Considering soil moisture in models of climate impacts on child health in farming-centric countries

Ruthie Burrows[1,2], Kathryn Grace[1,2], Molly E Brown[3], Amy McNally[4,5]

1. University of Minnesota, Department of Geography, Environment, and Society, Minneapolis, MN
2. Minnesota Population Center, Minneapolis, MN
3. University of Maryland, Department of Geographical Sciences, College Park, MD
4. Science Applications International Corporation, Inc., McLean, VA
5. NASA Goddard Space Flight Center, Greenbelt, MD 20771, United States

Corresponding author: Ruthie Burrows, burro191@umn.edu

ORCID
Ruthie Burrows – 0000-0001-6886-7995
Molly Brown – 0000-0001-7384-3314
Amy McNally - 0000-0001-7094-7599

Author contributions

Conceptualization: Ruthie Burrows, Kathryn Grace, Molly Brown, Amy McNally; Methodology: Ruthie Burrows, Kathryn Grace, Molly Brown; Formal analysis and investigation: Ruthie Burrows; Writing - original draft preparation: Ruthie Burrows; Writing - review and editing: Ruthie Burrows, Kathryn Grace, Molly Brown, Amy McNally

Funding information

The authors gratefully acknowledge support from the Minnesota Population Center (P2C HD041023) funded through a grant from the Eunice Kennedy Shriver National Institute for Child Health and Human Development (NICHD). This study was also supported by the Feed the Future Innovation Lab for Collaborative Research on Sustainable Intensification (SIIL) at Kansas State University through funding from the United States Agency for International Development (USAID) under the Cooperative Agreement (Grant number AID-OAA-L-14-00006)

Declaring conflict of interest

The authors declare that there is no conflict of interest.

Abstract

Soil moisture reflects the amount of water available to crops in the top layer of soil. As such, considering soil moisture provides important insight into water availability and ultimately crop yields in agricultural settings. In studies of climate change, food security, and health, however, soil moisture is rarely empirically considered despite its connection to crop health and yields. In this project, we aim to advance understanding of climate impacts on food security by incorporating soil moisture into quantitative models of child health. Combining spatially referenced health survey data from the Demographic and Health Surveys for 2005 and 2010 in Senegal and 2007, 2011, and 2014 in Bangladesh, with soil moisture data from the Famine Early Warning System Network Land Data Assimilation System, we explore the linkages between sub-annual and sub-seasonal climate conditions and child malnutrition in two rainfed agriculture dependent countries - Bangladesh and Senegal. Results suggest that soil moisture, measured on very short time scales, may be associated with reductions in anthropometric weight-for-height z-scores but the relationship is highly dependent upon geographic context.

Introduction

Food security is defined as having continued, stable access to safe, affordable, and nourishing food (Barrett, 2010). When one of these conditions are not met, the risk of food insecurity increases with impacts on human health and development in the short- and long-term (Pinstrup-Anderson, 2009; Wheeler & Von Braun, 2013). When children experience food insecurity, they are at an increased risk for adverse health outcomes like increased risk of infections and mortality, as well as undernutrition, including wasting and stunting (Balk et al., 2005; Akresh et al., 2011; Black et al., 2013; Brown et al., 2020; Randell et al., 2020). Because of food insecurity's importance on child health outcomes, global campaigns aimed to reduce hunger, such as the Sustainable Development Goals and Zero Hunger, maintain a large focus on decreasing child food insecurity.

Local, rainfed agricultural production provides an important source of food and income for rural households in low-income countries when access to food markets is sparse (Di Prima et al. 2022). Due to its increased availability and decreased cost, locally-produced food is important for ensuring food security of households and individuals and for providing a coping mechanism of distress selling when growing season conditions are poor (Iizumi et al. 2013; Grace et al., 2014; Musyoka et al., 2021). Farmers and farming reliant communities depend upon relatively consistent rainfall during key growing seasons for ensuring food and income security in communities and households where community-level food production is common. Climate change is associated with increased frequency and intensity of droughts and floods and with a shifting seasonality of precipitation leading to a potential for adverse impacts on agricultural yields (Verhagen et al. 2004; Easterling et al. 2007; Jalloh et al. 2013). When yields are poor, children may face an increased risk of undernutrition as the availability of local food decreases and as household income decreases (Brown et al., 2014; Grace et al., 2016). Yearly varying measures of community-level agricultural yield are not routinely collected in low-income countries, however, leaving researchers to rely on remotely sensed rainfall datasets to help determine the quality of the growing season (Lobell et al. 2019; Kugler et al., 2019). Research that incorporates remotely-sensed data has found that excessive precipitation or a lack of precipitation may be associated with food insecurity in children (Chotard, 2011; Shively et al., 2015; Randel et al., 2020).

As part of early warning efforts to support health and agricultural interventions before food insecurity sets in, it is particularly important to understand the role of climate on localized production of agriculture (Grace et al., 2016). However, despite increased attention to child food insecurity and climate conditions, the mechanisms that link exposure to climate conditions and undernutrition remain confusing in the literature. Key measurement issues related to temporal and spatial data harmonization remain an ongoing challenge in this research. In much of the previous literature of quantitative analyses on food insecurity climate measures are operationalized as seasonal totals or averages of precipitation and temperature (Balk et al., 2005; Grace et al., 2012; Davenport et al., 2017; Thiede & Strube, 2020). However, research of climate and soil science suggests that sub-seasonal measures with finer temporal scales may better capture environmental interactions that are more relevant to plant growth and agricultural production (De Camargo & Hubbard, 1999, Eggen et al., 2019). For acute and reversible child health outcomes, like wasting, improving scientific understanding of the role of climate in child health is vital.

In this paper, we explore the use of two different remotely sensed measures for approximating local agricultural yields and food availability, soil moisture, a measure of below-ground moisture, and Normalized Difference Vegetation Index (NDVI), a measure of above-ground moisture. We include these variables in quantitative models to explore the variability of indicators of acute child health across space and time in two different countries with relatively high levels of child undernutrition and a high reliance on rainfed agriculture, Senegal and Bangladesh. To conduct this analysis we use spatially referenced, nationally representative data from the Demographic and Health Surveys (DHS) retrieved via IPUMS DHS linked to high spatial resolution data from the Famine Early Warning System Network Land Data Assimilation System (FLDAS) and NDVI (MODIS) datasets to explore temporal measures of growing season conditions on individual-level weight-for-height and wasting.

Background

Measuring food security

Food security can be described using four pillars – availability, stability, utilization, and access (Barrett, 2010; Wheeler & VonBruan, 2013). Agricultural production is a major component of food availability, and in low-income countries like Senegal and Bangladesh where people depend on farming for livelihoods, food production, when combined with other pillars, is especially important for food security (Phalkey et al., 2015). While food stability, utilization, and access are influenced by many outside factors like the political, social, and economic environment of a community or country, food availability is directly affected by the climate in low income, rural, and rainfed agricultural settings. These four concepts – food availability, stability, utilization, and access are interrelated and all four must be satisfied for an individual or household to be considered food secure. Food insecurity occurs when one of these are insufficient and not meeting the needs of an individual or household.

The measurement and conceptualization of food security in quantitative studies varies, highlighting the importance of understanding the local contexts of each analysis. As such, the choice of measure can influence the conclusions and policy implications of an analysis. It is important to ensure we are capturing the underlying mechanisms that relate these pillars to real-world experiences of food security. While a direct measure of food security would be ideal for these quantitative analyses (Jones & Thornton, 2003), researchers often rely on proxy measures of food security through anthropometric growth. Weight-for-height z-scores (WHZ), a measure of acute nutrition are often used to approximate experiences with short-term food insecurity (Black et al., 2013; Johnson & Brown, 2014; Shively et al., 2015; Grace et al., 2022)

Much of the food security research is focused on food availability, especially studies of climate and food security, because it measures a direct effect on crop production, the amount of available food in communities, and the amount of available income a household can spend on food (Wheeler & von Braun, 2013; Phalkey et al., 2015; Thiede & Gray, 2020). Since crop production, a measure of food availability, is not regularly assessed at nationally representative scales in low-income countries, proxies like Normalized Difference Vegetation Index (NDVI) can be used to indicate community or regional crop production (Shively etl., 2015; Grace et al., 2021).

Climate indicators, like time-lagged measures of seasonal rainfall and less commonly temperature, are often used to characterize the quality of the growing season assuming that poorer growing seasons climate conditions would lead to poorer agricultural yields (Dos Santos & Henry, 2008; Davenport et al., 2017). Climate anomalies such as drought, floods, or extreme heat can lead to perturbations in crop production, directly reducing the amount of and stability of crop yields that are available for households and communities (Frelat et al., 2016). For example, Shively et al. (2015) found that child nutrition and growth is sensitive to anomalies in vegetation and crop production in Nepal. Temperature is sometimes considered in tandem with precipitation as a climate variable that can influence crop yields (Brown et al., 2020). Higher temperatures combined with varying availability of moisture is expected to affect crop yields in a mostly adverse direction though uncertainty remains based on a variety of factors like agricultural management practices, crop type, and soil properties (Lobell et al., 2011). Grace et al. (2012) found that warming and drying was associated with poorer child nutrition in Kenya; however, Thiede & Gray (2020) did not find a statistically significant relationship with temperature and acute undernutrition in Indonesia. Weather and climate can also influence food insecurity indirectly through infectious disease, altered childcare practices, and changes in food prices (Grace et al., 2014; Brown & Kshirsagar, 2015).

