Burden of Child Malnutrition in India

A View from Parliamentary Constituencies

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In India, monitoring and surveillance of health and well-being indicators have been focused primarily on the state and district levels. Analysing population data at the level of parliamentary constituencies has the potential to bring political accountability to the data-driven policy discourse that is currently based on district-level estimates. Using data from the fourth National Family Health Survey 2016, two geographic information systems methodologies have been developed and applied to provide estimates of four child malnutrition indicators (stunting, underweight, wasting, and anemia) for the 543 parliamentary constituencies in India. The results indicate that several constituencies experience a multiple burden of child malnutrition that must be addressed concurrently and as a priority.

(Appendix Figures A1–A6 and Tables A1–A4 accompanying this article are available on the *EPW* website.)

Alok Kumar and R Venkataramanan would like to state that interpretations made in this article do not reflect the views of their respective affiliated institutions.

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In India, monitoring and surveillance of health and well-being indicators have largely focused on states, and increasingly on districts. For instance, the National Institution for Transforming India (NITI) Aayog, the premier think tank of the Government of India (GoI), continues to release financial, labour, education, health, infrastructure, and poverty statistics only at the state and district levels. Since many of the most prominent sources of population data now report district-level outcomes, districts have become the unit of interest and intervention in policy discourse. For instance, the fourth National Family Health Survey 2016 (NFHS-4), conducted across India, released district-level data on a variety of health, nutrition and population indicators. The NITI Aayog Aspirational Districts Programme, which aims to prioritise 115 districts across India for intervention—identified due to their lagging development indicators—is one example of an increased focus on districts in development policy (NITI Aayog 2018). An increased policy focus on districts creates a virtuous cycle, which in turn necessitates even more data collection at the district level, resulting in discourse that is evidence-based.

Another decentralised geographical unit of substantial political influence in India is the parliamentary constituencies (PCs): the 543 geographical regions represented by the members of Parliament (MPs) of the Lok Sabha. The MPs of the Lok Sabha are elected by first-past-the-post universal adult suffrage and serve five-year terms in the lower house of the Parliament (Parliament of India 2017). Unlike districts that do not have any direct governmental accountability, a focus on PCs can bring a greater degree of accountability to policy vision and implementation since the MPs are directly responsible for the well-being of their constituents. Whereas health and development indicators and other population data are widely available at the district level, there is a notable scarcity of PC-level data. This lack of PC-level data steers policy discourse away from PCs, which in turn discourages data collection at the PC level.

PCs are relevant not only due to their direct representation of people, but also because of the resources allocated to them by the national government. In 1993, the GoI established the Members of Parliament Local Area Development Scheme (MPLADS), wherein each year every MP may receive up to ₹5 crore to carry out development projects in their respective PCs (MoSPI 2017a). To date, ₹31,833.35 crore has been disbursed to Lok Sabha MPs by the GoI as part of the MPLADS programme (MoSPI 2017b).

Determining the most appropriate interventions to fund requires understanding the local context. For example, an MP seeking to reduce the prevalence of stunting in their PC, first and foremost, requires current, accurate stunting prevalence estimates for their PC. They also require PC-specific economic, infrastructural, and demographic data in order to carry out a successful intervention to prevent stunting.

Several efforts have been recently established to aid MPs in understanding their constituents' needs. In early 2016, for instance, a select group of MPs, along with the Swaniti Initiative and Tata Trusts, launched an initiative, "Supporting Parliamentarians in Analysis and Research in the Constituency" (SPARC), which assigns 20 young professionals to 20 MPs across India to aid in implementing PC-specific development projects (Swaniti Initiative 2017). The SPARC programme arose when a group of MPs "came together to brainstorm ways through which Parliamentarians can become more effective leaders" (Swaniti Initiative 2017). Similarly, the Parliamentary Research Service (PRS), established in 2011, is a think tank and resource base that provides PC-specific data and research to support MPs, but with a focus on legislative matters (PRS Legislative Research 2018). The PRS publishes legislation analyses, statistical reports, research notes, and has also established the PRS Legislative Assistants to Members of Parliament (LAMP) fellowship, which, similar to SPARC, pairs young professionals with MPs to aid in research and policymaking. The combination of federal funding programmes for PC development and supporting resources for MPs makes the PC an important focus for population data analysis.

In order to address the data gap for health and development indicators at the PC-level, we developed and applied two novel methodologies to generate estimates of child malnutrition at the PC level. Specifically, using the NFHS-4 data on indicators of child malnutrition, we do three things. First, we present a state-of-the-art geographic information system (GIS)-based methodology to use district-level estimates and create a "crosswalk" to generate PC-level estimates. Second, we present a method of generating PC-level estimates by directly aggregating individual data in instances where one can link individual data to their PCs. Third, we apply these methodologies to rank PCs on indicators of child malnutrition (that is, stunting, underweight, wasting, and anaemia) and assess the patterns of PC variability across these indicators. We exemplify our methods using indicators of child malnutrition in order to provide timely evidence to inform current discussion on POSHAN Abhiyaan, a three-year programme launched in March 2018 that aims to "reduce the level of stunting, undernutrition, anaemia and low birth weight babies" (PIB 2018).

Data

We use three main sources of data for our analysis. The first is the district-level fact sheet and individual data on child malnutrition indicators from the NFHS-4. The NFHS-4 is a national survey conducted by the Ministry of Health and Family Welfare, and has collected information from 6,01,509 households on socio-demographic characteristics, water and sanitation, child health, women's and men's health, and other health-related variables (IIPS 2016). This survey also comes under the larger framework of the global demographic and health surveys (DHS) that are conducted across a wide range of low- and middle-income countries about every five years (DHS 2018a). Although the individual data is available for NFHS-4, using the district-level aggregate data is relevant because one of our methodologies to generate PC-level estimates only requires data at the district level. In our case, individual data is not necessary, thus making this approach widely applicable to many data sets where district-level estimates are available, but individual data are not.

The second data source is the geographic data provided by the DHS, where sampling clusters—from which households are sampled—are geo-referenced by latitude and longitude coordinates and available via special request (Burgert et al 2013). These survey cluster coordinates are mostly collected in the field using global positioning system (GPS) receivers, which are accurate to +/- 15 metres. The GPS positions are then displaced randomly to maintain respondent confidentiality. The displacement distance is a maximum of 2 kilometres (km) for urban clusters and 5 km for rural clusters. The displacement is restricted so that the displaced cluster locations stay within the districts. For clusters without GPS readings, coordinates are extracted from a paper map or a gazetteer of settlement names, or from pre-existing census data provided by the country's census agency/ministry. We used the geographic data collected in 2015–16, which has a total of 28,526 clusters in India (DHS 2018b).

The third data source was the boundary shapefiles for PCs and districts. The "India–Map of Parliamentary Constituencies, 2014" GIS shapefile was downloaded and used as the PC boundaries for this project (Github 2014a). This data set has boundaries mapped for 543 PCs in polygon format. The "India–District Map" GIS shapefile was downloaded from GitHub, and contains 641 mapped district boundaries in polygon format, and will be referred hereafter as "Districts" (GitHub 2014b). Note that this shapefile reflects the district boundaries from the 2011 Census of India, and was published on 6 April 2016.

We considered four indicators of child malnutrition (Subramanian et al 2016; Corsi et al 2016; Balarajan et al 2011). These four indicators were: (i) the percentage of stunting for children under five years (defined as height for age below -2 standard deviation (SD) of the age- and sex-specific median according to the World Health Organization [WHO] Child Growth Standards [Onis 2006]); (ii) the percentage of underweight children under five years (weight for age < -2 SD); (iii) the percentage of wasting for children under five years (weight for height < -2 SD); and (iv) the percentage of children aged 6–59 months who are anaemic (haemoglobin concentration <11.0 g/dl) (Table 1, p 46).

