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ORIGINAL PAPER

Rainfall shocks, soil health, and child health outcomes

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Abstract
This paper estimates the moderating effect of soil organic carbon content (a measure of soil health) on child health in response to rainfall shocks in a low-income country setting. Focusing on rural India, I leverage the Demographic and Health Survey data set and high-resolution spatial data on soil organic carbon content and meteorological variables. The results show that a high level of soil organic carbon significantly reduces the negative impact of rainfall shock on children's weight-for-height z-scores, but not on height-for-age z-scores.

Keyword Rainfall shock · Soil organic carbon · Child health · Matching

Introduction

India consistently ranks low on the global hunger index, according to four indicators: malnutrition prevalence, child wasting (a measure of short-term inadequate nutrition), child stunting (a measure of long-term inadequate nutrition), and under-five mortality (Wiesmann, 2006). Many of India's villages in 2016 showed alarming levels of anthropometric measurements in children (Kim et al., 2021). According to the 2015–2016 India Demographic and Health Survey, 38% of children under the age of 5 are stunted (too short for their age) and 21% of children under the age of 5 are wasted (too thin for their height). Indian agricultural production is vulnerable to climate change and, without effective adaptation, can reduce food crop yields in the future by up to 9% (Guiteras, 2009). Moreover, in India's recent past, shortages of staple food crops, wheat and rice are associated with severe droughts and extreme rainfall (Zaveri & Lobell, 2019; Auffhammer et al., 2012). Child nutrition and agricultural production in rural areas in the developing world are closely linked (Webb & Block, 2012). Bakhtsiyarava and Grace (2021) in Ethiopia demonstrated that

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more diversity in agricultural production during periods of low rainfall can reduce the risk of chronic food insecurity among children.

Food shortages caused by crop failures due to extreme weather conditions, and the resulting nutritional deprivation can negatively impact children's health (Grace et al., 2012). Improved soil quality as measured by soil organic carbon (SOC), commonly used in the literature, increases agricultural production (Lal, 2006). Because of the water holding capacity, a high level of SOC offers long-term drought resistance and reduces the frequency of crop failures (Huang et al., 2021; Kane et al., 2021). SOC also provides agricultural profits for small landowners in developing countries (Bhargava et al., 2018). My research asks if SOC affects children's nutrition and health in a low-income country. Then, I explore to what extent SOC offers resilience during periods of low rainfall.

This article examines whether natural variation in soil organic carbon levels mitigates the impact of non-linear weather variables by crop growth on children's health. Focusing on rural India, I leverage the 2015 Demographic and Health Survey dataset and high-resolution spatial data on soil organic carbon content and meteorological variables. Following Bakhtsiyarava and Grace (2021), I evaluate the variation in anthropometric measurements, height-for-age (HAZ), and weight-for-height z-scores (WHZ) to measure child malnutrition in India. Inadequate nutrition can cause childhood stunting (if HAZ is below 2 standard deviation) and wasting (if WHZ is below 2 standard deviation). Unlike stunting, wasting may be reversed by increasing nutritional intake (Victora, 1992). In this study, I focus on HAZ and WHZ scores to measure malnutrition linked to weather-induced food insecurity.

While the exact relationship between soil quality and crop production under dry conditions is complex and multidimensional. Huang et al. (2021) and Kane et al. (2021) in the USA show that a higher soil organic carbon content can moderate the impact of weather shocks by retaining soil water in the agricultural systems. Children's nutrition also depends on food quality, which is partly dependent on soil micro-nutrients (Berkhout et al., 2019; Kim & Bevis, 2019). Berkhout et al. (2019), based on their study in Sub-Saharan Africa, highlight the importance of soil micro-nutrients such as zinc, copper, and manganese in reducing the malnutrition in children.

This article is informed and contributes to two main strands of the literature: the first is the relationship between soil agronomy and climate; the second is the relationship between children's health and SOC. While there are studies that examine the impact of climate on children's health in India (e.g., Dimitrova and Muttarak (2020) and McMahon and Gray (2021)), these studies have overlooked the importance of soil health. In this article, I contribute to the literature by demonstrating the direct and indirect effects of SOC. By enhancing the SOC, households would have access to greater food availability that could support children's nutrition and health. This is a direct result of SOC. The SOC may also help mitigate the impact of adverse weather conditions on food quantity. This is an indirect effect of SOC.

The results show that a high level of soil organic carbon significantly reduces the negative impact of rainfall shock on children's weight-for-height z-scores, but not on height-for-age z-scores. I also explore heterogeneity in children's health outcomes by gender, household wealth index and land ownership, and climate zone. This suggests that efforts to improve soil quality should be adjusted to address these heterogeneous impacts. The results of the paper provide new evidence and inform policy-makers on the impact of high organic carbon in soils on children's health.

Conceptual framework

Figure 1 depicts a simple conceptual connection between soil health and childhood nutrition. The figure can be used to examine the impact of a rainfall shock with different levels of SOC. Because periods of low precipitation reduce crop yields, food shortages affect food intake and thus nutrition (Grace et al., 2012). Higher SOC levels increase in agricultural production, particularly during a drought (Lal, 2006), which contributes to food availability and supports nutrition through consumption of output and income from crop sales that can be used to purchase food. Because of the water holding capacity, a high level of SOC offers long-term drought resistance and reduces the frequency of crop failures (Huang et al., 2021; Kane et al., 2021). This reduction in crop failure increases agricultural income overall (Bhargava et al., 2018) and can thus contribute to food security and nutrition for children by providing an extra cushion against shocks.

Furthermore, the level of education of the mother, the gender of the child, and the wealth of the household can also influence the nutrition of the children (Almond & Currie, 2011). Moreover, SOC mitigation effects may vary depending on climate regions and the ability of households to cope with rain shocks. Later in the "Results" section, I estimate the heterogeneity in children's health outcomes by region, climate zone, gender, household wealth, and land ownership. Also, there may be unobserved covariates which may be correlated with children's nutrition and soil organic carbon levels and therefore may bias my results downwards.

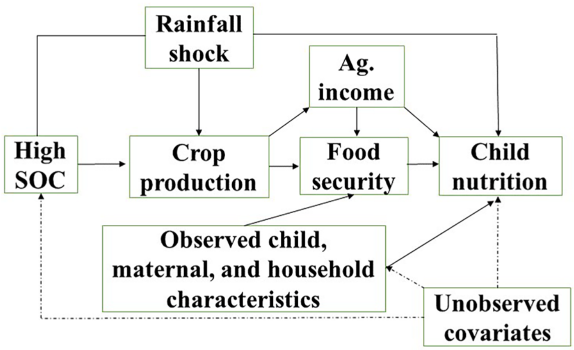


Fig. 1 A simple conceptual relationship between soil and children's health

Data and descriptive statistics

To demonstrate how soil organic carbon levels moderate the effect of monsoon activity on the health of Indian children, I leverage the Demographic and Health Survey dataset and high-resolution spatial data on soil organic carbon levels and weather variables.

Demographic and health data

I use the cross-sectional data from the fourth round of the Demographic and Health Survey (DHS) for India collected in 2015–2016. DHS uses a multi-stage stratified sampling design, with enumeration areas, hereinafter referred to as clusters (equivalent to census villages), being the smallest unit. In the clusters, households are randomly selected to be interviewed. DHS also collects the GPS locations of each cluster, enabling researchers to link DHS dataset to other geo-coded data, including soil organic carbon levels, precipitation, and temperature, at the cluster level. In order to preserve the anonymity of the villages, DHS randomly displaces the GPS coordinates of clusters up to 2 km in urban areas and up to 5 km in rural areas, and 1% of rural clusters are further displaced up to 10 Km. This displacement introduces measurement errors and may bias my results downwards.

A total of 131 of the 28,526 geo-referenced clusters did not have information and were dropped. I extracted environmental data using the DHS geo-referenced cluster for a 10-km buffer.[1]

DHS has a nationwide representative sample of children. In my analysis, the sample size for children aged 0 to 4 years was 259,627; 34,625 observations were excluded from the child data file that contained missing or invalid data. Invalid cases include children over plausible limits, age over plausible limits, and flagged cases. Additionally, observations with invalid woman's body mass index (BMI) information (636 observations), missing data (6447 observation) on caste, and not useful information (929 observations had "don't know" on caste) were excluded. Furthermore, I restrict the sample to focus exclusively on rural parts of the country as defined in the DHS dataset. To sum up, I analyzed a sample of 169,904 rural Indian children.

Rainfall data

I draw monthly rainfall data from Climate Hazards Group Infrared Precipitation (CHIRPS) using DHS cluster geocordinates. CHIRPS is a quasi-global that extends over 50 S-50 N, with a gridded resolution of 0.05 degrees, from 1981 to near-real time precipitation time series (Funk et al., 2014).

[1] As a sensitivity test, I run every analysis for a 20-km buffer. Appendix Table 14 reports the main results.

