

Research Paper

Child Undernutrition: Spatial Heterogeneity and Determinants in Low Sociodemographic Index States of India

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ABSTRACT

Background: Childhood malnutrition is a leading cause of under-five mortality, particularly in developing nations, like India. Despite some reductions in underweight and stunting rates among children under five from 2005-2016, progress has been inadequate given India's economic growth. Moreover, one-third of children under five remain stunted and underweight, especially in populous, states such as Uttar Pradesh, Bihar, Rajasthan, and Madhya Pradesh, which rank low on the socio-demographic index (SDI). Further, identifying target areas can enable more focused resource allocation to meet community needs, which can be done using geospatial mapping and modeling of public health events.

Methods: The study utilized data from the national family health survey, covering 82,784 children under five. A spatial analysis was conducted to examine the distribution of malnutrition in the low SDI states of India. Spatial lag models were used to assess the association between malnutrition and its determinants across these regions.

Results: The study found that 39.1% of children were stunted, 32.9% were underweight, and 19.3% were wasted. Significant spatial variation in malnutrition was identified across the regions, as indicated by the local Moran index for stunting ($I=0.3464$; $P<0.0001$), wasting ($I=0.373$; $P<0.0001$), and underweight ($I=0.590$; $P<0.0001$). Key factors contributing to regional malnutrition disparities included higher birth order, poor sanitation, non-institutional deliveries, low household wealth, poor maternal body mass index (BMI), and religion.

Conclusion: The study highlights significant spatial disparities in child malnutrition across low SDI states in India. Addressing malnutrition in these regions requires targeted public health interventions focusing on poverty alleviation, improving women's education, and enhancing maternal health, particularly in areas with a high prevalence of undernutrition.

Keywords: Under-five children, Stunting, Wasting, Underweight, Spatial lag model, local indicator of spatial association (LISA)

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Introduction

Undernutrition is a health issue that occurs when there is insufficient food consumption or when the body is unable to adequately utilize the food that is consumed. This can lead to stunted growth, being underweight, or wasting of the body. It has a global impact on over 149 million children under the age of five [1]. Stunting, wasting, and underweight are standard indices used to quantify undernutrition; these indices represent distinct aspects of undernutrition. Lack of proper nutrition can have detrimental effects on one's health, particularly for children in developing nations. This condition is known as undernutrition [2].

Malnutrition in childhood accounts for a significant portion of child deaths under the age of five, and it is particularly common in developing nations. With high prevalence rates of stunting, wasting, and underweight among children under five, malnutrition is a serious public health issue [3, 4]. The prevalence of malnutrition among under-five children is high globally, with South Asia having a particularly high prevalence [5]. Although India has experienced economic development and a decrease in poverty, the prevalence of malnutrition remains significant. The prevalence of underweight decreased from 53% to 36%, stunting decreased from 52% to 38%, whereas wasting increased from 17% to 21% [6].

Between 2005–06 and 2015–16, India made a modest decrease in the prevalence of stunting and underweight in children under five years, but the progress is insufficient compared to its economic growth. Although there was a moderate decline in child undernutrition during this period, over one-third of children under five years old remain stunted and underweight [7]. Addressing poverty, enhancing education and healthcare, increasing sanitation, and promoting understanding about child feeding may successfully reduce malnutrition in India [8]. This situation of undernutrition in India is quite evident in highly populated regions, namely Uttar Pradesh, Bihar, Rajasthan, Madhya Pradesh, etc. These states also rank at the lower end of socio-demographic index (SDI) paradigm. The SDI is a composite index of development that is significantly associated with health impact. It represents the geometric mean of the indices ranging from zero to one for mean education among individuals aged 15 or older (EDU15+), total fertility rate under 25 (TFU25), and lag distributed income (LDI) per capita. A location with an SDI of zero has a theoretical minimal level of health-related development, whereas a location

with an SDI of one has a theoretical maximum level [9]. The SDI quantiles are utilized for classification. Based on their SDI, the states Uttar Pradesh, Bihar, Rajasthan, Madhya Pradesh, Chhattisgarh, and Jharkhand fall into the category of low socio-demographic index (LSDI) states. Recent advancements in public health research indicate that geospatial mapping and modeling of various demographic and epidemiological events, by integrating different exposure factors, are instrumental in identifying specific areas of concern. This approach enhances the accuracy of resource allocation, aiding government and policymakers in addressing community needs more effectively. Hence, this study aimed to identify spatial clustering and autocorrelation of child undernutrition at the district level, as well as to identify the spatially associated determinants of child undernutrition.

