Working paper

Impacts of droughts on undernutrition among children aged under five in Ethiopia

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Abstract

Chronic seasonal crop and livestock loss due to heat stress and rainfall shortages can pose a serious threat to human health, especially in Sub-Saharan Africa where subsistence and small-scale farming dominate. Young children are particularly susceptible to undernutrition when households experience food insecurity because nutritional deficiencies affect their growth and development. With crop yields projected to be affected by climate change, this can potentially pose serious health impacts on children. However, the evidence is inconclusive and rather limited to small-scale local contexts. Furthermore, little is known about the differential impacts of climatic shocks on health of population subgroups. This study aims to investigate the impacts of climate variability on child health using data from three nationwide Demographic and Health Surveys (DHS) for Ethiopia conducted in 2005, 2011 and 2016 (n=22,467). Undernutrition, measured as stunting, wasting and being underweight among children under five, is used as a health indicator. Climate variability is measured by the Standardized Precipitation Evapotranspiration Index (SPEI), a multi-scalar drought index. This study finds a negative association between SPEI and the risk of stunting and being underweight, especially for children exposed to droughts during the first two years of life. The climate impacts vary with population subgroups whereby boys and children whose mothers have no formal education are more vulnerable to drought exposure. Those living in the rural area and whose households are engaged in agricultural activities are also more likely to be affected. This suggests that nutritional intervention should target these particularly vulnerable groups of children.

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Introduction

Climate change poses serious risks to populations in Sub-Saharan Africa (SSA), mainly through undermining food security (Funk & Brown 2009; FAO, IFAD, UNICEF 2018). Over half of the population in the region is employed in the agricultural sector (World Bank 2020), which highly depends on seasonal rainfall. Rising temperatures and irregular rainfall patterns have increased the frequency of droughts in the region, putting a strain on food production (Vogel et al. 2019) and food prices, which in turn gives rise to human conflicts (Hsiang et al. 2013). According to recent estimates, world hunger has increased continuously since 2015, reaching 821 million people in 2018 (FAO, IFAD, UNICEF 2019). This trend has been most pronounced in Africa where nearly 20% of people were undernourished in 2018.

The increase in the frequency and intensity of extreme weather events has also raised concerns about its impacts on child undernutrition. Not only is undernutrition one of the main causes of death for children under five years of age (Caulfield et al. 2004; Black et al. 2008), it also affects growth and development and has long-term effects on health, wellbeing and labor market productivity in adulthood (Matrins et al. 2011; McGovern et al. 2017; Adair et al. 2013). Understanding to what extent and how climate change can impact child health is therefore of high policy relevance since childhood undernutrition can hinder a country's economic and social progress. Indeed, ending all forms of malnutrition is a top priority in the Sustainable Development Goals (SDGs) since it is key to the success of the entire sustainable development agenda.

One of the main channels through which climate shocks are expected to affect child nutrition is food security. All four dimension of food security – food availability, access, utilization and stability – can be affected by climatic shocks (FAO, IFAD, UNICEF 2018). Among all natural hazards, droughts are the most destructive for the agricultural sector and frequently contribute to food shortages in countries lacking the capacity to absorb such shocks (FAO 2018). Loss of agricultural income and a surge in food prices in turn reduce households' access to food. In fact, exposure to high temperatures and rainfall shortages during pregnancy have been linked to lower birthweight and higher risk of pre-term birth (Bakhtsiyarava et al. 2018; Grace et al. 2015), both of which increase the risk of childhood undernutrition (Ntenda 2019; Rahman et al. 2016; Akombi et al. 2017). Likewise, household food insecurity can affect infants' and young children's feeding practices, for example by reducing diet quality and diversity. In can also exacerbate existing inequalities within the household, such as the intra-household nutrient allocation according to child gender and birth order preference. Climate-induced reduction in crop yields can also bring about social unrest and conflict (Hsiang et al. 2013), which in turn affects food access and stability (Martin-Shields & Stojetz 2018). All of these channels can negatively impact children's health and nutrition status.

Another channel through which climate shocks can affect child undernutrition are infectious diseases. During droughts, consumption of unsafe water is likely to increase, leading to higher incidence of water-borne illnesses (Westerhoff & Smit 2009). Diarrhea is one such disease which can severely affect young children, causing acute weight loss and even death (Caulfield et al. 2004; Prüss-Ustün et al. 2014). Indeed, research shows that rainfall shortages and increased monthly maximum temperature in SSA are associated with increased risk of diarrhea in young children under the age of three (Bandyopadhyay et al. 2012; Epstein et al. 2020). Furthermore, households struggling with reduced agricultural income during droughts are likely to cut expenditure on non-food items (Mehar et al. 2016), which can include spending on health-care and children's immunization. This further increases the risk of disease outbreaks.

Regardless of climate change, as many as 38% of children in Ethiopia are stunted (being too short for their age) and 10% suffer from wasting (too light for their height) (Tekile et al. 2019). These are some of the highest levels observed worldwide (UNICEF et al. 2019). A systematic review and meta-analysis of 18 studies on undernutrition in Ethiopia has reported an upward trend in the prevalence of stunting in recent years (2010-2014) with respect to the earlier period (1996-2010) (Abdulahi et al. 2017). Indeed, climatic factors may have played a role in reversing progress towards reducing the levels of childhood undernutrition in Ethiopia, given that the country has experienced a series of severe droughts in recent years (Liou & Mulualem 2019; Funk et al. 2015). In 2015, parts of northern and central Ethiopia were affected by the worst drought in decades (Philip et al. 2018). In response, the government called for emergency assistance for 10.2 million people (USAID 2016). Climate projections for Ethiopia show a further reduction in rainfall and temperature increase until the end of the century (Teshome & Zhang 2019), which will put additional pressure on food production. These trends are alarming. Not only is the country prone to droughts, but the high dependence on subsistence farming coupled with outdated agricultural technology means climatic conditions are vital for livelihoods and well-being (World Food Programme 2019). It is therefore important to understand to what extend climate change will affect child health in order to design and implement early interventions.

A few studies have identified a link between climatic conditions and childhood undernutrition in low- and middle-income countries. Generally, deficient rainfall has been associated with an increased risk of undernutrition among young children in drought-prone areas of SSA (Rabassa et al. 2014; Hoddinott & Kinsey 2001; Woldehanna 2009; Chotard et al. 2010). Exposure to droughts seems to be particularly detrimental to child health in this region because of poverty, conflict and poor governance, which reduce the capabilities to cope with drought impacts. Outside SSA, the evidence is limited and mostly constrained to South Asia (Kumar et al. 2016; Singh et al. 2006; Maccini & Yang 2009).

With respect to Ethiopia, the evidence is mixed. A study focusing on a cohort of school age children found that concurrent and long-term exposure to droughts was associated with a reduced child growth potential (Bahru et al. 2019). The effects of droughts can be long-lasting: children exposed to a drought at age 5 were still significantly shorter than their peers who did not get exposed to a drought when measured at age 12. The study also reported that participation in a safety net program lessened but did not eliminate the negative effect of droughts on child growth. An earlier study using nationally representative data for Ethiopia found that crop damage due to droughts reduced child growth substantially but food aid played a protective role in communities that received such assistance (Yamano et al. 2005).

Other studies, however, did not find a conclusive evidence that droughts affect child undernutrition in Ethiopia (Ledlie et al. 2018; Delbiso et al. 2017; Hirvonen et al. 2018). One study, which used macro-level data by agro-ecological zone in Ethiopia, even reported that above average rainfall increased child stunting (Hagos et al. 2014). Indeed, a number of studies have found a link between exposure to excessive rainfall and child undernutrition, possibly due to the increase in vector- and water-borne illnesses and damages caused by floods (Alderman et al. 2012). A recent study of 53 developing countries found a strong association between rainfall extremes (both above and below the norm) and child undernutrition (Cooper et al. 2019).

There remains limited reliable evidence and robust study designs on the impacts of extreme climate events on child undernutrition (Phalkey et al. 2015; Belesova et al. 2019). Most studies focus on small-scale local context, fail to report data quality control procedures and represent shortcomings in the climate exposure assessment methods, e.g. lack of a clear drought definition and direct measures of drought. The lack of nationally representative study further makes it difficult to assess the extent to which climate change affects child undernutrition.

To this end, this study aims to explore the impacts of droughts on the nutrition status of children aged under five in Ethiopia using the nationally representative data obtained from three rounds of the Demographic and Health Surveys (DHS) for Ethiopia. Child undernutrition is measured as stunting, wasting and being underweight. To measure climatic conditions, gridded climate data was used and an index for droughts was constructed based on a widely accepted indicator, which is a major improvement to previous studies.

This study additionally considers differential vulnerability (Muttarak et al. 2016), investigating the extent to which droughts affect the health outcome of children of different demographic and socioeconomic groups. The degree to which climate shocks affect human health depends not only on the level of exposure to such shocks but also on the underlying level of vulnerability (Stanke et al. 2013). Understanding which population subgroups are particularly vulnerable to climactic shocks allow for policy planning to identify target areas for intervention. Despite that, few studies have investigated such inequalities in climate-induced undernutrition, possibly due to small sample sizes.

Moreover, the study pinpoints critical periods of children's life when exposure to climatic shocks can be most detrimental to their physical development. To model the effects of droughts on the risk of stunting, for example, exposure was considered at each age of the child's life and also climatic conditions were aggregated over their observed lifetime. For wasting, the focus was on the latest agricultural season, since a more immediate effect of droughts is expected.

The rest of this paper is organized as follows: Section 2 describes the data and methods employed in the study. Section 3 presents the results of multivariate regression models. Section 4 provides a discussion of the main findings and concludes.

Data and methods

Two datasets are used to assess the impacts of droughts on the nutrition status of children: 1) multiple rounds of Demographic and Health Surveys for Ethiopia and 2) gridded climate data from the Climatic Research Unit (CRU) at the University of East Anglia.

