ORIGINAL RESEARCH PAPER

Volume-8 | Issue-7 | July - 2019 | PRINT ISSN No. 2277 - 8179

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH

UNDERNUTRITION IN CHILDREN UNDER FIVE YEAR IN NORTHEASTERN STATES, INDIA: A DISTRICT LEVEL GEOSPATIAL ANALYSIS

Community Medicine

Kh. Jitenkumar Singh ICMR-National Institute of Medical Statistics, New Delhi, India

Vekutulu Chiero* International Institute for Population Sciences, Mumbai, India *Corresponding Author

ABSTRACT

Introduction: Malnutrition is responsible for ill health; good health is not possible without good nutrition. The term malnutrition covers two conditions, one is 'undernutrition'—which includes stunting (low height for age), wasting (low weight for height), underweight (low weight for age). Undernutrition explains around 45% of deaths among children under five, mainly in low and middle-income countries. Five million children die every year due to malnutrition, of which two million are from India. The aim of this study is to identify the hotspot and cold spot clusters/areas of undernutrition i.e. stunting, wasting, and underweight in children in northeastern states.

Methods: This study used data collected in the fourth round of the National Family Health Survey (NFHS-4), 2015-2016. A total of 32,005 children under five years were included in the analysis. The Getis-Ord spatial statistical tool was used to identify high and low hotspots areas of undernutrition. The resultant Z score tells where features with either high or low values cluster spatially.

Results: The highest prevalence of stunting was observed in Ribhoi, Jaintia Hills, West Khasi Hills, East Khasi Hills in the district of Meghalaya, and Dhubri districts of Assam, and the highest prevalence of wasting was observed in South Garo Hills district of Meghalaya, Cachar district of Assam, and Upper Siang in Arunachal Pradesh, whereas the highest prevalence of underweight was observed in Dhubri, Goalpara and Darang district of Assam. Statistically significant hotspots of stunting were found mostly in the district of Assam and Meghalaya, for wasting, significant hotspots were mostly found in the district of Assam and Arunachal Pradesh, whereas in underweight most of the hotspot were found in the district of Assam and Meghalaya.

Conclusions: This study demonstrates the geographical variation of undernutrition in children under five years in northeastern states of India. The study illustrates a technique using geospatial data to understand how a nutrition situation in children varies across a district. Spatial distribution of health inequality is observed within the district. The districts with high hotspots of child undernutrition should be targeted with additional resources. Besides, further careful investigation of childcare practices is essential for assessing and measuring child health.

KEYWORDS

Stunting, Wasting, Underweight, Spatial autocorrelation, Moran's I, Hotspot analysis

INTRODUCTION

Good nutrition allows children to survive, grow, develop, learn, play, participate and contribute, while malnutrition robs children of their futures and leaves young lives hanging in the balance [1]. Malnutrition refers to deficiencies, excesses or imbalances in a person's intake of energy and/or nutrients. The term malnutrition covers two broad groups of conditions. One is 'undernutrition'—which includes stunting (low height for age), wasting (low weight for height), underweight (low weight for age) and micronutrient deficiencies or insufficiencies (a lack of important vitamins and minerals) [2, 3]. Malnutrition is responsible for more ill health than any other cause – good health is not possible without good nutrition. All forms of malnutrition are associated with various forms of ill health and higher levels of mortality. Undernutrition explains around 45% of deaths among children under five, mainly in low and middle-income countries [4, 5]. Globally in 2018, stunting affected an estimated 21.9 per cent or 149 million children under five, and wasting continued to threaten the lives of an estimated 7.3 per cent or 49 million children under five [6]. In 2018, more than half of all stunted children under five lived in Asia, and more than two thirds of all wasted children under five lived in Asia [6, 7]. Five million children die every year due to malnutrition, of which two million are from India [8]. Malnutrition has become a major health problem for children. Nearly half of all deaths in children under five are attributable to undernutrition; undernutrition puts children at greater risk of dying from common infections, increases the frequency and severity of such infections, and delays recovery [1]. India is home to the largest number of malnourished children in the world [9]. Therefore, it has become one of the greatest challenges to health care. Undernutrition effect all sexes and ages, however children are the most vulnerable victims.

In India, 38.4% of children under age five years are stunted. 21% of children under age five years are wasted. while 35.7% of children under age five years are underweight [10]. The prevalence of underweight among children in India is amongst the highest in the world, and nearly double that of Sub-Saharan Africa [11]. The challenges of widespread undernutrition among the infants and the children are the most important prevailing concerns in India [12].