Methods

Data

Children's recode (KR) data used in this study were obtained from the recently conducted national family health survey (NFHS- 5), 2019-21. This dataset has one record for every child of interviewed women, born in the five years preceding the survey. Unit-level data is accessible through the demographic health survey (DHS) data repository [10]. The unit of analysis in this research is the districts of LSDI states in India, which comprise 248 districts, including a total of 104692 children under the age of five years at the time of survey. A total of 81278 children was included in the final analysis sample, after removing missing values from one or more variables under consideration [11]. This study focused on three anthropometric indicators that assess the nutritional status of under-five children: Stunting (height-for-age), underweight (weight-for-age), and wasting (weight-for-height). These indicators serve as the target variables in our investigation and are widely utilized in academic literature as standardized measures of children's nutritional well-being [12, 13]. Underweight denotes both acute and chronic forms of malnutrition, stunting represents chronic malnourishment while wasting in children denotes acute malnutrition [14]. The independent variables included place of residence, maternal education, improved drinking water, sanitation facility, religion, caste, wealth index, maternal BMI, maternal anemia, birth order, institutional birth, infectious disease in the past two weeks, and whether the child was put on the mother's chest immediately after birth.

Statistical analysis

Descriptive statistics, univariate local Moran's I statistics, and a set of spatially weighted regression models were used in this study. The univariate local indicator of spatial association (LISA) maps were used to assess the association between neighborhood values surrounding a certain spatial location. This method quantifies the level of geographical randomization and clustering in the data. The values of Moran's I can range from -1 to +1; clustering of similar values is indicated by positive values, while dissimilar values are indicated by negative values. If the value is zero, it indicates the absence of spatial autocorrelation, and the pattern is completely random [15-19]. A typical Moran's I formula can be expressed as follows (Equation 1):

1.

$$\text{Univariate Moran's } I = \frac{n}{S_0} \times \frac{\sum_i \sum_j W_{ij} (x_i - \bar{X}) [x_j - \bar{X}]}{\sum_i [x_i - \bar{X}]^2}$$

Where, x is the target variable, \bar{X} is the average value of x ; n represents the number of spatial units, W_{ij} represents the standardized weight matrix between observations i and j (with zeroes along the diagonal), and S_0 is the total of all spatial weights, i.e. $S_0 = \sum_i \sum_j W_{ij}$

The univariate LISA method computes spatial autocorrelation of neighboring values at a particular spatial location. It assesses the degree of spatial randomness and clustering within the data [18]. The measure I_i is defined as follows: The univariate LISA method computes spatial autocorrelation of neighboring values at a particular spatial location. It assesses the degree of spatial randomness and clustering within the data [18]. The measure $[I_i]$ is defined as follows (Equation 2):

2.

$$\text{Univariate LISA: } I_i = \frac{n \cdot [x_i - \bar{X}]}{\sum_i [x_i - \bar{X}]^2} \sum_j W_{ij} [x_j - \bar{X}]$$

To identify probable spatial correlates of undernutrition, a set of regression models was utilized to provide the best fit to the data and comprehend the relationships involved. Initially, we employed K-Best feature selection techniques to identify the most important features in the dataset, providing insights into the underlying relationships between the features and the target variable.

