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ORIGINAL ARTICLE

Spatial modeling of child malnutrition attributable to drought in India

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Abstract

Objectives Indian agriculture is mostly dependent on monsoon. Poor and irregular rainfall may result in crop failure and food shortage among the vulnerable population. This study examined the variations in drought condition and its association with under age 5 child malnutrition across the districts of India.

Methods Using remote sensing and National Family Health Survey (NFHS-4) data, univariate Moran's *I* and bivariate local indicator of spatial autocorrelation (LISA) maps were generated to assess the spatial autocorrelation and clustering. To empirically check the association, we applied multivariate ordinary least square and spatial autoregressive models.

Results The study identified highly significant spatial dependence of drought followed by underweight, stunting, and wasting. Bivariate LISA maps showed negative spatial autocorrelation between drought and child malnutrition. Regression results suggest agricultural drought is substantially associated with stunting. An increasing value of drought showed statistical association with the decreasing ($\beta = -8.251$; p value < 0.05) prevalence rate of child stunting across India.

Conclusions This study provides evidence of child undernutrition attributable to drought condition, which will further improve the knowledge of human vulnerability and adaptability in the climatic context.

Keywords Child nutrition · Climate · Drought · India · LISA

Abbreviations

DEM	Digital elevation model
FAO	Food and Agricultural Organization
IPCC	Intergovernmental panel on climate change
LISA	Local indicator of spatial autocorrelation
LST	Land surface temperature
MODIS	Moderate resolution imaging spectroradiometer
NDVI	Normalized Difference Vegetation Index
NFHS	National family health survey
OLS	Ordinary least squares
PCI	Precipitation condition index
PoU	Prevalence of undernutrition
SDCI	Scaled drought condition index
SRTM	Shuttle radar topography mission
TCI	Temperature condition index
TRMM	Tropical rainfall measuring mission
VCI	Vegetation condition index

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Introduction

Malnutrition is a health condition resulting from either an insufficient or excessive intake of various nutrients. It is a broad term that includes both undernutrition and overnutrition. Stunting, wasting, and underweight are composite anthropometric measures of child malnutrition (Gillespie and McNeill 1992; Arnold et al. 2004). Globally, a significant number of people are affected by malnutrition (undernutrition). The Food and Agriculture Organization (FAO) estimated that approximately 795 million people suffered from undernutrition globally during 2014–2016 (Black et al. 2013). The prevalence of undernourishment and underweight among children under age 5 was primarily used internationally to measure and compare the burden of undernutrition.

Human health is linked with the environment through a complex web of vicious circle model describing the interrelationships among population growth, poverty, health impairment and environmental degradation such as climate change (Jankowska et al. 2012). There is a strong consensus among the scientists that with climate change, meteorological factors like temperature, precipitation, and humidity will increasingly influence human health (McGuire 2013). The intergovernmental panel on climate change (IPCC) has declared with "very high confidence" that climate change already contributes to the global burden of disease (Confalonieri et al. 2007). The change in the climate can result in drought and famine. Indian agriculture is mostly dependent on rainfall, and irregularities may result in crop failure and food shortage among the vulnerable population. Hence, rainfall is an important factor influencing the livelihoods of farmers (Haile 2005).

Globally, for children under 5 years of age, climate change is predicted to worsen all of the top five causes of death, namely malnutrition, neonatal deaths, acute respiratory illness, diarrhea, and malaria (Kiang et al. 2013). The global trend in undernourishment has shown substantial improvement as the prevalence of undernutrition (PoU) had decreased globally from 18.6% in (1900–1992) to 10.9% in (2014–2016). However, there is a wide variation in PoU among regions. Two regions, southern Asia and sub-Saharan Africa account for approximately 35.4% and 27.7% of the shares of global undernourishment, respectively (FAO 2015). Current estimates show the stunting prevalence is 23.8% globally, with approximately 159 million children affected (Unicef 2015). Within a similar period, the prevalence of underweight (weight-for-age *Z*-score of less than − 2 SD) has decreased from 30.1 to 19.4%, with more than 100 million children being underweight. The corresponding estimate for wasting (weight-for-height *Z*-score of less than − 2 SD) is approximately 52 million children (Black et al. 2013).