Demographic and health data

The DHS surveys are repeated cross-sectional surveys conducted in over 90 low- and middle-income countries. Based on nationally representative samples of households and women of reproductive age (15-49 years), DHS surveys are an important source of data on health and demographic behavior, including fertility, infant and child mortality, child and reproductive health, nutrition status, family planning and other health-related issues. The surveys also include socioeconomic information such as education level of household members, household wealth, place of residence, and occupation. For the purpose of this analysis, three survey rounds of DHS Ethiopia are merged – 2005, 2011 and 2016, with a combined sample size of 31,096 children under the age of five. The selected DHS rounds also include GPS coordinates of household clusters,[1] which are used to link the DHS surveys with the gridded climate data (see Section 2.2).

To measure child undernutrition, I use anthropometric data for children aged under five and construct indicators for stunting, wasting and being underweight as binary outcome variables. Stunting refers to children with a low height-for-age (HAZ) defined as below -2 standard deviations (SD) of the WHO Child Growth Standards median (de Onis 2007). Wasting and underweight refer to children with a low weight-for-height (WHZ) and weight-for-age (WAZ), respectively, both defined as below -2 SD of the WHO Child Growth

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[1] Household clusters are enumeration areas used in DHS, which usually refer to villages in rural areas and city blocks in urban areas.

Standards median. Observations were dropped if the anthropometric scores were less than -6 or above 6, which are due to errors in the recording. In total, 22,467 observations are left with available data for at least one of the three indicators for undernutrition.

Stunting captures the cumulative effects of undernutrition (chronic malnutrition) while wasting indicates acute weight loss caused by low food intake or presence of diseases (WHO 2010). Children suffering from wasting have an increased risk of mortality. Being underweight can indicate both acute and chronic malnutrition; It is often used in combination with the above measures as an operational indicator. Figure S1 in the Appendix shows the distribution of HAZ, WAZ and WHZ z-scores for the sample population from each DHS round included in the study (2005, 2011 and 2016). Overall, 40% of children in the sample are stunted, 12% are wasted and 28% are underweight. No notable reduction in all three forms of undernutrition can be seen between 2005 and 2016.

Climate data

Gridded climate data on monthly precipitation and evapotranspiration are retrieved from the Climatic Research Unit at the University of East Anglia (time series 3.25). The data are available at 0.5° spatial resolution for the whole globe and cover the periods from 1901 to 2016 (Harris et al. 2014). The R package 'SPEI' is used to generate monthly values for Standardized Precipitation Evapotranspiration Index (SPEI) based on the input CRU data.

SPEI measures the intensity and spatial distribution of droughts. It is considered superior to other drought indices (such as the SPI) since it captures the effects of evaporation and transpiration caused by temperature, along with precipitation (Vicente-Serrano et al. 2010). Additionally, SPEI can be calculated at different time scales (from 1 to 48 months) to account for the cumulative effect of deficient precipitation and/or excessive evapotranspiration over the previous periods. In this analysis, I use a 3-month time scale, which has been found to detect drought conditions in the Sahel region more accurately than longer time scales (Beguería et al. 2010).

SPEI is measured on an intensity scale with both negative values, indicating drought conditions, and positive values, indicating wet conditions. The index can be used to further categorize droughts into mild ($-1 < \text{SPEI} < 0$), moderate ($-1.5 < \text{SPEI} \leq -1$), severe ($-2 < \text{SPEI} \leq -1.5$), and extreme ($\text{SPEI} \leq -2$) (Mckee et al. 1993; Paulo & Pereira 2006).

Figure 1 shows the climatic conditions in Ethiopia for the period 2000-2016. The country lies in the tropical zone but geographical variations in temperature and precipitation can be observe due to varying elevation levels. The Ethiopian highlands are characterized by temperate climate, while the lowlands are hot and dry. Pronounced temperature increases can be observed in the last five decades (Figure 2, left panel) corresponding to the global temperature rise (IPCC 2018). No clear trend in precipitation and SPEI change can be observed in the same time period (Figure 2, center and right panels).

Figure 1. Annual mean temperature (left), annual total precipitation (center) and annual minimum 3-month SPEI (right) at 0.5° spatial resolution, Ethiopia, 2000-2016. Own estimates based on CRU TS 3.25 data.

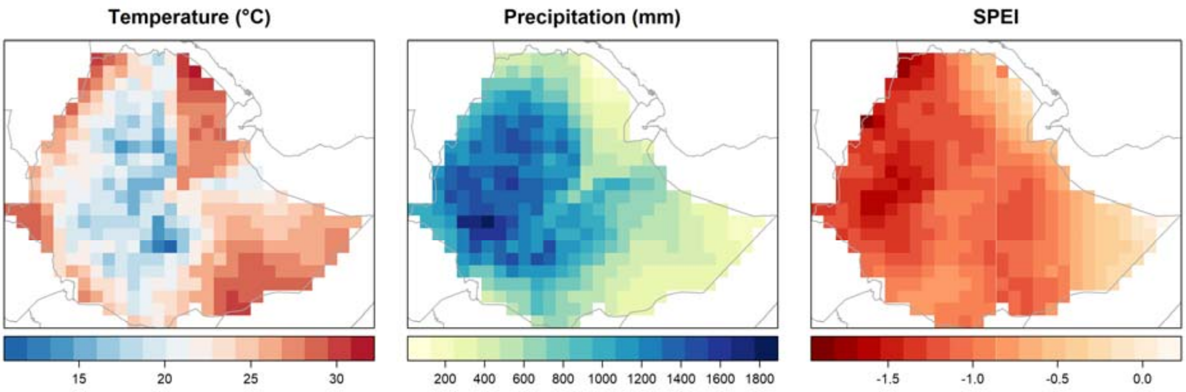
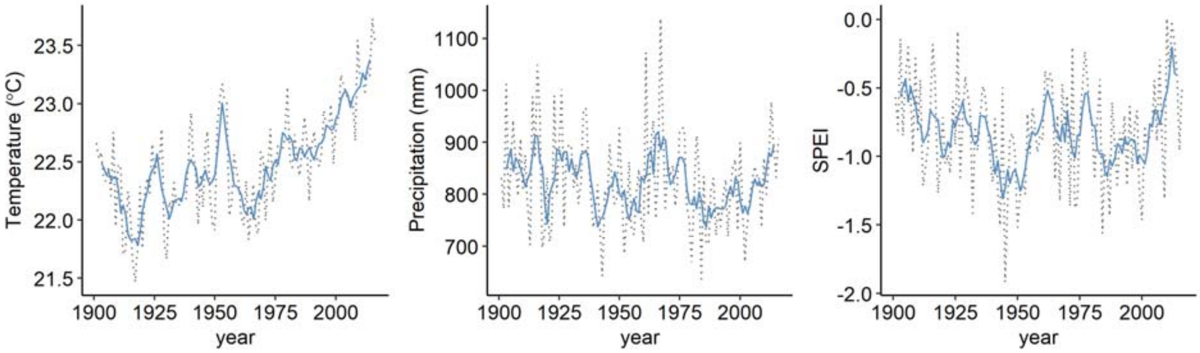


Figure 2. Country average of annual mean temperature (left), annual total precipitation (center) and annual minimum 3-month SPEI (right). Own estimates based on CRU TS 3.25 data. Dashed grey lines indicate yearly values and solid blue lines indicate five-year running means.



For the purpose of this analysis, SPEI data is restricted to the summer season only (months June to September), which is the main growing season for agricultural crops in Ethiopia. 60–80% of annual rainfall is received during this short period of time (Liou & Mulualem 2019). Deficient and/or delayed rainfall during the summer season impacts both crop and livestock production. It can indirectly affect human health through reduced food intake and lower the availability and quality of drinking water.

Once the SPEI data is restricted to the summer months, I generate seasonal averages for each grid-cell based on the monthly SPEI values. To link the DHS and climate data, I use information on the geographical location of household clusters which are available in recent DHS rounds. Figure S2 in the Appendix shows the GPS locations of household clusters in the three DHS rounds. To keep the identity of survey participants confidential, DHS displaces household clusters in a random direction by 2km for urban areas, 5km for rural areas, and additional 10km for 5% of all clusters (Burgert et al. 2013). I account for this by creating a 10km radius around each cluster and averaging the climate information for all grid cells that fall within that area. The 10km buffer also accounts for the fact that household may be affected not only by climate conditions in their immediate location but also in nearby locations, for example if household members travel some distance to farm or collect water.

Estimation strategy

A logistic regression models is used to quantify the impact of climatic shocks on child nutrition status. The regression analysis is run separately for each outcome variable: stunting, wasting and being underweight. The basic model takes the following form:

$$y_{i,g} = \beta_1 clim_{t,g} + \delta Z_i + f(a_6, a_{12}, a_{18}, a_{24}, a_{36}, a_{48})_i + \alpha_g + \epsilon_{i,g}$$

where $y_{i,g}$ takes the value 1 if child i in grid-cell g is stunted, wasted or underweight, respectively, and 0 otherwise. $clim_{t,g}$ is the climate condition in the period of exposure t in grid-cell g. Z is a column vector of individual, maternal and household variables which are expected to affect a child's nutrition status. The function $f(\cdot)$ is a restricted cubic age spline with knots at 6, 12, 18, 24, 36, and 48 months of age at interview. The spline function fits polynomials of degree 3 between the defined knots in a way which ensures that levels and derivatives are equal on each side, and quadratic terms at each end. α_g are grid fixed effects which control for location-specific time-invariant factors. Errors are clustered at the grid-cell level.

The following variables are included in the column vector Z: sex of the child, whether the child is a twin, birth order, highest level of education of the mother (no education, primary, secondary, and higher), mother's age at giving birth, mother's height, household wealth quintile, sex of the household head, place of residence (urban or rural), and occupation of the household head (agriculture, non-agriculture, not working, and other). I additionally control for seasonality by including fixed effects for quarter of birth and a quarter of interview (January to March, April to June, July to September, and October to December). Survey fixed effects are also included (2005, 2011, and 2016) to account for time-trending factors.