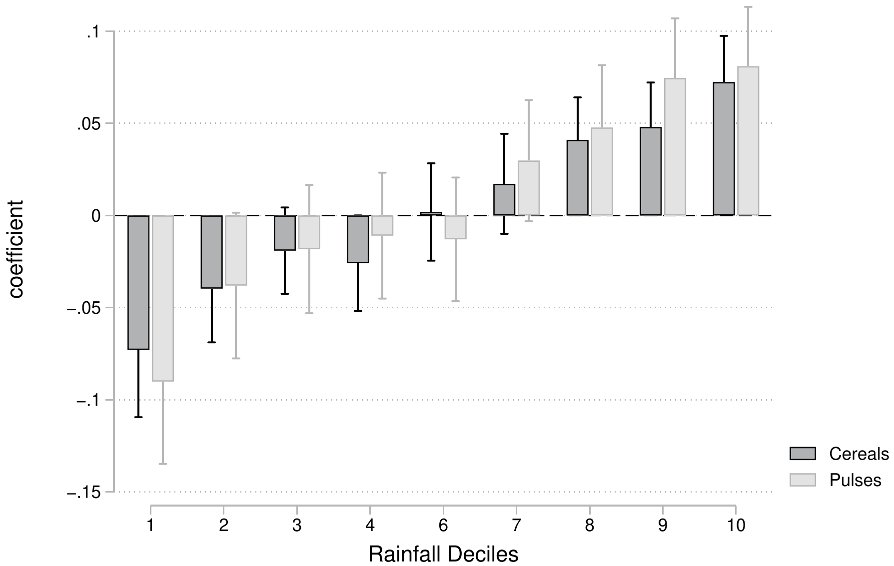


Fig. 2 Coefficient for rainfall deciles and 95% CI in India. The dependent variable is the natural logarithm of annual crop yield (kg per hectare) from 2001 to 2015. The specification includes district and year fixed effects. The 5th decile is selected as reference

There is not much guidance available in the literature about defining rain shock. For my purpose, I need to define a rainfall shock based on a threshold that lowers yields on India's major crops. Therefore, like Feeny et al. (2021), I adopt an empirical strategy to determine the threshold. Using data from the International Crops Research Institute for the Semi-Arid Tropic (ICRISAT), I regress the natural log of the annual crop yield (kg per hectare) from 2001 to 2015 on rainfall deciles controlling for year and district fixed effects.[2] The unit of analysis for the yield data is the district-year. As shown in Fig. 2, results indicate that rainfall below the 20th percentile reduces crop yield of grains and pulses in India.[3]

Additionally, I also check the moderating effects of high SOC on crop yields. I interact with rainfall deciles and high SOC levels. The absolute impact of a high level of SOC is not statistically significant. But, the terms of interaction between precipitation deciles and high SOC are statistically significant for rainfall deciles 1 and 7. The results suggest that SOC moderated the impact of fluctuations in precipitation on yields in my analysis. Appendix Table 5 reports the results.

I define rain shock as a monsoon rain that is below the 20th percentile of the long-term historical mean within the DHS cluster (Shah & Steinberg, 2017).[4]

[2] Crop yield data (unapportioned) are available at http://data.icrisat.org/dld/index.html.

[3] In the Appendix, Fig. 6, I also show the negative effects of lower precipitation on selected staple and cash crops. Corn, soybeans, and cotton appear to differ and not increase monotonously with precipitation, suggesting a non-linear response to weather conditions in some field crops.

[4] India receives the majority of its rainfall during the monsoon from June to September.

I used a measure of rainfall shock, which has already been used in the literature (Feeny et al., 2021; Dinkelman, 2017). Following Dinkelman (2017), I calculate the fraction of shocks:

$$\text{Fraction shocks}_{ij} = \frac{[\text{child's exposure to shocks in-utero through age 4}]_{ij}}{(\text{in-utero} + \text{child's age})_{ij}}.$$

where the subscripts i represent every child in the sample living in clusters j. By using the shock fraction, I capture the variation in the rain shock specific to the child living in the clusters.

A child under the age of 5 years may be exposed to one, many, or no monsoon rainfall shock; the fraction of shocks captures that intensity of shock. For example, if a child of age 3 was exposed twice to rainfall shocks over his or her lifetime, then the fraction of shocks for that child is given by 2/4. To measure the *in-utero* exposure to rainfall shock, I used the birthyear of the individuals observed in the DHS data. Appendix 7 shows how the shock fraction is distributed.

To serve as a robustness check, I construct a population-weighted monthly rain measure based on gridded population data provided by the Center for International Earth Science Information Network (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018).[5]

Growing degree days

Daily temperature was sourced from Indian Monsoon Data Assimilation and Analysis (IMDAA) reanalysis portal, managed by the National Centre for Medium Range Weather Forecasting (NCMRWF), India (Rani et al., 2021). Reanalysis Data Service (RDS) is a regional atmospheric reanalysis over the Indian subcontinent at a high resolution 0.12 x 0.12 from 1979 to 2018.[6] I have followed the formulation used in previous studies using meteorological measures which affect crop losses (Guiteras, 2009).[7]

Using the maximum and minimum daily temperature, the lower and upper threshold for calculating growing degree days (GDD) during a growing season were set to $8C$ and $32C$, respectively.

Soil data

Soil organic carbon data were obtained from OpenLandMap (Hengl & Wheeler, 2018).[8] Global soil maps were produced based on machine learning predictions

[5] For my analysis, I use a resolution of 2.5 arc-minute for the year 2015. Data is available at https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev11/data-download.

[6] Available at https://rds.ncmrwf.gov.in/datasets.

[7] Following Guiteras (2009), I convert the daily mean temperature to GDD:

$$GDD(T)_j = \begin{cases} 0, & \text{if } T \leq 8C \\ T - 8, & \text{if } 8C < T \leq 32C \\ 24, & \text{if } T \geq 32C \end{cases}$$

[8] Soil data are available at https://www.openlandmap.org.

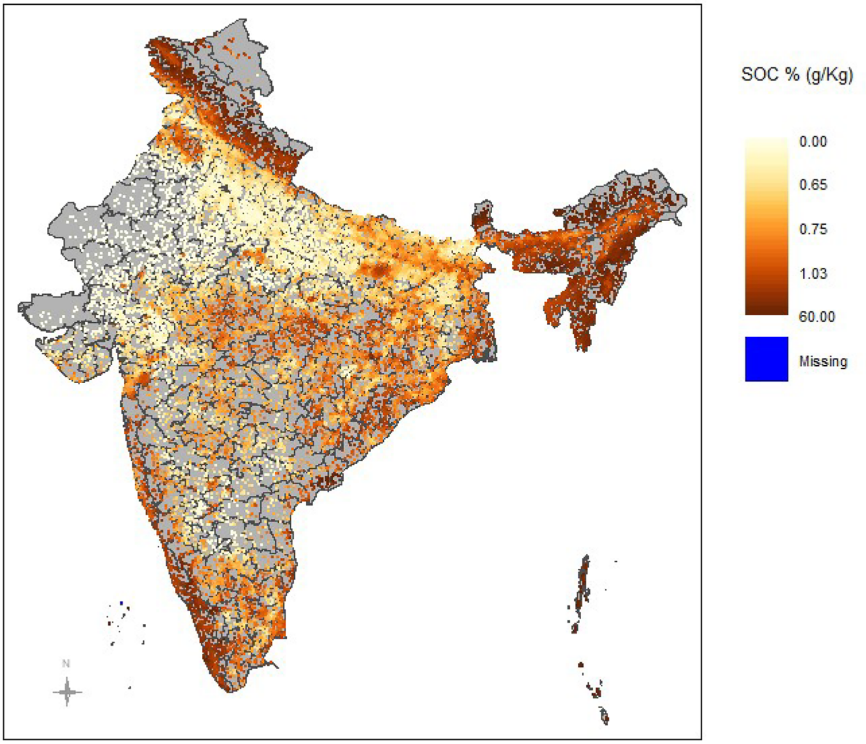


Fig. 3 The dots represent the average soil organic carbon content of the DHS rural clusters in India. The missing in the map indicates the null values for union territory Lakshadweep. The dark lines in the background are the district borders

from global soil profile compilations at a resolution of 250 m. Following Huang et al. (2021), I extracted the mean soil organic carbon content around the DHS geocoded clusters at four standard depths: 0, 10, 30, and 60 cm. I then calculated the depth-weighted soil organic carbon content at 0–60 cm interval for the analysis.[9]

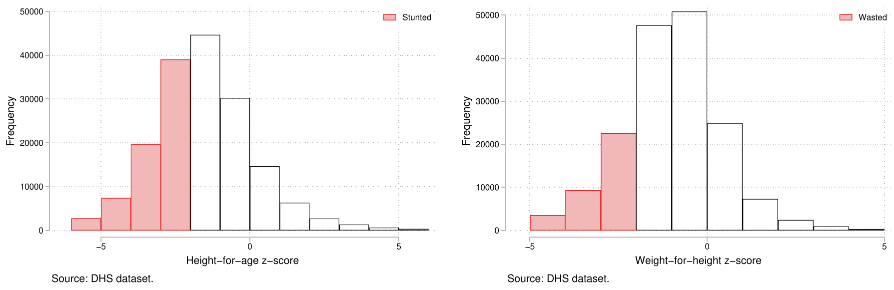
The literature does not provide clear information about the threshold for classifying soil as high or low quality. Therefore, I have identified two categories of soil organic carbon content: low, below the 50th percentile, and high, above the 50th percentile.[10]

Figure 3 shows the soil organic carbon map for the rural DHS clusters. The missing area in the map indicates the null values for union territory Lakshadweep. Much of India is categorized as having low levels of soil organic carbon. The average soil

[9] Following Huang et al. (2021), I used the trapezoidal rule to estimate the depth-weighted 0–60 cm interval:

$$(S_{0-60cm})_j = \left(\frac{[(S_0 + S_{10}) * 10 * 0.5] + [(S_{10} + S_{30}) * 20 * 0.5] + [(S_{30} + S_{60}) * 30 * 0.5]}{60} \right)_j$$

[10] I also perform the sensitivity test for different threshold values such as 25th and 75th percentile of high soil organic carbon. Appendix Tables 12 and 13 report the results.