Nutrition situation in India

A large proportion of children and women are suffering from severe malnutrition, especially in developing countries like India. Evidence suggests that there has been a significant decline in the level of stunting from 52% in (1992–1993) to 38% by (2015–2016). On the contrary, wasting had increased from 17% to 21% among the children (Khan and Mohanty 2018). According to National Family Health Survey (NFHS-II) (1998–1999), there were 51%, 20%, and 43% of children below 3 years suffering from stunting, wasting, and underweight, respectively, which decreased to 45%, 23%, and 40% during 2005–2006.

What are the factors affecting child undernutrition? It is well known that child undernutrition is affected by multiple factors like sociocultural, economic, and demographic factors, while climate change is one of the challenges against the efforts undergoing to combat child undernutrition through improved household food security. A study on Ethiopia has identified climatic factors as a predictor of child undernutrition (Hagos et al. 2014). A similar study had measured the vegetation health, as Normalized Difference Vegetation Index (NDVI) to quantify the association with child nutritional status across four countries of Africa (Johnson and Brown 2014). Children possess the major risk due to climate change as their bodies are at a growing stage and long-term exposure to nutritional deficiency could grave to health vulnerabilities (McCartney 2007). And in a country like India, where pulses are preferred over meat as a source of protein, the climate change will affect the quality of food crops which in turn will accelerate the epidemic of "hidden hunger" or micronutrient deficiency (Myers et al. 2014; Swaminathan et al. 2012). A handful of empirical studies have investigated the correlation of weather and climate variability to crop yields and undernutrition (Phalkey et al. 2015). In this context, the present study explores the drought condition to expose the burden of child undernutrition across the districts in India.

Methods

Study area and population

The study is based on a nationally representative family health survey and covers the population which includes women aged between 15 and 49 years, men aged 15–54 years, and children under age 5 in particular. The survey is being conducted across all the 640 districts in India and constitutes the spatial units for this district-level study. The study sample for this specific study comprises 259,627 children under age 5, and the necessary variable information is aggregated at the district level to conduct this study.

Data sources for meteorological indices and topographic information

The datasets used for the study is mainly comprised of two categories. Those are products derived from the satellite sensors and ancillary data from National Family Health Survey (NFHS-4). Terra MODIS surface reflectance MOD13Q1 (250 m) was used to compute Normalized

Difference Vegetation Index (NDVI) 2015–2016 and Vegetation Condition Index (VCI) 2015–2016. MODIS LST of MOD11A2 (1 km) was used to compute Temperature Condition Index (TCI) 2015–2016, and TRMM 3B43 (0.25 × 0.25) precipitation estimate was used to compute Precipitation Condition Index (PCI) for the year 2015–2016. The elevation data were derived from Shuttle Radar Topography Mission (SRTM), which provides digital elevation model (DEM) downloaded from USGS Earth Explorer. The summary of datasets is presented in Electronic supplementary material (ESM): Table S1.

Scaled Drought Condition Index (SDCI) has been considered to capture the agricultural drought condition prevailing across districts of India during the reference period of the study. With the existing remote sensing indices, SDCI has been identified as one of the apt remote sensing-based drought index. Some indices like vegetation Health Index (VHI) has been developed with the combination of VCI and TCI along with weighted linear function. With the development and popularity of precipitation and moisture index, SDCI was developed combining TCI, PCI, and VCI that can be used for agricultural drought monitoring in both arid/semiarid and humid regions (Rhee et al. 2010; AghaKouchak et al. 2015) considering NDVI, LST, and TRMM datasets (all three scaled from 0 to 1) for composite drought assessment. Electronic supplementary material (ESM): Table S2 provides a detailed description on the constructs of SDCI.

$$\mathrm{SDCI} = 0.25\mathrm{TCI} + 0.5\mathrm{PCI} + 0.25\mathrm{VCI}$$

where low values of SDCI close or equals to 0, imply a serious drought condition and at wet conditions, the value of SDCI is close to 1.

The reference period for this study is 2015–2016. The study is being conducted in a cross-sectional setting. As in Indian context, data sources are limited. Though the variable information on climatic components is available over time, there is no population-based longitudinal or panel data available for child health components to examine the climatic variability in child health indicators. Taking care of the data limitation, this study examined drought association of child malnutrition in a spatial context where 640 districts of India are the units of analyses. So, districts (spatial units) are being grouped to make the panel and district-level variation in child malnutrition is predicted with the associated drought condition across those districts. Thus, this study does not consider time into account instead within a cross-sectional setting the spatial phenomenon of drought and child malnutrition has been examined.