Using the data sources described above, we generate PC-level estimates of child malnutrition through two distinct methodologies. The first method involves using the boundary shapefiles to build a crosswalk between districts and PCs. Using this crosswalk, district-level data can be transformed and aggregated to generate PC-level estimates. We apply this crosswalk methodology to the district-level NFHS-4 malnutrition data to

Figure 1: Box Plots Showing the Distribution of Child Malnutrition Indicators across PCs

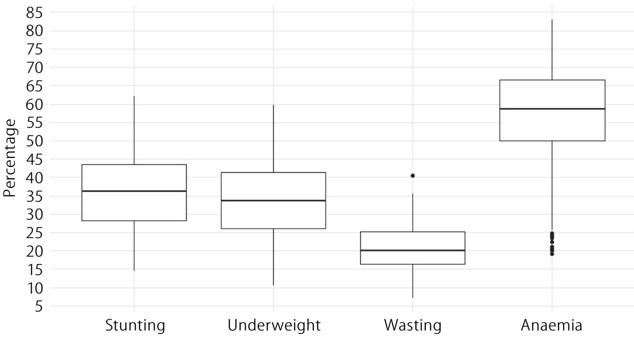
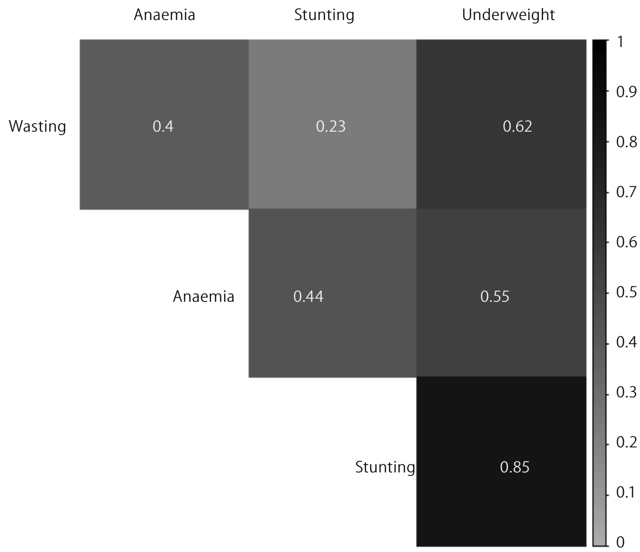


Figure 2: Correlation Matrix of Child Malnutrition Indicators across PCs



generate estimates for the PCs. The second method involves directly aggregating the individual malnutrition data to the PC level. Aggregation to the PC level is possible since the randomly displaced GPS locations of the sampling clusters are provided in the data source, so that the PC of each individual data point can be determined.

Developing a Crosswalk from Districts to PCs

Methods for geographic interpolation using GIS have been previously described (Loganet al 2014; Hibbert et al 2009; Forsyth et al 2006), but their applications to public health have not been thoroughly explored. We apply these methods to interpolate PC-level child malnutrition data given district boundaries. Briefly, we superimposed the shapefiles for district and PC boundaries, revealing segments of districts contained within each PC (see Figure A1). A given district could have segments that fall in several different PCs. For each of these district segments, the proportion of the total district area and population was calculated using raster maps, allowing us to calculate area and population estimates for PCs. For example, if a PC is made up of 40% district A and 60% district B, the total area and population of the PC can be calculated by computing the weighted average of the area and population of the two districts. A data set was generated in which each row corresponded to a segment of a district, and columns included the district ID, the PC ID in which the segment fell, the proportion of the district's population in that segment, and the proportion of the district's area in that segment.

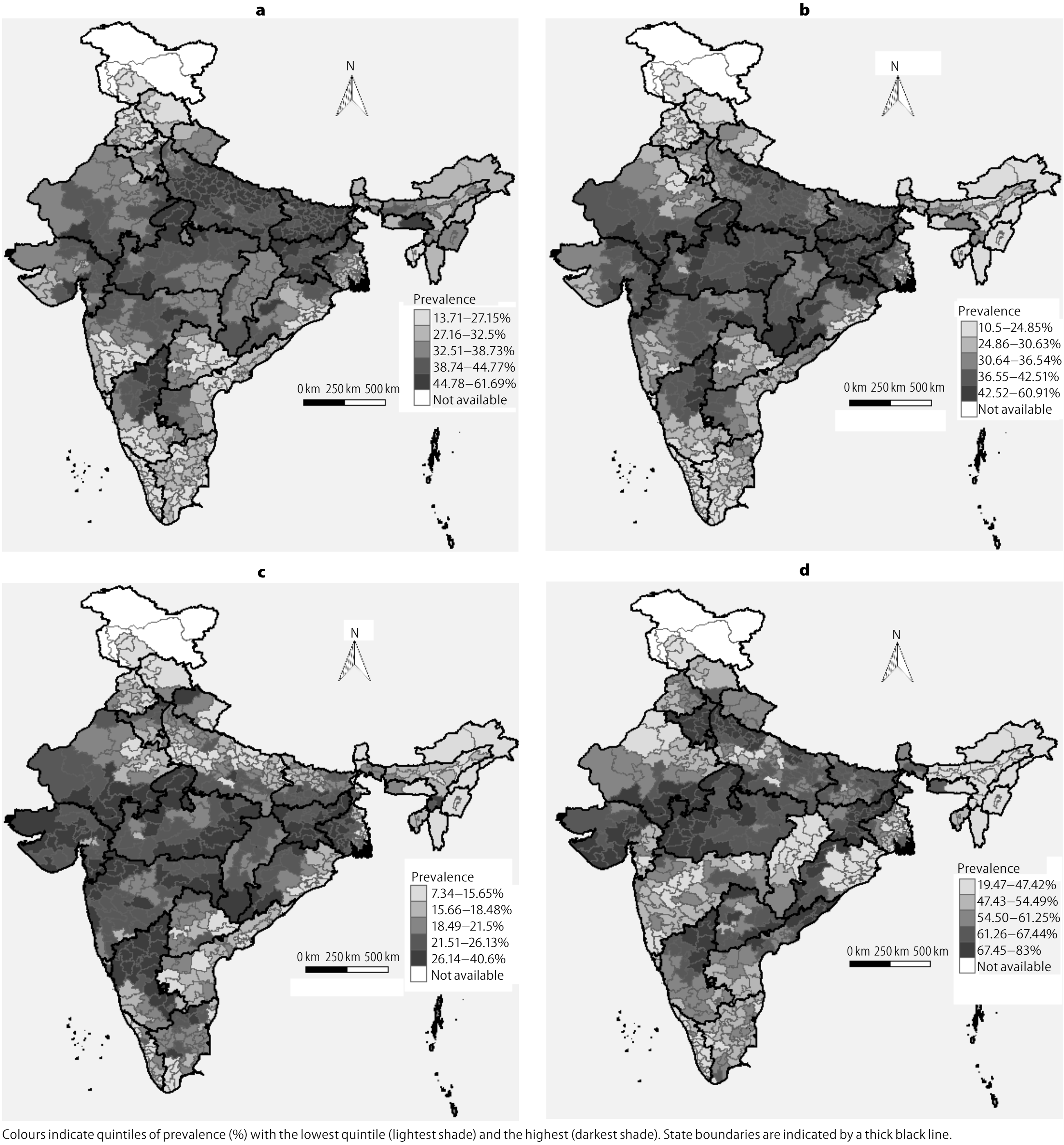
Using ArcGIS Pro version 2.0 (Esri, Redlands, California), the geographic area in square kilometres of each district was calculated using the Kalianpur 1975/India Zone IIA coordinate system (EPSG:24379), and saved into a field called Tot_Area. The Intersect command was used with the PCs and districts as the input shapefiles. This command creates a new shapefile, (named PC_District_Intersect) splitting the polygons where they are not identical, creating new geometric shapes. The new geometries are given the attributes of both, the overlapping PC and district. Next, the area in square kilometres of the new polygons was calculated using the Kalianpur 1975/India Zone IIA coordinate system into a field named AREA_GEO. A new field Pct_Area was calculated with the formula: "AREA_GEO/Tot_Area." The values in this Pct_Area field represent the percentage of district area contained in each new shape. Next, all polygons with a Pct_Area value less than .0001 (less than a hundredth of a percent of the area) were deleted. These extremely small areas are "slivers" that act as noise, and are created from slight boundary inaccuracies between the district and PC shapefiles.

Then, the Zonal Statistics command was performed using the district shapefile as the "zone" and the AsiaPop2015 population raster (www.asiapop.org) as the underlying data raster. This raster contains population estimates for all of India at a resolution of 100 metres, updated as of 2015. Results from this were saved in the Tot_pop field, and represent total population in the district. Then, the Zonal Statistics command was performed on the PC_District_Intersect shapefile, using the AsiaPop2015 population raster. These results were saved in the POP field, and represent the population in each portion of the PC/district intersection. Then the percentage of population for each apportioned area contains was calculated with a formula: "POP/Tot_pop." This was saved in the Pct_pop field. The PC_District_Intersect attribute table was exported to excel and eventually to R.

