Discover Sustainability

RESEARCH

Open Access

# Spatial association between nutrient deficiency and agricultural diversity in India

Arup Jana[1,2*], Aparajita Chattopadhyay[2] and Srijit Mishra[3]

*Correspondence:
Arup Jana
arupjana0000@gmail.com
[1]National Centre for Good Governance, New Delhi, India
[2]International Institute for Population Sciences, Mumbai, India
[3]University of Hyderabad, Hyderabad, India

**Abstract**
Hidden hunger remains a major public health challenge in India, yet it has not received the attention it deserves in research and policy. Despite significant progress in food production, micronutrient deficiencies continue to affect large sections of the population, particularly in rural areas. This study investigates the spatial association between agricultural diversity and nutrient deficiency at the district level across India, addressing a critical evidence gap in understanding how cropping patterns influence nutritional outcomes. Using data from NSS (2011–12) and employing the Small Area Estimation technique, we estimated the prevalence of protein, iron, and folate deficiencies at the district level, accounting for sampling variability and regional heterogeneity. Our analysis reveals that higher crop diversity is concentrated across western, central, and southern India, with prominent pockets in Rajasthan, Gujarat, Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu, along with select districts in Madhya Pradesh, Telangana, Uttarakhand, and Himachal Pradesh. The spatial analysis identifies significant associations between agricultural diversity and nutrient deficiency. Districts with more diversified farming systems tend to exhibit lower levels of micronutrient deficiency, with protein, iron, and folate showing consistent High Low clustering across the western and central regions of India, including large parts of Rajasthan, Gujarat, Maharashtra, and Madhya Pradesh, along with smaller pockets in adjoining states. These findings highlight the crucial role of agricultural diversification in improving dietary quality and nutritional outcomes. The study underscores the need for region-specific agricultural policies and recommends the implementation of conditional incentive programs to promote crop diversification as a sustainable approach to combat micronutrient malnutrition in India.

**Keywords** Agricultural diversity, Nutrient deficiency, Small area estimation, Spatial analysis, District

## 1 Introduction

Micronutrient deficiency, also known as “hidden hunger,” exerts a significant influence on malnutrition, particularly in developing nations such as India, profoundly impacting the health and well-being of individuals as well the human capital of a country [1]. Recognizing the urgency of this issue, the Sustainable Development Goals (SDGs) have established targets to eliminate micronutrient deficiencies by 2030 [2]. Despite modernization and globalization, an estimated 2 billion people worldwide continue to experience malnutrition and its associated health consequences [3]. India, in particular, faces a considerable challenge with the highest number of stunted children and a significant prevalence of anaemia among women and children [4, 5]. Although the Indian government has implemented supplementary and biofortification programs since the 1970s, malnutrition persists, underscoring the urgency of the nutrition crisis.

Recently, many developing nations have entered the later stages of the nutrition and epidemiological transitions [6, 7]. This shift has led to a transformation in food consumption patterns, with a move away from staple foods towards a more diversified diet. However, a significant proportion of the Indian population still relies on staple foods due to their widespread availability and affordability [8]. Moreover, public awareness of the nutritional content of consumed foods remains low [9]. Government nutrition policies in many regions still emphasize caloric sufficiency over nutrient adequacy [10]. In India, efforts to combat micronutrient deficiencies have encompassed strategies such as food fortification and supplementation programs [11]. Despite these efforts, a substantial portion of the population remains undernourished or affected by hidden hunger. Therefore, agricultural diversification should be considered a complementary strategy to address malnutrition in India while existing supplementation and biofortification programs are refined.

Information on macro and micronutrient deficiencies at the district level in India is limited due to data unavailability. This study estimates the prevalence of macro and micronutrient deficiencies at the district level using National Sample Survey Office (NSSO) data and the Small Area Estimation (SAE) technique. Singh et al. (2005) proposed a spatial regression model for SAE using the Mean Squared Error (MSE) technique and they validated the model using time series monthly per capita expenditure data of NSSO [12]. Srivastava et al. (2007) have used SAE to estimate the amount of loan at the district level in the rural areas of Uttar Pradesh using the data from debt investment survey of NSSO [13]. Chandra et al. (2018) estimated the district level poverty in Bihar using the Household Consumer Expenditure Survey 2011–12 of NSSO and the Population Census 2011 [14]. The present study draws methodological inspiration from Pyne et al. (2023) who estimated food security across districts of the Indo-Gangetic Plain using NSS data and the SAE technique [15].

A growing body of empirical evidence underscores the significant connections between agricultural diversity and nutritional consumption [15–19]. Research has consistently demonstrated that expanding the array of crops cultivated on farms can result in enhanced dietary diversity and improved nutritional quality, particularly among rural and economically disadvantaged populations [18]. For instance, a study conducted in Ethiopia revealed a positive association between increased crop diversity on farms and enhanced dietary diversity and micronutrient intake among women and children [20]. Similarly, in Nepal, research indicated that greater crop diversity on farms correlated with improved dietary diversity and nutrient sufficiency [16]. Agricultural diversity can shape diets through two main pathways. In subsistence settings it affects the foods households produce and consume, while in market-oriented settings it influences the availability and affordability of diverse foods through local markets [21]. These findings underscore the potential advantages of promoting agricultural diversity as a means to enhance nutrition outcomes, particularly in low-income settings where access to diverse and nutritious food options may be constrained.

Despite India's rich agro-biodiversity, the adoption of diversified cropping practices remains limited, particularly among farmers in Northern India [22]. A study conducted by the Indian Council of Agricultural Research (ICAR) reveals that farmers in states such as Punjab, Haryana, and western Uttar Pradesh have historically prioritized high-yielding but genetically uniform crops like rice and wheat, often overlooking alternative crops and practices that could bolster agricultural diversity and resilience [23]. Nevertheless, the promotion of local diversity strategies has been identified as a best practice in addressing malnutrition, as previously underscored in existing research [24–26]. While studies on protein consumption patterns utilizing NSS data are available at the state level, a district-wise assessment of micronutrient deficiency remains absent. The present study examines the spatial association between agricultural diversity and nutrient deficiency across Indian districts, with the aim of identifying spatial patterns that can inform region-specific, nutrition-sensitive agricultural interventions. It investigates how agricultural diversity has changed between 2001 and 2012, how protein, iron, and folate deficiencies vary spatially across districts, and how agricultural diversity and its growth relate to these nutrient deficiencies. The study is based on three main questions: first, is agricultural diversification spatially clustered across districts in India; second, do nutrient deficiencies vary substantially across states and districts; and third, whether districts with higher and increasing agricultural diversity tend to exhibit lower levels of nutrient deficiency. It is expected that diversified cropping systems improve dietary quality by enhancing the availability and access to nutrient-rich foods, thereby contributing to better nutritional outcomes across India's diverse agro-ecological regions.

## 2 Data and methods

### 2.1 Agricultural data

The District Agricultural Contingency Plan Network (DACNET), is a database maintained by the Ministry of Agriculture and Farmers Welfare in India. The database comprises information on various agricultural parameters, including cropping patterns and land use statistics collected from all districts in the country. DACNET provides district-level information on crop area, total production, and yield rates for all of India's crops. This information covers all seasons, including autumn, kharif, Rabi, summer, winter, and the entire year, spanning from 1997–98 to the present. This study utilized district-level data on land area under specific crops in India for 2011–12.

### 2.2 National sample survey data

The Household Consumer Expenditure Surveys (HCES) of the National Sample Survey Office (NSSO) are the primary source of data on various indicators of the population's level of living at National and State levels. The NSSO surveys have been conducted quinquennially from the 27th round (October 1972–September 1973). The 68th round survey carried out from July 2011 to June 2012 was the ninth survey, which is the latest data on consumption at the national level. These surveys collect detail information of over 400 food and non-food items in a reference period of 7 days, 30 days and 365 days. The food items have been collected both in quantity and price and estimate the population's nutritional intake. The detailed questionnaire, sampling and the finding are available in the respective report [27].

### 2.3 Census of India

To enhance the SAE analysis, we incorporated a comprehensive set of auxiliary variables sourced from the 2011 Population Census of India. This encompassed a total of 20 auxiliary variables, including critical factors such as the gender-specific proportions of main and marginal workers, the proportions of main and marginal cultivators segmented by gender, as well as the proportions of main and marginal agricultural laborers and literacy rates, all categorized by gender. Additionally, we integrated demographic indicators like sex ratio, the presence of scheduled castes and tribes, poverty rates, and data on sanitation, electricity, and cooking facilities into our analytical framework.

## 3 Analysis

### 3.1 Crop diversity index

In the present study, the Herfindahl index ($H$) was used to calculate the district-wise crop diversity index [28]. $H$ is a quantitative measure used to assess diversification or specialization. Mathematically, it is calculated as the sum of the squared shares of area under crops:

$$H = \Sigma_{i=1}^{m} A_i^2 \tag{1}$$

where, $H$ is Herfindahl index, $A_i$ is the proportion of area under $i^{th}$ crop, calculated as $A_i = a_i / \Sigma_{i=1}^{n} a_i$ in which $a_i$ is the area under $i^{th}$ crop and $\Sigma_{i=1}^{n} a_i$ denotes the total cropped area at the district level. $H \in (0,1)$; $0$ indicates perfect diversification and $1$ indicates perfect specialization.

### 3.2 Calculation of macro & micronutrient deficiency

Protein, iron and folate deficiencies were calculated using data on food consumption collected by NSS, taking into account the Recommended Dietary Allowances (RDA) established by the Indian Council of Medical Research (ICMR) for people of different ages and sexes. We use the quantity spent and transform the NSS unit level data to convert it to the proper nutritional values based on composition tables given by [29].