Parameters from ancillary data

Three commonly utilized measures of nutrition were selected from the NFHS-2015–2016 for the analysis: the child's measure of stunting, the height-for-age *Z*-score which is a measure of linear growth retardation, and cumulative growth deficits. Children whose height-for-age *Z*-score is below minus two standard deviations (− 2 SD) from the median of the reference population are considered short for their age (stunted). Child's underweight status is defined in terms of the weight-for-age *Z*-score which is a composite index of height-for-age and weight-for-height. Underweight as a measure of child undernutrition takes into account both acute and chronic undernutrition. Children whose weight-for-age *Z*-score is below minus two standard deviations (− 2 SD) from the median of the reference population are classified as underweight, while child's wasting status which is measured through the weight-for-height *Z*-score measures the body mass by body height or length and describes current nutritional status of the children. Children whose weight-for-height *Z*-score is below minus two standard deviations (− 2 SD) from the median of the reference population are considered as thin (wasted). To define the measures of stunting, underweight and wasting, we followed the guidelines by WHO and UNICEF (WHO 2009; UNICEF 2008).

While measuring the anthropometric measures of child's nutritional status, we dropped the flagged cases and values of height and weight out of possible limits. We did not employ any missing data analysis in this present study. ESM (Table S3) gives detailed information on the variables used.

Analytical approach

To examine the spatial clustering of drought and child malnutrition, local Moran's I statistic was computed which measures the spatial autocorrelation and indicates the degree to which data points are similar or dissimilar to their neighbors. p value of local Moran's I was generated using a randomization test on a Z-score with 9999 permutations.

$$\text{Moran's } I = C \times \frac{\sum_i \sum_j W_{ij} Z_i Z_j}{\sum_i Z_i^2}$$

where z_i is the standardized variable of interest; W_{ij} is the standardized weight matrix with zeroes on the diagonal, and C is the multiplier equivalent to $= N/S_0$. Here N is the number of spatial units indexed by i and j; S_0 is the sum of all W_{ij}'s. A Moran's I statistic tends to be larger positive (or negative) value between (− 1 and 1). Positive spatial autocorrelation would indicate that regions with similar attribute values are more clustered, whereas a negative spatial autocorrelation would indicate a dissimilarity in associated regions. Furthermore, univariate local indicators of spatial association (LISA) measures the correlation of neighborhood values around a specific spatial location and determines the extent of spatial randomness and clustering to detect spatial heterogeneity. It is given by

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

where x is the variable of interest and $\bar{X}$ is the mean of x; n is the number of spatial units; W_{ij} is the standardized weight matrix between observation i and j with zeroes on the diagonal; and S_0 is the aggregate of all spatial weights, i.e., $S_0 = \sum_i \sum_j W_{ij}$.

Likewise, aiming to measure the local variation between two distinctive variables, bivariate Moran's I statistic had been used to check the association between two matrices across a spatial unit and is expressed as follows:

$$\text{Bivariate Moran's } I = \frac{n}{S_0} \times \frac{\sum_i \sum_j W_{ij}(x_i - \bar{X})(y_j - \bar{Y})}{\sum_i (y_i - \bar{Y})^2}$$

where x and y are the variables of interest; $\bar{X}$ is the mean of x; $\bar{Y}$ is the mean of y; n is number of spatial units; W_{ij} is the standardized weight matrix between observation i and j with zeroes on the diagonal; and S_0 is the aggregate of all spatial weights, i.e. $S_0 = \sum_i \sum_j W_{ij}$.

To examine the empirical association between SDCI and the measures of child undernutrition, we regressed district-level prevalence of child undernutrition based on the set of independent variables where SDCI is the key exposure variable. Primarily, we fitted ordinary least square model (OLS) without considering the spatial accountability of the data. Employing the OLS model, we checked the spatial autocorrelation (Moran's I) measure of the residuals from the model and observed a statistically significant autocorrelation in the residuals. Thus, we fitted the spatial lag model (spatial autoregressive model) taking care of the spatial nature of the dataset. The main advantage of employing a spatial model is that spatial lag model removes the bias of spatial endogeneity due to spatial autocorrelation from the data while estimating the coefficients. Estimated results from the OLS as well as spatial lag model are shown in the study where OLS estimates are the primary check of the associations, while the results from the SLM model are the final estimates.

