavur	25.5	463	14.2	377	24.3	431	19.9	249	55	326
		517	Tiruchirappalli	27.5	413	15.6	291	26.7	389	19.1	274	54.2	339
		518	Pollachi	25	474	14.2	384	22.7	454	21.2	205	46	449
		519	Karur	26	447	13.4	431	26.3	399	20.6	234	50.3	399
		520	Dharmapuri	24.7	478	12	502	26	403	28.6	48	57.8	272
		521	Madurai	22.2	512	17.1	210	19.5	502	14	463	50.6	392
		522	Virudunagar	27	429	19.2	137	23.8	437	15.1	431	51.3	382
		523	Tiruppur	25.6	456	12.8	463	20.3	488	18	314	49.7	409
		524	Salem	25.5	460	12	506	21.4	471	21.1	207	55.4	315
34	Puducherry	525	Puducherry	25.7	453	15.1	318	20.6	487	16.5	381	43.8	466
35	Andaman & Nicobar Island	526	Andaman & Nicobar Islands	25.6	458	16.2	266	20.2	490	15.4	421	50.1	402
36	Telangana	527	Zahirabad	33.8	283	18.4	156	35.4	228	20.6	231	69.1	102
		528	Khammam	26.6	436	11.9	507	22	465	13.7	470	70.7	83
		529	Medak	31.6	323	20.9	86	35.4	229	20.3	241	68.2	117
		530	Bhongir	27.1	423	14.8	344	29.8	331	19.8	257	68.9	104
		531	Chevella	28.8	385	16.7	240	28.5	358	17.5	331	55.2	319
		532	Secunderabad	19.3	529	12	503	21.2	475	17.2	353	64.1	188
		533	Peddapalle	27.2	422	18.2	165	27.4	374	19	279	60.7	236
		534	Nalgonda	28.3	397	17.5	194	31.3	302	21.2	204	69.2	101
		535	Nagarkurnool	34.6	270	14	394	32.7	276	17.7	324	64.1	190
		536	Karimnagar	24.9	476	15.7	282	25.4	416	19.1	278	56.1	303
		537	Nizamabad	31.9	317	19.2	136	34.5	246	20.1	244	66.4	145
		538	Adilabad	34.8	265	18.8	147	34.1	257	20.8	221	66.5	141
		539	Mahabubabad	26.1	443	14.6	355	26.4	396	15.2	426	67.3	132
		540	Mahbubnagar	32.1	313	13.9	400	29.2	342	17.1	356	64.6	177
		541	Warangal	25.8	452	18.9	146	29.1	345	16.9	365	63.9	192
		542	Hyderabad	20.6	522	12.2	499	23.3	449	19.9	250	60	247
		543	Malkajgiri	25	475	14.2	383	24.5	430	16.1	395	53.5	353

(r > 0.80) indicating that these methodologies work consistently even for self-reported indicators and with smaller sample sizes.

For analyses involving complex survey-based sample for which it is possible to identify a potential PC membership, $D_{modeled}$ estimates are preferred for their simplicity and robustness. While we presented application of the $D_{modeled}$ methodology for child malnutrition indicators, we encourage further replication with other indicators of population health and development. For the different child malnutrition indicators, we detected clustering in contiguous PCs with high burden of child malnutrition that transcended state boundaries. Further interpretation of this spatial patterning is beyond the scope of this paper; nevertheless, this initial observation suggests the potential importance of spatial analysis at the PC-level to foster collaboration between Parliamentarians to find effective strategies to improve child health and well-being. When it is not possible to link the data to potential PC, but district membership is available, then developing a cross-walk is a viable option either after modeling for sampling variability for individual unit data or using the raw aggregated data if available only at the district level.

5. Conclusion

The academic and policy discourse around child malnutrition in India continue to emphasize district-level data and intervention with a good intention to strengthen localized action to support the NNM targets. However, there are no political representatives, equivalent to MPs in the case for PCs, directly accountable for the performance at district level. At the same time, there is no systematic evidence on key developmental measures at the PC level to guide Parliamentarians. This disconnection between the unit at which policy discussion occurs and where political actions take place results in a missed opportunity for more efficient, data-driven programming and robust policy evaluations to advance the rate of progress in diverse health and developmental sectors in India. In the absence of identifiers for PCs in the current surveys and Census data, one immediate step towards improving the accountability and coordination for MPs is to use the different methodologies outlined in this paper to produce PC-level estimates. Similar approaches can be developed for other countries where the administrative divisions and political boundaries do not share a direct correspondence.

Ethics statement

The study was reviewed by Harvard T.H. Chan School of Public Health Institutional Review Board and was considered exempt from full review because the study was based on an anonymous public use data set with no identifiable information on the study participants.

Authors' contributions

R Kim and SV Subramanian conceptualized and designed the study. R Kim analyzed the data, interpreted the findings, and wrote the first draft of the manuscript. A Swaminathan and R Kumar contributed to analysis of data, interpretation of findings, and reviewed the manuscript for important intellectual content. Y Xu and J Blossom contributed to analysis of data, visualization of findings, and reviewed the manuscript for major revisions. R Venkataramanan and A Kumar contributed to interpretation of policy relevance of findings, and reviewed the manuscript for major revisions. W Joe and SV Subramanian contributed to interpretation of findings and reviewed the manuscript for important intellectual content. SV Subramanian provided overall supervision. All authors approved of the final decision to submit for publication.

Declaration of interests

All authors declare no conflict of interest.

Role of funding sources

None.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ssmph.2019.100375.

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