(a) Stunted (HAZ< -2) (b) Wasted (WHZ< -2)

Fig. 4 Distribution of childhood health outcomes. Source: Own calculations based on DHS dataset (2015–2016)

organic carbon concentration is 0.945 %(g/kg). Coastal regions in the west and east, most in the northeast and central plains are characterized by moderate to high soil carbon levels. Also, to explore what determines SOC variation, I do the Pearson correlation coefficient test between soil organic carbon and the historical enhanced vegetation index.[11] The Pearson coefficient of correlation between these two variables is 0.38 (p-val = 0.000).

Descriptive statistics

Anthropometric data or body measurements for children, such as weight-for-age and weight-for-height, are taken and compared to a table in the World Health Organization (WHO) Child Growth Standards to calculate z-scores (WHO, 2006). The WHO Child Growth Standards are based on a sample of children from six countries: Brazil, Ghana, India, Norway, Oman, and the USA. The z-score value can be either negative or positive depending on whether a child's anthropometric measurement is below or above the population average for the child's age and sex. The children in the sample have a negative value of z-scores, suggesting infants with low birth weight, on average. The distribution of each anthropometric measure within the sample differs for boys and girls. Among boys, the height-for-age is −1.597, the weight-for-age z is −1.602, and the weight-for-height is −1.017. In girls, the height-for-age z-score is −1.516, the weight-for-age is −1.572, and the weight-for-height is −0.963.

Figure 4a and b show the distribution of height-for-age and weight-for-height z-scores of children under 5 years of age. The shaded portion in the figure shows the frequency indicating the absolute magnitude of child stunting and wasting. In my sample, approximately 41% of children are stunted and approximately 21% of children are wasted.

[11] I observe the enhanced vegetation index in the DHS dataset from 1985 to 2015 at 5-year intervals.

Table 1 Summary statistics

	Observation	Mean	Std. dev.
Child health measures			
Height-for-age z-score	169,904	−1.558	1.681
Weight-for-height z-score	169,904	−0.991	1.381
Rainfall below 20th percentile, yes=1			
Rainfall shock - in-utero	169,904	0.110	0.313
Rainfall shock - birth year	169,904	0.110	0.312
Rainfall shock - 1st year	137,807	0.125	0.331
Rainfall shock - 2nd year	103,642	0.148	0.355
Rainfall shock - 3rd year	69,621	0.168	0.374
Rainfall shock - 4th year	33,951	0.167	0.373
Fraction of shocks	169,904	0.134	0.182
Soil health measure			
Soil organic carbon (SOC) %(g/Kg)	169,897	0.945	0.675
25th percentile level of SOC	169,904	0.633	
50th percentile level of SOC	169,904	0.733	
75th percentile level of SOC	169,904	0.965	

The rain shocks for the 1st to the 4th year have different observations to adjust the age of the child. The sample is composed of 33,951 4-year-olds; 69,621 3-year-olds; 103,642 2-year-olds; 137,807 1-year-olds; and 169,904 in-utero. Source: DHS and CHIRPS data

Table 1 reports the summary statistics for the data used in this study.[12] About 11% of children were exposed to at least one rainfall shock in their birth year and in-utero. Children aged 2 to 4 are more exposed to cumulative shocks ranging from 0.15 to 0.17. This means that children aged 2 to 4 may have been exposed to at least one rainfall shock in their lifetime. The average value of the fraction of shocks as an intensity measure is 0.13 (Table 7).

In my sample, the average age of children is 30 months. Fifty-one percent are boys, and 49% are girls. On average, mothers are 27 years of age, and approximately half of the women have a high school or higher education. A little over half the households have agricultural land. Just under a third of households have potable water lines, and a third have flush toilets. Twenty-three percent of families in my sample are poor. Appendix Table 8 presents summary statistics for all control variables used in this study.

[12] Appendix Table 6 describes the variables included in the research.

Empirical framework

I estimate an OLS regression model to investigate the impact of high soil organic carbon levels on children's nutrition and health and mitigate the negative impact of shocks on children's health. The main specification is given by

$$\begin{aligned} h_{ij} = & \beta_1 shock_{ij} + \beta_2 soc_j + \beta_3 (shock_{ij} * soc_j) + f(\theta)_{ij} \\ & + \xi \mathbf{X}_i + f(a)_i + \delta_d + \phi_{my} + \varepsilon_{ij} \end{aligned} \tag{1}$$

where h_{ij} denotes child health outcomes measured by the height-for-age, weight-for-age, and the weight-for-height z-scores for child i at the DHS cluster level, j; $shock_{ij}$ represents the fraction of rain shocks experience by child i residing at DHS cluster level, j; soc_j represents the mean soil organic carbon content at the DHS cluster level, j; $\mathbf{X}_i$ is a set of explanatory variables including child, mother, and household characteristics. Child characteristics include age, gender, and order of birth; mother characteristics include age, level of education, and diet; and household characteristics include religion, social group, household income, and the wealth index (see Appendix Table 6 for a complete list of control variables); δ_d denotes district fixed effects and captures the time-invariant unobserved heterogeneity at the district level; ϕ_{my} denotes child birth year-month specific fixed effects and captures within cohort variations, and ε_{ij} denotes the disturbance terms. I cluster the standard errors at the level of DHS cluster (equivalent to Census village).

Additionally, I control precipitation and temperature derivatives (growth degree-days and harmful degree-days) during a growing season (June through September) throughout a child's life. $f(\theta)_{ij}$ is a non-linear function of precipitation and temperature. I followed Dimitrova and Muttarak (2020) to include a restricted cubic age spline, $f(a)_i$ with knots 6, 12, 18, 24, 36, and 48 months of age to control for non-linearity in children's growth trajectory. The key parameters are β_1, β_2, and β_3. β_1 represents the impact of cumulative periods of low precipitation on children's health; β_2 represents the direct impact of a high level of SOC on children's health; and β_3 represents the mitigation effects of a high level of SOC during cumulative periods of low rainfall.

In this study, I assume the soil endowments are exogenous. Because any change in agriculture, including climate change, takes a long time to get reflected in the soil system (Lal, 2004). This can mean that investment in soil or soil degradation by intensive cropping may take a long time to be reflected in the soil system. Also, because of India's low weather-induced internal migration rate (Viswanathan & Kumar, 2015). Because in my analysis, I look at short-term weather conditions on children's nutrition and health. That is a plausible assumption.

There may be a potential threat to identification. Some regions may experience larger declines in soil organic carbon content than others, resulting in measurement errors. For example, in wheat fields, stubble burning is often done after harvest, which can disrupt the natural cycle of soil organic carbon replenishment. However, because of the invariant time measure of the soil, I am unable to capture this variation. Nevertheless, I take advantage of the coarsened exact matching method to estimate causal effects by reducing the covariate imbalance between treatment and control groups (Iacus et al., 2012). However, it may not circumvent the sample selection problem. I present the results for the matched sample in the online supplement section.

Results

Rainfall shocks, soil health, and child health

Table 2 presents impact of rainfall shock and soil health on children's health. The OLS model takes into account the characteristics of the child, the mother, and the household. Moreover, the model controls a child's lifetime exposure to rain and temperature during a growing season. The model includes district and month and year of birth fixed effects. Standard errors are clustered at the DHS cluster level. Because the dependent variables (HAZ/WHZ scores) are measured as standard deviation, this is not a simple linear interpretation of a unit change in the exposure variable that results in a linear change in outcomes. The shock fraction shows a significant negative association with child WHZ. A one standard deviation increase in rainfall shock exposure above the child's mean years of exposure implies that the child will have negative WHZ score of −0.029 (−0.161*0.182). The standard deviation for the fraction of shocks is 0.182. A high level of SOC has no effect on children's health at its main term, but substantially reduces the negative effect of the precipitation shock

Table 2 Impact of high levels of SOC on the health of children

	HAZ	WHZ
Fraction of shocks	0.058	-0.161^{***}
	(0.050)	(0.042)
High SOC	−0.011	−0.023
	(0.018)	(0.015)
High SOC × fraction of shocks	−0.023	0.136^{**}
	(0.072)	(0.059)
DHS controls	Yes	Yes
Weather controls	Yes	Yes
P-val: High SOC + high SOC × fraction of shocks = 0	0.611	0.036
Mean dependent. var.	−1.558	−0.991
SD dependent var.	1.681	1.381
Observations	169,904	169,904
R-square	0.148	0.090

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high level of SOC is a dummy variable, 1 for the value above the 50th percentile of SOC and 0 otherwise. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time by 13.6 percentage points. The interaction term between high SOC and fraction of shocks in the specification captures the moderating effect of a high soil quality on child health outcomes. A one standard deviation increase in rainfall shock exposure above the child's average years of exposure in high SOC region leads to a positive WHZ score of 0.025 (0.136*0.182). This implies that high levels of SOC have a moderator effect of 3% ((−0.161+0.136)/−0.991 = 0.025). The mean WHZ score is −0.991. The *p*-value in the row shows the joint hypothesis test for high SOC and high SOC*fraction of shocks. The effect of a high and low level of SOC is statistically same for the child's HAZ scores, but statistically different for the WHZ scores.