Food security is also dependent upon a stable supply of food. Breastfeeding provides an important source of nutrition for infants and can play an important role in the stability of food for children. The World Health Organization recommends breastfeeding as the sole source of nutrition for children up to six months of age (WHO, 2018). In Bangladesh, breastfeeding is highly prevalent with about 98% of pregnant mothers expressing a desire to breastfeed and about 65% of women exclusively breastfeeding until a child is six months of age (UNICEF, 2022). Breastfeeding is lower in Senegal where about 40% of mothers breastfeed until the child is 6 months of age (World Bank, 2019-a). If mothers follow these recommendations of exclusive breastfeeding then it is possible that young breastfed babies may be buffered from some adverse climate impacts (Maxwell, 1995; Dos Santos & Henry, 2008). However, new research connecting breastfeeding with climate found that when growing season conditions are more favorable for crop growth, breastfeeding women spend more time with agricultural activities leading to a lower likelihood of exclusive breastfeeding (Randell et al., 2021). Breastfeeding is a critical source of nutrition for young children and may also be a source of instability brought on by climate and weather conditions.

Challenges with measurements of food security

While framing food security using these pillars helps researchers conceptualize certain measures in their quantitative analyses, in reality, experiences with food security are much more complex than can be captured by discrete pillars. Issues of temporal and spatial scale complicate the relationship between many indicators used in quantitative studies of food security. Certain measures often work across multiple scales to influence food security and can be correlated with each other which makes it difficult to statistically model (Shively, 2017). For example, researchers sometimes include a household variable of electricity to measure economic access to food (Davenport et al., 2017). However, electricity could also indicate the household's ability to store food, indicating a measure of stability.

In the case of acute measures of food insecurity, the temporal resolution of cross-sectional and observational data can limit the ability to use certain measures in analyses. This is especially relevant to time-varying climate indicators used to approximate food availability and food stability. However, many countries worldwide do not collect spatially specific agricultural production information, even on an annual basis. Barrett (2010) discusses the issues related to using aggregated variables in that they often miss important heterogeneity that could explain the relationship between factors that affect food security. This highlights the importance of creating climate measures that reflect the complicated spatial and temporal dimensions of the climate and food security nexus.

Strategies to overcome these limitations

Remotely sensed or composite measures of proxy indicators of food availability are increasingly becoming a solution to address the need for spatially and temporally detailed data (Funk & Budde, 2009; Brown et al., 2015; Grace et al., 2021). These data types are recorded at daily time intervals and are often available at a relatively fine spatial resolution of less than one kilometer. The normalized difference vegetation index (NDVI) is most commonly used to estimate interannual food availability anomalies due to abiotic and biotic stress. NDVI provides an estimate of photosynthetic activity and can be used to predict crop yields. The greenness of vegetation, as measured by NDVI, is a direct correlate of precipitation (Lotsch et al., 2003) and temperature conditions (Lokupitiya et al., 2010) is a good indicator of food availability due to its ability to capture the effect of moisture and temperature of crop conditions. By measuring greenness of vegetation, NDVI can serve as a proxy measure of community-level food availability (Phalkey et al., 2015; Bakhtsiyarava et al., 2018; Brown et al., 2014; Shively et al., 2015). The climate pathways that we seek to define are highly variable across space and time, so these remotely sensed measures allow us to capture agricultural production at a relevant resolution.

We also consider an additional remote sensing-derived climate measure, soil moisture, in our analysis. Soil moisture is defined as the amount of water in the unsaturated soil zone, or the soil that is above the groundwater table (Seneviratne et al., 2010). One major role of soil moisture in the climate system is that it provides a source of water for the atmosphere through direct soil evaporation. The moisture in soil influences the atmosphere through land-surface fluxes and is involved in local, regional, and global climate feedbacks (Seneviratne et al., 2010).

Soil moisture also provides the atmosphere with water through plant evapotranspiration (Seneviratne et al., 2010). This conceptually links soil moisture with crop yields as an important constraining factor on agricultural productivity. There is compelling evidence that soil moisture could potentially be a more accurate measure of crop-available moisture than precipitation as rainfall does not measure processes like runoff, drainage, and evaporation on crop water availability (Rigden et al., 2020; Proctor et al., 2022). In a retrospective study of crop yields in the United States, soil moisture and atmospheric demand model parameters significantly outperformed precipitation and temperature in their ability to predict crop yields (Rigden et al., 2020). Despite this promise, users of soil moisture data have struggled to represent the spatially and temporally varying nature of soil moisture due to varying soil composition, organic matter, land cover and soil depth across regions, while also capturing variations in crop water demand. These challenges have limited the use of soil moisture in food security analyses. Rapidly improving soil moisture datasets which have recently become available offer the opportunity to demonstrate the potential of these data to estimate food security (McNally et al., 2017).

We employ the utility of these remotely sensed measures in our analysis to address some of the challenges related to food security measurements discussed above. Both soil moisture and NDVI could be important measures of production because they are sensitive to the timing of climate variability. Instead of using seasonal totals of these measures which often do not consider phenologically important timing, we focus instead on using sub-annual and early growing season estimates to link variability in soil moisture and NDVI to estimates of child food insecurity.

Data

Population data

We use population data from the Demographic and Health Surveys (DHS) via IPUMS DHS in Senegal and Bangladesh (Heger-Boyle et al., 2022). The cross-sectional Senegal surveys were taken in 2005 and 2010 and the Bangladesh surveys were taken in 2007, 2011, and 2014. Because of consistency across time periods and geographic coverage within countries, this data is widely used for research and policy related to global health and development in many low- to middle-income countries. The DHS also collects individual- and household-level information on educational attainment, health, demography, and household assets and attributes. The DHS also collects retrospective information on children, as reported by their mother, related to health and anthropometric growth.

The DHS are spatially referenced with the latitude and longitude of each sampling cluster. A cluster references the geographic center of the residential area in which the household is located. To de-identify the cluster locations and maintain confidentiality of the survey respondents, the DHS displaces the coordinates of each sampling cluster by up to 10 kilometers. Consistent with previous population and environment research, when merging the DHS data with other spatially referenced data we assume that the sampling cluster is located within a 10-kilometer buffer of the given cluster coordinate locations (Burgert et al., 2013).

Environmental Data

We retrieved soil moisture data from the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS) (McNally et al., 2017). This is a globally gridded 0.1-degree spatial resolution monthly dataset ranging from 1982 to present. To create this simulated dataset, FEWS NET combined Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data with reanalysis climate data from the Modern-Era Retrospective analysis for Research and Application, version 2 (MERRA-2). The FLDAS data is a product of several data types: satellite remote sensed, weather observations, and reanalysis data. Because of its global coverage and complete temporal record, this can be merged with DHS records.

Soil moisture data through FLDAS is available in multiple soil depth layers up to 100 cm underground. We focus our analysis on using the top layer of soil (0-10 cm underground) to characterize the upper layer of soil moisture. We assume that the upper layer will be the most impacted by short-term changes in precipitation, and therefore the best indicator of food availability. While there are other indicators of soil health such as soil pH, respiration, and organic matter these data are not regularly collected with sufficient temporal and spatial scale in Senegal and Bangladesh to facilitate the linking of these environmental data with population data.

Vegetation Data

We use Normalized Difference Vegetation Index (NDVI) derived from MODIS Terra satellite imagery (250km resolution) (Huete et al. 2002) as a measure of the effects of soil moisture on the health of vegetation, including crops and pastures (Assogba et al. 2022; Lokupitiya et al., 2010; Islam & Mamun, 2015). While household-level crop yield data would be ideal, regularly collected yield data does not exist for households in our case study settings. Because the soil moisture dataset is available at a monthly time step, we chose to use a 15-day NDVI composite period from 2000-2020 so the data can be easily temporally connected with the DHS and soil moisture data (Huete et al., 2002). The variability in NDVI has been shown to be related to variations in crop yields in semiarid Senegal (Fensholt et al., 2004; Groten, 1992) and for potatoes (Bala & Islam, 2009) and Boro Rice (Refat Faisal et al 2019) in Bangladesh. We consider June root zone soil moisture and NDVI to be a proxy for growing season climate conditions, crop production, and food availability.

Measures

The climate and food security nexus is complex and multiple pathways can connect climate with child health both indirectly and directly. We conceptualize food security indirectly through an outcome variable measuring child anthropometry, specifically weight-for-height z-scores. Lower valued z-scores (z-score less than -2 SD away from the mean) indicate wasting (low WHZ) which reflects acute experiences of undernutrition. To account for the range of categories of factors (food availability, stability, utilization, and accessibility) that may influence food security, we incorporate child-, mother-, and household-level determinants of food security in our models following the literature (e.g., Brown et al., 2020). Table 1 summarizes the data, by country, for all the variables used in our analysis. For each variable, we report means or percentages depending on the type of variable.

