Public Health Nutrition: 24(10), 2808–2822 doi:10.1017/S1368980021001634

Double burden of underweight and overweight among Indian adults: spatial patterns and social determinants

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Submitted 26 June 2020: Final revision received 21 March 2021: Accepted 9 April 2021: First published online 20 April 2021

Abstract

Objective: The current study explores the spatial patterns of underweight and overweight among adult men and women in districts of India and identifies the micro-geographical locations where the risks of underweight and overweight are simultaneously prevalent, after accounting for demographic and socio-economic factors.

Design: We relied on BMI (weight (kg)/height squared (m^2)), a measure of nutritional status among adult individuals, from the 2015–2016 National Family and Health Survey. Underweight was defined as <18·5 kg/m^2 and overweight as ≥25·0 kg/m^2.

Setting: We adopted Bayesian structured additive quantile regression to model the underlying spatial structure in underweight and overweight burden.

Participants: Men aged 15–54 years (sample size: 108 092) and women aged 15–49 years (sample size: 642 002).

Results: About 19·7 % of men and 22·9 % of women were underweight, and 19·6 % of men and 20·6 % of women were overweight. Results indicate that malnutrition burden in adults exhibits geographical divides across the country. Districts located in the central, western and eastern regions show higher risks of underweight. There is evidence of substantial spatial clustering of districts with higher risk of overweight in southern and northern India. While finding a little evidence on double burden of malnutrition among population groups, we identified a total of sixty-six double burden districts.

Conclusions: The current study demonstrates that the geographical burden of overweight in Indian adults is yet to surpass that of underweight, but the coexistence of double burden of underweight and overweight in selected regions presents a new challenge for improving nutritional status and necessitates specialised policy initiatives.

Keywords
Bayesian spatial modelling
Underweight
Overweight
Obesity
Quantile regression
India

Globally, undernutrition burden in adult population has reduced promisingly in recent years, but at the cost of increasing rates of overweight and obesity. Between 1985 and 2017, the global mean BMI (calculated as weight (kg) divided by height squared (m^2)) increased from 22·6 to 24·7 kg/m^2 in adult women and from 22·2 to 24·4 kg/m^2 in adult men[1]. In many low- and middle-income sub-regions of Asia-Pacific, South and South East Asia, and Central and East Africa, the BMI is increasing at a much faster rate, thereby contributing to a rapid increase in the burden of overweight in these regions[2]. Moreover, it is increasingly being recognised that the emerging problem of overweight often coexisted with the burden of undernutrition in most low- and middle-income countries (LMIC), and thus creating a double burden of malnutrition (DBM) in these countries[3]. Recent Lancet series on DBM[4–7] analysed the dynamics of DBM in 123 LMIC and the findings made it clear that the problem of DBM has increased in the poorest LMIC, mainly due to the steady increase in overweight and obesity. Rapid economic development and growing trends in rural–urban migration expose increasing number of people to unhealthy diet, that is, readily available, less nutritious and highly processed foods and beverages; reduced physical activity at work and transportation, all

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of which accelerate the risk of overweight and obesity in LMIC[4]. To date, national nutrition policies and interventions in most LMIC have focused on the undernutrition aspect of malnutrition[6], but the growing evidence of DBM indicates that there is no longer just undernutrition to eradicate but also overweight and obesity to deal with.

In India, the prevalence of overweight (defined as BMI $\geq$ 25 kg/m^2) in adult men and adult women increased from 9·7 to 19·6 % and 12·6 to 20·7 %, respectively, between 1992 and 2016, at an annual rate of nearly 1 %[8,9]. Overweight individuals are particularly susceptible to many non-communicable diseases such as hypertension, type 2 diabetes and pulmonary illness[10,11], which, in turn, elevate mortality and disability rates[12], inflate health care costs[13] and impair overall quality of life[14]. At the lower end of nutritional spectrum, undernutrition still affects more than one out of five Indian adults, leading to wasting of skeletal muscle[15], pregnancy complication and adverse birth outcomes[16], and reduced physical work capacity and thus reduced economic output[17]. Consequently, the presence of both nutrition conditions, particularly in population of developing countries like India, deserves serious policy attention, because of the huge cost implications of managing nutritional disorder at both extremes of nutritional spectrum.

A vast array of nutritional epidemiology and public health research suggests that several biological aspects (e.g., age and sex), socio-economic status (individual and neighbourhood wealth) along with a number of environmental factors (urban residence, food environment and local-level economic development) consistently determine the social distribution of malnutrition[18–22]. Some previous studies have also documented that, in most developing countries, malnutrition tends to be clustered in specific geographical regions, where a group of people account for the larger burden[20,23,24]. In India, limited attention has been given to the analysis that explores the spatial patterns of malnutrition, particularly in adult population. In a bid to explain spatial heterogeneity in nutritional disorder among Indian adults, Dutta and colleagues[25] relied on sub-national-level estimates, even though within states distribution of individual's body weight is highly spatially uneven. Indeed, the spatial heterogeneity that occurs at micro-geographical level needs to be estimated at a finer scale. As a consequence, sub-national maps relating to underweight and overweight can paint a parsimonious picture of the actual nutritional status of Indian adults. Furthermore, all existing studies pertaining to DBM among Indian adults[26,27] have so far addressed the co-occurrence of underweight and overweight within the same household (i.e., dual-burden households), established linkages with rising income inequality, but failed to describe the extent of geographical variations, especially at micro-spatial scale. Efforts aimed at achieving rapid reduction of nutritional disorder among Indian adults should include an in-depth investigation into the correlates and geographical context of different dimensions of malnutrition, as this can help promote geographically targeted direct nutrition intervention among the vulnerable groups.

In the current study, we aim to explore the spatial patterns of underweight (as a measure of undernutrition) and overweight at micro-geographical scale (district level) in India, after accounting for the effects of observable demographic and socio-economic determinants. We are also interested in identifying the locations, if any, where the risks of DBM are prevalent. The rationale for using the districts as the spatial unit is to allow for assessing the spatial variability at a much smaller unit, as we believe that a state level or other higher level analysis would conceal local variations within the locations. Obtaining anthropometric data (height and weight) from a large, nationally representative sample, we estimate BMI and use as a measure of nutritional status among adult men and women. We relied on Bayesian semiparametric additive quantile regression[28] that allows us to simultaneously consider the effects of different types of covariates such as the linear effects of categorical covariates, non-linear effects for metrical covariates, spatial effects for the location of residence and a random component to account for hierarchical nature of most survey data, on the response variable. The choice of Bayesian quantile regression is considered appropriate for a study of malnutrition because the indicators of overweight and underweight are measured at the extremes of the BMI variable and thus, a regression model that estimates the mean, which is at the centre of the distribution, would be inappropriate to capture the situation at the ends of the variable. Quantile regression offers some mechanism for estimating regression parameters when the conditional quantile, rather than the mean, is of interest. A previous study[29] on the global burden of malnutrition adopted a multinomial logistic model that classified women respondents into one of three categories of underweight, overweight or normal weight. Considering that in many surveys, only scanty observations may be available in some spatial locations, Bayesian spatial analytical technique has been shown to allow for borrowing strength from neighbouring geographical locations to improve local estimates at every point under consideration, thus accounting for data sparseness and spatial association.