Using the size of the home and the total number of nutrients consumed by the household, the per capita daily consumption of protein and micronutrients was computed. Using the methods outlined by Hari and Mishra, the study adjusted for meals consumed by visitors and meals taken free of cost [30]. Following that, in the current exercise we also use the additional assumptions as explained below:

$$c = C \times Z; Z = \frac{M_h + M_f}{M_h + M_g} \tag{2}$$

where,

$Z = 1$ if $M_h = 0$ and $M_f = 0$, and $Z = M_f$ if $M_h = 0$ and $M_g = 0$.

Here, $c$ represents adjusted consumption, $C$ represents consumption before adjustment, $Z$ represents the adjustment factor, $M_h$ represents the number of meals that members of the household consumed inside the home, $M_f$ represents the number of meals that members of the household had consumed outside the home without paying for them, and $M_g$ represents the number of meals that were provided to visitors and employees without requiring payment. Be aware that if $M_f > M_g$, the household is a net beneficiary and $Z > 1$, but if $M_f$, dietary inequalities exist. The extra presumptions are to take $Z$ as $1$ if the numerator is zero ( $M_h = 0$ and $M_f = 0$) and to consider $Z = M_f$ if the denominator is zero ( $M_h = 0$ and $M_g = 0$) in order to avoid certain computing issues.

In order to determine the deprivation lines, we first need to establish the adult equivalency scale for a household based on adjusted consumption (separately for all the micronutrients). If the household falls below these thresholds, we determine how many people are deprived on a per capita basis (rather than how many adult equivalents are deprived). This is in line with [30] and [31] used to determine macro and micronutrient deficiency and an extension of the formula in [32]. The equation is given below

$$P_\alpha = \frac{\sum_{j=1}^{J} d_j^\alpha n_j}{\sum_{j=1}^{J} n_j} \tag{3}$$

For our purpose, $P_\alpha$ is the alpha class of deprivation measure, $d_j = (r_j - c_j)/r_j$ is the normalized deprivation gap for the $j^{th}$ household such that $d_j > 0$ if $r_j > c_j$ otherwise $d_j = 0$ if $r_j \leq c_j$, $r_j$ is required dietary allowance for the $j^{th}$ household, $c_j$ is the adjusted consumption for the $j^{th}$ household (obtained after adjustments indicated in Eq. (2)), $n_j$ is the adult equivalent scale of the $j^{th}$ household, $\sum_{j=1}^{J} n_j$ is total adult equivalent scale (the reference population) summed over all $j$ or for a sub-group. Thus, $P_0$ will give us incidence (head count ratio) or prevalence of deprivation for the reference population. Based on this, one could use the sample data to directly estimate the prevalence of nutrient deficiencies at the district level. However, as the sample design from NSSO is not meant to represent the district, a small area estimation technique is being used to estimate the district-level micronutrient deficiencies.

### 3.3 Small area estimation of the incidence of macro & micronutrient deficiencies

NSSO surveys are dependable and representative when it comes to generating estimates at the state and national level. However, due to limited sample sizes, it is not possible to directly obtain trustworthy estimates at the district level using these surveys. Despite the significance of districts in the planning process of India, there is a lack of surveys specifically designed to generate estimates at this level. Insufficiently strong and dependable outcome measures at the district level pose limitations on devising focused interventions and formulating policies. The 2011–12 Household Consumer Expenditure Survey (HCES) surveyed 101,651 households with 464,730 individuals.

From the 2011–12 HCES survey data, an individual is denoted with $Y_l; l = 1, \ldots, L$ representing a binary variable indicating whether the $l^{th}$ individual is deficient in a specific micronutrient or not. Note that if the $j^{th}$ household has been identified to be deficient in a specific micronutrient as per Eq. (3) then all individuals in that household will be identified as deficient in that micronutrient or $Y_l = 1 \,\forall\, l \in j;\ d_j > 0$ and $Y_l = 0 \,\forall\, l \in j;\ d_j = 0$.

If universe, $U$, with a finite population, $N$, is partitioned into non-overlapping and mutually exclusive (small) areas, $s = 1, \ldots .S$, such that $U = \bigcup_{s=1}^{S} U_s$ and $N = \sum_{s=1}^{S} N_s$. Further, in each small area, the population, $N_s$, can be divided into sample,

$n_s = \sum_{l=1}^{L} l^0 \forall\ l \in\ s$, and non-sample components, $b_s = N_s - n_s$. It can be assumed that the sample count for population deficient for a small area follows a binomial distribution, $Y_{n_s}|U_s \sim\ Bin\left(n_s,\ P_{0s}\right)$. And, that the non-sample count for population deficient for a small area follows a binomial distribution, $Y_{b_s}|U_s \sim\ Bin\left(N_s - P_{0s},\ P_{0s}\right)$. Further, $Y_{n_s}$ and $Y_{b_s}$ are assumed to be independent binomial variables with $P_{0s}$ being a common success probability. This leads to their expected values being $E(Y_{n_s}\,|U_s) = n_s P_{0s}$ and $E\left(Y_{b_s}|U_s\right) = (N_s - n_s)P_{0s}$, respectively.

Let $X_s$ be the $k$ dimensional vector of covariates for area $s$, available from secondary data sources. There are nearly 20 auxiliary variables considered in the analysis. Following previous literature [14, 33, 34], the model linking the probability $p_s$ with the transposed covariates $X_s^T$ is the logistic linear mixed model (LLMM) of form:

$$logit\left(P_{0s}\right) = In\left\{P_{0s}(1 - P_{0s})^{-1}\right\} = \eta_{\ s} = X_s^T\beta\ + \varepsilon_{\ s} \tag{4}$$

with $P_{0s} = \exp\left(X_s^T\beta\ + \varepsilon_{\ s}\right) /\ \left\{1 + \exp(X_s^T\beta\ + \varepsilon_{\ s})\right\} = expit\left(X_s^T\beta\ + \varepsilon_{\ s}\right)$. Here $\beta$ is the $k$ dimensional vector of regression coefficients, and $\varepsilon_s$ is the area specific random effect that capture the area dissimilarities. We assume that $\varepsilon_s$ is independent and normally distributed with mean zero and a constant variance $\varphi$. The total population count $Y_s$ = $Y_{n_s} + Y_{b_s}$ where $Y_{n_s}$, the sample count is known, whereas $Y_{n_s}$, the non-sample count is unknown. In Eq. (5), a plug-in empirical best predictor (EBP) of $Y_s$ in area $s$ is

$$\widehat{Y}_s^{EBP} = Y_{n_s} + (N_s - n_s)expit\left(X_d^T\widehat{\beta}\ + \widehat{\varepsilon}_{\ s}\right) \tag{5}$$

An estimate of the corresponding proportion in area $s$ is

$$\widehat{P}_{0s}^{EBP} = N_s^{-1}\widehat{Y}_s^{EBP} \tag{6}$$

Using data from all small areas, we use an iterative procedure that combines the penalized quasi-likelihood estimation of $\widehat{\beta}$ for the $k$ covariates and $\widehat{\varepsilon}_{\ s}$ with restricted maximum likelihood estimation of $\varphi$ to estimate the total population count. In other words, the model followed a binomial distribution with a logit link function to estimate the prevalence of micronutrient deficiencies at the district level.

### 3.4 LISA map

Bivariate Local Indicators of Spatial Association (LISA) is a geospatial technique that enables the assessment of local spatial autocorrelation between two variables at the same time. It extends the traditional LISA framework to a bivariate context, allowing us to explore joint spatial patterns and identify regions where associations between the variables are statistically significant. The bivariate LISA statistic used in this study is defined as:

$$\gamma_{\ s} = \frac{|H_s - \overline{H}|}{V}\sum\nolimits_{w_s=1}^{W_s}\omega_{\ w_s}|\widehat{P_{0s}}^{EBP} - \overline{\widehat{P_0}}| \tag{7}$$

where $\gamma_{\ s}$ represents the bivariate LISA statistic for a given small area or district $s$, $H_s$ and $\widehat{P_{0s}}^{EBP}$ denote the values of agricultural diversity (recall Eq. (1)) and nutrient deficiency (recall Eq. (6)) for district *s*, respectively. $\overline{H}$ and $\overline{\widehat{P_0}}$ represent the means of the two variables and $V$ is their pooled variance. The summation is performed over all neighbouring districts $w_s$ with spatial weights $\omega_{w_s}$ describing the spatial relationship. We applied bivariate LISA to examine the spatial relationships between agricultural diversity and selected nutrient deficiencies in India. This method identifies areas where both variables exhibit significant clustering, revealing spatial co-occurrence patterns. The results classify each location into distinct categories of spatial association: bright red indicates high-high clusters, bright blue indicates low-low clusters, light blue represents low-high associations, and light red represents high-low associations.

