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Understanding the Burden of Anaemia among Children in North-eastern States, India: Evidence From National Family Health Survey

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Abstract

The likely cause of childhood anaemia varies depending on the area of the world that the child lives in. Pregnant women and children are particularly vulnerable for anaemia. The 2011 estimates suggest anaemia affects around 800 million children and women (WHO). Childhood anaemia poses a major public health issue leading to an increased risk of child mortality, as well as the negative consequences of iron-deficiency anaemia on cognitive and physical development. The study is conducted to identify the areas where the nutritional level is poor leading to anaemia among children in North eastern states, India. The data from the fact sheet of NFHS-2, NFHS-3 and NFHS-4 is used. In the study, we have applied Spatial analysis to attain the significant determinants of anaemia among children and visualize the spatial patterns of anaemia among children across the Northeast states. This analysis provides a quantitative assessment of anaemia across the states and helps in identifying areas with statistically significant clustering of high values (hot spots) and low values (cold spots), as well as spatial outliers for anaemia. Bivariate and multivariate statistical tools are used for analysis. This analysis provides a statistical intra-assessment of relatively high and low performing areas with respect to geographical proximal areas. **Result:** In the analysis, the maximum anaemic children were observed in North and South districts of Sikkim and Changlang district of Arunachal Pradesh depicting the worse nutritional level whereas the good nutritional level is observed in Mamit, Aizawl and Champhai districts of Mizoram; Phek, Mon, Kiphire, Dimapur, Tuensang and Paren districts of Nagaland and Churachandpur district of Manipur.

Background

Anaemia is a condition in which the amount of red blood cells in the body is decreased below normal for your child**'s** age. It can make your child appear pale in colour and feel cranky, tired, or weak. The likely cause of childhood anaemia varies depending on the area of the world that the child lives in. Pregnant women and children are particularly vulnerable for anaemia. The 2011 estimates suggest anaemia affects around 800 million children and women (WHO). Childhood anaemia poses a major public health issue leading to an increased risk of child mortality, as well as the negative consequences of iron-deficiency anaemia on cognitive and physical development.

Data and methods

The present study was based on a publicly available National Family Health Survey (NFHS-4), 2015-16 fact sheets data. NFHS-4, the fourth in the NFHS series, provides information on population, health and nutrition for India and each state/ Union territory. NFHS-4 was conducted under the stewardship of the Minister of Health and Family Welfare, coordinated by the International Institute for Population Sciences, Mumbai. The survey covered a range of health related issues, including child health, maternal, fertility, malaria, reproductive health, infant and child mortality, non-communication diseases and HIV knowledge. The NFHS-4 fact sheets provides information on key indicators of all the districts. And helps to produce reliable estimates of most indicators for rural, urban and total of the districts as a whole[5]. We obtained fact sheet data for selected maternal health indicators of 87 districts of 8 states in northeastern states viz., 27 in Assam, 16 in Arunachal Pradesh, 9 in Manipur, 7 in Meghalaya, 8 in Mizoram, 12 in Nagaland, 4 in Sikkim and 4 in Tripura, respectively.

Spatial Analysis

Spatial analysis refers to "a general ability to manipulate spatial data into different forms and extract additional meaning as a result". Specifically, spatial analysis comprises a body of techniques "requiring access to both the locations and the attributes of objects" [6]. Spatial statistics quantify geographic variation in geographic variables, and it can identify violations of assumptions of independence required by many epidemiological statistics; and measure how populations, their

characteristics, covariates and risk factors vary in geographic space (Rushton and Lolonis 1996, Haining 1998).

Spatial autocorrelation

Spatial autocorrelation analysis was applied to summarise the extent to which persons with a similar health status tend to occur next to each other i.e., form spatial clusters[7]. Spatial autocorrelation statistics depend on the definition of neighbourhood relationships through which the spatial configuration of the sampled subpopulation was defined prior to analysis. High or low values for a random variable tend to cluster in space (positive spatial autocorrelation) or location tend to be surrounded by neighbours with very dissimilar values (negative spatial autocorrelation). We used a binary weight matrix to assign weights to the neighbours. This binary weight matrix assigns a weight of unity for neighbours and zero for non-neighbours. The spatial patterns were investigated by global measures that allowed for spatial clustering tests.The present study used exploratory spatial data analysis (ESDA) techniques to measure the spatial autocorrelation among districts that are spatially contiguous. The first measure used in this study is global Moran's *I*, which gives an indication of the overall spatial autocorrelation of a dataset. The second measure is a local indicator of spatial association (LISA) measure of local Moran's *I*, which indicates the "presence or absence of significant spatial clusters or outliers for each location" in a dataset.