Data and methods

Data source

Analysis presented in this paper is based on unit-level cross-sectional data from the 2015–2016 National Family and Health Survey (NFHS), which is the most recent round of the survey. The survey is periodically conducted by the International Institute for Population Sciences, Mumbai, and the Inner City Fund International, Maryland with an aim of providing reliable estimates on socio-demographic and health indicators at the population level. The NFHS adopted a stratified two-stage sampling design in both rural and urban areas. At the first stage, primary sampling units (PSU: village as a rural PSU and census enumeration block as an urban PSU) were selected through probability proportion to size sampling scheme and subsequently, the sample households were drawn from each of the selected PSU, using systematic random sampling. The selection of the PSU was based on the enumeration areas from the 2011 population census. Data were collected from a total of 28 522 PSU, covering all 640 administrative districts of India[9].

The total number of households targeted for the survey sample was 628 900. Of these, 601 509 were successfully interviewed. All women aged 15–49 years in these households were invited to participate in an in-depth individual interview. On the other hand, men aged 15–54 years were invited to participate in a random subsample of 16 % of these households. The decision to interview more women than men in the NFHS-4 was made due to the survey's main focus on maternal and child health[9]. Thus, a total of 723 875 women and 122 051 men in all interviewed households were eligible for the survey, of which 699 686 women and 112 122 men were successfully interviewed, yielding response rates of 97 and 92 %, respectively. In our analysis, we exclude four island districts (South Andaman, North and Middle Andaman, Nicobars and Lakshadweep) located in the Union Territories of Andaman and Nicobar Islands and Lakshadweep, as they are geographically disconnected and located far from the mainland, and thus our analysis is based on 636 districts. We also restrict our study sample to non-pregnant women irrespective of their marital status. Finally, after excluding the adults with missing information on the anthropometric measures (height and weight) or any independent variables included in our analysis, the final analytic sample included 108 092 men and 642 002 women. Descriptive analysis of the study sample is presented in Table 1 by nutritional indicator type, for each of the independent variables considered in the current study.

Reporting of the present study has been verified as per the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines (see online supplementary, Supplemental Appendix 1).

Ethical consideration

The present study analysed publicly available secondary data drawn from 2015–2016 NFHS-4. The dataset comes with no identifiable information of the survey participants. NFHS-4 protocols, questionnaire and verbal consent forms were assessed and approved by the ethics committee at the International Institute for Population Sciences, Mumbai. Written informed consent was obtained from each participant. Given these, no separate ethics committee approval was required regarding this research work. The NFHS datasets are freely available for download upon request from the Demographic and Health Surveys (DHS) Program website (https://dhsprogram.com/data/dataset/India_Standard-DHS_2015.cfm?flag=0).

Variables

Outcome variable

Based on the anthropometric data (height and weight) collected at the time of survey, NFHS provides individual's BMI (in kg/m^2) to assess nutritional status among adult men and adult women. We adopted the WHO recommended cut-off points in BMI classification and considered the individual's nutritional status based on the following three groups: underweight (<18·5 kg/m^2), normal (18·5–24·9 kg/m^2) and overweight (≥25·0 kg/m^2).

Independent variables

Independent variables were considered similarly for men and women, except for birth parity and current breast-feeding status which were applicable to female only. The following variables were included in the study: age, marital status, educational attainment, religion, caste, type of place of residence, household wealth status, tobacco consumption, alcohol consumption, birth parity, breast-feeding status and dietary habit. Individual's age was considered as continuous variable. Dietary intake and food choices are closely associated with the nutritional status of a person. A well-balanced diet comprises foods from all major food groups that provide the body adequate amounts of nutrition. In NFHS-4, individual's usual dietary intake was recorded through a FFQ. The questionnaire assessed frequency of intake (i.e., daily, weekly, occasionally or never) of several food items including green vegetables, fruits, milk, pulses, eggs, fish, meat, fried foods and aerated drinks, which are commonly consumed all over the Indian sub-continent. The FFQ has been earlier validated in India in a population-based survey conducted in Tamil Nadu[30]. The FFQ responses were intended to reflect basic nutrient intake patterns, available from the commonly consumed food items. For example, meat, fish, eggs and milk are rich in protein, and daily consumption of these foods may be an indicative of adequacy in dietary protein. In our analysis, for each food item, we classify FFQ data using a four-point scale ranging from 4 = daily intake, 3 = weekly, 2 = occasionally and 1 = never. For the spatial unit, we used district as a micro-level geographical unit, where the respondents were residing at the time of survey, to generate the location variable. All 636 districts included in the present study were geo-referenced.

Statistical analysis

When analysing the impact of covariates on the conditional quantiles of a response variable, y_i, the linear quantile regression introduced by Koenker and Basset[31] assumes the following functional relation:

https://doi.org/10.1017/S1368980021001634 Published online by Cambridge University Press

Table 1 Descriptive statistics for the variables included in the analysis

	Male								Female							
	BMI category								BMI category							
	Underweight (<18·5 kg/m^2)		Normal (18·5–24·9 kg/m^2)		Overweight (≥25·0 kg/m^2)		Sample size		Underweight (<18·5 kg/m^2)		Normal (18·5–24·9 kg/m^2)		Overweight (≥25·0 kg/m^2)		Sample size	
Variables	%/mean	SD	%/mean	SD	%/mean	SD	*n*	%	%/mean	SD	%/mean	SD	%/mean	SD	*n*	%
Total	19·74		60·70		19·56		108 092	100·0	22·89		56·55		20·55		642 002	100·0
Residence type																
Rural	22·62		62·61		14·77		74 283	68·7	26·79		58·31		14·90		452 570	70·5
Urban	14·93		57·33		27·54		33 809	31·3	15·49		53·23		31·28		189 432	29·5
Marital status																
Never married	30·59		59·23		10·18		38 309	35·4	37·40		56·01		6·59		164 188	25·6
Ever married	13·92		61·49		24·59		69 783	64·6	18·42		56·72		24·86		477 814	74·4
Parity																
0	–		–		–		–		34·43		56·86		8·71		201 387	31·4
1	–		–		–		–		19·05		57·87		23·08		80 101	12·5
2	–		–		–		–		15·62		55·20		29·18		146 034	22·8
3	–		–		–		–		17·80		56·20		26·00		101 110	15·8
≥4	–		–		–		–		21·21		57·42		21·37		113 370	17·7
Currently breast-feeding																
No	–		–		–		–		22·02		55·90		22·08		534 887	83·3
Yes	–		–		–		–		27·58		60·09		12·34		107 115	16·7
Educational attainment																
None	22·63		64·90		12·47		14 555	13·5	24·65		58·63		16·71		184 110	28·7
Primary	21·31		61·82		16·87		13 886	12·9	22·05		56·41		21·54		81 142	12·6
Secondary	21·63		59·49		18·87		62 876	58·2	23·94		54·90		21·16		305 057	47·5
High	10·05		60·72		29·23		16 775	15·5	15·87		58·33		25·80		71 693	11·2
Religious groups																
Hindu	20·31		60·70		19·00		80 907	74·9	23·60		56·75		19·64		477 233	74·3
Non-Hindu	17·20		60·73		22·07		27 185	25·2	19·95		55·72		24·33		164 769	25·7
Caste groups																
General	15·84		59·69		24·48		27 566	25·5	18·03		55·35		26·62		156 888	24·4
Scheduled Castes (SC)	22·51		61·82		15·68		19 243	17·8	25·28		57·60		9·85		114 281	17·8
Scheduled Tribes (ST)	24·79		65·17		10·04		19 182	17·8	31·78		58·38		20·69		115 774	18·0
Other Backward Classes (OBC)	19·90		59·93		20·17		42 101	39·0	22·89		56·42		26·62		255 059	39·7
Wealth status																
Poorest	31·79		63·17		5·04		17 953	16·6	35·73		58·46		5·80		123 450	19·2
Poorer	26·21		63·75		10·04		22 570	20·9	29·45		59·25		11·30		138 617	21·6
Middle	20·09		62·88		17·02		23 511	21·8	23·04		58·29		18·68		135 193	21·1
Richer	15·67		59·22		25·11		22 336	20·7	17·04		54·86		28·09		125 713	19·6
Richest	10·18		56·00		33·81		21 722	20·1	11·54		52·37		36·09		119 029	18·5
Tobacco consumption																
No	20·14		58·76		21·10		61 830	57·2	22·58		56·54		20·88		583 967	91·0
Only smoking	17·59		63·97		18·44		20 559	19·0	31·48		57·57		10·95		9902	1·5
Only chewing	20·91		62·02		17·07		16 741	15·5	26·98		56·68		16·44		46 086	7·2
Smoking and chewing	19·45		66·81		13·74		8962	8·3	28·91		57·01		14·08		2047	0·3