## 4 Results

### 4.1 Spatial distribution of crop diversity

The spatial distribution of crop diversity (Fig. 1) in 2011–12 shows pronounced regional variation across India, and suggests clustering at different levels of crop diversity, including for high and low levels. Higher levels of crop diversity are observed across western, central, and southern India, with prominent concentrations in Rajasthan, Gujarat, Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu. In addition, some parts of Madhya Pradesh, along with select districts in Telangana, Uttarakhand, and Himachal Pradesh, also exhibit relatively high crop diversity. These patterns reflect more diversified

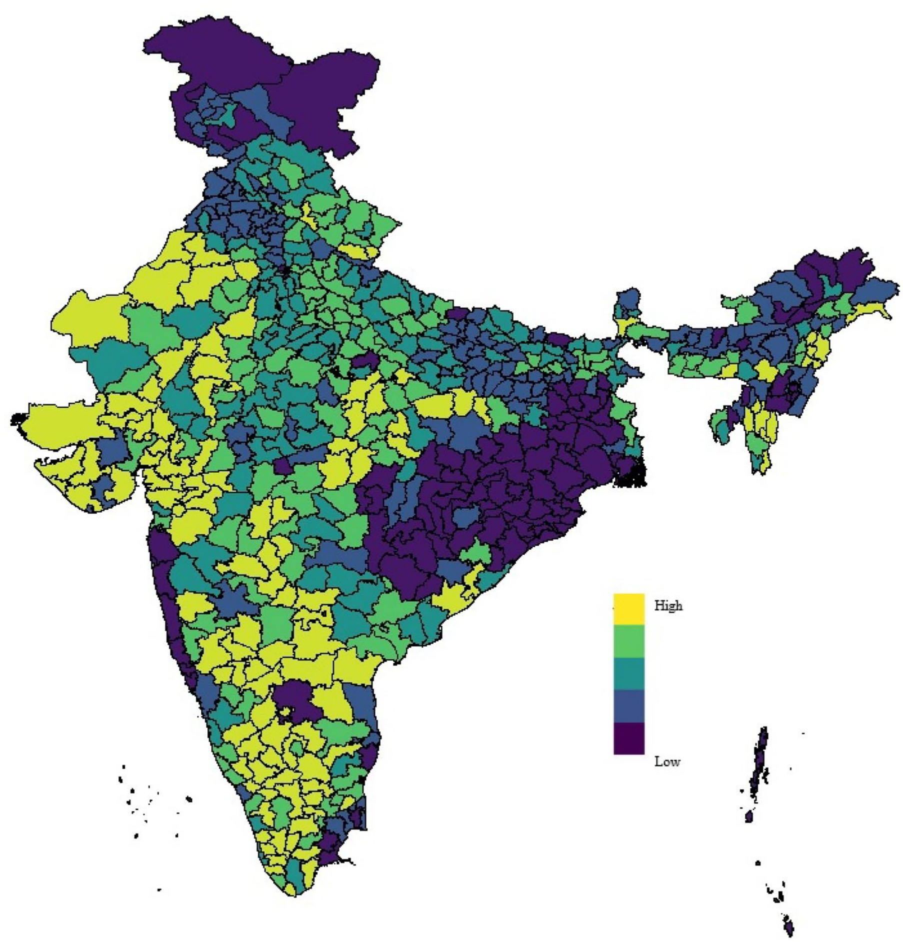



**Fig. 1** District level distribution of crop diversity in India, 2011–12

cropping systems shaped by agroclimatic conditions and mixed farming practices. In contrast, lower crop diversity is concentrated in parts of eastern and central India, indicating the continued dominance of specialised cropping systems. A detailed state-wise distribution of agricultural diversity is reported by Jana and Chattopadhyay [22].

### 4.2 Per capita per day consumption of nutrients

Table 1 shows state-wise average daily consumption of protein, iron, and folate across rural and urban households. These results suggest wide inter-state differences in dietary intake. Protein intake ranges from 41.6 g in Meghalaya to 71.4 g in Himachal Pradesh, with consistently lower values in rural areas. Iron intake varies from 5.8 mg in Manipur to 20.3 mg in Rajasthan, while folate consumption ranges from 119.6 µg in Manipur to 325.3 µg in Puducherry. Overall, urban households exhibit slightly higher consumption levels, particularly for folate.

**Table 1** State wise distribution of per capita per day consumption of protein, iron and folate

| State name | Protein (g) | | Iron (mg) | | Folate ((µg) | |
|---|---|---|---|---|---|---|
| | Rural | Urban | Rural | Urban | Rural | Urban |
| Jammu | 63.30 | 62.93 | 11.97 | 11.80 | 227.62 | 230.30 |
| Himachal Pradesh | 71.44 | 70.72 | 15.27 | 15.13 | 281.97 | 300.77 |
| Punjab | 66.43 | 62.00 | 16.35 | 14.86 | 292.23 | 269.30 |
| Chandigarh | 58.55 | 56.81 | 12.83 | 12.99 | 235.92 | 253.55 |
| Uttarakhand | 68.20 | 66.24 | 15.50 | 14.89 | 266.36 | 266.95 |
| Haryana | 67.86 | 61.58 | 16.45 | 14.80 | 274.24 | 274.91 |
| Delhi | 61.25 | 56.50 | 14.53 | 12.57 | 265.91 | 249.73 |
| Rajasthan | 68.44 | 62.65 | 20.34 | 16.86 | 292.92 | 272.12 |
| Uttar Pradesh | 60.11 | 57.20 | 14.65 | 13.89 | 236.77 | 234.62 |
| Bihar | 57.25 | 58.35 | 13.33 | 13.86 | 221.82 | 231.75 |
| Sikkim | 51.11 | 50.82 | 7.50 | 7.38 | 175.27 | 214.65 |
| Arunachal Pradesh | 47.40 | 53.28 | 8.27 | 8.95 | 139.28 | 161.29 |
| Nagaland | 51.50 | 54.01 | 6.89 | 7.43 | 149.42 | 164.91 |
| Manipur | 46.73 | 45.95 | 5.83 | 5.89 | 119.56 | 117.33 |
| Mizoram | 48.12 | 53.53 | 7.66 | 9.23 | 151.32 | 172.69 |
| Tripura | 54.46 | 56.93 | 8.59 | 9.39 | 183.96 | 188.86 |
| Meghalaya | 41.61 | 46.01 | 6.22 | 7.22 | 133.43 | 152.26 |
| Assam | 49.29 | 52.07 | 7.87 | 8.80 | 154.83 | 184.18 |
| West Bengal | 51.66 | 53.83 | 9.62 | 10.77 | 183.04 | 203.72 |
| Jharkhand | 51.35 | 57.67 | 9.71 | 12.67 | 204.21 | 244.07 |
| Odisha | 49.91 | 52.82 | 7.92 | 9.51 | 178.63 | 213.97 |
| Chhattisgarh | 47.58 | 51.09 | 7.36 | 9.23 | 185.32 | 216.02 |
| Madhya Pradesh | 61.75 | 57.96 | 16.09 | 15.10 | 265.45 | 248.51 |
| Gujrat | 50.85 | 54.07 | 13.80 | 13.34 | 246.21 | 259.91 |
| Daman | 54.21 | 51.58 | 11.07 | 11.01 | 273.21 | 237.67 |
| Dadra | 39.62 | 49.74 | 6.22 | 10.29 | 197.03 | 234.66 |
| Maharashtra | 56.01 | 55.21 | 14.15 | 12.56 | 259.97 | 257.01 |
| Andhra Pradesh | 53.63 | 54.23 | 7.95 | 8.31 | 245.75 | 254.66 |
| Karnataka | 50.37 | 51.56 | 11.24 | 10.41 | 243.18 | 252.04 |
| Goa | 51.06 | 56.49 | 8.64 | 9.84 | 198.68 | 206.84 |
| Lakshadweep | 69.73 | 65.05 | 10.88 | 9.95 | 308.77 | 268.27 |
| Kerala | 54.61 | 56.82 | 9.00 | 8.98 | 245.50 | 260.59 |
| Tamil Nadu | 48.78 | 51.09 | 7.42 | 7.70 | 233.79 | 255.66 |
| Puducherry | 56.41 | 60.79 | 8.81 | 9.20 | 325.29 | 339.75 |
| Andaman & Nicobar Islands | 61.91 | 65.42 | 10.59 | 11.30 | 287.94 | 308.98 |
| India | 56.52 | 55.67 | 12.52 | 11.92 | 233.60 | 246.99 |

### 4.3 Small area estimation

Given the limited district level representativeness of the NSSO HCES survey, SAE was used to generate reliable micronutrient deficiency estimates. SAE provides improved precision where direct estimates are unstable due to small samples. The 2011–12 HCES surveyed 101,651 households (464,730 individuals), with an average district sample size of 727. The uneven sample distribution (26 to 3753 individuals, Table 2) underscores the need for SAE (Fig. 2a, b and c).

### 4.4 Weighted and unweighted direct estimates

Figure 3 illustrates the differences between weighted and unweighted direct estimates. The unweighted estimates consistently underestimate micronutrient deficiencies, confirming that survey design effects are non-negligible. The adjustment using effective sample sizes, following Korn and Graubard [35], was therefore necessary to ensure unbiased estimates.

### 4.5 Indirect estimation of nutrient deficiency

Under the SAE framework, a binomial model was specified for effective district-level sample counts. Diagnostic checks (Figs. 4 and 5) confirmed model validity. The model-based estimates show substantially improved precision, with lower coefficients of variation compared to the direct estimates (Table 3). While direct estimates exhibit high and uneven variability across districts, the SAE estimates are more stable, as further illustrated by the district-wise distribution of CVs in Fig. 6. Supplementary Table 4 presents the statistical diagnostics, including residual normality tests, RMSE values, and model selection criteria, which further support the adequacy of the SAE models. Overall, the results indicate that the SAE-based estimates provide more reliable district-level prevalence patterns for micronutrient deficiencies.

### 4.6 State-wise distribution of nutrient deficiency

This section presents state-level prevalence of protein, iron, and folate deficiency, providing an aggregated overview (Table 3). The findings indicate pronounced regional variation: protein deficiency is highest in Meghalaya (54.3%) and lowest in Himachal Pradesh (4.9%). Iron deficiency is most severe in Nagaland (91.7%) and lowest in Punjab (28.2%). Folate deficiency peaks in Manipur (80.0%) and remains low in Puducherry (6.9%). These state-level scemarios also indicate variation in nutrient deficicncy, showing that northeastern states consistently experience higher micronutrient deficiencies relative to northern and western India.