Next, the ordinary least squares (OLS) method has been employed with each outcome variable (stunting, wasting, and underweight) and various selected important features to estimate the presence of spatial autocorrelation in the error term and to calculate the corresponding Moran's I statistics. Subsequently, LM Diagnostics are instituted post-OLS regression to subject the model to rigorous statistical scrutiny, specifically to identify potential misspecification [20]. A consequential examination for significance follows: If neither LM-error nor LM-lag proves significant, the analysis halts, retaining the OLS outcomes. Conversely, if there is significance in either LM-error or LM-lag, the analytical trajectory pivots toward the relevant error or lag model. In instances where both LM-error and LM-lag exhibit significance, further diagnostic scrutiny becomes imperative to inform subsequent decisions. Robust LM diagnostics are subsequently deployed, differentiating between robust LM-error and robust LM-lag. The conclusive step involves the implementation of the appropriate model—either the spatial error model or the spatial lag model—based on the discerned diagnostic outcomes (Figure 1) [21]. In accordance with the model diagnostics test, for all three types of child undernutrition—stunting, wasting, and underweight—the spatial lag model performed better with the data than the other models given [Table 2].

A trial version of Arc-GIS 10.1 (Esri, California), R Studio version 2023.12.1+402 (2009–2024 Posit Software, PBC), and Geo-Da version 1.20.0.36 (2011–2023 by Luc Anselin) was used for the analysis. All estimates in this study relied on appropriate sampling weights given by the NFHS-5, 2019-21 [10].

Results

Out of a total of 81278 children under five years of age, the prevalence of stunting and underweight is nearly 10% higher in rural areas, with rates of 40.64% for stunting and 34.24% for underweight, respectively. For wasting, it is almost the same in rural and urban areas. Among children of uneducated mothers, 47.62% are stunted, 21.36% are wasted, and 40.75% are underweight. In families with unimproved drinking water, 37.83% of children are stunted, followed by 35.52% who are underweight and 16.81% who are wasted. In households having unimproved sanitation facilities, 45.94% of children were stunted, 20.89% were wasted, and 39.55% were underweight. Among children from the poorest families, the rates are 48.03% for stunting, 21.99% for wasting, and 42.26% for underweight. Similarly, among poorer children, the rates are 40.99% for stunting, 18.87% for wasting, and 34.04% for underweight [Table 1].

