International Institute for Applied Systems Analysis
IIASA www.iiasa.ac.at

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria
Email: repository@iiasa.ac.at **Telephone:** +43 (0)2236 807 342

YSSP Report
Young Scientists Summer Program

Which Children Are Most Vulnerable to Climate Change? Mapping the Effects of Meteorological Extremes on Child Stunting

Matthew Cooper, mattcoop@terpmail.umd.edu

Approved by

Supervisor: Steffen Fritz, Stefan Hochrainer-Stigler
Program: ESM, RISK
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This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

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Supervisor signature:

Steffen Fritz
Stefan Hochrainer-Stigler

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Table of Contents

Abstract iv

Introduction v

Data Used vi

- Nutrition Data vi
- Extracting Spatial Data vii
- Climate Data viii
- Other Spatial Data viii

Methods 1

- Rainfall and Undernutrition 1
- Factors Moderating the Effects of Rainfall Extremes 2
- Mapping Vulnerability 2

Results 3

- Rainfall and HAZ Scores 3
- Regression Model 4
  - Individual and Household Variables 4
  - Geographic Variables 5
  - Geographic Variables Moderating Shocks 6
- Mapping Combined Effects 6

Discussion 7

Conclusion 9

Acknowledgements 9

Bibliography 9

About the authors 13

Abstract

Climate change is expected to have major impacts on child nutrition outcomes, and these impacts will be moderated by a variety of governmental, economic, infrastructural, and environmental factors. To date, attempts to map the vulnerability of food systems to climate change and drought have focused on mapping these factors alone and have not incorporated empirical observations of historic climate shocks or nutrition outcomes. Here, we use over 590,000 observations of children from 53 countries to examine how historic climate shocks have been amplified or mitigated by a variety of geographic factors to affect nutrition outcomes. We show that minor to severe droughts as well as severely wet periods are associated with worse child nutrition. We further show that the effects of precipitation extremes on child undernutrition are amplified by higher temperatures and mitigated by higher national crop production per capita, local crop nutrition diversity, lower rates of violence, and irrigated agriculture. Finally, we combine current global data on factors influencing the impacts of droughts and wet periods to make a global map of expected changes in child height-for-age Z scores during droughts. As climate change makes meteorological extremes more frequent, these results will aid policymakers by highlighting which geographies are most vulnerable as well as which factors contribute the most to creating resilient food systems.

Introduction

Currently, one in nine people around the world are undernourished and nearly half of deaths in children under five are caused by poor nutrition (UNICEF et al., 2017). One of the consequences of poor child nutrition is stunting, which affects more than one in three children in many developing countries (UNICEF et al., 2017). Stunting can lead to a higher risk of mortality as a child (Black et al., 2010), as well as reduced physical, cognitive, and educational attainments and lifelong health problems from reduced immunity and increased disease susceptibility (Arthur et al., 2015). The effects of stunting on a population are long term: the children of parents who experienced early childhood stunting are in turn at higher risk for lower developmental levels (Walker et al., 2015). Due to decreased earnings and economic output, child stunting can hamper a countries long-term economic growth for generations (Heltberg, 2009). Thus, ameliorating child stunting is a critical component of sustainable development (Daelmans et al., 2017). While rates of stunting have been in decline globally over the past few decades, hotspots of stunting remain in Africa and in South Asia (Osgood-Zimmerman et al., 2018; Phalkey et al., 2015), and climate change could stall or even reverse current gains.

Climate change is now widely acknowledged to be a threat to food security and nutrition globally. Overall rising temperatures due to increased greenhouse gas emissions will change local patterns of precipitation and temperature around the world, in turn affecting food production and infrastructure critical to food distribution (IPCC, 2014). All of these impacts will affect child nutrition outcomes, which is why both the WHO and the IPCC have named undernutrition as a major expected health impact of climate change (IPCC, 2014; WHO, 2014). Most directly, climate change will affect crop production and therefore food availability (Schlenker and Lobell, 2010; Thornton et al., 2009). In some areas, climate change will lead to abnormally high rainfall levels, increasing rates of crop spoilage and pest outbreaks (Tefera, 2012). In other parts of the world, rainfall levels will decrease, lowering potential crop yields (Schmidhuber and Tubiello, 2007; Wheeler and von Braun, 2013). Furthermore, rising temperatures will increase rates of evapotranspiration, decreasing the amount of water available to plants and potentially causing drought conditions even in areas with ample rainfall (Milly and Dunne, 2016). In the developing world, where people depend on local agriculture both as a source of income and to produce their own food, these impacts on food production will lead to even worsened child nutrition outcomes than today. Even when local food production is unaffected by climate change, food prices may increase globally and still decrease food access for the poor communities (Brown et al., 2012). Secondary effects of climate change will also increase rates of undernutrition. Climate change can also affect the infrastructure necessary to distribute food, as heat waves can cause power outages and floods can wipe out roads. Additionally, rising temperatures and wetter conditions will increase the risk of parasitic and infectious diseases (Delpla et al., 2009; Paterson and Lima, 2010), hampering individuals' ability to fully utilize the food that they eat .

While climate change is recognized to be a major threat to child nutrition, a 2015 review paper of the effects of climate change on undernutrition noted that current evidence associating climate change and undernutrition is "scattered and limited" (Phalkey et al., 2015). The paper documented 15 studies that used regression techniques to find an association between meteorological or agricultural variables and child stunting (Phalkey et al., 2015). In this literature review, only two studies were multinational, and the largest sample size was about 19,000 children. Since 2015, more work has been done to confirm associations between low rainfall and rates of stunting, as well as to examine factors that can mitigate the effects of low rainfall (Gerald E. Shively, 2017). Nevertheless, there is still a significant dearth of research that draws on empirical observations of child nutrition and climate impacts, especially using large pools of data with the spatio-temporal variability that is needed to model outcomes across geographical contexts.

While large-scale data-driven analyses based on historical observations of climate shocks on nutrition have not been conducted, much work has been done to create indicators that highlight hotspots of expected vulnerability. A critical part of this process is identifying the factors that are expected to increase the vulnerability of child nutrition to meteorological extremes such as market access, wealth, environmental health, and livelihood diversity (de Sherbinin, 2014; Moss et al., 2010). Drawing on these factors that are known or suspected to influence vulnerability, there have been efforts to map drought risk (Carrão et al., 2016), the risk of climate change impacts on food security (Ericksen et al., 2011; Krishnamurthy et al., 2014), as well as to map climate risk on security more broadly (Busby et al., 2014). While these represent useful attempts to locate the populations most vulnerable to climate impacts, they rely largely on highly aggregated data and make no predictions about actual impacts, but simply highlight areas of general risk. Furthermore, because these studies lack an empirical basis to model how different factors affect climate change vulnerability, they often weigh diverse variables equally when combining them into an indicator. In this study, we improve upon these methods by using an econometric approach to estimate the degree to which various factors influence vulnerability and then aggregate global data on these factors according to their estimated impact in order to map the anticipated effects of drought on child stunting.

To map where child nutrition is vulnerable to precipitation shocks, we draw on Demographic and Health Surveys (DHS). The DHS program has been collecting data on health and nutrition for nearly 30 years and is considered the "gold standard" of health data from developing countries. The data collected by the DHS is frequently geolocated, and has been used to create maps of health variables such as child growth failure (Osgood-Zimmerman et al., 2018), prevalence of malaria (Bhatt et al., 2015), and child mortality (Burke et al., 2016). Here, we present a novel methodology to use DHS data to model the relationship between precipitation shocks and child nutrition outcomes in order to explore the factors that create resilience or exacerbate vulnerability, as well as to map where climate shocks would be expected to adversely affect child nutrition. The paper begins by explaining the variables used from DHS surveys and the geographic variables analyzed. It goes on to explain the methods used to model the impact of precipitation shocks on nutrition outcomes and the geographic factors that moderate that impact. Finally, it presents the results and discusses their implications.