Table 1: Summary Statistics for Child Malnutrition Indicators across PCs, States and India (%)

Indicator	Description	Mean India	Min State	Max State	IQR State	Min PC	Max PC	IQR PC
Stunting	Children under 5 years who are stunted (height-for-age)	35.90	19.34	47.98	27.33, 36.47	13.71	61.69	28.47, 43.50
Underweight	Children under 5 years who are underweight (weight-for-age)	33.58	14.85	48.58	22.62, 34.83	10.50	60.91	26.59, 41.30
Wasting	Children under 5 years who are wasted (weight-for-height)	20.77	7.48	29.95	15.51, 23.09	7.34	40.60	16.60, 25.16
Anaemia	Children aged 6–59 months who are anaemic (<11.0 g/dl)	56.83	20.17	76.75	45.66, 62.19	19.47	83.00	49.93, 66.06

Figure 3: Geographic Distribution of Stunting (a), Underweight (b), Wasting (c), and Anaemia (d) across PCs



Colours indicate quintiles of prevalence (%) with the lowest quintile (lightest shade) and the highest (darkest shade). State boundaries are indicated by a thick black line.
The maps in the article show the 2014 PC borders due to issues of data availability as the only existing shapefiles for India's PCs are for the 2014 PC borders.

The PC_District_Intersect attribute table contained 1,530 rows, corresponding to 1,530 segments of districts. In order to calculate PC-level estimates, this attribute table was merged with the NFHS-4 district-level data, and the district malnutrition data columns were multiplied by the Tot_pop field, resulting in columns representing the estimated number of individuals in each district segment with a particular malnutrition state. The data set was then aggregated by PC ID, and the resulting malnutrition data columns represented the estimated number of individuals in each PC with a particular malnutrition state. These columns were then divided by the Tot_pop field and multiplied by 100, resulting in columns representing the estimated percent prevalence of malnutrition in each PC.

Generating Direct Estimates by Linking Clusters to PC

Direct aggregation from individual data to PCs was possible because the NFHS-4 utilised DHS sampling cluster locations, for which GPS coordinates are available. In the DHS geographic data, the centre of the populated place of each cluster is recorded with a GPS receiver. These locations are listed in degrees of latitude and longitude. We generated a GIS map of cluster points using the latitude–longitude coordinates and the ArcGIS Add Data from the XY Coordinates tool. We then combined this map with the PC boundary map using the ArcGIS Spatial Join tool. This tool determines which PC each cluster falls into and adds this information to the cluster attribute table. Then, the number of individuals in clusters that linked to each PC constitute the "sample population" for that PC, and the prevalence was computed as number of individuals with anthropometric failure divided by the total number of individuals in each PC.

Statistical Analysis

We adopted the following analytical approaches. First, summary statistics (mean, median, interquartile range) were calculated to describe the distribution of indicators of child malnutrition. Second, we present how the geographies of PC are correlated between the indicators. Then, maps were generated to visualise the geographic variation in the prevalence of child malnutrition and to identify "hotspots" of PCs with particularly high (that is, darker shades in Figure 3, p 47) or low (that is, lighter shades in Figure 3) burdens. All maps show quintiles of prevalence on indicators of child malnutrition.

We also compare the district–PC crosswalk with the direct aggregation method by repeating the above analyses using the directly aggregated data (see Tables A1, A2, A3, and Figures A2, A3, A4, A5 and A6). We also compare the PC rankings produced by both methodologies. For each malnutrition indicator, we rank the PCs using the district–PC crosswalk data, and then using the directly aggregated data. We then calculate the Pearson's correlation coefficient between the crosswalk rankings and the direct aggregation rankings. Finally, we compare the two methods by calculating the difference between the two prevalence estimates for each PC across all indicators. All statistical analyses were conducted using R version 3.2.

Results

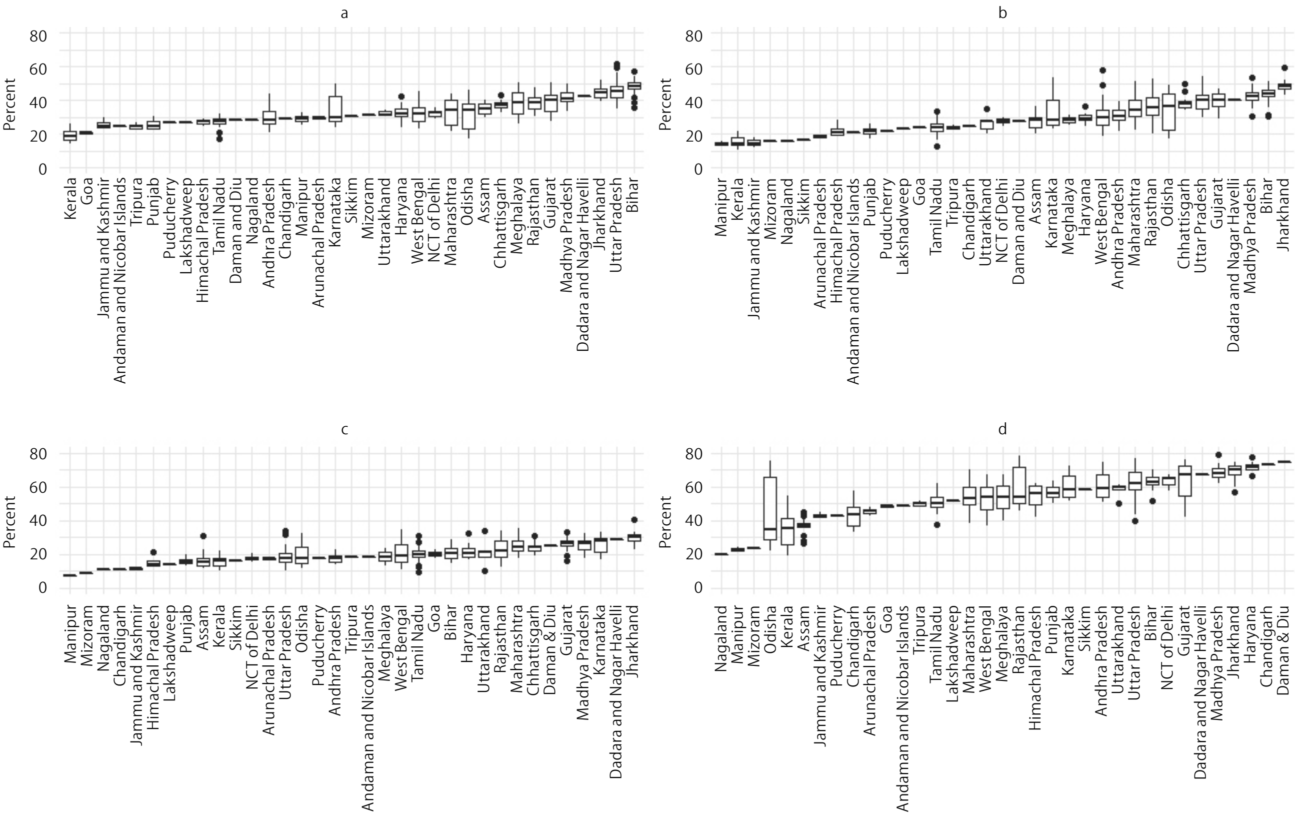
While we have provided rankings of PCs using both GIS methodologies, we discuss the observed empirical patterns based on the results obtained from the district–PC crosswalk data. This is

Table 2: PCs in the Top Two and Bottom Two Quintiles of All Child Malnutrition Indicators

