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Modeling the potential impacts of improved monthly income on child stunting in India: a subnational geospatial perspective

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ABSTRACT

Objectives Approximately one-third of the world's stunted (low height-for-age) preschool-aged children live in India. The success of interventions designed to tackle stunting appears to vary by location and depth of poverty. We developed small-area estimation models to assess the potential impact of increments in household income on stunting across the country.

Design Two nationally representative cross-sectional datasets were used: India's National Family Health Survey 4 (2015–2016) and the 68th round of the National Sample Survey on consumer expenditure. The two datasets were combined with statistical matching. Gaussian process regressions were used to perform geospatial modelling of 'stunting' controlling for household wealth and other covariates.

Setting and participants The number of children in this sample totalled 259 627. Children with implausible height-for-age z-scores (HAZs) >5 or <−5, or missing data on drinking water, sanitation facility, mother's education, or geolocation and children not residing in mainland India were excluded, resulting in 207 695 observations for analysis.

Results A monthly transfer of ~$7 (500 Indian rupees) per capita to every household (not targeted or conditional) was estimated to reduce stunting nationally by 3.8 percentage points on average (95% credible interval: 0.14%–10%), but with substantial variation by state. Estimated reduction in stunting varied by wealth of households, with the poorest quintile being likely to benefit the most.

Conclusion Improving household income, which can be supported through cash transfers, has the potential to significantly reduce stunting in parts of India where the burdens of both stunting and poverty are high. Modelling shows that for other regions, income transfers may raise incomes and contribute to improved nutrition, but there would be a need for complementary activities for alleviating stunting. While having value for the country as a whole, impact of income gained could be variable, and underlying drivers of stunting need to be tackled through supplementary interventions.

INTRODUCTION

Recent burden of disease studies in India have mapped the variability in underlying risk

Strengths and limitations of this study

► This is the first study to use statistical matching to merge two nationally representative surveys of India to arrive at estimates of stunting based on household income rather than the widely used metric of household wealth.

► It resolves estimates to a small-area level ($14 \times 14 \, km^2$), thereby supporting policy and implementation targeting local administrative units.

► A limitation of the study is the 4-year gap between the two datasets used.

► An additional limitation is that stunting estimates modelled on wealth index assumed a one-to-one correlation between the wealth index (based on household asset scores) and household income.

factor for child stunting, which is a leading contributor to disease in children under 5 years.[1 2] Stunting (low height-for-age relative to global standards established by the WHO)[3] affects most low-income and middle-income countries. India is one of the worst affected, having a mean stunting prevalence estimated at 34.7% in 2018,[4] varying from 12.4% to 65.1% in different locations.[5 6]

Economic growth is known to be weakly associated with reduction in stunting at the state level, and household-level wealth is one of the strongest contributors to changes in stunting prevalence in a country over time.[7 8] In India, the average district-wide difference in stunting between the richest and poorest wealth quintiles has been reported to be 26.8%.[8] Wealth is measured using a wealth index, which is a composite measure of a household's cumulative living standard.[9] Wealth assessed this way has implications for health, because it allows us to identify problems particularly affecting the poor, such as unequal access to food and access to healthcare services.[9]

Many single interventions aimed at reducing stunting and combinations of these interventions have been assessed globally. These include targeted nutrition interventions, social and behaviour change communication, and cash transfer schemes.[10] India has been at the forefront in attempting to reduce stunting through interventions such as the Integrated Child Development Services,[11] which has been implemented nationally with an annual budget of about US$0.4 billion. However, slow progress and variability in the quality and fidelity of implementation point to the need for alternate or complementary strategies, such as cash transfers. A recent meta-analysis of cash transfer programmes showed a significant effect on height-for-age z-scores (HAZs), a 2.5% reduction in stunting prevalence; however, this analysis did not include any study from India.[12] In Myanmar, maternal cash transfers coupled with behaviour change communication have been observed to reduce the prevalence of mild stunting ($-3 <$HAZs< -2) by 4% points over a 30-month intervention period.[13]

Given the strong association between wealth and stunting in India, one would expect that higher incomes would have significant impacts on nutrition across the nation. However, policies are implemented variably by local administration at the district level; therefore, it is important to estimate nutrition impacts at a geographical resolution that is relevant to local administrative structures. In this study, we modelled geographical variation at a small-area (more granular) level in terms of the potential impact of income improvement through regular cash transfers on stunting prevalence across India. The models use child height-for-age data from the Fourth Round of the National Family Health Survey (NFHS4)[14] and monthly household expenditure data from the National Sample Survey Office Round 68, Consumer Expenditure (NSS68).[15] We also modelled the expenditure on food groups with change in total expenditure to explore causal pathways of improvement in income with height-for-age mediated through improved nutrition.

METHODS
Overview
The NFHS4 provides detailed nationwide information on household wealth and anthropometry of children <5 years.[14] It used a multistage stratified cluster sampling (see details in online supplemental material A) with villages in rural and census enumeration block within wards as primary sampling units (PSUs). The PSUs were georeferenced by latitude and longitude coordinates. The coordinates were collected in the field using global positioning system (GPS) receivers, which are accurate to±15 m. To maintain respondent confidentiality, GPS positions were displaced randomly by up to 2 km for urban clusters and 5 km for rural clusters, with a few being displaced up to 10 km.[16] A total of 507 clusters without valid GPS readings were excluded, and the remaining 28 019 PSUs were used for this analysis.

