Geostatistical Exploratory Analysis on Child Malnutrition and its Determinants in India

Mandadi, R. R.,[1*] Tripathi, N. K.,[2] Pal, I.,[3] Mozumder, C.[4] and Gonzales, A. L.[5]
Asian Institute of Technology, Thailand
E-mail: ranadheer@ait.ac.th,[1] nitinkt@ait.ac.th,[2] indrajit-pal@ait.ac.th,[3] chitrini@ait.ac.th,[4] algonzales@mmsu.edu.ph[5]
[*]*Corresponding Author*

DOI: https://doi.org/10.52939/ijg.v19i6.2699

Abstract

Child malnutrition is often the most common factor that causes child mortality rate. In the study of child malnutrition, there is limited evidence on spatial analysis to identify spatial trends and hotspots of indicators and contextual factors contributing to geographical inequalities in child malnutrition. This study aims to investigate the spatial distribution and heterogeneity of Malnutrition across districts and states of India and examine the influence of determinants on wasting, stunting, and underweight children under five-year-of age. The spatial variation in Malnutrition and the influencing determinants were determined across India at district levels using the National Family Health Survey 3 and 4 (2006–16) data. Results show that out of the 640 districts in India, a very high prevalence of stunting, wasting, and underweight occurs in 236, 472, and 370 districts, respectively. The spatial error regression model showed that maternal health, such as low mother BMI, anemia during pregnancy, absence of antenatal care, early marriage and pregnancy, and lack of improved sanitation facilities in the household, were the most significant factors influencing Malnutrition in India. Furthermore, the Bivariate LISA analysis revealed that malnutrition prevalence was higher in the geographical pockets where maternal care is low and mainly clustered in the country's western, central, and eastern districts. The influencing factors in every malnutrition indicator vary in different districts. A notable observation was that the factors influencing a larger spatial scale (state level) might not necessarily be the attributing factors to the prevalence and occurrence of Malnutrition at a smaller spatial scale (district level). The geocoded data is more detailed using household level was used to show the chronic areas of Malnutrition and develop a strategy/policy to reduce Malnutrition efficiently.

Keywords: Child Malnutrition, Choropleth Map, Spatial Analysis, Stunting Underweight and Wasting

1. Introduction

Malnutrition is one of the most critical conditions and is responsible for higher mortality levels; children under five years are vulnerable to Malnutrition. Malnutrition is the primary cause of a child's death as it lowers infection resistance and is a socio-economic problem restricting development worldwide [1]. Child malnutrition manifests as being underweight, stunting, and wasting, a clinical sign of nutrient deficiency [2]. The World Health Organization [3] established an anthropometric measurement guideline for Malnutrition as *wasting* or low weight-for-height, which indicates inadequate food intake causing the child to lose weight; *stunting* or low height-for-age, which indicates long-term insufficient nutrient intake (chronic Malnutrition); and *underweight* or low weight-for-age which is a composite index of wasting and stunting. Child malnutrition is not just about the lack of nutritious food; it is a combination of multiple causes, such as the frequent occurrence of disease, poor healthcare practices, accessibility, and other social services. More than two decades ago, The United Nations International Children's Emergency Fund [4] created a conceptual framework that outlines the multifactorial determinants of child malnutrition. That includes economic and employment situations, access to food, good sanitation, awareness, social and institutional practices, program implementation, and data availability. This framework evolved as it continuously incorporated new knowledge and evidence on the impacts, consequences, and causes of Malnutrition.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

Several experts identified ancillary factors potentially responsible for Malnutrition, such as incidence of diarrhoea or acute respiratory infection (ARI) for the child, food insecurity, low maternal education and lack of vitamin supplements or fortified food, access to clean drinking water, sanitation infrastructure facilities, hygiene knowledge and practices, lack of access to health services, inadequate child feeding practices and unavailability of food [5]. Food insecurity is a persistent problem in most countries. According to the 2020 Global Report on Food Crises (GRCF), as mentioned by [6], ~ 135 million people in 55 countries and territories were experiencing acute food insecurity in 2019. Household sanitation reduces the risk of infection and positively associates with linear growth in children [7].

Adequate nutrition is requisite for human development. Poor nutrition in the first 1000 days of a child's life can lead to stunted growth, which is associated with impaired cognitive ability and reduced school and work performance [8]. Malnourished children fail to attain optimal growth and development, physical ability to work, and economic productivity in a later phase of life [1]. Despite the improving economy and largest anti-malnutrition program, India is among the countries with the worst child malnutrition level [9]. Malnutrition is a chronic problem and a longstanding challenge for India. Despite decades of investment to tackle this problem, India's child malnutrition rates are still one of the most alarming worldwide, where the bane of child and maternal Malnutrition is responsible for 15% of India's total disease [10]. However, malnutrition prevalence is not equally distributed across India, where vast spatial heterogeneity in social, cultural, demography, and economy [11]. With these considerations, a different approach should be adopted to plan policies and interventions to reduce Malnutrition that will suit a particular geographical location.

It is evident from the existing literature that there is a need to examine the spatial distribution of childhood malnutrition in India to help improve programs by allocating limited resources to priority districts. Therefore, this study focuses on understanding the spatial distribution and heterogeneity of Malnutrition across the districts and states of India and examines the determinants of wasting, stunting, and underweight in children under the age of five. Spatial analysis using GIS brings a new approach in understanding priority problems at a broad scale, thus identifying actual need-based problems and formulating solutions for the malnutrition crisis in India.

2. Data Source

This study used the secondary data from the National Family Health Survey (NFHS) of India from 2005-2006 (NFHS-3) and 2015–16 (NFHS-4) at the state and district level, respectively. The details about the sampling procedure of the survey can be found in Survey (DHS) under USAID (https://dhsprogram.com/data/dataset/India_Standard-DHS_2015.cfm?flag=1).

The data factsheets provide comprehensive information on fertility, mortality, maternal and child health, including child nutrition status and factors influencing it, such as immediate, intermediate, and underlying determinants were adopted from the UNICEF conceptual framework for the states and districts of India. Earlier data of NFHS-3 was limited to state representation covering 29 states with a household sample size of 109,000 and a sample representing 230,000 women aged 15-49 years and 200,000 below aged five children were tested on health and nutrition indicators, whereas for NFHS-4 data covered states (29 + 7 union territories) and districts of 640 according to 2011 national census with a sample size of 566,200 households representing 625,104 women aged 15–49 years and 265,653 below age five children in India).

This study was conducted at the state and the district level covering two different survey periods, 2005-2006 (NFHS-3) and 2015–16 (NFHS-4). Comparison between state and district levels is a limitation due to an unequal number of states and districts from the earlier data set compared to the latest data of NFHS-4. The digital administrative shapefile of the state and district of 2005 and 2016 was obtained from GitHub (https://github.com/datameet/maps/tree/master/Districts), which is shared under Creative Commons Attribution 2.5 India license. The maps were re-projected in WGS 1984 UTM zone 43N for conducting spatial analysis. This study did not include parts of Jammu & Kashmir, as the survey estimates were unavailable for these areas.

2.1 Data Management

This study classified Malnutrition based on the factors of immediate determinants, nutrition-specific interventions, and underlying determinants. The critical determinants of Malnutrition were chosen based on the conceptual frameworks from previous studies, particularly UNICEF (1990). Of the many influencing factors from UNICEF Framework, this study selected specific factors associated with malnutrition indicators.