**Table 2** Summary of sample size, count of micronutrient deficiencies and sampling fraction in 2011–12 HCES data

| Features | Minimum | Maximum | Average | Total |
|---|---|---|---|---|
| Sample size | 26 | 3,753 | 727 | 464,730 |
| Sample fraction | 0.000002 | 0.015 | 0.0009 | 0.57 |
| Sample count iron deficiency | 22 | 3698 | 552 | 353,596 |
| Sample count folate deficiency | 2 | 3149 | 210 | 146,274 |
| Sample count protein deficiency | 0 | 1673 | 186 | 118,311 |

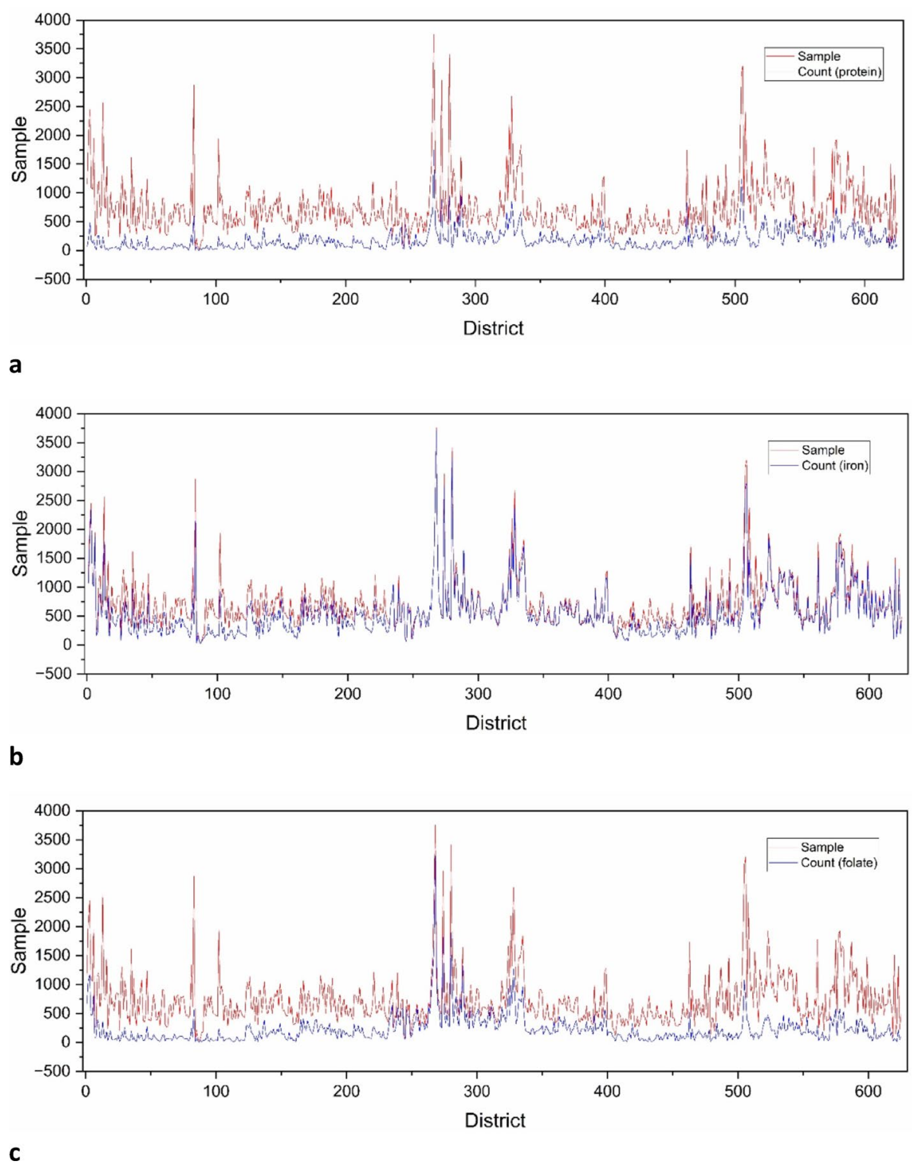



**Fig. 2** **a** distribution of sample in NSS survey and count of protein deficiency. **b** distribution of sample in NSS survey and count of iron deficiency. **c** distribution of sample in NSS survey and count of folate deficiency

### 4.7 Spatial distribution of nutrient deficiency

District-level spatial heterogeneity (Fig. 7) also points to localized deficiency patterns beyond state averages. About 25% of Indians are protein deficient, with severe prevalence in northeastern and eastern districts. More than 50% of Odisha's districts report protein deficiency above 38%. Iron deficiency affects nearly three fourths of the population, with prevalence exceeding 90% in several northeastern districts. Folate deficiency, which is approximately 46% nationally, is concentrated in West Bengal, Odisha, and the southern states. This spatial mapping underscores strong intra-state disparities that cannot be captured by state-level statistics alone.

### 4.8 Spatial association between nutrient deficiency and agricultural diversity

Bivariate LISA cluster maps (Fig. 8) help assess the spatial association between agricultural diversity and micronutrient deficiencies. High Low clusters, which indicate

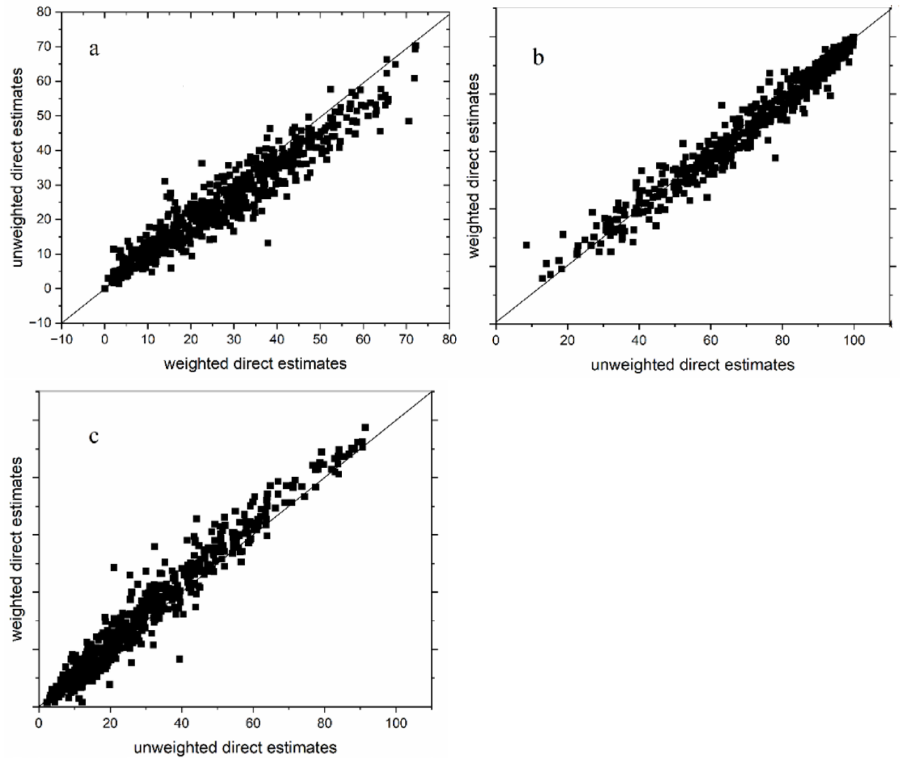



**Fig. 3** District-wise survey weighted direct estimates versus unweighted direct estimates of proportion for protein (**a**), iron (**b**) and folate (**c**)

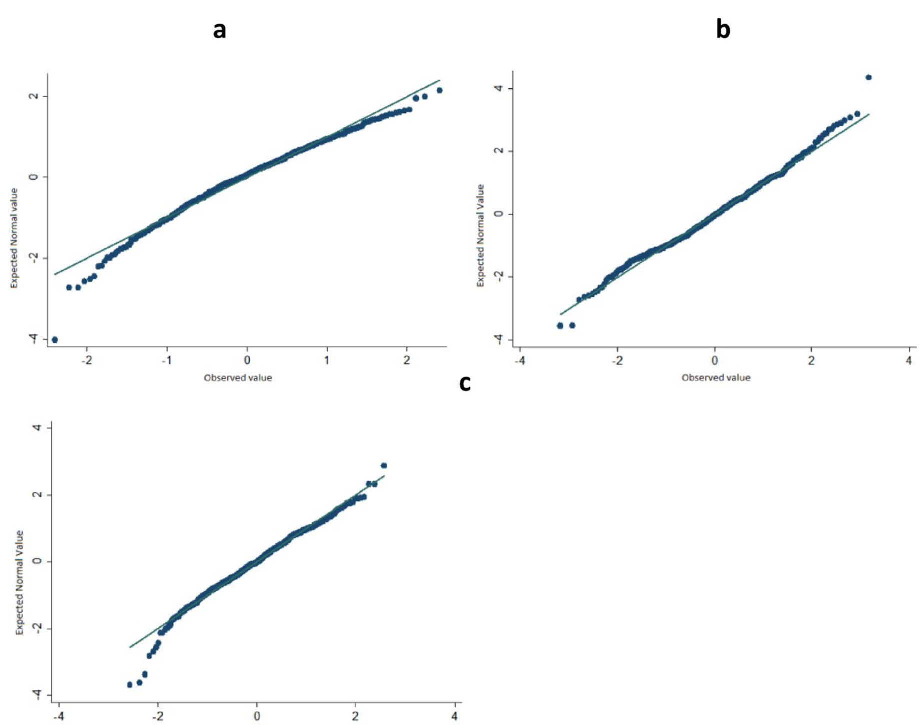



**Fig. 4** q-q plot of observed value and expected normal value for protein (**a**), iron (**b**) and folate (**c**) deficiency