Measures

Dependent variables

The anthropometric data on height and weight and age in months were collected in the NFHS-4 (2015–2016) to measure the nutritional status of young children in India. The most distinctive measures, namely stunting, wasting, and underweight, are three widely recognized indicators of child's nutritional status has been used in the present study.

Independent variables

Key exposure variable To measure the deficit of moisture in soil, Scaled Drought Condition Index (SDCI), a remote sensing-based drought index, has been used in this study. SDCI successfully measures the deficit of soil moisture, precipitation and difference in temperature in both arid and humid regions.

Covariates The study has used background socioeconomic variables and average elevation of a district (representing the topography of the district) as the covariates. Background variables included proportion of male children, proportion of rural children, proportion Hindu children, proportion of scheduled caste (SC)/scheduled tribe (ST) children, proportion of children whose mother do not have any formal education, proportion of poor children and proportion of children whose mother had no media exposure in the household. All the covariates were controlled to get the adjusted effect (β coefficient) of SDCI on child undernutrition.

The unit-level data of NFHS collects the background information of the surveyed children. Child's sex is coded as 1 'male' and 2 'female'. Place of residence is a dichotomous variable with the specification: 1 'urban' and 2 'rural' respectively. The religion variable is coded as, 1 'Hindu'; 2 'Muslim'; 3 'Christian'; 4 'Sikh'; 5 'Buddhists/Neo-Buddhist'; 6 'Jains'; 7 'Jewish'; 8 'Parsi/Zoroastrian'; 9 'no religion' and 98 'others' in the present study. Indian society is subdivided into different social groups: 1 'Scheduled Caste' (SC); 2 'Scheduled Tribe' (ST); 3 'other backward class' (OBC); 4 'none of them' and 5 'don't know' where the SC/ST population are mostly devoid from the privileges, socially excluded and are vulnerable. Thereby, the proportion of 'SC and ST' children have been compiled in the study. In order to measure the wealth/economic status of the population across the households, a predefined wealth index variable with the quintile categories, 1 'poorest'; 2 'poor'; 3 'middle'; 4 'rich'; and 5 'richest' has been used from the dataset. Further, the categories—'poorest and poor'—have been combined together to measure the proportion of poor children across the districts. Child's mother's level of educational attainment is coded as: 0 'no education'; 1 'incomplete primary'; 2 'complete primary'; 3 'incomplete secondary'; 4 'complete secondary'; and 5 'higher' in the dataset. We extracted the 'no education' category only to calculate the district-level proportion of mother having no formal education. To measure the media/mass media exposure among child's mother, the information on reading of newspaper, listening to radio, and watching television has been combined. The combined variable is a dichotomous variable which is coded as: 1 'having exposure to media/mass media' and 2 'not having any exposure to media/mass media'.

The aforesaid variables have been considered as a moderator in the present study. As we dealt with categorical covariates from NFHS-4, we could extract only one category information for each of the variables to put into the system of equation subject to the correlation structure of a multivariate framework of a district-level analysis and to remove the bias of autocorrelation and dependency.

Result

Spatial pattern of agricultural drought condition

Among the different natural hazards, drought is one of the most disastrous as it inflicts untold numerous miseries on human societies. For a country like India, where rainfall is seasonal in nature, agriculture often becomes tuned with the rainy season. Any deficiency of significant amount of rainfall thus directly affects agriculture, ruining the economy.

Spatial distributions of the drought indicator, SDCI for (2015–2016) has been shown in Fig. 1. The severity of the drought is restricted to northern uplands and southern Peninsular regions of the subcontinent. The variability of SDCI ranged between (0.97 and 0.03). Lower frequencies were recorded in the states of Deccan plateau of Maharashtra, India. Moreover, the northern plains remained wet throughout the study period except in a few clusters. A similar type of picture can be seen in the eastern and north-east frontier. The rain shadow zone of South India has been devoid of major wet condition. In this present study, SDCI has been a good predictor to estimate the burden of child nutritional status which has been validated in the subsequent sections.