Outcome variable

The outcome variable is a continuous measure of weight-for-height, which reflects a short-term experience of food security. Weight-for-height is measured through z-scores which are standard from the World Health Organization. Low weight-for-height z-scores (WHZ) are usually associated with food insecurity and insufficient caloric intake (Black et al., 2013). Because WHZ is a measure of short-term nutrition, it is very sensitive to recent changes in diet or illness, so we focus on recent climate conditions that occur close in time to the survey date (within one year) (Grace et al., 2022). We consider WHZ for children ages 6-23 months. We restrict the analysis to these ages because the majority of growth faltering and wasting occurs in children 23 months and younger (Alderman & Headley, 2017). We further restrict our sample to exclude infants younger than six months. The complementary feeding period, which occurs after six months of age, is when a child transitions from exclusive breastfeeding to incorporating family foods like fruits, eggs, fish, and grains (Kuchenbecker et al., 2017; Aguayo 2017). As children transition away from the protective effects of maternal breastfeeding their diets become more vulnerable to the effects of climate variability on agricultural production.

Independent Variables: food insecurity

In this analysis we focus on sub-annual and sub-seasonal measures of growing season climate for three reasons 1) start of season/seasonal onset may better predict quality of growing season than seasonal averages 2) certain times of the growing season are more crucial to plant growth 3) short term climate indicators are more appropriate for early warning systems especially for wasting which is occurs on short time scales and can be improved if preventative interventions are in place.

Research suggests that climate conditions at certain time periods within the growing season are significant indicators of the quality of seasonal yields. Emerging evidence suggests that seasonal onset may be a better measure of the quality of growing season yields. For example, Shukla et al. (2021) and Davenport et al. (2021) both found that late seasonal onset of precipitation was significantly related to poor seasonal food production. Lee et al. (2022) compared the performance of sub-monthly (10-day time periods) climate measures to monthly climate measures in Sub-Saharan Africa and found that sub-monthly measures were better at predicting yields throughout the growing season. Sub-seasonal climate measures can better capture variability in time periods of vegetative growth that would otherwise be missed by using seasonal averages.

The sensitivity of the life cycles of certain crop varieties to the timing of seasonal precipitation is a possible mechanism to explain the importance of sub-seasonal climate in food security analyses. In other words, too much or too little rain during certain periods of the growing season are more critical for plant growth and production than other periods (Ademe et al., 2021). For example, Sorghum yields are highly variable with respect to the timing of seasonal rainfall (Eggen et al., 2019). Failure of early growing season rains is likely to have a negative impact on yields even if there is a recovery of rainfall totals later in the season and even if these rainfall totals are not different from the long-term normal. Therefore, sub-seasonal measures may more accurately capture climate conditions associated with yields compared to seasonal rainfall totals.

Finally, by focusing on short-term climate measures, this research can support early warning systems that can work to prevent undernutrition that occurs on shorter time scales. Wasting which reflects experiences of undernutrition on short time scales and is sensitive to recent climate variability (Shively et al., 2015). Brown et al. (2014) suggests that the most relevant climate time period may be just the month immediately prior to when the anthropometric measurement was taken. Grace et al. (2022) used the average temperature and precipitation conditions three months prior to the DHS survey when analyzing the environment/child health linkages in countries across sub-Saharan Africa finding that recent weather conditions are significantly correlated to WHZ in these geographic contexts. Further exploring how short-term climate measures may be connected to undernutrition could offer greater insight to inform early warning decisions to prevent food insecurity.

Given this emerging body of evidence supporting the significance of timing of rainfall on crop yields, we build our food insecurity variables to investigate fine-scale temporal linkages of weather, seasonal yields, and child food security with the goal of capturing the heterogeneity in population-environmental exposures. Based on growing evidence, we assume that an increase in soil moisture or NDVI during the first month of the growing season corresponds to a greater amount of food produced during the full growing season. Because we want to capture the quality of the completed growing season closest in time to when the DHS survey was recorded, we link the DHS data to the most recently completed growing season's soil moisture and NDVI conditions. For example, the growing season in Senegal is generally from June-August. If an anthropometric measurement was taken in July we link the soil moisture and NDVI conditions from the previous year's growing season since this is the most recently completed growing season.

We then explore the utility of sub-annual measures by building models that link average soil moisture and NDVI conditions 1-3, 1-2, and 1 months prior to the month of the survey. By constructing weather variables close in time to the survey collection these measures are motivated and build upon the methods described by Grace et al (2021). Our goal in creating these measures is to compare how they perform to sub-seasonal climate measures. Since wasting occurs on short time scales, it may be possible that sub-seasonal measures are not sufficiently close in time to the anthropometric measurement.

Analytic Approach

We use a suite of regression models to explore the relationship between acute child undernutrition (WHZ) and sub-seasonal and sub-annual climate indicators via soil moisture, and NDVI. The main model we use in our approach is a linear fixed effects regression with clustered standard errors with a continuous WHZ outcome variable. The equation below describes our regression modeling approach.

$$Y_{ijk} = \beta_0 + \beta_1(climate_k) + \beta_n(X_{ijk}) + u_k + v_z + e_k$$

In the equation, Y is a continuous WHZ score for a child *i* from a mother *j* in a DHS cluster *k*. Parameter B_1 is the term for soil moisture or NDVI. These variables are dependent upon the survey date and the cluster location. The model also controls for child-, mother-, and household-level variables (X_{cn}) including sex of child, age of child in months, birth order, mother's age, recent fever, recent diarrhea, mother's education, household floor type, urban/rural, and month of interview. We account for fixed effects of the survey year and DHS cluster as represented by the parameter u_z and v_z respectively. We adjust our standard errors to the DHS cluster level.

To account for possible collinearity between these climate variables and to see how soil moisture and NDVI perform separately, we consider each variable in separate models. The soil moisture dataset is created using precipitation and other meteorological inputs like temperature, humidity, radiation, and wind (McNally et al., 2017). NDVI is a direct reflection of temperature and precipitation conditions on vegetation health (Lotsch et al., 2003). Since soil moisture and NDVI have similar inputs, we tested for collinearity and found a correlation coefficient of .85. Additionally, soil moisture sees the impact of wetness over very large areas (25km) whereas NDVI shows the effect of changes in wetness on the overlying canopy. Therefore, the two vary at different time steps, have different intensities, and are highly correlated so we choose to model them in separate models.

Our conceptual framework presented in Figure 1 (see appendix) explains the specific pathways that we model in this analysis. In this conceptual framework, we connect soil moisture, precipitation, and temperature to food insecurity through their effects on crop production and food availability. These weather variables can affect each other and lead to increases or decreases in crop production. These increases and decreases in crop yields, in part, determine the amount of food that is available for consumption and the amount of income available to households to purchase food. Other variables like individual, maternal, and household factors that are measured by the DHS also affect WHZ and are accounted for in our models. We also incorporate measures of recent (within the past two weeks) diarrhea and febrile illness since these factors can affect a child's ability to physiologically uptake nutrients and can acutely affect a child's nutrition (De Sherbinin, 2011).

Finally, we explore the sensitivity of our primary regression approach when considering the most undernourished children in Senegal and Bangladesh. We create a binary outcome variable using the World Health Organization's guidelines for which any child with a weight-for-height z-score below -2 is considered wasted. We estimate the parameters of the model using this binary outcome variable of wasted/not wasted and compare these results to those using a continuous outcome variable.

Geographic setting

We use Senegal and Bangladesh, where subsistence agricultural livelihoods are prevalent, as case studies to explore how growing season climate conditions affect child health. In these low-input agricultural settings farmers are more heavily reliant on climate and weather patterns for the success of their crops, and in subsistence settings where most crops are grown for household consumption and income there are direct connections between climate and health (Kim & Bevis, 2019). In fact, despite improvements in nutrition outcomes in Bangladesh, the percentage of children experiencing wasting remains at about 10% (World Band, 2019-b). In Senegal there has been negligible improvement in child wasting and has remained about 8-9% at the national level since the early 2000s (World Band, 2019-c). We use these two countries as cases to explore how well soil moisture and vegetation health explain child wasting in countries with different climate settings but similar prevalence of wasting.

Senegal, as displayed on the top row of figure 2, is on average, drier than Bangladesh. There is a steep north/south precipitation gradient in Senegal, where the northern portion of the country has a dry, Sahelian climate, and the southern portion has a more temperate climate. Bangladesh is generally much wetter with more vegetation compared to Senegal. The low-lying plains that cover the majority of Bangladesh are primarily covered with perennial vegetation which has a high NDVI value, and is associated with higher agricultural output than regions with lower agroecological potential (Brown, 2006, Ritzema et al 2017). The more mountainous northeastern region of Bangladesh is where there is the least amount of green vegetation (corresponding to lower NDVI values).