Table 1 *Continued*

	Male								Female							
	BMI category								BMI category							
	Underweight (<18·5 kg/m^2)		Normal (18·5–24·9 kg/m^2)		Overweight (≥25·0 kg/m^2)		Sample size		Underweight (<18·5 kg/m^2)		Normal (18·5–24·9 kg/m^2)		Overweight (≥25·0 kg/m^2)		Sample size	
Variables	%/mean	SD	%/mean	SD	%/mean	SD	*n*	%	%/mean	SD	%/mean	SD	%/mean	SD	*n*	%
Alcohol consumption																
No	21·06		61·90		17·05		74 024	68·5	22·86		56·61		20·63		625 734	97·5
Yes	15·33		65·87		18·80		34 068	31·5	25·56		59·97		14·46		16 268	2·5
Dietary habits																
Green vegetables	1·56	0·6	1·64	0·7	1·69	0·7	1·64	0·7	1·59	0·7	1·65	0·7	1·70	0·7	1·65	0·7
Fruits	2·20	0·8	2·36	0·7	2·44	0·7	2·35	0·8	2·25	0·8	2·42	0·8	2·49	0·8	2·41	0·8
Milk	1·54	0·8	1·69	0·9	1·74	0·9	1·67	0·9	1·59	0·9	1·72	1·0	1·79	1·0	1·71	0·9
Pulses	1·58	0·7	1·66	0·7	1·67	0·7	1·65	0·7	1·64	0·7	1·69	0·7	1·69	0·7	1·69	0·7
Eggs	1·81	1·1	1·91	1·1	1·88	1·1	1·89	1·1	1·59	1·2	1·72	1·2	1·71	1·2	1·69	1·2
Fish	1·69	1·2	1·77	1·2	1·74	1·3	1·75	1·2	1·49	1·3	1·61	1·3	1·59	1·3	1·58	1·3
Meat	1·82	1·1	1·91	1·2	1·89	1·2	1·89	1·2	1·62	1·2	1·73	1·3	1·73	1·3	1·71	1·3
Fried	2·16	0·9	2·19	0·9	2·23	0·9	2·19	0·9	2·25	0·9	2·28	0·8	2·33	0·8	2·29	0·8
Aerated	2·22	1·0	2·23	1·1	2·25	1·0	2·23	1·1	2·27	1·1	2·22	1·1	2·19	1·7	2·23	1·1

$$Q_\tau(y_i|X) = \eta_{i,\tau} + \varepsilon_{i,\tau} \quad (1)$$

where Q_τ is a conditional quantile for y_i given X, a vector of covariates, $\eta_{i,\tau}$ is a predictor for the τ^{th} quantile expressed as $\eta_{i,\tau} = X\beta_\tau$ such that $\tau \in (0,1)$ and $\varepsilon_{i,\tau}$ is the error term. The error term is assumed to have a cumulative distribution function $F(\varepsilon_\tau|\theta)$ which depends on some parameter θ. In the classical quantile regression, no assumption is made on the distribution of the error term, and the estimation of the quantile-specific coefficients β_τ is based on the minimisation of the sum of asymmetrical weighted absolute deviation.

In the current study, we adopt a semiparametric quantile regression as proposed by Waldmann *et al.*[28] which is basically an extension of equation (1) to allow for variables of different types beyond the classical linear term. In this case, the predictor $\eta_{i,\tau}$ is extended in line with the concept of geo-additive regression as

$$\eta_{i,\tau} = v\beta_\tau + f_\tau(u) + f_{\tau,spat}(s) \quad (2)$$

where v is a vector of categorical covariates, u is a vector of metrical covariates such as the age of the respondent and s denotes the spatial location where the respondent resides. The function f_τ is a smooth function assumed for the non-linear effect of u and $f_{\tau,spat}$ is a function for the spatial effect, each of them estimated at τ^{th} quantile.

Parameter estimations are based on Bayesian formulation where, unlike in the classical case, it is necessary to specify a distribution for the error term in order to obtain the likelihood. Consequently, an asymmetric Laplace distribution is considered as an auxiliary error distribution as suggested by Yu and Moyeed[32]. Thus, $y_i \sim ALD(\eta_{i,\tau}, \delta^2, \tau)$ where $\eta_{i,\tau}$ is the location parameter, δ^2 is the precision parameter and τ is the asymmetric parameter. The density yields posterior mode estimates that are equivalent to asymmetrical weighted absolute deviation. For more details about this procedure, we refer to Yu and Moyeed[32] and particularly Waldmann *et al.*[28] for the semiparametric geo-additive procedure.

To approximate the non-linear effects, we specified Bayesian P-spline[33,34], where the smooth function is approximated by a polynomial spline of degree l. The spline is subsequently represented as a linear combination of B-spline basis function evaluated at equally spaced knots. We used cubic splines with 20 equidistance knots. Gaussian Markov random field prior was considered for the spatial effects, which is commonly used in spatial statistics[35]. The prior introduces a neighbourhood structure to the spatial locations such that two sites s_j and s_k are considered as neighbour if they share common boundary. For the linear terms, noninformative independent diffuse prior was assumed. Markov chain Monte Carlo (MCMC) simulation based on Gibbs sampling was used to draw sample from the posterior distribution. More details about the different component that can be considered in the model and details about the Bayesian framework for quantile and other similar regression models including the possible choice of prior distributions are available elsewhere[36]. We provide more details about the model and the choice of our prior distributions in the online 'Supplementary Material 1'. Sample codes for estimating the Bayesian quantile regression are given in the online 'Supplementary Material 2'.