Bottom Two Quintiles		Top Two Quintiles		Bottom Two Quintiles		Top Two Quintiles	
PC	State	PC	State	PC	State	PC	State
Chevella	Telangana	Bhagalpur	Bihar	Sangli	Maharashtra	Guna	Madhya Pradesh
Nellore	Andhra Pradesh	Banka	Bihar	**Inner Manipur**	**Manipur**	Khajuraho	Madhya Pradesh
Malkajgiri	Telangana	Arrah	Bihar	Mizoram	Mizoram	Satna	Madhya Pradesh
Secunderabad	Telangana	Sasaram	Bihar	Nagaland	Nagaland	Nandurbar	Maharashtra
Hyderabad	Telangana	Supaul	Bihar	**Cuttack**	**Odisha**	Chandrapur	Maharashtra
Arunachal West	Arunanchal Pradesh	Araria	Bihar	**Kendrapara**	**Odisha**	Yavatmal–Washim	Maharashtra
Arunachal East	Arunanchal Pradesh	Amreli	Gujarat	**Jagatsinghpur**	**Odisha**	Bolangir	Odisha
Jorhat	Assam	Bhavnagar	Gujarat	**Puri**	**Odisha**	Nabarangapur	Odisha
Lakhimpur	Assam	Patan	Gujarat	**Bhubaneshwar**	**Odisha**	Koraput	Odisha
Autonomous District	Assam	Sabar Kantha	Gujarat	**Aska**	**Odisha**	**Jalore**	**Rajasthan**
Tezpur	Assam	Haveri	Karnataka	Jajapur	Odisha	Udaipur	Rajasthan
North Goa	Goa	Davanagere	Karnataka	Bathinda	Punjab	**Banswara**	**Rajasthan**
Kangra	Himachal Pradesh	Belgaum	Karnataka	Khadoor Sahib	Punjab	Chittaurgarh	Rajasthan
Mandi	Himachal Pradesh	Bagalkot	Karnataka	Faridkot	Punjab	Rajsamand	Rajasthan
Hamirpur	**Himachal Pradesh**	Bijapur	Karnataka	Jhunjhunun	Rajasthan	Jhalawar–Baran	Rajasthan
Srinagar	**Jammu and Kashmir**	**Gulbarga**	**Karnataka**	Tiruvallur	Tamil Nadu	Shahjahanpur	Uttar Pradesh
Anantnag	**Jammu and Kashmir**	**Raichur**	**Karnataka**	Chennai South	Tamil Nadu	Amethi	Uttar Pradesh
Udhampur	**Jammu and Kashmir**	**Bidar**	**Karnataka**	Shivaganga	Tamil Nadu	Pratapgarh	Uttar Pradesh
Dakshina Kannada	Karnataka	**Koppal**	**Karnataka**	Theni	Tamil Nadu	Jalaun	Uttar Pradesh
Kasaragod	**Kerala**	**Bellary**	**Karnataka**	**Kanyakumari**	**Tamil Nadu**	Hamirpur	Uttar Pradesh
Thrissur	**Kerala**	**Morena**	**Madhya Pradesh**	Sriperumbudur	Tamil Nadu	Banda	Uttar Pradesh
Chalakudy	**Kerala**	Rewa	Madhya Pradesh	**Kancheepuram**	**Tamil Nadu**	Nagina	Uttar Pradesh
Ernakulam	**Kerala**	Sidhi	Madhya Pradesh	Tripura West	Tripura	Kaushambi	Uttar Pradesh
Kottayam	Kerala	Shahdol	Madhya Pradesh	Tripura East	Tripura	Puruliya	West Bengal
Alappuzha	Kerala	Vidisha	Madhya Pradesh	**Krishnanagar**	**West Bengal**	**Rajmahal**	**Jharkhand**
Mavelikkara	Kerala	Bhopal	Madhya Pradesh	**Ranaghat**	**West Bengal**	**Singhbhum**	**Jharkhand**
Pathanamthitta	Kerala	**Bhind**	**Madhya Pradesh**	**Bangaon**	**West Bengal**	**Khunti**	**Jharkhand**
Kollam	**Kerala**	Rajgarh	Madhya Pradesh	Barakpur	West Bengal	Lohardaga	Jharkhand
Attingal	**Kerala**	Dewas	Madhya Pradesh	Dum Dum	West Bengal	Hazaribagh	Jharkhand
Kannur	**Kerala**	Mandsaur	Madhya Pradesh	Barasat	West Bengal	Dumka	Jharkhand
Thiruvananthapuram	**Kerala**	Ratlam	Madhya Pradesh	Basirhat	West Bengal	**Godda**	**Jharkhand**
Vadakara	**Kerala**	Dhar	Madhya Pradesh	Shrirampur	West Bengal	Kodarma	Jharkhand
Kozhikode	**Kerala**	Khargone	Madhya Pradesh	**Hugli**	**West Bengal**	Giridih	Jharkhand
Ponnani	Kerala	Khandwa	Madhya Pradesh	Lakshadweep	Lakshadweep	Dhanbad	Jharkhand
Palakkad	**Kerala**	Betul	Madhya Pradesh			Ranchi	Jharkhand
Alathur	**Kerala**	Gwalior	Madhya Pradesh			Jamshedpur	Jharkhand

Bold values are in the top or bottom quintiles, and represent the highest priority and lowest priority PCs, respectively.

Figure 4: Boxplots Showing the Distribution across PCs for Stunting (a), Underweight (b), Wasting (c), and Anaemia (d), Showing Median, IQR, 95% Range, and Outliers in Each State



because we believe that this methodology has the potential to be more widely utilised, since the direct aggregation method was only possible given the availability of the survey cluster GPS data, which is generally not provided in most population data sets. Furthermore, the substantive empirical patterns as well as PC rankings were highly similar between the two methods, as evidenced by the results obtained from repeating all analyses using the direct aggregation method (see Tables A1, A2 and A3, Figures A2, A3, A4, A5 and A6).

Distribution and Correlation Indicators across PCs

Across India, over 20% of children under five experienced wasting, over one-third were underweight, over one-third were stunted, and nearly 60% of children aged 6–59 months were anaemic (Table 1). India's 57% prevalence of child anaemia is a "severe" public health problem, based on the WHO cut-off of greater than or equal to 40% prevalence (WHO 2015). Across PCs, stunting ranged from 13.7% to 61.7%, underweight ranged from 10.5% to 60.9%, wasting ranged from 7.3% and 40.6%, and anaemia ranged from 19.5% to 83.0%. Stunting, underweight, and wasting were approximately symmetrically distributed across PCs, while anaemia was left-skewed (Figure 1, p 46).

Across PCs, stunting was strongly correlated with underweight ($r = 0.85$). PCs with higher levels of underweight were more likely to be also PCs with higher levels of wasting ($r = 0.61$). Anaemia showed moderate correlations with other malnutrition indicators ($0.35 < r < 0.55$) (Figure 2, p 46). In general, PCs with high prevalence of one form of child malnutrition are also likely to suffer from high prevalence of other forms of malnutrition.

Mapping Indicators of Child Malnutrition across PCs

Stunting: PCs in central and north-eastern India show the highest burden of stunting, particularly in Uttar Pradesh, Jharkhand, Bihar, and Madhya Pradesh (Figure 3a, p 47). Shrawasti (Uttar Pradesh, 61.7%), Kaisarganj (Uttar Pradesh, 61.4%), and Bahraich (Uttar Pradesh, 60.6%) are the PCs with the highest burden of stunting. PCs in northern and southern India, in Punjab, Himachal Pradesh, Telangana, Tamil Nadu, and Kerala, show the lowest burden of stunting. Pathanamthitta (15.9%), Kottayam (15.8%), and Idukki (13.7%) in Kerala are the PCs with the lowest burden of stunting. Karnataka, Maharashtra, and Odisha, the states with the highest interquartile range (IQR) for stunting, contain several PCs in the top two and bottom two quintiles of stunting prevalence. Of these states, Karnataka and Maharashtra have a similar distribution where northern PCs show higher prevalence of stunting than southern PCs.

Underweight: The distribution of underweight shows trends similar to that of stunting (Figure 3b, p 47). PCs in central and northeastern India show the highest burden of underweight, particularly in Uttar Pradesh, Jharkhand, Bihar, Chhattisgarh and Madhya Pradesh. The PCs with the highest prevalence of underweight are Singhbhum in Jharkhand (60.9%), Puruliya in West Bengal (58.2%), and Shahjahanpur in Uttar Pradesh (54.3%).

PCs in northern, southern, and eastern India show the lowest burden of stunting, such as in Punjab, Himachal Pradesh, Uttarakhand, Telangana, Tamil Nadu, Kerala, Sikkim, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, and Tripura. Kottayam (12.3%), Kasaragod (11.6%), and Kannur (10.5%) in Kerala are the PCs with the lowest burden of underweight. Karnataka, Odisha, Rajasthan, Maharashtra and West Bengal, the states with the highest IQR for underweight, contain several PCs in the top two and bottom two quintiles. Of these states, Karnataka and Maharashtra have a similar distribution where northern PCs show higher prevalence of underweight than southern PCs. West Bengal and Rajasthan show the opposite pattern where southern PCs show a higher prevalence of underweight than northern PCs.

Wasting: Prevalence of wasting is highest in central and western India (Figure 3c, p 47), particularly in Madhya Pradesh, Gujarat, Maharashtra, Chhattisgarh, and Jharkhand. The PCs with the highest prevalence of wasting are Jamshedpur in Jharkhand (40.6%), Puruliya in West Bengal (34.6%), and Nandurbar in Maharashtra (34.5%). Parts of southern, eastern and northern India show the lowest rates of wasting, such as in Himachal Pradesh, Punjab, Andhra Pradesh, Sikkim, West Bengal, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, and Tripura. The PCs with the lowest prevalence of wasting are Kanyakumari in Tamil Nadu (9.0%), and Inner Manipur (7.6%) and Outer Manipur (7.6%). West Bengal, Odisha, Rajasthan, Karnataka, Bihar, and Tamil Nadu show high within-state, between-PC variability. Of these states, Karnataka and Tamil Nadu have a similar distribution where northern PCs show higher prevalence of wasting than southern PCs. In West Bengal, western PCs show a higher prevalence of wasting than eastern PCs.