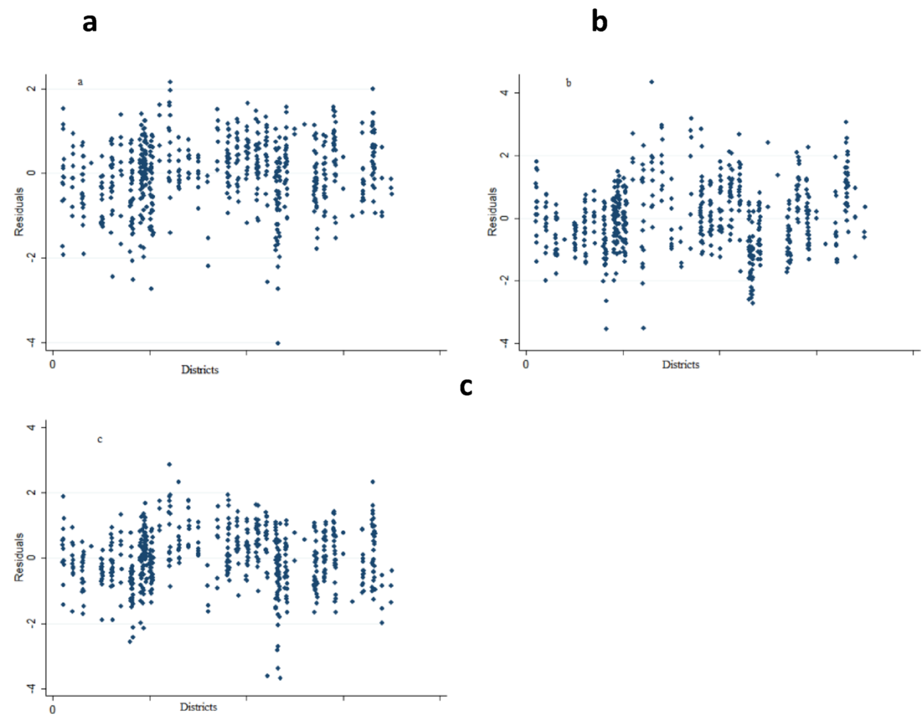



**Fig. 5** Distributions of the district-level residuals for protein (**a**), iron (**b**) and folate (**c**)

districts with high agricultural diversity and low micronutrient deficiency, show strong regional concentration. For protein, 107 districts fall into this category, largely distributed across the western and central belt (Rajasthan, Gujarat, Maharashtra, Madhya Pradesh, Chhattisgarh) and extending into parts of the southern states (Karnataka, Kerala, Andhra Pradesh), with smaller pockets in the eastern and northern hills (Jharkhand, Odisha, Punjab, Himachal Pradesh, Uttarakhand, Bihar). Iron shows a similar pattern, with 113 districts forming High Low clusters, again concentrated in the western and central region, with a few additional clusters in Uttarakhand and Uttar Pradesh. Folate displays the largest High Low cluster set, with 129 districts, mostly within the central and western region, particularly Madhya Pradesh, Gujarat, Rajasthan, Maharashtra, and the northern hill states.

## 5 Discussion

The study examines the spatial distribution of agricultural diversity in India during 2011–12 and its association with micronutrient deficiency at the district level. The results reveal pronounced regional variation in crop diversity across the country, with higher levels concentrated in western, central, and southern India, while lower diversity persists in parts of eastern and central regions. A study conducted by Jana and Chattopadhyay [22] in 2023 reports similar findings. That study suggests that drought occurrences and improved irrigation facilities positively influence the practice of diversified agriculture, while government subsidies and infrastructure indicate intensified agricultural practices. Consequently, there is a need for the government to consider implementing a conditional beneficial program to encourage farmers to adopt agricultural diversity.

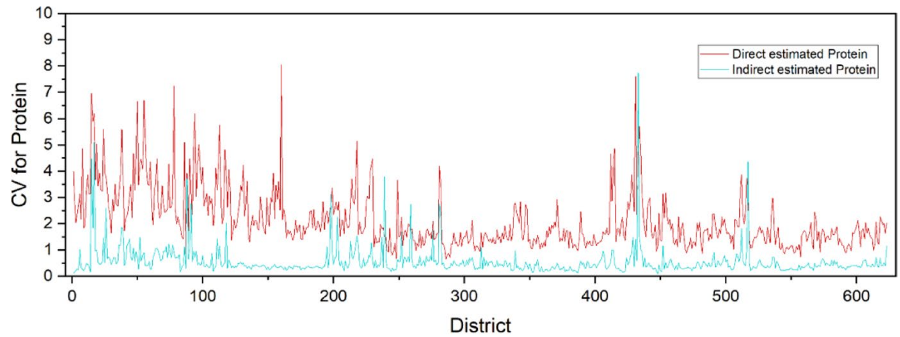
Surprisingly, Northeast India and states such as West Bengal, Jharkhand, Odisha, Tamil Nadu, and Andhra Pradesh, despite a predominantly non vegetarian diet, still

**Table 3** State wise distribution of protein, iron and folate deficiency in India

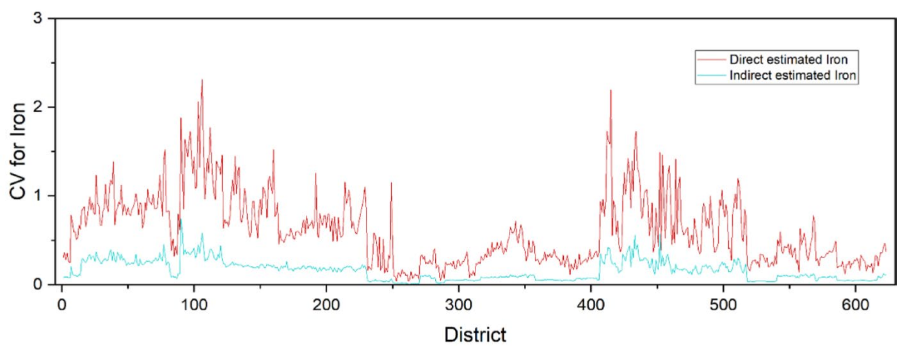
| State /District name | Protein deficiency | | | | | | Iron deficiency | | | | | | Folate deficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Direct survey estimates | | | Model based estimates | | | Direct survey estimates | | | Model based estimates | | | Direct survey estimates | | | Model based estimates | | |
| | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV |
| Jammu & Kashmir | 12.82 | 0.00 | 2.61 | 12.33 | 0.00 | 0.31 | 76.18 | 0.00 | 0.45 | 76.54 | 0.00 | 0.14 | 35.20 | 0.00 | 1.36 | 36.64 | 0.00 | 0.66 |
| Himachal Pradesh | 4.91 | 0.00 | 4.40 | 4.00 | 0.00 | 1.05 | 51.87 | 0.01 | 0.84 | 53.31 | 0.00 | 0.31 | 11.70 | 0.00 | 2.75 | 12.48 | 0.00 | 1.17 |
| Punjab | 13.17 | 0.00 | 2.57 | 11.79 | 0.00 | 0.81 | 49.01 | 0.00 | 0.89 | 48.26 | 0.00 | 0.33 | 12.61 | 0.00 | 2.63 | 12.77 | 0.00 | 0.91 |
| Chandigarh | 20.45 | 0.01 | 1.97 | 16.85 | 0.01 | 1.11 | 64.58 | 0.01 | 0.63 | 59.87 | 0.01 | 0.24 | 22.14 | 0.01 | 1.88 | 17.12 | 0.01 | 1.16 |
| Uttarakhand | 5.98 | 0.01 | 3.96 | 4.60 | 0.00 | 0.75 | 51.06 | 0.03 | 0.85 | 52.08 | 0.00 | 0.28 | 13.34 | 0.02 | 2.55 | 13.81 | 0.00 | 0.98 |
| Haryana | 12.34 | 0.00 | 2.67 | 11.81 | 0.00 | 0.87 | 46.06 | 0.00 | 0.94 | 45.88 | 0.00 | 0.31 | 13.07 | 0.00 | 2.58 | 14.18 | 0.00 | 1.03 |
| Delhi | 21.59 | 0.01 | 1.91 | 21.36 | 0.00 | 0.93 | 66.99 | 0.01 | 0.59 | 69.12 | 0.00 | 0.14 | 20.46 | 0.01 | 1.97 | 23.99 | 0.01 | 0.99 |
| Rajasthan | 9.44 | 0.00 | 3.10 | 7.76 | 0.00 | 0.65 | 28.19 | 0.00 | 1.36 | 27.26 | 0.00 | 0.42 | 9.05 | 0.00 | 3.17 | 8.60 | 0.00 | 0.93 |
| Uttar Pradesh | 20.52 | 0.00 | 1.97 | 19.71 | 0.00 | 0.38 | 57.71 | 0.00 | 0.74 | 57.86 | 0.00 | 0.23 | 26.77 | 0.00 | 1.65 | 28.08 | 0.00 | 0.60 |
| Bihar | 16.36 | 0.00 | 2.26 | 15.15 | 0.00 | 0.74 | 58.70 | 0.00 | 0.72 | 59.65 | 0.00 | 0.21 | 24.43 | 0.00 | 1.76 | 25.22 | 0.00 | 0.74 |
| Sikkim | 36.22 | 0.01 | 1.33 | 34.41 | 0.00 | 0.48 | 89.76 | 0.00 | 0.18 | 89.05 | 0.00 | 0.04 | 58.29 | 0.01 | 0.85 | 58.70 | 0.00 | 0.32 |
| Arunachal Pradesh | 37.45 | 0.01 | 1.29 | 39.72 | 0.00 | 0.57 | 80.02 | 0.00 | 0.39 | 80.31 | 0.00 | 0.12 | 65.17 | 0.01 | 0.73 | 68.26 | 0.00 | 0.27 |
| Nagaland | 27.16 | 0.01 | 1.64 | 31.56 | 0.01 | 0.68 | 91.70 | 0.00 | 0.12 | 90.77 | 0.00 | 0.02 | 69.63 | 0.01 | 0.66 | 76.86 | 0.00 | 0.23 |
| Manipur | 38.59 | 0.00 | 1.26 | 41.44 | 0.00 | 0.53 | 91.97 | 0.00 | 0.10 | 91.00 | 0.00 | 0.01 | 80.04 | 0.00 | 0.50 | 80.49 | 0.00 | 0.23 |
| Mizoram | 27.62 | 0.01 | 1.62 | 26.04 | 0.00 | 0.74 | 85.42 | 0.00 | 0.29 | 84.22 | 0.00 | 0.10 | 56.62 | 0.01 | 0.88 | 57.58 | 0.00 | 0.39 |
| Tripura | 21.02 | 0.01 | 1.94 | 19.72 | 0.00 | 0.81 | 84.88 | 0.00 | 0.30 | 84.62 | 0.00 | 0.08 | 50.66 | 0.01 | 0.99 | 50.72 | 0.00 | 0.45 |
| Meghalaya | 54.25 | 0.01 | 0.92 | 56.67 | 0.00 | 0.38 | 90.72 | 0.00 | 0.15 | 90.63 | 0.00 | 0.03 | 73.73 | 0.01 | 0.60 | 76.64 | 0.00 | 0.27 |
| Assam | 36.86 | 0.00 | 1.31 | 37.95 | 0.00 | 0.48 | 87.94 | 0.00 | 0.23 | 87.73 | 0.00 | 0.05 | 64.69 | 0.00 | 0.74 | 66.89 | 0.00 | 0.31 |
| West Bengal | 31.96 | 0.00 | 0.48 | 30.96 | 0.00 | 0.48 | 79.51 | 0.00 | 0.40 | 80.36 | 0.00 | 0.09 | 47.19 | 0.00 | 1.06 | 49.79 | 0.00 | 0.41 |
| Jharkhand | 25.76 | 0.00 | 1.70 | 25.94 | 0.00 | 0.51 | 71.87 | 0.00 | 0.52 | 74.98 | 0.00 | 0.12 | 32.86 | 0.00 | 1.43 | 37.59 | 0.00 | 0.54 |
| Odisha | 31.91 | 0.00 | 1.46 | 35.82 | 0.00 | 0.37 | 85.30 | 0.00 | 0.29 | 87.18 | 0.00 | 0.06 | 46.63 | 0.00 | 1.07 | 53.78 | 0.00 | 0.37 |
| Chhattisgarh | 35.99 | 0.01 | 1.33 | 37.05 | 0.00 | 0.47 | 84.84 | 0.00 | 0.30 | 85.02 | 0.00 | 0.08 | 41.70 | 0.01 | 1.18 | 45.36 | 0.00 | 0.50 |
| Madhya Pradesh | 18.91 | 0.00 | 2.07 | 16.71 | 0.00 | 0.71 | 46.79 | 0.00 | 0.93 | 44.49 | 0.00 | 0.43 | 20.61 | 0.00 | 1.96 | 19.38 | 0.00 | 0.89 |
| Gujrat | 34.54 | 0.00 | 1.38 | 34.77 | 0.00 | 0.42 | 61.44 | 0.00 | 0.68 | 61.73 | 0.00 | 0.28 | 19.82 | 0.00 | 2.01 | 20.14 | 0.00 | 0.81 |
| Daman & Diu | 37.88 | 0.02 | 1.28 | 41.52 | 0.01 | 0.56 | 81.33 | 0.01 | 0.36 | 83.05 | 0.01 | 0.13 | 27.65 | 0.02 | 1.62 | 28.22 | 0.01 | 0.88 |