Results

The findings presented in this section are based on the Bayesian quantile model, as described in the section 'Statistical analysis'. In order to access nutritional status categories of underweight and overweight at the lower and upper tails of the BMI, respectively, appropriate quantile (τ) needs to be assigned for each type of the nutritional indicators. To this end, we based this quantile parameter on the proportion of men and women whose BMI fall below the threshold for each nutritional status category[23]. Accordingly, underweight among adult men and adult women was analysed at 19·74 and 22·89 % quantile, respectively. On the other hand, for overweight, models were fitted at 80·44 and 79·45 % quantile, respectively, in men and women (see Table 1). In the following, we will first describe the results of spatial effects, followed by those for non-linear and linear effects.

Spatial effects

Figures 1–4 show the posterior estimates of spatial effects on the nutritional indicators for men and women, respectively. The left panel of these figures presents district-specific posterior mean estimates, where locations with deeper red colour indicate higher levels of underweight and overweight. The right panels present the 95 % credible interval (CI) to represent the significance of the corresponding posterior mean estimates. Districts with black (white) shading in the CI maps are significantly associated with negative (positive) posterior estimates, while the estimates for districts with grey shading are not statistically significant.

The risk of underweight in adult male is clearly spatially segregated (Fig. 1(a)), with districts located in the central, western, north-eastern and eastern regions having a greater underweight burden. States where the level of underweight was significantly higher are: Mizoram (six out of eight districts), Nagaland (eight out of eleven districts), Madhya Pradesh (thirty-three out of fifty districts), Bihar (twenty-two out of thirty-eight districts), Meghalaya (four out of seven districts), Chhattisgarh (ten out of eighteen districts) and Manipur (five out of nine districts). Although appearing more widespread, underweight burden in women was tracked in the same geographical regions as that of the men (Fig. 2(a)). The estimates suggest that as many as 35 % of the districts (221 out of 636 districts) in India have increased risk of underweight among women, with the highest proportion from Bihar (thirty-two out of thirty-eight districts) followed by Jharkhand (eighteen out of twenty-four districts), Madhya Pradesh (thirty-six out of fifty districts) and Chhattisgarh (ten out of eighteen districts).

The districts with high overweight vulnerability are, for both men and women, also spatially segregated and formed a number of clusters in the southern, northern and western regions. Apparently, the burden of overweight, as depicted in Figs 3(a) and 4(a), was slightly more pronounced among women (with 194 out of 636 districts having a higher likelihood of overweight) than men (183 out of 636 districts). Districts with significantly higher overweight burden in adult men and adult women are located in the states of Kerala, Goa, Delhi, Tamil Nadu, Punjab and Gujarat, whereas significantly lower burden districts are from Bihar and West Bengal.

Double burden of underweight and overweight

In Fig. 5, we identify the location of double burden districts where the estimates show significantly higher spatial effects for both underweight and overweight, that is, places where the sample population is simultaneously vulnerable to underweight and overweight. Thirty-seven and twenty-nine number of districts are categorised as double burden districts for men and women, respectively. For both men and women, the state of Gujarat has the highest number of double burden districts. We list out all the double burden districts with their corresponding states in online Table 1a (appendix).

Non-linear effects

The non-linear effects of age on the nutritional indicators for men and women are depicted in Figs 6 and 7. For all graphs displaying non-linear effects, lines with deep black colour indicate the posterior mean estimates, while the dotted lines mark the boundaries of upper and lower limit of 95 % CI. As shown in Fig. 6(a), the likelihood of being underweight decreases in men with every unit increase in age up to around 32 years and beyond that a sinusoidal pattern is evident up to the age of 54 years. In the case of overweight, with the exception of the bump in 39–42 years, the estimates indicate that the risk of becoming overweight increases sharply up to the age of 47, after which a sinusoidal pattern was observed (Fig. 6(b)).

As far as underweight in women is concerned, the results present a *U* shape indicating that the likelihood of being underweight increases with every unit increase in age up to 23 years and this pattern reverses afterwards (Fig. 7(a)). The results for overweight reveal a constantly fluctuating pattern between the ages of 15 and 35 years, and beyond, the severity of overweight increases sharply with every unit increase in women's age (Fig. 7(b)). The

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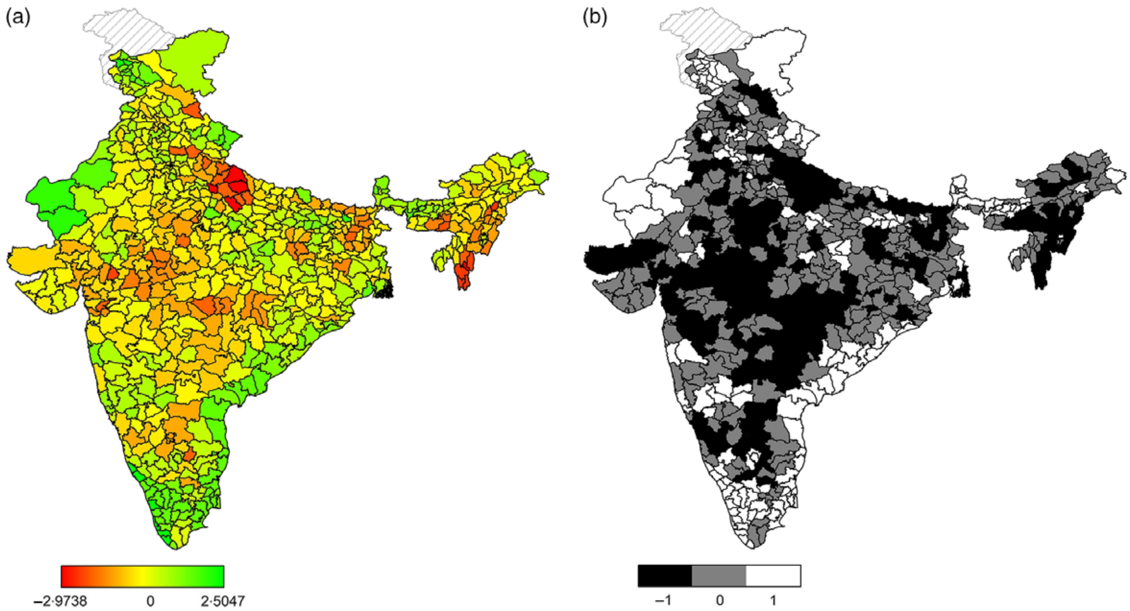

Fig. 1 (colour online) Maps of India showing spatial effects of (a) underweight and (b) the location of the 95 % CI among men (black colour signifies districts with significantly lower estimate; white colour signifies those with significantly higher estimates, while estimates for districts shaded grey are not significant)