Spatial autocorrelation results

Estimating the potential health impacts of drought is facilitated by multi-determinant models that integrate and influence the public health responses by identifying regions

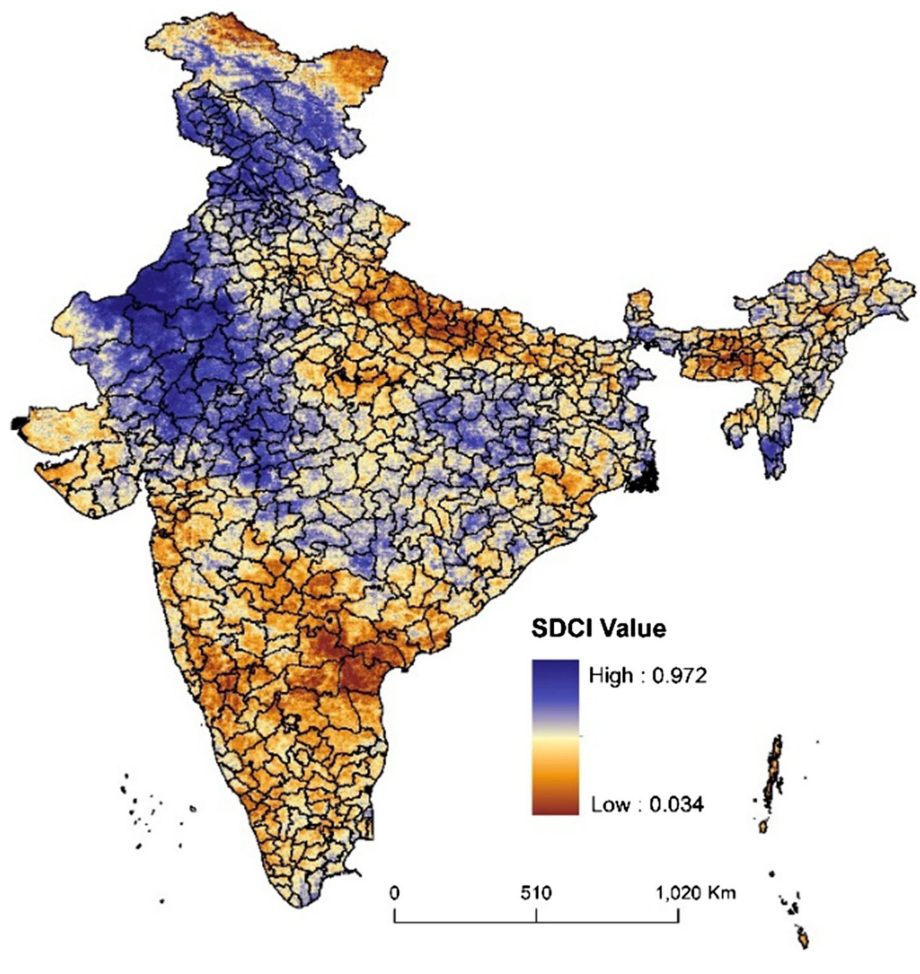

Fig. 1 Annual distribution of Scaled Drought Condition Index (SDCI) across India during the year (2015–2016). Brown color indicates severe drought condition; blue represents wet condition

Table 1 Univariate Moran's *I* result, India, 2015–2016

	Moran's *I*	*p* value
Under 5 children nutrition variables		
Stunting	0.641	0.001
Underweight	0.748	0.001
Wasting	0.486	0.001
Geo-climatic variables		
Scaled drought condition index (SDCI)	0.779	0.001
Elevation	0.726	0.001
Sociodemographic variable		
Proportion of male children	0.026	0.122
Proportion of rural population	0.408	0.001
Proportion of Hindus	0.748	0.001
Proportion of SC/ST	0.589	0.001
Proportion of illiterate mothers	0.710	0.001
Proportion of poor people	0.764	0.001
Proportion of non-media exposed	0.740	0.001

and population groups (children under age 5) that may be more vulnerable. The spatial analyses discuss about the possible pathways that the child nutrition parameters could get affected under different assumptions of geographic and socioeconomic factors.

Table 1 identifies spatial autocorrelation of nutritional health variables of the children (stunting, underweight, and wasting), geographical climate variables (SDCI and elevation), and sociodemographic variables (proportion of male population, rural population, Hindu religion, scheduled caste and scheduled tribes (SC/ST), illiterate mothers, poor population, and no media exposure group). Estimated univariate Moran's *I* statistic values indicate highly significant spatial dependence in stunting in comparison with underweight and wasting across the districts of India. Among the geographical climate variables, SDCI records the Moran's *I* value as: (0.779) and 99% significance level. Further, among the sociodemographic confounders, the proportion of poor population is highly spatially autocorrelated followed by proportion of Hindu population, proportion of no media exposed people and others. The proportion of male children has the lowest spatial autocorrelation across the districts.