- The **immediate determinants** of child malnutrition are related to the child's diet and mother's breastfeeding practice, maternal health condition (e.g. low mother BMI and anemia during pregnancy), and prevalence of non-communicable diseases (diarrhoea and acute respiratory infection causing high fever) in a child.

- The **nutrition-specific interventions** are the programs by the government [8]. These are classified under maternal healthcare and supplementation support, such as antenatal care services during pregnancy and provision of iron and folic acid supplementation in the first 100 days of pregnancy. Childcare is also another component that includes immunization and vitamin A supplementation. Government assistance schemes such as food supplementation to registered pregnancies in rural areas and financial assistance for institutional delivery under the JSY program [9]

- The **underlying determinants** included household conditions such as sanitation, drinking water sources, access to total electricity and clean cooking fuel, and early marriage and pregnancy [11].

3. Method

To analyze the spatial clustering and dependency of child nutrition outcomes and predictors at the state and district level. A series of thematic maps were also developed using ArcMap and Geoda using Geostatistical tools such as Local Indicator Spatial Autocorrelation for (Univariate Moran's I), and a set of Spatial regression models were adopted to analyze the factor spatial and child nutrition outcomes. Finally, the fit model was chosen based on R-Square and AIC (Akaike information criterion) value. Bivariate LISA is adopted to understand the spatial relation and dependency between malnutrition indicators and predictors, illustrated in Figure 2. State and District level thematic maps were generated to examine the geographical variation of Malnutrition based on WHO standard classification [12] for assessing the severity of Malnutrition by percentage prevalence ranges of three indicators among children less than five years of age were followed.

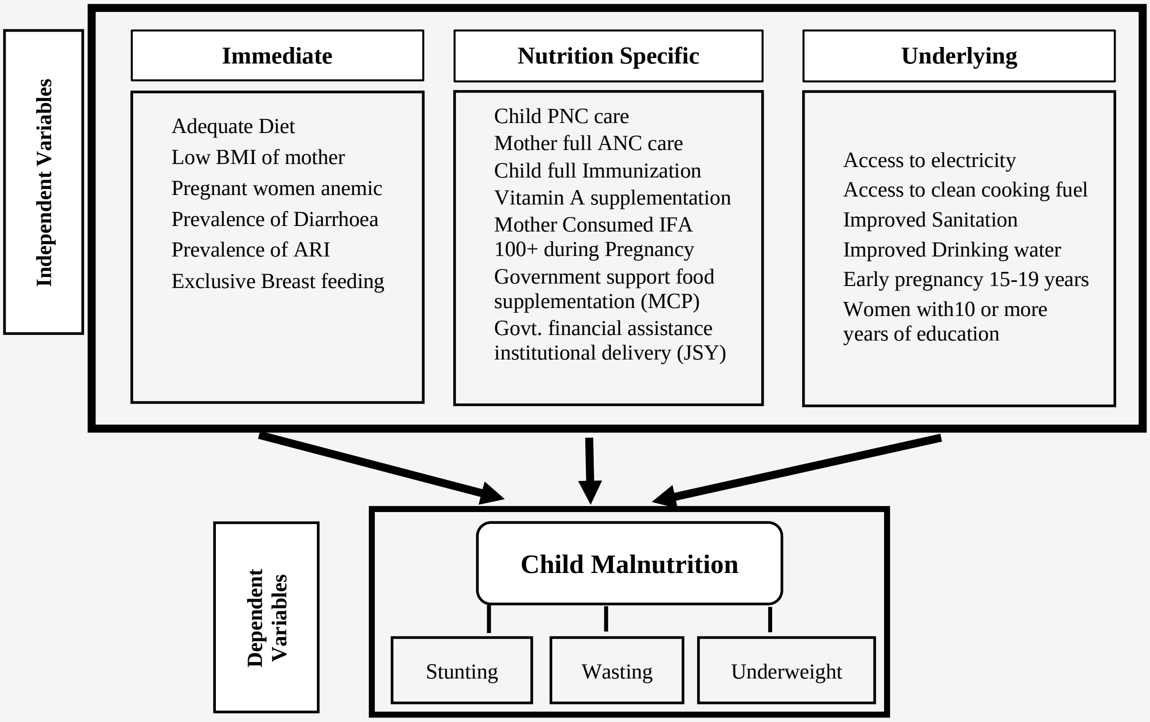

Figure 1: Overall research analysis of relationships of various variables with dependent variables for child malnutrition

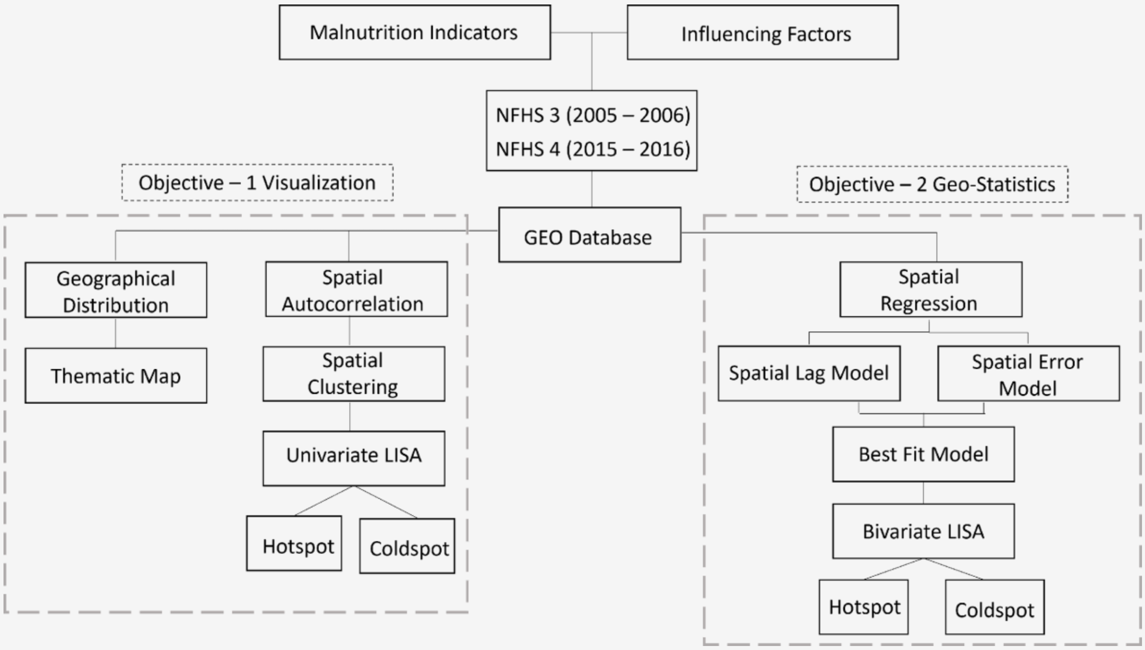

Figure 2: Geospatial data analysis and mapping of malnutrition in India

To examine spatial clustering of child nutrition outcomes- Spatial Autocorrelation was performed by Moran's I statistic. The results can range from -1 to 1, where positive results indicate a positive spatial correlation while negative results indicate a negative correlation. Zero result means no spatial autocorrelation or no linear correlation. The basic formula of Moran's I is as below [15]:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}\ (x_i - x_m)(x_j - x_m)\ /\ \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}}{\sum_{i=1}^{n}(x_i - x_m)^2\ \ /\ n}$$

Equation 1

Where:

x_i is the value at i^{th} district, x_j is the value at j^{th} district, which is the neighbour of x_i, x_m is the mean value of the variable x, w_{ij} is the weighted coefficient value at (i,j) districts of the weight matrix, and n, m is the spatial units of x.