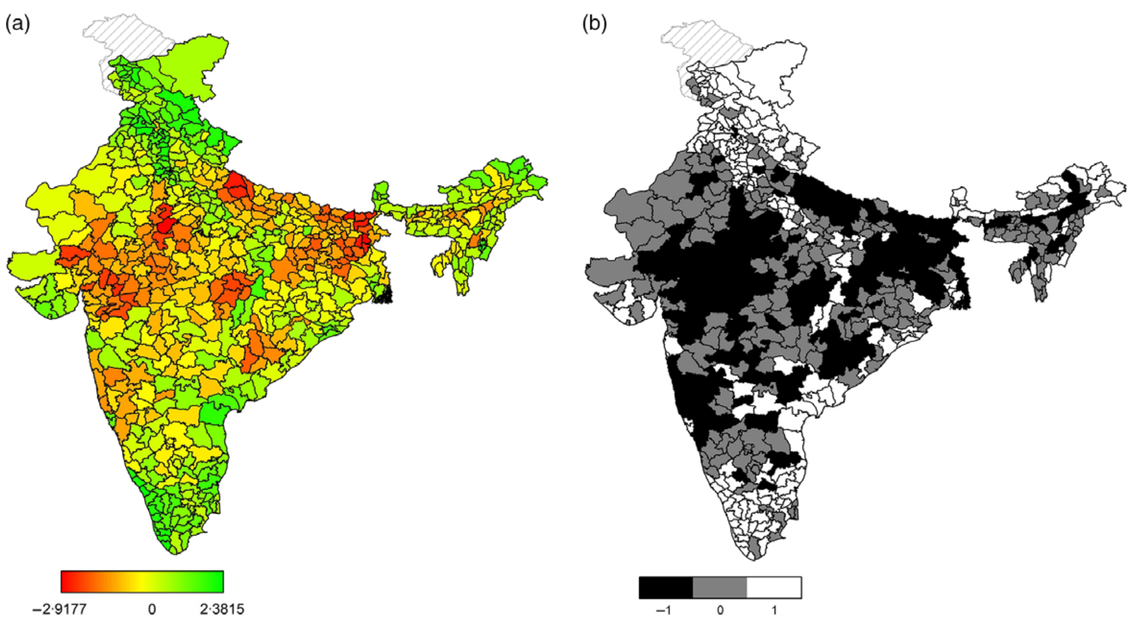

Fig. 2 (colour online) Maps of India showing spatial effects of (a) underweight and (b) the location of the 95 % CI among women (black colour signifies districts with significantly lower estimate; white colour signifies those with significantly higher estimates, while estimates for districts shaded grey are not significant)

analysis reveals that women in young ages between 20 and 35 showed much improved nutritional status, but adult men showed a worsening nutritional status from the very young ages in the adult age group.

Linear effects

We investigated the spatial and non-linear effects. After this, it is important to look into the linear effect of socio-economic factors on nutritional indicators. In Table 2, we presented posterior means and 95 % CI to show independent effect of each potential determinant on nutritional indicators after the estimates of the linear model were adjusted for spatial and non-linear effects. The findings suggest that, compared with their rural counterparts, adult men and adult women living in the urban areas are less likely for underweight but more likely for overweight, though the estimate for underweight among

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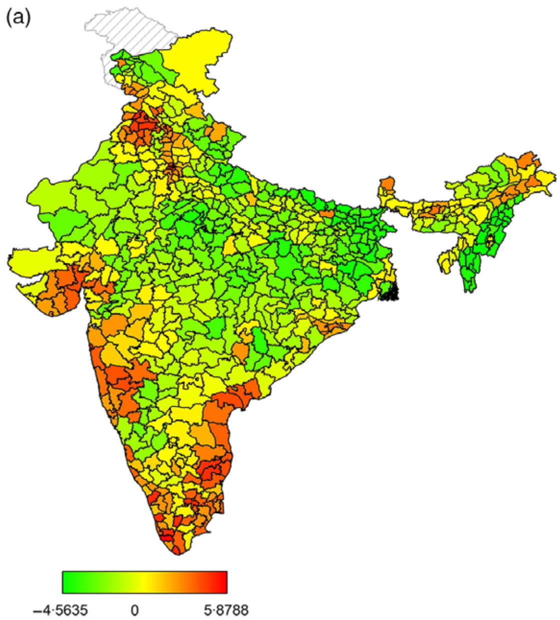

Fig. 3 (colour online) Maps of India showing spatial effects of (a) overweight and (b) the location of the 95 % CI among adult men (black colour signifies districts with significantly lower estimate; white colour signifies those with significantly higher estimates, while estimates for districts shaded grey are not significant)

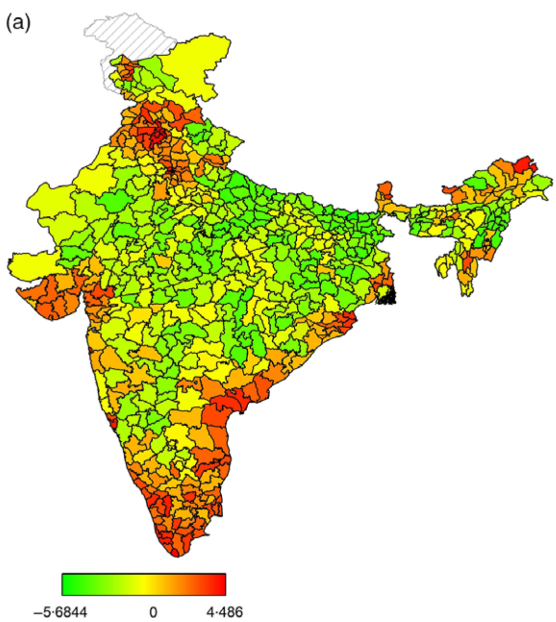

Fig. 4 (colour online) Maps of India showing spatial effects of (a) overweight and (b) the location of the 95 % CI among adult women (black colour signifies districts with significantly lower estimate; white colour signifies those with significantly higher estimates, while estimates for districts shaded grey are not significant)

adult men was not significant. It is evident that the risk of being underweight was significantly lower among married men and married women; however, both men and women are more prone to overweight. Also, the likelihood of being overweight increased among women with higher birth parity but those women who are currently breast-feeding are more likely for underweight. The results further show that men and women who attained at least secondary level of education are comparatively less underweight than those who have no formal education. However, increasing educational attainment was positively associated with overweight burden among men and women, with the exception of women who attained level of education more than graduation and above.

Results further suggest that the likelihoods of being underweight are lower for both men and women from

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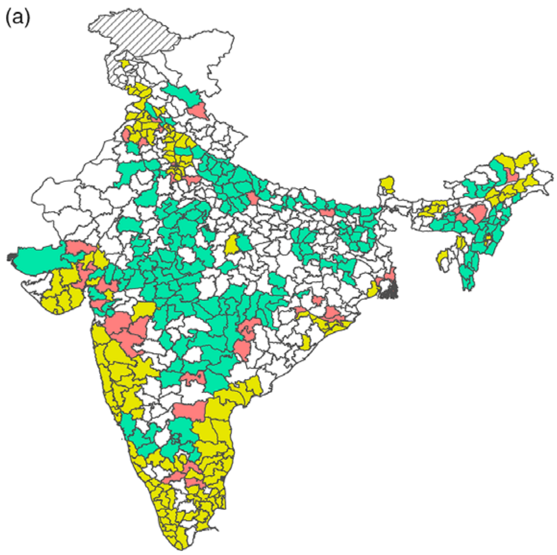

Fig. 5 (colour online) Maps of India showing districts with elevated risk of malnutrition among adult (a) men and (b) women. Figure 5 is plotted using data from Figs 1–4. Statistically significant districts are identified based on their exposure to underweight and overweight. ▭, normal; ▭, underweight; ▭, overweight; ▭, double burden; ▨, data unavailable