Need for the study

The latest survey "Rapid Survey on Children – 2013-14" the Ministry of Women, and Child Development shows the deprived condition of children in the country [13]. In India, northeast region that contains small states namely Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura, were found to have, infant mortality rates (IMR) lower than the country's average of 34 deaths per 1000 live births in all the states except Assam (44), Arunachal Pradesh (36) and Meghalaya (39) according to Sample Registration System 2017 [14]. And northeast region is not only physically isolated from the rest of the country due to mountainous terrain and poor infrastructure, it also has diverse socio-cultural practices of bringing up children, which directly or indirectly effect the prevalence of undernutrition in these region due to its geographical location, tradition, culture, religious belief and social behaviour which significantly contributes to the nutritional status of children[8].

The northeastern region is lagging behind in every aspect including health [15]. The health care sector is unevenly distributed throughout the country, and there is an evident urban-rural disconnect, especially in the rural and the tribal areas more so of the northeastern states of India [16, 17]. Primary health care services exist but funtioning is poor. Although there has been improvement with the operation of NRHM for affordable and accountable quality health services to rural areas, the improvement has been quite uneven across region [15, 17], which have an impact on the health of children in the region.

In recent years, there has been a marked increase in the numbers of studies drawing on geospatial technique to either map health indicators or examine geographical access to services [18,19,20]. Georeferenced data available in NFHS-4 provide further opportunities to use geospatial technique to guide policy and practice in states and districts. Geospatial technique can identify the hotspots cluster or areas or pockets and provide policy-makers with the information needed to target areas of high prevalence and can assist district level policy makers in setting priorities. The aim of this study is to identify the hotspot and coldspot clusters/areas of undernutrition i.e. stunting, wasting, and underweight in children in northeastern states.

Data and Methods

Data source

This study utilizes data collected in fourth round of National Family Health Survey (NFHS-4), which was conducted during 2015-2016, it provides information on population, health, and nutrition for India and each state/ Union territory. NFHS-4 conducted under the Stewardship of Ministry of Health and Family Welfare (MoHFW), Government of India, 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 and provide information on key indicators of all the districts above state and national level. And helps to produce reliable estimates of most indicators for rural, urban and total of the districts as a whole. We obtained data for 86 districts of 8 states in northeastern states viz., 27 in Assam, 16 in Arunachal Pradesh, 9 in Manipur, 7 in Meghalaya, 8 in Mizoram, 11 in Nagaland, 4 in Sikkim and 4 in Tripura, respectively [10]. We used STATA 14, [Texas 77845USA College Station, Stata corp] with SVY command to take into account survey design i.e., sampling weight with clustering and strata.

Northeastern states shape file were extracted from India shape file after downloading through Diva GIS, the final feature class had 86 polygons representing each survey district in NFHS-4. Then, selected estimates maternal health indicator from the district factsheet were joined to the polygon dataset. We produced maps visualization, one of the first steps in exploratory spatial data analysis (ESDA) using QGIS-3.6.0, then, Moran's-*I* and LISA was carried out through GeoDa-1.12.1.161 with 999 permutations and a pseudo p-value for cluster of <0.05 computed. Hotspot analysis is done using ArcGIS-10.5.

Variables: Three indices of nutritional status i.e., (a) wasting (weight-for-height) (b) stunting (height-for-age) and (c) underweight (Weight-for-age) were assessed using the WHO references for Northeast Asia. The WHO Multicenter Growth References Study provides the standards for weight for age, weight for height and height for age for different ages and sexes. The classification of nutritional deficiency for the children was derived under-nutrition. Indices were classified into two categories present and not present i.e., recoded as 'yes' if the standard deviation is less than -200 (as the values of the variables were given as standard deviation and were not converted into z-scores) and 'no' for the rest of the values. Unit of analysis is child in the dataset.

Methods

In this study we used 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's *I* 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* 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.

Negative values indicate negative spatial autocorrelation and the inverse for positive values. Values range from −1 (indicating perfect dispersion) to +1 (perfect correlation). A zero value indicates a random spatial pattern.

The Global Moran's *I* and LISA analyses were conducted in the software package GeoDa with 999 permutations and a pseudo-p-value for a cluster of <0.05 specified.

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 outcome's values surrounded by areas with low outcomes values.