Data Used

Nutrition Data

For our data on child nutrition observations, we use geolocated surveys from the Demographic and Health Surveys (DHS) program. Our dataset consists of 591,436 children from 127 surveys conducted in 53 countries over 26 years. The DHS collects data not only on child nutrition status, but also a variety of covariates that can also affect nutrition outcomes. Furthermore, many DHS surveys release GPS coordinates for each site, making it possible to associate each child nutrition observation with geographic and meteorological data.

Locations of DHS Sites

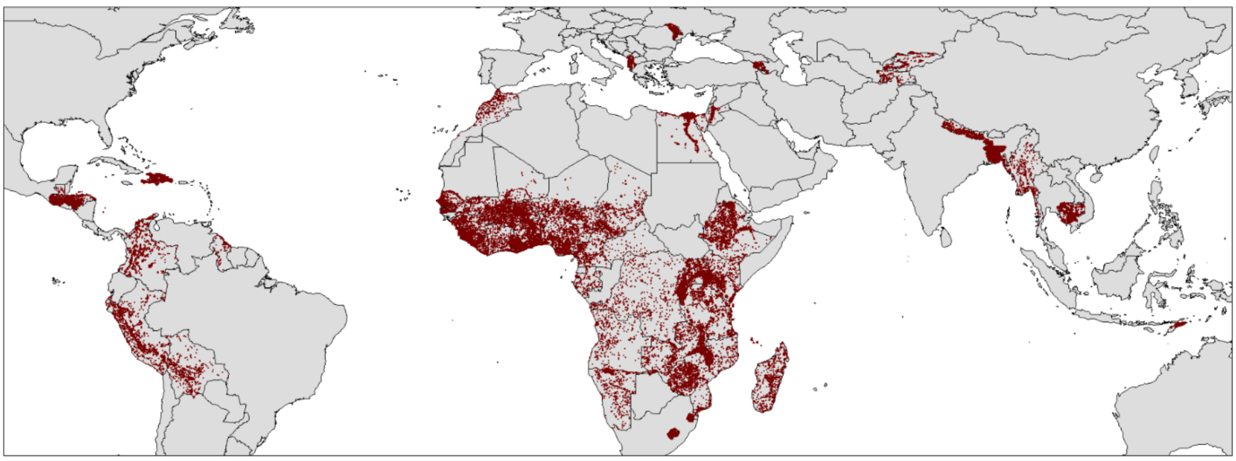

Figure 1: Locations of all DHS sites used in the study.

Our primary variable of interest is the height-for-age Z-score (HAZ) for children under 5 years old, a common indicator of stunting. This indicator compares a child's height to the distribution of heights of healthy children of the same age and gender and assigns a Z-score. The percent of children with a Z-score less than -2 in a given population is the rate of stunting for that population. This indicator is most appropriate for analyses at population scales such as this one, as natural variation in human height makes it impossible to say whether or not an individual is stunted from their height alone (Perumal et al., 2018).

To better estimate the impact of climate shocks on an individual child's HAZ score, it is important to control for individual and household level variables that can also affect child health outcomes. The DHS includes many such variables, although few are collected in all surveys. We found 10 variables that are included in 127 DHS surveys and predict child HAZ scores with reasonable accuracy (RMSE=1.509). We conducted a sensitivity analysis by subsetting the data to only surveys that included other co-variates, such as whether the child was breastfed, had diarrhea in the past two weeks, was a twin, as well as household water sources. We found that including these covariates only improved the RMSE by 0.009 while necessitating the omission of hundreds of thousands of observations (See Appendix A). Thus, we include only the original 10 variables available across a broad range of DHS surveys in all our models. Furthermore, while not all the surveys in our dataset asked how long the households had been residing at the site or whether they were visitors, for those that did, if the households were visitors or had been residing at the site for less than three years, we excluded them from the model.

Level	Variable
Individual	Age
Individual	Birth Order
Individual	Birth Month
Individual	Sex
Household	Toilet facilities
Household	Household Head Age
Household	Household Head Sex
Household	Household Size
Household	Household Wealth Quintile
Household	Mother's Years of Education

Table 1: Individual and Household variables used in the analysis

Extracting Spatial Data

This analysis relies on combining geolocated DHS surveys with a wide variety of geographic datasets. However, the GPS points given by the DHS are displaced to maintain respondent anonymity. Urban points are displaced by up to 2km, while 99% of rural points are displaced by up to 5km and 1% are displaced by up to 10km (Burgert et al., 2013). To account for this jittering when extracting geospatial data we used the same methodology as Grace et al (Grace et al., 2012). We first resampled all the geographic data to a 5 arc-minute resolution, or about a 5-km resolution at the equator. We then took the average value of the grid cell in which a GPS point fell, as well as all of the neighboring grid cells. This accounts for the lack of specificity in the location of the DHS GPS points and also reflects the fact that livelihoods can be affected by processes over 5km away, as households will sometimes have distant fields or may travel several kilometers to collect water (Grace et al., 2012).

Climate Data

As an indicator of climate shocks, we use a derivative of the Standardized Precipitation Index (SPI), a measure of how recent rainfall levels over a given timeframe vary with respect to long-term norms. This is because what would be a precipitation shock in areas with very consistent rainfall levels is different from what would be a shock in areas with highly variable rainfall. Thus, the SPI can more accurately characterize a shock than absolute precipitation levels when comparing between locations, because food and livelihood systems in a given location are adapted to the normal range of rainfall variation for that location. Because the SPI is similar to a Z-score, values can be interpreted probabilistically: about 68 out of 100 years will have a SPEI score between -1 and 1, while 95 out of 100 years will have an SPI score between -2 and 2. Only about five out of 100 years will have an SPI score of less than -2 or greater than 2. The SPI can be extended to account for water lost to evapotranspiration with an index called the Standardized Precipitation with Evapotranspiration Index, or SPEI (Beguería et al., 2014). Potential evapotranspiration (PET) can be estimated using the Hargreaves method if a location's monthly rainfall totals, average daily minimum and maximum temperature, and latitude are known (Hargreaves and Samani, 1982). By accounting for water lost to evapotranspiration, the SPEI can more accurately indicate the overall water availability at a location.

We calculated each of our precipitation indices at 12, 24, and 36-month intervals, reflecting the fact that children's HAZ scores are an indicator of long-term, chronic undernutrition. Some researchers have found that child undernutrition is particularly sensitive to growing season rainfall (Hagos et al., 2014; Gerald E. Shively, 2017), so we also tested both SPI and SPEI, across all time intervals, for both annual rainfall totals and growing-season only rainfall. For our data on precipitation, we used the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015). For data on temperature, we used a reanalysis dataset developed by Sheffield et al (Sheffield et al., 2006), and for growing seasons we used data from the JRC ASAP project (Rembold et al., 2018). Both CHRIPS and the Sheffield dataset are based on ensembles of ground observations and satellite data, while the ASAP dataset is based on observed green up and senescence times using MODIS NDVI data.

We assessed the various precipitation indices using both Akaike Information Criterion (AIC) as well as by running locally weighted (loess) regressions to determine which indices were observed to be related to worse nutrition outcomes during extremes. For the AIC tests, we ran hierarchical linear models with the child's HAZ score as the outcome variable, the precipitation index and relevant covariates as predictors, as well as varying intercepts at the country and survey level. For the locally weighted regression models, we first modeled HAZ as a function of the household covariates, again using a hierarchical linear model, and then modeled the relationship between the residuals from that model and each precipitation index. After conducting these tests, we found that 24-month SPEI using annual rainfall performed best (See Appendix B).