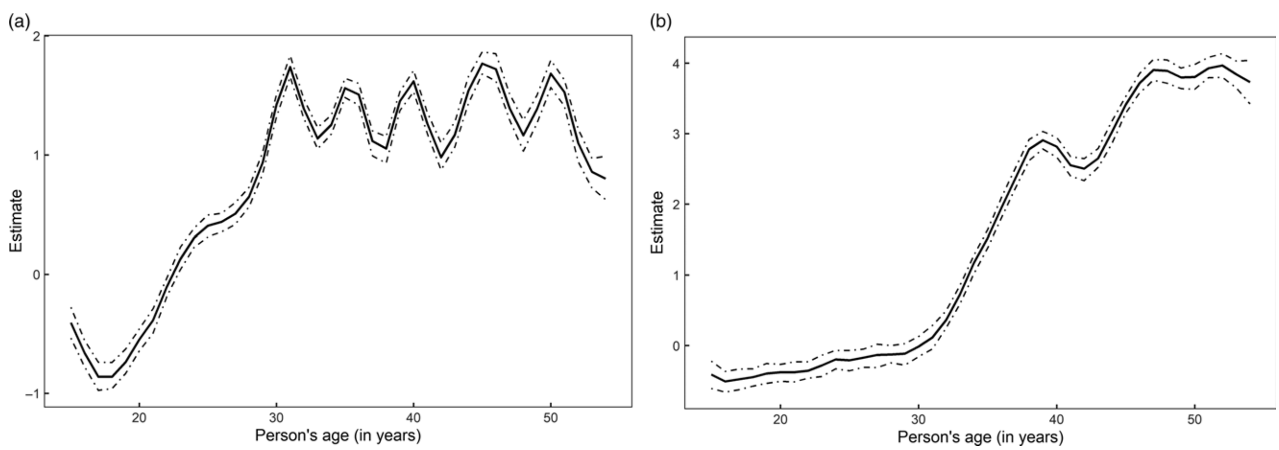

Fig. 6 Non-linear effects of men's age on (a) underweight and (b) overweight. Estimate (on Y-axis) refers to posterior means. Dot-dashed lines indicate 95 % credible intervals

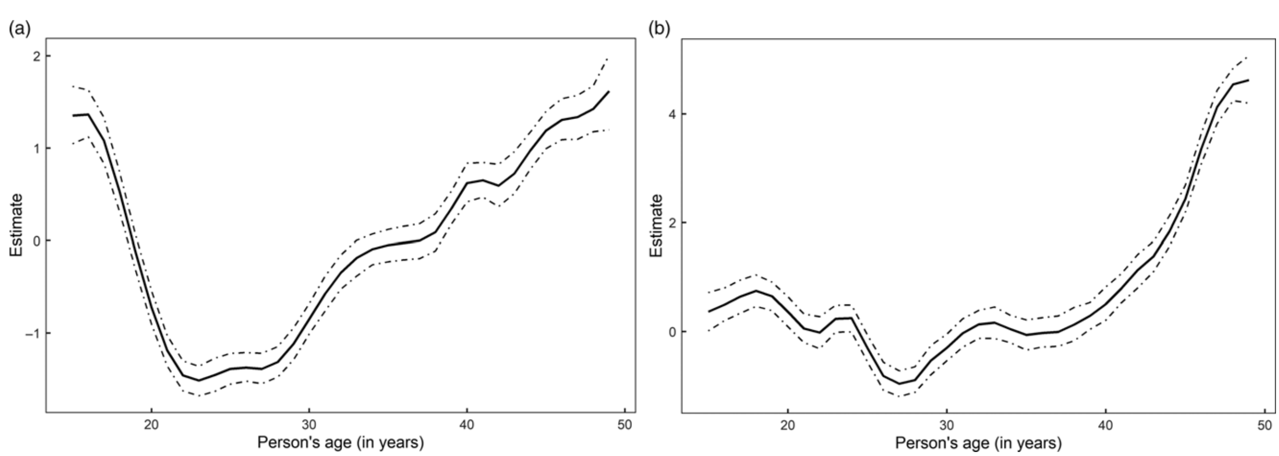

Fig. 7 Non-linear effects of women's age on (a) underweight and (b) overweight. Estimate (on Y-axis) refers to posterior means. Dot-dashed lines indicate 95 % credible intervals

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Table 2 Posterior mean estimates from Bayesian quantile regression models for the association of nutritional status with selected socio-economic variables, among adult men and women, National Family and Health Survey, 2015–2016

	Male				Female			
	Underweight		Overweight		Underweight		Overweight	
Variables	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI
Residence type								
Rural								
Urban	−0·02	−0·06, 0·02	0·13	0·09, 0·17	0·13	0·08, 0·18	0·28	0·23, 0·33
Marital status								
Never married								
Ever married	0·85	0·81, 0·89	1·15	1·10, 1·20	1·15	1·11, 1·19	1·91	1·85, 1·98
Parity								
0	–	–, –	–	–, –				
1	–	–, –	–	–, –	0·30	0·27, 0·33	0·52	0·49, 0·55
2	–	–, –	–	–, –	0·43	0·40, 0·46	0·78	0·75, 0·80
3	–	–, –	–	–, –	0·44	0·42, 0·47	0·87	0·84, 0·90
≥4	–	–, –	–	–, –	0·42	0·40, 0·45	0·96	0·93, 0·99
Currently breast-feeding								
No	–	–, –	–	–, –				
Yes	–	–, –	–	–, –	−0·59	−0·61, −0·57	−0·01	−0·03, 0·01
Educational attainment								
None								
Primary	−0·03	−0·09, 0·03	0·10	0·03, 0·17	0·04	−0·02, 0·09	0·11	0·07, 0·13
Secondary	0·09	0·04, 0·14	0·08	0·02, 0·14	0·07	0·05, 0·08	0·24	0·20, 0·28
High	0·77	0·69, 0·84	0·31	0·24, 0·39	0·19	0·13, 0·26	−0·32	−0·39, −0·25
Religious groups								
Hindu								
Non-Hindu	0·39	0·35, 0·43	0·13	0·09, 0·17	0·10	0·08, 0·12	0·13	0·07, 0·18
Caste groups								
General								
SC	−0·20	−0·25, −0·15	−0·19	−0·24, −0·14	−0·17	−0·22, −0·12	−0·48	−0·54, −0·42
ST	−0·34	−0·39, −0·30	−0·23	−0·28, −0·17	−0·23	−0·37, −0·08	−0·51	−0·72, −0·29
OBC	−0·20	−0·24, −0·16	−0·11	−0·15, −0·07	−0·17	−0·22, −0·13	−0·29	−0·33, −0·24
Wealth status								
Poorest								
Poorer	0·29	0·24, 0·34	0·57	0·49, 0·65	0·20	0·15, 0·24	0·50	0·43, 0·57
Middle	0·57	0·52, 0·63	1·09	1·01, 1·18	0·39	0·34, 0·44	0·89	0·81, 0·96
Richer	0·78	0·72, 0·84	1·50	1·42, 1·59	0·62	0·56, 0·68	1·30	1·22, 1·38
Richest	1·15	1·08, 1·22	1·85	1·76, 1·93	1·02	0·95, 1·10	1·81	1·72, 1·90
Tobacco consumption								
No								
Only smoking	−0·08	−0·12, −0·03	−0·27	−0·32, −0·22	−0·53	−0·66, −0·39	−0·23	−0·42, −0·05
Only chewing	−0·10	−0·15, −0·05	−0·18	−0·23, −0·13	−0·19	−0·26, −0·12	−0·08	−0·17, 0·00
Smoking and chewing	−0·14	−0·15, −0·12	0·08	0·00, 0·17	0·23	−0·15, 0·61	0·40	−0·11, 0·91
Alcohol consumption								
No								
Yes	0·28	0·24, 0·32	0·18	0·14, 0·22	−0·05	−0·43, 0·33	−0·01	−0·02, 0·01
Dietary habits								
Green vegetables	0·00	−0·05, 0·05	−0·03	−0·09, 0·03	0·07	0·04, 0·11	−0·03	−0·06, 0·01
Fruits	0·10	0·06, 0·14	0·00	−0·05, 0·05	0·06	0·02, 0·09	0·04	−0·03, 0·12
Milk	0·12	0·08, 0·16	0·07	0·03, 0·11	0·09	0·05, 0·12	0·00	−0·04, 0·04
Pulses	−0·02	−0·06, 0·24	−0·03	−0·07, 0·01	−0·03	−0·08, 0·02	0·08	0·01, 0·14
Eggs	0·00	−0·04, 0·04	0·07	0·02, 0·11	−0·02	−0·08, 0·03	−0·05	−0·11, 0·01
Fish	0·10	0·05, 0·14	0·14	0·09, 0·18	0·06	0·01, 0·11	0·17	0·13, 0·21
Meat	0·05	0·01, 0·10	0·09	0·04, 0·13	0·07	0·00, 0·13	0·04	0·00, 0·09
Fried	0·00	−0·04, 0·03	−0·06	−0·10, −0·02	0·00	−0·04, 0·03	−0·05	−0·09, -0·01
Aerated	−0·03	−0·07, 0·01	0·00	−0·04, 0·04	0·01	−0·03, 0·05	−0·02	-0·06, 0·03