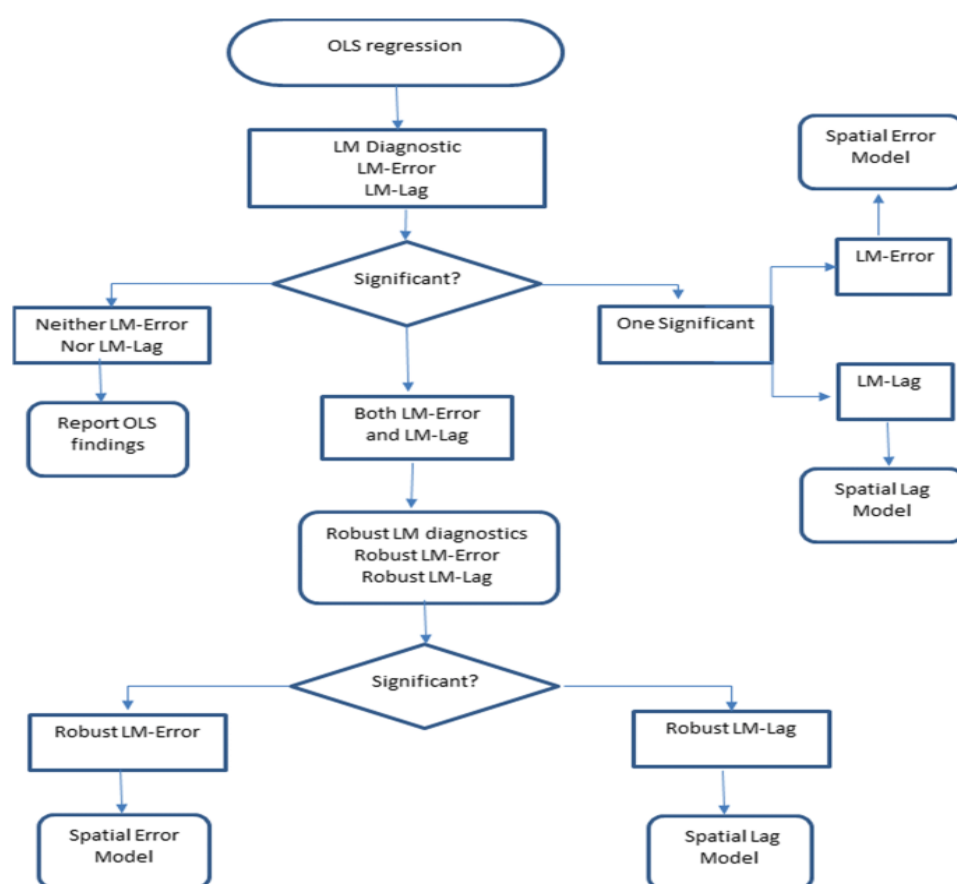


Figure 1. The decision tree of diagnostic procedures for spatial model selection Source: Anseline, 2005 [21]



Figures 2A, 2B and 2C show the prevalence pattern of stunting, wasting, and underweight across districts in LSDI states of India, which range from 16.94 in Bhopal to 63.7 in Pashchimi Singhbhum for stunting, 8.54 in Sant Ravidas Nagar (Bhadohi) to 37.53 in Arwal for wasting, and 16.87 in Jhunjhunun to 60.82 in Pashchimi Singhbhum for underweight, respectively. The higher prevalence of stunting and underweight was mainly concentrated in the eastern region, particularly in Uttar Pradesh, Bihar, and Jharkhand. However, the higher prevalence of wasting is scattered in clusters across various regions.

Moreover, all three outcomes of child undernutrition (stunting, wasting, and underweight) showed noticeably higher spatial autocorrelation. Spatial clustering is most pronounced for childhood underweight (Moran's $I=0.59$, $P<0.01$). Out of the total of 424 districts, 47 hotspots and 37 cold spots were recognized (maps F-1 and F-2). In the univariate LISA cluster map of childhood stunting, 35 'hotspots' and 40 'cold spots' were identified (map D-1) (Moran's $I=0.464$, $P<0.01$). The majority of the hotspots were located in parts of Uttar Pradesh (UP), Jharkhand, and Bihar (map D-2), while lower rates are observed in the

states of Rajasthan, parts of Madhya Pradesh (MP), and Chhattisgarh. A statistically significant geospatial clustering with Moran's $I=0.61$ ($P=0.001$) was also observed for childhood wasting (map E-1), where 24 'hotspots' and 26 'cold-spots' were identified. The hotspots were mainly located in parts of Bihar, Jharkhand, and two districts of Madhya Pradesh (MP), i.e. Khandwa and Indore, while the cold spots were located in parts of Rajasthan and Uttar Pradesh (map E-2 & E-3).

Spatial lag models (SLMs) explained 54.50%, 36.88%, and 64.62% of the variations in the rates of stunting, wasting, and underweight, respectively. The estimated coefficients for the lag model of stunting, wasting, and underweight were 0.37, 0.442, and 0.47, respectively, indicating high significance and positivity. This suggests that the prevalence of childhood undernutrition in one district directly depends on the prevalence in neighboring districts.

The estimated coefficient for childhood stunting indicates that the district proportion of households with unimproved sanitation facilities, mothers with higher birth orders, no institutional births, and the Muslim religion