Local Indicators of Spatial Autocorrelation (LISA) measure the extent of autocorrelation among the neighbourhood districts. To perform LISA, a spatial weight matrix was adopted for which a spatial weight matrix was devised. (*w*) of first-order using the Queen's contiguity method (neighbours sharing a common boundary of non-zero length). After spatial dependency was analyzed, LISA maps are helpful in identifying the local hotspot and cold spot of a univariate and bivariate variable over a space. The LISA values allow the computation of its similarity with its neighbourhood districts and test each location's significance. In this analysis, five scenarios may take place cluster with high values - hot spots (districts with high values, with similar neighbours), cluster with low values – cold spots (districts with low values, with similar neighbours), and a spatial outlier in which (districts with high values surrounded by low-value neighbours and vice-versa) and no significant local autocorrelation [15].

The *special choropleth map* is a cluster map showing the locations with a significant local Moran's *I* statistic classified by the type of spatial autocorrelation where hotspots are represented by red colour, blue represents the cold spots, and the light blue and light red colour is the spatial outliers. State and District level thematic maps were generated to examine the geographical variation of Malnutrition based on WHO standard classification [14] for assessing the severity of Malnutrition by percentage prevalence ranges of three indicators among children less than five years of age were followed. To examine spatial clustering of child nutrition outcomes- Spatial Autocorrelation was performed by Moran's I statistic. The results can range from -1 to 1, where positive results indicate a positive spatial correlation while negative results indicate a negative correlation. Zero result means no spatial autocorrelation or no linear correlation. The basic formula of Moran's I is as below [15]. The study confirms the significant spatial autocorrelation in child nutrition outcomes across districts of India.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Spatial regression models were adopted ("Spatial Lag" and "Spatial Error" Models) to analyze the spatial influence and relation between child nutrition indicators and factors influencing. The spatial lag model assumes that the dependent variable in one area is affected by the dependent variable nearby. Figure 3 shows the spatial lag model.

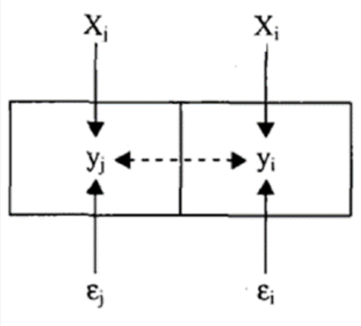

Figure 3: Basic concept for spatial lag model [17]

$$y_i = \delta \sum_{J \neq 1} w_{iJ} y_j + \beta X_J + \varepsilon_J$$

Equation 2

Where:

Y_i is a dependent variable denoting the malnutrition prevalence for the i^{th} district, ρ is the spatial autoregressive coefficient, W_{ij} is a spatial weight matrix and proximity between district i and j, Y_j is the prevalence of Malnutrition in the i^{th} district, β is a vector of regression model coefficients X_j is the predictor variable, and ε_j is a vector of independent and identically distributed error terms [18].

The Spatial Error Model measures the spatial dependency in error terms and is referred to as nuisance dependence. It assumes that the residuals correlate in the neighbourhoods of the spatial units (Figure 4).

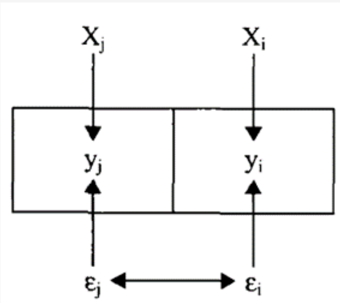

Figure 4: Basic concept for spatial error model [17]

$$Y_i = \beta X_j + \lambda \sum_{j \neq 1} W_{ij} Y_j \varepsilon_j + \varepsilon_i$$

Equation 3

Where:

Y_i denotes the prevalence of Malnutrition for the i^{th} district, λ is the spatial autoregressive coefficient, Y_j is the prevalence of Malnutrition in the j^{th} district, and W is a spatial weight matrix used to compute spatial lagged error terms W_{ε}. β means regression coefficients of the explanatory variable and X_j are the predictor variable, and ε_i is the residual [18].

4. Results

4.1 Malnutrition Prevalence at State Level

The levels of child malnutrition prevalence map at the state level from NFHS-3 (2005-06) and NFHS-4 (2015-16) showed all-around improvement over the last decade. The stunting of children in India was gradually reduced by 10% in the last few years. However, a striking geographical disparity was observed where 17 states with an extremely high (>40%) stunting prevalence in the NFHS-3 survey was reduced to 5 states at NFHS-4. The states such as Uttar Pradesh, Madhya Pradesh, Jharkhand, Bihar, and Meghalaya remained with a very high stunting prevalence which is above the national average of 25% even in NFHS-4. Two states remained stunted below the national standards of 25% or less stunting prevalence even after a decade. On the other hand, there was an improvement in 2 states in 2005-2006 to 14 states in 2015-2016 which are below the national average.

Wasting, an acute form of Malnutrition, has witnessed an uptick in the past decade from 2006 to 2016 by 9%. In the last NFHS-4 survey, 28 states suffered from very high wasting (>15%) compared to the previous 19 states in NFHS-3. With this, child wasting was more pronounced across India, as shown in Figure 5. According to NFHS-4, out of 36 states, only Mizoram and Manipur show a low prevalence of child wasting. States such as Punjab, Andhra Pradesh, Uttar Pradesh, Sikkim, and Assam are worse in child wasting. The prevalence of children underweight in India from 2006-2016 remained at a higher scale. Even after a decade, underweight and an enormous geographical area of India remained high, as shown in Figure 6. The distribution of Malnutrition is significantly uneven across the large geographical area of India. Most states attributing to very high stunting prevalence are clustered in the country's central (99) and eastern regions (69).