Bivariate LISA estimates of spatial autocorrelation show compelling evidence of spatial autocorrelation between the different components of child nutrition with the key exposure variable and most of the covariates considered in this study. SDCI shows the maximum negative spatial autocorrelation with stunting (− 0.125) followed by underweight and wasting (Table 2). The proportion of illiterate mothers, no media exposures, and proportion of poor people showed a positive and statistically significant spatial autocorrelation with each of the child nutrition indicators. In case of wasting, proportion of SC/ST population has shown a negative & significant spatial autocorrelation at (5%) significance level.

The variation in the observed association is shown in Fig. 2. We have found the highest number of districts (92) clustered for higher prevalence of stunting against low values of SDCI (drought) in the northern plains. While a spatial clustering of 68 districts with lower prevalence of stunted children is observed against the higher values of SDCI (Fig. 2a). This signifies that with acute agricultural drought condition there is a deficiency in nutritional intake and children are likely to get stunted. Similarly, bivariate LISA map for underweight and drought clustering shows, with lower values of SDCI there is a higher prevalence of underweight among the children in 72 districts (Fig. 2b). Further, the spatial pattern can be observed with wasting

Table 2 Bivariate Local Moran's *I* result, India, 2015–2016

	Stunting		Underweight		Wasting	
	Moran's *I*	*p* value	Moran's *I*	*p* value	Moran's *I*	*p* value
Geo-climatic variables						
Scaled drought condition index (SDCI)	− 0.125	0.001	− 0.058	0.001	0.034	0.033
Elevation	− 0.277	0.001	− 0.374	0.001	− 0.198	0.001
Sociodemographic variable						
Proportion of male children	0.067	0.001	0.077	0.001	0.020	0.118
Proportion of rural population	0.225	0.001	0.152	0.001	0.013	0.251
Proportion of Hindus	0.245	0.001	0.462	0.001	0.396	0.001
Proportion of SC/ST	− 0.064	0.001	− 0.126	0.001	− 0.050	0.004
Proportion of illiterate mothers	0.524	0.001	0.435	0.001	0.121	0.001
Proportion of poor people	0.502	0.001	0.440	0.001	0.155	0.001
Proportion of non-media exposed	0.555	0.001	0.440	0.001	0.114	0.001

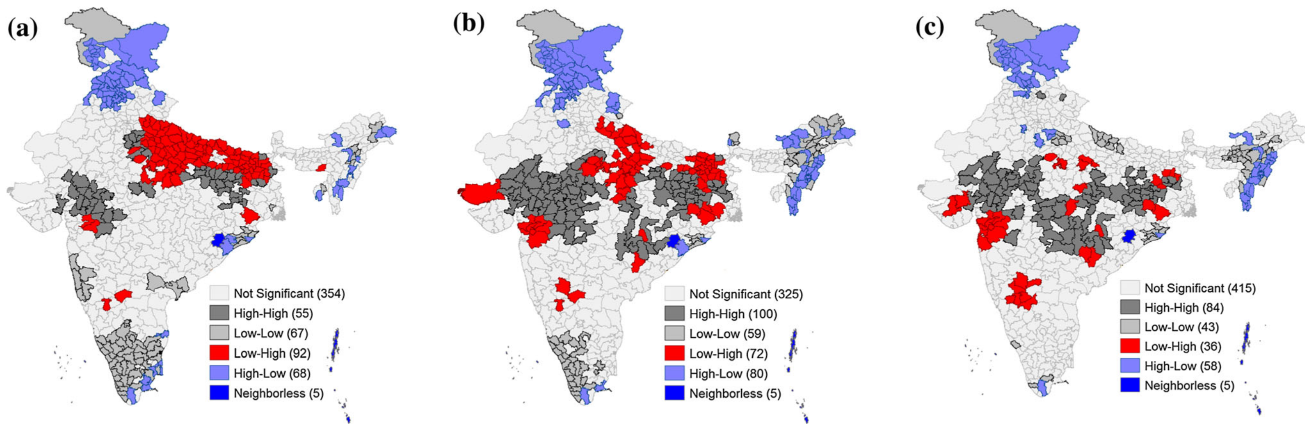

Fig. 2 Bivariate local indicator of spatial autocorrelation (LISA) cluster maps showing the spatial clustering of scaled drought conditioned index (SDCI) with **a** stunting; **b** underweight and **c** wasting among the children under age 5 across the districts of India (2015–2016)

also. The clustering of low SDCI and higher prevalence of wasting can be observed across 36 districts (Fig. 2c).