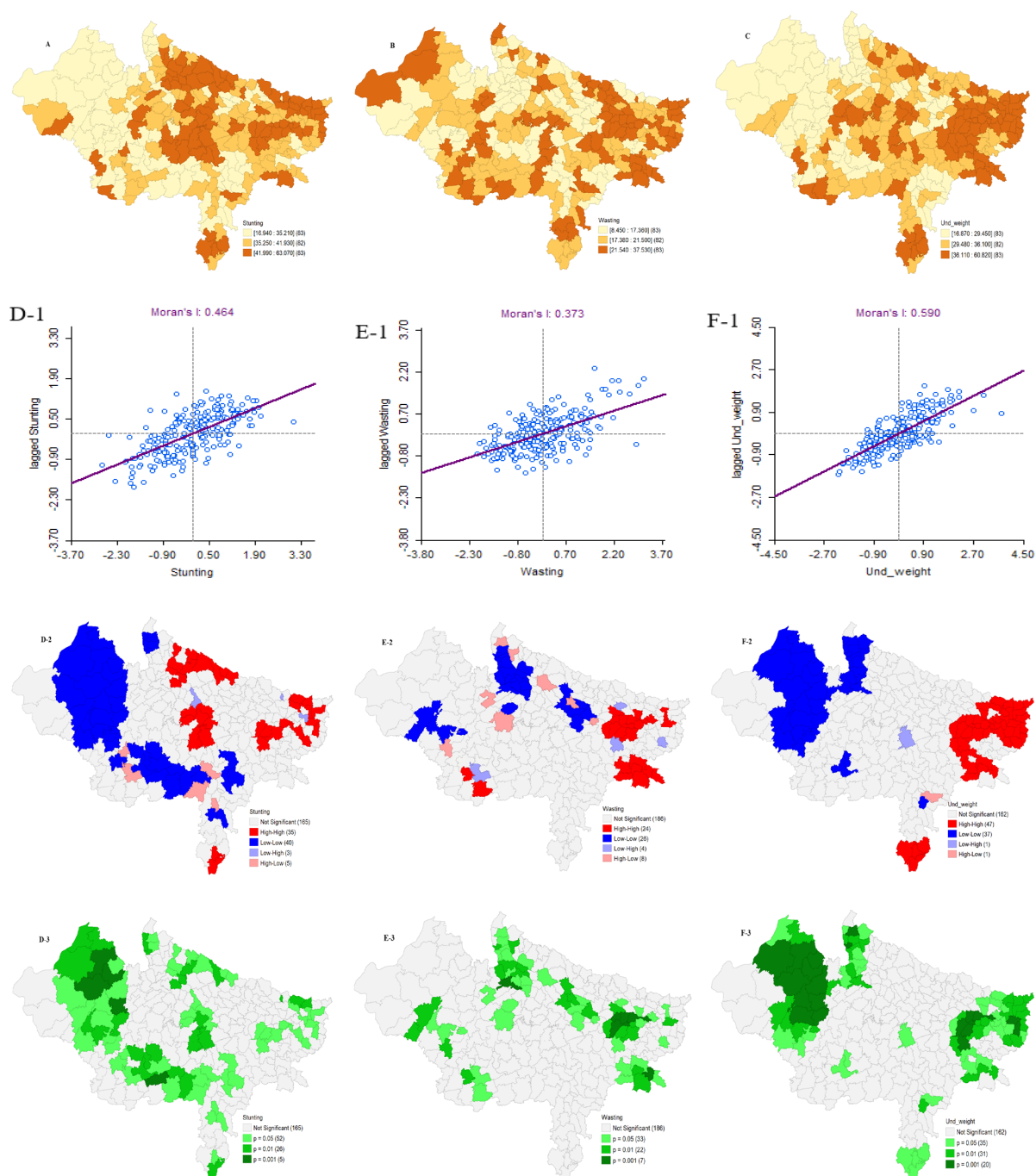


Figure 2. Spatial choropleth, cluster, and LISA map of child undernutrition at the district level in LSDI states of India, NFHS-5 (2019-21)

were associated with stunting in children under five years of age. Thus, the coefficient estimate for four or more birth orders confirms that a 10-point increase in the proportion of women with higher birth orders across the district was associated with a 3.6-point ($\beta=0.36$; 95% CI, 0.202%, 0.518%) increase in stunting prevalence. Similarly, a 10-point increase in the proportion of non-

institutional births across the districts is associated with a 1.13-point ($\beta=0.113$; 95% CI, 0.012%, 0.214%) increase in stunting prevalence. While showing a negative association, the corresponding beta coefficients suggested that one unit increase in the proportion of the Muslim population across the districts was associated with a 0.094-point ($\beta= -0.094$; 95% CI, - 0.167%, -0.02%) re-