The NSS68 provides information on household consumer expenditure. A stratified multistage sampling strategy was employed, with the sample size comprising 101 662 households. Variables of interest included monthly per-capita consumer expenditure (MPCE) of the household, and household characteristics like urban/rural, number of residents, religion, caste, cooking fuel type, ration card type, educational attainment, presence of children and monthly expenditure on foods.

Outcome measures
In the NFHS4 survey, urban and rural households with ever-married women aged 15–49 years were sampled, and women who resided the previous night in that household qualified to be respondents in the survey. The height of 259 627 children aged <5 years, was recorded using standing height for children >2 years and recumbent length for children aged <2 years. Stunting was defined as a child's HAZ ≥2 SD below the median of the WHO child growth reference standards.[3] Data on ~52 000 children with HAZ >5 or <−5 were considered as values <−5 and >+5 are either unlikely to exist due to nutritional deficiencies or are nutritionally implausible. Data with missing covariates (water, sanitation, mother's education and geolocation data) and residence not in mainland India were also excluded, resulting in data on 207 695 children for analysis. Within the sample of children included for the analysis, the stunting prevalence was 37.4%.

Household wealth
The NFHS4 dataset includes a household wealth index that was computed through a principal component analysis on the availability of consumer goods, housing characteristics, type of water and toilet used, electricity access, bank and land possession. However, household income was not recorded in the NFHS4 survey. To translate the wealth index to a corresponding income value and to model the potential impact of monthly per-capita income increments on stunting, the MPCE values from NSS68 were used as a proxy for household income. The household wealth index was matched to an MPCE value based on a set of selected matching variables. The 'nearest-neighbour hot deck' method from the R package StatMatch was used for statistical matching of every household from NFHS4 to a household in NSS68 (many to one).[17] Common variables in both datasets (were household size, religion, caste (in broad terms), cooking fuel, urban/rural, ration card, education and presence of children aged <5 years in the household) were the matching variables used to compute Euclidean distances between households from NFHS4 to households in NSS68, existing in the same district (distribution of distances is provided in online supplemental material B). The nearest household in NSS68 was subsequently assigned to the household in NFHS4. Statistically matching the two datasets allows us to obtain estimates for income and expenditure for NFHS4 datasets, which can subsequently be used to model small-area estimates of income levels throughout the country. The nearest

Table 1 Endogenous and exogenous variables and details of the Gaussian process regression model

S. no	Response variable	Link function	Endogenous	Exogenous	Loss term
1	Residence (urban/rural)	Probit	Long, Lat	–	Predictive log likelihood
2	Water	Probit	Long, lat, residence	–	Predictive log likelihood
3	Sanitation	Probit	Long, lat, residence	Water	Predictive log likelihood
4	Education	Proportional odds (logit)	Long, lat, residence	Water, sanitation	Predictive log likelihood
5	Wealth index	Gaussian	Long, lat, residence	Water, sanitation, education	Predictive log likelihood
6	Stunting	Probit	Long, lat, residence, wealth index	Water, sanitation, education, wealth index	Variational evidence lower bound
7	Log (MPCE)	Gaussian	Long, lat, residence	Water, sanitation, education	Predictive log likelihood

lat, latitude; long, longitude; MPCE, monthly per-capita consumer expenditure.

neighbour hot deck method has been previously used to combine these two datasets, and the predictability of the household level food intake by the matching variables was used to validate the matching technique using k-fold cross-validation technique.[18] The statistical matching did not result in any changes in sample size, outcome variables or covariates.

Geospatial modelling

The spatial modelling of stunting was performed through Gaussian process regressions (GPRs)[19] combined with additional linear effects for exogenous variables (listed in table 1). This was done because stunting is multifactorial and the variables were identified based on prior literature and by examining the effect of these variables in the current datasets. GPR is a machine learning technique that provides flexibility to handle arbitrary probability distributions whose parameters vary spatially and is commonly used in geospatial modelling of health indices.[20 21] The models were used to predict distributions of the covariates and the outcome variable on a $14 \times 14 \, km^2$ grid of India, which were the used to create the maps (details of mapping are provided in online supplemental material C).

The exogenous covariates used in the model were (1) type of sanitation available to the household; (2) source of drinking water (through water, sanitation and hygiene (WASH) approaches), as in the UNICEF strategy[22]; (3) mother's education; and (4) the wealth index (details of classification are provided in online supplemental material D). These variables were chosen after assessing the impact of the variable inclusion on the linear coefficient of wealth.

Models included covariates listed (table 1) as well as the binary outcome variable, stunting (online supplemental material E). The endogenous variables (latitude, longitude, wealth index and urban/rural) were used as endogenous covariates in the GPR with the outcome variable distributed as a Gaussian process in the input space of the endogenous variables. We used sparse variational GPR by gpytorch,[23] a GPR implementation that used graphics processing units to accelerate computation speeds. Inducing points for the sparse method were randomly picked from each district, totalling to 4998 inducing points. Each inducing point had a mean and variance value, and the predicted distribution was created by marginalising over the values of these inducing points.