To model the effects of climatic shocks on child stunting, I look at exposure at each age, starting from birth until the age at interview. SPEI values are also averaged within the whole time period to observe the impact of repeated exposure to climatic shocks. For wasting, I consider exposure to climatic shocks during the latest agricultural season prior to the interview because wasting is characterized by a rapid deterioration in nutrition status as an immediate response to droughts (see Figure 3). For underweight, both long-term (from birth until age at interview) and short-term (latest agricultural season) exposure to climatic shocks is considered. Table 1 presents the variable descriptive statistics.

Figure 3. Critical periods of exposure to climate shocks in early childhood

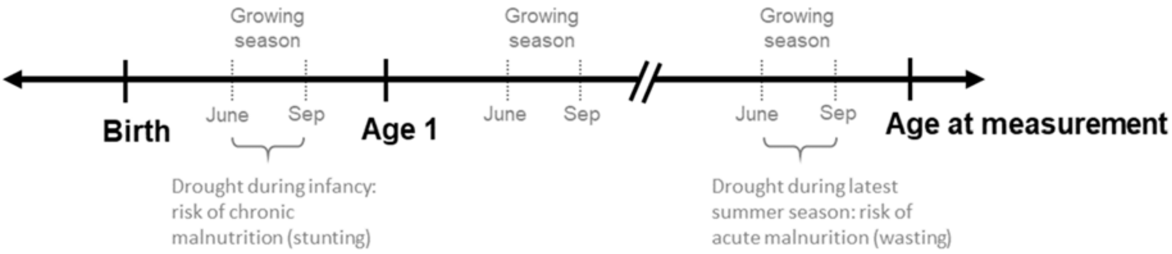


Table 1. Descriptive statistics

Variable	Unit	Mean	Std. Dev.
Outcome variables			
Stunted	0/1	0.4	
Wasted	0/1	0.12	
Underweight	0/1	0.28	
Climate variables			
Average SPEI since birth	SPEI units	-0.02	0.44
SPEI latest summer season	SPEI units	0.10	0.59
Drought in infancy (SPEI ≤ -1)	0/1	0.04	
Drought latest summer season (SPEI ≤ -1)	0/1	0.05	
Individual characteristics			
Sex			
Female	0/1	0.51	
Male	0/1	0.49	
Twin			
No	0/1	0.98	
Yes	0/1	0.02	
Birth order	number	3.92	2.54
Maternal characteristics			
Age at giving birth	years	27.24	6.50
Height	cm	157.57	6.67
Education			
No	0/1	0.67	
Primary	0/1	0.24	
Secondary	0/1	0.05	
Higher	0/1	0.02	
Household characteristics			
Wealth			
Bottom quintile	0/1	0.31	
2nd quintile	0/1	0.18	
3rd quintile	0/1	0.16	
4th quintile	0/1	0.15	
Top quintile	0/1	0.19	
Household head			
Male	0/1	0.82	
Female	0/1	0.18	
Residence			
Urban	0/1	0.16	
Rural	0/1	0.84	
Occupation			
Non-agricultural	0/1	0.23	
Agricultural	0/1	0.61	
Not working	0/1	0.13	
Other	0/1	0.03	

Note: DHS 2005, 2011 and 2016 combined sample.

Additionally, potential differential vulnerabilities across population subgroups are investigated by including an interaction term between the climate variable and a categorical variable D_i, which captures certain individual and socio-demographic characteristics of the child. The model with interaction term takes the following form:

$$y_{i,g} = \beta_1 clim_{t,g} + \beta_2\left(clim_{t,g} * D_i\right) + \gamma D_i + \delta Z_i + f(\mathrm{a}_6, \mathrm{a}_{12}, \mathrm{a}_{18}, \mathrm{a}_{24}, \mathrm{a}_{36}, \mathrm{a}_{48})_i + \alpha_g + \epsilon_{i,g}$$

Population subgroups are distinguished by child's sex, mother's level of education, and household's wealth, place of residence and occupation. Mother's level of education and household's wealth status are combined into a single four-level variable, which allows us to detect an interaction effect between the two variables. The following categories are created: "uneducated and poor," which includes children whose mothers have not completed primary education and whose households are in the lowest two income quintiles; "educated and poor", including children whose mothers have completed primary education or higher, and whose households are in the lower two income quintiles; "uneducated and poor", including children whose mothers have not completed primary education and whose households are in the upper three income quintiles; and "educated and rich", including children whose mothers have at least primary level of education and whose households are in the upper three income quintiles.

Table 2. Share of stunted, wasted and underweight children by individual and socio-economic characteristics, children age 0-5

	Number of observations*	Nutrition status		
		% stunted	% wasted	% underweight
Sex of child				
Male	11,084	44.66	11.35	29.52
Female	10,737	39.97	9.51	25.97
Education and wealth group				
Uneducated & poor	11,502	46.21	12.6	32.6
Educated & poor	2,940	42.65	10.06	25.58
Uneducated & rich	3,477	42.25	7.72	25.82
Educated & rich	3,902	30.01	6.71	16.15
Residence and occupation group				
Rural & non-agriculture	2,541	40.97	7.99	23.83
Rural & not working	2,689	41.35	10.24	28.13
Rural & agriculture	13,110	44.66	11.36	30.15
Urban & non-agriculture	2,482	27.21	7.45	14.13
Urban & not working/other	999	34.68	6.22	19.09

Notes: Number of observations may vary due to few missing observations for stunting, wasting and being underweight. Sampling weights are applied for the calculation of stunting, wasting and underweight prevalence. Percentage shares are based on combined samples from 2005, 2011 and 2016 DHS surveys. Education group refers to the mother's level of education and wealth group refers to household's wealth quintile.

Similarly, household's place of residence and occupation of the household head are combined into a single variable, allowing us to pinpoint potential population subgroups most vulnerable to climatic shocks, such as rural households working in the agricultural sector. Previous studies point that the socioeconomic impacts of climate change are most pronounced among those who rely on natural resources for their livelihoods, such as the agricultural rural households. Since only a small number of households in urban areas are employed in the agricultural sector (<300 obs.), this group is combined with "urban not working" households.

In Table 2, we can see large differences in stunting prevalence by residence and occupation group. Among rural households employed in the agricultural sector, nearly half of children are stunted (45%), as compared to 27% among urban households employed in non-agricultural activities. Similar trends can be seen for wasting and being underweight. Indeed, a high share of rural households in Ethiopia are subsistence farmers and are therefore most vulnerable to climatic shocks. The results of the regression analysis are presented in the next section.

Results

Main results

Tables 3 and 4 present regression estimates of the odds of stunting, wasting and being underweight for children aged under five. We can see that for every one unit increase in the SPEI index during the observed lifetime, the odds of a child being stunted and underweight are reduced by 22% (0.1% significance level) and 16% (1% significance level), respectively. This is not a trivial effect. As can be seen in Table 3, one unit increase in the SPEI index has the same effect on the risk of stunting as moving children from the lowest to the third highest wealth category. SPEI increase during the latest summer season does not seem to affect the risk wasting or being underweight (Table 4).

The control variables included in the regression analysis show significant effects in the expected direction: girls are on average less likely to be stunted, wasted and underweight than boys, which has been previously pointed in the literature in the context of SSA (Wamani et al. 2007). Higher birth order and having a twin are associated with an increased risk of undernutrition. Better education of the mother and a higher wealth status are both associated with a reduced risk of undernutrition. Additionally, children whose parents are employed in the agricultural sector are more likely to be wasted and underweight compared to those employed in a non-agricultural sector.

Potential non-linear effects of SPEI on child undernutrition are also investigated. For this purpose, a restricted cubic spline transformation of the SPEI index is applied with knots at -1, 0 and 1 standard deviation. Figure 4 shows the predicted probabilities of stunting (left panel) and being underweight (right panel) at different levels of SPEI derived from the non-linear model. The results show that children who have been continuously exposed to dry weather (SPEI < -1) are considerably more likely to be stunted and underweight; the percentage of stunted children increases from 49% at SPEI 0 to 73% at SPEI -2, holding other variables constant. Likewise, the percentage of underweight children increases from 39% at SPEI 0 to 58% at SPEI -2. We can also see a slight increase in the percentage of stunted and underweight children at moderately wet values of SPEI (≥ 1) as well, possibly due to the transmission infectious diseases in humid conditions, however the effects are not statistically significant. The results suggest that exposure to droughts poses a significant risk of chronic malnutrition to young children.

Table 3. Effects of summer season SPEI during the observed lifetime on stunting and being underweight, children age 0-5

	(1) stunted		(2) underweight	
average SPEI since birth	0.78***	(0.06)	0.84**	(0.05)
Individual characteristics				
Sex (ref.=male)	0.85***	(0.03)	0.85***	(0.03)
female				
Twin (ref.=no)	1.98***	(0.26)	2.09***	(0.28)
yes				
Birth order	1.05***	(0.01)	1.05***	(0.01)
Maternal characteristics				
Age at giving birth	0.98***	(0.00)	0.98**	(0.00)
Height	0.95***	(0.00)	0.96***	(0.00)
Education (ref.=no)				
primary	0.93	(0.05)	0.84***	(0.04)
secondary	0.65***	(0.07)	0.60***	(0.09)
higher	0.53**	(0.11)	0.32***	(0.07)
Household characteristics				
Wealth (ref.=bottom quintile)				
2nd quintile	0.92⁺	(0.05)	0.89*	(0.05)
3rd quintile	0.80***	(0.05)	0.75***	(0.04)
4th quintile	0.73***	(0.05)	0.59***	(0.04)
top quintile	0.50***	(0.05)	0.49***	(0.05)
Household head (ref.=male)				
female	1.14*	(0.07)	1.12*	(0.07)
Residence (ref.=urban)				
rural	1.15	(0.14)	1.16	(0.16)
Occupation (ref.=non-agri.)				
agricultural	1.05	(0.06)	1.16*	(0.07)
not working	0.98	(0.07)	1.07	(0.08)
other	1.01	(0.13)	1.19	(0.16)
Age splines	YES		YES	
Grid-cell FEs	YES		YES	
Survey FEs	YES		YES	
Quarter of birth Fes	YES		YES	
Quarter of interview FEs	YES		YES	
Obs.	18,503		18,897	
Pseudo R^2	0.118		0.093	