Other Spatial Data

We modeled how various factors mitigate or amplify the impacts of rainfall shocks on child HAZ scores. We included in our model factors that had been empirically demonstrated to affect child nutrition, such as GDP per capita and infrastructure (Gerald E. Shively, 2017; Smith and Haddad, 2000), as well as various factors that have been used in previous efforts to model vulnerability (Busby et al., 2014; Carrão et al., 2016; Krishnamurthy et al., 2014). For each variable that moderates the effect of precipitation shocks, we include the measurement of that variable for the nearest available year to the time of the DHS observation.

In addition to their use in previous analyses and indicators, we further selected these variables because of their orthogonality, excluding for example variables like the Human Development Index (HDI), which is strongly collinear with GDP per capita. Thus, every pair of these variables has a Pearson's correlation coefficient of less than 0.5. Finally, we aimed to select variables that were either time-invariant or for which quality multiannual data was available. We here give an overview of each variable:

GDP Per Capita: Wealth is a major determinant of nutrition outcomes overall both within and between nations. Countries with higher GDPs per capita have diverse economies that are less dependent on agriculture, are better integrated into global trade, and have more infrastructure to support agriculture and distribute food during shocks. A 2000 study found that per capita national incomes were a major determinant of a nation's overall nutrition status (Smith and Haddad, 2000). The dataset we draw on has GDP per capita in purchasing power parity (PPP) at the subnational level (Kummu et al., 2018), allowing us to explore differences in GDP per capita even within a given country and year. One disadvantage of GDP as an indicator is that is does not take into account income inequality and many resource-rich but highly unequal countries may have both high GDP per capita values and large populations that are impoverished and food insecure. While data on GINI coefficients or below poverty line estimates was not available for every country and year in our dataset, using subnational GDP estimates does account for some of the inequality within countries.

Crop Production Per Capita: National crop supplies can be vital as a backstop during years where shocks diminish yields, and per capita food availability was found to be an underlying determinant in country-level rates of underweight (Smith and Haddad, 2000). We used data on per-capita food production from the FAO and included cereals and grains as well as other starches that are staple foods in some countries, like roots and tubers.

Government Effectiveness: Effective governments are critical for ensuring populations receive adequate nutrition during years of climate shocks and decreased yields. More effective governance can foster improved national infrastructure and support national economies, which in turn have second-order effects on nutrition outcomes. This indicator was developed by the World Bank as a World Development Indicator, and has been used in studies of drought risk (Carrão et al., 2016) as well as the climate change – food security vulnerability index (Krishnamurthy et al., 2014).

Irrigation: Because irrigated agriculture utilizes water from distant sources, irrigated agriculture is much more resilient to local rainfall deficits than rainfed agriculture. In our model, we use the FAO's Global Map of Irrigated Areas, estimated for the year 2000. This is the same dataset that was used in Carrao's drought risk analysis (Carrão et al., 2016).

Normalized Difference Vegetation Index: The Normalized Difference Vegetation Index, or NDVI, is a measure of the productivity of vegetation. It has been associated with child nutrition outcomes in several studies (Brown et al., 2014; Johnson and Brown, 2014). It is derived from the red band (RED) and the near infrared band (NIR) of satellite imagery, using the following formula:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Equation 1: How the Normalized Difference Vegetation Index (NDVI) is calculated

The dataset on NDVI that we used is derived from Advanced Very High Resolution Radiometer (AVHRR) data estimated annually (Song et al., 2018).

Variable	Organization/Project	Temporal Resolution	Value Range			Value	Citation
			Min	Max	Mean		
GDP per Capita (PPP)		Annual	0.311	24.3	3.69	Thousands of 2011 USD	(Kummu et al., 2018)
Crop Production	FAO	Annual	0.0246	1.21	0.357	Thousands of Tonnes of Cereals, Roots, and Tubers produced per year per capita	(FAOSTAT, 2014)
Government Effectiveness	World Bank – World Governance Indicators	Annual	-1.75	0.227	-0.685	Indicator of Government Effectiveness, lower scores indicating less effective governments	(Kaufmann et al., 2011)
Irrigation	FAO - Global Map of Irrigated Areas	2000	0	1	0.0801	Percent of a given pixel with irrigated agriculture	(Siebert, S., Döll, P., Feick, S., Frenken, K., Hoogeveen, 2013)
NDVI		Annual	-0.0553	1	0.646	Normalized Difference Vegetation Index	(Song et al., 2018)
Nutrition Diversity of Crops		2017	0	0.807	0.581	Shannon diversity index for 8 nutrients per pixel	(Herrero et al., 2017)
Population	WorldPop	1990, 2000, 2005, 2010, 2015, 2020	0	640	14.8	Thousands of Individuals per 2.5-arcminute pixel	(Lloyd et al., 2017)
Stability and Absence of Violence	World Bank – World Governance Indicators	Annual	-2.19	1.05	-0.711	Indicator of Political Stability and Absence of Violence/Terrorism, with more stable and less violent countries having a higher score	(Kaufmann et al., 2011)
Average Max Temperature		Monthly	1.07	39.5	29.8	Average maximum temperature over the previous 10 years (C)	(Sheffield et al., 2006)
Distance from Cities	JRC	2000, 2015	0	26.7	0.82	Number weeks to travel to a city with over 50,000 people	(Uchida and Nelson, 2008; Weiss et al., 2018)

Table 2: Summaries of the geographic variables used in the analysis

Nutrition Diversity of Crops: Consuming a diversity of nutrients is critical for adequate nutrition (Arimond and Ruel, 2004) and at the national level, nutritionally diverse food supplies have been associated with better anthropometric outcomes (Remans et al., 2014). While crop production diversity has been underexplored as a factor contributing to resilience during climate shocks, there is some evidence that it mitigates the effects of other types of household-level shocks (Malapit et al., 2015). To model crop diversity, we draw on a dataset created by Herrero et al (Herrero et al., 2017) which modeled the Shannon diversity of 8 critical nutrients in cropping systems worldwide.

Population Density: Population density can affect child undernutrition and vulnerability to shocks in a variety of ways. In some cases, greater population densities can lead to greater competition for limited resources, smaller farm sizes, and a greater disease burden (Halpenny et al., 2012; Masters et al., 2013). At the same time, population density can be an indicator of greater urbanization, available infrastructure and trade, as well as opportunities for off-farm income (Masters et al., 2013). To measure population density, we use the WorldPop dataset, with global population estimates given by combining satellite imagery and national censuses for the years 1990, 2000, 2005, 2010, 2015, and 2020 (Tatem, 2017).

Stability and Violence: Violence can be a major cause of undernutrition and increased vulnerability, as it disrupts markets and infrastructure providing access to food and agricultural inputs. There is some evidence that the impacts of violence disproportionately affect children (Ghobarah et al., 2003). For this indicator, we use data from the World Bank's World Development Indicators.

Average 10-Year Maximum Temperature: Temperatures are rising globally. Higher temperatures have been found to impact economic production (Burke et al., 2015) as well as child birth weight (Grace et al., 2015), a major risk factor for lower child HAZ scores later in life (Wrottesley et al., 2015). To account for the possible effects of changing temperatures and shifting isotherms, we measure the average daily maximum temperature for the decade before a child health observation rather than the multidecadal temperature average. For our data on temperature, we use a reanalysis product combining remote sensing, on-the-ground measurements and geophysical models (Sheffield et al., 2006).