Hot spot analysis: Hotspot Analysis uses vectors to identify locations of *statistically significant* hot spots and cold spots in data by aggregating points of occurrence into polygons or converging points that are in proximity to one another based on a calculated distance. The analysis groups feature when similar high (hot) or low (cold) values are found in a *cluster.* The polygons usually represent administration boundaries or a custom grid structure. Two available methods are **Moran's I** (Global) and **Getis-Ord General G** (Global). Hotspot analysis *requires* the presence of clustering within the data. The two methods mentioned will return values, including a z-score, and when analysed together will indicate if clustering is found in the data or not. Data will need to be aggregated to polygons or point of incident convergence before performing the spatial autocorrelation analysis [21].

The Hot Spot Analysis tool calculates the Getis-Ord Gi* statistic for each feature in a dataset. The resultant Z score tells you where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighbouring features. A feature with a high value is interesting, but may not be a statistically significant hot spot. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbours is compared proportionally to the sum of all features; when the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score results [22].

The Getis-Ord local statistics is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{[n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}} \qquad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the number of feature and

$$\bar{X} = \frac{\sum_{i=1}^{n} x_j}{n} \qquad (2)$$

$$s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \qquad (3)$$

The G_i* statistics is a z- score so no further calculation is required.

The p-values are numerical approximations of the area under the curve for a known distribution, limited by the test statistic. The Gi* statistic returned for each feature in the dataset is a Z score [22]. A high z-score and a low p-value indicates a significant hotspot. A low negative zscore and a small p-value indicates a significant cold spot. The higher (or lower) the z-score, the more intense the clustering. A z-score near 0 means no spatial clustering [21].

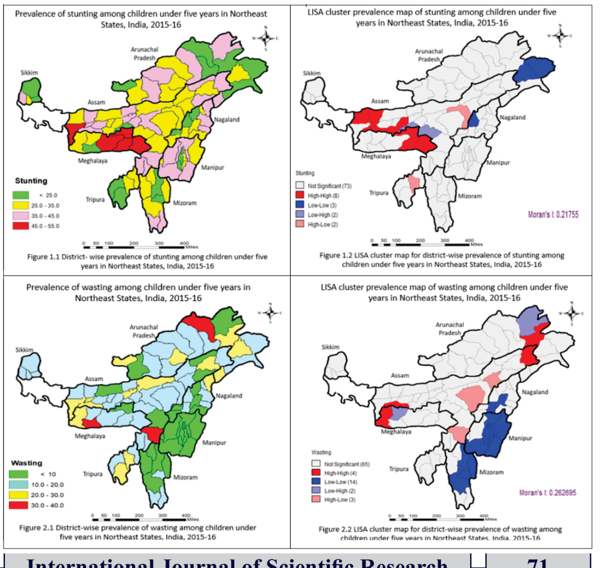


Figure 1.1 District- wise prevalence of stunting among children under five years in Northeast States, India, 2015-16

Figure 1.2 LISA cluster map for district-wise prevalence of stunting among children under five years in Northeast States, India, 2015-16

Figure 2.1 District-wise prevalence of wasting among children under five years in Northeast States, India, 2015-16

Figure 2.2 LISA cluster map for district-wise prevalence of wasting among children under five years in Northeast States, India, 2015-16

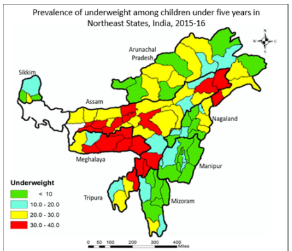


Figure 3.1 District- wise prevalence of underweight among children under five years in Northeast States, India, 2015-16

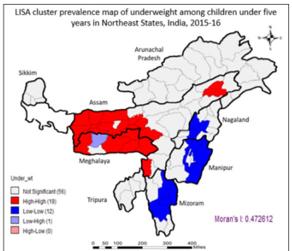


Figure 3.2 LISA cluster map for district-wise prevalence of underweight among children under five years in Northeast States, India, 2015-16

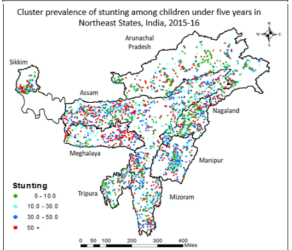


Figure 4.1 Cluster prevalence of stunting among children under five year in Northeast States, India 2015-16