Moran *I*

Moran's statistics: Global spatial autocorrelation, measured by Moran's I, captures the extent of overall clustering or quantify the degree of spatial autocorrelation that exists in a dataset across all the districts. A Moran's I value near +1.0 indicates clustering; 0 indicates randomness; and a value near -1.0 indicates dispersion. The value of Moran's I statistics ranges from -1 to 1, where positive values indicate observations with similar values being close to each other and negative values suggest observations with high values are near those with low values, or vice-versa.

Moran's I can be depicted in a scatter plot categorized into 4 groups as-

High-high: High values surrounded by high values
Low-high: Low values surrounded by high values
Low-low: Low values surrounded by low values
High-low: High values surrounded by low values

High-high, low-low is positive autocorrelation and high-low, low-high is negative autocorrelation.

Moran's *I* is defined as

$$\mathrm{I} = \frac{\mathrm{N}}{\sum_{\mathrm{i}}\sum_{\mathrm{j}} \mathrm{w_{ij}}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}$$

Where N is the number of spatial units indexed by I and j ; X is the variable of interest; $\bar{X}$ is the mean of X; and w_{ij} is an element of a matrix of spatial weights.

The expected value of Moran's *I* under the null hypothesis of no spatial autocorrelation is

$$E(I) = \frac{-1}{N\ -\ 1}$$

Its variance equals

$$Var(I) = \frac{NS_4 - S_3 S_5}{(N-1)(N-2)(N-3)\left(\sum_i \sum_j wij\right)^2} - (E(I))^2$$

Where

$$S_1 = \frac{1}{2}\sum_i \sum_j \left(w_{ij} + w_{ji}\right)^2$$

$$S_2 = \sum_i \left(\sum_j w_{ij} + \sum_j w_{ji}\right)^2$$

$$S_3 = \frac{N^{-1}\sum_i (x_i - \bar{x})^4}{(N^{-1}\sum_i (x_i - \bar{x})^2)^2}$$

$$S_4 = (N^2 - 3N + 3)S_1 - NS_2 + 3\left(\sum_i \sum_j w_{ij}\right)^2$$

$$S_5 = (N^2 - N)S_1 - 2NS_2 + 6\left(\sum_i \sum_j w_{ij}\right)^2$$

Local Indicators of Spatial Association (LISA) statistics

The index used to observe spatial autocorrelation at local level is Anselin's LISA (Local Indicator of Spatial Autocorrelation), which can be seen as the local equivalent of Moran's-*I*. LISA essentially measures the statistical correlation between the value in subarea *I* and the values in nearby subareas. Univariate LISA statistics is used for the purpose which measures the extent of spatial non-stationary and clustering to its neighbourhood values.

$$I_i = \ Z_i \sum_j w_{ij} z_j$$

Where observation z_i, z_j are in deviations from the mean from i^{th} location to j^{th} location and the summation over j such that only neighbouring values $j \varepsilon J_i$ are included. And w_{ij} is a spatial weight measuring the nearness of subareas i and j. For ease of interpretation, the weights w_{ij} may be in row standardized form, though this not necessary and by convention, w_{ij}=0.. LISA values close to zero indicate little or no statistical association among neighbouring values.
A positive LISA statistic identifies a spatial concentration of similar values. When the LISA statistic is negative, we have a spatial cluster of dissimilar values, such as an area with a high outcomes values surrounded by areas with low outcomes values.