Regression result (OLS estimation)

Findings from Table 3 show the effect of agricultural drought condition on under 5 child nutrition across 640 districts of India computed with a simple OLS regression. Investigating the multivariate relationships through OLS estimation we checked the primary association between SDCI and measures of child undernutrition.

OLS estimation shows that SDCI is significantly associated with stunting and indicates a negative relationship with child stunting prevalence across the districts. And it is observed that increasing value of SDCI is statistically associated with the decreasing burden of child stunting in India. This result is also quite consistent with the previous bivariate result confirming that districts, where SDCI value is lower carried the higher burden of child stunting in India. Though in the multivariate framework, SDCI failed to predict the other forms of malnourishment like underweight and wasting prevalence across the districts. Among the covariates, the proportion of illiterate mothers across districts shows a highly significant association with the district-level prevalence of child malnutrition. This signifies that educational attainment for mothers plays an important role in providing better nutritious food and care to the child (Table 3).

Spatial regression (spatial lag model)

Spatial lag model estimation of the data shows that SDCI is a statistically significant predictor of child stunting (Table 4). In contrast, within this cross-sectional setting, SDCI could not statistically predict the district-level burden of child underweight and wasting prevalence across the panel of districts. The possible reason could be that the district-level prevalence of underweight and wasting are systematically distributed across the country subject to socioeconomic characteristics of the population wherein

Table 3 Estimated result from the multivariate ordinary least squares (OLS) regression, India, 2015–2016

Covariates	Stunting			Underweight			Wasting		
	Beta	SE	p	Beta	SE	p	Beta	SE	p
Scaled drought condition index (SDCI)	− 8.251***	2.745	0.003	0.454	3.133	0.884	6.607**	2.857	0.021
Elevation	− 0.001***	0.000	0.001	− 0.001***	0.000	< 0.001	− 0.000	0.000	0.594
Proportion of male children	0.196***	0.075	0.009	0.058	0.086	0.497	0.032	0.078	0.686
Proportion of rural population	− 0.017	0.017	0.317	− 0.046**	0.019	0.017	− 0.054***	0.018	0.002
Proportion of Hindus	0.055***	0.011	< 0.001	0.171***	0.013	< 0.001	0.126***	0.012	< 0.001
Proportion of SC/ST	− 0.004	0.014	0.798	0.021	0.017	0.205	0.052***	0.015	0.001
Proportion of illiterate mothers	0.181***	0.023	< 0.001	0.169***	0.026	< 0.001	0.026	0.023	0.268
Proportion of poor people	0.055**	0.024	0.024	0.100***	0.028	< 0.001	0.041	0.025	0.110
Proportion of non-media exposed	14.878***	3.233	< 0.001	9.120**	3.391	0.014	2.683	3.366	0.426
Adjusted R^2	0.569			0.583			0.226		

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 4 Estimated result from spatial lag model (SLM), India, 2015–2016

Covariates	Stunting			Underweight			Wasting		
	Beta	SE	p	Beta	SE	p	Beta	SE	p
Scaled drought condition index (SDCI)	− 5.95**	2.45	0.015	− 1.82	2.44	0.455	2.55	2.51	0.308
Elevation	0.00**	0.00	0.028	0.00***	0.00	0.005	0.00	0.00	0.814
Proportion of male children	0.16**	0.07	0.020	0.04	0.07	0.528	0.08	0.07	0.227
Proportion of rural population	0.01	0.02	0.668	0.01	0.02	0.701	− 0.03*	0.02	0.086
Proportion of Hindus	0.02**	0.01	0.020	0.07***	0.01	< 0.001	0.06***	0.01	< 0.001
Proportion of SC/ST	0.00	0.01	0.902	0.01	0.01	0.320	0.03**	0.01	0.014
Proportion of illiterate mothers	0.13***	0.02	< 0.001	0.10***	0.02	< 0.001	0.02	0.02	0.338
Proportion of poor people	0.04*	0.02	0.050	0.05**	0.02	0.014	0.02	0.02	0.273
Proportion of non-media exposed	6.86**	2.91	0.019	1.90	2.89	0.511	1.35	2.94	0.647
ρ	0.42***	0.04	< 0.001	0.59***	0.03	< 0.001	0.51***	0.04	< 0.001
AIC	4157.66			4184.34			4197.86		
Adjusted R^2	0.66			0.75			0.41		