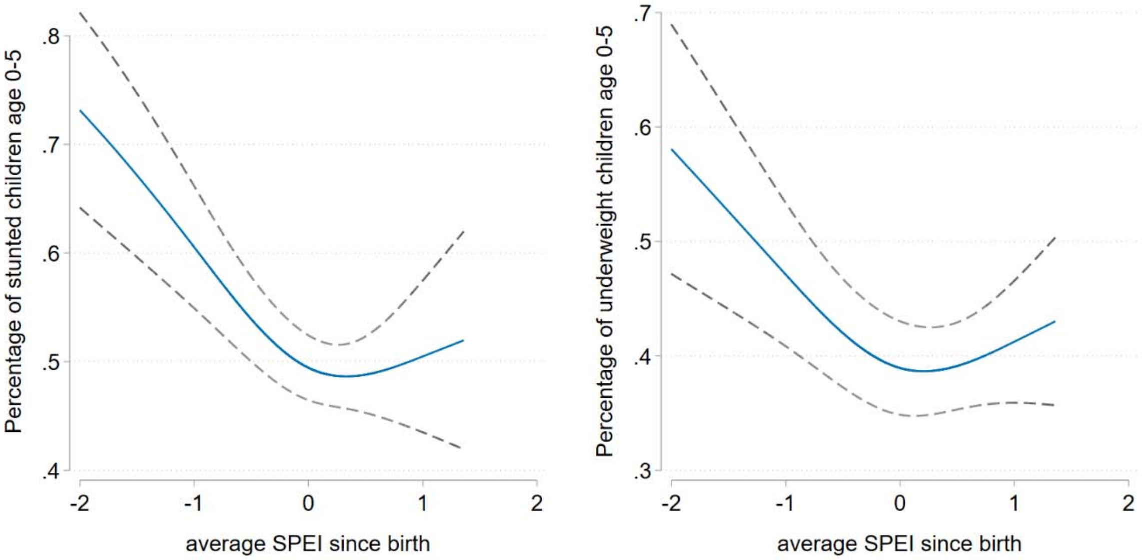
Notes: ⁺p<0.1, **p* <0.05, ***p* <0.01, ****p* <0.001. Robust standard errors reported in parenthesis. Standard errors are clustered at the grid-cell level.

Table 4. Effects of SPEI in the latest summer season before measurement on wasting and being underweight, children age 0-5

	(1) wasted		(2) underweight	
SPEI latest summer	0.97	(0.06)	0.92	(0.05)
Individual characteristics				
Sex (ref.=male)				
female	0.79***	(0.03)	0.85***	(0.03)
Twin (ref.=no)				
Yes	1.51**	(0.22)	2.30***	(0.3)
Birth order	1.03$^+$	(0.02)	1.04*	(0.01)
Maternal characteristics				
Age at giving birth	0.99	(0.01)	0.99*	(0.00)
Height	0.99	(0.00)	0.96***	(0.00)
Education (ref.=no)				
primary	0.86**	(0.05)	0.84***	(0.04)
secondary	0.64**	(0.1)	0.57***	(0.08)
higher	0.61**	(0.1)	0.35***	(0.07)
Household characteristics				
Wealth (ref.=bottom quintile)				
2nd quintile	0.96	(0.06)	0.89*	(0.04)
3rd quintile	0.92	(0.07)	0.75***	(0.04)
4th quintile	0.70***	(0.05)	0.60***	(0.04)
top quintile	0.59***	(0.06)	0.50***	(0.05)
Household head (ref.=male)				
female	1.16*	(0.08)	1.09	(0.06)
Residence (ref.=urban)				
rural	0.75*	(0.09)	1.14	(0.15)
Occupation (ref.=non-agri.)				
agricultural	1.20*	(0.09)	1.11$^+$	(0.06)
not working	1.07	(0.08)	1.04	(0.07)
other	1.03	(0.16)	1.21	(0.17)
Age splines	YES		YES	
Grid-cell FEs	YES		YES	
Survey FEs	YES		YES	
Quarter of birth FEs	YES		YES	
Quarter of interview FEs	YES		YES	
Obs.	21,409		22,150	
Pseudo R^2	0.076		0.107	

Notes: $^+p<0.1$, $*p<0.05$, $**p<0.01$, $***p<0.001$. Robust standard errors reported in parenthesis. Standard errors are clustered at the grid-cell level.

Figure 4. Impacts of summer season SPEI on stunting and being underweight. Figures show predicted probabilities and 95% CIs. Model specification: same as Table 3. Results tables are available in Table S1 Appendix B.



A a number of robustness checks were performed to eliminate potential biases in the sample composition and model specification. Since climate conditions are back tracked up to five years before children's anthropometric measures were taken, the location of children at the time of exposure may be different from their location at the time of measurement. To account for this, children are excluded from the sample if they are not usual residents in the place where the interview took place, and additionally children are excluded if their households have lived less than five years at the current location. Finally, a control variable for low birthweight is included in the model. It was not included in the main model specification since it was expected that birthweight correlates with past climatic conditions. The alternative specifications did not change the baseline results presented above (See Appendix C).

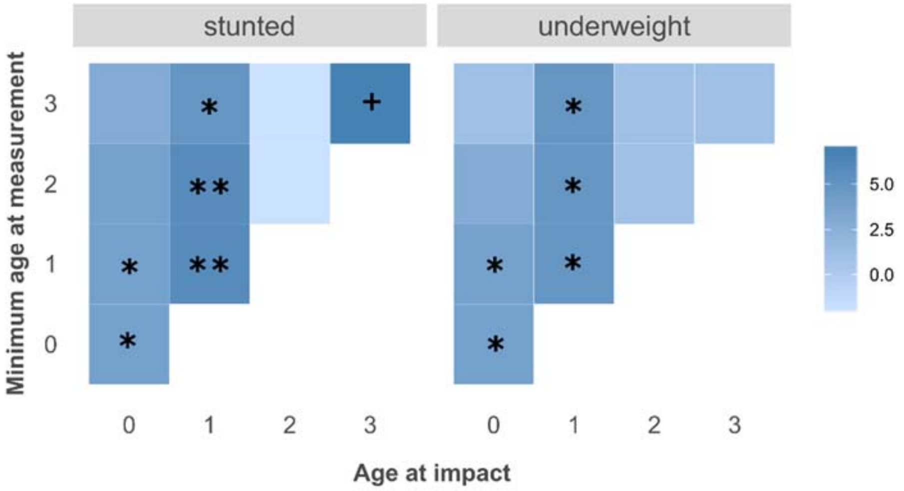
One disadvantage of averaging climate conditions over the child's observed lifetime is that extreme SPEI values would be smoothed out. For example, a child who has been exposed to a severe drought, followed by a few years of neutral or positive SPEI shocks, would receive the same SPEI score as a child who has been repeatedly exposed to mild droughts. To address this issue, a separate regression analysis is performed for each period of exposure to climate shocks, starting from the year of birth until the year of measurement. This approach also allows us to identify which periods of a child's life are most critical for their physical development. In each period of exposure, climate conditions are classified as droughts if SPEI ≤ -1, and non-droughts otherwise.

In Figure 5, the x-axis shows the age at impact, meaning the age at which the child was exposed to a drought. The y-axis shows the minimum age at which the child was measured until five years of age. For example, a minimum age at measurement 3 means that the sample was restricted to children aged 3 to 5. Each rectangle represents a separate regression model with a specified age at impact and minimum age at measurement. The figure shows predicted changes in stunting prevalence due to a drought.

The results shown in Figure 5 indicate that droughts are most critical to children's physical development during the first two years of life. A drought experienced in infancy (between age 0 and 1) increases the share of stunted children aged 0-5 and 1-5 by 4 percentage points (5% significance level), other variables held constant. Similarly, a drought at age 1 increases the share of stunted children aged 1-5 and 2-5 by 6 percentage points (1% significance level). At age 3 and above, the share of stunted children is still 5 percentage points higher (at 5% significance) if they have been exposed to a drought at age 1. This implies that the effect of a drought can be long lasting. Similar results are found for the risk of being underweight (Figure 5, right panel). No significant association is found between exposure to droughts at a later age (beyond age 1) and the risk of stunting and being underweight.

The above results suggest a persistent effect of droughts on child undernutrition. A drought in early childhood is still associated with an increased risk of stunting two or more years after the exposure. This means that early interventions would be critical for reducing the burden of malnutrition in drought affected areas. It is also interesting to note that the effect of a drought experienced in infancy (age 0) seems to reduce over time, particularly beyond age 1. Once the child reaches age 2, the disadvantage in their height seems to disappear. One explanation for this is that children catch up with their peers as they get older. There is indeed some evidence which shows that "catch-up" growth can occur (Desmond & Casale 2017; Adair 1999). Another possibility is selective survival: children who are severely stunted at this early age are more likely to die and therefore drop from the sample. If this is the case, the remaining healthier children would bias the results. To determine whether these effects are driven by "catch-up" growth or selective survival would require the use of panel data.

Figure 5. Impacts of droughts on stunting (left) and being underweight (right) in percentage points by age at exposure and minimum age at measurement



Notes: The figure shows average marginal effects (AME) based on logistic regression models calculated separately for each minimum each age at measurement and age at exposure. Droughts are defined as SPEI ≤ -1 at each period of exposure. Model specification: same as Table 3. Results tables are available in Tables S2 and S3 in Appendix B. $^+$p<0.1, *p <0.05, **p <0.01.