The parameters of the model were the linear coefficients for the exogenous variables, means and variance for each inducing point, the output scale and the length scale of the covariance kernel function, the mean of the Gaussian process and the additional diagonal noise for the Gaussian link functioned models. Final small-area estimates of stunting prevalence were obtained by marginalising model predictions over the small-area predictive distributions of each covariate. We also subdivided each model into eight local expert models, the predictions of which were combined using a Bayesian committee machine.[24] The method for choosing inducing points and working of the Bayesian committee machine are available in online supplemental material F. The loss term used was either the predictive log likelihood[25] or the variational evidence lower bound (ELBO)[19] weighted with survey weights. Details of the eight local expert regions are given in online supplemental material G. The predicted wealth-index distributions were used to obtain location-specific wealth quintiles (LSWQs). Stunting estimates and maps were generated for each LSWQ separately. Ninety-five per cent uncertainty intervals were also calculated. The ELBO and predictive log likelihood obtained were verified using fivefold cross validation, with nearly equal results for the training and test datasets. We also compared district-level stunting prevalence estimates from the NFHS4 report with our stunting estimates (aggregated to each district using simple means of estimates of each grid point in the district). The correlation between the two was found to be 0.87.

Change in stunting prevalence due to simulated increments of income (proxying for cash transfers) was estimated by assuming a perfect correlation between wealth index and income. Higher incomes were used to transform corresponding wealth-index predicted distributions. New stunting prevalence was predicted by marginalising model predictions on the transformed wealth index predicted distribution. The change in prevalence of stunting was the difference between the new prevalence and the original predicted prevalence. Estimated changes in stunting prevalence with corresponding credible intervals (CI) are reported. The details of the simulation of change in MPCE are provided in online supplemental material H, and the details on the computation of CI are provided in online supplemental material I.

Food group analysis

We used food consumption data from the NSS68 to model the percentage allocation of incremental income to consumption of items within food groups. We performed segmented linear regressions of the following food groups: cereals, pulses, and non-vegetarian and milk-based foods segmented by state. The response variable was the expense on a food group, with the explanatory variable being the total expense on food. Segmented linear regression allowed multiple linear regressions to be fitted to the range of total food expense, where points of change in regression estimate were the boundaries between total expense quintiles, determined for each state.

The geospatial modelling was performed using Python V.3.9[26] and PyTorch V.1.6.[27] All other analyses and data processing steps were performed on R V.3.6.[28] The R libraries used were "sp", "rgeos", "rgdal", "data.table", "magrittr" and "ggplot2".

Patient and public involvement

Neither patients nor the public were involved in the design, conduct, reporting or dissemination of this study.

RESULTS

The Gangetic plain suffers from the highest stunting rates in India (figure 1), with North Central Uttar Pradesh appearing to be the most affected with almost 58% stunting (95% uncertainty interval, CI of 52.5%–62.7%). High stunting rates (>45%) were observed in large areas of Uttar Pradesh, Bihar, Odisha, Gujarat-Madhya Pradesh Border and Meghalaya, interspersed by small areas of low prevalence. Spatial heterogeneity in prevalence was observed in the other areas. Figure 2A–E illustrates the stunting prevalence in each of the LSWQ. Stunting rates decreased from the poorer to the wealthier quintiles, but the reduction in prevalence with wealth is not uniform across the country. The stunting prevalence is high even within the upper wealth quintiles in areas with a high burden of stunting (figure 2A). In the poorest quintile (figure 2E), large parts of the Gangetic plain, as well
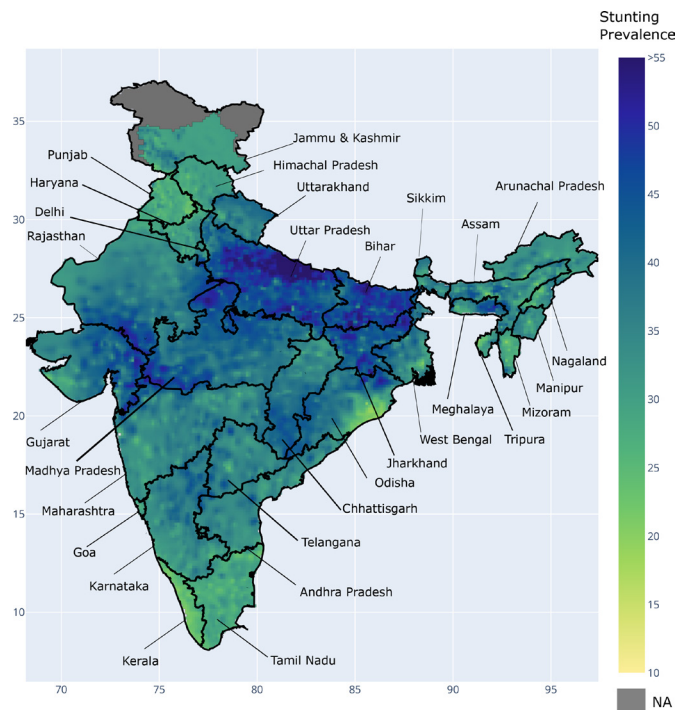

Figure 1 Stunting prevalence in India. Percentage of stunted children in India (2015–2016) resolved to 14×14 km² resolution estimated using geospatial modelling using the Fourth Round of the National Family Health Survey data. The states of India are named. NA = not applicable.

as pockets in western and Northeastern India, exhibit stunting prevalence exceeding 55%, which represents a very serious public health concern.