Table 1. Summary statistics of undernutrition (stunting, wasting, and underweight) based on background variables, NFHS-5 (2019-21)

Variables	Categories	No. (%)		
		Stunting	Wasting	Underweight
Place of residence	Urban	4934(32.39)	2993(19.65)	4168(27.36)
	Rural	26842(40.64)	12702(19.23)	22612(34.24)
Highest educational level	No education	11448(47.62)	5135(21.36)	9797(40.75)
	Primary	4983(43.6)	2155(18.86)	4048(35.42)
	Secondary	12978(35.87)	6787(18.76)	10969(30.32)
	Higher	2368(24.58)	1619(16.81)	1966(20.41)
Improved drinking water	Unimproved	1418(39.38)	749(20.79)	1279(35.52)
	Improved	30358(39.08)	14947(19.24)	25500(32.83)
Sanitation facility	Unimproved	12252(45.94)	5571(20.89)	10548(39.55)
	Improved	19524(35.75)	10125(18.54)	16232(29.72)
Religion	Hindu	27057(38.8)	13252(19)	22821(32.72)
	Muslim	4218(41.29)	2142(20.97)	3455(33.82)
	Others	501(37.93)	301(22.77)	504(38.15)
Caste	SC	8351(43.78)	3731(19.56)	6987(36.63)
	ST	4077(41.56)	2182(22.24)	3756(38.29)
	OBC	15535(38.44)	7754(19.19)	12966(32.08)
	Other	3814(31.84)	2028(16.94)	3072(25.65)
Wealth index	Poorest	12979(48.03)	5941(21.99)	11420(42.26)
	Poorer	8097(40.99)	3728(18.87)	6725(34.04)
	Middle	5047(36.35)	2484(17.89)	4105(29.56)
	Richer	3483(30.21)	1997(17.32)	2799(24.28)
	Richest	2170(23.88)	1545(17)	1731(19.04)
Maternal BMI	Underweight	8030(45.7)	4077(23.21)	7519(42.79)
	Normal weight	20525(38.6)	10265(19.3)	17083(32.12)
	Overweight	2642(31.31)	1121(13.29)	1784(21.14)
	Obese	579(27.69)	231(11.06)	394(18.83)
Maternal anemia	No	11819(37.27)	6030(19.02)	9772(30.82)
	Yes	19957(40.26)	9666(19.5)	17008(34.31)

Variables	Categories	No. (%)		
		Stunting	Wasting	Underweight
Birth Order	4 or more	6414(46.55)	2807(20.37)	5382(39.06)
	3	6215(42.23)	3019(20.51)	5330(36.22)
	2	9618(37.63)	4926(19.27)	8150(31.89)
	1	9529(35.01)	4943(18.16)	7917(29.08)
Institutional Births	No	6090 (47.49)	2632 (20.53)	5205 (40.59)
	Yes	25686 (37.52)	13063 (19.08)	21575 (31.52)
Infectious diseases in the past 2 weeks	No	25031 (38.94)	12229 (19.02)	20998 (32.66)
	Yes	6746 (39.69)	3466 (20.4)	5782 (34.02)
Immediately after birth, the child was placed on the mother's chest	No	5615 (37.53)	2589 (17.30)	4463 (29.83)
	Yes	26161 (39.45)	13107 (19.76)	22317 (33.65)



duction in the stunting prevalence. On the other hand, sanitation estimates suggested that a 10-point increase in the proportion of unimproved sanitation facilities across the districts was associated with a 0.96-point ($\beta=0.096$; 95% CI, 0.042%, 0.149%) increase in the stunting prevalence (Table 2).