**Table 3** (continued)

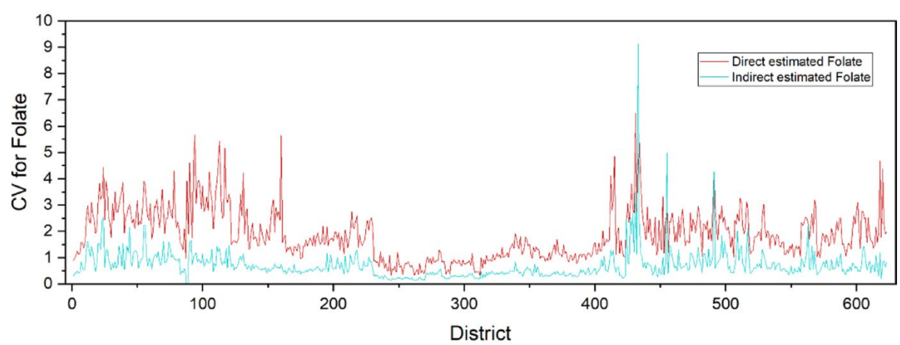
| State /District name | Protein deficiency | | | | | | Iron deficiency | | | | | | Folate deficiency | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Direct survey estimates | | | Model based estimates | | | Direct survey estimates | | | Model based estimates | | | Direct survey estimates | | | Model based estimates | | |
| | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV | % | SE | CV |
| Dadar And Nagar Haveli | 51.02 | 0.02 | 0.98 | 52.18 | 0.01 | 0.25 | 83.07 | 0.01 | 0.33 | 85.07 | 0.00 | 0.08 | 37.36 | 0.02 | 1.30 | 39.15 | 0.01 | 0.57 |
| Maharashtra | 23.45 | 0.00 | 1.81 | 23.04 | 0.00 | 0.63 | 58.68 | 0.00 | 0.72 | 59.65 | 0.00 | 0.28 | 18.62 | 0.00 | 2.09 | 19.67 | 0.00 | 0.88 |
| Andhra Pradesh | 30.54 | 0.00 | 1.51 | 30.93 | 0.00 | 0.47 | 86.77 | 0.00 | 0.26 | 86.67 | 0.00 | 0.04 | 25.30 | 0.00 | 1.72 | 27.75 | 0.00 | 0.69 |
| Karnataka | 40.23 | 0.00 | 1.22 | 42.62 | 0.00 | 0.36 | 76.28 | 0.00 | 0.45 | 77.28 | 0.00 | 0.12 | 27.49 | 0.00 | 1.62 | 30.49 | 0.00 | 0.70 |
| Goa | 30.67 | 0.01 | 1.50 | 32.86 | 0.00 | 0.42 | 85.68 | 0.01 | 0.28 | 87.15 | 0.00 | 0.04 | 43.94 | 0.01 | 1.13 | 47.94 | 0.01 | 0.41 |
| Lakshadweep | 23.01 | 0.01 | 1.83 | 21.77 | 0.01 | 0.95 | 80.22 | 0.01 | 0.38 | 82.04 | 0.00 | 0.10 | 27.73 | 0.01 | 1.62 | 27.57 | 0.01 | 0.78 |
| Kerala | 30.10 | 0.00 | 1.52 | 32.77 | 0.00 | 0.52 | 81.85 | 0.00 | 0.35 | 83.22 | 0.00 | 0.09 | 26.16 | 0.00 | 1.68 | 29.59 | 0.00 | 0.69 |
| Tamil Nadu | 35.42 | 0.00 | 1.35 | 38.71 | 0.00 | 0.43 | 87.91 | 0.00 | 0.23 | 88.04 | 0.00 | 0.05 | 23.98 | 0.00 | 1.78 | 27.92 | 0.00 | 0.69 |
| Pondicherry | 18.47 | 0.01 | 2.10 | 18.26 | 0.00 | 0.67 | 83.72 | 0.01 | 0.32 | 84.84 | 0.00 | 0.09 | 6.88 | 0.01 | 3.68 | 7.44 | 0.00 | 1.18 |
| Andaman Nicobar Island | 20.66 | 0.01 | 1.96 | 20.02 | 0.00 | 0.66 | 78.14 | 0.01 | 0.42 | 80.63 | 0.00 | 0.12 | 17.17 | 0.01 | 2.20 | 17.11 | 0.00 | 0.84 |
| India | 26.78 | 0.01 | 1.83 | 27.11 | 0.00 | 0.60 | 73.32 | 0.01 | 0.49 | 73.70 | 0.00 | 0.15 | 34.25 | 0.01 | 1.64 | 35.94 | 0.00 | 0.67 |




**a**




**b**




**c**

**Fig. 6** **a** District wise coefficient of variation for protein deficiency in India. **b** District wise coefficient of variation for iron deficiency in India. **c** District wise coefficient of variation for folate deficiency in India

exhibit inadequate micronutrient intake. Odisha, Maharashtra, Gujarat, and Jharkhand face food security challenges that are strongly linked to micronutrient consumption [36]. Odisha, Jharkhand, parts of West Bengal, and certain districts in Karnataka also experience high poverty rates, where limited access to quality education and employment opportunities perpetuates deprivation. In many areas with high micronutrient deficiency, the frequency of non-vegetarian food consumption is low because of its cost, while northern Indian states tend to prefer vegetarian diets rich in pulses, nuts, seeds, whole grains, fruits, and vegetables, which provide essential nutrients [37]. In addition, a study using the same dataset found that calorie consumption estimates were lower in southern states such as Kerala and Tamil Nadu and higher in Uttar Pradesh and Bihar.