Figure 5 illustrates the predictive margins and average marginal effects of high SOC on HAZ and WHZ scores. Panels (a) and (b) show the predicted margins of HAZ and WHZ scores stratified by high and low SOC levels at each precipitation shock level. In panel (a), the predicted margins of the child's HAZ scores are on an upward slope. This means that the predicted HAZ scores for a child living in both low and high SOC areas become less negative at high shock intensity. In contrast, in panel (b), the predicted margins of the child's WHZ scores are declining. This means that the predicted WHZ scores for a child living in both low and high SOC areas become more negative. However, the magnitude of the predicted WHZ score

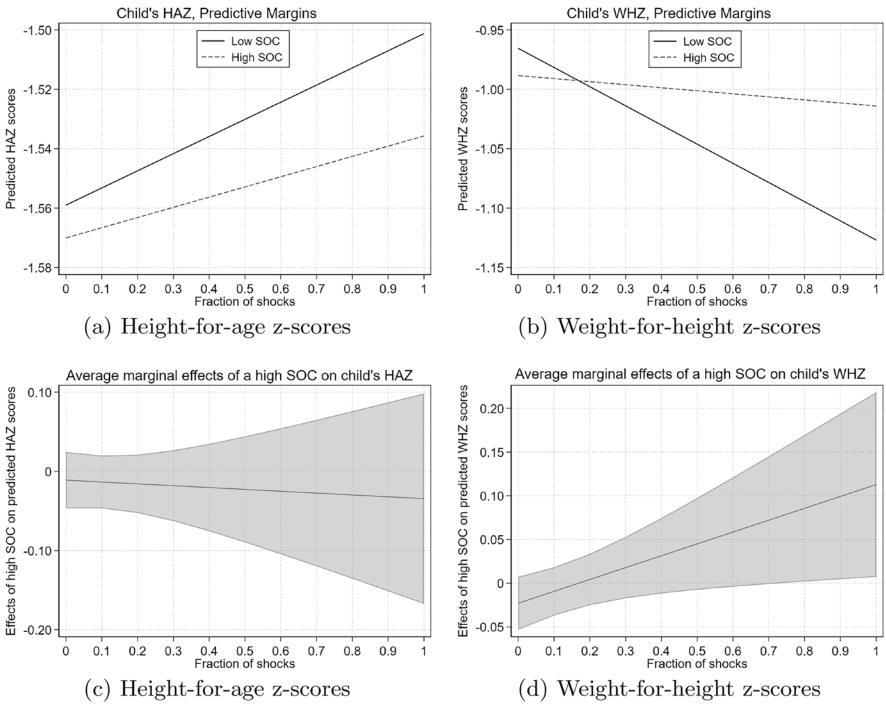


Fig. 5 Predictive margins stratified by high and low SOC levels and average marginal effects of high SOC levels on HAZ and WHZ scores. Notes: **a/b** was derived by predicting HAZ/WHZ scores to specified precipitation shock values per high/low SOC level. **c/d** was obtained from a partial derivative of HAZ/WHZ scores with respect to high SOC. **c** and **d** are shaded with a 95% confidence interval

is significantly smaller for a child living in a high SOC area. Panels (c) and (d) tell us the difference in HAZ and WHZ scores between high and low SOC groups at each precipitation shock level. The difference between low and high SOC areas is approximately zero for HAZ scores, while it is greater than zero for WHZ scores. This suggests that a high level of SOC significantly affects the child's WHZ scores, but not the HAZ scores.

Next, there is a concern that soil organic carbon measurement may be confounded by other associated agronomic attributes. With SOC as the choice variable, it is difficult to remove concerns related to the omitted variable bias. Nevertheless, I approach this concern by including soil texture, slope, and vegetative index as control variables in Eq. 1.[13][14] In order to assess the influence of the different soil attributes used in this study on children's health, I ran a correlation between child WHZ and soil attributes. This demonstrates no concern for multicollinearity in the model. Table 10 in the Appendix provides the correlation matrix for the soil attributes used in this study. Appendix Table 11 reports the results. It reads similar effects of high SOC on child health outcomes.

As a robustness check, I perform regressions on the matched sample after applying the matching algorithm (discussed in the online supplement) and on the population-weighted monthly rainfall measurements. Appendix Table 16 presents the results after applying the coarsened exact matching weights to the OLS model. The sign of the estimated coefficients is identical to that of the main results. However, the key coefficients are not significant at the 5% significance level in the matched sample. Next, Appendix Table 9, which uses the population-weighted monthly rain measures, reads similar effects on child health.

Heterogeneity

As mentioned earlier in the conceptual section, I use the subset of the sample to explore these heterogeneous effects of different climate zones, gender, and the household wealth index, common in the development and climate literature. I also explore the heterogeneous effect that soil health has on the health outcomes of children in households with and without agricultural land. To check whether the differences between heterogeneous groups are statistically different, I perform a simple statistical test (two-sample *t*-test). The results suggest that the differences in mean HAZ/WHZ scores between groups differ statistically.

Heterogeneity by climate zone

The impact of soil organic carbon on children's health can vary according to climate zones in India. Following Dimitrova and Bora (2020), I constructed six major

[13] I used OpenLandMap to extract clay, sand, and silt content in $\%(kg/kg)$ at a depth of 60 cm in the DHS cluster (Hengl, 2018a, b, c).

[14] I used the enhanced vegetation index for 2015 available in the DHS dataset as a proxy for agricultural output.

climate zones at the district level based on the basis of the climate classification Köppen Geiger.[15] They are tropical wet, tropical wet and dry, arid, semi-arid, humid sub-tropical, and mountainous. The Köppen classification map is based on local vegetation which, in turn, is based on local precipitation and temperature. The tropical rainforest and the tropical monsoon are reclassified as tropical humid, while the tropical savannah is reclassified as tropical humid and dry. The wet season in summer and the dry season in winter are the characteristics of the humid and dry tropical region. A one-way ANOVA test for average differences in HAZ/WHZ scores indicates a significant difference between different climate zones.[16] Appendix Fig. 8 shows the major climatic zones of India.

Heterogeneous effects across climate zones suggest that high SOC has a significant effect on children's WHZ scores in semi-arid and humid sub-tropical areas. The impact of high SOC is larger in semi-arid areas. In contrast, cumulative precipitation shocks are positively associated with child WHZ scores in the wet and dry tropical climate area. This can be due to a reduction of diseases that are common during monsoon weather such as diarrhea and malaria. But this requires further research, and the results should be interpreted cautiously. The results do not suggest any impact of a high level of SOC on children's HAZ scores in major but semi-arid climate zones. Table 3 summarizes the heterogeneous effects across climate zones.

Heterogeneity by gender

Next, I disaggregate the sample into boys and girls. There is evidence of gender discrimination in the literature in response to different types of household shocks, including environmental shocks. SOC may have no direct relationship to gender. But the moderating effect of a high level of SOC against crop failure contributes to children's food and nutritional security.

Table 4 presents the heterogeneous effects of rainfall shocks and soil health on children's HAZ and WHZ scores by gender. Cumulative rain shock has a negative impact on girls' and boys' WHZ scores. Girls are more affected by rain shocks, as suggested by the larger coefficient. The point estimation is −0.205 for girls and −0.112 for boys. A high level of SOC mitigates the negative impact of precipitation shock on girls' WHZ scores, but not for boys. This implies that the nutrition of girls is addressed where resilience to climate-induced food insecurity exists through a high level of SOC. On the other hand, the results show no effect of a high level of SOC on children's HAZ scores.

Heterogeneity by household wealth index

Household characteristics, such as household wealth, directly impact the resilience of households to absorb shocks, including environmental shocks. Poor households have less resilience than non-poor households. In the DHS dataset, I observe five

[15] I am grateful to Anna Dimitrova for sharing the data and code with me.