Figure 3A–E illustrates estimated change in stunting rates associated with change in MPCE (proxy for per-capita income) of Indian rupee (INR) 500. These changes are illustrated across the five wealth quintiles. Online supplemental figure 1 illustrates the same for INR 1000. The average stunting reduction for India with INR 500 was 3.8% (95% uncertainty interval 0.14%–10.0%). The areas with the potential for most benefit in reduction in stunting associated with increased income were Northeastern Odisha, with a reduction in stunting prevalence of almost 11% (CI of 8.8%–12.7%) and Southwest Bihar with reduction of 10% (CI 2.8%–17.7%). Reductions in Northeast India ranged from 0 to 9 percentage points.

It is important to note that there was variation in the stunting reduction that could be attained by each wealth quintile. The poorest quintile showed the greatest potential for stunting reduction. For example, in Northeast Odisha, the estimated reduction in stunting prevalence among poorest quintile households was 14.5% (CI 11.5%–17.3%) but 6.3% (CI 3.8%–8.2%) for the richest quintile. Similarly, in Southwest Bihar, the poorest quintile would see an estimated stunting reduction of 11.3% (CI 3.9%–19.1%), compared with 3.6% (CI 4.7%–11.75%) for the highest wealth quintile in this area. Parts of central Uttar Pradesh and southwest Madhya Pradesh were also areas that could substantially benefit with an increase in income (figure 3A). In Madhya Pradesh, the West central area
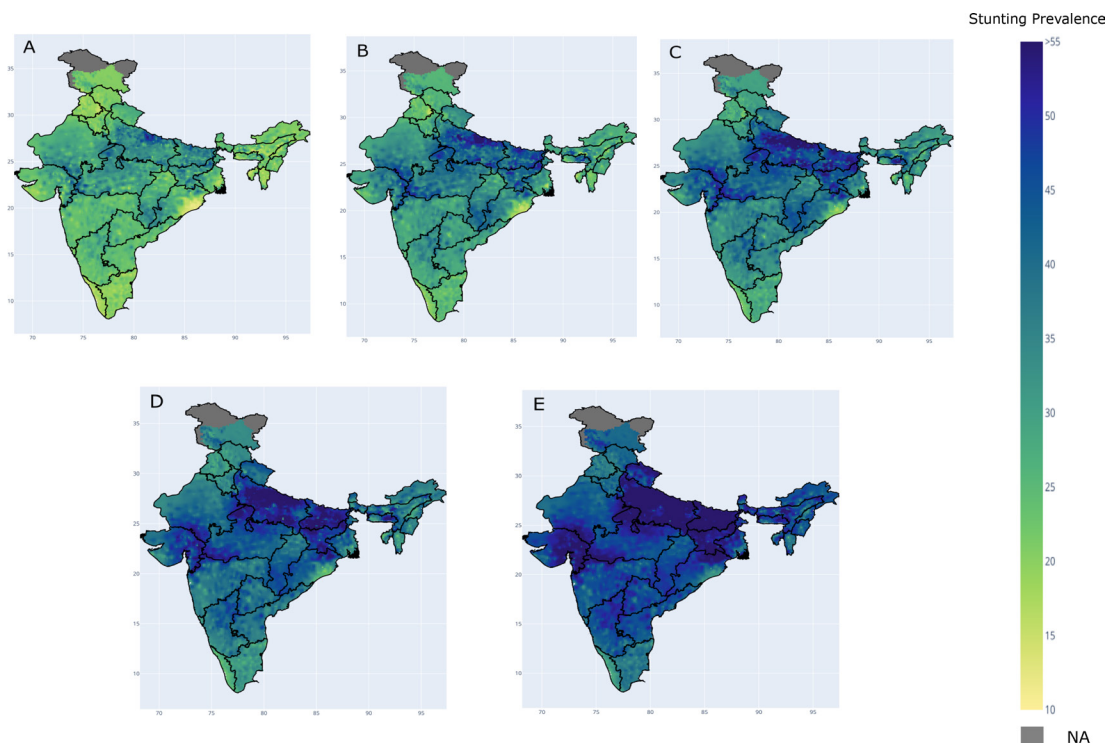
Figure 2 Stunting prevalence ordered through LSWQ. Percentage of children stunted children in India (2015–2016) resolved to 14×14 km² resolution estimated using geospatial modelling using NFHS4 data. For each LSWQ ordered through (A) richest, (B) rich, (C) middle, (D) poor and (E) poorest. LSWQ, location-specific wealth quintile; NA, not applicable; NFHS4, Fourth Round of the National Family Health Survey.

showed a lower response to income increase compared with the rest of the state.