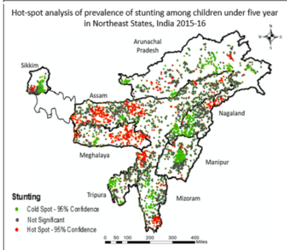


Figure 4.2 Hot-spot analysis of prevalence of stunting among children under five year in Northeast States, India 2015-16

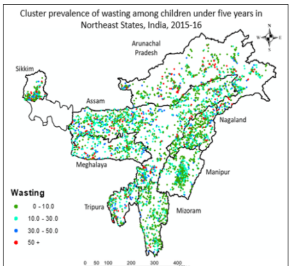


Figure 5.1 Cluster prevalence of wasting among children under five year in Northeast States, India 2015-16

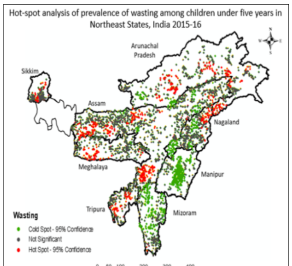


Figure 5.2 Hot-spot analysis of prevalence of wasting among children under five years in Northeast States, India 2015-16

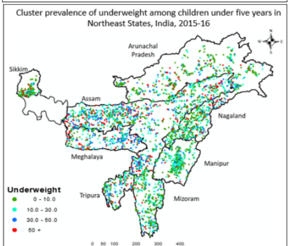


Figure 6.1 Cluster prevalence of underweight among children under five year in Northeast States, India 2015-16

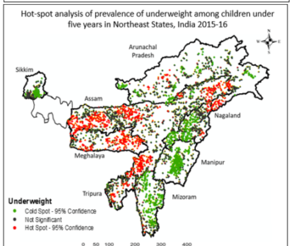
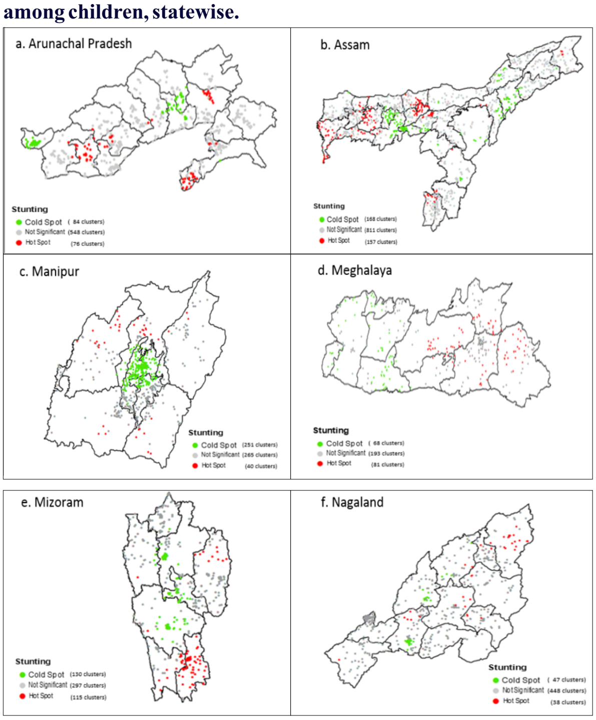
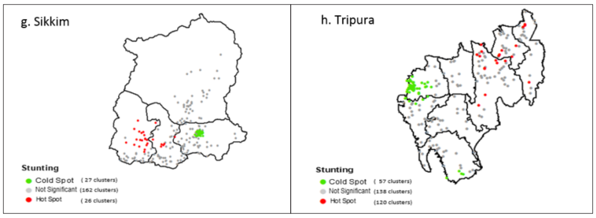