In Senegal, the seasonal rains begin in June (FEWSNET, 2022). According to crop calendars it is during this month that the main rainfed crops, groundnuts, cereals, and cowpeas are planted (FEWSNET, 2022). In Bangladesh where rice is the staple crop, there are three planting seasons—*aman*, *boro*, and *aus*. While the boro and aus rice planting seasons rely primarily on irrigation, aman rice grows during the monsoon season when precipitation is plentiful (Ruane et al., 2013). The aman rice season accounts for 40% of the country's rice production and is typically planted in June and July (USDA, 2020). Because the aman rice season relies on seasonal weather patterns and may be vulnerable to climate variability we focus our analysis on this rice planting season. We use the start of the monsoon season, June, to conceptualize the sub-seasonal soil moisture and NDVI variables for Senegal and Bangladesh in our quantitative models.

Results

We first present the results for models 1-4 which solely look at the start of season soil moisture and NDVI for Senegal and Bangladesh. We then summarize the results for models 5-8 which use average soil moisture and NDVI for 1-3 months prior to when the surveys were taken in Senegal and Bangladesh. Models 9-12 use average soil moisture and NDVI conditions 2 months prior to the survey and finally models 13-16 consider the soil moisture and NDVI conditions for the month prior to when the survey was collected.

Table 2 shows the regression results for child-, mother-, and household, and cluster-level variables using the IPUMS Demographic and Health Survey data in Senegal and Bangladesh. In these models presented in table 2, the main climate variable of interest is the June (start of season) soil moisture and NDVI. We do not see a statistical relationship between soil moisture or NDVI and WHZ for our samples in Senegal or Bangladesh. For both models 1 and 2 which show the associations of June soil moisture and NDVI on WHZ respectively, in Senegal we find that certain child-level and maternal characteristics are significantly related to WHZ. When interpreting WHZ values, the lower the WHZ, the poorer the child’s health and the more likely the child is to be wasted. We find a strong negative association ($p < .05$) between birth order and WHZ when considering either soil moisture or NDVI in the model. In other words, as a child’s order of birth increases, their WHZ decreases within our samples in Senegal. We also find recent fever to be negatively associated with WHZ. In terms of maternal characteristics, we find that compared to a child’s mother with no formal education, a child with a mother who has secondary education is more likely to have higher WHZ.

Within table 2, models 3 and 4 reflect results of considering June soil moisture and NDVI on WHZ in Bangladesh. Similar to Senegal we do not see any statistical relationship between our June climate measures and WHZ. Here, many of the same demographic control variables are statistically associated with WHZ as they are in Senegal. Notably, in Bangladesh, recent diarrhea is negatively associated with WHZ in addition to recent fever. In other words, children with recent diarrhea when the survey was taken were more likely to have lower WHZ. Children who were currently breastfeeding at the time of the survey were found to have lower WHZ than children without recent diarrhea. We also found several positive associations with WHZ in our samples in Bangladesh. As a mother's age increases, a child's WHZ in our sample also increases. We also find floor type, a household characteristic that is a proxy measure for household wealth, is positively associated with WHZ. In other words, compared to children in households with unfinished and rudimentary floors, children in households with finished floors had higher WHZ in our samples.

We then compare our results in table 2 with results of models using averages of soil moisture and NDVI 1-3, 1-2, and 1 months prior to the survey date in Senegal and Bangladesh. Table 3 shows the results of models with the average soil moisture and NDVI 3 months prior to the survey date. We find that soil moisture averaged 3 months before the survey date is associated with lower WHZ in our samples in only Bangladesh but this relationship is not statistically significant. There are again statistically significant associations between the demographic control variables and WHZ for both Senegal and Bangladesh. Notably birth order, recent fever, and rural households are consistently negatively associated with WHZ while a mother's formal secondary education is consistently positively associated with WHZ across all models for Senegal and Bangladesh.

We then move to models using soil moisture and NDVI averaged 2 months prior to the survey date as the main climate variable of interest in table 4. Model 11 shows the results of average soil moisture 2 months prior to the DHS survey in Bangladesh. We again do not see any statistically significant relationships between the soil moisture or NDVI variables. The statistical relationships between WHZ and demographic control variables remain.

Finally, we test the utility of soil moisture and NDVI measured one month prior to the survey date in Senegal and Bangladesh in table 5. The magnitude of the effect of soil moisture on WHZ in Bangladesh has increased compared to previous models (-.04) and the relationship has become statistically significant ($p < .04$) compared to all previous models. Using this very short timescale of soil moisture and NDVI one month prior to the survey we see statistical significance of a negative relationship with soil moisture and WHZ in Bangladesh but not in Senegal. Further, we continue to see statistical relationships with demographic control variables (birth order, age, breastfeeding, fever, mother's education) and WHZ.

Categorical wasting analysis

Finally, to test the sensitivity of our models by isolating the most undernourished children in the samples we construct the outcome as a binary variable, comparing wasted children to children with healthy weight-for-height z-scores. We focus our dichotomous analysis on soil moisture conditions in Bangladesh since it is in this context that we find a statistically significant relationship using the continuous outcome variable, WHZ. We do not find a statistically significant relationship between soil moisture and the binary outcome variable for June soil moisture, 1-3, 1-3, or 1 month averages leading up to the anthropometric measurement.

The results (available in the supplementary material) show that some of the same individual-, maternal-, and household-level characteristics are statistically associated with wasting in the same way they are associated with a continuous outcome variable. At the individual level we find that recent fever and recent diarrhea increases the odds of being wasted. We find that formal maternal education decreases the odds of being wasted.

Discussion and conclusion

Given the predicted increase in severity and variability of global climate patterns, there is an increasing focus on understanding the implications of climate variability through the relationship between climate and weather and health outcomes. The risk of food insecurity in children may especially be modified by climate and weather patterns in low- and middle-income countries where farming systems are predominantly rainfed. In this analysis, we explored the associations between sub-seasonal and sub-annual soil moisture and NDVI conditions and continuous measures of acute nutrition in children in two farming centric countries, Senegal and Bangladesh. We merged soil moisture and NDVI data to population data using the Demographic and Health Surveys which include information on individual children, mothers, and household characteristics and we used linear regression models with clustered standard errors to explore the associations between these variables. We employed two approaches to link soil moisture and

NDVI to the DHS data and to further explore the effect of choice of temporal scale in studies of child health and climate 1) using the start of growing season as an indicator to summarize the soil moisture and NDVI conditions of each sampling cluster 2) using a series of models that link average soil moisture and NDVI 1-3, 1-2, and 1 months prior to the survey date.

Pathways supported in this analysis

This study demonstrates the complexity of quantitative population-environment research. While the start of growing season indicators were not significantly related to weight-for-height z-scores in our samples, we did find evidence that soil moisture, when operationalized on very short time scales relative to the survey date, is statistically associated with WHZ in the DHS samples in Bangladesh. We found that in our samples in Bangladesh an increase in soil moisture one month before a DHS survey is associated with lower WHZ. These results are consistent with previous research from Grace et al. (2021) who found that recent average precipitation and temperature averaged 1-3 months prior to DHS surveys were negatively associated with WHZ in Nigeria and Kenya.

In Bangladesh where our sample was generally younger and had a lower WHZ than the samples in Senegal we expect to see a stronger effect on recent weather conditions and child health. In their study in Niger, Kohlmann et al. (2021) found wasting in children to peak at 11 months of age. Additionally, since we are considering children ages 6-23 months, we can also assume that the number of exclusively breastfed children is low and therefore the children's diets in these DHS samples may be more vulnerable to external factors modified by changes in soil moisture conditions. Another explanation as to why we may be seeing the negative association with WHZ and soil moisture in Bangladesh is due to disruptions in breastfeeding practices while mothers partake in agricultural labor while soil moisture conditions are favorable.

The associations between climate conditions and breastfeeding have been previously described by Randell et al. (2021) who found that increased rainfall during the primary agricultural season in Ethiopia was associated with a greater number of days women spend in agricultural labor and was associated with a decreased likelihood of exclusive breastfeeding in infants. The associations that we found between WHZ and soil moisture in Bangladesh could be explained by disruptions in breastfeeding brought on by changes in labor demand. This may be especially plausible for Bangladesh where breastfeeding is more prevalent than in Senegal. In the context of our study, short-term increases in soil moisture could require women to spend more time in income-earning roles and less time breastfeeding and caring for their children which may explain the negative associations between soil moisture and WHZ in the Bangladeshi DHS samples.

While indicators of sub-seasonal vegetation and moisture and child health are not consistent across settings, we find that fine temporal scale soil moisture measure close in time to the DHS survey is consistently related to acute undernutrition in Bangladesh. We interpret these inconsistent findings as suggesting there are local strategies that households and individuals use to manage the risk to their child's health. These strategies may be rooted in place-based historical contexts and may not be measured by common survey questions (Grace et al., 2022). Additionally, it is likely that soil moisture in Bangladesh is not measuring total food produced but the ability of households to access food. In the case of the climate measures in this study we are measuring interannual variability due to weather which affects how much income households and individuals earn from year to year (Ritzema et al., 2017). It is possible that families in Bangladesh have less diverse income-earning opportunities and thus their income stability is more vulnerable to changing climate and weather patterns.