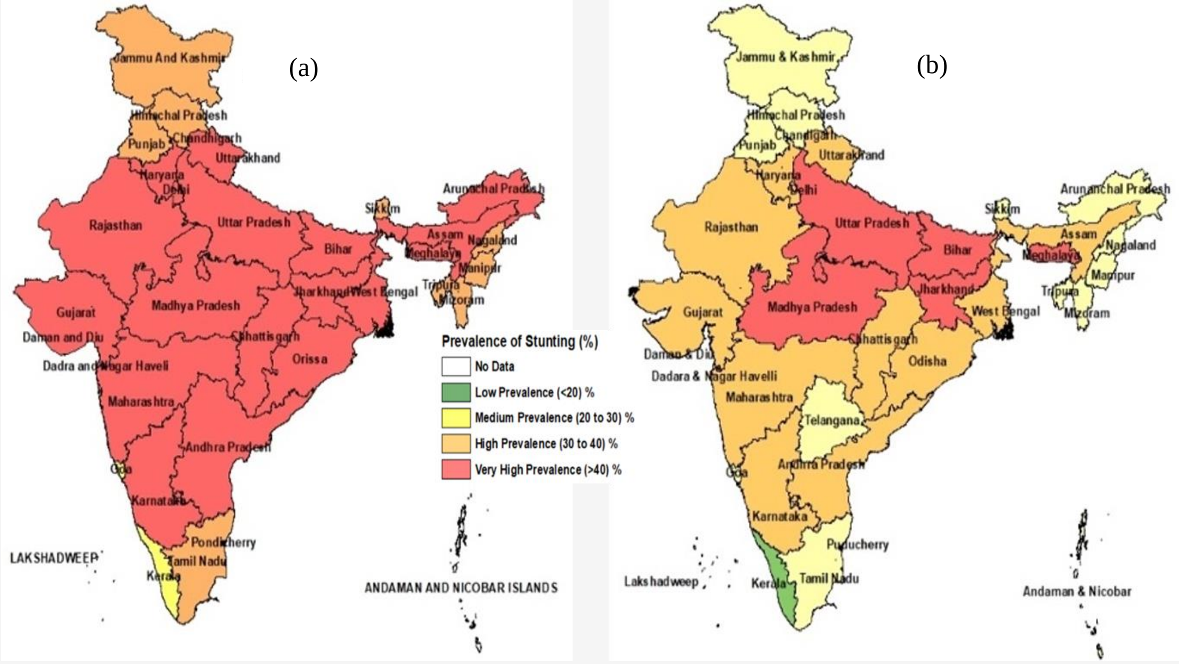

Figure 5: Stunting prevalence of malnutrition in the last decade (a) 2005-2006 (b) 2015-2016 at the state level in India

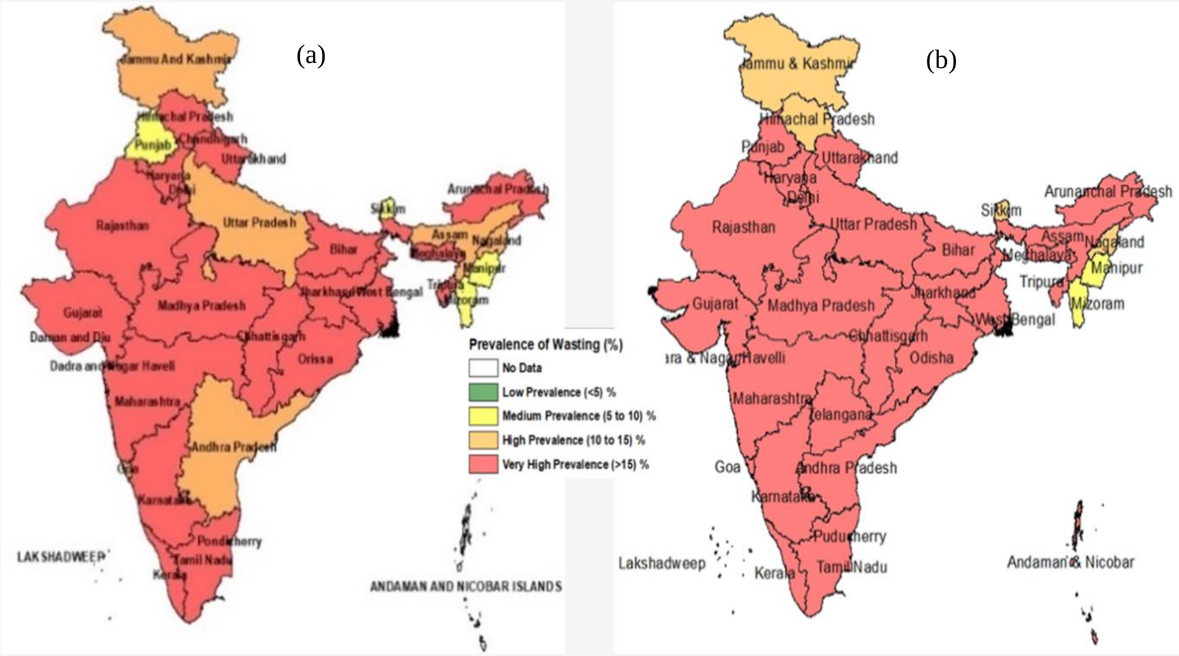

Figure 6: Wasting prevalence of Malnutrition in the last decade (a) 2005-2006 (b) 2015-2016 at the state level in India

The cluster of very high prevalence is observed in Madhya Pradesh, Uttar Pradesh, Bihar, and Jharkhand. On the other hand, very high wasting prevalence is more or less equally occurring in a large geographic area of India. Districts suffering from a very high waste are the districts located in the central, east, and south region. This is particularly the same in the analysis of the state-level stunting prevalence. Moreover, the underweight prevalence distribution is all over India and mainly concentrated in the districts of central (139) and east (91) regions of India.

However, this very high prevalence in states was reduced by 5% from the NFHS-3 survey to the recent NFHS-4 survey, but medium to high prevalence doubled over a decade. The situation in Kerala, Northeastern, and newly formed Telangana states has improved, but Andhra Pradesh's state has shown degradation to a very high percentage of underweight.

4.2 Malnutrition Prevalence at District Level

District-level malnutrition prevalence in Figure 7 shows high interstate variation. Child wasting and underweight prevail across a vast region in India with a clustering distribution. The states that are not categorized with very high malnutrition prevalence appear to have districts with very high malnutrition prevalence (Figure 7). Of the 640 districts in India, 237 districts have a very high prevalence of stunting (>40%), 482 districts with high wasting prevalence (>15%) and 373 districts are with high underweight prevalence (>30%). Compared to the developing country's national average for stunting of 25%, India has 100 districts above the mentioned average, while 34 districts are above the wasting national average (8.9%). The established result shows a pattern of concentration and clustering of districts where Malnutrition is prevalent. The malnutrition indicators of stunting, wasting, and underweight were noted to consistently occur in India's central, east, and south zones (Figure 8).

4.3 Spatial Heterogeneity of Malnutrition

The univariate LISA analysis for child malnutrition indicators such as stunting, wasting, and underweight is represented in Figure 8. The LISA cluster maps yielded four types of geographical clustering. As described by [19], the LISA cluster map represents four classifications of geographical clustering of interest variables. In this study, "high-high" or *hotspots* means that areas with above-average child malnutrition rates also share boundaries with neighbouring regions with above-average values of the same variables. Whereas "low-low" or cold spots are the regions with below-average malnutrition rates that share boundaries with neighbouring regions that have below-average of the same variable. However, a "high-low" means regions with below-average values surround the region with above-average malnutrition indicator rates. Moreover, "low-high" means areas with above-average values surround below-average malnutrition indicator values. The three malnutrition indicators show a positive spatial autocorrelation, among which *underweight* shows the highest Moran' I value of 0.712, and 165 districts were found to be hotspots Figure 9 (On the other hand, the Moran's I value for *stunting* was 0.62, which showed 138 districts as hotspots. *Wasting,* too, had a positive but low spatial autocorrelation (Moran's I value of 0.461), with 105 districts as hotspot areas.