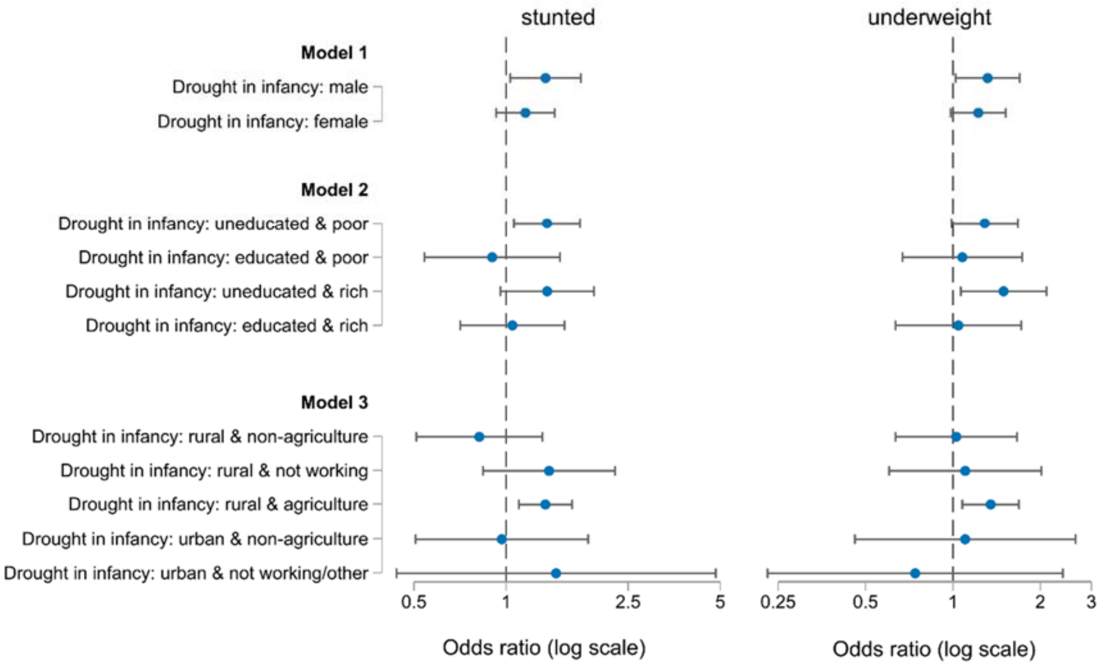
Differential vulnerabilities

In the following analysis, the baseline model is extended by including an interaction term between the climate measure and a vector of individual and socio-demographic variables. Above, I identified that exposure to droughts in the first two years of life is most critical to children's physical development, therefore, I chose to focus on this early life period in the following analysis. In order to maximize the sample size, I model the effect of a drought exposure during infancy (age 0) on the risk of stunting and being underweight. To capture short-term effects, I also look at the impact of a drought exposure in the latest summer season before measurement on the risk of wasting and being underweight.

Figures 6 and 7 show the results of the models with an interaction term. First of all, notable gender differences in climate-related vulnerability can be seen: droughts experienced in infancy are associated with an increased risk of stunting and being underweight for boys, while no significant effects for girls are found (Figures 6, Model 1). Likewise, exposure to droughts in the latest summer season is associated with an increased risk of wasting for boys but not for girls (Figure 7, Model 1). The risk of being underweight due to short-term drought exposure is increased for both sexes, however, the effect is more pronounced for boys. Second, the results show that children born to uneducated mothers, regardless of the family's wealth status, are more susceptible to stunting and being underweight due to droughts than children born to educated mothers (Figures 6 and 7, Model 2). Among children whose mothers have at least primary level of education, the impact of droughts on undernutrition is not statistically significant. Interestingly, higher wealth status does not seem to provide the same level of protection as education. Children born in wealthy households but to uneducated mothers are 50% more likely to be underweight (5% significance level) if they have experienced a drought during infancy and 93% more likely to be underweight (1 % significance level) if they have experienced a drought in the latest summer season. Regarding the risk of wasting, no statistically significant effects of droughts are found in either of the education-wealth groups.

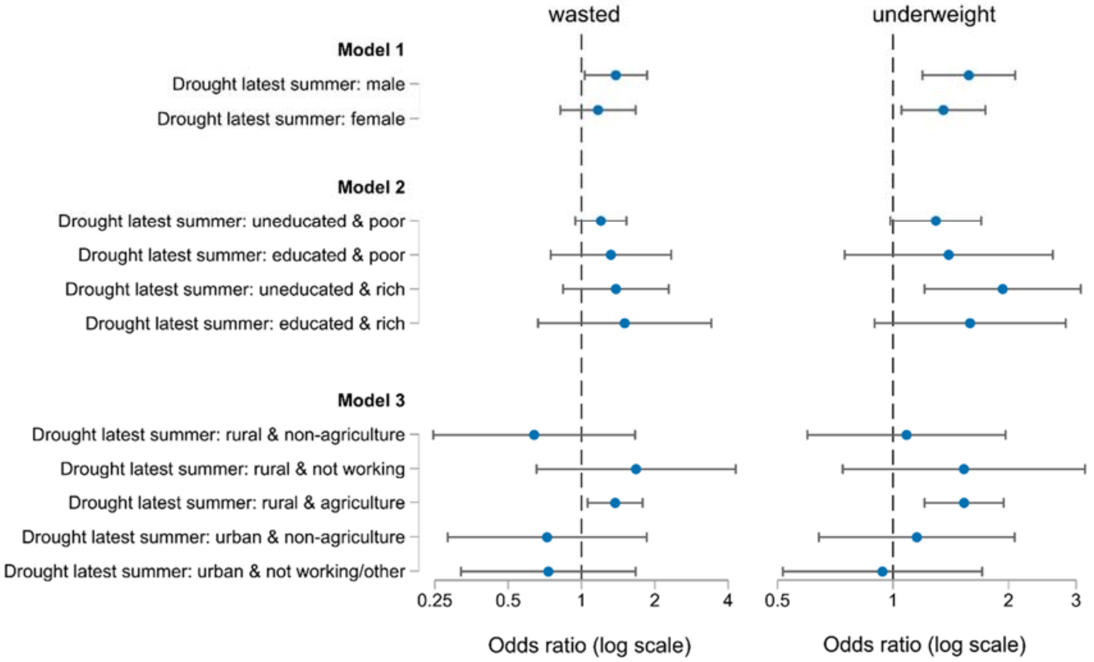
The third finding concerning differential vulnerabilities to droughts is shown in Figures 6 and 7, Model 3. It can be observed that children living in rural areas whose households are employed in the agricultural sector are highly susceptible to droughts. The risk of stunting, wasting and being underweight for this group of children increases by more than 30% after drought exposure. In contrast, no significant effects are found for children residing in urban areas and/or children whose parents are not engaged in the agricultural sector.

Figure 6. Interaction effects between summer drought in infancy and individual and household characteristics



Notes: Models 1 to 3 show the results of separate logistic regression models. Odds ratios are displayed on a log scale. The blue dot represents the odds ratio. Error bars represent the 95% confidence interval. The coefficients are interaction terms between summer season drought and population subgroups. Control variables included but not displayed: same as Table 3. Results tables are available in Tables S4 and S5 in Appendix B.

Figure 7. Interaction effects between drought during the latest summer season before measurement and individual and household characteristics



Notes: Models 1 to 3 show the results of separate logistic regression models. Odds ratios are displayed on a log scale. The blue dot represents the odds ratio. Error bars represent the 95% confidence interval. The coefficients are interaction terms of summer season drought and population subgroups. Control variables included but not displayed: same as Table 3. Results tables are available in Tables S6 and S7 in Appendix B.

Discussion and conclusions

I used nationally representative survey data for Ethiopia in combination with gridded climate data to assess the link between climate shocks and child undernutrition. A measure of droughts is constructed based on the Standardized Precipitation and Evapotranspiration Index, which measures both the intensity and spatial distribution of droughts.

The results show that exposure to droughts increases the likelihood of undernutrition among children aged under five in Ethiopia. Children who were exposed to a drought during the first two years of life are particularly vulnerable to stunting and being underweight. Indeed, the first 24 months of age are critical for children's physical development (Black et al. 2008; Victora et al. 2010); Poor diet and presence of infectious diseases during this early period can impair children's growth and development, causing irreversible damage for the rest of their life (de Onis 2017).

Overall, the findings of this study are in line with previous research, which has found a negative effect of droughts on child nutrition in SSA (Rabassa et al. 2014; Hoddinott & Kinsey 2001; Woldehanna 2009; Chotard et al. 2010; Cooper et al. 2019). Hence, protecting children's health in the region is likely to become increasingly more challenging, given that the incidence of droughts is projected to increase in the coming decades (Teshome & Zhang 2019). It is therefore important to understand which groups of children are most vulnerable to climatic shocks in order to allocate limited resources more effectively.

Following the so called demographic differential vulnerability approach (Muttarak et al. 2016), I have managed to pinpoint several population sub-groups which have higher degree of vulnerability. First, boys are more likely to be undernourished compared to girls both in normal time and time of droughts. These findings are in line with previous research, which has revealed a female advantage in anthropometric status at young ages in SSA (Wamani et al. 2007). Some speculations as to why this is the case include behavioral patterns, for example feeding practices which benefit female children (Svedberg 1990), and biological differences which are also related to higher mortality among male children (Wells 2000). However, none of these mechanisms have been thoroughly investigated in the literature yet. In any case, the results of this study show that the male disadvantage in anthropometric status is likely to be amplified during adverse climate conditions, such as droughts.

Furthermore, children whose mothers have no formal education are found to be more vulnerable to drought-induced undernutrition than those whose mothers have at least primary level of education. The importance of parental education, particularly of the mother, for improving child nutrition has previously been stressed in the literature (Alderman & Headey 2017). Mother's education is associated with behaviors that contribute to better child health, such as improved dietary diversity, utilization of antenatal and post-natal care, lower fertility (which means more resources available to fewer children), and higher autonomy in decision-making. Such behaviors may in turn protect children against the adverse effects of climatic shocks. The results of this study point that mother's education may even be more important than higher wealth status in reducing children's climate-related vulnerability. Climate shocks may damage assets and wealth, but it is unlikely that human capital acquired through education would depreciate due to such shocks. Indeed, the important role education plays and can play in reducing vulnerability and enhancing adaptive capacity in the context of climate change has been previously stressed in the literature (Lutz et al. 2014; Muttarak & Lutz 2014; Bengtsson et al. 2018). The findings of this study therefore have significant implications for developing countries in the race to achieve the SDGs. With limited budgets and resources, investment in universal education may have positive externalities in achieving other SDGs, including climate change adaptation.