Also, from the analysis of the wasted model, we conclude that the prevalence of wasted children under five at the district level is primarily influenced by maternal nutrition (BMI status) and the Muslim religion within the districts. The corresponding association between wasting and BMI suggests that a 10-point increase in the BMI of overweight mothers is associated with a 0.33-point ($\beta=-0.33$; 95% CI, -0.479%, -0.182%) decrease in the prevalence of wasted children across the district. Conversely, a one-point increase in the prevalence of the Muslim population is associated with a 0.093-point ($\beta=0.093$; 95% CI, 0.155%, 0.12%) increase in the proportion of wasted children. Unimproved sanitation facilities, other castes, the Muslim population, and maternal anemia showed a strong statistical association with the prevalence of childhood underweight in each district. It was found that a 10-point increase in unimproved sanitation facilities across the districts leads to a 0.92 unit ($\beta=0.092$; 95% CI, 0.041%, 0.143%) increase in childhood underweight prevalence, whereas a 10-point increase in the population of other castes results in a decrease of 1.15 points ($\beta=-0.115$; 95% CI, -0.212%, -0.018%) in childhood underweight across the districts. Similarly, a 10-point increase in the proportion of anemic mothers across the districts is associated ($\beta=0.064$; 95% CI, 0.003%, 0.125%) increase

in the prevalence of underweight across districts. On the other hand, the wealth quantile suggests that a 10-point increase in the share of the rich wealth index population contributes to a reduction in the prevalence of childhood underweight by 1.77 units ($\beta=-0.177$; 95% CI, -0.014%, -0.146%) (Table 2).

Discussion

The findings from the study indicated a distinct spatial distribution of stunting, underweight, and wasting across the districts of LSDI states in India. The Moran's I statistics indicated the level of spatial dependence, with the highest value observed for underweight, followed by stunting and wasting. This finding confirms the existence of a regional gradient of malnutrition in LSDI states of India. While a significant prevalence of malnutrition was observed in several states and regions, the concentration was most pronounced in the districts of Uttar Pradesh, Bihar, and Jharkhand. Predictors of various undernutrition statuses among children have been considered based on the k-best feature selection technique. The regression analysis (SLM) indicated a spatially significant association between malnutrition (specifically stunting, underweight, and wasting) and characteristics, such as higher birth order and lack of institutional birth, unsafe drinking water, schedule caste status, BMI of mothers, maternal education, and unimproved sanitation. No institutional delivery and higher birth order were significantly associated with a higher prevalence of stunting among children. Districts with a rich wealth index are at a lower risk of increased prevalence of wasting and being underweight.

Table 2. Parameter estimations of stunting, wasting, and underweight using the spatial lag model, NFHS-5 (2019-21)

Variables	Stunted		Wasted		Underweight	
Fixed part	Coef. (95% CI)	P	Coef. (95% CI)	P	Coef. (95% CI)	P
CONSTANT	8.204 [-0.123, 16.532]	0.0535	23.62 [14.802, 32.437]	0.0000*	13.073 [6.658, 19.488]	0.0001*
Birth order (4 or more)	0.36 [0.202, 0.518]	0.0000*				
No institutional birth (%)	0.113 [0.012, 0.214]	0.0287*				
Immediately put on chest after birth (%)	0.056 [-0.03, 0.143]	0.2003				
Unimproved sanitation facility (%)	0.096 [0.042, 0.149]	0.0005*			0.092 [0.041, 0.143]	0.0004*
Schedule caste (%)	0.071 [-0.008, 0.151]	0.0782				
Other castes (%)			-0.088 [-0.19, 0.014]	0.0905	-0.115 [-0.212, -0.018]	0.0207*
No infectious disease (%)			-0.016 [-0.073, 0.041]	0.5894		
Rural areas (%)			-0.056 [-0.117, 0.005]	0.0743		
Maternal BMI (%)			-0.33 [-0.479, -0.182]	0.0000*		
Maternal primary education (%)			-0.139 [-0.289, 0.011]	0.0687	-0.07 [-0.211, 0.071]	0.332
Muslim religion (%)	-0.094 [-0.167, -0.02]	0.0128*	0.093 [0.031, 0.155]	0.0033*	0.064 [0.003, 0.125]	0.0407*
Unimproved drinking water (%)			-0.087 [-0.178, 0.003]	0.0584	-0.071 [-0.159, 0.016]	0.1115
Rich wealth index (%)			-0.086 [-0.193, 0.021]	0.1134	-0.177 [-0.292, -0.061]	0.0028*
Anaemic mother (%)					0.08 [0.014, 0.146]	0.0176*
Lag coeff. (Rho)	0.379 [0.246, 0.511]	0.0000*	0.461 [0.321, 0.601]	0.0000*	0.509 [0.391, 0.628]	0.0000*
R ²	0.545		0.363		0.632	
AIC	1559.4		1478.6		1485	
Diagnostics test for spatial dependence	Value	P	Value	P	Value	P
Moran's I (error)	5.2652	0.0000*	6.701	0.000*	6.044	0.0000*
Lagrange multiplier (lag)	28.742	0.0000*	40.163	0.000*	51.704	0.0000*
Robust LM (lag)	7.2092	0.0073*	4.391	0.036*	23.345	0.0000*
Lagrange multiplier (error)	21.8854	0.0000*	35.91	0.000*	28.784	0.0000*
Robust LM (error)	0.3526	0.5527	0.138	0.711*	0.424	0.5149*
Lagrange multiplier (SARMA)	29.0946	0.0000*	40.301	0.000*	52.129	0.0000*