Similar patterns could be observed with INR 1000 increments in MPCE (online supplemental figure 1), showing benefits for all wealth quintiles. However, the scale of improvement across areas differed widely. For example, there was a 26 percentage-point reduction in stunting for the poorest quintile in some areas (online supplemental figure 1A), the greatest effect being seen in Assam. The variability across neighbouring states is also noteworthy, with Rajasthan showing little heterogeneity compared with Punjab, which had a high heterogeneity (online supplemental figure 1). Estimated state-level changes (along with 95% CI) in stunting prevalence (increase set at INR 500 and INR 1000 separately) are shown in online supplemental table 1 and district-wise change in online supplemental table 2.

Stunting reduction is due in part to use of increased income to purchase more and better quality food, thereby improving diets. We therefore examined the consumer expenditure data to identify foods that were likely to be purchased more with increased income, by wealth quintile (figure 4A–J). We focused particularly on cereals (the main source of energy), pulses, milk, fruits and vegetables, and non-milk animal sourced foods. The least increase in absolute food expenditure was observed in the highest quintile. Patterns were different by food item, reflecting unobserved cross-price elasticities of demand. For example, spending on pulses increased considerably

compared with other foods, as did the purchase of cereals by households in the lowest quintile. Expenditure on pulses was projected to increase most significantly in central and southern India, and particularly in the second to fourth quintiles of wealth. Spending on milk was projected to increase in northern and western parts of India. Increased expenditure on non-vegetarian (animal sourced) food was observed mainly in the states of Kerala and Northeastern India (figure 4A–J).

DISCUSSION

This study examined the spatial distribution of child stunting in India and provides a quantification at high resolution (14×14 km grid). In light of existing literature on the association between stunting and household wealth in India, this study also examined the heterogeneity of linkages in the context of a hypothetical income increase.

The analysis showed that some states with currently high levels of stunting and poverty could achieve substantial reductions in stunting via increased incomes, mediated at least in part through enhanced food purchases. However, other states would see limited effects. The differential effect of the increment of INR 500 in per-capita income shows that even within states there is a variation in the potential associations between income and stunting rates, and that these associations also vary by the current household wealth status. The foods most likely to be purchased
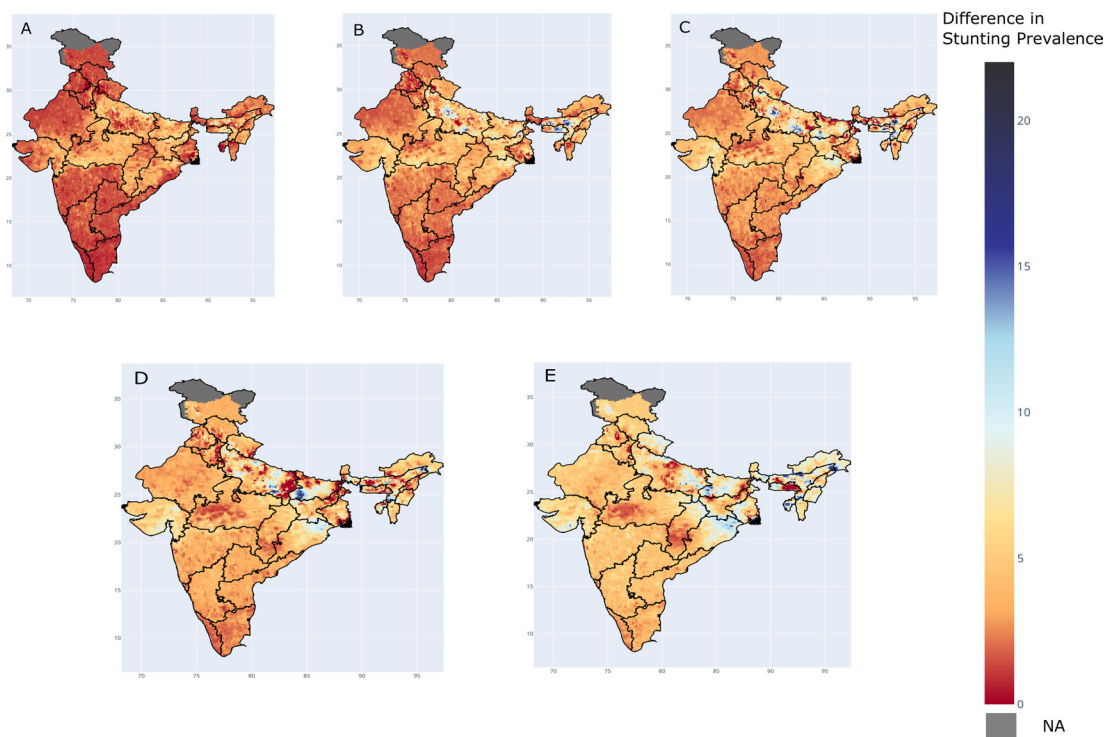
Figure 3 Change in stunting prevalence due to 500 INR (~$7) monthly income increment, ordered through LSWQ. Potential Improvement in stunting rates (expressed as percentage points) in India after an increment of 500 INR (~$7) MPCE, resolved to a 14×14 km^2 resolution, ordered through LSWQ: (A) richest, (B) rich, (C) middle, (D) poor and (E) poorest. These estimates were derived using geospatial modelling from the NFHS4 (2015–2016) data. INR, Indian rupee; LSWQ, location-specific wealth quintile; MPCE, monthly per-capita consumer expenditure; NA, not applicable; NFHS4, Fourth Round of the National Family Health Survey.

with increased income would be energy-rich staples and/or nutrient-rich foods like pulses and milk (a major animal source food in India).