Table 3: Positive Deviant PCs

Child Malnutrition Indicator	PC	State
Stunting	Jamnagar	Gujarat
Underweight	Baramati	Maharashtra
	Shirur	Maharashtra
	Mumbai–South	Maharashtra
	Sangli	Maharashtra
	Pune	Maharashtra
	Jaipur	Rajasthan
	Jhunjhunun	Rajasthan
	Sikar	Rajasthan
Wasting	Vadodara	Gujarat
	Puri	Odisha
	Berhampur	Odisha
	Cuttack	Odisha
	Aska	Odisha
	Bhubaneshwar	Odisha
	Kendrapara	Odisha
	Jagatsinghpur	Odisha
	Jajapur	Odisha
	Dausa	Rajasthan
	Jaipur	Rajasthan
	Jhunjhunun	Rajasthan
	Sikar	Rajasthan
Anaemia	Agra	Uttar Pradesh
	Barabanki	Uttar Pradesh
	Hardoi	Uttar Pradesh
	Fatehpur	Uttar Pradesh
	Firozabad	Uttar Pradesh
	Farrukhabad	Uttar Pradesh
	Etah	Uttar Pradesh
	Kheri	Uttar Pradesh
	Bardoli	Gujarat
	Surat	Gujarat
	Navsari	Gujarat

Positive deviant PCs are PCs with a low prevalence of child malnutrition in a state with high prevalence, where high and low prevalence are defined by the 75th and 25th percentile, respectively.

Anaemia: The highest rates of anaemia are found mostly throughout central India, particularly in Madhya Pradesh, southern Rajasthan, Haryana, and Gujarat (Figure 3d, p 47). Madhya Pradesh and Haryana have the highest rates of anaemia, with Haryana containing PCs only in the top two quintiles. The PCs with the highest prevalence of anaemia are Singhbum in Jharkhand (83.0%), Banswara in Rajasthan (79.3%), and Khargone in Madhya Pradesh (79.1%). States in southern, eastern, and parts of northern India have PCs in the bottom two quintiles of anaemia, such as Tamil Nadu, Kerala, Maharashtra, Punjab, Chhattisgarh, Sikkim, West Bengal, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, and Tripura. The PCs with the lowest prevalence of anaemia are Nagaland (20.2%), Attingal (19.5%), and Kollam (19.5%) in Kerala. In Odisha, western PCs show higher rates of anaemia than eastern PCs. In Karnataka, northern PCs show higher rates of anaemia than southern PCs. In Rajasthan, southern PCs show higher rates of anaemia than northern PCs. And, in Gujarat, western PCs show higher rates of anaemia than eastern PCs.

A total of 72 PCs were in the top two quintiles of prevalence for all indicators of child malnutrition (Table 2, p 48). Of these, 12 PCs were in Jharkhand, 19 in Madhya Pradesh, 10 in Karnataka, six in Rajasthan and eight in Uttar Pradesh. Of these 72, 13 PCs were also in the top quintile of all variables (in bold in Table 2). Twenty-nine PCs were in the bottom quintile for all four outcome variables (in bold in Table 2). Of these, 12 were in Kerala, four were in West Bengal, and six in Odisha.

State-specific Variations and Deviant PCs

Kerala and Goa had the lowest median prevalence of stunting, and Bihar and Uttar Pradesh had the highest (Figure 4a, p 49). Karnataka had the highest IQR of stunting among PCs. Jammu and Kashmir, and Kerala had the lowest median prevalence of underweight, and Jharkhand and Bihar had the highest (Figure 4b, p 49). Odisha had the highest IQR of underweight among PCs. Manipur and Nagaland had the lowest median prevalence of wasting (Figure 4c, p 49). Daman and Diu, Dadra and Nagar Haveli, and Jharkhand had the highest median prevalence of wasting. West Bengal had the highest IQR of wasting among PCs. Nagaland and Manipur had the lowest median prevalence of anaemia, and Chandigarh and Daman and Diu had the highest (Figure 4d, p 49). Odisha had the highest IQR of anaemia among PCs. Overall, Nagaland, Manipur, Mizoram, and Kerala showed low median prevalence of the variables of interest. Jharkhand showed high median prevalence of all variables.

We identify positive deviant PCs, that is, PCs with low prevalence nested within states with high prevalence (Table 3). The positive deviant PCs provide an opportunity to identify best practices within states that have a high prevalence of child malnutrition. Jamnagar in Gujarat is the only positive deviant for stunting. The positive deviants for underweight are located entirely in Maharashtra and Rajasthan, those for wasting are located almost entirely in Odisha and Rajasthan, and those for anaemia are located entirely in Uttar Pradesh and Gujarat. Jaipur, Jhunjhunun, and Sikar in Rajasthan are positive deviants for both wasting and underweight. Positive deviant PCs were not found in states other than Gujarat, Maharashtra, Rajasthan, Odisha, and Uttar Pradesh. Future studies should focus on these PCs to find positive practices or characteristics that can be applied to other PCs to improve child malnutrition outcomes. We found no negative deviant PCs, that is, PCs with high prevalence nested within states with low prevalence.

Comparison with Direct Aggregation Method

In order to directly compare the results of the district–PC crosswalk method and the direct aggregation method, we first compare PC rankings. For each malnutrition indicator, the 543 PCs were ranked based on the crosswalk data and then by the directly aggregated data. The correlations between these two rankings were positive and strong for all indicators, as is reflected by r = 0.92 for stunting, r = 0.92 for underweight, r = 0.84 for wasting, and r = 0.89 for anaemia. We also compared the two prevalence estimates generated by the two methodologies for each PC across all indicators. The absolute value of the difference in prevalence estimates between the two methods had a mean of 2.9% and a SD of 2.7% for stunting, a mean of 3.1% and a SD of 3.1% for underweight, a mean of 2.6% and a SD 2.8% for wasting, and a mean of 3.8% and a SD of 4.0% for anaemia.

The overall trends described above are recapitulated in the malnutrition data generated by direct aggregation to the PC level. Summary statistics (Table A1) are similar to those obtained with the crosswalk data, although the directly aggregated data shows a wider IQR across PCs. The list of PCs in the top and bottom quintiles showed overlap with that generated by the crosswalk method (Table A2). Twenty-eight out of 57 PCs that were in the bottom two quintiles of all indicators and 44 out of 62 PCs that were in the top two quintiles of all indicators also appeared on the list generated by the crosswalk method. The direct aggregation method led to identification of notably more positive deviant PCs than the crosswalk method (Table A3). All-India box plots and correlations are very similar to those produced using the crosswalk method (Figures A2 and A4). Maps produced using the directly aggregated data show similar national and intra-state trends across PCs (Figure A4).

Discussion

Our study has three salient findings. First, prevalence of child stunting, underweight, wasting, and anaemia was highly variable across PCs. State-specific analysis showed that the relative importance of the PC level may be different across states. Second, there were moderate/high correlations between malnutrition indicators at the PC level, indicating that several PCs experience a multiple burden of child malnutrition that must be addressed concurrently. Third, we found several PCs in Madhya Pradesh and Jharkhand that had high prevalence of all indicators of interest, and may represent the highest priority for health interventions. We also found PCs that show low prevalence for all indicators, and represent positive deviant PCs that should be investigated to elucidate best practices for child nutrition.

Why might one expect substantial variation at the PC level in indicators of child malnutrition? One, such variation may simply reflect how risk factors for malnutrition are distributed across PCs. For example, household poverty has been shown to be a significant risk factor for stunting, wasting, and underweight in India (Corsi et al 2016; Kim et al 2017), so certain PCs that have a large proportion of poor households may also show high prevalence of child malnutrition. A prior multilevel analysis of household poverty and health spending indeed reported significant variation at the local level (Kim et al 2016; Mohanty et al 2018). Thus, PC-level variation in malnutrition may be a result of the underlying distribution of malnutrition risk factors. This may also explain intra-state variation in states like Karnataka, Odisha and Maharashtra, which have PCs in the top two and bottom two quintiles across many indicators. Indeed, further research is required to determine the exact mechanism for intrastate malnutrition variation across PCs.