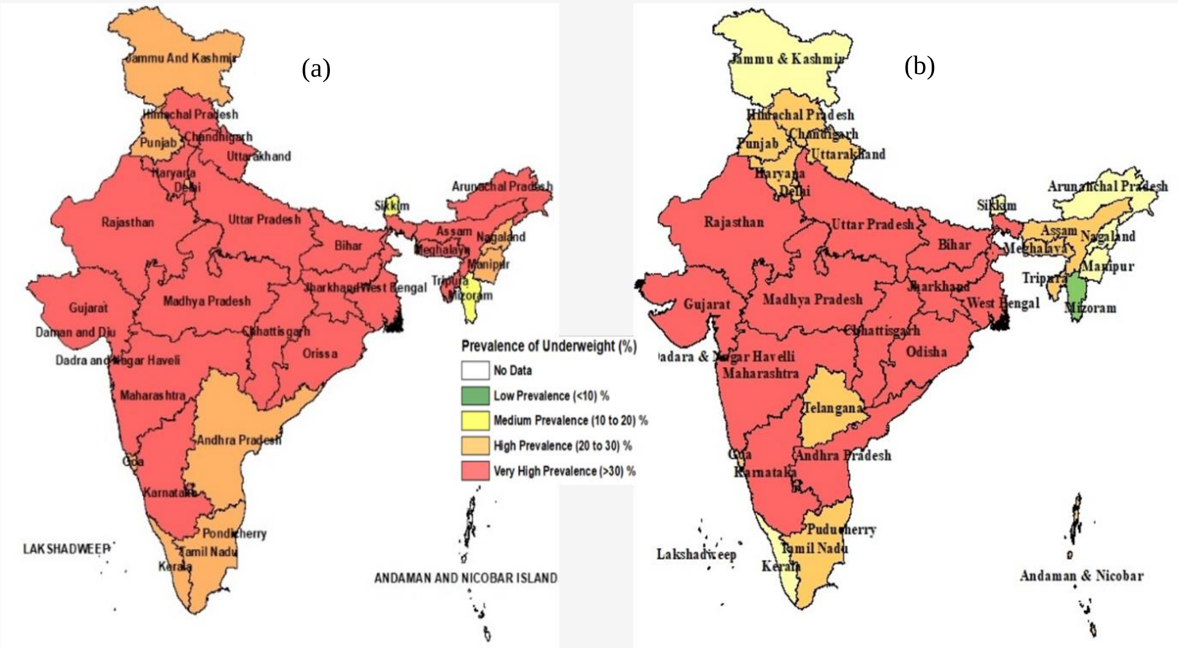

Figure 7: Underweight prevalence of Malnutrition in the last decade (a) 2005-2006 (b) 2015-2016 at the state level in India

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

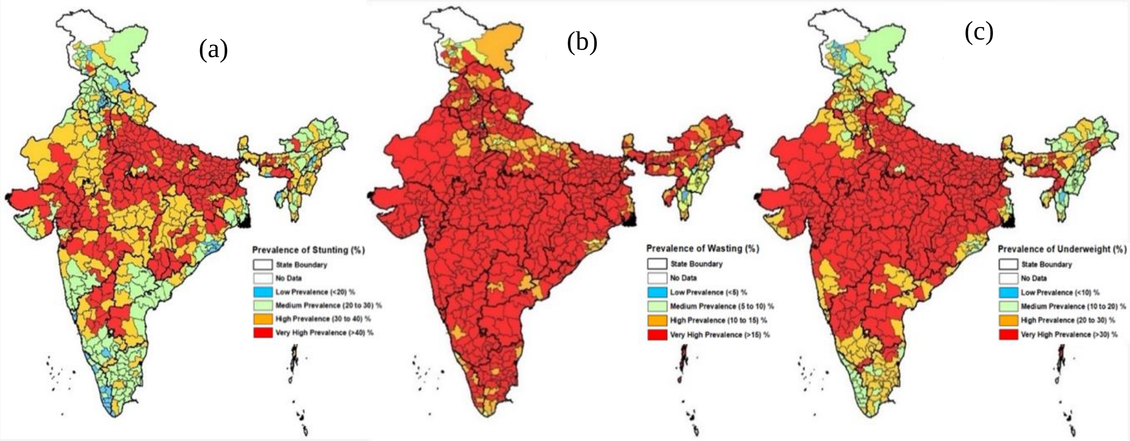

Figure 8: Geographical distribution of Malnutrition (a) stunting, (b) wasting, and (c) underweight across districts in India

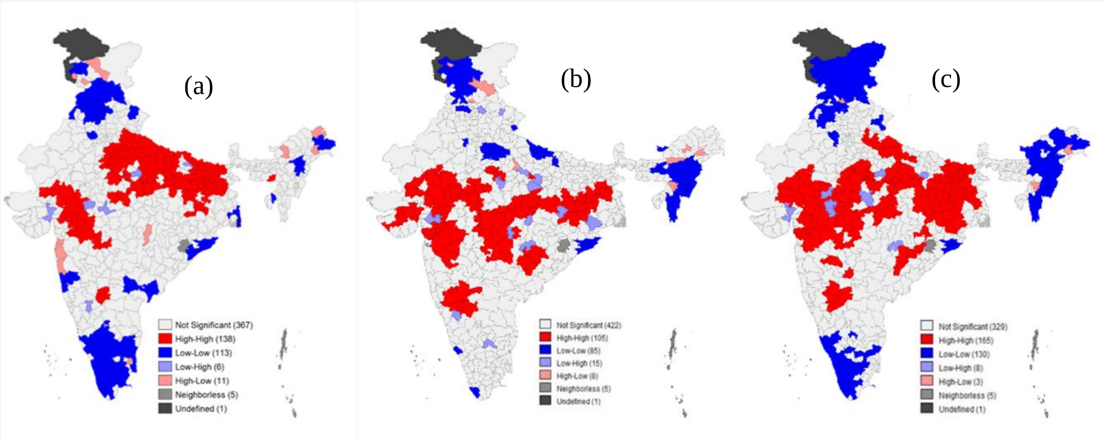

Figure 9: Univariate maps depict spatial clustering and outliers (a) stunting, (b)wasting, and (c) underweight across districts of India malnutrition

Table 1 presents the relationship between the outcome indicators and the specific influencing factors. Since there is significant geospatial clustering in the three outcome variables of Malnutrition, an SEM was used to understand the spatial relation and strength between child malnutrition indicators (stunted, wasting, and underweight) and influencing factors. Furthermore, a spatial correlation analysis was performed using bivariate LISA to check the geospatial clustering in the exposure and outcome variable. It is observed that under the immediate cause, the three forms of Malnutrition (stunting, wasting, and underweight) are significantly influenced by low mother BMI (<18.5 kg/m^2) and anemia in the mother during pregnancy. In contrast, the prevalence of diarrhoea and pregnant women having anemia shows a positive relationship but low influence on the three malnutrition indicators. On the other hand, children who received an adequate diet show a significant and negative relation between stunting and being underweight. Under the nutrient-specific intervention, a mother receiving complete antenatal care shows a significant negative relation with stunting and underweight. Whereas both children fully immunized and receiving vitamin A supplementation shows a low significant influence with the three malnutrition indicators, while postnatal care received child shows a low significant influence with stunting and underweight. Both factors of improved household sanitation and households using clean cooking fuel are seen to have a negative relation to child malnutrition. On the other hand, early pregnancy (15-19 years) shows a positive and significant relation with stunting and being underweight. The bivariate LISA examined the spatial relationship between the factors and the outcome variable for the different geographic areas of India and was used to answer a pertinent question – is the prevalence of Malnutrition across India constantly influenced by the identified factors.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 1: Spatial Error Model between influencing factors and outcome indicators