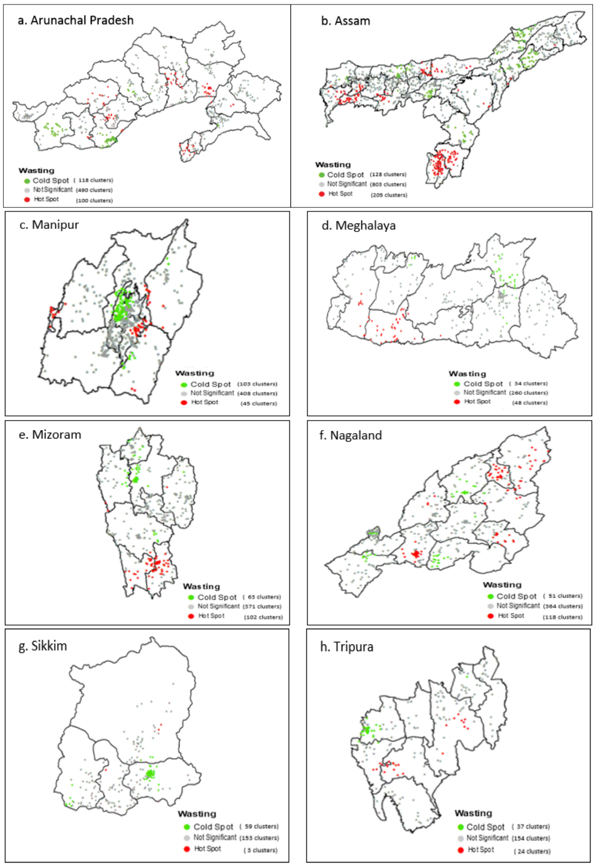
Figure 6.2 Hot-spot analysis of prevalence of underweight among children under five years in Northeast States, India 2015-16

7.1 (a-h) District- level hot spot analysis of prevalence of stunting among children, statewise.

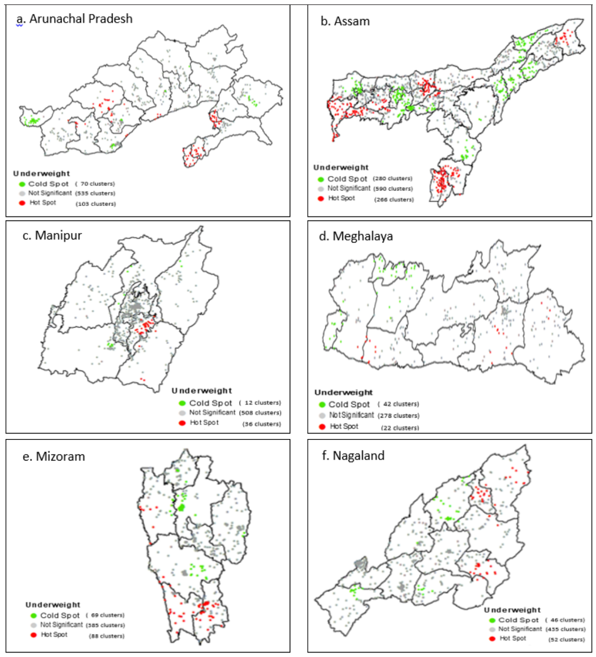


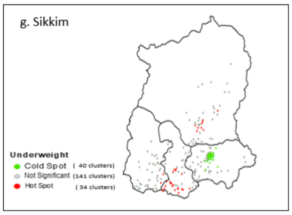


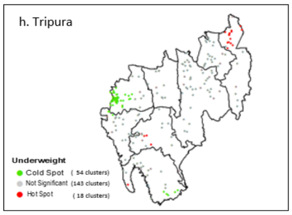
7.2 (a-h) District- level hot spot analysis of prevalence of wasting among children, statewise.



7.3 (a-h) District- level hot spot analysis of prevalence of underweight among children, statewise.







RESULT

Table 1: Number of children under five year by states in northeastern states, India, NFHS-4 (2015-16).

States	Number of districts	Number of clusters (PSU)	Number of children
Arunachal Pradesh	16	604	3851
Assam	27	1136	8855
Manipur	9	556	5256
Meghalaya	7	342	3823
Mizoram	8	542	4309
Nagaland	11	533	3825
Sikkim	4	215	898
Tripura	4	315	1188
Total	86	4243	32,005

Figure 1.1 represents the district wise prevalence of stunting among children under five years in northeastern states, India, 2015-16. The highest prevalence was observed in Ribhoi, West Khasi Hills, Jaintia Hills, East Khasi Hills district of Meghalaya, and Dhubri districts of Assam, and lower prevalence is detected in South Garo Hills district of Meghalaya, Wokha district of Nagaland, and Tawang district of Arunachal Pradesh. **Figure 1.2** shows the LISA cluster prevalence map of stunting the dark red color represents High-High cluster (8 district), dark blue indicates the low-low clusters (3 district), light blue indicates the low-high spatial outliers (2 district), and light red represent the high-low spatial outliers (2 district).