[16] See Appendix Table 15

Table 3 Heterogeneity by selected climate zones

	HAZ			
	Tropical wet	Tropical wet and dry	Semi arid	Humid sub-tropical
Fraction of shocks	–1.204	−0.167	0.130	0.062
	(1.661)	(0.167)	(0.130)	(0.061)
High SOC	0.451	−0.009	0.023	−0.031
	(0.284)	(0.029)	(0.051)	(0.027)
High SOC × fraction of shocks	1.084	0.175	−0.767**	0.052
	(1.661)	(0.183)	(0.322)	(0.094)
Mean dependent var.	−1.258	−1.538	−1.516	−1.647
Observations	7036	40,607	25,517	86,254
R-square	0.146	0.130	0.144	0.160
	WHZ			
	Tropical wet	Tropical wet and dry	Semi arid	Humid sub-tropical
Fraction of shocks	−0.325	0.292**	−0.280**	−0.133***
	(0.813)	(0.139)	(0.111)	(0.051)
High SOC	0.314*	0.016	−0.054	−0.021
	(0.175)	(0.026)	(0.041)	(0.023)
High SOC × fraction of shocks	0.200	−0.416***	0.547**	0.180**
	(0.819)	(0.153)	(0.275)	(0.075)
Mean dependent var.	−0.861	−1.197	−1.025	−0.934
Observations	7036	40,607	25,517	86,254
R-square	0.079	0.075	0.072	0.093

Levels of significance: $p< 0.01$***, $p< 0.05$**, $p< 0.1$*. Robust standard errors in parentheses are clustered at the DHS cluster level. The high level of SOC is a dummy variable, 1 for the value above the 50th percentile of SOC and 0 otherwise. Each regression includes district and month-birth year specific fixed effects. All regressions include demographic controls, such as child, mother, and household level characteristics, and weather controls. Arid and mountain are limited by very small sample to provide meaningful estimates and hence excluded. A one-way ANOVA test for average differences in HAZ/WHZ scores indicates a significant difference between different climate zones (see Appendix Table 15)

different indices: the poorest, the poorer, the middle, the richer, and the richest. For my purpose, I code the poorest and the poorer as the poor and the middle, the richer, and the richest as the non-poor.

Table 4 presents the heterogeneous effects of rainfall shocks and soil health on children's HAZ and WHZ scores by household wealth index, as defined in the DHS data. Unsurprisingly, the results indicate that poor households are negatively affected by precipitation shocks. The point estimate is −0.197 and significant at the 5% significance level. Children WHZ scores in poor rural households are negatively impacted by rainfall shocks. A high level of SOC does not significantly reduce the adverse effect of the rainfall shock on poor households. The ability of rural households to influence SOC and directly benefit from high SOC may depend on their

Table 4 Heterogeneity by individual and household characteristics

	Boys		Girls	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.011	–0.112**	0.108	–0.205***
	(0.065)	(0.057)	(0.067)	(0.055)
High SOC	–0.023	–0.005	0.003	–0.041**
	(0.022)	(0.020)	(0.024)	(0.020)
High SOC × fraction of shocks	0.022	0.110	–0.068	0.152**
	(0.093)	(0.079)	(0.094)	(0.077)
Mean dependent. var.	–1.597	–1.017	–1.516	–0.963
Observations	87,643	87,643	82,259	82,259
R-square	0.142	0.096	0.165	0.093
Difference of average HAZ scores by gender	–0.081***			
Difference of average HAZ scores by gender	–0.054***			
	Poor		Non-poor	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.060	–0.197***	0.056	–0.110*
	(0.069)	(0.056)	(0.069)	(0.060)
High SOC	–0.000	–0.012	0.019	–0.029
	(0.026)	(0.022)	(0.024)	(0.020)
High SOC × fraction of shocks	0.002	0.114	–0.038	0.133*
	(0.104)	(0.081)	(0.092)	(0.080)
Mean dependent. var.	–1.847	–1.135	–1.321	–0.873
Observations	76,633	76,633	93,259	93,259
R-square	0.128	0.088	0.137	0.090
Difference of average HAZ scores by wealth	0.525***			
Difference of average WHZ scores by wealth	0.262***			
	Has ag. land		Has no ag. land	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.083	–0.190***	0.033	–0.110*
	(0.063)	(0.054)	(0.075)	(0.062)
High SOC	–0.015	–0.025	–0.006	–0.012
	(0.023)	(0.020)	(0.026)	(0.021)
High SOC × fraction of shocks	–0.112	0.119	0.089	0.132
	(0.090)	(0.076)	(0.104)	(0.083)
Mean dependent. var.	–1.511	–0.976	–1.617	–1.009
Observations	94,065	94,065	75,838	75,838
R-square	0.152	0.100	0.153	0.089
Difference of average HAZ scores by landowner	–0.106***			
Difference of average WHZ scores by landowner	–0.033***			

Levels of significance: $p< 0.01$***, $p< 0.05$**, $p< 0.1$*. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high level of SOC is a dummy variable, 1 for the value above the 50th percentile of SOC and 0 otherwise. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The difference in mean HAZ/WHZ scores by heterogeneous groups was obtained from a two-sample t-test with equal variances association with farms. I explore that in more detail in the next section by disaggregating the sample by landowner.

Heterogeneity by land ownership

To show the relationship between SOC and landowners, I look at the heterogeneity by land ownership: has agricultural land and does not have agricultural land. Table 4 presents the results for households that own and do not own farmland. The results suggest that rain shocks negatively affect households that own land, suggesting they are rain-dependent. However, a high level of SOC does not reduce the negative impact of rainfall shock on households that own land.

Conclusion

Summary

This paper examines the relationship between SOC and the impact of rainfall shocks on children's health. Based on the conceptual framework developed in this paper, I examine the impact of rainfall shock with different levels of SOC. The results show that a high level of SOC significantly reduces the negative impact of rainfall shock on children's WHZ scores in rural India. My findings are consistent with two separate literatures: (1) studies (e.g., Dimitrova and Muttarak (2020)) which show the negative impact of precipitation shock on children's health and (2) studies (e.g., Berkhout et al. (2019)) that show the importance of soil quality in the reduction of malnutrition in low- and middle-income countries. In this paper, I show a significant moderating effect of a high level of SOC offering resilience from the rainfall shock on short-term inadequate nutrition in rural areas of India. I find significant reduction in children's negative WHZ scores and thus a resistance to child wasting during periods of low precipitation in a rain-fed farming country. However, I find no effect of a high level of SOC on children's HAZ scores suggesting that a high SOC does not reduce chronic malnutrition among children.

Analyses of heterogeneous impacts suggest that high SOC significantly moderates the precipitation shocks in semi-arid and humid sub-tropical climate zones. The results suggest that the nutrition of girl child is addressed in high level of SOC areas in response to rainfall shock. The results also suggest that a high level of SOC does not significantly mitigate the negative impact of rainfall shocks for children from poor households and farm landowners. One plausible reason of these results is that poor households and farm landowners in rural areas of India are characterized by a small landholding size (the average landholding in India is 1 ha), and therefore, we may not expect a stronger effect of a high SOC.

Limitation

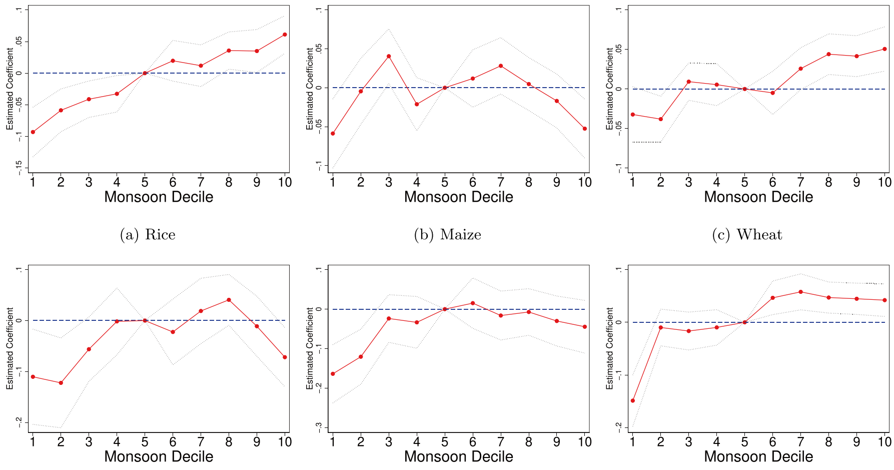
A major limitation of this paper is that the soil organic carbon content variable used is time invariant. Existing research shows that agricultural practices that cause pollution, such as stubble burning (Singh et al., 2019) and fertilizer use (Brainerd & Menon, 2014), can have negative impacts on children's health. These agricultural practices may also affect soil organic carbon concentrations, leading to endogeneity issues in the estimates. Due to a lack of data, I am unable to control for these agricultural practices and address the endogeneity problem.

Conclusions

Since it takes longer to reflect changes in soil organic carbon concentrations, policies may include both long-term and short-term measures. One long-term policy to enhance SOC would be to incentivize the adoption of agricultural best management practices. This can increase resilience to shocks over time, particularly as climate changes. Indian child development programs could be improved by considering the impact of climate change on the incidence of droughts and, consequently, on children's health.

In the short term, soil health in a region could be used to inform the likely impacts of precipitation shocks, which could better target relief efforts. Nutrition and soil conditions are linked to agriculture, and high soil quality contributes to reducing malnutrition, particularly during precipitation shocks. Therefore, there may be a greater need for food relief aid in low SOC areas.