Distance from Cities: Food access can be a major driver of child nutrition outcomes and living close to cities can greatly improve nutrition outcomes by increasing a household's access to markets and hospitals. Proximity to cities can be an indicator of local road density, which has been demonstrated to mitigate the effects of climate shocks on child HAZ scores (Gerald E Shively, 2017). For this indicator, we use two datasets developed by the European Joint Research Council (JRC), one for the year 2000 (Uchida and Nelson, 2008), and one for the year 2015 (Weiss et al., 2018).

Methods

Rainfall and Undernutrition

We began our analysis by looking at the effects of rainfall on observed child HAZ scores using a loess regression, which can model the anticipated non-linear relationship between rainfall and child HAZ scores. However, a child's raw HAZ scores are influenced by many individual, household, and national factors beyond just rainfall. Thus, to control for these factors, we first modeled HAZ scores as a function of the 10 variables given in table 1, with varying intercepts at the country and DHS survey level. We then predicted the residuals from this linear regression as a function of the 24-month SPEI using a loess model. Conceptually, this means that we looked at the relationship between precipitation levels and how far off the observed HAZ score was from what other factors, such as wealth and maternal education, would otherwise predict.

Factors Moderating the Effects of Rainfall Extremes

Based on the results of the loess model, we identified the points at which low and high rainfall levels are associated with worsened child nutrition outcomes. We then created a categorical variable derived from the 24-month SPEI score consisting of "wet," "dry," and "normal," with the cutoffs between categories determined by the points at which SPEI was associated with a HAZ score worse than household and individual variables would have otherwise predicted. Using this variable, we modeled child HAZ scores as a function of household, individual, and geographic factors, and we model each geographic factor interacting with the categorical variable for whether the child was observed during a wet, dry, or normal period. Formally, we ran the following linear regression:

$$y_{ij} = \beta X_i + \alpha_j S_j + \epsilon_i$$

$$\alpha_j = \gamma G_j$$

Equation 2: Model specification

Where i is the index for each individual child and j is the index for DHS site, y_{ij} is a child's HAZ score, β is a vector of coefficients for a matrix individual, household and geographic factors X_i, and S_j is a vector of categorical values for the observed 24-month SPEI score at a DHS site at the time the child health observation was made. The model is extended by letting the coefficients for S_j at each DHS site, α_j, be estimated by a matrix of geographic variables, G_j, which are in turn moderated by a vector of coefficients γ. The model was fit using by robust regression using an M estimator fitted by iterated re-weighted least squares. This method diminishes the effects of outliers on the estimated coefficients.

Because the geographic variables included in the regression explained much of the DHS site-level variation in nutrition outcomes, we avoided including terms that are typically used in multinational DHS analyses, such as a term for the interview year, a term for whether the site was urban or rural, as well as random effects at the country or survey level. This allowed the spatio-temporal variation in HAZ scores to be explained by only by the geographic variables included in the regression. Moreover, this allowed us to predict potential HAZ scores under drought conditions as a function of only those geographic variables.

Mapping Vulnerability

Having estimated coefficients for the impact of each geographic factor on SPEI outcomes, we then created maps of areas vulnerable to drought by weighing each geographic variable according to estimated coefficient. We use geographic data for as close to the year 2020 as possible. This approach is similar to previous index-based efforts (Carrão et al., 2016; Krishnamurthy et al., 2014), but rather than weighing factors equally, they are weighed according to how they have historically moderated the effects of drought on child nutrition outcomes.

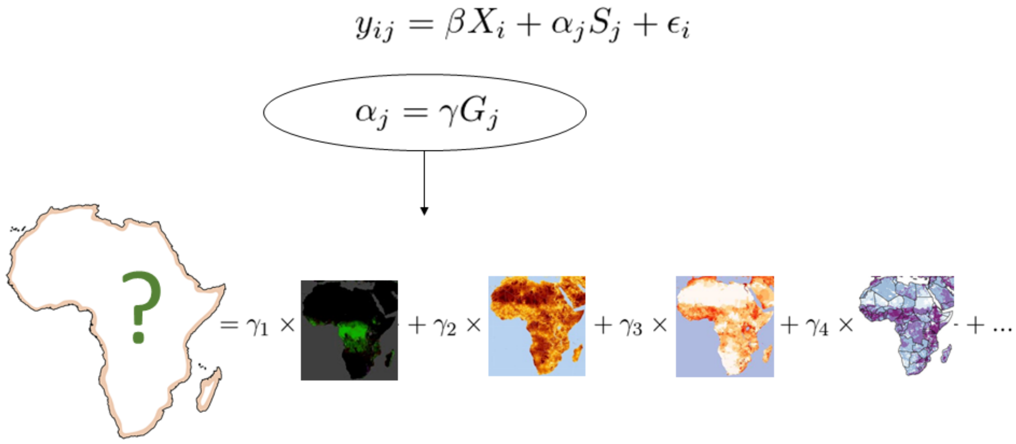

Figure 2: Schematic representation of how model coefficients are used to produce final maps of expected change in average HAZ scores during wet or dry periods.

Results

Rainfall and HAZ Scores

There was a clear relationship between the 24-month SPEI and child HAZ scores, after controlling for the effects of individual, household, and other factors. Figure 3 shows this relationship. The fitted loess curve shows that children have the highest HAZ scores when rainfall is between the long-term norm (SPEI=0) and a mildly wet period (SPEI=1). As rainfall levels increase relative to long-term norms, HAZ scores decline slightly, and then as the SPEI increases beyond 1.5, child HAZ scores decline sharply. Negative SPEI scores seem to be related to worse HAZ scores at all levels. Even when the previous 24 months were only slightly drier than a locations long-term norm, HAZ scores were slightly worse, and SPEI scores less than -0.4 were associated with children shorter than other relevant factors would otherwise predict. Beyond SPEI scores of less than -0.4, there is a somewhat linear relationship between SPEI and HAZ scores.