Immediate Causes – SEM			
Influencing Factors	**Stunting Coefficient**	**Wasting Coefficient**	**Underweight Coefficient**
1. Exclusive breastfeeding (6 months)	0.102	0.033	0.123
2. Adequate diet (6-23 months)	-0.18*	-0.015	-0.209**
3. Mother with low BMI (<18.5 kg/m^2)	0.563***	0.281***	0.702***
4. Pregnant women anemia	0.068***	0.051***	0.088***
5. Prevalence of ARI	-0.017**	-0.030***	-0.024***
6. Prevalence of Diarrhea	0.024***	0.010	0.018**
Nutrition Specific Intervention - SEM			
1. Mother consumed IFA 100+ pregnancy	0.07	0.044	0.730
2. Mother had full ANC	-0.192***	-0.079	-0.167***
3. Child received PNC	0.058**	-0.001	0.057**
4. The child received Vit A – for 6 months	0.095***	0.068***	0.083***
5. Child fully immunized	0.075***	0.055***	0.085***
Underlying Causes - SEM			
1. Households improved sanitation	-0.155***	-0.070***	-0.173***
2. Households using clean cooking fuel	-0.086***	-0.044**	-0.080***
3. Households with electricity	0.093***	0.148***	0.136***
4. Households with improved drinking water	0.243***	0.068***	0.194***
5. A mother who did not have 10 or more years of schooling	-0.035	-0.039	-0.039
6. Early pregnancy (15-19 years)	0.22***	-0.062	0.135*
*****p<0.01, **p<0.05, *p<0.10**			

Table 2: Status of malnutrition indicators using Bivariate LISA Moran's I Values

Malnutrition	Bivariate	Hotspots
Immediate		
Stunting - Low BMI	0.508	127
Wasting - Low BMI	0.410	113
Underweight - Low BMI	0.642	139
Nutrition Specific Intervention		
Stunting- Antenatal care to Mother	-0.458	142
Underweight – Antenatal care for Mother	-0.317	128
Underlying Causes		
Stunting – Improved Sanitation	-0.508	146
Underweight – Improved Sanitation	-0.538	147
Stunting – Early Pregnancy (15-19 years)	0.186	76

Table 2 shows the Bivariate Moran's *I* statistics for stunting, wasting, and underweight against the correlates. Results show that the spatial autocorrelation of underweight, stunting, and wasting with low mother BMI was 0.64, 0.50, and 0.41, respectively (Table 2). This indicates a strong association between women's BMI with all three nutritional indicators.

These findings are consistent with previous studies that mentioned the influence of women's low BMI would likely have greater malnutrition prevalence among children [3]. In fact, low mother nutrition is a significant risk factor for poor fetal development, and undernourished mothers cannot provide adequate milk during breastfeeding, which results in Malnutrition in children.

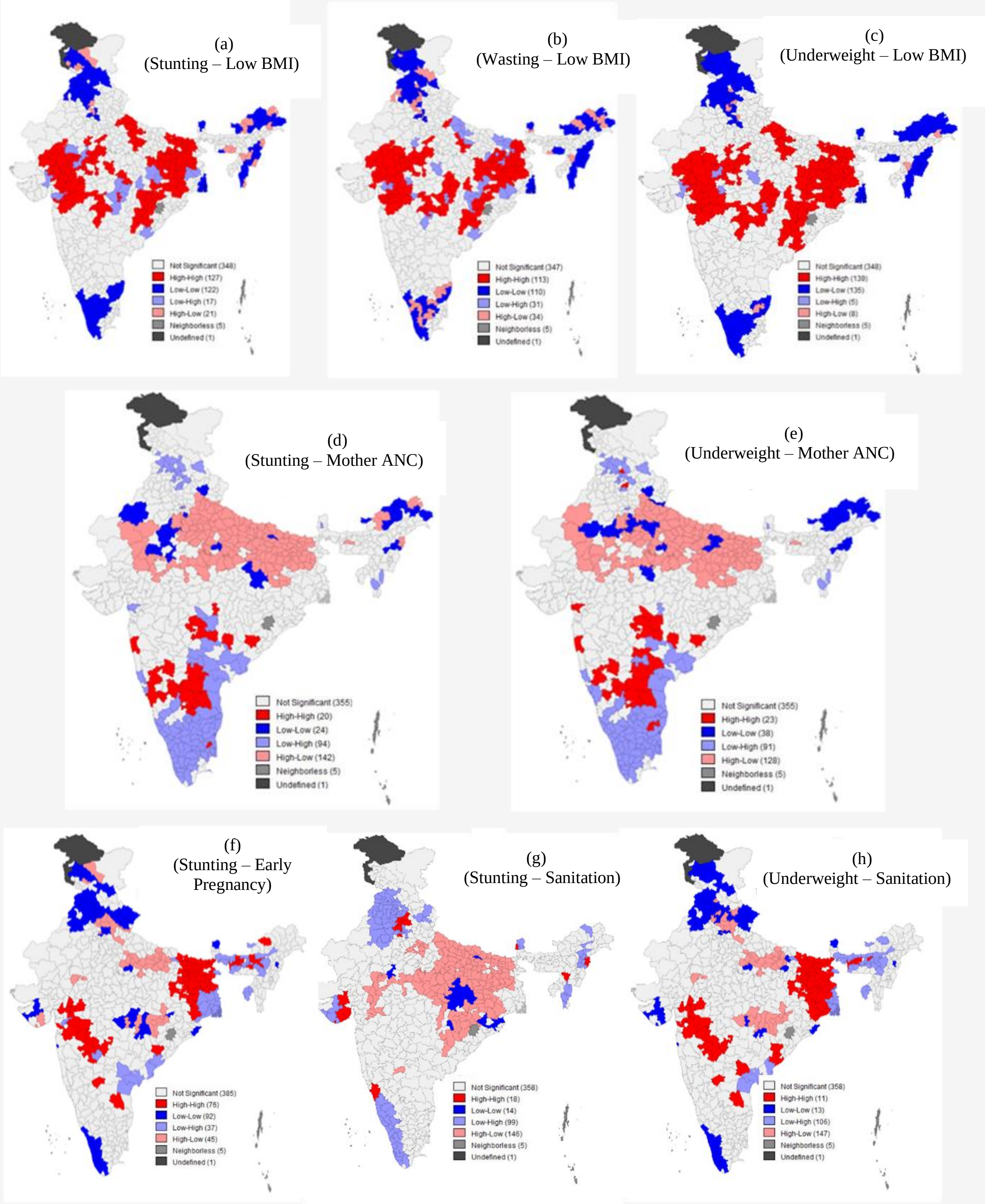

Figure 10: Cluster maps showing the geographic clustering (hotspots & cold spots) of (a) BMI of mothers vs stunting (b) BMI of mothers vs underweight (c) mother antenatal care vs stunting (d) mother antenatal care vs underweight (e) early pregnancy vs stunting (f) sanitation vs underweight (g) sanitation vs stunting (h) sanitation vs underweight across districts of India, 2015-16

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Generally, the low BMI of the mother showed a high positive spatial autocorrelation in all three measures of Malnutrition, while antenatal mother care and improved sanitation are negatively correlated with stunting and underweight. Moreover, the spatial autocorrelation of stunting and underweight with improved sanitation was -0.508 and -0.538, respectively (Table 2).