The state prevalence of stunting varied across India from 13% to 64% in the NFHS4 survey.[14] However, stunting has been identified to be geographically correlated in India; spatial autocorrelation (Moran's I) for stunting measured at 0.65 using the NFHS4 data indicating significant spatial clustering of stunting at a district level.[29]

The household wealth index is considered to be one of the strongest predictors of stunting,[9] and the average wealth disparity for stunting has been found to be the highest (26%) among all malnutrition indicators, and this disparity existed across all states.[20] At the household level, children from 'wealthy households with good health outcomes' have been identified to be a distinct group, while 'poor, young and poorest health outcome' is another distinct group of children.[30] In sub-Saharan
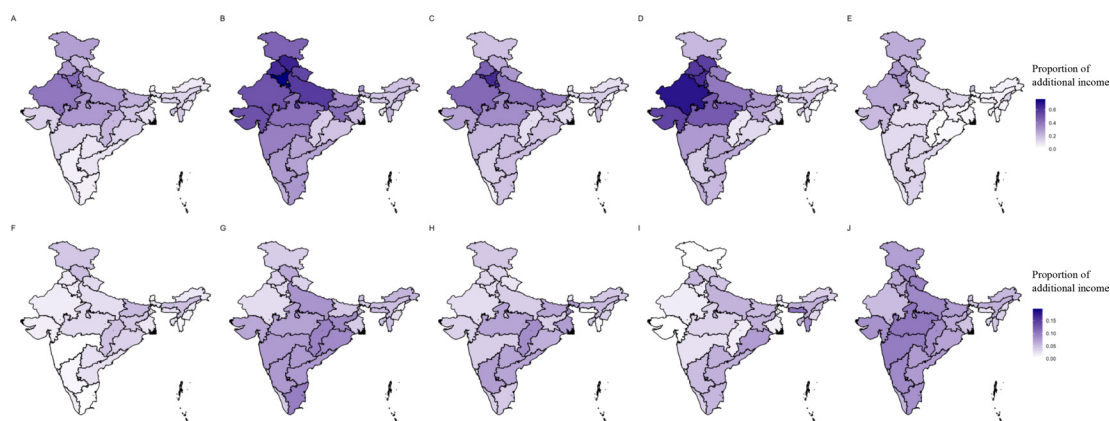
Figure 4 Proportion of additional income spent on milk/milk products for quintiles richest to poorest (A–E) and pulses (F–J). Proportion of any marginal income an individual in India will spend on food belonging to food groups (A–E) milk and milk-based products and (F–J) pulses, statewise, across statewise wealth quintiles: (A,F) richest (B,G) rich (C,H) middle (D,I) poor and (E,J) poorest.

Africa, stunting reduction has been associated with an increase in per-capita GDP at national level, such that for every US$1000 increment in GDP, the odds of stunting reduced by 23%.[31] Thus, one would expect that a significant reduction in stunting could be achieved by improving wealth, although the improvement would vary, depending on pre-existing burdens of poverty and stunting. Our study observed spatial clustering as well as variability of association between wealth index and stunting, and this variability was present even within wealth quintiles underscoring the relative nature of wealth in each area. The income and characteristics of the poorest (classifying wealth at the $14 \times 14 \text{ km}^2$ level) are very different across the country.

Conditional cash transfers have been identified as an effective means for increasing purchasing power to improve health outcomes. This intervention has had positive impacts on diet quality and nutrition in a variety of contexts. For example, in Brazil, 82.4% of the beneficiaries of a conditional cash transfer scheme reported eating better and had stunting prevalence lowered by 29% compared with non-beneficiary families.[32] In Colombia, it was observed that 12-month old boys grew 0.44 centimetres more in households that participated in a conditional cash transfer programme.[32] However, a meta-analysis of cash transfer programmes showed a small but non-significant effect on height-for-age.[33] The reason could be that these cash transfers were short term unlike the income improvement model used for this study. A more recent meta-analysis showed significant improvement in HAZ and reduction in stunting mediated through increased purchase of animal source foods, which is in line with the increased consumption of milk observed in the current study as incomes rise.[12] The average estimated difference in stunting rate over INR 500 (3.8%) is comparable to the reduction estimated due to increase in asset index (3%) in low-income and middle-income countries. This is greater in magnitude than improvements due to any other factors such as WASH, health services and maternal characteristics.[31] There is also a non-linear dose response as additional change in income of INR 500 is associated with change in stunting rate by only another 2.8%.

In a note of caution, the potential for intermittent or occasional cash transfer programmes on improving stunting in India is significant but not automatic. Large windfall incomes are typically not spent in the same way as smaller, more regular increments of income. If cash transfers are introduced, they should be sustained for at least a year to translate to a monthly income increment of INR 500, thereby household income increase of INR 2000 in a four-person household and a massive additional INR 6000 per annum per capita for a two million population per district. The modelling points out the utility of precision public health by targeting such interventions in areas that are most likely to benefit and particularly the lower wealth quintiles. The Government of India's Poshan Abhiyan scheme targets a reduction in stunting

by 2% per annum.[34] An income increment of INR 250 ($3.5) per capita per month can induce this improvement in stunting while assuming status quo for all other programmes.