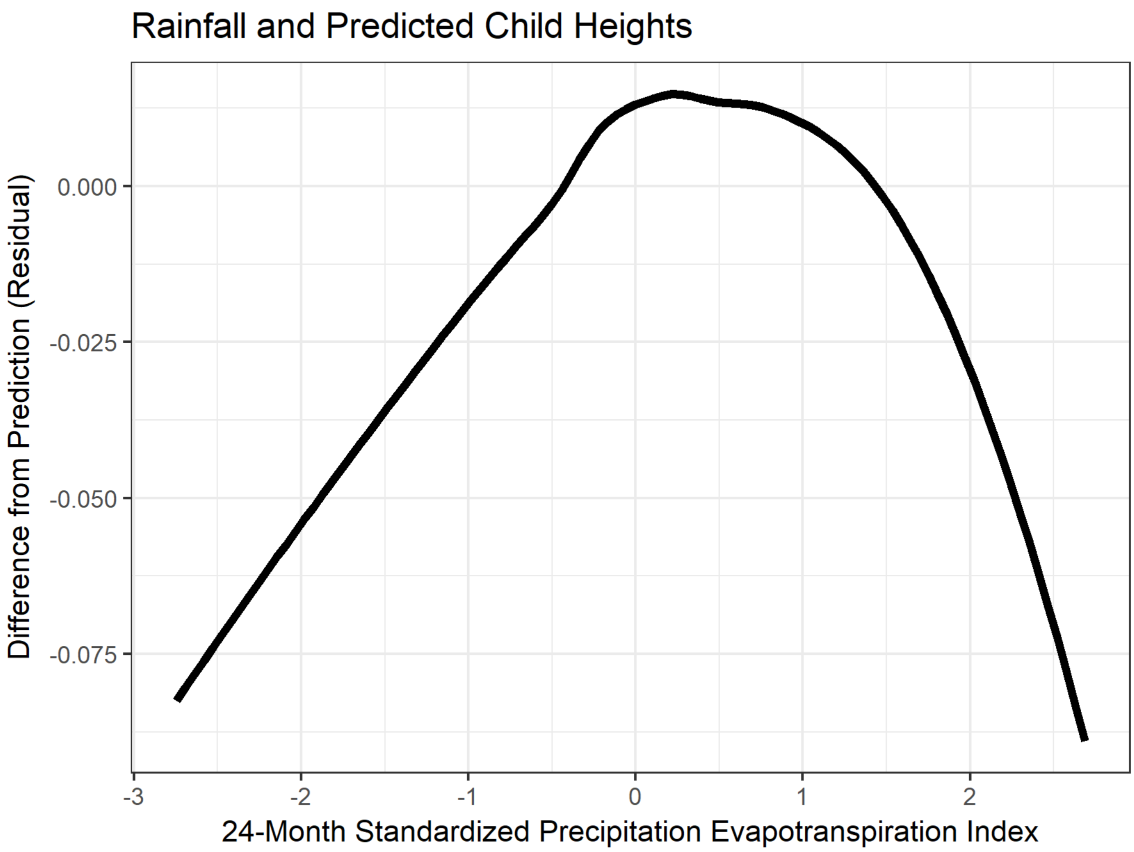

Figure 3: Relationship between 24-Month SPEI and Residual Z-scores, fit with a loess curve.

Using the values at which the loess regression shows the 24-month SPEI as being associated lower HAZ scores (residual < 0), we created a categorical variable, with SPEI scores less than -0.4 being classed as "dry," scores between -0.4 and 1.5 being classed as "normal," and scores greater than 1.5 classed as "wet." Overall, 175,178 children were observed during a period dry enough to be related to worse HAZ scores, 371,745 children were observed during a normal period, and 44,503 children were observed during a period wet enough to be related to worse HAZ scores.

Regression Model

We ran a regression to predict child HAZ scores based on individual and household factors, geographic factors, as well as the climate conditions at the time of the observation, moderated by geographic factors. We included a dummy variable for the month of birth because of recent studies suggesting that misreporting birth months is a major source of measurement error in the DHS (Agarwal et al., 2017; Larsen et al., 2017). The resulting regression had a root mean square error (RMSE) of 1.5002 and an adjusted R-squared of 0.1173.

Individual and Household Variables

In the regression, individual and household factors were all highly significant, except for household size. Household wealth quintile in particular had strong predictive power in explaining child HAZ scores. The signs of the coefficients were all in the direction that the previous literature would suggest. For the categorical variables, the reference month is January, the reference toilet type is a flush toilet, and the reference wealth quintile was the middle quintile.

Term	Estimate	Std Error	
(Intercept)	-0.48	0.03	***

Birthmonth - February	0.0049	0.009	
Birthmonth - March	0.016	0.0089	
Birthmonth - April	0.033	0.0089	**
Birthmonth - May	0.047	0.0089	***
Birthmonth - June	0.062	0.0089	***
Birthmonth - July	0.068	0.009	***
Birthmonth - August	0.091	0.0089	***
Birthmonth - September	0.1	0.0088	***
Birthmonth - October	0.15	0.0089	***
Birthmonth - November	0.16	0.0091	***
Birthmonth - December	0.19	0.009	***
Child's Age (Months)	-0.016	0.00011	***
Child is Male	-0.097	0.0037	***
Child's Birth Order	-0.0087	0.00084	***
Household Head Age	0.0032	0.00016	***
Household Head is Male	-0.028	0.005	***
Household Size	-0.00071	0.00054	
Mother's Years of Education	0.033	0.00051	***
Toilet is No Facility	-0.12	0.0057	***
Toilet is Other	-0.12	0.017	***
Toilet is Pit Latrine	-0.17	0.005	***
Wealth Quintile - Poorest	-0.16	0.0057	***
Wealth Quintile - Poorer	-0.076	0.0057	***
Wealth Quintile - Richer	0.11	0.0061	***
Wealth Quintile - Richest	0.35	0.0069	***

Table 3: Individual and Household coefficient estimates. One star (*) means p < 0.05; Two stars (**) means p < 0.01; Three stars (***) means p < 0.001.

Geographic Variables

Table 4 shows the effects of geographic factors on child HAZ scores, independent of precipitation patterns. For these variables, every variable was significant except for the estimated effect of whether it was a wet or dry period.

Term	Estimate	Std Error	
Crop Production Per Capita	-0.29	0.012	***
Government Effectiveness	0.087	0.0067	***
GDP Per Capita (PPP)	0.042	0.00086	***
Irrigation	0.0017	0.00013	***
Distance from Cities Over 50k	-0.057	0.0019	***
NDVI	-0.031	0.0072	***
Crop Nutrition Diversity	-1.7	0.029	***
Population	-0.00018	6.10E-05	**
Dry Period	-0.053	0.048	
Wet Period	0.12	0.082	
Stability/Absence Of Violence	-0.045	0.0033	***
10-year Mean Maximum Daily Temperature	0.018	0.00057	***

Table 4: Geographic factor coefficient estimates. One star (*) means p < 0.05; Two stars (**) means p < 0.01; Three stars (***) means p < 0.001.

Geographic Variables Moderating Shocks

The key variables of interest are presented in table 5. These coefficients show the estimated effects of various geographic factors on child HAZ scores during a wet period or a dry period. All the geographic variables examined were found to be significant during either dry periods or wet periods, with most being significant during both. Most variables were also found to have the same effect on nutrition during both wet and dry periods. National levels of crop production per capita, irrigation, NDVI, the nutritional diversity of cropping systems, and stability/absence of violence all increased child's HAZ scores during both wet and dry periods, whereas increases in daily mean temperature were associated with lower HAZ scores during both wet and dry periods. Finally, GDP per capita, government effectiveness, and population density were found to have split effects, improving HAZ scores during certain precipitation extremes but harming HAZ scores during other types of extremes.

Term	Dry Period			Wet Period		
	Estimate	Std Error		Estimate	Std Error	
Crop Production Per Capita	0.11	0.023	***	0.13	0.028	***
Government Effectiveness	0.11	0.014	***	-0.064	0.023	**
GDP Per Capita (PPP)	0.0024	0.0015		-0.02	0.0032	***
Irrigation	0.0016	0.00024	***	0.00078	0.00068	
Distance from Cities Over 50k	0.018	0.0032	***	-0.022	0.0097	*
NDVI	0.1	0.012	***	0.023	0.026	
Crop Nutrition Diversity	0.24	0.055	***	0.55	0.064	***
Population	-0.00042	0.0001	***	0.00053	0.00027	
Stability/Absence of Violence	0.0048	0.0069		0.071	0.01	***
10-year Mean Maximum Daily Temperature	-0.0066	0.001	***	-0.014	0.0018	***

Table 5: Coefficient estimates for geographic factors during a wet period and during a dry period. One star (*) means $p < 0.05$; Two stars (**) means $p < 0.01$; Three stars (***) means $p < 0.001$.

Mapping Combined Effects

We combined a global stack of geographic layers corresponding to each of the factors known to amplify or mitigate the effects of drought. In combining these layers, we weighed them according the coefficients that were estimated by the model, shown for dry periods in table 5, yielding the following map. This map depicts how much the average child's HAZ score would be expected to change during a drought in a given location. Arid parts of the middle east and Africa are where child nutrition would be most affected by drought. Somalia is particularly vulnerable, due to low crop production per capital, poor government effectiveness, low GDP, low vegetation productivity, high rates of local violence, and high overall temperatures. Other countries where child HAZ scores would be most affected by a drought, dropping by potentially -0.25 on average, include Haiti, Sudan, South Sudan, Chad, Libya, Syria, and Iraq, all of which have relatively low GDP per capita, poorly functioning governments, and high rates of violence. Additionally, the Sahel and parts of south Asia are predicted to have decreases in HAZ scores around -0.15. Finally, much of Africa and southwest Asia are predicted to have some impact on child HAZ scores in the event of a drought.