Appendix A: Additional figures and tables



(a) Rice (b) Maize (c) Wheat

(d) Soybean (e) Cotton (f) Groundnut

Fig. 6 Effects of monsoon rainfall on crop yields. Notes: The dependent variable is the natural logarithm of annual crop yield (kg per hectare) from 2001 to 2015. The specification includes district and year fixed effects. The figure plots the point estimate are plotted with 95% confidence intervals. The 5th decile is selected as reference. The monsoon rainfall deciles were constructed using monthly Climate Hazards Group InfraRed Precipitation (CHIRPS) data in a growing season (June through September) from year 1982 to 2015 (Funk et al., 2014)

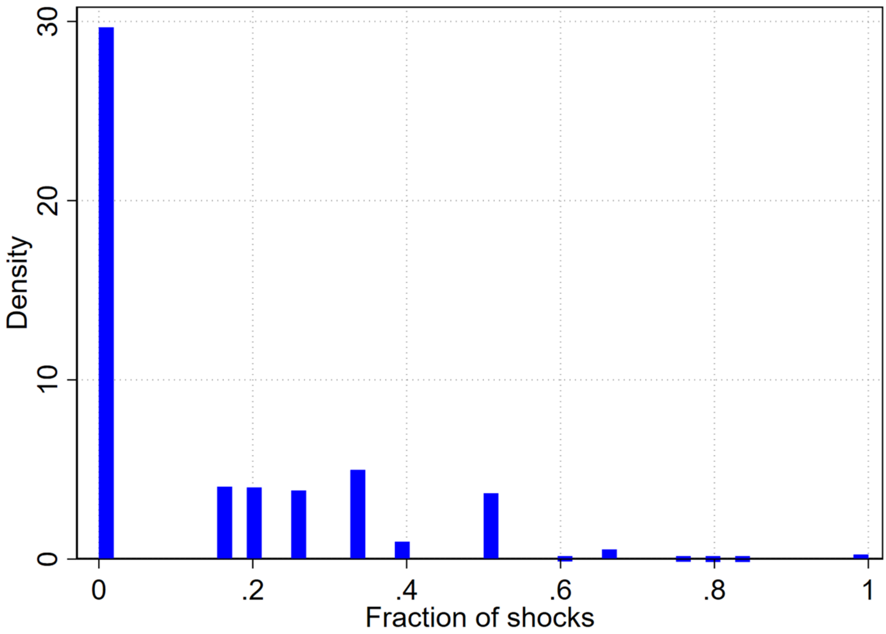


Fig. 7 The distribution of fractional shocks

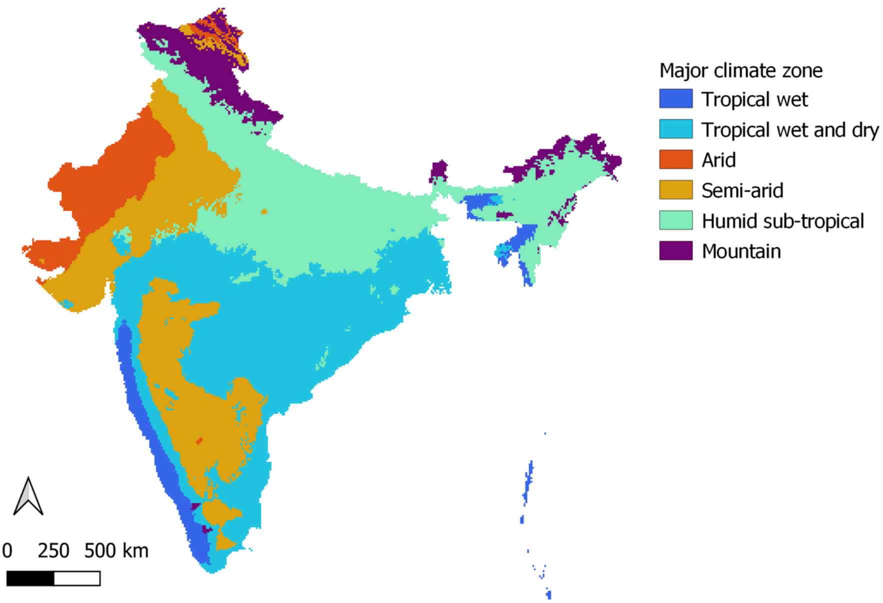


Fig. 8 Major climate zones in India based on Köppen Geiger climate classification

Table 5 Moderating impacts of high SOC on crop yields

	Cereal
SOC (%)	0.018
	(0.020)
Rainfall decile 1	–0.129***
	(0.029)
Rainfall decile 1 × SOC	0.038**
	(0.018)
Rainfall decile 2	–0.051*
	(0.027)
Rainfall decile 2 × SOC	0.010
	(0.020)
Rainfall decile 3	–0.016
	(0.024)
Rainfall decile 3 × SOC	0.004
	(0.019)
Rainfall decile 4	–0.045
	(0.030)
Rainfall decile 4 × SOC	0.034
	(0.022)
Rainfall decile 6	–0.016
	(0.025)
Rainfall decile 6 × SOC	0.015
	(0.021)
Rainfall decile 7	–0.049
	(0.031)
Rainfall decile 7 × SOC	0.060***
	(0.023)
Rainfall decile 8	0.049**
	(0.021)
Rainfall decile 8 × SOC	–0.001
	(0.020)
Rainfall decile 9	0.071**
	(0.028)
Rainfall decile 9 × SOC	–0.015
	(0.026)
Rainfall decile 10	0.084***
	(0.025)
Rainfall decile 10 × SOC	–0.001
	(0.019)
Observations	7091
Adjusted R^2	0.460

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the district level. The dependent variable is the natural logarithm of annual crop yield (kg per hectare) from 2001 to 2015. The specification includes state and year fixed effects. SOC is continuous. The 5th decile is selected as reference

Table 6 Description for variables included in the study

Variable	Description
Child-specific	
bord	Order of birth
malechild	Dummy for male child
childsizelarge	Dummy for child was large at birth
childsizeavg	Dummy for child was average at birth
numfemalesib	Number of female siblings
nummalesib	Number of male siblings
*age*510	Dummy for child with sibling between the age 5 and 10 years
*age*1115	Dummy for child with sibling between the age 11 and 15 years
*age*16	Dummy for child with sibling above 16 years
*hw*1	Child's age in months
Woman-specific	
*v*012	Woman's age in years
womanpriedu	Dummy for woman has primary education
womansecedu	Dummy for woman has secondary or higher level education
womanbmi	Woman's body mass index
womaneatfruits	Dummy for woman consumes fruits daily or weekly
womaneatveges	Dummy for woman consumes vegetables daily or weekly
womaneateggs	Dummy for woman consumes eggs daily or weekly
womaneatmeat	Dummy for woman consumes chicken/meat/fish daily or weekly
womansmoke	Dummy for woman smokes
womandrink	Dummy for woman drinks alcohol
womanprenataldoc	Dummy for had prenatal care with doctor
Household-specific	
*v*104	Years lived in place of residence
*hv*220	Age of household head in years
hhheadmale	Dummy for male household head
hhhindu	Dummy for household religion is Hinduism
hhmuslim	Dummy for household religion is Islam
hhscst	Dummy for household belongs to SC/ST
hhradio	Dummy for household owns a radio/transistor
hhtv	Dummy for household owns a television
hhrefri	Dummy for household owns a refrigerator
hhmotorcycle	Dummy for household owns a motorcycle
hhcar	Dummy for household owns a car
hhelec	Dummy for household has electricity
*hv*244	Dummy for household owns agricultural land
hhirragland	Dummy for household irrigate agricultural land
*sh*52*a*	Dummy for household owns cows/bulls/buffaloes
*sh*52*b*	Dummy for household owns camels
*sh*52*c*	Dummy for household owns horses/donkeys/mules
*sh*52*d*	Dummy for household owns goats

Table 6 (continued)

Variable	Description
sh52e	Dummy for household owns sheep
sh52f	Dummy for household owns chickens/ducks
hhpipewater	Dummy for source of drinking water: piped water
hhgroundwater	Dummy for source of drinking water: ground water
hhsurfacewater	Dummy for source of drinking water: surface water
hhrainwater	Dummy for source of drinking water: rain water, tanker water, etc
hhflushtoilet	Dummy for toilet facility: flush toilet
hhpit	Dummy for toilet facility: pit toilet/latrine
hhnofacility	Dummy for toilet facility: no facility/bush/field
hhpoorest	Dummy for household wealth index: poorest
hhpoorer	Dummy for household wealth index: poorer
hhmiddle	Dummy for household wealth index: middle
hhricher	Dummy for household wealth index: richer

For the analysis, *hw*1 was transformed with restricted cubic spline, and knots are placed at the interval of 6, 12, 18, 24, 36, and 48

Table 7 Description for variables included in the study

Variable	Description
Weather-specific	
childrain	June-September daily accumulation of rainfall over child's life time
childgdd	Growing degree days over child's life time
childhdd	Harmful degree days over child's life time

For the analysis, *childrain* and *childgdd* were transformed by squaring the variable; *childhdd* was transformed by taking a square root of the variable

Table 8 Summary statistics ($N = 169{,}904$)