In separate models, purchases of milk and pulses increased across India with an INR 500 increase in income. Earlier studies from India have shown that the consumption of pulses is responsive to change in income of households.[35] Income doubling has been shown to increase the consumption of non-staple foods, including non-vegetarian foods by about 110%.[36] Here, more cash in hand was projected to increase food purchases at various levels, which varied across states. In Haryana, which showed the largest increased expenditure on milk, an additional INR 225 is likely to be spent on milk monthly; this translates to approximately an additional 7 litres/month per household. The additional expenditure on pulses was also variable across the country and across wealth quintiles, with expenditure likely to increase up to INR 300 in some states, translating to an additional 4 kg/month (figure 4A–J). Household expenditure on food, particularly fats, is associated with future height in India.[37]

There are a number of limitations to this analysis. There is a 4-year gap between the NFHS4 and NSS68. The requirement for modelling of a one-to-one correlation between wealth index and expenditure on food is not justifiable in the real world. However, earlier studies have shown a strong association between the two when classified by their percentiles.[38] As such, these findings are estimates of impact intended to be indicative only. Additionally, this correlation could vary geographically, thus introducing additional variability in the estimates of stunting reduction. How well a household wealth index serves as a proxy for income is not well understood,[35] and there are concerns that, given alternative demands for cash expenditure such as housing and education, cash transfers may not be spent on nutrient-rich foods or on supporting more healthy diets.

A strength of this analysis is that we used statistical matching to directly explore the association between income increments and stunting. To our knowledge, this is the first such attempt for India. An advantage of GPR method of modelling is the separation of rural and urban households, and this is critical as the behaviour and infrastructure difference in these populations is different.

In conclusion, optimal strategies to reduce stunting are ones that are carefully tailored to needs across a country. Small-area estimation techniques can be used to identify locations that could benefit most from any proposed intervention. This becomes increasingly pertinent as India's heterogenous population continues to grow and resources for public programmes become increasingly constrained. The areas with potential for positive change associated with income increase are predictably those areas where income disparities are already high. These are areas with greater potential for impacts on nutrition conditional on the income transfers being used to improve the diets of children. The reverse applies to areas with

lower income disparities. It is also important to consider that, while this study explored the impacts of a monthly income increase on the prevalence of stunting, there would likely be gains to participating households that go beyond nutrition to increase health-seeking behaviour, improved housing, education and more. In other words, well-targeted income transfers have an important potential to achieve multiple country-level and state-defined goals simultaneously.

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REFERENCES

1. India State-Level Disease Burden Initiative Collaborators. Nations within a nation: variations in epidemiological transition across the states of India, 1990-2016 in the global burden of disease study. *Lancet* 2017;390:2437–60.
2. India State-Level Disease Burden Initiative CGF Collaborators. Mapping of variations in child stunting, wasting and underweight within the states of India: the global burden of disease study 2000-2017. *EClinicalMedicine* 2020;22:100317.
3. World Health Organization. The who child growth standards. Available: http://www.who.int/childgrowth/standards/en/ [Accessed 01 Dec 2020].
4. Ministry of Health and Family Welfare (MoHFW), Government of India, UNICEF and Population Council. Comprehensive national nutrition survey (CNNS) national report. New Delhi, 2019. Available: https://www.unicef.org/india/media/2646/file/CNNS-report.pdf [Accessed 01 Dec 2020].
5. Menon P, Headey D, Avula R, *et al*. Understanding the geographical burden of stunting in India: a regression-decomposition analysis of district-level data from 2015-16. *Matern Child Nutr* 2018;14:e12620.
6. Subramanyam MA, Kawachi I, Berkman LF, *et al*. Is economic growth associated with reduction in child undernutrition in India? *PLoS Med* 2011;8:e1000424.
7. Nie P, Rammohan A, Gwozdz W, *et al*. Changes in child nutrition in India: a decomposition approach. *Int J Environ Res Public Health* 2019;16:1815.
8. Liou L, Kim R, Subramanian SV. Identifying geospatial patterns in wealth disparity in child malnutrition across 640 districts in India. *SSM Popul Health* 2020;10:100524.
9. Karlsson O, Kim R, Joe W, *et al*. The relationship of household assets and amenities with child health outcomes: an exploratory cross-sectional study in India 2015-2016. *SSM Popul Health* 2020;10:100513.
10. Hossain M, Choudhury N, Adib Binte Abdullah K, *et al*. Evidence-Based approaches to childhood stunting in low and middle income countries: a systematic review. *Arch Dis Child* 2017;102:903–9.
11. Ministry of Women and Child Development Government of India. Annual report 2019–20, 2020. New Delhi. Available: https://wcd.nic.in/sites/default/files/WCD_AR_English_2019-20.pdf [Accessed 01 Dec 2020].
12. Manley J, Balarajan Y, Malm S, *et al*. Cash transfers and child nutritional outcomes: a systematic review and meta-analysis. *BMJ Glob Health* 2020;5:e003621.
13. Field E, Maffioli EM. Are behavioral change interventions needed to make cash transfer programs work for children? experimental evidence from Myanmar, 2020. Available: https://ssrn.com/abstract=358478 [Accessed 01 Dec 2020].
14. International Institute for Population Sciences - IIPS/India and ICF. *India national family health survey NFHS-4 2015-16*. Mumbai, India: IIPS and ICF, 2017. http://dhsprogram.com/pubs/pdf/FR339/FR339.pdf
15. National Sample Survey Office. Level and pattern of consumption expenditure, 2011–12. NSS 68th round. NSS report no: 555. New Delhi (India). Available: http://microdata.gov.in/nada43/index.php/catalog/1/related_materials [Accessed 22 Dec 2021].
16. Spatial Anonymization. Guidance Note prepared for the Inter-Secretariat Working Group on Household Surveys. January 2021. *Statistical Commission Fifty-second session*. Item 3(l) of the provisional agenda. Available: https://unstats.un.org/unsd/statcom/52nd-session/documents/BG-3l-Spatial_Anonymization-E.pdf [Accessed 19 Feb 2022].
17. D'Orazio M. StatMatch: statistical matching or data fusion. R package version 1.2.5, 2016. Available: http://CRAN. R-project.org/package=StatMatch
18. Swaminathan S, Ghosh S, Varghese JS, *et al*. Dietary iron intake and anemia are weakly associated, limiting effective iron fortification strategies in India. *J Nutr* 2019;149:831–9.