There are several factors that could explain the lack of consistency in our results. Our goal in measuring the start of season soil moisture and NDVI is to capture an indicator of the quality of growing season harvests and subsequent lean season food stores. These findings could suggest that month-long intervals measuring the start of season vegetation do not capture the impact of crop yields on acute child health that is measured at very short-term scales. Other mechanisms like household economic characteristics and illnesses may instead be driving the risk of a child experiencing wasting. It is possible that the child-, mother-, and household-level demographic factors that influence a child's ability to access and utilize food are important mediators of the relationship between climate and acute food insecurity.

Soil moisture and NDVI as climate indicators in population and environment studies

Although NDVI has been used in previous studies of climate and health (Johnson & Brown, 2014; Shively et al., 2015; Grace et al., 2021) soil moisture is an uncommon climate indicator to be used in population and environment studies compared to temperature and precipitation. While these results suggest that soil moisture may provide insight into the linkages of climate and child health, more research is needed to understand how soil moisture and NDVI vary both spatially and temporally compared to temperature and precipitation. For example, the moisture in soil can reflect a many month's worth of cumulative precipitation while observed precipitation will only reflect the measurement in that point in time. How we operationalize these variables across time may be different compared to temperature and precipitation and more research is needed to investigate these temporal linkages.

Our dichotomous wasting analysis illustrates the importance of linking the correct timing of the climate indicator variable with the outcome of interest. Our analysis did not provide significant results for soil moisture. We believe that a dichotomous relationship may be stronger for longer-time frames seen in stunting (Cooper et al., 2019) since a child may recover from wasting quickly and these relationships may not be captured by a dichotomous variable at one point in time.

Future steps in climate and health research

The inconsistency in our results demonstrates the importance of quantitatively defining climate variables to match the temporal scale at which these population-environment interactions occur. When temporally aggregating climate data to operationalize parameters within a quantitative model, finer-scale spatial and temporal aggregations may better capture relevant time- and space-varying attributes of explanatory climate variables. This is especially apparent when the processes that are being modeled occur at small time scales as in the case of wasting. As wasting occurs on shorter time scales and is reversible, it is often difficult to capture the relationship with external factors like soil moisture and NDVI. We demonstrate here that temporal linkages between climate variables and child health vary and more research is needed to understand how these relationships operate on different time-scales.

While this study provides a first glimpse into the relationship between sub-annual and sub-seasonal growing conditions and child food insecurity, it is important to consider the limitations. WHZ information was reported for approximately 63% of children across our samples, with a disproportionate amount of missing WHZ data for children in Senegal. While we estimated our models separately for Senegal and Bangladesh to account for this, a bias could still remain and this would most likely skew the results towards the null and underinflate significance with our Senegal results. Furthermore, because wasting is a short-term experience with food insecurity, it is not always captured with cross-sectional survey designs. For example, there may be a child who experienced wasting because of a recently poor growing season but has since recovered at the time the survey is taken so that statistical relationship between climate variability and WHZ will not be captured in the DHS survey round. When we created our binary variables to explore the sensitivity of our models about 11% and 19% of children in the Senegal and Bangladesh surveys were considered wasted, respectively. Further research should explore the utility of this conceptualization of sub-seasonal soil moisture and vegetation indices in different geographic contexts and with multiple rounds of DHS surveys.

We see that children who share similar environmental exposures often have very different outcomes. It is clear from this study and from previous quantitative research (Grace et al., 2012; Johnson & Brown, 2014; Shively et al., 2015; Davenport et al., 2017; Cooper et al., 2019; Randell et al., 2020) that anthropometric growth in children is a product of interrelated factors that affect a child's ability to consistently access and utilize a sufficient amount of food. Using gridded climate data and integrating a novel soil moisture dataset into our analyses we find that sub-annual soil moisture indicators may be associated with acute measures of undernutrition but more research is needed to the significance of this indicator across geographic contexts. While this analysis proposes a method to refine the conceptualization of food security measures in quantitative population-environment research, it is clear that identifying key timing intervals that link real-world experiences with climate remains an ongoing goal to support early warning interventions.

References

Ademe, D., Zaitchik, B. F., Tesfaye, K., Simane, B., Alemayehu, G., & Adgo, E. (2021). Analysis of agriculturally relevant rainfall characteristics in a tropical highland region: An agroecosystem perspective. *Agricultural and Forest Meteorology*, *311*(November), 108697. https://doi.org/10.1016/j.agrformet.2021.108697

Aguayo, V. M. (2017). Complementary feeding practices for infants and young children in South Asia. A review of evidence for action post-2015. *Maternal & Child Nutrition*, *13*, e12439. https://doi.org/10.1111/mcn.12439

Akresh, R., Verwimp, P., & Bundervoet, T. (2011). Civil War, Crop Failure, and Child Stunting in Rwanda. *Economic Development and Cultural Change*, *59*(4), 777–810.

Alderman, H., & Headey, D. (2018). The timing of growth faltering has important implications for observational analyses of the underlying determinants of nutrition outcomes. *PLOS ONE*, *13*(4), e0195904. https://doi.org/10.1371/journal.pone.0195904

Assogba, G. G. C., Adam, M., Berre, D., & Descheemaeker, K. (2022). Managing biomass in semi-arid Burkina Faso: Strategies and levers for better crop and livestock production in contrasted farm systems. *Agricultural Systems*, *201*(103458). https://doi.org/10.2139/ssrn.4005268

Bakhtsiyarava, M., Grace, K., & Nawrotzki, R. J. (2018). Climate , Birth Weight , and Agricultural Livelihoods in Kenya and Mali, *108*, 144–151. https://doi.org/10.2105/AJPH.2017.304128

Bala, S. K., & Islam, A. S. (2009). Correlation between potato yield and MODIS-derived vegetation indices. *International Journal of Remote Sensing*, *30*(10), 2491–2507. https://doi.org/10.1080/01431160802552744

Balk, D., Storeygard, A., Levy, M., Gaskell, J., Sharma, M., & Flor, R. (2005). Child hunger in the developing world: An analysis of environmental and social correlates. *Food Policy*, *30*, 584–611. https://doi.org/10.1016/j.foodpol.2005.10.007

Barrett, C. B. (2010). Measuring food insecurity. *Science*, *327*(5967), 825–828. https://doi.org/10.1126/science.1182768

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., De Onis, M., … Uauy, R. (2013). Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet*, *382*(9890), 427–451. https://doi.org/10.1016/S0140-6736(13)60937-X

Brown, M. E., Backer, D., Billing, T., White, P., Grace, K., Doocy, S., & Huth, P. (2020). Empirical studies of factors associated with child malnutrition: highlighting the evidence about climate and conflict shocks. *Food Security*.

Brown, M. E., & Kshirsagar, V. (2015). Weather and international price shocks on food prices in the developing world. *Global Environmental Change*, *35*, 31–40. https://doi.org/10.1016/j.gloenvcha.2015.08.003

Brown, M. E., Backer, D., Billing, T., White, P., Grace, K., Doocy, S., & Huth, P. (2020). Empirical studies of factors associated with child malnutrition: highlighting the evidence about climate and conflict shocks. *Food Security*, *12*(6), 1241–1252. https://doi.org/10.1007/s12571-020-01041-y

Brown, M. E., De Beurs, K. M., & Grace, K. (2015). Global land surface phenology and implications for food security. *Land Resources Monitoring, Modeling, and Mapping with Remote Sensing*, (Fao 2012), 353–363. https://doi.org/10.1201/b19322

Brown, M. E., Grace, K., Shively, G., Johnson, K. B., & Carroll, M. (2014). Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. *Population and Environment*, *36*(1), 48–72. https://doi.org/10.1007/s11111-013-0201-0

Burgert, C. R., Colston, J., Roy, T., & Zachary, B. (2013). *Geographic Displacement Procedure and Georeferenced Data Release Policy for the Demographic and Health Surveys*.