	Mean	Std. dev.
Child birth order number	2.343	1.521
Male child	0.516	0.500
Child with greater than average size at birth	0.165	0.371
Child with average size at birth	0.691	0.462
Number of female siblings	0.828	1.050
Number of male siblings	0.662	0.852
Number of child with sibling between the age 5 and 10 years	0.691	0.878
Number of child with sibling between the age 11 and 15 years	0.176	0.506
Number of child with sibling above 16 years	0.062	0.358
Child's age in months	29.895	17.034
Woman's age in years	27.079	5.178
Woman has primary edu	0.156	0.363
Woman has secondary or higher edu	0.494	0.500
Woman's body mass index	20.775	3.465
Woman consumes fruits daily or weekly	0.333	0.471
Woman consumes vegetables daily or weekly	0.945	0.227
Woman consumes eggs daily or weekly	0.340	0.474
Woman consumes chicken/meat/fish daily or weekly	0.356	0.479
Woman smokes	0.007	0.084
Woman drinks alcohol	0.024	0.153
Access to prenatal care with doctor	0.361	0.480
Years lived in place of residence	15.460	25.387
Age of household head	44.360	15.216
Male household head	0.879	0.326
Household religion is Hinduism	0.744	0.436
Household religion is Islam	0.137	0.344
Household belongs to SC/ST	0.420	0.494
Household owns a radio/transistor	0.086	0.280
Household owns a television	0.495	0.500
Household owns a refrigerator	0.165	0.371
Household owns a motorcycle	0.311	0.463
Household owns a car	0.042	0.200
Household has electricity	0.814	0.389
Household owns ag. land	0.554	0.497
Irrigated ag land only	0.278	0.448
Household owns cows/bulls/buffaloes	0.523	0.499
Household owns camels	0.004	0.064
Household owns horses/donkeys/mules	0.007	0.086
Household owns goats	0.225	0.417
Household owns sheep	0.022	0.148
Household owns chickens/ducks	0.220	0.414
Source of drinking water: piped water	0.295	0.456

Table 8 (continued)

	Mean	Std. dev.
Source of drinking water: ground water	0.626	0.484
Source of drinking water: surface water	0.054	0.226
Toilet facility: flush toilet	0.337	0.473
Toilet facility: pit toilet/latrine	0.105	0.306
Toilet facility: no facility/bush/field	0.541	0.498
Wealth index: poorest	0.232	0.422
Wealth index: poorer	0.219	0.414
Wealth index: middle	0.200	0.400
Wealth index: richer	0.180	0.384

Source: DHS and CHIRPS data

Table 9 Alternative main regression results using population-weighted rain measures

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.027	−0.143***	−0.016	−0.046
	(0.050)	(0.042)	(0.062)	(0.052)
High SOC	−0.011	−0.020	−0.008	−0.021
	(0.018)	(0.015)	(0.021)	(0.018)
High SOC × fraction of shocks	−0.017	0.102*	−0.073	0.038
	(0.072)	(0.058)	(0.089)	(0.071)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	−1.558	−0.991	−1.573	−1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	102,296	102,296
R-square	0.148	0.090	0.144	0.079

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time

Table 10 Means, standard deviation, and Pearson correlation matrix for soil attributes (N = 169,897)

	Means	SD	WHZ	SOC	Clay	Sand	Silt	EVI	Slope
WHZ	–0.99	1.38	1.00						
SOC	0.94	0.67	0.12[a]	1.00					
Clay	32.44	5.33	–0.09[a]	–0.08[a]	1.00				
Sand	38.18	5.58	0.02[a]	0.02[a]	–0.57[a]	1.00			
Silt	29.39	5.08	0.07[a]	0.06[a]	–0.43[a]	–0.50[a]	1.00		
EVI	2927.33	702.22	0.10[a]	0.38[a]	0.02[a]	–0.15[a]	0.14[a]	1.00	
Slope	0.29	111.22	0.00	–0.25[a]	0.00	0.00	0.00	0.21[a]	1.00

[a]$p < .01$. *EVI* Enhanced Vegetation Index for 2015

Table 11 Robustness check: confounding variables included as controls

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.056	−0.166***	0.070	−0.152***
	(0.050)	(0.042)	(0.063)	(0.053)
High SOC	−0.011	−0.023	−0.005	−0.016
	(0.018)	(0.016)	(0.021)	(0.018)
High SOC × fraction of shocks	−0.022	0.135**	−0.089	0.098
	(0.072)	(0.059)	(0.090)	(0.072)
DHS controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	−1.558	−0.991	−1.572	−1.061
SD dependent var.	1.681	1.381	1.667	1.369
Observations	169,897	169,897	102,296	102,296
R-square	0.148	0.090	0.142	0.080

Levels of significance: $p< 0.01$***, $p< 0.05$**, $p< 0.1$*. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Other controls include confounding variables such as soil texture, slope, and vegetation

Table 12 Sensitivity test for various thresholds: high soil organic carbon content above 25 percentile

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.153**	−0.233***	0.155**	−0.214***
	(0.063)	(0.055)	(0.067)	(0.059)
High SOC	0.012	−0.026	0.016	−0.017
	(0.022)	(0.018)	(0.027)	(0.022)
High SOC × fraction of shocks	−0.147**	0.186***	−0.233***	0.151**
	(0.072)	(0.061)	(0.086)	(0.076)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	−1.558	−0.991	−1.573	−1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	80,253	80,253
R-square	0.148	0.090	0.145	0.094

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 25th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of the following: the number of balanced matched observations is 40,129 for treatment and control, and the unmatched observation is 2354 out of 42,483 for control and 87,292 out of 127,421 for treatment

Table 13 Sensitivity test for various thresholds: high soil organic carbon content above 75 percentile

	Full		Matched	
	HAZ	WHZ	HAZ	WHZ
Fraction of shocks	0.048	−0.114***	0.122	−0.091
	(0.042)	(0.037)	(0.093)	(0.080)
High SOC	−0.015	−0.022	−0.022	−0.000
	(0.028)	(0.023)	(0.034)	(0.029)
High SOC × fraction of shocks	−0.003	0.066	−0.122	−0.020
	(0.085)	(0.072)	(0.124)	(0.106)
DHS controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Mean dependent. var.	−1.558	−0.991	−1.573	−1.059
SD dependent var.	1.681	1.381	1.667	1.366
Observations	169,904	169,904	45,498	45,498
R-square	0.148	0.090	0.145	0.094

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The high SOC level is fixed above the 75th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of the following: the number of balanced matched observations is 22,749 for treatment and control, and the unmatched observation is 104,676 out of 127,425 for control and 19,730 out of 42,479 for treatment

Table 14 Sensitivity test for different DHS cluster level: 20 km

	(1) Full	(2) Full	(3) Full	(4) Matched
Fraction of shocks	–0.241***	–0.242***	−0.260***	−0.229***
	(0.054)	(0.054)	(0.055)	(0.060)
High SOC	−0.017	−0.023	−0.023	−0.008
	(0.018)	(0.018)	(0.018)	(0.022)
High SOC × fraction of shocks	0.129**	0.154**	0.163***	0.109
	(0.061)	(0.061)	(0.061)	(0.076)
Marginal effects	−0.144***	−0.127***	−0.137***	−0.174***
	(0.034)	(0.033)	(0.034)	(0.047)
Mean dependent variable	−0.991			−1.075
Average years of exposure	0.133			0.150
DHS controls	No	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes
Observations	169,904	169,904	169,904	80,254
Adjusted R^2	0.067	0.086	0.086	0.068

Levels of significance: $p< 0.01$***, $p< 0.05$**, $p< 0.1$*. Robust standard errors in parentheses are clustered at the DHS cluster level. The high SOC level is fixed above the 25th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. All regressions include district and month-birth year specific fixed effects. The matching summary includes 40,129 matched out of 42,483 observations for control and 40,129 matched out of 127,421 for treated

Table 15 ANOVA test

	Sum of square	Degree of freedom	Mean square	F	Prob > F
HAZ scores					
Between groups	3108.95	5	621.79	221.46	0.000
Within groups	476230.63	169619	2.81		
WHZ scores					
Between groups	4316.99	5	863.40	458.79	0.000
Within groups	319203.80	169619	1.88		

A one-way ANOVA test was performed to test if there is a difference in the mean HAZ/WHZ scores between different climate zones

Table 16 Impact of high levels of SOC on the health of children

	HAZ	WHZ
Fraction of shocks	0.011	−0.063
	(0.063)	(0.053)
High SOC	−0.008	−0.023
	(0.021)	(0.018)
High SOC × fraction of shocks	−0.071	0.057
	(0.089)	(0.071)
DHS controls	Yes	Yes
Weather controls	Yes	Yes
Mean dependent. var	−1.573	−1.059
SD dependent var	1.667	1.366
Observations	102,296	102,296
R-square	0.144	0.079

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The matched weights, *cem*, are applied on all regressions. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time

Appendix B: Online supplement

The main idea of this paper was to use soil organic carbon (as a measure of soil health) as a moderator in response to rainfall shock. In the long run, the soil organic carbon may not be exogenous and may be correlated to an omitted variable, resulting in biased estimates. I take advantage of the coarsened exact matching method to estimate causal effects by reducing the covariate imbalance between treatment (high SOC region) and control (low SOC region) groups.

Matching methods

The coarsened exact matching method estimates the average effect of treatment on the treated sample (Blackwell et al., 2009). I use data knowledge to search for a better match. The coarsened variables used were (a) child-specific (child's birth order, child's gender and age), (b) mother-specific (mother's age and education level), and (c) household-specific (religion, caste, source of drinking water, and toilet facility).[17] I apply the software package, *cem*, created by Blackwell et al. (2009) to calculate the weights, and these weights were used in a simple

[17] I also included the month of birth as part of the matching algorithm. I calculated if a child was born during the dry season (the first 6 months of the year) or the wet season (the last 6 months of the year). Then, I included that as an additional variable in the matching algorithm. Appendix Table 17 presents the results. It reads findings similar to those of the main specification.