non-Hindu religious group, but the likelihoods of being overweight are higher for non-Hindu religious groups compared with their Hindu counterparts. Individual's lower social position with respect to traditional caste hierarchy appears to be disadvantageous. Both men and women belonging to Scheduled Tribes (ST) and Scheduled Castes (SC) are more vulnerable to underweight. However, the burden of overweight was significantly lower among these groups. Results reveal that wealth index is negatively associated with underweight but has a positive association with overweight resulting increase in the burden of overweight in a graded manner. Compared with the poorest wealth group, men and women in the poorer, middle, richer and richest groups have shown lower likelihoods of underweight, but they are at higher risk of being overweight. The use of tobacco increases the likelihood of

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being underweight among both adult men and adult women. On the contrary, consumption of alcohol decreases the risk of being underweight but increased the risk of being overweight among men only. Regarding dietary behaviours, the results show that higher frequency of eating fruits, milk, meat, eggs and green vegetables was associated with lower level of underweight among men and women. On the other hand, higher frequency of consuming fish, meat and milk was associated with a higher level of overweight among men and women.

Sensitivity analysis

Following the Expert Consultation from WHO[37], which suggests that the lower BMI cut-off for overweight and obesity for the Asian population should be 23 and 25 kg/m^2, respectively, we reanalysed the data for overweight using this cut-off (i.e., $\geq$23 kg/m^2 to represent both overweight and obesity) for both men and women. Based on this cut-off, the proportion of overweight men and women was, respectively, 32·9 and 30·8 %. We note that the results of the sensitivity analysis are largely similar to those of our main analysis; thus, these results are not presented.

Discussion

The current study aimed to model spatial variability of nutritional disorders in Indian adults, using unit-level data from a nationally representative survey. We adopted the Bayesian semiparametric quantile regression approach to measure the burden of underweight and overweight across districts and for adult men and adult women. Our findings revealed striking nutritional variations at the district level, indicating that malnutrition burden in adults clearly exhibits geographical divides across the country. Districts located in the central, western and eastern parts of the country have a higher level of underweight, whereas southern and northern districts are at lower risk of underweight. As for overweight, the spatial patterns were reversed from the underweight, with most overweight districts clustering in the southern and northern parts of the country. However, the geographical variation in underweight and overweight could well be the consequence of uneven distribution of available resources across the districts, and this uneven distribution may further influence living environment, occupational structure, dietary and sedentary behaviours, thus affecting one's BMI. Moreover, the existence of clusters with higher malnutrition burden provides evidence of strong spatial structure. It shows that neighbouring districts from different states have a similar pattern of distribution of malnourishment among adults. This is due to the common socio-cultural norms in the region which may influence the dietary practices, general health beliefs and overall lifestyles of the population[23].

Geographically, the spread of underweight appears to be higher among adult women than it is for adult men. Parallel to the low allocation of household foods due to gendered norm, where female members receive comparatively less energy than the male members[38], some studies have reported that women in some regions of the country are restricted to eat certain kind of foods (e.g., fruits and vegetables, animal protein-based foods) due to, for instance, social taboos or religious beliefs, with the result that women are deprived of the necessary nutrients[39].

It should be noted that there are locations in the north-eastern region where overweight is quite high among the adults. This finding, however, goes against the widespread belief that people living in the north-eastern hilly states are not at risk of being overweight due to the difficult terrain habitation and their physically active lifestyle. An exploratory study, among high-altitude tribal women, reported an increased risk of overweight and obesity and further concluded that the influence of modernisation and increased motorised transportation changes the lifestyle of local inhabitants, thereby affecting their traditional dietary practices and physical activity levels which might have contributed to the problem of increasing body fats among them[40].

Besides the spatial results, our analyses of demographic and socio-economic variables offer valuable insights into the variation in the burden of malnutrition among vulnerable groups. Results show that underweight among Indian men and women is more prevalent in early adulthood than in the middle ages. In contrast, overweight is more common in middle-aged men and women. In general, weight gain during the middle ages is an indication of the accumulation of body fat in response to an increase in food consumption and a decrease in the rate of metabolism[41]. Additionally, the increase in BMI among middle-aged women could also be attributed to the fact that many Indian women undergo multiple pregnancies, which is potentially associated with increased abdominal obesity in women[42,43]. This can also explain why the present study finds that higher birth parity leads to a significant weight gain in women.

Consistent with the result of other studies conducted in India and other countries[19,21,44,45], our results revealed higher levels of overweight for men and women living in urban areas in India. Several epidemiological studies recognising the linkages between urban dwelling and increased body weight have supported the fact that nutrition transition is occurring at a faster rate in the urban areas of developing countries and this could be attributed to rapid economic development, adoption of western cultures and physically inactive lifestyle[46–48].

Both education and household wealth protect Indian adults from underweight, but at the same time, they also increase the risk of being overweight. It is obvious that, with higher education and increased wealth status, persons are likely to be in good jobs, which in turn enable them to afford good diets and health care services. These

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individuals could also be engaged in occupations that promote sedentary lifestyles with less physical activities. On the other hand, less educated and socio-economically poor persons are mostly confined to low-waged labour-intensive jobs which may restrict them to avail adequate nutritious foods and other well-being services. Perhaps, these differences could explain the strong observed association of BMI with educational attainment and wealth status.