Figure 2.1 represents the district wise prevalence of wasting among children under five years in northeastern states, India, 2015-16. The highest prevalence was observed in South Garo Hills district of Meghalaya, Cachar in Assam, and Upper Siang in Arunachal Pradesh, and lowest is observed in Mokokchung and Peren district of Nagaland, and Aizawl district of Mizoram. **Figure 2.2** represents the LISA cluster prevalence map of wasting, the dark red color denotes High-High cluster (4 district), dark blue indicates the low-low clusters (14 district), light blue shows the low-high spatial outliers (2 district), and light red indicates the high-low spatial outliers (3 district).

Figure 3.1 shows the district wise prevalence of underweight among children under the age of five years in northeastern states, India, 2015-16. The highest prevalence was observed in Dhubri, Goalpara and Darang district of Assam, and lowest is observed in Mokokchung district of Nagaland, Aizawl district of Mizoram, and Imphal west district of Manipur. **Figure 3.2** represent the LISA cluster prevalence map of underweight, the dark red color signifies High-High cluster (19 district), dark blue indicates the low-low clusters (12 district), light blue shows the low-high spatial outliers (1 district), and light red indicates the high-low spatial outliers (0 district).

Figure 4.1 shows cluster prevalence of stunting among children under five years in northeastern states, India, 2015-16. The green spot depicts low prevalence, whereas the red spot shows high prevalence. **Figure 4.2** depicts the hot spots and cold spots for stunting at 90-99% confidence limit, results reveals that most of the hot spots clusters are in Meghalaya and Assam, whereas most of the cold spot is in Nagaland, Manipur, Mizoram, Tripura, and Sikkim.

Figure 5.1 shows cluster prevalence of wasting among children under five years in northeastern states, India, 2015-16. The green spot depicts low prevalence, while the red spot shows high prevalence. **Figure 5.2** depicts the hot spots and cold spots for wasting at 90-99% confidence limit, hot spot analysis shows that most of the hot spots cluster are in Assam and Arunachal Pradesh, while most of the cold spot is in Nagaland, Manipur, and Mizoram.

Figure 6.1 shows cluster prevalence of underweight among children under five years in northeastern states, India, 2015-16. The green spot depicts lowest prevalence, whereas the red spot shows highest prevalence. **Figure 6.2** depicts the hot spots and cold spots for underweight at 90-99% confidence limit, result reveals that most of the hot spots clusters are in Meghalaya, Assam and Arunachal Pradesh, while most of the cold spot is in Nagaland, Manipur, Mizoram, and Sikkim.

Figure 7.1 (a-h) shows the results of district level hotspot analysis of stunting in each state, maximum hotspot cluster falls in the district of Tirap, East Kameng, and Lower Dibang Valley in Arunachal Pradesh, whereas, most of the cold spot cluster falls in the district Tawang, East Siang, and Upper Siang. In Assam, maximum hotspot cluster falls in the district of Udalguri, Darrang, and Barpeta, while, most of the cold spot cluster falls in the district of Nalbari, Kamrup, and Dispur. In Manipur, maximum hotspot cluster falls in the district of Tamenglong and Senapati, while, most of the cold spot cluster falls in the district of Imphal East, Imphal West, Bishnupur, and Thoubal. In Meghalaya, maximum hotspot cluster falls in the district of West Khasi Hills, Ribhoi and Jaintia hills, whereas, most of the cold spot cluster falls in the district of South Garo Hills, and East Garo hills. In Mizoram, maximum hotspot cluster falls in the district of Sahai, Lawngtlai, and Champhai, whereas, most of the cold spot cluster falls in the district of Aizawl, Serchip, and Lunglei. In Nagaland, maximum hotspot cluster falls in the district of Mon, whereas, most of the cold spot cluster falls in the district of Kohima and Wokha. In Sikkim, maximum hotspot cluster falls in the west and south district, whereas, most of the cold spot cluster falls in the East district. In Tripura, maximum hotspot cluster falls in the district of Dhalai and North Tripura, while, most of the cold spot cluster falls in the district of West Tripura.