There are also factors relating to the MPs that may notably impact child malnutrition at the PC level, specifically with regards to the MPLADS. This programme has grown significantly since its inception, with the annual allotted budget per MP increasing 100-fold from ₹0.05 crore in 1993 to ₹5 crore in 2011 and onwards (MoSPI 2016). Since 2015, there have been several approved MPLADS relating to health, such as the equipment of local hospitals, purchase of ambulances and hearse vans, and the installation of outdoor gyms (MoSPI 2015a, 2015b, 2015c). Thus, the MPLADS has the potential to significantly influence PC-level health outcomes, especially since "preference is given to works relating to national priorities, such as ... public health" (MoSPI 2016). Given the distinct nutritional profile of each PC, PC-level interventions should be developed considering the local context. This is precisely where programmes such as SPARC, PRS, and LAMP are needed to support MPs in understanding their constituents' needs and in making informed decisions about policy and resource allocation.

The role of MPs in MPLADS is of particular interest in the context of political business cycles, defined by Blair (2017) as "increased spending by governments just before elections in the hope of staying in power." During the term of the 15th Lok Sabha from 2009 to 2014, MPs vying for re-election in 2014 strategically spent the bulk of their allotted MPLADS funds towards the end of their term (Blair 2017). Additionally, the age of the MP significantly affects MPLADS spending to promote political business cycles, with younger MPs utilising funds more uniformly across time than older ones (Pal and Das 2010). Overall, there was considerable variation in MPLADS spending, with a mean and SD of 0.46 and 0.38, respectively, for the proportion of allotted funds spent from May 2004 to October 2006. It is clear that several personal attributes of MPs, such as age and intention to rerun, all significantly impact MPLADS spending and, thus, development and health at the PC level.

It may also be that constituents' demands ultimately determine PC-level spending. Pal and Das (2010) found that constituents' awareness and demands significantly have an impact on the implementation of MPLADS funds, with more awareness leading to more consistent usage of funds, and "[leave] less scope for the MPs to utilize funds with political motives." This suggests that MPs may be less likely to spend funds as a means to promote political business cycles if their constituents are informed and proactive about their demands.

Our methods can be easily extended to estimate population outcomes at other geopolitical levels. One reasonable extension, especially relevant for child malnutrition, is calculating estimates for the 4,120 assembly constituencies (ACs), represented by members of the legislative assembly (MLAs) who are elected to the legislature of the state governments (ECI 2018). We found considerable intra-state variation of child malnutrition, which underscores the importance of understanding the local context when developing health interventions. Since MLAs are representatives of smaller geopolitical units than MPs, understanding AC-level outcomes may better inform local interventions and increase accountability for MLAs as well as MPs. Additionally, calculating AC-level estimates may promote the success of POSHAN Abhiyaan, since the impact of national efforts is supplemented by the support of representatives at all political levels.

In summary, the large variations across PCs suggest that one needs to focus on both describing the magnitude of differences across various health and development indicators, as well as understanding to what extent these differences are a consequence of PC-specific processes as opposed to reflecting the characteristics endogenous to the PC. In this article, we present a methodology that should enable researchers and policymakers to generate PC estimates from abundant data available at the district level from multiple sources. We believe that, in order for the policy discourse to be effective, there needs to be a complementary data-driven discourse in the political domain. Data can be empowering to the MPs as well as their constituents. The ranking of PCs on indicators of child malnutrition, we hope, will help prioritise which PCs need targeting in order to realise the goals of the national POSHAN Abhiyaan programme.

[S V Subramanian conceptualised and designed the study. Akshay Swaminathan contributed to the conceptualisation and led the data analysis, co-wrote the first draft, and led the revision. Rockli Kim contributed to the conceptualisation, analysis and interpretation of the results, and writing. Jeffrey C Blossom, William Joe, Yun Xu and S V Subramanian contributed to the data analysis, interpretation of the results and writing. Alok Kumar and R Venkataramanan contributed to critical revisions. S V Subramanian provided overall supervision to the study. All authors approved the final submission of the study.]

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Appendix

Table A1: PCs with High Prevalence of Stunting Located in States with High Prevalence of Stunting, Where High is Defined as 75th Percentile

PC_Name	State	PC_Name	State
Valmiki Nagar	Bihar	Bhind	Madhya Pradesh
Katihar	Bihar	Shillong	Meghalaya
Patna Sahib	Bihar	Banswara	Rajasthan
Darbhanga	Bihar	Udaipur	Rajasthan
Buxar	Bihar	Jalore	Rajasthan
Banka	Bihar	Bareilly	Uttar Pradesh
Madhepura	Bihar	Kannauj	Uttar Pradesh
Sitamarhi	Bihar	Deoria	Uttar Pradesh
Vaishali	Bihar	Kaushambi	Uttar Pradesh
Purnia	Bihar	Rampur	Uttar Pradesh
Khagaria	Bihar	Aonla	Uttar Pradesh
Muzaffarpur	Bihar	Shahjahanpur	Uttar Pradesh
Jehanabad	Bihar	Bahraich	Uttar Pradesh
Hajipur	Bihar	Firozabad	Uttar Pradesh
Sheohar	Bihar	Pilibhit	Uttar Pradesh
Jamui	Bihar	Farrukhabad	Uttar Pradesh
Aurangabad	Bihar	Maharajganj	Uttar Pradesh
Kishanganj	Bihar	Jaunpur	Uttar Pradesh
Maharajganj	Bihar	Gonda	Uttar Pradesh
Bhagalpur	Bihar	Kanpur	Uttar Pradesh
Supaul	Bihar	Machhlishahr	Uttar Pradesh
Sasaram	Bihar	Kushinagar	Uttar Pradesh
Jhanjharpur	Bihar	Aligarh	Uttar Pradesh
Begusarai	Bihar	Mainpuri	Uttar Pradesh
Madhubani	Bihar	Etawah	Uttar Pradesh
Nawada	Bihar	Ambedkar Nagar	Uttar Pradesh
Gaya	Bihar	Banda	Uttar Pradesh
Karakat	Bihar	Varanasi	Uttar Pradesh
Nalanda	Bihar	Mohanlalganj	Uttar Pradesh
Munger	Bihar	Kheri	Uttar Pradesh
Bhavnagar	Gujarat	Chandauli	Uttar Pradesh
Anand	Gujarat	Allahabad	Uttar Pradesh
Chhota Udaipur	Gujarat	Barabanki	Uttar Pradesh
Vadodara	Gujarat	Fatehpur	Uttar Pradesh
Bharuch	Gujarat	Akbarpur	Uttar Pradesh
Godda	Jharkhand	Amethi	Uttar Pradesh
Kodarma	Jharkhand	Dhaurahra	Uttar Pradesh
Khunti	Jharkhand	Etah	Uttar Pradesh
Rajmahal	Jharkhand	Hardoi	Uttar Pradesh
Chatra	Jharkhand	Faizabad	Uttar Pradesh
Singhbhum	Jharkhand	Hathras	Uttar Pradesh
Dumka	Jharkhand	Unnao	Uttar Pradesh
Palamu	Jharkhand	Agra	Uttar Pradesh
Ratlam	Madhya Pradesh	Sitapur	Uttar Pradesh
Morena	Madhya Pradesh	Robertsganj	Uttar Pradesh
Khargone	Madhya Pradesh	Mirzapur	Uttar Pradesh
Khandwa	Madhya Pradesh	Misrikh	Uttar Pradesh
Tikamgarh	Madhya Pradesh	Sambhal	Uttar Pradesh
Damoh	Madhya Pradesh	Fatehpur Sikri	Uttar Pradesh
Gwalior	Madhya Pradesh	Sant Kabir Nagar	Uttar Pradesh
Guna	Madhya Pradesh	Sultanpur	Uttar Pradesh

Table A2: PCs with High Prevalence of Underweight Located in States with High Prevalence of Underweight, Where High is Defined as 75th Percentile