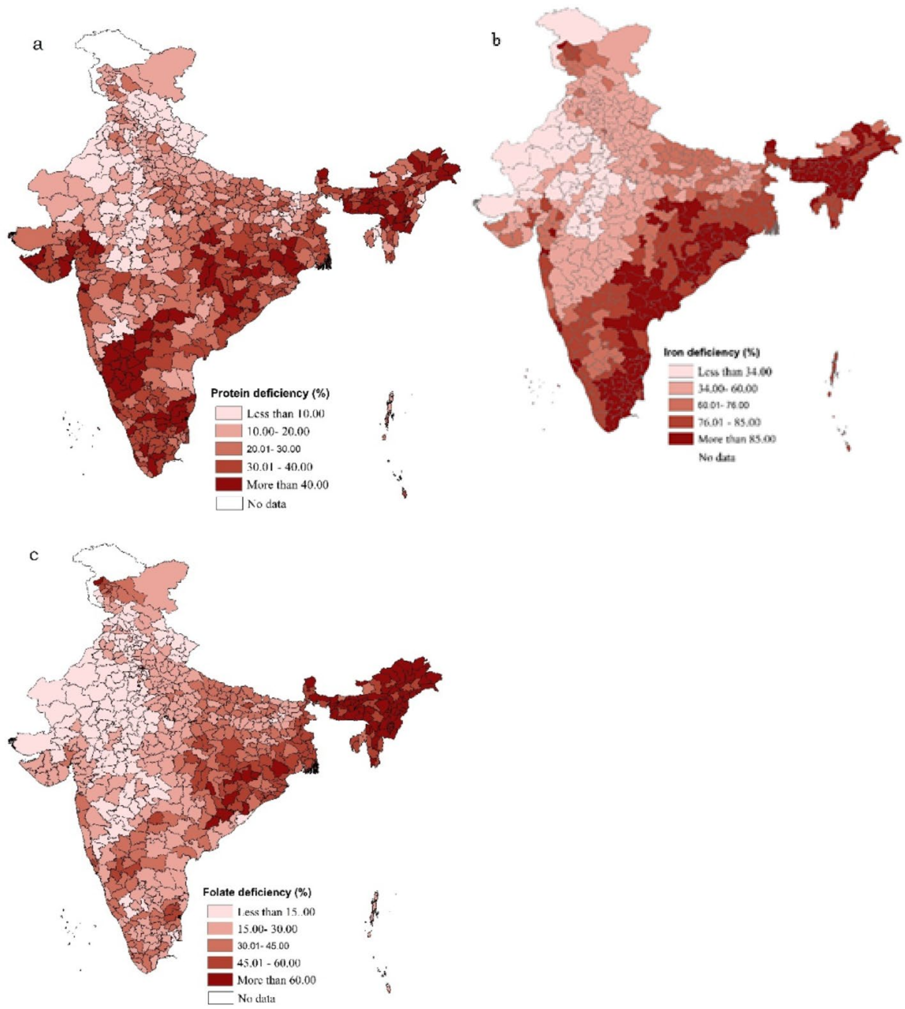



**Fig. 7** District wise spatial distribution of protein (**a**), iron (**b**)and folate (**c**) deficiency in India

However, after adjusting for contextual factors such as disease environment and human development indicators, the spatial distribution shifted in the opposite direction [38].

Agricultural diversity plays a crucial role in reducing micronutrient deficiency by providing a wide range of nutrient-rich foods that contribute to a balanced and varied diet [39]. The availability and consumption of diverse crops and agricultural products can improve dietary diversity, ensuring access to essential vitamins and minerals necessary for overall health and well-being [40]. This positive association between agricultural diversity and improved nutrition is supported by numerous studies. For instance, Ruel [41] highlighted that increased dietary diversity is positively correlated with improved micronutrient intake. Different crops have varying nutrient profiles, and their cultivation in diverse agricultural systems can enhance the availability of specific micronutrients. For example, pulses contain a higher amount of micronutrient which is more than Chicken [42]. Thus, our study also found a lower prevalence of micronutrient deficiency in the Northern districts.

Agricultural diversity is fostered through practices such as crop rotation and intercropping, which improve soil health and nutrient availability. Vanlauwe et al. [43] emphasized that healthy soils facilitate nutrient uptake by crops, resulting in improved

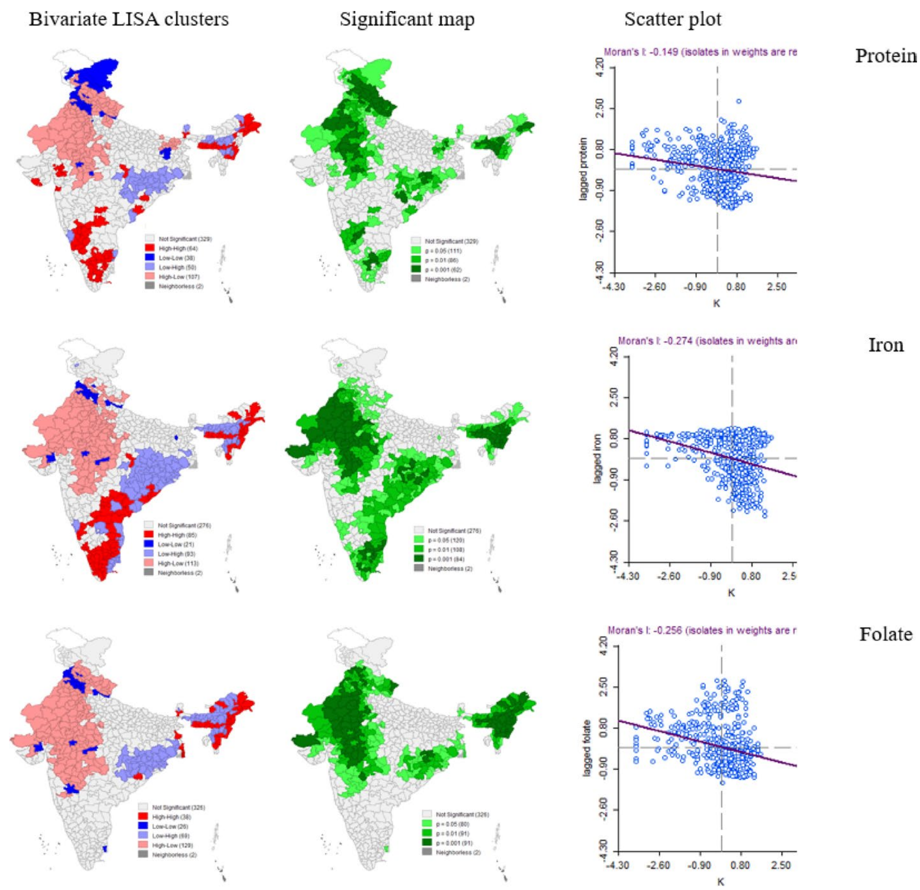



**Fig. 8** Results of Bivariate LISA shows spatial association between agricultural diversity and micronutrients deficiency in India

micronutrient content in harvested produce. Promoting traditional and indigenous crop varieties further enhances agricultural diversity and helps preserve nutrient rich foods that are often overlooked in modern agricultural systems. Padulosi et al. [44] highlighted the importance of neglected and underutilized species in addressing poverty, hunger, and malnutrition, noting that these crops often possess unique micronutrient profiles and strong adaptability to local environments. Agricultural diversity can also improve income diversification for farmers, enabling better access to a varied diet. Jones et al. [20] underscored the role of income in ensuring food security and reducing the risk of micronutrient deficiencies [31].

Diversified agricultural systems are generally more resilient to climate change and extreme weather events. Thornton and Herrero [45] highlighted that such resilience ensures food security during adverse climate conditions, preventing malnutrition and micronutrient deficiencies among vulnerable populations. Additionally, implementing nutrition-sensitive agricultural practices considers the nutritional aspects of food production and ensures the cultivation of nutrient-rich crops. Government policies that promote agricultural diversification and support the cultivation of nutrient-rich crops can contribute significantly to reducing micronutrient deficiencies. Thus, adopting local agricultural diversity approach would be a best initiate to improve nutrition.

## 6 Limitations

This study contributes to understanding how agricultural diversity relates to nutrient deficiency across districts in India by integrating spatial analysis with small area estimation. The analysis relies on household food availability data (purchased plus net of stock including own production) from the 2011–12 consumption survey, which may not reflect current dietary patterns and does not capture wastage, storage losses, sharing practices, or price variation. Although age and sex adjustments were applied, intra household food allocation cannot be observed. Nutrient estimates are based on standardized food composition tables and the RDA values provided by ICMR, which represent population level averages and do not account for regional variation in nutrient content, preparation and cooking losses, nutrient absorption, or the specific needs of different demographic groups. There is also a time gap between the NSS consumption data and the nutrient composition tables, and even though nutrient values change slowly, this mismatch may introduce uncertainty. The analysis focuses solely on dietary intake and does not include non-dietary determinants of nutritional status such as infection, sanitation, morbidity, or access to healthcare. Unmeasured economic and institutional factors may influence both agricultural diversity and dietary behaviour, and the analysis cannot distinguish between subsistence based and market mediated pathways. Future research should integrate individual level dietary information, region specific nutrient composition and biochemical indicators to improve the precision and validation of nutrient intake estimates.

## 7 Conclusion

This study points to clustering at different levels of crop diversity including that for high and low levels, to the existence of variation in dietary intake and in nutritient deficiency across states and districts, and to an association between high agricultural diversification with low nutrient defficiency. It underscores the crucial role of agricultural diversity in mitigating micronutrient deficiencies in India. The analysis reveals pronounced spatial variation in agricultural diversity, with higher levels concentrated in western, central, and southern regions. Districts with more diversified farming systems show lower protein, iron, and folate deficiency, particularly across western and central India. Agricultural diversity plays an important role in reducing micronutrient deficiency by providing a wider range of nutrient-rich foods that contribute to balanced and diverse diets. In light of these findings, promoting agricultural diversity, traditional crop varieties, and neglected species, while supporting income diversification for farmers, can enhance food security and help combat micronutrient deficiencies. Embracing a localized approach to agricultural diversity represents an effective strategy for improving nutrition. There is an urgent need for the government to consider implementing conditional incentive programs to encourage farmers to adopt diversified cropping systems. Recently, the Government of India has increased its focus on millet production to address nutrient deficiencies, and further crop diversification is expected in the future.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s43621-026-02688-x.

Supplementary Material 1

**Acknowledgements**
The authors gratefully acknowledge the valuable suggestions provided by anonymous peer reviewers, Somnath Jana, Ph.D. Scholar at the International Institute for Population Sciences (IIPS), Mumbai, and Dr. Md Zakaria Siddiqui, Associate Professor in the Department of Economics at Jamia Millia Islamia. Their insights were helpful in refining the analytical approach and overall presentation of this study.

**Author contributions**
A.J. conceptualized the study, performed analysis, and wrote the initial draft of the manuscript. A.C. contributed to the conceptualization, methodology, visualization, supervision, and validation of the study. S.M. provided supervision, contributed to validation, conceptualization, methodology, and critically reviewed and revised the manuscript. All authors reviewed and approved the final version of the manuscript.