Finally, the results of this study show that children living in the rural areas whose households are engaged in agricultural activities are particularly vulnerable to drought-induced undernutrition. Indeed, smallholder and subsistence farmers are among the poorest groups in less developed countries and also one of the most vulnerable groups to the impacts of climate change because their livelihoods are highly dependent on natural resources. There are multiple channels through which their livelihoods can be impacted by climate shocks (Morton 2007). Among other issues, rising temperatures and water stress increase the likelihood of crop failure, reduce crop yields, and increase the prevalence of diseases on livestock. The loss of agricultural income is likely to pressure households to reduce the quantity and quality of food consumed and forgo non-food expenses, such as healthcare. Rural households affected by droughts are also likely to take their children out of school (Randell & Gray 2016), which creates an intergenerational poverty trap.

Although some adaptation strategies at the household level have been pointed out in the literature, such as herd accumulation, crop and income diversification, and migration (Morton 2007), it is unlikely that these would be enough to reverse the negative impacts of droughts on rural livelihoods. Larger efforts would be necessary to build drought resilience through better water resource management, irrigation system, soil conservation, and drought monitoring (Gebremeskel et al. 2019; FAO 2014), as well as the provision of safety nets (Alderman 2010; Ruel & Alderman 2013), among other efforts. In the short-term, providing relief would be important to address the burden on children from drought-induced undernutrition. Nutritional interventions should be considered at the most critical periods of exposure and should target vulnerable population groups in order to reverse the long-lasting effects of droughts on child health.

This study utilizes large and nationally representative data for Ethiopia from multiple survey rounds. However, the cross-sectional design of the data does not allow causal interpretation of the results. Another limitation of this study is that the channels through which climate affects child health are not directly identified. Given the disproportionate impact of droughts on agriculturally dependent rural households, it is possible that the effects of climatic shocks run through a reduction in crop yields which affect household food security directly or indirectly through a reduction in agricultural income. The sample may also be biased due to selective mortality of the most undernourished children. If this is the case, the effect of climate shocks on child undernutrition would be underestimated. Future studies should investigate the link between climate shocks and child mortality due to undernutrition.

In conclusion, this study finds a strong association between drought exposure and childhood undernutrition in Ethiopia. It also demonstrates that vulnerability can be influenced by a number of factors at the household level, such as parental education and source of livelihood. It also shows that climate shock may amplify gender differences in nutrition status. Children exposed to droughts in the first two years of life are found to be particularly vulnerable to chronic malnutrition. Therefore, nutritional intervention should target these particularly vulnerable groups of children.

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Appendix

Appendix A. Data

Figure S1. Distribution of height-for-age (HAZ), weight-for-age (WAZ) and weight-for-height (WHZ) z-scores of children age 0 to 5 in Ethiopia by DHS survey. The vertical dashed lines indicate the -2 z-score threshold which corresponds with stunting (left), being underweight (centre) and wasting (right).

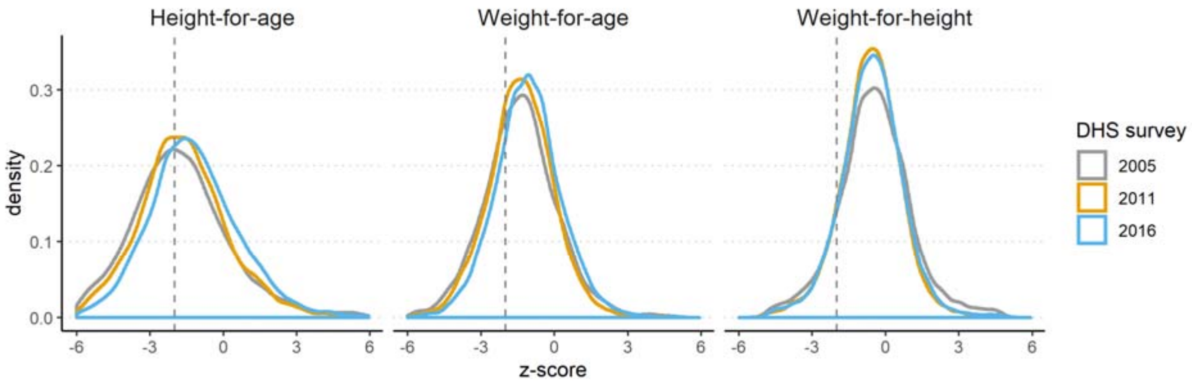
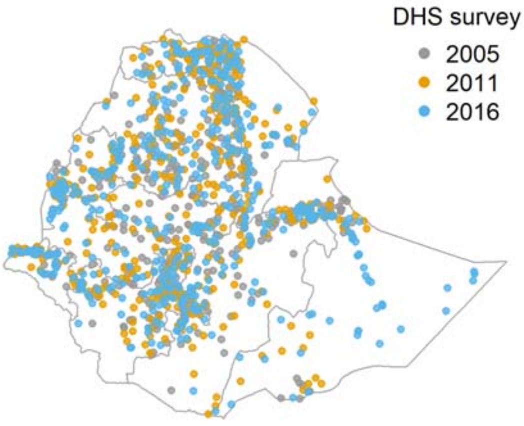


Fig. S2. Location of DHS clusters used in the study by survey year and regional boundaries of Ethiopia



Appendix B. Results tables

Table S1. Effects of summer season SPEI on stunting and being underweight, children age 0-5

	(1)		(2)	
	stunted		underweight	
average SPEI since birth spline 1	0.56***	(0.07)	0.64***	(0.08)
average SPEI since birth spline 2	1.64**	(0.3)	1.54**	(0.24)
Individual characteristics				
Sex (ref.=male)	0.84***	(0.03)	0.85***	(0.03)
female				
Twin (ref.=no)	1.97***	(0.26)	2.09***	(0.28)
yes				
Birth order	1.05***	(0.01)	1.05***	(0.01)
Maternal characteristics				
Age at giving birth	0.98***	(0.00)	0.98**	(0.00)
Height	0.95***	(0.00)	0.96***	(0.00)
Education (ref.=no)				
primary	0.93	(0.05)	0.84***	(0.04)
secondary	0.65***	(0.07)	0.60***	(0.09)
higher	0.53**	(0.11)	0.32***	(0.07)
Household characteristics				
Wealth (ref.=bottom quintile)				
2nd quintile	0.92^{+}	(0.05)	0.89*	(0.05)
3rd quintile	0.80***	(0.05)	0.76***	(0.04)
4th quintile	0.73***	(0.05)	0.59***	(0.04)
top quintile	0.50***	(0.05)	0.49***	(0.05)
Household head (ref.=male)				
female	1.14*	(0.07)	1.12	(0.07)
Residence (ref.=urban)				
rural	1.15	(0.14)	1.16	(0.16)
Occupation (ref.=non-agri.)				
agricultural	1.04	(0.06)	1.16*	(0.07)
not working	0.98	(0.07)	1.07	(0.08)
other	1.01	(0.13)	1.18	(0.16)
Age splines	YES		YES	
Grid-cell FEs	YES		YES	
Survey FEs	YES		YES	
Quarter of birth FEs	YES		YES	
Quarter of interview FEs	YES		YES	
Obs.	18,503		18,897	
Pseudo R^2	0.119		0.094	

Notes: $^{+}p<0.1$, *$p<0.05$, **$p<0.01$, ***$p<0.001$. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S2. Impacts of droughts on stunting by age at exposure and minimum age at measurement

	Minimum age at measurement									
	Age 0	Age 1	Age 1	Age 2	Age 2	Age 2	Age 3	Age 3	Age 3	Age 3
Drought age 0	0.04*	0.04*		0.04			0.03			
	(0.02)	(0.02)		(0.02)			(0.03)			
Drought age 1			0.06**		0.06**			0.05*		
			(0.02)		(0.02)			(0.02)		
Drought age 2						-0.02			-0.02	
						(0.02)			(0.02)	
Drought age 3										0.07^{+}
										(0.04)
Obs.	18,503	18,397	14,045	15,742	13,950	9,820	11,612	11,612	9,724	5,475

Notes: Cell entries are average marginal effects (AME) based on logistic regression models calculated separately for each minimum each age at measurement and age at exposure. Droughts are defined as SPEI ≤ -1 at each period of exposure. Control variables included but not displayed: same as Table 2 in the main text. $^{+}p<0.1$, *$p<0.05$, **$p<0.01$, ***$p<0.001$. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S3. Impacts of droughts on being underweight by age at exposure and minimum age at measurement

	Minimum age at measurement									
	Age 0	Age 1	Age 1	Age 2	Age 2	Age 2	Age 3	Age 3	Age 3	Age 3
Drought age 0	0.04*	0.04*		0.03			0.01			
	(0.02)	(0.02)		(0.02)			(0.03)			
Drought age 1			0.05*		0.05*			0.05*		
			(0.02)		(0.02)			(0.03)		
Drought age 2						0.01			0.01	
						(0.03)			(0.03)	
Drought age 3										0.02
										(0.03)
Obs.	18,897	18,784	14,326	16,070	14,231	9,955	11,856	11,856	9,857	5,509

Notes: Cell entries are average marginal effects (AME) based on logistic regression models calculated separately for each minimum each age at measurement and age at exposure. Droughts are defined as SPEI ≤ -1 at each period of exposure. Control variables included but not displayed: same as Table 2 in the main text. $^{+}p<0.1$, *$p<0.05$, **$p<0.01$, ***$p<0.001$. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S4. Effects of summer season SPEI on stunting by individual and socio-economic group, children age 0-5