PC_Name	State	PC_Name	State
Arrah	Bihar	Balaghat	Madhya Pradesh
Katihar	Bihar	Morena	Madhya Pradesh
Patna Sahib	Bihar	Khargone	Madhya Pradesh
Darbhanga	Bihar	Khandwa	Madhya Pradesh
Buxar	Bihar	Tikamgarh	Madhya Pradesh
Banka	Bihar	Rajgarh	Madhya Pradesh
Madhepura	Bihar	Gwalior	Madhya Pradesh
Sitamarhi	Bihar	Betul	Madhya Pradesh
Vaishali	Bihar	Chhindwara	Madhya Pradesh
Purnia	Bihar	Bhopal	Madhya Pradesh
Khagaria	Bihar	Khajuraho	Madhya Pradesh
Muzaffarpur	Bihar	Mandla	Madhya Pradesh
Jehanabad	Bihar	Guna	Madhya Pradesh
Hajipur	Bihar	Bhind	Madhya Pradesh
Sheohar	Bihar	Dindori	Maharashtra
Jamui	Bihar	Dhule	Maharashtra
Aurangabad	Bihar	Nashik	Maharashtra
Pataliputra	Bihar	Nandurbar	Maharashtra
Kishanganj	Bihar	Aurangabad	Maharashtra
Bhagalpur	Bihar	Chandrapur	Maharashtra
Supaul	Bihar	Kota	Rajasthan
Sasaram	Bihar	Banswara	Rajasthan
Jhanjharpur	Bihar	Udaipur	Rajasthan
Madhubani	Bihar	Bhilwara	Rajasthan
Nawada	Bihar	Jalore	Rajasthan
Gaya	Bihar	Bareilly	Uttar Pradesh
Karakat	Bihar	Nagina	Uttar Pradesh
Nalanda	Bihar	Kaushambi	Uttar Pradesh
Munger	Bihar	Rampur	Uttar Pradesh
Kanker	Chhattisgarh	Aonla	Uttar Pradesh
Bhavnagar	Gujarat	Shahjahanpur	Uttar Pradesh
Chhota Udaipur	Gujarat	Lucknow	Uttar Pradesh
Bardoli	Gujarat	Bahraich	Uttar Pradesh
Valsad	Gujarat	Pilibhit	Uttar Pradesh
Bharuch	Gujarat	Jaunpur	Uttar Pradesh
Dhanbad	Jharkhand	Machhlishahr	Uttar Pradesh
Ranchi	Jharkhand	Banda	Uttar Pradesh
Jamshedpur	Jharkhand	Varanasi	Uttar Pradesh
Godda	Jharkhand	Jhansi	Uttar Pradesh
Kodarma	Jharkhand	Mohanlalganj	Uttar Pradesh
Khunti	Jharkhand	Chandauli	Uttar Pradesh
Rajmahal	Jharkhand	Allahabad	Uttar Pradesh
Lohardaga	Jharkhand	Amethi	Uttar Pradesh
Hazaribagh	Jharkhand	Dhaurahra	Uttar Pradesh
Chatra	Jharkhand	Faizabad	Uttar Pradesh
Singhbhum	Jharkhand	Sitapur	Uttar Pradesh
Dumka	Jharkhand	Hamirpur	Uttar Pradesh
Palamu	Jharkhand	Mirzapur	Uttar Pradesh
Giridih	Jharkhand	Jalaun	Uttar Pradesh
Ratlam	Madhya Pradesh	Sambhal	Uttar Pradesh
Shahdol	Madhya Pradesh	Pratapgarh	Uttar Pradesh
Jabalpur	Madhya Pradesh	Sultanpur	Uttar Pradesh
Dewas	Madhya Pradesh		

Table A3: PCs with High Prevalence of Wasting Located in States with High Prevalence of Wasting, Where High is Defined as 75th Percentile

PC_Name	State	PC_Name	State
Raigarh	Chhattisgarh	Uttara Kannada	Karnataka
Korba	Chhattisgarh	Gulbarga	Karnataka
Kanker	Chhattisgarh	Bangalore Central	Karnataka
Bhavnagar	Gujarat	Ratlam	Madhya Pradesh
Jamnagar	Gujarat	Shahdol	Madhya Pradesh
Gandhinagar	Gujarat	Jabalpur	Madhya Pradesh
Amreli	Gujarat	Dewas	Madhya Pradesh
Chhota Udaipur	Gujarat	Balaghat	Madhya Pradesh
Bardoli	Gujarat	Morena	Madhya Pradesh
Rajkot	Gujarat	Satna	Madhya Pradesh
Surat	Gujarat	Rajgarh	Madhya Pradesh
Kheda	Gujarat	Hoshangabad	Madhya Pradesh
Valsad	Gujarat	Gwalior	Madhya Pradesh
Bharuch	Gujarat	Betul	Madhya Pradesh
Surendranagar	Gujarat	Chhindwara	Madhya Pradesh
Navsari	Gujarat	Bhopal	Madhya Pradesh
Kachchh	Gujarat	Sidhi	Madhya Pradesh
Porbandar	Gujarat	Mandla	Madhya Pradesh
Dhanbad	Jharkhand	Guna	Madhya Pradesh
Ranchi	Jharkhand	Bhind	Madhya Pradesh
Jamshedpur	Jharkhand	Dindori	Maharashtra
Godda	Jharkhand	Palghar	Maharashtra
Khunti	Jharkhand	Kolhapur	Maharashtra
Rajmahal	Jharkhand	Maval	Maharashtra
Lohardaga	Jharkhand	Dhule	Maharashtra
Chatra	Jharkhand	Ramtek	Maharashtra
Singhbhum	Jharkhand	Nashik	Maharashtra
Dumka	Jharkhand	Beed	Maharashtra
Palamu	Jharkhand	Jalgaon	Maharashtra
Giridih	Jharkhand	Kalyan	Maharashtra
Bagalkot	Karnataka	Nagpur	Maharashtra
Chikkodi	Karnataka	Nandurbar	Maharashtra
Bidar	Karnataka	Akola	Maharashtra
Tumkur	Karnataka	Aurangabad	Maharashtra
Bangalore South	Karnataka	Chandrapur	Maharashtra
Koppal	Karnataka	Raver	Maharashtra
Chitradurga	Karnataka	Wardha	Maharashtra
Raichur	Karnataka	Kota	Rajasthan
Haveri	Karnataka	Banswara	Rajasthan
Belgaum	Karnataka	Udaipur	Rajasthan
Bangalore North	Karnataka	Bhilwara	Rajasthan
Bijapur	Karnataka	Jalore	Rajasthan
Bellary	Karnataka	Rajsamand	Rajasthan
Dharwad	Karnataka		

Table A4: PCs with High Prevalence of Anemia Located in States with High Prevalence of Anemia, Where High is Defined as 75th Percentile

PC_Name	State	PC_Name	State
Arrah	Bihar	Jamshedpur	Jharkhand
Darbhanga	Bihar	Godda	Jharkhand
Banka	Bihar	Kodarma	Jharkhand
Madhepura	Bihar	Khunti	Jharkhand
Sitamarhi	Bihar	Rajmahal	Jharkhand
Bhagalpur	Bihar	Lohardaga	Jharkhand
Supaul	Bihar	Hazaribagh	Jharkhand
Chandigarh	Chandigarh	Singhbhum	Jharkhand
New Delhi	Delhi	Dumka	Jharkhand
Bhavnagar	Gujarat	Giridih	Jharkhand
Jamnagar	Gujarat	Ratlam	Madhya Pradesh
Gandhinagar	Gujarat	Shahdol	Madhya Pradesh
Amreli	Gujarat	Sagar	Madhya Pradesh
Junagadh	Gujarat	Dewas	Madhya Pradesh
Rajkot	Gujarat	Morena	Madhya Pradesh
Patan	Gujarat	Satna	Madhya Pradesh
Surendranagar	Gujarat	Khargone	Madhya Pradesh
Kachchh	Gujarat	Khandwa	Madhya Pradesh
Porbandar	Gujarat	Ujjain	Madhya Pradesh
Karnal	Haryana	Dhar	Madhya Pradesh
Faridabad	Haryana	Tikamgarh	Madhya Pradesh
Hisar	Haryana	Vidisha	Madhya Pradesh
Gurgaon	Haryana	Rajgarh	Madhya Pradesh
Sirsa	Haryana	Damoh	Madhya Pradesh
Sonipat	Haryana	Hoshangabad	Madhya Pradesh
Ambala	Haryana	Indore	Madhya Pradesh
Rohtak	Haryana	Betul	Madhya Pradesh
Dhanbad	Jharkhand	Bhopal	Madhya Pradesh
Ranchi	Jharkhand	Mandla	Madhya Pradesh
		Bhind	Madhya Pradesh

Appendix

Figure A1: Map of PCs That are in the Top Quintile for Prevalence of All Four Child Malnutrition Indicators

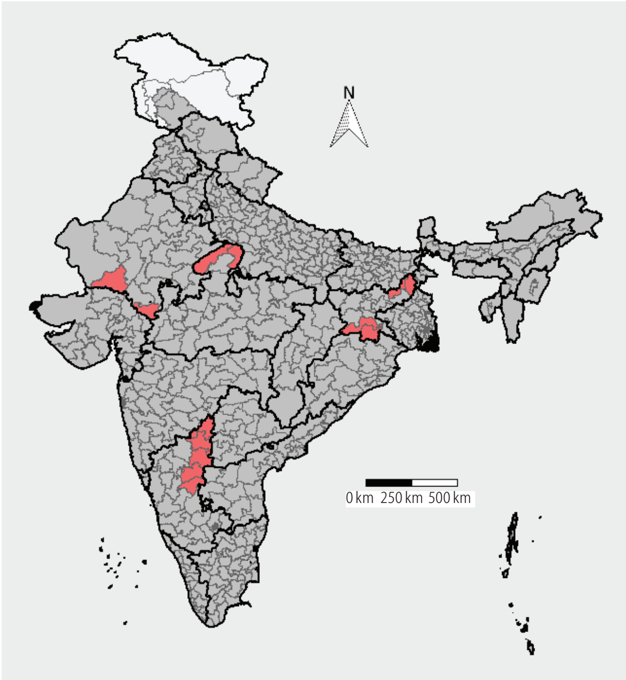


Figure A2: Map of PCs That Are in the Top Two Quintiles for Prevalence of All Four Child Malnutrition Indicators