The bivariate LISA cluster map shows that 127 and 113 districts constitute hot spots - a high proportion of low mother BMI and a high prevalence of stunting and wasting, respectively. On the other hand, 122 and 110 districts are observed as cold spots (low proportion of low mother BMI and low prevalence of stunting and wasting). Similarly, mother antenatal care showed a negative spatial autocorrelation with stunting and underweight. Improved sanitation showed high and negative autocorrelation with stunting and underweight, while early pregnancy indicated a low but positive relation with stunting. There are 142 out of 640 districts (22%) with the highest prevalence of stunting in relation to the influencing factor of antenatal care. Similarly, 20% of the districts in India (128) constitute the hotspots for underweight antenatal care. These are primarily observed in Bihar, Uttar Pradesh, and parts of the borders of Madhya Pradesh. In comparison, the state-level analysis did not capture this point which is very important for the strategy to improve the situation. Figure 10(a-c) show the district-level clustering and prevalence of stunting, wasting, and underweight with a common association with mothers with low BMI (<18.5 kg/m^2). Similarly, hotspots for stunting and underweight are influenced by mother antenatal care, early pregnancy, and sanitation (Figure 10 (d-e)). The light pink colour on the map represents the hotspots. Meanwhile, hotspot districts for stunting in relation to early pregnancy (15-19 years) in Figure 10 f are observed in 78 districts (12%). Figures 10(g-h) represent the hotspot districts of stunting and underweight associated with sanitation, indicated in light pink. There are 146 and 147 hotspot districts for stunting and underweight as influenced by low sanitation. A total of 132 (low-high) hotspot districts are observed where Uttar Pradesh, Bihar, and parts of the borders of Madhya Pradesh are among the few. Cold spots (high-low), as represented by the pink colour, occur in fifty-nine districts and are mainly seen in Kerala, Punjab, Himachal Pradesh, and a few districts in the northeastern region. At the same time, 403 districts do not have any significant spatial autocorrelation with the neighbouring districts.

The analysis of prevalence coverage of antenatal care (ANC) to mothers and underweight (Figure 10(e)) gives a negative spatial autocorrelation, thus, giving importance to outliers. The light blue colour (low-high) is considered the hotspot, meaning that districts with mothers not consuming IFA have high child stunting prevalence. A total of 140 (low-high) hotspot districts were distributed in central, east, and west regions as well as in Uttar Pradesh, Bihar, and Madhya Pradesh. The pink colour represents cold spot areas (high-low) in sixty-seven districts, mainly in Kerala, Punjab, Himachal Pradesh, and a few districts in the northeastern region. On the other hand, 335 districts have no significant spatial autocorrelation with their neighbouring districts. The bivariate LISA result of underweight and improved sanitation facilities (f) shows a negative spatial autocorrelation and low Moran's I value (-0.383); thus, outliers are considered more important. The light blue colour (low-high) is considered the hotspot, which means that there is a higher prevalence of underweight if there are poor sanitation facilities. In relation to this, there are 147 (low-high) hotspot districts distributed in Rajasthan, Madhya Pradesh, Gujarat, Maharashtra, Chhattisgarh, Odisha, Uttar Pradesh, Bihar, West Bengal, Karnataka, and Jharkhand. Meanwhile, there are 86 cold spots (high-low) districts that are indicated in light pink colour which are clustered in the southern region like Kerala, northeastern region – Nagaland, Mizoram, Manipur, Assam, and Tripura, in the northern region – Himachal Pradesh, Punjab, Uttarakhand. On the other hand, stunting and improved sanitation facilities (g) give a negative spatial autocorrelation, thus, giving importance to outliers. The light blue colour (low-high) is considered the hotspot, which means that poor sanitation facilities would result in high stunting. There are 125 (low-high) hotspot districts that are observed in Uttar Pradesh, Bihar, and parts of the borders of Madhya Pradesh, Gujarat, and Maharashtra. The pink colour represents cold spots (high-low). It was encouraging to find 60 districts in a cold spot which is mainly seen in Kerala, Punjab, Himachal Pradesh, and a few districts in the northeastern region.

5. Discussion

Child malnutrition in India continues to be high, and the crisis seems challenging to solve [1] This study determined the pattern and prevalence of Malnutrition among children across states and districts of India. Factors influencing the prevalence of Malnutrition and their geographical distribution were also examined to determine the high-risk district clusters. Below are the notable findings from the study.

The analysis results revealed a spatial pattern of stunting, wasting, and underweight across the states and districts of India. Moreover, based on the data of

NFHS-4, stunting and underweight prevalence across India witnessed a lower rate of 47% and 28%, respectively, over the last decade, while wasting prevalence increased by 10%. Of the 640 districts of India, wasting was highly observed in 75% of the states, followed by underweight (58%) and stunting (37%). This implies that the most dominant form of Malnutrition in India is wasting. According to (International Food Policy Research Institute, 2016), India ranks as the top country in child waste globally, where 90 per cent of children aged between 6 and 23 months do not even get the minimum required food.

In addition, a series of spatial clustering maps were developed to find out the different malnutrition indicators among districts and to determine if there is a relationship to the malnutrition levels of the neighbouring districts. Moran's I statistics suggest that there is spatial dependence and was found highest for underweight (0.71), followed by stunting (0.62) and wasting (0.46), proving the geographical gradient of Malnutrition in India. The same observation was obtained by Khan and Mohanty [5] indicating that malnutrition prevalence among children in India is not distributed uniformly across districts but instead occurs in clusters. Though there is a high level of Malnutrition in selected states and regions, a more significant clustering was observed in the districts of Uttar Pradesh, Madhya Pradesh, Bihar, and Jharkhand. According to [9], Malnutrition is scattered across states and the nation as a whole, but it is highly concentrated among districts in the central regions, particularly in the rural parts along with the so-called "tribal belt", while the districts in the southern region are with improved nutritional status. This result can be linked to the conclusion of [20] that attention needs to be paid to building neighbourhood health and nutrition profiles and carrying out interventions based on identified needs.

The spatial analysis suggests a statistically high significant association of different forms of Malnutrition (stunting, wasting, and underweight) with the factors such as maternal (status of mother BMI, anemia during pregnancy, mother antenatal care) and child health (prevalence of Acute Respiratory Infection (ARI) and diarrhoea, a child receiving Vitamin A and full immunization) and access to needed household services (improved sanitation, clean cooking fuel, electricity and improved drinking water). These factors correlate well with areas where high Malnutrition is prevailing (central regions), as these are the areas where access to medical facilities is complicated and limited. The majority of the mentioned influencing factors on Malnutrition in this study were also proven by other researchers. According to pieces of literature, poverty, low women's education, low body-mass-index of mothers, poor sanitation and drinking water supply, high fertility, increased prevalence of teenage pregnancies, and lack of immunization are among the influencing factors of Malnutrition in India [8]; [21]. Studies indicate that there is a significant relationship between maternal nutritional status with the well-being of a child [22]. This conclusion supports our findings that the lack of supplementation of iron and folic acid and non-access to antenatal care of the mother is the significant influencing factors in child stunting and being underweight. Failure to supply an adequate amount of nutrients to meet fetal demand can lead to fetal Malnutrition. The fight against persistent underweight, stunting, and wasting among children in developing countries is based on the appropriate maternal nutrition and preventing micro-nutrient deficiency as their deficiency leads to severe problems during the gestation period in the mother and stunting in a child after pregnancy [23].