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

the socioeconomic factors like mother's educational attainment and poverty situation of the district mostly determine the nature of those two child undernutrition burden in that particular district and not necessarily disadvantaged in terms of the agricultural drought (SDCI). Stunting model shows that SDCI has a strong association with child stunting burden ($\beta = -5.95$, p value = 0.015) across India and indicates that an increasing value of SDCI across the districts is statistically associated with a decreasing burden of child stunting (Table 4). From the spatial estimation, it is also evident that covariates like mother's educational attainment and district-level poverty condition substantially determine the pattern of child undernutrition-stunting and underweight. On the other hand, the wasting model is quite anomalous and does not show any predictability within this study framework.

Discussion

Satellite remote sensing observations provide a unique toolset for studying droughts and its association with biophysics and health. Drought poses an economic and environmental crisis in terms of the food security concerns for developing countries (Godfray et al. 2010). In this present study, we have explored the spatial variation of agricultural drought, and the associated variation in child nutrition parameters of interest across India. These variations might be due to better agricultural production or prolific drought condition across the country. Historical records account that the failure of rain results in crop failure, impacts food productions and usually results in food shortages in vulnerable parts of the population (Kloos and Lindtjorn 1994). In many geographical pockets of India, the SDCI values are higher because of irrigation and modernization of agriculture and thus prevails more wet condition in the soil. Although the drought remained sporadic over the geographical space, the results of this study demonstrate that SDCI has a significant effect on child stunting and underweight.

A similar approach was used to explore the evidences on the association of climatic variability and nutritional status of the child across Mali, Africa (Jankowska et al. 2012). The study has found district-level prevalence of stunting to be highly associated with the arid climatic condition across India. Another study on climatic variability and health has shown significant association between vegetation health and child stunting and vegetation health gets affected by temperature and rainfall (Johnson and Brown 2014). During 2014–2015 and 2015–2016 large parts of the country were affected by drought causing widespread hardships to the affected population since the calamity encompassed major agricultural states across the country (India 2016). Rainfall deficiency can have a reparative effect on depletion of soil moisture, fall in the groundwater level and cumulatively will trigger to crop failure under natural condition (Mason et al. 1987). Moreover, the prevalence of child undernutrition has declined from the last few decades but the future perspective of climatic condition (drought) is uncertain. According to the climate change experts, there is a threat of rainfall deficit in the coming future across the Indian ocean (Funk et al. 2008).

In a previous study, a conceptual framework was developed to understand the complex pathways of climate/weather variability in undernutrition (Phalkey et al. 2015). While this study contributed to the understanding of the prevailing drought condition across districts of India and the associated burden of child malnutrition in terms of stunting, underweight and wasting. This study suggests a negative association between SDCI and stunting, underweight burden across the districts of India. Though SDCI (a refined measure of drought) appeared to be a good predictor of child stinting and underweight burden, however, we cannot overlook the sociodemographic predictors.

Conclusion

With this empirical study, we have demonstrated the association of drought on child nutrition outcomes in India. It is well known that the human population is exposed to climatic variabilities. And this study shows the associations between environmental growing conditions and food security-related outcomes. Due to increased climatic variability and drastic changes in the environment the whole population is at risk especially the children under age 5, an age when undernutrition can cause irreparable damage to a child's intellectual and physical development. Hence, it is critical for informing evidence-based policies and programs designed to mitigate the worst impact on the country's economic and environmental crisis. With the contribution to the understanding of the interaction between drought condition and child nutrition, this paper recommends further work but at a microlevel using new approaches and modeling to better understand the inherent complexities of these relationships.

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Availability of data and materials The NFHS-4 or DHS (2015–2016) survey data for India are publicly available free of charge and archived at https://www.dhsprogram.com/data/available-datasets.cfm. The metrological index data, SDCI was generated and archived athttps://mirador.gsfc.nasa.gov/ (TRMM 3B43); https://earthexplorer.usgs.gov/ (MOD13Q1 and MOD11A2).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval and consent to participate The analysis is based on secondary data available in public domain for research; thus, no approval was required from any institutional review board (IRB).

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