19 Rasmussen CE, Williams CK I. *Gaussian processes for machine learning*. the MIT Press, 2006. www.GaussianProcess.org/gpml

20 India State-Level Disease Burden Initiative Malnutrition Collaborators. The burden of child and maternal malnutrition and trends in its indicators in the states of India: the global burden of disease study 1990-2017. *Lancet Child Adolesc Health* 2019;3:855–70.

21 Osgood-Zimmerman A, Millear AI, Stubbs RW, *et al*. Mapping child growth failure in Africa between 2000 and 2015. *Nature* 2018;555:41–7.

22 UNICEF. *Strategy for water, sanitation and hygiene 2016–2030*. New York, 2016.

23 Gardner J, Pleiss G, Bindel D. GPyTorch: Blackbox Matrix-Matrix Gaussian process inference with GpU acceleration. *Adv Neural Inf Process Syst* 2018;31:7576–86.

24 Tresp V. The generalized Bayesian Committee machine. *Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2000:130–9.

25 Jankowiak M, Pleiss G, Gardner JR. Parametric Gaussian process Regressors. *Proceedings of the 37th International Conference on Machine Learning* 2020;119:4702–12.

26 Python Software Foundation. Python language reference, version 3.9. Available: http://www.python.org

27 Paszke A, Gross S, Massa F. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In: *Advances in Neural Information Processing Systems 32 [Internet*. Curran Associates, Inc, 2019: 8024–35. http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf

28 R Core Team. *R: a language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing, 2019. https://www.R-project.org/

29 Khan J, Mohanty SK. Spatial heterogeneity and correlates of child malnutrition in districts of India. *BMC Public Health* 2018;18:1027.

30 Green MA, Corsi DJ, Mejía-Guevara I, *et al*. Distinct clusters of stunted children in India: an observational study. *Matern Child Nutr* 2018;14:e12592.

31 Yaya S, Uthman OA, Kunnuji M, *et al*. Does economic growth reduce childhood stunting? A multicountry analysis of 89 demographic and health surveys in sub-Saharan Africa. *BMJ Glob Health* 2020;5:e002042.

32 United Nations Development programme, India. Conditional cash transfer schemes for alleviating human poverty: relevance for India, 2009. Available: http://www.in.undp.org/content/dam/india/docs/cct_dp.pdf [Accessed 01 Dec 2020].

33 Manley J, Gitter S, Slavchevska V. How effective are cash transfers at improving nutritional status? *World Dev* 2013;48:133–55.

34 Ministry of Women and Child Development. Implementation of POSHAN Abhiyan scheme. press information bureau government of India. Available: https://pib.gov.in/Pressreleaseshare.aspx?PRID=1596112 [Accessed 01 Dec 2020].

35 Umanath M, Chengappa PG, Vijayasarathy K. Consumption pattern and nutritional intake of pulses by segregated income groups in India. *Agricultural Economics Research Review* 2016;29:53.

36 Poirier MJP, Grépin KA, Grignon M. Approaches and alternatives to the wealth index to measure socioeconomic status using survey data: a critical interpretive synthesis. *Soc Indic Res* 2020;148:1–46.

37 Weingarten SE, Dearden KA, Crookston BT, *et al*. Are Household Expenditures on Food Groups Associated with Children's Future Heights in Ethiopia, India, Peru, and Vietnam? *Int J Environ Res Public Health* 2020;17:4739.

38 Grimm M, Harttgen K, Klasen S, *et al*. Inequality in human development: an empirical assessment of 32 countries. *Soc Indic Res* 2010;97:191–211.