For each location, LISA values allow for the computation of its similarity with its neighbours and also test its significance. Five scenarios may emerge: (a) location with high values with similar neighbours: high-high spatial clusters (red dot marks), also known as "Hot-Spots"; (b) location with low values with similar neighbours: low-low spatial clusters (blue dot marks), also known as "Cold spots", they represent positive spatial autocorrelation or locations neighbours: high-low (light pink dot marks); (d) locations with low values with high-value neighbours: low-high (light blue dot marks), these locations are "Spatial outliers" which represent negative spatial autocorrelation or locations surrounded by neighbours with dissimilar values; and (e) locations with no significant, there is no autocorrelation.

Northeastern states shape file were extracted from India shape file after downloading through Diva GIS, the final feature class had 87 polygons representing each survey district in NFHS-4. Then, selected estimates maternal health indicator from the districts factsheet were joined to the polygon dataset. We produced maps visualization, one of the first steps in exploratory spatial data analysis (ESDA) using QGIS, then, Moran's-*I* and LISA was carried out through GeoDa with 999 permutations and a pseudo p-value for cluster of <0.05 computed.

Results

Child Anaemia: Figure 1.1 represents the district wise coverage of anaemic children under five years, where green colour stands for high proportion and red colour for lowest proportion. Child anaemia has striking coverage variation among the Northeast part of country in this analysis. Percentage coverage is highest in East Garo Hills and South Garo Hills districts of Meghalaya whereas lowest in Kiphire, Zunheboto and Wokha districts of Nagaland; Cachar district of Assam and Serchipp and Champhai districts of Mizoram.