Chotard, S., Mason, J. B., Oliphant, N. P., Mebrahtu, S., & Hailey, P. (2011). Fluctuations in wasting in vulnerable child populations in the Greater Horn of Africa. *Food and Nutrition Bulletin*, *32*(3 SUPPL.), 219–233. https://doi.org/10.1177/15648265100313s302

Cooper, M., Brown, M. E., Azzarri, C., & Meinzen-Dick, R. (2019). Hunger, nutrition, and precipitation: Evidence from Ghana and Bangladesh. *Population and Environment*, *41*(2), 151–208. https://doi.org/10.1007/s11111-019-00323-8

Davenport, F. M., Shukla, S., Turner, W., Funk, C., Krell, N., Harrison, L., … Peterson, S. (2021). Sending out an SOS: Using start of rainy season indicators for market price forecasting to support famine early warning. *Environmental Research Letters*, *16*(8). https://doi.org/10.1088/1748-9326/ac15cc

Davenport, F., Grace, K., Funk, C., & Shukla, S. (2017). Child health outcomes in sub-Saharan Africa: A comparison of changes in climate and socio-economic factors. *Global Environmental Change*, *46*(September 2016), 72–87. https://doi.org/10.1016/j.gloenvcha.2017.04.009

De Camargo, M. B., & Hubbard, K. G. (1999). Drought sensitivity indices for a Sorghum crop. *Journal of Production Agriculture*, *12*(2), 312–316. https://doi.org/10.2134/jpa1999.0312

De Sherbinin, A. (2011). The biophysical and geographical correlates of child malnutrition in Africa. *Population, Space and Place*, *17*(1), 27–46. https://doi.org/10.1002/psp.599

Di Prima, S., Wright, E. P., Sharma, I. K., Syurina, E., & Broerse, J. E. W. (2022). Implementation and scale-up of nutrition-sensitive agriculture in low- and middle-income countries: a systematic review of what works, what doesn't work and why. *Global Food Security*, *32*, 100595. https://doi.org/10.1016/j.gfs.2021.100595

Dos Santos, S., & Henry, S. (2008). Rainfall variation as a factor in child survival in rural Burkina Faso: The benefit of an event-history analysis. *Population, Space and Place*, *14*(1), 1–20. https://doi.org/10.1002/psp.470

Easterling, W. E., P. Aggarwal, P. Batima, K. M. Brander, L. Erda, S. M. Howden, A. Kirilenko, et al. 2007. "Food, Fibre and Forest Products."

Eggen, M., Ozdogan, M., Zaitchik, B., Ademe, D., Foltz, J., & Simane, B. (2019). Vulnerability of sorghum production to extreme, sub-seasonal weather under climate change. *Environmental Research Letters*, *14*(045005), 1–10.

Faisal, B. M. R., Rahman, H., Sharifee, N. H., Sultana, N., Islam, M. I., & Ahammad, T. (2019). Remotely Sensed Boro Rice Production Forecasting Using MODIS-NDVI: A Bangladesh Perspective. *AgriEngineering*, *1*(3), 356–375. https://doi.org/10.3390/agriengineering1030027

FEWSNET. (2022). Senegal crop calendar. Retrieved from https://fews.net/west-africa/senegal

Fensholt, R., Sandholt, I., & Rasmussen, M. S. (2004). Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements. *Remote Sensing of Environment*, *91*(3–4), 490–507. https://doi.org/10.1016/j.rse.2004.04.009

Frelat, R., Lopez-Ridaura, S., Giller, K. E., Herrero, M., Douxchamps, S., Djurfeldt, A. A., … Van Wijk, M. T. (2016). Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(2), 458–463. https://doi.org/10.1073/pnas.1518384112

Funk, C., & Budde, M. E. (2009). Phenologically-tuned MODIS NDVI-based production anomaly estimates for Zimbabwe. *Remote Sensing of Environment*, *113*, 115–125. https://doi.org/10.1016/j.rse.2008.08.015

Grace, K., Brown, M., & McNally, A. (2014). Examining the link between food prices and food insecurity: A multi-level analysis of maize price and birthweight in Kenya. *Food Policy*, *46*, 56–65. https://doi.org/10.1016/j.foodpol.2014.01.010

Grace, K., Davenport, F., Funk, C., & Lerner, A. M. (2012). Child malnutrition and climate in Sub-Saharan Africa : An analysis of recent trends in Kenya. *Applied Geography*, *35*(1–2), 405–413. https://doi.org/10.1016/j.apgeog.2012.06.017

Grace, K., Nagle, N. N., & Husak, G. (2016). Can small-scale agricultural production improve children's health? Examining stunting vulnerability among very young children in Mali, West Africa. *Annals of the American Association of Geographers*, *106*(3), 722–737. https://doi.org/10.1080/24694452.2015.1123602

Grace, K., Verdin, A., Dorélien, A., Davenport, F., Funk, C., & Husak, G. (2021). Exploring strategies for investigating the mechanisms linking climate and individual-level child health outcomes: an analysis of birth weight in Mali. *Demography*, 1–32. https://doi.org/10.1215/00703370-8977484

Grace, K., Verdin, A., Brown, M., Bakhtsiyarava, M., Backer, D., & Billing, T. (2022). Conflict and Climate Factors and the Risk of Child Acute Malnutrition Among Children Aged 24–59 Months: A Comparative Analysis of Kenya, Nigeria, and Uganda. *Spatial Demography*, *10*(2), 329–358. https://doi.org/10.1007/s40980-021-00102-w

Groten, S. M. E. (1993). NDVI—crop monitoring and early yield assessment of Burkina Faso. *International Journal of Remote Sensing*, *14*(8), 1495–1515. https://doi.org/10.1080/01431169308953983

Elizabeth Heger Boyle, Miriam King and Matthew Sobek. IPUMS-Demographic and Health Surveys: Version 9 [dataset]. IPUMS and ICF, 2022. https://doi.org/10.18128/D080.V9

Huete, A., Didan, M., Miura, T., Rodriquez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, *83*, 1–3. https://doi.org/10.1016/S0020-1693(00)85959-9

Iizumi, T., Sakuma, H., Yokozawa, M., Luo, J. J., Challinor, A. J., Brown, M. E., … Yamagata, T. (2013). Prediction of seasonal climate-induced variations in global food production. *Nature Climate Change*, *3*(10), 904–908. https://doi.org/10.1038/nclimate1945

Islam, M. M., & Mamun, M. M. I. (2015). Variations of NDVI and Its Association with Rainfall and Evapotranspiration over Bangladesh. *Rajshahi University Journal of Science and Engineering*, *43*, 21–28. https://doi.org/10.3329/rujse.v43i0.26160

Jalloh, Abdulai, Gerald C. Nelson, Timothy S. Thomas, Robert Bellarmin Zougmoré, and Harold Roy-Macauley. 2013. West African Agriculture and Climate Change: A Comprehensive Analysis. Intl Food Policy Res Inst.

Johnson, K., & Brown, M. E. (2014). Environmental risk factors and child nutritional status and survival in a context of climate variability and change. *Applied Geography*, *54*, 209–221. https://doi.org/10.1016/j.apgeog.2014.08.007

Jones, P., & Thornton, P. (2003). The potential impacts of climate change on maize production in Africa and Latin America in 2055. *Global Environmental Change*, *13*(1), 51–59. https://doi.org/10.1016/S0959-3780(02)00090-0

Kim, K., & Bevis, L. (2019). *Soil Fertility and Poverty in Developing Countries*.

Kuchenbecker, J., Reinbott, A., Mtimuni, B., Krawinkel, M. B., & Jordan, I. (2017). Nutrition education improves dietary diversity of children 6-23 months at community-level: Results from a cluster randomized controlled trial in Malawi. *PLOS ONE*, *12*(4), e0175216. https://doi.org/10.1371/journal.pone.0175216

Kugler, T. A., Grace, K., Wrathall, D. J., de Sherbinin, A., Van Riper, D., Aubrecht, C., … Van Den Hoek, J. (2019). People and Pixels 20 years later: the current data landscape and research trends blending population and environmental data. *Population and Environment*, *41*(2), 209–234. https://doi.org/10.1007/s11111-019-00326-5

Lee, D., Davenport, F., Shukla, S., Husak, G., Funk, C., Harrison, L., McNally, A., Rowland, J., Budde, M., & Verdin, J. (2022). Maize yield forecasts for Sub-Saharan Africa using Earth Observation data and machine learning. *Global Food Security*, *33*, 100643. https://doi.org/10.1016/j.gfs.2022.100643

Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change*, *1*(4), 42–45. https://doi.org/10.1038/nclimate1043

Lobell, D. B., Azzari, G., Burke, M., Gourlay, S., Jin, Z., Kilic, T., & Murray, S. (2019). Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis. *American Journal of Agricultural Economics*, *102*(1), 202–219. https://doi.org/10.1093/ajae/aaz051

Lokupitiya, E., Lefsky, M., & Paustian, K. (2010). Use of AVHRR NDVI time series and ground-based surveys for estimating county-level crop biomass. *International Journal of Remote Sensing*, *31*(1), 141–158. https://doi.org/10.1080/01431160902882579

Lotsch, A., Friedl, M. A., Anderson, B. T., & Tucker, C. J. (2003). Coupled vegetation-precipitation variability observed from satellite and climate records: VEGETATION-PRECIPITATION DYNAMICS. *Geophysical Research Letters*, *30*(14). https://doi.org/10.1029/2003GL017506

Lokupitiya, E., Lefsky, M., & Paustian, K. (2010). Use of AVHRR NDVI time series and ground-based surveys for estimating county-level crop biomass. *International Journal of Remote Sensing*, *31*(1), 141–158. https://doi.org/10.1080/01431160902882579

Maxwell, D. (1995). *Measuring food insecurity: the frequency and severity of "coping strategies." FCND Discussion Paper*.