**Funding**
No funding has been received to conduct the study.

**Data availability**
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request **.

## Declarations

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Clinical trial number**
Not applicable.

**Competing interests**
The authors declare no competing interests.

Received: 20 July 2025 / Accepted: 19 January 2026
Published online: 17 February 2026

**References**

1. Lowe NM. The global challenge of hidden hunger: perspectives from the field. Proc Nutr Soc. 2021;80:283–9. https://doi.org/10.1017/S0029665121000902.
2. Ayala A, Meier BM. A human rights approach to the health implications of food and nutrition insecurity. Public Health Rev. 2017;38:10. https://doi.org/10.1186/s40985-017-0056-5.
3. UN. UN report sends sobering message of deeply entrenched hunger globally. 2020.
4. Jana A, Chattopadhyay A, Saha UR. Identifying risk factors in explaining women's anaemia in limited resource areas: evidence from West Bengal of India and Bangladesh. BMC Public Health. 2022;22:1433. https://doi.org/10.1186/s12889-022-13806-5.
5. Jana A, Dey D, Ghosh R. Contribution of low birth weight to childhood undernutrition in india: evidence from the national family health survey 2019–2021. BMC Public Health. 2023;23:1336. https://doi.org/10.1186/s12889-023-16160-2.
6. Law C, Fraser I, Piracha M. Nutrition transition and changing food preferences in India. J Agric Econ. 2020;71:118–43. https://doi.org/10.1111/1477-9552.12322.
7. Yadav S, Arokiasamy P. Understanding epidemiological transition in India. Global Health Action. 2014;7:23248. https://doi.org/10.3402/gha.v7.23248.
8. Sharma M, Kishore A, Roy D, Joshi K. A comparison of the Indian diet with the EAT-Lancet reference diet. BMC Public Health. 2020;20:812. https://doi.org/10.1186/s12889-020-08951-8.
9. Ritchie H, Roser M. Three billion people cannot afford a healthy diet. Our world in data. 2023.
10. Sendhil R, Kiran Kumara TM, Ramasundaram P, Sinha M, Kharkwal S. Nutrition status in India: dynamics and determinants. Global Food Secur. 2020;26:100455. https://doi.org/10.1016/j.gfs.2020.100455.
11. Vijayaraghavan K. Control of micronutrient deficiencies in India: Obstacles and strategies. Nutr Rev. 2002;60(5 Pt 2):S73–76. https://doi.org/10.1301/00296640260130786.
12. Singh B, Shukla G, Kundu D. Spatio-temporal models in small area estimation. Surv Methodol. 2005;31.
13. Srivastava AK, Sud UC, Chandra H. Small areaestimation an application to national sample survey data. J Indian Soc Agric Stat. 2007;61:249–54.
14. Chandra H, Aditya K, Sud UC. Localised estimates and spatial mapping of poverty incidence in the state of Bihar in India—an application of small area estimation techniques. PLoS ONE. 2018;13. https://doi.org/10.1371/journal.pone.0198502.
15. Balagamwala M, Gazdar H. Agriculture and nutrition in Pakistan: pathways and disconnects1. IDS Bull. 2013;44:66–74. https://doi.org/10.1111/1759-5436.12032.
16. Fanzo J. Strengthening the engagement of food and health systems to improve nutrition security: synthesis and overview of approaches to address malnutrition. Global Food Secur. 2014;3:183–92. https://doi.org/10.1016/j.gfs.2014.09.001.
17. Remans R, Wood SA, Saha N, Anderman TL, DeFries RS. Measuring nutritional diversity of national food supplies. Global Food Secur. 2014;3:174–82. https://doi.org/10.1016/j.gfs.2014.07.001.
18. Wendt AS, Sparling TM, Waid JL, Mueller AA, Gabrysch S. Food and agricultural approaches to reducing malnutrition (FAARM): protocol for a cluster-randomised controlled trial to evaluate the impact of a homestead food production

programme on undernutrition in rural Bangladesh. BMJ Open. 2019;9:e031037. https://doi.org/10.1136/bmjopen-2019-031037.
19. Yosef S, Jones AD, Chakraborty B, Gillespie S. Agriculture and nutrition in bangladesh: mapping evidence to pathways. Food Nutr Bull. 2015;36:387–404. https://doi.org/10.1177/0379572115609195.
20. Jones AD, Ngure FM, Pelto G, Young SL. What are we assessing when we measure food security? A compendium and review of current metrics. Adv Nutr. 2013;4:481–505. https://doi.org/10.3945/an.113.004119.
21. Sparling TM, White H, Kadiyala S. PROTOCOL: evidence and gap map protocol: Understanding pathways between agriculture and nutrition: an evidence and gap map of tools, metrics and methods developed and applied in the last 10 years. Campbell Syst Rev. 2019;15:e1035. https://doi.org/10.1002/cl2.1035.
22. Jana A, Chattopadhyay A. Drought and socioeconomic drivers of crop diversity in India: a panel analysis. Agric Res. 2023. https://doi.org/10.1007/s40003-023-00665-8.
23. Rajender P, Ajit VR. Indian council of agricultural research annual report 2021-22. 2022.
24. Frison EA, Smith IF, Johns T, Cherfas J, Eyzaguirre PB. Agricultural biodiversity, nutrition, and health: making a difference to hunger and nutrition in the developing world. Food Nutr Bull. 2006;27:167–79. https://doi.org/10.1177/156482650602700208.
25. Frison EA, Cherfas J, Hodgkin T. Agricultural biodiversity is essential for a sustainable improvement in food and nutrition security. Sustainability. 2011;3:238–53. https://doi.org/10.3390/su3010238.
26. Keatinge JDH, Yang R-Y, Hughes J, d'A., Easdown WJ, Holmer R. The importance of vegetables in ensuring both food and nutritional security in attainment of the millennium development goals. Food Sect. 2011;3:491–501. https://doi.org/10.1007/s12571-011-0150-3.
27. NSSO. Household consumer expenditure in India. NSS 68th Round (July 2011 to June 2012). 2014.
28. Rhoades SA. The Herfindahl-Hirschman index. Fed Res Bull. 1993;79:188.
29. Gopalan C, Sastri BV. Rama and Balasubramanian, SC nutritive value of Indian foods. Hyderabad: Nat Inst Nutrition Indian Counc Med Res. 1971.
30. Hari L, Mishra S. Nutritional deficiencies in Maharashtra, 2004-05 and 2011-12. Nabakrushna Choudhury Centre for Development Studies, Odisha, India. 2019; Working Paper 77.
31. Samal RR, Mishra S. Food security among Kandhas of Kandhamal, Odisha, India: a mixed method study. J Asian Afr Stud. 2023;58:1443–64. https://doi.org/10.1177/00219096221086525.
32. Foster J. On economic poverty: a survey of aggregate measures. 1983.
33. Anjoy P, Chandra H, Basak P. District and social group-wise estimation and spatial mapping of food insecurity in the state of Odisha in India. 2020;74:107–20.
34. Chandra H, Verma B. Small area Estimation of food insecurity prevalence for the state of Uttar Pradesh in India. Model Assist Stat Appl. 2022;17:73–85. https://doi.org/10.3233/MAS-220011.
35. Korn EL, Graubard BI. Confidence intervals for proportions with small expected number of positive counts estimated from survey data. Surv Methodol. 1998;24:193–201.
36. Jun S, Cowan AE, Dodd KW, Tooze JA, Gahche JJ, Eicher-Miller HA, et al. Association of food insecurity with dietary intakes and nutritional biomarkers among US children, National health and nutrition examination survey (NHANES) 2011–2016. Am J Clin Nutr. 2021;114:1059–69. https://doi.org/10.1093/ajcn/nqab113.
37. Shridhar K, Dhillon PK, Bowen L, Kinra S, Bharathi AV, Prabhakaran D, et al. Nutritional profile of Indian vegetarian diets–the Indian migration study (IMS). Nutr J. 2014;13:55. https://doi.org/10.1186/1475-2891-13-55.
38. Siddiqui MZ, Donato R, Jumrani J. Looking past the Indian calorie debate: what is happening to nutrition transition in India. J Dev Stud. 2019;55:2440–59. https://doi.org/10.1080/00220388.2017.1408798.
39. Alam MJ, Begum IA, Mastura T, Kishore A, Woodhill J, Chatterjee K, et al. Agricultural diversification and intra-household dietary diversity: panel data analysis of farm households in Bangladesh. PLoS ONE. 2023;18:e0287321. https://doi.org/10.1371/journal.pone.0287321.
40. Weerasekara PC, Withanachchi CR, Ginigaddara GAS, Ploeger A. Understanding dietary diversity, dietary practices and changes in food patterns in marginalised societies in Sri Lanka. Foods. 2020;9:1659. https://doi.org/10.3390/foods9111659.
41. Ruel MT. Operationalizing dietary diversity: a review of measurement issues and research priorities. J Nutr. 2003;133:3911S–26S. https://doi.org/10.1093/jn/133.11.3911S.
42. Robinson GHJ, Balk J, Domoney C. Improving pulse crops as a source of protein, starch and micronutrients. Nutr Bull. 2019;44:202–15. https://doi.org/10.1111/nbu.12399.
43. Vanlauwe B, Coyne DL, Gockowski J, Hauser S, Huising JE, Masso C, et al. Sustainable intensification and the African smallholder farmer. Curr Opin Environ Sustain. 2014. https://doi.org/10.1016/j.cosust.2014.06.001.
44. Padulosi S, Thompson J, Rudebjer P. Fighting poverty, hunger and malnutrition with neglected and underutilized species (NUS): needs, challenges and the way forward. 2013. https://doi.org/10.13140/RG.2.1.3494.3842
45. Thornton P, Herrero M. Adapting to climate change in the mixed crop and livestock farming systems in Sub-Saharan Africa. Nat Clim Change. 2015;5:830–6. https://doi.org/10.1038/NCLIMATE2754.

## Publisher's note