We observed adults from SC and ST communities were at lower risk of overweight, which seems to have occurred at the cost of high underweight among them. Caste-based discriminations in different aspects of health including energy intakes, medical care access, and hygiene and sanitary practices have been widely reported in India[49–51]. Evidence also suggests that, being economically deprived and socially segregated, members of lower caste hierarchy (SC and ST) have limited access to health care and other well-being services, and that made them trapped into poor health outcomes[52].

Consistent with previous studies conducted in both rural[53] and urban India[54], our findings reveal that any type of tobacco consumption (chewing, smoking and both) is associated with lower BMI in adults. Although the connection between tobacco consumption and poor nutritional status is extremely complex, it is likely that nicotine, the primary chemical component of most tobacco products, is a toxic alkaloid that can result in appetite suppression or attitudes towards meal[55]. Therefore, it is reasonable to expect that nutritional status of tobacco users and non-users may differ in the way in which they consume meals. In our study, we find alcohol consumption to be negatively associated with underweight but positively associated with overweight. These relations were significant in men only, in agreement with previous studies[56–58] that show a dose-dependent relationship between quantity of alcohol consumed and overweight prevalence. Regarding dietary behaviours, we found that increasing the frequency of eating green vegetables and fruits reduces the risk of underweight. One general explanation would be that since fruits and vegetables are important source of carbohydrates and dietary fibre, increased consumption of such foods may lead to increased energy intake, resulting in weight gain. Several studies from the Western countries have also shown that increased intake of green vegetables and fruits maintains body weight by preventing overweight and obesity[59–61], and thus, dietary guidelines of many developed countries highlight the importance of a diet high in green vegetables and fruits[62,63]. However, in the present study, we do not find any significant association between intake of vegetables and fruits and overweight. We also found that increasing the frequency of eating egg, fish, milk and meat reduced the risk of underweight but increased the risk of overweight among adults. Egg, fish, milk and meat are high protein foods and are also important sources of several vitamins and micronutrients, and therefore, it is expected that increased consumption of such foods can have positive impact on body weight gain[64]. Our finding that there is an increased risk of being overweight with increased consumption of animal-based foods corroborates published evidence from India[65] and elsewhere[66–68]. The biological mechanisms of how animal-based food intake can cause detrimental effects on body weight are still unclear. Researchers suspect that the presence of high cholesterol, SFA and C-reactive protein in certain animal-based foods may have detrimental impacts on the body weight[69,70]. Additionally, we believe that the cooking process of most animal-based foods in Indian subcontinent that is often loaded with oil and butter increases fat consumption and overall energy intake, and can further enhance the risk of overweight and obesity.

In order to determine the most efficient policies for tackling the malnutrition burden, it is important to understand where malnutrition is most manifested. In the current study, the maps generated for nutritional indicators have pinpointed specific districts with high and low likelihood of underweight and overweight trajectory in adult populations, which may help policy makers in recognising the nutritional situation and need of each district allowing for specialised policy initiatives. Further, these maps could also be linked to those of other socio-economic and epidemiological indicators, revealing further explanations for the observed spatial patterns. For example, districts with increased risk of underweight, identified from the maps, could be linked to their respective poverty levels. With striking nutritional variations at the district level, even after controlling for the confounders, the findings suggested the need for district-level planning for managing nutritional inequalities at the grass root levels. Effective nutritional interventions and programmes that could contribute to a greater reduction in underweight should be prioritised in the lagging districts. Also, there is a need to revisit the strategies on which the current nutrition enhancement programmes and poverty alleviation programmes are based, especially for those districts where burden of underweight is significantly higher. Since higher education is not always associated with better nutritional health, as findings revealed that the risk of being overweight increases with level of education, further efforts to increase nutritional health awareness among Indian adults are also needed to ensure that they are aware of the dangers of nutritional disorders and its preventive measures. Findings from the current study provide limited evidence of double burdens of underweight and overweight disorder within the population subgroups, which tells us that the population subgroups at high risk of underweight tend to be those with low risk of overweight and vice versa. But at the same time, the coexistence of double burden of underweight and overweight in selected districts indicates that there is an urgent need to move forward with double-duty actions[6,71], an integrated approach that aims to simultaneously prevent

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or reduce the risk of both underweight and overweight and obesity, through common interventions, programmes and policies. Rationale for the double-duty actions is based on the fact that the double burden stems from the shared drivers (i.e., biological, socio-economic and environmental) behind various forms of malnutrition, and thus the shared platforms (i.e., national dietary guidelines, national policies for overweight, obesity and nutrition, health systems, etc.) could be used to address the malnutrition in its different forms.

Study limitations

The present study's findings should be considered in light of several limitations. Firstly, BMI was used as a measure of body fatness instead of waist and hip circumference or waist-to-hip ratio or skinfold thickness, which are more appropriate and clinically relevant methods to detect excess body fat and categorising overweight in adult populations[72]. Secondly, our analysis for male and female sample has been restricted to age 15–54 and 15–49 years, respectively, and this has restricted the generalisability of our results to advanced age groups. Thirdly, NFHS-4 lacks data on individual's physical activity level, amounts of food intake, household food security, disposable income for availing foods, among other important factors which are likely to impact nutritional health of population[73–75]. Also, studies have increasingly identified that consumption of highly processed foods has a strong linkage with the different forms of malnutrition[4,76–78] but, due to lack of data in the NFHS-4, we are unable to adjust for the intake pattern of highly processed foods and that might have contributed to the residual confounding. Fourthly, food systems involving food production, supply and food security at district level play important role in the nutritional health of the locals. However, this information is not captured in our data source and so not included in the study. Also, using Parliamentary constitutes as a unit of analysis that has gained recent research attention[79] would have allowed for the exploration of the spatial variability at much finer scale, but our data source does not avail the data at such scale. Finally, we could not assess nutritional trend at the district level, because earlier waves of NFHS did not include micro-level geographical information.

Conclusion

The geographical burden of underweight was, in both adult men and women, slightly more pronounced than that of overweight. Mostly, the districts with high likelihood of underweight had low likelihood of overweight and vice versa. However, there are some districts where the likelihood of both underweight as well as overweight remained significantly high. Given the fact that overweight and obesity are increasing gradually in India, and that a large proportion of Indian adults are still suffering from undernourishment, it is high time to identify, promote and implement the double-duty actions that will simultaneously and synergistically address several forms of malnutrition, including underweight, overweight and obesity.

Acknowledgements

Acknowledgements: The authors appreciate the DHS Program for granting access to the data analysed. Authors are thankful to an anonymous associate editor and two anonymous reviewers for their excellent comments and suggestions which have greatly improved the clarity of the study outcomes. *Financial support:* This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors. *Conflicts of interest:* There are no conflicts of interest. *Authorship:* P.B. conceived the idea, extracted the data, analysed the data and drafted the article. E.G. proposed the modelling technique, software and drafted the article. S.Y. participated in drafting the article and supervision. *Ethics of human subject participation:* not applicable

Supplementary material

For supplementary material accompanying this paper visit https://doi.org/10.1017/S1368980021001634

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