Table 17 Including dry and rainy seasons as an additional variable in the matching algorithm

	HAZ	WHZ
Fraction of shocks	0.030	−0.102*
	(0.063)	(0.053)
High SOC	−0.011	−0.016
	(0.021)	(0.018)
High SOC × fraction of shocks	−0.072	0.036
	(0.091)	(0.072)
DHS controls	Yes	Yes
Weather controls	Yes	Yes
Mean dependent. var	−1.580	−1.065
SD dependent var	1.665	1.366
Observations	97,441	97,441
R-square	0.147	0.080

Levels of significance: $p< 0.01^{***}$, $p< 0.05^{**}$, $p< 0.1^{*}$. Robust standard errors in parentheses are clustered at the DHS cluster level. Each regression includes district and month-birth year specific fixed effects. The matched weights, *cem*, are applied on all regressions. The high SOC level is fixed above the 50th percentile. DHS controls include child, mother, and household level characteristics. Weather controls include non-linear transformation of precipitation and temperature over child's life time. The match summary consists of the following: the number of balanced matched observations is 48,721 for treatment and control, and the unmatched observation is 36,229 out of 84,950 for control and 36,233 out of 84,954 for treatment

weighted regression. The *cem* command with a *k2k* option in STATA produces a match result which has the same number of treated and control in each matched strata by dropping the observations randomly. The treatment variable treat is 1 for high soil organic carbon content (in treatment group) and 0 for low soil organic carbon content (control group). Here is the summary of the match: the number of balanced matched observations is 51,148 for treatment and control, and the unmatched observation is 33,802 out of 84,950 for control and 33,806 out of 84,954 for treatment.

The estimating equation is similar to the Eq. (1):

$$h_{ij} = \beta_1 shock_{ij} + \beta_2 soc_j + \beta_3(shock_{ij} * soc_j) + f(\theta)_{ij} + \xi\mathbf{X}_i + f(a)_i + \delta_d + \phi_{my} + \varepsilon_{ij},$$

where the terms are defined same as the Eq. (1). I applied the package in STATA, cem, to compute the weights, and those weights were used in a simple weighted regression.

References

Almond, D., & Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of economic perspectives, 25*(3), 153–72.

Auffhammer, M., Ramanathan, V., & Vincent, J. R. (2012). Climate change, the monsoon, and rice yield in India. *Climatic change, 111*(2), 411–424.

Bakhtsiyarava, M., & Grace, K. (2021). Agricultural production diversity and child nutrition in Ethiopia. *Food Security, 13*(6), 1407–1422.

Berkhout, E. D., Malan, M., & Kram, T. (2019). Better soils for healthier lives? An econometric assessment of the link between soil nutrients and malnutrition in sub-saharan africa. *PloS one, 14*(1), e0210642.

Bhargava, A. K., Vagen, T., & Gassner, A. (2018). Breaking ground: Unearthing the potential of high-resolution, remote-sensing soil data in understanding agricultural profits and technology use in Sub-Saharan Africa. *World Development, 105*, 352–366.

Blackwell, M., Iacus, S., King, G., et al. (2009). cem: Coarsened exact matching in Stata. *The Stata Journal, 9*(4), 524–546.

Brainerd, E., & Menon, N. (2014). Seasonal effects of water quality: The hidden costs of the green revolution to infant and child health in India. *Journal of Development Economics, 107*, 49–64.

Center for International Earth Science Information Network - CIESIN - Columbia University. (2018). Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11. https://doi.org/10.7927/H4JW8BX5, place: Palisades, New York.

Dimitrova, A., & Bora, J. K. (2020). Monsoon weather and early childhood health in India. *PLOS ONE, 15*(4), e0231479. https://doi.org/10.1371/journal.pone.0231479, https://dx.plos.org/10.1371/journal.pone.0231479

Dimitrova, A., & Muttarak, R. (2020). After the floods: Differential impacts of rainfall anomalies on child stunting in India. *Global Environmental Change, 64*(102), 130. https://doi.org/10.1016/j.gloenvcha.2020.102130, https://www.linkinghub.elsevier.com/retrieve/pii/S0959378020307135

Dinkelman, T. (2017). Long-run health repercussions of drought shocks: Evidence from South African homelands. *The Economic Journal, 127*(604), 1906–1939.

Feeny, S., Mishra, A., Trinh, T. A., et al. (2021). Early-life exposure to rainfall shocks and gender gaps in employment: Findings from Vietnam. *Journal of Economic Behavior & Organization, 183*, 533–554. https://doi.org/10.1016/j.jebo.2021.01.016, https://www.linkinghub.elsevier.com/retrieve/pii/S0167268121000275

Funk, C. C., Peterson, P. J., Landsfeld, M. F., et al. (2014). A quasi-global precipitation time series for drought monitoring. *US Geological Survey data series, 832*(4), 1–12.

Grace, K., Davenport, F., Funk, C., et al. (2012). Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya. *Applied Geography, 35*(1–2), 405–413. https://doi.org/10.1016/j.apgeog.2012.06.017, https://www.linkinghub.elsevier.com/retrieve/pii/S0143622812000768

Guiteras, R. (2009). *The impact of climate change on Indian agriculture*. Manuscript: Department of Economics, University of Maryland, College Park, Maryland.

Hengl, T. (2018a). Clay content in % (kg / kg) at 6 standard depths (0, 10, 30, 60, 100 and 200 cm) at 250 m resolution. https://doi.org/10.5281/zenodo.2525663

Hengl, T. (2018b). Sand content in % (kg / kg) at 6 standard depths (0, 10, 30, 60, 100 and 200 cm) at 250 m resolution. https://doi.org/10.5281/zenodo.2525662

Hengl, T. (2018c). Silt content in % (kg / kg) at 6 standard depths (0, 10, 30, 60, 100 and 200 cm) at 250 m resolution. https://doi.org/10.5281/zenodo.2525676

Hengl, T., & Wheeler, I. (2018). Soil organic carbon content in x 5 g / kg at 6 standard depths (0, 10, 30, 60, 100 and 200 cm) at 250 m resolution. https://doi.org/10.5281/zenodo.2525553, https://doi.org/10.5281/zenodo.2525553

Huang, J., Hartemink, A. E., & Kucharik, C. J. (2021). Soil-dependent responses of US crop yields to climate variability and depth to groundwater. *Agricultural Systems, 190*(103), 085. https://doi.org/10.1016/j.agsy.2021.103085, https://www.linkinghub.elsevier.com/retrieve/pii/S0308521X2100038X

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis, 20*(1), 1–24.

Kane, D. A., Bradford, M. A., Fuller, E., et al. (2021). Soil organic matter protects US maize yields and lowers crop insurance payouts under drought. *Environmental Research Letters, 16*(4), 044018.

Kim, K., & Bevis, L. (2019). Soil fertility and poverty in developing countries. *Choices, 34*(2), 1–8.

Kim, R., Bijral, A. S., Xu, Y., et al. (2021). Precision mapping child undernutrition for nearly 600,000 inhabited census villages in India. *Proceedings of the National Academy of Sciences, 118*(18), e2025865118. https://doi.org/10.1073/pnas.2025865118, http://www.pnas.org/lookup/doi/10.1073/pnas.2025865118

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *Science, 304*(5677), 1623–1627.
Lal, R. (2006). Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. *Land degradation & development, 17*(2), 197–209.
McMahon, K., & Gray, C. (2021). Climate change, social vulnerability and child nutrition in South Asia. *Global Environmental Change, 71*(102), 414.
Rani, S. I., Arulalan, T., George, J. P., et al. (2021). IMDAA: High-resolution satellite-era reanalysis for the Indian monsoon region. *Journal of Climate, 34*(12), 5109–5133.
Shah, M., & Steinberg, B. M. (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy, 125*(2), 527–561.
Singh, P., Dey, S., Chowdhury, S., et al. (2019). Early life exposure to outdoor air pollution: Effect on child health in India. Brookings India. http://hdl.handle.net/11540/9783
Victora, C. G. (1992). The association between wasting and stunting: An international perspective. *The Journal of nutrition, 122*(5), 1105–1110.
Viswanathan, B., & Kumar, K. K. (2015). Weather, agriculture and rural migration: Evidence from state and district level migration in India. *Environment and Development Economics, 20*(4), 469–492.
Webb, P., & Block, S. (2012). Support for agriculture during economic transformation: Impacts on poverty and undernutrition. Proceedings of the National Academy of Sciences 109(31):12,309–12,314. https://doi.org/10.1073/pnas.0913334108, http://www.pnas.org/cgi/doi/10.1073/pnas.0913334108
WHO. (2006). Reliability of anthropometric measurements in the WHO Multicentre Growth Reference Study. *Acta Paediatrica, 95*, 38–46.
Wiesmann, D. (2006). A global hunger index measurement concept, ranking of countries, and trends. FCND discussion paper ; 212, International food policy research institute (IFPRI). Food consumption and nutrition division (FCND), Washington, DC.
Zaveri, E., & Lobell, B. D. (2019). The role of irrigation in changing wheat yields and heat sensitivity in India. *Nature communications, 10*(1), 1–7.