The spatial relationship between factors and outcome variables indicated that the hotspots were influenced by the low BMI of the mother, antenatal care, sanitation, and early pregnancy. These are primarily found in the districts located in the central regions. This information highlighted the need for access to the necessities to proceed towards a healthy pregnancy. At the same time, the child's growth pattern was found to be at lower levels in most places.

5. Conclusion

This study was based on the notions of the geostatistical pattern analysis to understand the prevalence of Malnutrition at the state and district levels in India. The study disclosed that some of the indicators and contextual factors which cause Malnutrition in an area might be divergent when viewed at state and district levels. With these results, the government can focus on addressing other influencing factors on Malnutrition, such as early pregnancy and antenatal care support. Therefore, the result of this study would be helpful in further planning malnutrition interventions as hotspot areas can be identified straight away. This will eliminate the old practice of implementing a generic solution to Malnutrition that is often ineffective. Study results suggested that a district-level strategy should be in place for effective results. With the influencing factors that have improved along with malnutrition indicators, the government can strengthen the programs on sanitation, child immunization, and maternal and childcare support programs. Further, the annual malnutrition status in India will present a reliable basis for determining changes in the malnutrition status of children in India. The study helps the government and NGOs to focus on areas that need attention to support Malnutrition. Prime

Ministers' "Nutrition Mission" initiated in the year 2017 may also reveal astonishing benefits once the results are analyzed using the methodology proposed in this study. Malnutrition status can be better monitored if the government can improve the data collection process and data analysis using the "mobile app" at village levels and make them GIS-ready for spatial analysis.

Acknowledgement

This research was conducted for my thesis at the Asian Institute of Technology under the guidance of a faculty advisor. I am grateful for the scholarship provided by the Asian Institute of Technology under the Unified Program with Jawaharlal Nehru Technical University.

References

[1] Global Nutrition Report, (2020). Action on Equity to end Malnutrition. Bristol, UK, Retrieved from: https://globalnutritionreport.org/documents/566/2020_Global_Nutrition_Report_2hrssKo.pdf.

[2] Habyarimana, F., Zewotir, T., Ramroop, S. and Ayele, D. G., (2016). Spatial Distribution of Determinants of Malnutrition of Children under Five Years in Rwanda: Simultaneous Measurement of Three Anthropometric Indices. *Journal of Human Ecology*, Vol. 54(3). 138–149. https://doi.org/10.1080/09709274.2016.11906996.

[3] World Health Organization, (2010). Nutrition Landscape Information System (NLIS), Country Profile Indicators Interpretation Guide, https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1538-4632.1995.tb00338.x

[4] United Nations International Children's Emergency Fund, https://www.un.org/en/academic-impact/unicef.

[5] Khan, J. and Mohanty, S. K., (2018). Spatial Heterogeneity and Correlates of Child Malnutrition in Districts of India. *BMC Public Health*, Vol. 18(1). https://doi.org/10.1186/s12889-018-5873-z

[6] Udmale, P., Pal, I., Szabo, S., Pramanik, M. and Large, A., (2020). Global Food Security in the Context of COVID-19: A Scenario-Based Exploratory Analysis. *Progress in Disaster Science*, Vol. 7. https://doi.org/10.1016/j.pdisas.2020.100120.

[7] Rah, J. H., Cronin, A. A., Badgaiyan, B., Aguayo, V. M., Coates, S. and Ahmed, S., (2015). Household Sanitation and Personal Hygiene Practices Are Associated with Child Stunting in Rural India: A Cross-Sectional Analysis of Surveys. *BMJ Open*, Vol. 5(2). https://doi.org/10.1136/bmjopen-2014-005180.

[8] Singh, S., Srivastava, S. and Upadhyay, A. K., (2019). Socio-Economic Inequality in Malnutrition among Children in India: An Analysis of 640 Districts from National Family Health Survey (2015–16). *Int J Equity Health*, Vol. 18(1). https://doi.org/10.1186/s12939-019-1093-0.

[9] Striessnig, E. and Bora, J. K., (2020). Under-Five Child Growth and Nutrition Status: Spatial Clustering of Indian Districts. *Spat Demogr*, Vol. 8(1), 63–84. https://doi.org/10.1007/s40980-020-00058-3.

[10] The Global Hunger Index, (2020). One Decade to Zero Hunger Linking Health and Sustainable Food Systems, https://www.globalhungerindex.org/pdf/en/2020.pdf

[11] NITI Aayog Annual Report, (2018–2019). https://niti.gov.in/sites/default/files/2019-11/AnnualReport2019.pdf.

[12] Menon, P., Nguyen, P. H., Mani, S., Kohli, N., Avula, R. and Tran, L. M., (2017). *Trends in Nutrition Outcomes, Determinants, and Interventions in India (2006–2016)*. POSHAN Report 10. New Delhi, India: International Food Policy Research Institute (IFPRI). http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/131341.

[13] Food and Nutrition Security Analysis, India, (2019). New Delhi, India, 2019. https://www.mospi.gov.in/sites/default/files/publication_reports/document%281%29.pdf.

[14] World Health Organization, (2010). Nutrition Landscape Information System (NLIS) Country Profile Indicators: Interpretation Guide. 1-38. https://apps.who.int/iris/handle/10665/44397.

[15] Anselin, L., (1995). Local Indicators of Spatial Association-LISA. *Geogr Anal*, Vol. 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338x.

[16] Lee, S., (2001). Developing a Bivariate Spatial Association Measure: An Integration of Pearson's r and Moran's I. *J Geogr Syst*, Vol. 3(4). 369–385. https://doi.org/10.1007/s101090100064.

[17] Catma, S., (2021). The Price of Coastal Erosion and Flood Risk: A Hedonic Pricing Approach. *Oceans*, Vol. 2. 149–161. https://doi.org/10.3390/oceans2010009.

[18] Anselin, L., (2002). Under the Hood: Issues in the Specification and Interpretation of Spatial Regression Models. *Agricultural Economics*, Vol. 27(3). 247–267. https://doi.org/10.1016/S0169-5150(02)00077-4.

[19] Singh, P., (2011). Performance Pay and Information: Reducing Child Malnutrition in Urban Slums. *Munich Personal RePEc Archive*. 1-53. https://mpra.ub.uni-muenchen.de/29403/

[20] Aijaz, R., (2017). Preventing Hunger and Malnutrition in India. *ORF Issue Brief*. https://www.orfonline.org/wp-content/uploads/2017/06/ORF_IssueBrief_182_ Hunger.pdf

[21] Rao, G., Ladusingh, L. and Pritamjit, R., (2004). Nutritional Status of Children in North-East India. *Asia Pac Popul J*, Vol. 19, 39–56. https://doi.org/10.18356/2d9a4fd8-en.

[22] Narayan, J., John, D. and Ramadas, N., (2019). Malnutrition in India: Status and Government Initiatives, *J Public Health Policy*, Vol. 40(1). 126–141. https://doi.org/10.1057/s41271-018-0149-5.

[23] Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Parul Christian, P., Mercedes de Onis, M., Majid Ezzati, M., Grantham-McGregor, S., Joanne Katz, J., Martorell, R., Uauy, R. and Maternal and Child Nutrition Study Group, (2013). Maternal and Child Undernutrition and Overweight in Low-Income and Middle-Income Countries. *The Lancet*, Vol. 382, 427–451. https://doi.org/10.1016/S0140-6736(13)60937-X.