Figure 7.2 (a-h) shows the results of district level hotspot analysis of wasting in each state, maximum hotspot cluster falls in the district of Tirap, Lower Dibang Valley, and East Saing in Arunachal Pradesh, while, most of the cold spot cluster falls in the district West Kameng, Papumpare. In Assam, most of the hotspot cluster falls in the district of Goalpara, Cachar, Karimganj, Hailakandi, whereas, most of the cold spot cluster falls in the district of Marigaon, Dhemaji, Sibsagar. In Manipur, most of the hotspot cluster falls in the district of Imphal East and Toubal, while, most of the cold spot cluster falls in the district of Imphal West and Chandel. In Meghalaya, most of the hotspot cluster falls in the district of West Garo Hills, and South Garo hills, whereas, most of the cold spot cluster falls in the district of Ribhoi. In Mizoram, most of the hotspot cluster falls in the district of Sahai, and Lawngtlai, while, most of the cold spot cluster falls in the district of Aizawl and Kolasib. In Nagaland, maximum hotspot cluster falls in the district of Kohima, Lonleng, and Mon, whereas, most of the cold spot cluster falls in the district of Phek and Mokokchung. In Sikkim, most of the hotspot cluster falls in the west and North district, whereas, most of the cold spot cluster falls in the East district. In Tripura, most of the hotspot cluster falls in the district of Dhalai and South Tripura, while, most of the cold spot cluster falls in the district of West Tripura.

Figure 7.3 (a-h) shows the results of district level hotspot analysis of underweight in each state, most of the hotspot cluster falls in the district of Tirap, Lohit, and Kurung Kumey in Arunachal Pradesh, whereas, most of the cold spot cluster falls in the district Tawang. In Assam, most of the hotspot cluster falls in the district of Udalguri, Darrang, Dhubri, Goalpara, Karimganj and Hailakandi, whereas, most of the cold spot cluster falls in the district of Nalbari, and Dhemaji. In Manipur, maximum hotspot cluster falls in the district of Thoubal, whereas, most of the cold spot cluster falls in the district of Churachandpur. In Meghalaya, most of the hotspot cluster falls in the district of and East Khasi Hills, and South Garo Hills whereas, most of the cold spot cluster falls in the district of west Garo hills. In Mizoram, maximum hotspot cluster falls in the district of Sahai, and Lawngtlai, whereas, most of the cold spot cluster falls in the district of Aizawl, and Lunglei. In Nagaland, most of the hotspot cluster falls in the district of Kiphire and Longleng, whereas, most of the cold spot cluster falls in the district of Mokokchung, and Peren. In Sikkim, maximum hotspot cluster falls in the north and south district, whereas, most of the cold spot cluster falls in the East district. In Tripura, maximum hotspot cluster falls in the district of North Tripura, whereas, most of the cold spot cluster falls in the district of West Tripura.

CONCLUSION

This study exhibited district level geographical variation of stunting, wasting, and underweight in children under five years in northeastern states, India. Amongst the three-nutritional status, stunting has a higher prevalence. Geographic barriers to child health possibly will comprise of climatic settings, as well as social and economic characteristics that cluster geographically, causing a spatial dispersal of health inequality. Therefore, more effort ought to be given toward the certain significant hotspot area or region which displays high prevalence [23]. The above evidence demonstrates that the prevalence of undernutrition is high in this region, and is a public and community health problem. The challenge of child health is enormous in this area. Hence further careful investigation in childcare practices is essential for assessing and measuring child health. The government must give more additional effort, and action to improve child undernutrition in the district where the prevalence is high. [24, 25]

Limitations and advantages of geospatial techniques

The geospatial techniques used in this paper have respective advantages and limitations for policy makers. The choropleths map, which does not need georeferenced data, presented in this study based on prevalence are easy to carry out and present a visual representation of direct estimates that is easy to interpret. The presence of spatial clustering is examined by Moran's I, a measured of spatial autocorrelation, in a dataset, is a requisite for hotspot analysis. The result indicates that clustering exists within the dataset for high positive values, and can continue with performing the hotspot analysis. Hotspot analysis, a geospatial technique, is to identify locations of clusters of statistically significant hotspots and cold spots by aggregating points of occurrence into converging points or polygons, usually represent administrative boundaries [26]. There are also possible limitations associated with the use of NFHS-4 data. Measurement error in NFHS/DHS will also tend to increase the standard deviations, leading to potential over-estimates of the prevalence of malnutrition [27].

Ethical approval: The study is based on data available in the public domain, therefore no ethical issue is involved.

Funding: No funding sources

Competing Interests: The authors declare that they have no competing interests.

Conflicts of Interest: None.

Author Contributions: Conceived and designed the experiments: JK. Performed the experiments: JK and VC. Analyzed the data: JK and VC. Wrote the paper: JK and VC.

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