McNally, A., Arsenault, K., Kumar, S., Shukla, S., Peterson, P., Wang, S., … Verdin, J. P. (2017). A land data assimilation system for sub-Saharan Africa food and water security applications. *Scientific Data*, *4*, 1–19. https://doi.org/10.1038/sdata.2017.12

Musyoka, P. K., Onjala, J., & Mureithi, L. P. (2021). Determinants of distress sales of farmland in rural Kenya. *Development Studies Research*, *8*(1), 317–345. https://doi.org/10.1080/21665095.2021.1974918

Phalkey, R. K., Aranda-Jan, C., Marx, S., Höfle, B., & Sauerborn, R. (2015). Systematic review of current efforts to quantify the impacts of climate change on undernutrition. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(33), E4522–E4529. https://doi.org/10.1073/pnas.1409769112

Pinstrup-Andersen, P. (2009). Food security: definition and measurement. *Food Security*, *1*(1), 5–7. https://doi.org/10.1007/s12571-008-0002-y

Proctor, J., Rigden, A., Chan, D., & Huybers, P. (2022). More accurate specification of water supply shows its importance for global crop production. *Nature Food*, *3*(9), 753–763. https://doi.org/10.1038/s43016-022-00592-x

Randell, H., Grace, K., & Bakhtsiyarava, M. (2021). Climatic Conditions and Infant Care: Implications for Child Nutrition in Rural Ethiopia. *Population and Environment*, *42*(4), 1–28. https://doi.org/10.1007/s11111-020-00373-3.Climatic

Randell, H., Gray, C., & Grace, K. (2020). Stunted from the start: Early life weather conditions and child undernutrition in Ethiopia. *Social Science & Medicine*, *261*. https://doi.org/10.1016/j.socscimed.2020.113234

Rigden, A. J., Mueller, N. D., Holbrook, N. M., Pillai, N., & Huybers, P. (2020). Combined influence of soil moisture and atmospheric evaporative demand is important for accurately predicting US maize yields. *Nature Food*, *1*. https://doi.org/10.1038/s43016-020-0028-7

Ritzema, R. S., Frelat, R., Douxchamps, S., Silvestri, S., Rufino, M. C., Herrero, M., Giller, K. E., López-Ridaura, S., Teufel, N., Paul, B. K., & van Wijk, M. T. (2017). Is production intensification likely to make farm households food-adequate? A simple food availability analysis across smallholder farming systems from East and West Africa. *Food Security*, *9*(1), 115–131. https://doi.org/10.1007/s12571-016-0638-y

Ruane, A. C., Major, D. C., Yu, W. H., Alam, M., Hussain, S. G., Khan, A. S., … Rosenzweig, C. (2013). Multi-factor impact analysis of agricultural production in Bangladesh with climate change. *Global Environmental Change*, *23*(1), 338–350. https://doi.org/10.1016/j.gloenvcha.2012.09.001

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., … Teuling, A. J. (2010). Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*(3–4), 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004

Shively, G. E. (2017). Infrastructure mitigates the sensitivity of child growth to local agriculture and rainfall in Nepal and Uganda. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(5), 903–908. https://doi.org/10.1073/pnas.1524482114

Shively, G., Sununtnasuk, C., & Brown, M. (2015). Environmental variability and child growth in Nepal. *Health and Place*, *35*, 37–51. https://doi.org/10.1016/j.healthplace.2015.06.008

Shukla, S., Husak, G., Turner, W., Davenport, F., Funk, C., Harrison, L., & Krell, N. (2021). A slow rainy season onset is a reliable harbinger of drought in most food insecure regions in Sub-Saharan Africa. *PLoS ONE*, *16*(1 January), 1–21. https://doi.org/10.1371/journal.pone.0242883

Thiede, B. C., & Gray, C. (2020). Climate exposures and child undernutrition: Evidence from Indonesia. *Social Science and Medicine*, *265*(August), 113298. https://doi.org/10.1016/j.socscimed.2020.113298

Thiede, B., & Strube, J. (2020). Climate Variability and Child Nutrition: Findings from Sub-Saharan Africa. *Global Environmental Change*, *28*(2), 1–43. Retrieved from http://journals.sagepub.com/doi/10.1177/1120700020921110%0Ahttps://doi.org/10.1016/j.reuma.2018.06.001%0Ahttps://doi.org/10.1016/j.arth.2018.03.044%0Ahttps://reader.elsevier.com/reader/sd/pii/S1063458420300078?token=C039B8B13922A2079230DC9AF11A333E295FCD8

UNICEF. (2022). *Progress on breastfeeding in Bangladesh undermined by aggressive formula milk marketing – WHO*, Retrieved April 7, 2023, from https://www.unicef.org/bangladesh/en/press-releases/progress-breastfeeding-bangladesh-undermined-aggressive-formula-milk-marketing-who

USDA. (2020). *Crop Explorer—World Agricultural Production (WAP) Briefs—Bangladesh*. https://ipad.fas.usda.gov/cropexplorer/pecad_stories.aspx?regionid=bg&ftype=prodbriefs

Verhagen, J., Put, M., Zaal, F., & Keulen, H. (2004). Climate Change and Drought Risks for Agriculture. In A. J. Dietz, R. Ruben, & A. Verhagen (Eds.), *The Impact of Climate Change on Drylands* (Vol. 39, pp. 49–59). Kluwer Academic Publishers. https://doi.org/10.1007/1-4020-2158-5_6

Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science*, *341*(6145), 508–513. https://doi.org/10.1126/science.1239402

WHO. (2018). *Breastfeeding*. https://www.who.int/health-topics/breastfeeding#tab=tab_1

World Bank (2019-a). *Exclusive breastfeeding (% of children under 6 months)—Senegal | Data*. Retrieved April 7, 2023, from https://data.worldbank.org/indicator/SH.STA.BFED.ZS?locations=SN

World Bank. (2019-b). *Prevalence of wasting, weight for height (% of children under 5)—Bangladesh | Data*. Retrieved April 7, 2023, from https://data.worldbank.org/indicator/SH.STA.WAST.ZS?locations=BD

World Bank. (2019-c). *Prevalence of wasting, weight for height (% of children under 5)—Senegal | Data*. Retrieved April 7, 2023, from https://data.worldbank.org/indicator/SH.STA.WAST.ZS?locations=SN

Appendix

Figure 1

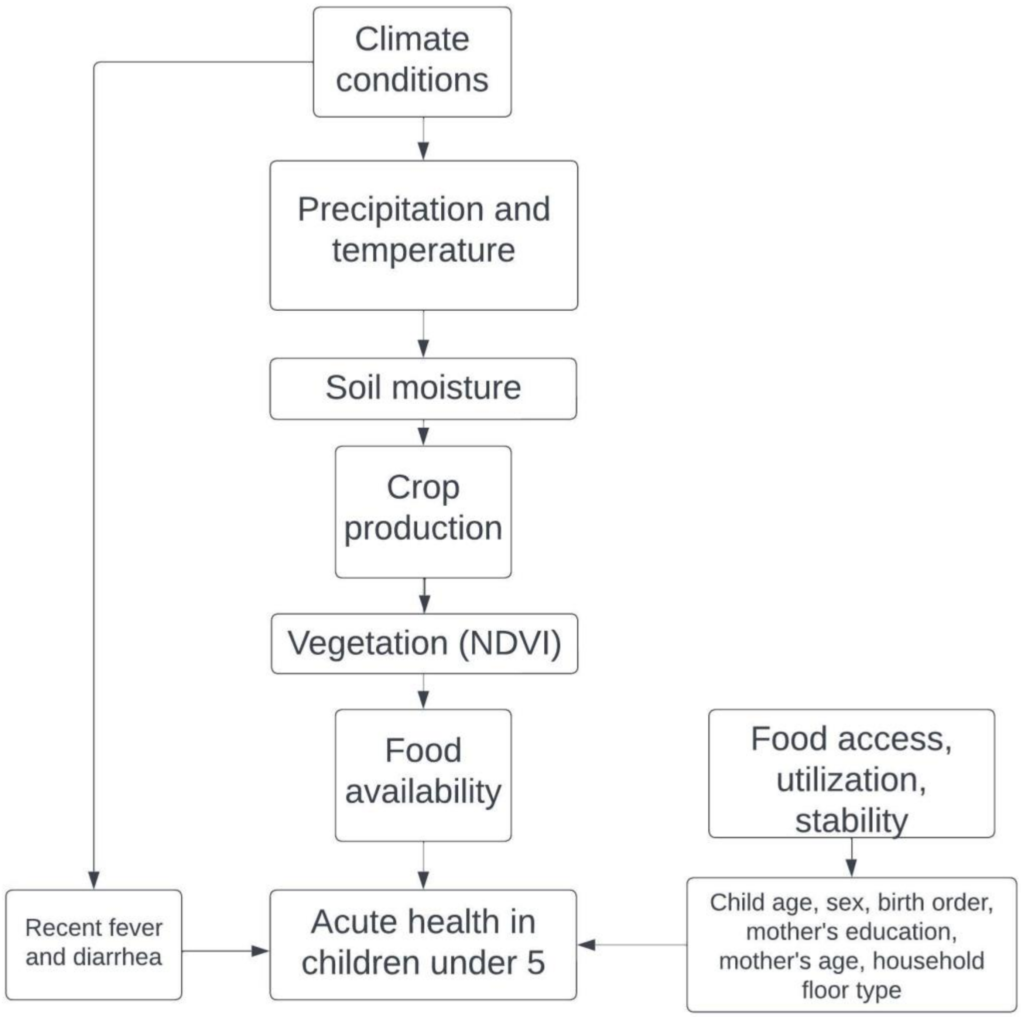

Figure 1: Conceptual framework to demonstrate the pathways used in our modeling approach. Precipitation and temperature not directly modeled but rather included to show how soil moisture and NDVI are inherently related to precipitation and temperature.