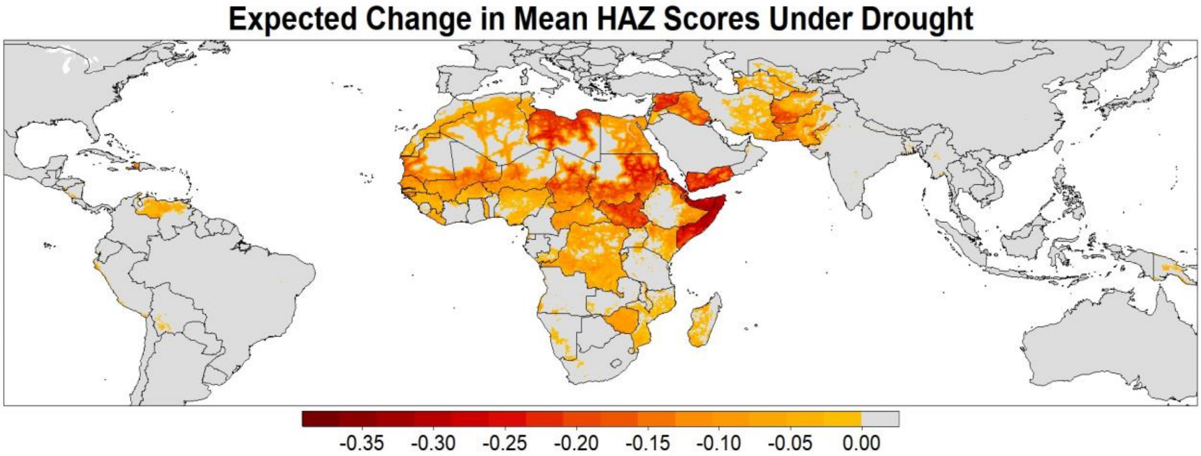

Figure 4: Expected change in mean child HAZ scores during drought conditions.

Discussion

This study found that precipitation deviations from long-term norms, such as dry periods and excessively wet periods, were associated with worse child HAZ scores. Using geographic data associated with the time and location of each child nutrition observation, we modeled how a variety of geospatial factors amplify or mitigate the effects of these precipitation shocks. Finally, we mapped where current geographic contexts would be predicted to lead to worse child nutrition outcomes during the event of a drought, based on how those factors were observed to moderate the effects of drought.

In examining different indicators of precipitation shocks, we found that the 24-month SPEI had the best AIC of all the possible time intervals. Although a child's HAZ score is affected by chronic, long-term undernutrition, the 24-month SPEI score performed better than 36-month. This may be due children experiencing rapid growth when they receive adequate nutrition following a period of poor nutrition, a phenomenon known as compensatory growth or catch-up growth (Victora et al., 2008). We further expect that the 24-month SPEI score would affect the HAZ scores even for children less than 24 months old because of lags between rainfall, agricultural production, and food consumption, as well as the fact that a child's HAZ score is influenced by the quality of their mother's diet while in utero (Wrottesley et al., 2015). The 24-month SPEI also had a loess curve in line with what the literature would predict: higher HAZ scores during periods with normal precipitation, and lower HAZ scores at extreme levels of precipitation. According to our analysis, even minor rainfall deficits are related to worse child nutrition outcomes, while greater-than-normal rainfall is not related to worse child nutrition outcomes until it is excessive (SPEI > 1.5).

A significant advantage of this study was using a very large dataset. This allowed us to draw on child nutrition outcomes under a wide range of conditions, from wet periods to dry periods, across a range of levels of GDP per capita, and across a variety of agro-ecological conditions. Our model found that many of these geographic factors play a significant role in affecting child nutrition outcomes and in moderating the effects of precipitation shocks. In fact, whether it was a wet period or dry period was only significant for HAZ scores when modeled in combination with those geographic factors, suggesting that the impact of precipitation shocks is entirely contingent on geographic context. Most of the factors affecting nutrition outcomes did so in the way the literature would predict: higher GDP, NDVI, crop production, government effectiveness, irrigation, crop nutritional diversity, and national stability were also associated with greater drought resilience. Higher temperatures were associated with worse nutrition outcomes during both droughts and wet periods, suggesting that the effects of climate change may not only lead to increased vulnerability from changing precipitation patterns, but rising temperatures will also exacerbate the effects of future shocks.

Some of the variables had counter-intuitive effects, especially during excessively wet periods. For example, both higher GDP per capita and higher government effectiveness were associated with worse HAZ scores during wet periods. This could be due to sampling bias: because of the higher cutoff for wet periods, we only had 71 DHS surveys where some of the sites were observed during wet periods, compared to 113 surveys with some sites observed during dry periods. However, these unexpected effects may also be indicative of how excessive rainfall impacts infrastructure in particular and the fact that only wealthier, better-governed countries have food systems that depend on such infrastructure in the first place.

The results of this analysis also highlight some of the tradeoffs that come with development. For example, some factors, such as crop nutritional diversity and NDVI, were found to be associated with worse child HAZ scores during periods with normal rainfall, but higher HAZ scores during precipitation extremes. This could be due to monocropping and clearing natural areas for farmland, which are associated with less nutrition diversity and lower NDVI. These economic strategies can lead to greater income and healthier children while rainfall is sufficient and agriculture is productive. However, during precipitation extremes areas that practice monocropping or have been deforested are likely to be more strongly impacted (Reed et al., 2016).

Beyond just showing which geographic factors amplify or mitigate vulnerability, this study also mapped the expected impact of drought on child HAZ scores. This improves upon previous mapping efforts that have relied on index-based approaches which take an *a priori* approach to combining geographic variables. By using an econometric approach, we are able to estimate coefficients from historical observations of meteorological impacts on HAZ scores that we then use to weigh various geographic factors when combining them. Another difference between this approach and that of index-based methods is that this approach makes a falsifiable prediction about an observable outcome that is critical to human well-being. Other approaches are difficult to validate, given that they are make qualitative predictions such as "high vulnerability" or "low severity."

The map of expected changes in child HAZ scores during dry periods highlights several areas as being particularly drought-vulnerable. The horn of Africa and Yemen, unstable middle eastern countries like Syria and Libya, as well as Sahelian countries from Senegal to Sudan are all predicted to see substantial declines in child HAZ scores during dry periods. Many areas could also be expected to see small decreases in child HAZ scores during droughts. This includes most of Africa, some parts of southwest Asia, as well as parts of Venezuela, Haiti, and Papua New Guinea. It should be noted that a wide range of shocks were combined into the category of "dry period" for this mapping analysis. Most of these shocks were moderate and not uncommon, with an SPEI between -0.4 and -1.5, and thus this map does not show the anticipated effects of severe droughts that could become more common under climate change. Many areas besides those highlighted in this map would likely see nutritional decreases under severe droughts, and areas shown in this analysis to be vulnerable to moderate drought, like Somalia and the Sahel, would likely see extreme increases in stunting under severe droughts.

Because only unusually excessive rainfall (SPEI > 1.5) was observed to affect child nutrition, we had fewer DHS surveys conducted during such periods and therefore less observed variation in geographic factors that could mitigate the impacts of excessive rainfall. Furthermore, the impacts of excessive rainfall are less localized than the effects of drought, with communities downstream or downhill often more affected by excessive rainfall. Thus, we only mapped expected change in HAZ scores under drought conditions.