	(1) stunted		(2) stunted		(3) stunted	
Drought in infancy: male	1.35*	(0.18)				
Drought in infancy: female	1.15	(0.13)				
Drought in infancy: uneducated & poor			1.36*	(0.17)		
Drought in infancy: educated & poor			0.9	(0.23)		
Drought in infancy: uneducated & rich			1.36^{+}	(0.24)		
Drought in infancy: educated & rich			1.03	(0.21)		
Drought in infancy: rural & non-agriculture					0.82	(0.2)
Drought in infancy: rural & not working					1.37	(0.35)
Drought in infancy: rural & agriculture					1.33**	(0.14)
Drought in infancy: urban & non-agriculture					0.99	(0.32)
Drought in infancy: urban & not working/other					1.39	(0.84)
Sex (ref.=male)						
female	0.85***	(0.03)	0.84***	(0.03)	0.84***	(0.03)
Twin (ref.=no)						
yes	1.95***	(0.25)	1.96***	(0.25)	1.95***	(0.25)
Birth order	1.06***	(0.01)	1.06***	(0.01)	1.06***	(0.01)
Age at giving birth	0.98***	(0.00)	0.98***	(0.00)	0.98***	(0.00)
Height	0.95***	(0.00)	0.95***	(0.00)	0.95***	(0.00)
Education & wealth (ref.=uneducated & poor)						
educated & poor	0.94	(0.06)	0.95	(0.06)	0.94	(0.06)
uneducated & rich	0.77***	(0.05)	0.77***	(0.05)	0.78***	(0.05)
educated & rich	0.59***	(0.05)	0.60***	(0.05)	0.59***	(0.05)
Household head (ref.=male)						
female	1.11^{+}	(0.06)	1.11^{+}	(0.06)	1.11^{+}	(0.06)
Residence & occupation (ref.=rural & non-agri.)						
rural & not working	1.04	(0.08)	1.04	(0.08)	1.01	(0.08)
rural & agriculture	1.05	(0.07)	1.05	(0.07)	1.03	(0.07)
urban & non-agriculture	0.65**	(0.09)	0.65**	(0.09)	0.65**	(0.09)
urban & not working/other	0.76*	(0.1)	0.76*	(0.1)	0.74*	(0.1)
Age splines	YES		YES		YES	
Grid-cell FEs	YES		YES		YES	
Survey FEs	YES		YES		YES	
Quarter of birth FEs	YES		YES		YES	
Quarter of interview FEs	YES		YES		YES	
Obs.	18,503		18,503		18,503	
Pseudo R^2	0.116		0.116		0.116	

Notes: $^{+}p<0.1$, $*p<0.05$, $**p<0.01$, $***p<0.001$. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S5. Effects of summer season SPEI on being underweight by individual and socio-economic group, children age 0-5

	(1)		(2)		(3)	
	underweight		underweight		underweight	
Drought in infancy: male	1.32*	(0.17)				
Drought in infancy: female	1.22^{+}	(0.14)				
Drought in infancy: uneducated & poor			1.29^{+}	(0.17)		
Drought in infancy: educated & poor			1.07	(0.26)		
Drought in infancy: uneducated & rich			1.50*	(0.26)		
Drought in infancy: educated & rich			1.03	(0.26)		
Drought in infancy: rural & non-agriculture					1.04	(0.26)
Drought in infancy: rural & not working					1.1	(0.33)
Drought in infancy: rural & agriculture					1.34*	(0.16)
Drought in infancy: urban & non-agriculture					1.16	(0.51)
Drought in infancy: urban & not working/other					0.77	(0.44)
Sex (ref.=male)						
female	0.86***	(0.03)	0.85***	(0.03)	0.85***	(0.03)
Twin (ref.=no)						
yes	2.08***	(0.28)	2.08***	(0.28)	2.08***	(0.28)
Birth order	1.05***	(0.01)	1.05***	(0.01)	1.05***	(0.01)
Age at giving birth	0.98***	(0.00)	0.98***	(0.00)	0.98***	(0.01)
Height	0.96***	(0.00)	0.96***	(0.00)	0.96***	(0.00)
Education & wealth (ref.=uneducated & poor)						
educated & poor	0.80***	(0.05)	0.81***	(0.05)	0.81***	(0.05)
uneducated & rich	0.65***	(0.04)	0.65***	(0.04)	0.64***	(0.04)
educated & rich	0.49***	(0.05)	0.49***	(0.05)	0.50***	(0.05)
Household head (ref.=male)						
female	1.09	(0.06)	1.09	(0.06)	1.09	(0.06)
Residence & occupation (ref.=rural & non-agri.)						
rural & not working	1.17*	(0.08)	1.16*	(0.08)	1.17*	(0.08)
rural & agriculture	1.18*	(0.08)	1.17*	(0.08)	1.18*	(0.08)
urban & non-agriculture	0.72**	(0.09)	0.71**	(0.09)	0.72**	(0.09)
urban & not working/other	0.86	(0.13)	0.86	(0.13)	0.86	(0.12)
Age splines	YES		YES		YES	
Grid-cell FEs	YES		YES		YES	
Survey FEs	YES		YES		YES	
Quarter of birth FEs	YES		YES		YES	
Quarter of interview FEs	YES		YES		YES	
Obs.	18,897		18,897		18,897	
Pseudo R^2	0.091		0.091		0.091	

Notes: $^{+}$p<0.1, **p* <0.05, ***p* <0.01, ****p* <0.001. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S6. Effects of SPEI during the latest summer season on wasting by individual and socio-economic group, children age 0-5

	(1)		(2)		(3)	
	wasted		wasted		wasted	
Drought latest summer: male	1.37*	(0.21)				
Drought latest summer: female	1.16	(0.21)				
Drought latest summer: uneducated & poor			1.2	(0.15)		
Drought latest summer: educated & poor			1.32	(0.38)		
Drought latest summer: uneducated & rich			1.38	(0.35)		
Drought latest summer: educated & rich			1.52	(0.64)		
Drought latest summer: rural & non-agriculture					0.64	(0.31)
Drought latest summer: rural & not working					1.64	(0.8)
Drought latest summer: rural & agriculture					1.37*	(0.18)
Drought latest summer: urban & non-agriculture					0.7	(0.34)
Drought latest summer: urban & not working/other					0.79	(0.34)
Sex (ref.=male)						
female	0.79***	(0.03)	0.79***	(0.03)	0.79***	(0.03)
Twin (ref.=no)						
yes	1.51**	(0.21)	1.50**	(0.21)	1.51**	(0.21)
Birth order	1.03^{+}	(0.02)	1.03^{+}	(0.02)	1.03^{+}	(0.02)
Age at giving birth	0.99	(0.01)	0.99	(0.01)	0.99	(0.01)
Height	0.99	(0.00)	0.99	(0.00)	0.99	(0.00)
Education & wealth (ref.=uneducated & poor)						
educated & poor	0.85*	(0.06)	0.85*	(0.06)	0.84*	(0.06)
uneducated & rich	0.71***	(0.05)	0.71***	(0.05)	0.70***	(0.05)
educated & rich	0.54***	(0.05)	0.54***	(0.05)	0.53***	(0.05)
Household head (ref.=male)						
female	1.17*	(0.08)	1.17*	(0.08)	1.17*	(0.08)
Residence & occupation (ref.=rural & non-agri.)						
rural & not working	1.09	(0.09)	1.07	(0.09)	1.09	(0.09)
rural & agriculture	1.25**	(0.1)	1.22*	(0.1)	1.25**	(0.1)
urban & non-agriculture	1.24^{+}	(0.14)	1.23^{+}	(0.15)	1.24^{+}	(0.14)
urban & not working/other	1.28^{+}	(0.18)	1.26^{+}	(0.18)	1.28^{+}	(0.18)
Age splines	YES		YES		YES	
Grid-cell FEs	YES		YES		YES	
Survey FEs	YES		YES		YES	
Quarter of birth FEs	YES		YES		YES	
Quarter of interview FEs	YES		YES		YES	
Obs.	21,409		21,409		21,409	
Pseudo R^2	0.075		0.076		0.075	

Notes: $^{+}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Table S7. Effects of SPEI during the latest summer season on being underweight by individual and socio-economic group, children age 0-5

	(1) underweight		(2) underweight		(3) underweight	
Drought latest summer: male	1.56**	(0.22)				
Drought latest summer: female	1.32*	(0.17)				
Drought latest summer: uneducated & poor			1.29^{+}	(0.18)		
Drought latest summer: educated & poor			1.39	(0.44)		
Drought latest summer: uneducated & rich			1.93**	(0.46)		
Drought latest summer: educated & rich			1.59	(0.46)		
Drought latest summer: rural & non-agriculture					1.07	(0.33)
Drought latest summer: rural & not working					1.49	(0.55)
Drought latest summer: rural & agriculture					1.50***	(0.18)
Drought latest summer: urban & non-agriculture					1.13	(0.33)
Drought latest summer: urban & not working/other					1.07	(0.37)
Sex (ref.=male)						
female	0.86***	(0.03)	0.85***	(0.03)	0.85***	(0.03)
Twin (ref.=no)						
yes	2.28***	(0.29)	2.28***	(0.29)	2.27***	(0.29)
Birth order	1.04**	(0.01)	1.04**	(0.01)	1.04**	(0.01)
Age at giving birth	0.99**	(0.01)	0.99**	(0.01)	0.99**	(0.01)
Height	0.96***	(0.00)	0.96***	(0.00)	0.96***	(0.00)
Education & wealth (ref.=uneducated & poor)						
educated & poor	0.81***	(0.04)	0.81***	(0.04)	0.81***	(0.04)
uneducated & rich	0.66***	(0.04)	0.66***	(0.04)	0.65***	(0.04)
educated & rich	0.49***	(0.04)	0.49***	(0.05)	0.49***	(0.05)
Household head (ref.=male)						
female	1.05	(0.06)	1.05	(0.06)	1.05	(0.06)
Residence & occupation (ref.=rural & non-agri.)						
rural & not working	1.13^{+}	(0.08)	1.12^{+}	(0.08)	1.13	(0.08)
rural & agriculture	1.12^{+}	(0.07)	1.1^{+}	(0.07)	1.12	(0.07)
urban & non-agriculture	0.72*	(0.09)	0.72*	(0.09)	0.73*	(0.09)
urban & not working/other	0.85	(0.11)	0.84	(0.12)	0.85	(0.11)
Age splines	YES		YES		YES	
Grid-cell FEs	YES		YES		YES	
Survey FEs	YES		YES		YES	
Quarter of birth	YES		YES		YES	
Quarter of interview	YES		YES		YES	
Obs.	22,150		22,150		22,150	
Pseudo R^2	0.105		0.105		0.105	

Notes: $^{+}$p<0.1, *p <0.05, **p <0.01, ***p <0.001. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.