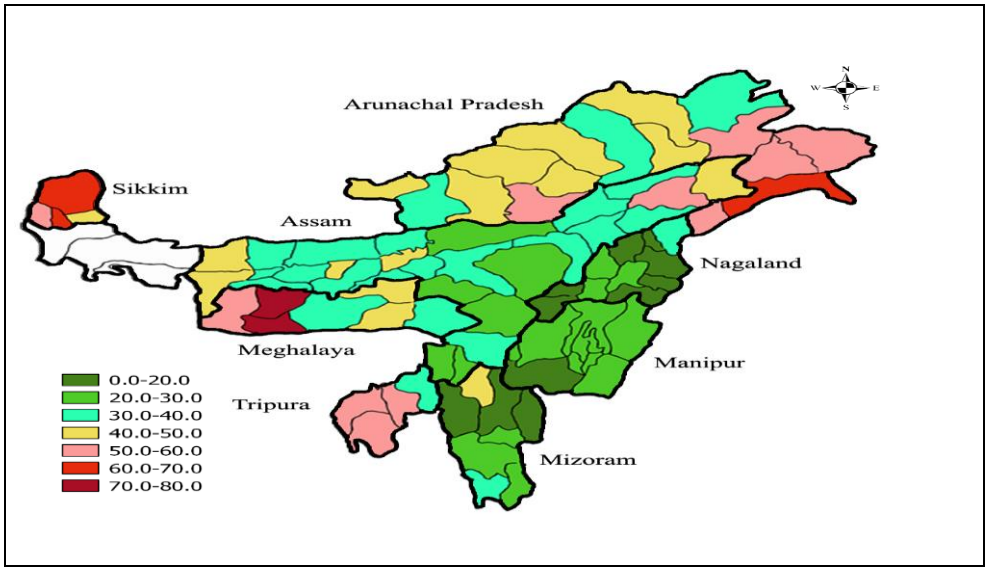


Fig 1.1 Percentage of anaemic children by districts

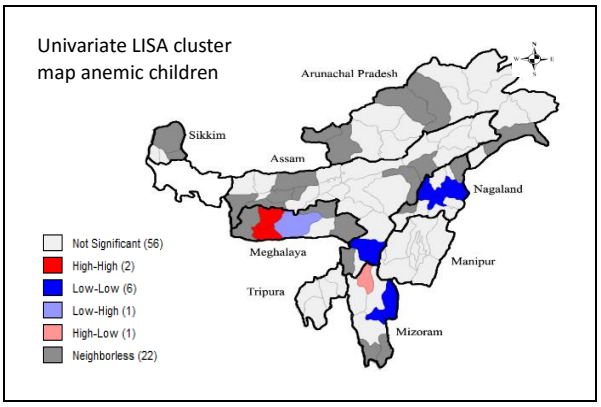


Fig 1.2 Univariate LISA Cluster map for anaemic childern by districs

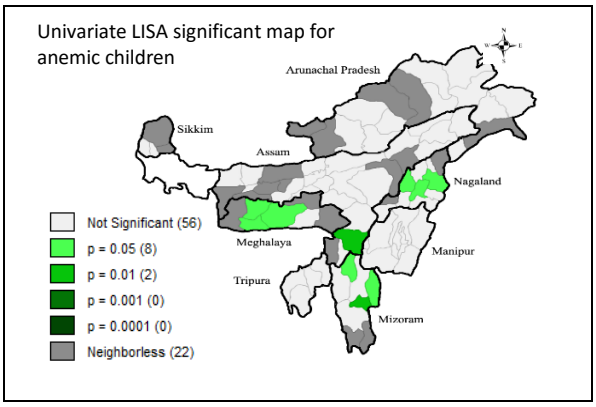
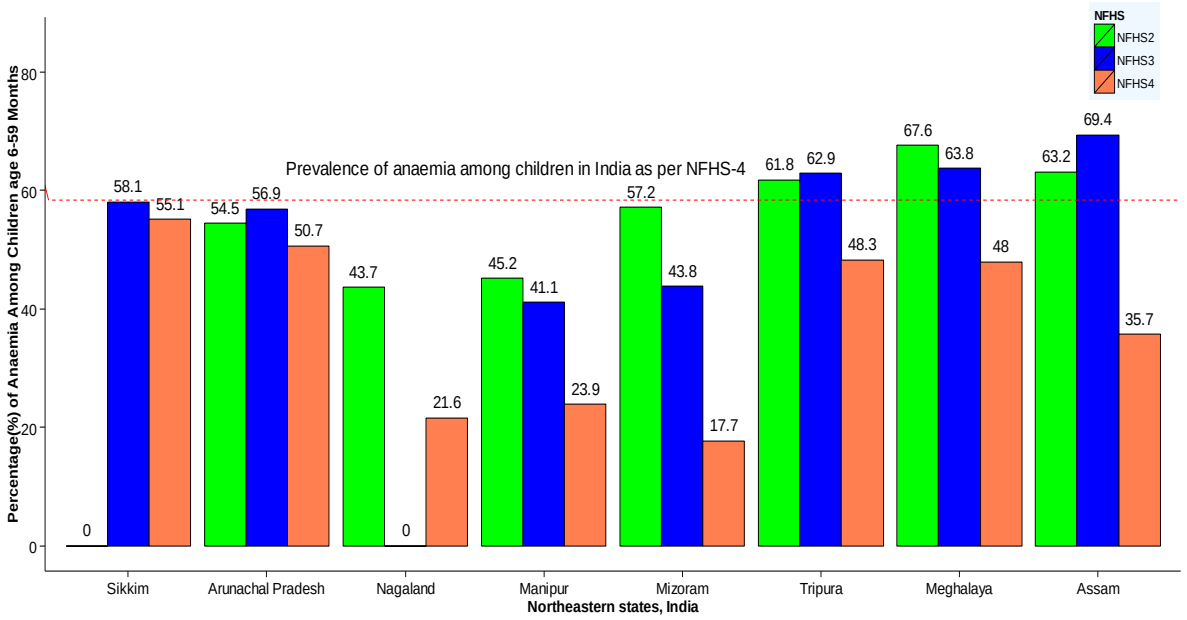


Fig 1.3 Univariate significant map for anaemic childern by districts



Conclusion

The indicator variable anaemia among children depicted the striking coverage variation across the north-east states, India in this analysis. The prevalence of anaemia among children was observed maximum in North and South districts of Sikkim and Changlang district of Arunachal Pradesh depicting the worse nutritional level whereas the good nutritional level was observed in Mamit, Aizawl and Champhai districts of Mizoram; Phek, Mon, Kiphire, Dimapur, Tuensang and Paren districts of Nagaland and Churachandpur district of Manipur. Low-low spatial association was found in Wokha districts of Nagaland; Cachar district of Assam and Serchhip and Champhai districts of Mizoram for child anaemia. High-high spatial association was found in East Garo Hills and South Garo hills districts of Meghalaya for child anaemia.

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