This map highlighting vulnerability could be combined with IPCC projections to highlight which areas will be most impacted in the future. For example, some areas in the southern Mediterranean were found to be drought vulnerable in our model; these areas are also expected to become much drier under various IPCC projections. Similarly, the western Sahel in Senegal and Mauritania is anticipated to get drier in some IPCC projections and according to our model would see a mean HAZ decrease of up to 0.2. This map could also be combined with local estimates of rates of stunting to convert decreases in HAZ scores into rates of stunting. While global subnational maps of current rates of stunting or HAZ scores do not exist, a conservative estimate of average HAZ scores in developing countries would be -1.25, although values in countries like South Sudan or Somalia could be much lower. Under such an assumption, the rate of stunting is likely around 22.6%. A decrease in mean HAZ scores of -0.25, as our model predicts would occur in some areas, would thus raise rates of stunting to 30.8%.

This model assumes the effects of geographic factors in mitigating climate shocks are independent and linear. Thus, if there are interactions between geographic factors in mitigating climate shocks, they are not captured by this model. Furthermore, this analysis relies on some geographic data that is only available at the national level. For example, government effectiveness is modeled as the same in all parts of a country, even though actual levels of government effectiveness may vary significantly within a country, especially in developing countries. This can diminish the impact of subnational heterogeneity in the final map. Finally, for some countries, this study modeled linear effects beyond the range of observed values in the resulting map. For example, the country with the lowest government effectiveness score in which a DHS was conducted was Congo-Kinshasa in the year 2007, with a score of -1.7. Nevertheless, we modeled outcomes for countries with lower scores than this, such as Syria, South Sudan, and Somalia. In spite of these modeling limitations, our final models and the maps we produce match the previous literature and theoretical expectations of which factors moderate climate shocks as well as which locations are most vulnerable to shocks, while at the same time providing new insight into how these factors rank in terms of importance for mitigating or amplifying the effects of shocks, as well as how different locations vary in terms of relative expected impact during a shock.

Conclusion

This study relied on historical observations of child health outcomes under a wide range of precipitation and geographic conditions. We found that moderate drought and excessive rainfall are associated with worse child nutrition outcomes as measured by HAZ scores. We modeled a variety of geographic factors as moderating the effects of shocks and found that factors like absence of violence, crop production, crop nutrition diversity and vegetation productivity were associated with resilience to precipitation shocks. Given the factors most associated with resilient nutrition outcomes, some policy interventions likely to lead to improved nutrition under climate change include building governing capacity; encouraging de-militarization and stability; increasing crop diversity; and restoring degraded areas. Finally, we mapped the areas most nutritionally at risk under drought conditions and found that many parts of the horn of Africa, the Sahel, and the middle east would see substantial increases in stunting under drought conditions. These finding can help NGOs, foundations, and multinational organizations to both effectively targeting aid and to foster interventions that will support child nutrition in the face of an uncertain climatological future.

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About the authors

Matthew Cooper is a PhD Student in Geographical Sciences at the University of Maryland. He has degrees in Geography from the University of North Carolina and the University of Florida. Outside of academia, Matt has worked for non-profits and government agencies throughout the world. (Contact: mattcoop@terpmail.umd.edu)

Appendix A

	Model with 10 Covariates		Model with 14 Covariates	
Term	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
(Intercept)	-0.8863	0.0153***	-0.5425	0.0221***
Birthmonth - February	0.0043	0.0116	0.0077	0.0116
Birthmonth - March	0.0223	0.0114	0.0244	0.0113
Birthmonth - April	0.0478	0.0115***	0.0534	0.0114***
Birthmonth - May	0.059	0.0115***	0.0649	0.0114***
Birthmonth - June	0.0808	0.0115***	0.0863	0.0114***
Birthmonth - July	0.0986	0.0115***	0.0998	0.0115***
Birthmonth - August	0.105	0.0114***	0.1062	0.0113***
Birthmonth - September	0.1341	0.0114***	0.1352	0.0113***
Birthmonth - October	0.1763	0.0114***	0.1791	0.0114***
Birthmonth - November	0.1786	0.0116***	0.1788	0.0115***
Birthmonth - December	0.2229	0.0116***	0.2225	0.0115***
Child's Age (Months)	-0.017	0.0001***	-0.0179	0.0001***
Child is Male	-0.0984	0.0047***	-0.0971	0.0047***
Child's Birth Order	-0.0135	0.0011***	-0.0088	0.0011***
Household Head Age	0.0031	0.0002***	0.0029	0.0002***
Household Head is Male	-0.0287	0.0064***	-0.0286	0.0064***
Household Size	0.0053	0.0007***	0.0054	0.0007***
Mother's Years of Education	0.047	0.0006***	0.0416	0.0006***

Toilet is No Facility	-0.4105	0.0068***	-0.3141	0.007***
Toilet is Other	-0.3338	0.022***	-0.2744	0.0219***
Toilet is Pit Latrine	-0.3713	0.0061***	-0.294	0.0062***
Wealth Quintile - Poorer	-0.0372	0.0072***	-0.0308	0.0072***
Wealth Quintile - Poorest	-0.0257	0.0073***	-0.0221	0.0073***
Wealth Quintile - Richer	0.0554	0.0078***	0.0399	0.0078***
Wealth Quintile - Richest	0.2204	0.0085***	0.1682	0.0085***
Child had Diarrhea in Past Two Weeks	NA	NA	-0.219	0.0064***
Child Is A Twin	NA	NA	-0.4709	0.0151***
Child Was Ever Breastfed	NA	NA	-0.167	0.0161***
Non-Drinking Water Source - Purchased	NA	NA	0.0828	0.0126***
Non-Drinking Water Source - Surface Water	NA	NA	-0.2268	0.0081***
Non-Drinking Water Source - Tube Well	NA	NA	-0.2692	0.0058***
RMSE	1.5093		1.5008	
AIC	1490016		1485392	

Comparison of 11 versus 15 variable regression for predicting child HAZ scores. Regressions run on the same dataset (n=406,955). One star (*) means p < 0.05; Two stars (**) means p < 0.01; Three stars (***) means p < 0.001.

Appendix B

	12-Month SPEI		24-Month SPEI		36-Month SPEI		12-Month SPI		24-Month SPI		36-Month SPI	
Term	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
(Intercept)	-0.8938	0.0515***	-0.8959	0.0513***	-0.8945	0.0513***	-0.8934	0.0516***	-0.8953	0.0514***	-0.8938	0.0515***
Birthmonth - February	0.0039	0.0095	0.0039	0.0095	0.0039	0.0095	0.0038	0.0095	0.0039	0.0095	0.0038	0.0095
Birthmonth - March	0.0207	0.0093*	0.0207	0.0093*	0.0207	0.0093*	0.0208	0.0093*	0.0208	0.0093*	0.0208	0.0093*
Birthmonth - April	0.0406	0.0094***	0.0405	0.0094***	0.0405	0.0094***	0.0406	0.0094***	0.0405	0.0094***	0.0405	0.0094***
Birthmonth - May	0.0588	0.0094***	0.0586	0.0094***	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***
Birthmonth - June	0.0793	0.0094***	0.0793	0.0094***	0.0793	0.0094***	0.0794	0.0094***	0.0793	0.0094***	0.0793	0.0094***
Birthmonth - July	0.0891	0.0095***	0.0889	0.0095***	0.089	0.0095***	0.0891	0.0095***	0.089	0.0095***	0.0891	0.0095***
Birthmonth - August	0.1112	0.0094***	0.1111	0.0094***	0.1111	0.0094***	0.1113	0.0094***	0.1112	0.0094***	0.1112	0.0094***
Birthmonth - September	0.1248	0.0093***	0.1247	0.0093***	0.1246	0.0093***	0.1248	0.0093***	0.1247	0.0093***	0.1247	0.0093***
Birthmonth - October	0.1718	0.0094***	0.1717	0.0094***	0.1718	0.0094***	0.1719	0.0094***	0.1718	0.0094***	0.1719	0.0094***
Birthmonth - November	0.1942	0.0095***	0.1941	0.0095***	0.1941	0.0095***	0.1944	0.0095***	0.1942	0.0095***	0.1943	0.0095***
Birthmonth - December	0.236	0.0095***	0.2359	0.0095***	0.236	0.0095***	0.2361	0.0095***	0.236	0.0095***	0.2361	0.0095***
Child's Age (Months)	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***
Child is Male	-0.1064	0.0039***	-0.1063	0.0039***	-0.1063	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***
Child's Birth Order	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***
Household Head Age	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***
Household Head is Male	-0.0239	0.0054***	-0.0239	0.0054***	-0.024	0.0054***	-0.0241	0.0054***	-0.0241	0.0054***	-0.0241	0.0054***
Household Size	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***