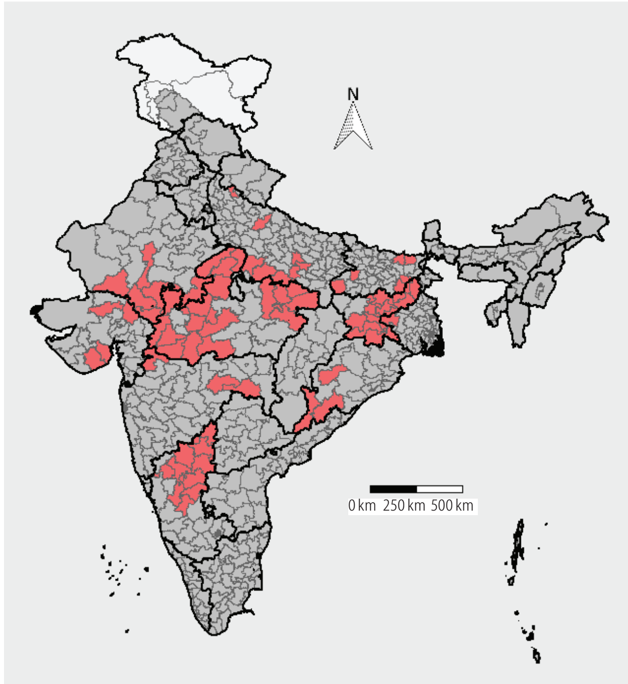


Figure A3: Map of PCs That Are in the Top Quintile for Prevalence of Anaemia and Bottom Two Quintiles for Prevalence of the Other Three Child Malnutrition Indicators

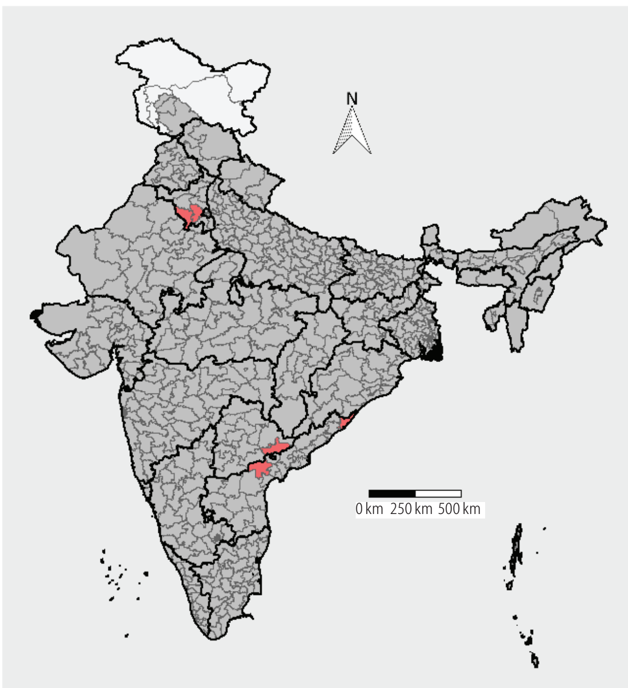


Figure 4: Map of PCs That Are in the Top Two Quintiles for Prevalence of Anaemia and Bottom Two Quintiles for Prevalence of the Other Three Child Malnutrition Indicators

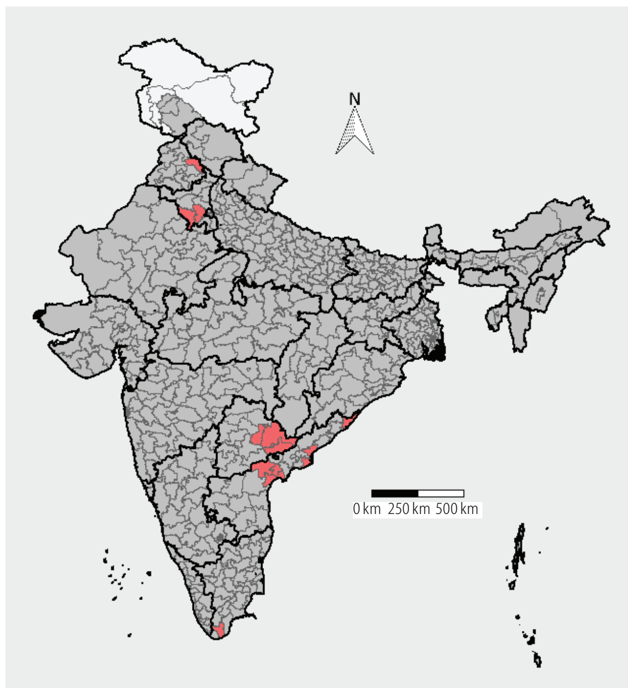


Figure A5: Map of PCs That Are in the Bottom Two Quintiles for Prevalence of All Four Child Malnutrition Indicators

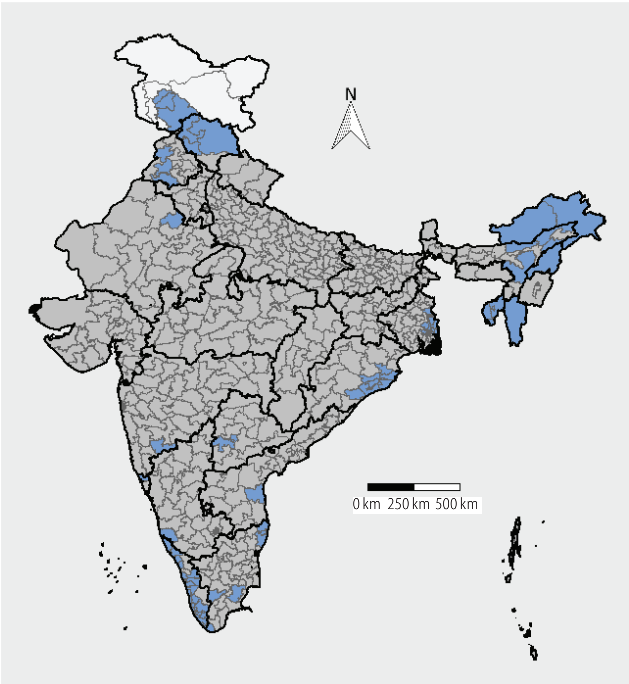
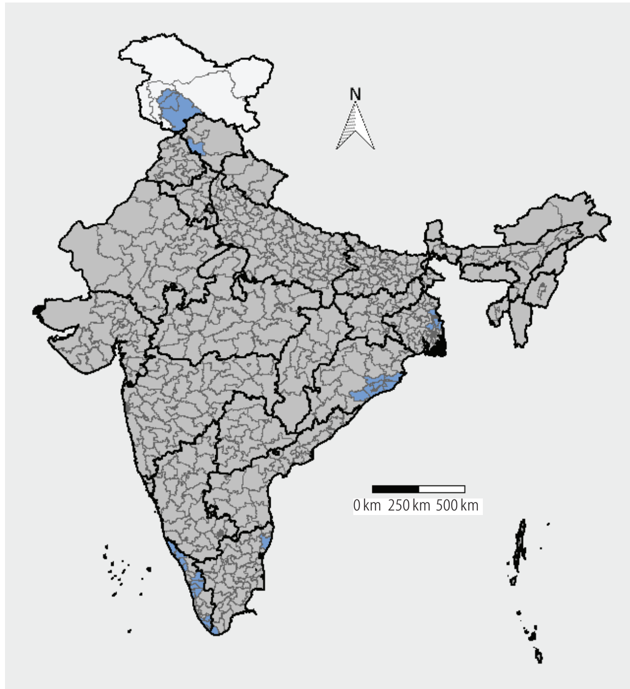


Figure A6: Map of PCs That Are in the Bottom Quintile for Prevalence of All Four Child Malnutrition Indicators



The maps in the article show the 2014 PC borders due to issues of data availability as the only existing shapefiles for India's PCs are for the 2014 PC borders.