Coeff: Coefficient; AIC: Akaike information criterion, LM: Lagrange multiplier.



*Significant at the 5% level.

Although the relationship between poverty and malnutrition varies by country setting, our results indicate that the rich wealth index is statistically significant only for underweight, while it does not emerge as an important feature for predicting the prevalence of undernutrition among children in the districts of LSDI states in India. However, earlier research conducted in impoverished countries demonstrated that poverty is a significant factor in the prevalence of child malnutrition [22]. It will be beneficial to concentrate on these districts to decrease malnutrition and improve the overall malnutrition problem in India. Districts in LSDI states of India with a higher percentage of families not using improved sanitation facilities have a higher prevalence of stunting and underweight. Poor sanitation in households can result in pediatric illnesses, including diarrhea and other infectious diseases [23, 24]. Similar to the sanitation aspect of child nutrition, it is worth noting that the government of India initiated a cleanliness campaign called “Swachh Bharat Abhiyan” to enhance sanitation and waste management nationwide [25].

Furthermore, there was a negative association between women's BMI and educational status with wasting. BMI is not a significant predictor for stunted and underweight individuals. Districts with a larger proportion of women with a high BMI ($>25 \text{ kg/m}^2$) were notably less likely to have a higher prevalence of wasting in children, aligning with earlier research. Maternal nutrition significantly influences the risk of poor intrauterine growth and low birth weight. Undernourished mothers may struggle to provide appropriate breastfeeding, leading to poor nutrition for their children [26–28]. Improving maternal health is essential for reducing malnutrition in children. The National Health Mission (NHM) project of the government of India aims to enhance child and maternal health throughout India [29, 30].

Conclusion

This study elucidates the spatial heterogeneity of malnutrition among children under five in districts of LSDI states in India. The findings have potential utility in improving public health strategies and identifying the root causes linked to child nutrition. It also proposes the distribution of health resources and the execution of child health interventions in the geographical hotspots with a greater prevalence of malnutrition. The occurrence of malnutrition is concentrated in specific geographic areas characterized by high poverty rates, low levels of women's education, and below-average BMI levels among women. An integrated approach involving coordination across multiple sectors is necessary to address child malnutrition in LSDI states of India. This approach should

focus on reducing poverty, boosting sanitation coverage, and improving maternal nutrition.

Ethical Considerations

Compliance with ethical guidelines

The study utilized a secondary dataset from the recent NFHS-5 survey, which contains no identifiable information about the participants. Consent was obtained by NFHS-5 before and during the survey. Since this dataset is publicly available for research purposes, no additional ethical approval was required for this study.

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Authors' contributions

Conceptualization, and writing of the original draft: Mukesh Vishwakarma and Gargi Tyagi; Methodology, visualization and formal analysis: Mukesh Vishwakarma, and Pawan Kumar Dubey; Software, resources and data curation: Mukesh Vishwakarma; Validation: All authors; Supervision, review, and editing: Gargi Tyagi

Conflict of interest

The authors declared no conflict of interest.

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