Mother's Years of Education	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***
Toilet is No Facility	-0.0808	0.0067***	-0.08	0.0067***	-0.0804	0.0067***	-0.0807	0.0067***	-0.0804	0.0067***	-0.0806	0.0067***
Toilet is Other	0.0215	0.0189	0.0222	0.0189	0.0212	0.0189	0.0208	0.0189	0.0214	0.0189	0.0207	0.0189
Toilet is Pit Latrine	-0.1064	0.0059***	-0.106	0.0059***	-0.1063	0.0059***	-0.1066	0.0059***	-0.1063	0.0059***	-0.1066	0.0059***
Wealth Quintile - Poorer	-0.0983	0.006***	-0.0982	0.006***	-0.0982	0.006***	-0.0983	0.006***	-0.0983	0.006***	-0.0983	0.006***
Wealth Quintile - Poorest	-0.1989	0.0062***	-0.1987	0.0062***	-0.1987	0.0062***	-0.199	0.0062***	-0.1989	0.0062***	-0.199	0.0062***
Wealth Quintile - Richer	0.1276	0.0064***	0.1278	0.0064***	0.1277	0.0064***	0.1277	0.0064***	0.1278	0.0064***	0.1277	0.0064***
Wealth Quintile - Richest	0.3901	0.0073***	0.3904	0.0073***	0.3904	0.0073***	0.3902	0.0073***	0.3905	0.0073***	0.3903	0.0073***
Precipitation Index	0.0118	0.0029***	0.02	0.0031***	0.0139	0.0031***	0.0043	0.0029	0.0118	0.003***	0.0061	0.0031*
AIC	2148843.069		2148816.695		2148838.167		2148856.87		2148843.852		2148855.105	

Regressions run with various precipitation indices. One star (*) means p < 0.05; Two stars (**) means p < 0.01; Three stars (***) means p < 0.001.

	12-Month Growing Season SPEI		**24-Month Growing Season SPEI**		**36-Month Growing Season SPEI**		**12-Month Growing Season SPI**		**24-Month Growing Season SPI**		**36-Month Growing Season SPI**	
Term	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
(Intercept)	-0.8939	0.0515***	-0.8961	0.0514***	-0.8935	0.0516***	-0.8938	0.0515***	-0.8958	0.0514***	-0.8932	0.0516***
Birthmonth - February	0.0039	0.0095	0.0039	0.0095	0.0038	0.0095	0.0039	0.0095	0.0039	0.0095	0.0038	0.0095
Birthmonth - March	0.0208	0.0093*	0.0208	0.0093*	0.0208	0.0093*	0.0208	0.0093*	0.0208	0.0093*	0.0208	0.0093*
Birthmonth - April	0.0406	0.0094***	0.0405	0.0094***	0.0405	0.0094***	0.0406	0.0094***	0.0405	0.0094***	0.0405	0.0094***
Birthmonth - May	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***	0.0587	0.0094***
Birthmonth - June	0.0794	0.0094***	0.0793	0.0094***	0.0793	0.0094***	0.0794	0.0094***	0.0793	0.0094***	0.0793	0.0094***
Birthmonth - July	0.0891	0.0095***	0.0891	0.0095***	0.0891	0.0095***	0.0891	0.0095***	0.0891	0.0095***	0.0891	0.0095***
Birthmonth - August	0.1113	0.0094***	0.1112	0.0094***	0.1112	0.0094***	0.1113	0.0094***	0.1112	0.0094***	0.1112	0.0094***

Birthmonth - September	0.1248	0.0093***	0.1248	0.0093***	0.1248	0.0093***	0.1248	0.0093***	0.1248	0.0093***	0.1248	0.0093***
Birthmonth - October	0.1719	0.0094***	0.1718	0.0094***	0.1719	0.0094***	0.1719	0.0094***	0.1718	0.0094***	0.1719	0.0094***
Birthmonth - November	0.1943	0.0095***	0.1942	0.0095***	0.1943	0.0095***	0.1943	0.0095***	0.1942	0.0095***	0.1943	0.0095***
Birthmonth - December	0.2361	0.0095***	0.236	0.0095***	0.2361	0.0095***	0.2361	0.0095***	0.236	0.0095***	0.2361	0.0095***
Child's Age (Months)	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***	-0.0169	0.0001***
Child is Male	-0.1064	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***	-0.1064	0.0039***
Child's Birth Order	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***	-0.0039	0.0009***
Household Head Age	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***	0.0023	0.0002***
Household Head is Male	-0.024	0.0054***	-0.024	0.0054***	-0.0241	0.0054***	-0.024	0.0054***	-0.024	0.0054***	-0.0241	0.0054***
Household Size	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***	-0.0038	0.0006***
Mother's Years of Education	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***	0.0314	0.0006***
Toilet is No Facility	-0.0808	0.0067***	-0.0803	0.0067***	-0.0806	0.0067***	-0.0809	0.0067***	-0.0804	0.0067***	-0.0806	0.0067***
Toilet is Other	0.0211	0.0189	0.0217	0.0189	0.0207	0.0189	0.021	0.0189	0.0216	0.0189	0.0206	0.0189
Toilet is Pit Latrine	-0.1065	0.0059***	-0.1061	0.0059***	-0.1066	0.0059***	-0.1065	0.0059***	-0.1061	0.0059***	-0.1067	0.0059***
Wealth Quintile - Poorer	-0.0983	0.006***	-0.0982	0.006***	-0.0983	0.006***	-0.0983	0.006***	-0.0982	0.006***	-0.0983	0.006***
Wealth Quintile - Poorest	-0.1989	0.0062***	-0.1988	0.0062***	-0.199	0.0062***	-0.1989	0.0062***	-0.1988	0.0062***	-0.199	0.0062***
Wealth Quintile - Richer	0.1276	0.0064***	0.1277	0.0064***	0.1277	0.0064***	0.1276	0.0064***	0.1277	0.0064***	0.1277	0.0064***
Wealth Quintile - Richest	0.3902	0.0073***	0.3903	0.0073***	0.3903	0.0073***	0.3902	0.0073***	0.3904	0.0073***	0.3903	0.0073***
Precipitation Index	0.0075	0.0027*	0.0149	0.0029***	0.0045	0.003*	0.0075	0.0028**	0.0138	0.003***	0.0029	0.003
AIC	2148851.712		2148833.037		2148856.788		2148852.059		2148837.601		2148858.16	

Regressions run with various precipitation indices. One star (*) means p < 0.05; Two stars (**) means p < 0.01; Three stars (***) means p < 0.001.