Appendix C. Robustness checks

Table S8. Effects of summer season SPEI on stunting and being underweight, children age 0-5. Robustness check: Excluding non-permanent residents

	(1)		(2)		(3)		(3)	
	stunted		underweight		wasted		underweight	
average SPEI since birth	0.77***	(0.06)	0.84**	(0.05)				
SPEI latest summer					0.96	(0.06)	0.92	(0.05)
Individual characteristics								
Sex (ref.=male)								
female	0.85***	(0.03)	0.86***	(0.03)	0.79***	(0.03)	0.85***	(0.03)
Twin (ref.=no)								
yes	1.98***	(0.26)	2.11***	(0.29)	1.47**	(0.22)	2.28***	(0.3)
Birth order	1.05***	(0.01)	1.05***	(0.01)	1.03	(0.02)	1.03*	(0.01)
Maternal characteristics								
Age at giving birth	0.98***	(0.00)	0.98**	(0.01)	0.99	(0.01)	0.99*	(0.01)
Height	0.95***	(0.00)	0.96***	(0.00)	1.00	(0.00)	0.96***	(0.00)
Education (ref.=no)								
primary	0.92	(0.05)	0.83***	(0.04)	0.85**	(0.05)	0.83***	(0.04)
secondary	0.64***	(0.07)	0.60***	(0.09)	0.64**	(0.1)	0.57***	(0.08)
higher	0.53**	(0.12)	0.32***	(0.08)	0.61**	(0.1)	0.35***	(0.08)
Household characteristics								
Wealth (ref.=bottom quintile)								
2nd quintile	0.92	(0.05)	0.89*	(0.05)	0.96	(0.07)	0.89*	(0.04)
3rd quintile	0.80***	(0.05)	0.75***	(0.04)	0.91	(0.07)	0.75***	(0.04)
4th quintile	0.73***	(0.05)	0.59***	(0.04)	0.69***	(0.05)	0.60***	(0.04)
top quintile	0.50***	(0.05)	0.49***	(0.05)	0.60***	(0.07)	0.50***	(0.05)
Household head (ref.=male)								
female	1.13*	(0.07)	1.12^{+}	(0.07)	1.16*	(0.08)	1.09	(0.06)
Residence (ref.=urban)								
rural	1.16	(0.15)	1.17	(0.16)	0.77*	(0.09)	1.15	(0.15)
Occupation (ref.=non-agri.)								
agricultural	1.04	(0.06)	1.16*	(0.07)	1.20*	(0.09)	1.11^{+}	(0.06)
not working	0.98	(0.07)	1.06	(0.08)	1.07	(0.08)	1.04	(0.07)
other	0.99	(0.13)	1.18	(0.15)	1.04	(0.16)	1.21	(0.17)
Age splines	YES		YES		YES		YES	
Grid-cell FEs	YES		YES		YES		YES	
Survey FEs	YES		YES		YES		YES	
Quarter of birth FEs	YES		YES		YES		YES	
Quarter of interview FEs	YES		YES		YES		YES	
Obs.	18,300		18,692		21,144		21,878	
Pseudo R^2	0.119		0.094		0.075		0.107	

Notes: $^{+}$p<0.1, *p <0.05, **p <0.01, ***p <0.001. Robust standard errors reported in parenthesis. Clustering at the grid-cell level. Sample excludes children who are visitors.

Table S9. Effects of summer season SPEI on stunting and being underweight, children age 0-5. Robustness check: Accounting for migration

	(1)		(2)		(3)		(3)	
	stunted		underweight		wasted		underweight	
average SPEI since birth	0.76***	(0.06)	0.84**	(0.05)				
SPEI latest summer					0.96	(0.06)	0.93	(0.06)
Individual characteristics								
Sex (ref.=male)								
female	0.84***	(0.03)	0.85***	(0.03)	0.79***	(0.03)	0.84***	(0.03)
Twin (ref.=no)								
yes	2.06***	(0.26)	2.16***	(0.29)	1.49**	(0.22)	2.35***	(0.31)
Birth order	1.05***	(0.01)	1.04**	(0.01)	1.02	(0.02)	1.03*	(0.01)
Maternal characteristics								
Age at giving birth	0.98***	(0.00)	0.99**	(0.01)	1.00	(0.01)	0.99*	(0.01)
Height	0.95***	(0.00)	0.96***	(0.00)	1.00	(0.00)	0.96***	(0.00)
Education (ref.=no)								
primary	0.94	(0.05)	0.83***	(0.04)	0.84**	(0.05)	0.83***	(0.04)
secondary	0.62***	(0.07)	0.57***	(0.09)	0.62**	(0.1)	0.54***	(0.08)
higher	0.54**	(0.11)	0.36***	(0.08)	0.61*	(0.13)	0.39***	(0.09)
Household characteristics								
Wealth (ref.=bottom quintile)								
2nd quintile	0.92^{+}	(0.05)	0.88*	(0.05)	0.96	(0.07)	0.88*	(0.04)
3rd quintile	0.80***	(0.05)	0.74***	(0.04)	0.9	(0.07)	0.74***	(0.04)
4th quintile	0.72***	(0.05)	0.59***	(0.04)	0.70***	(0.06)	0.59***	(0.04)
top quintile	0.51***	(0.05)	0.48***	(0.05)	0.58***	(0.07)	0.50***	(0.05)
Household head (ref.=male)								
female	1.16*	(0.07)	1.12^{+}	(0.07)	1.15*	(0.08)	1.1	(0.06)
Residence (ref.=urban)								
rural	1.17	(0.15)	1.17	(0.17)	0.76*	(0.1)	1.16	(0.17)
Occupation (ref.=non-agri.)								
agricultural	1.03	(0.06)	1.16*	(0.07)	1.21*	(0.09)	1.13*	(0.07)
not working	0.98	(0.07)	1.08	(0.08)	1.09	(0.08)	1.05	(0.08)
other	1.00	(0.13)	1.32*	(0.18)	1.1	(0.18)	1.32^{+}	(0.19)
Age splines	YES		YES		YES		YES	
Grid-cell FEs	YES		YES		YES		YES	
Survey FEs	YES		YES		YES		YES	
Quarter of birth FEs	YES		YES		YES		YES	
Quarter of interview FEs	YES		YES		YES		YES	
Obs.	17,647		18,028		20,304		21,039	
Pseudo R^2	0.118		0.092		0.076		0.105	

Notes: $^{+}$p<0.1, *p <0.05, **p <0.01, ***p <0.001. Robust standard errors reported in parenthesis. Clustering at the grid-cell level. Sample excludes households who have lived less than five years in their current location.

Table S10. Effects of summer season SPEI on stunting and being underweight, children age 0-5. Robustness check: Controlling for low birth weight

	(1) stunted		(2) underweight		(3) wasted		(3) underweight	
average SPEI since birth	0.77***	(0.06)	0.84**	(0.05)				
SPEI latest summer					0.95	(0.06)	0.91	(0.06)
Individual characteristics								
Sex (ref.=male)								
female	0.82***	(0.03)	0.82***	(0.03)	0.77***	(0.03)	0.82***	(0.03)
Twin (ref.=no)								
yes	1.91***	(0.25)	1.99***	(0.27)	1.45*	(0.21)	2.18***	(0.28)
Birth order	1.05***	(0.01)	1.05***	(0.01)	1.03^{+}	(0.02)	1.04**	(0.01)
Low birth weight (ref.=no)								
yes	1.49***	(0.07)	1.69***	(0.08)	1.40***	(0.07)	1.70***	(0.08)
Maternal characteristics								
Age at giving birth	0.98***	(0.00)	0.98**	(0.01)	0.99	(0.01)	0.99*	(0.01)
Height	0.95***	(0.00)	0.96***	(0.00)	0.99	(0.00)	0.96***	(0.00)
Education (ref.=no)								
primary	0.93	(0.05)	0.85**	(0.04)	0.86*	(0.05)	0.84***	(0.04)
secondary	0.65***	(0.07)	0.61**	(0.09)	0.65**	(0.1)	0.59***	(0.08)
higher	0.53**	(0.11)	0.33***	(0.08)	0.62**	(0.1)	0.36***	(0.07)
Household characteristics								
Wealth (ref.=bottom quintile)								
2nd quintile	0.93	(0.05)	0.9^{+}	(0.05)	0.98	(0.07)	0.90*	(0.05)
3rd quintile	0.81***	(0.05)	0.76***	(0.04)	0.93	(0.07)	0.76***	(0.04)
4th quintile	0.74***	(0.05)	0.60***	(0.04)	0.71***	(0.06)	0.61***	(0.04)
top quintile	0.51***	(0.05)	0.50***	(0.05)	0.61***	(0.07)	0.51***	(0.05)
Household head (ref.=male)								
female	1.14*	(0.07)	1.12^{+}	(0.07)	1.15*	(0.08)	1.08	(0.06)
Residence (ref.=urban)								
rural	1.14	(0.14)	1.16	(0.16)	0.75*	(0.09)	1.14	(0.16)
Occupation (ref.=non-agri.)								
agricultural	1.04	(0.06)	1.15*	(0.07)	1.20*	(0.09)	1.11^{+}	(0.07)
not working	0.97	(0.07)	1.05	(0.08)	1.07	(0.08)	1.01	(0.08)
other	1.00	(0.13)	1.17	(0.15)	0.99	(0.16)	1.18	(0.17)
Age splines	YES		YES		YES		YES	
Grid-cell FEs	YES		YES		YES		YES	
Survey FEs	YES		YES		YES		YES	
Quarter of birth FEs	YES		YES		YES		YES	
Quarter of interview FEs	YES		YES		YES		YES	
Obs.	18,403		18,795		21,288		22,025	
Pseudo R^2	0.122		0.1		0.078		0.114	

Notes: $^{+}$p<0.1, *p <0.05, **p <0.01, ***p <0.001. Robust standard errors reported in parenthesis. Clustering at the grid-cell level.