Figure 2

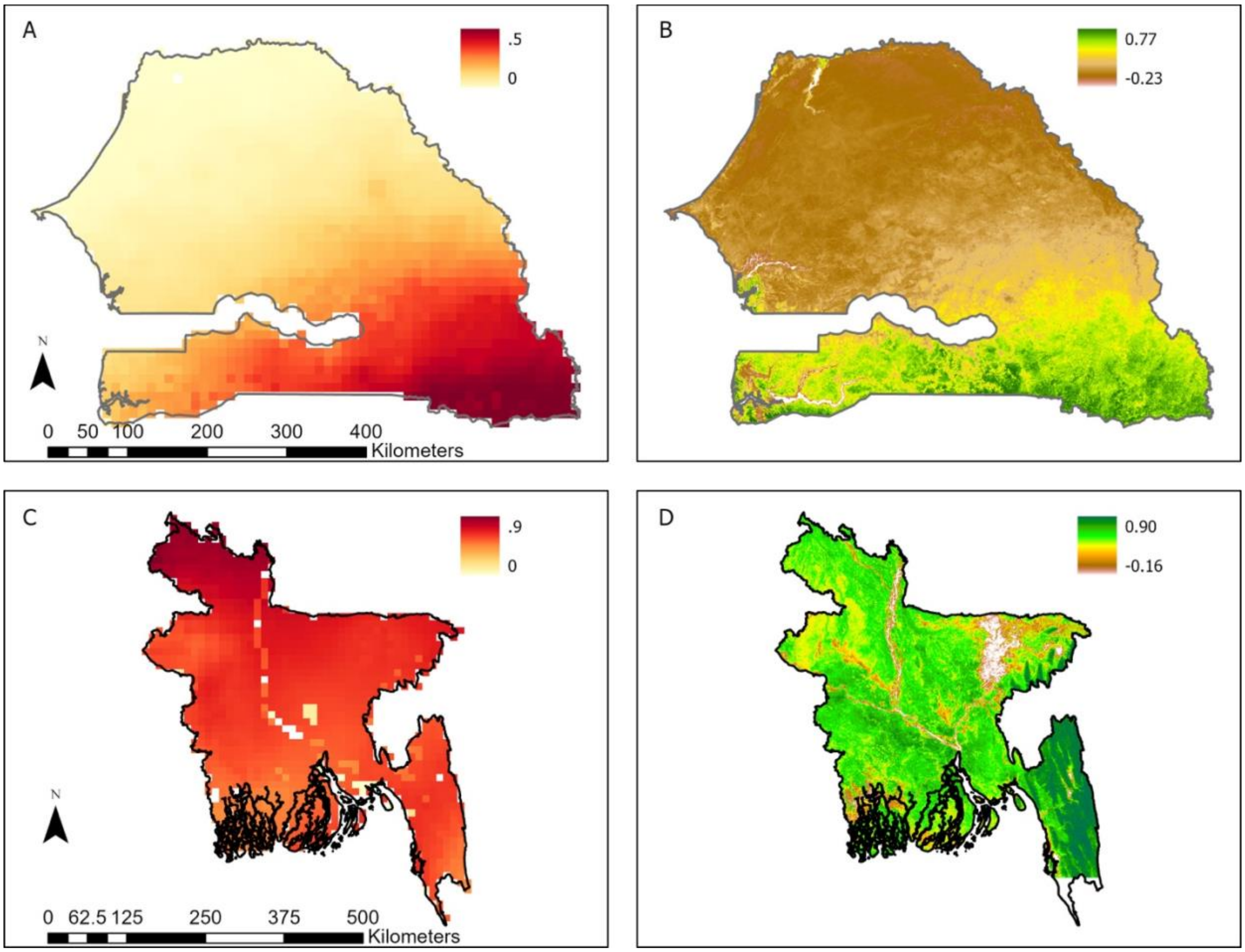

Figure 2: Average June soil moisture and NDVI for Senegal and Bangladesh. Senegal is displayed on the top row with panel A showing average June soil moisture and panel B showing average June NDVI. Bangladesh is displayed on the bottom row with panel C showing average June soil moisture and panel D showing average June NDVI. Figure was created in ArcGIS Pro.

Table 1

Variables	Senegal (n=6408) Mean (SD)	%	Bangladesh (n=5978) Mean (SD)	%
Child level				
Weight-for-height Z-score	-0.55(1.3)		-.88(1.3)	
Child sex: Male		53		51
Child sex: Female		47		49
Birth order	4(2)		2(2)	
Age (months)	14(5)		14(5)	
Not current breastfed		17		7
Current breastfed		27		91
Breastfeeding not recorded		45		2
Recent fever		31		42
Recent diarrhea		28		9
Mother level				
Age (years)	28(7)		24(6)	
No education		74		18
Primary education		20		29
Secondary education		6		53
Household level				
Natural floor		43		72
Rudimentary floor		1		1
Finished floor		56		28
DHS survey cluster level				
Urban		32		33
June soil moisture (m^3/m^3)	0.21(.05)		.40(.03)	
June NDVI	0.23(.10)		.50(.14)	
1-3 month average soil moisture	.19(.07)		.35(.07)	
1-3 month average NDVI	.31(.13)		.46(.10)	
1-2 month average soil moisture	.18(06)		.36(.07)	
1-2 month average NDVI	.28(.11)		.46(.12)	
1 month average soil moisture	.17(.05)		.37(.07)	
1 month average NDVI	.27(.10)		.47(.13)	

Table 1: Descriptive statistics of the study samples for Senegal and Bangladesh.

Table 2

	Senegal						Bangladesh					
	Model 1: Soil Moisture			Model 2: NDVI			Model 3: Soil Moisture			Model 4: NDVI		
Independent Variables	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
DHS survey cluster level												
June climate measure of most recent completed growing season	-0.02	0.03	0.51	0.01	0.03	0.85	-0.01	0.02	0.49	0.03	0.02	0.06
Urban (ref)												
Rural	**-0.20**	**0.07**	**0.01**	**-0.20**	**0.07**	**0.01**	**-0.13**	**0.04**	**0.00**	**-0.13**	**0.04**	**0.00**
Child level												
Male (Ref)												
Female	0.10	0.06	0.07	0.11	0.06	0.07	0.05	0.03	0.12	0.05	0.03	0.12
Birth order	**-0.05**	**0.02**	**0.02**	**-0.05**	**0.02**	**0.02**	**-0.06**	**0.02**	**0.00**	**-0.06**	**0.02**	**0.00**
Age (months)	-0.01	0.01	0.30	-0.01	0.01	0.29	**-0.02**	**0.00**	**0.00**	**-0.02**	**0.00**	**0.00**
Not current breastfeeding (ref)												
Current breastfeeding	-0.02	0.12	0.89	-0.02	0.12	0.86	**-0.26**	**0.08**	**0.00**	**-0.26**	**0.08**	**0.00**
Breastfeeding not recorded	-0.06	0.13	0.66	-0.06	0.13	0.67	-0.46	0.50	0.35	-0.47	0.50	0.34
Recent fever	**-0.19**	**0.06**	**0.00**	**-0.19**	**0.06**	**0.00**	**-0.15**	**0.03**	**0.00**	**-0.15**	**0.03**	**0.00**
Recent diarrhea	-0.01	0.07	0.92	-0.01	0.07	0.93	**-0.21**	**0.06**	**0.00**	**-0.21**	**0.06**	**0.00**
Mother level												
Age (years)	0.01	0.01	0.06	**0.01**	**0.01**	**0.05**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**
No education (Ref)												
Primary education	**0.16**	**0.08**	**0.05**	**0.15**	**0.08**	**0.05**	**0.11**	**0.05**	**0.03**	0.11	0.05	0.04
Secondary education	**0.30**	**0.12**	**0.02**	**0.29**	**0.12**	**0.02**	**0.35**	**0.05**	**0.00**	**0.35**	**0.05**	**0.00**
Household level												
Natural floor (Ref)												
Rudimentary floor	-0.41	0.73	0.57	0.10	0.06	0.13	0.15	0.31	0.63	0.15	0.31	0.63
Finished floor	0.09	0.06	0.18	-0.54	0.57	0.34	**0.18**	**0.04**	**0.00**	**0.19**	**0.04**	**0.00**

Table 2: *Estimates of linear regression models considering the effect of June soil moisture and NDVI on continuous measures of child growth in Senegal and Bangladesh. Bold text indicates statistical significance.*

Table 3

	Senegal						Bangladesh					
	Model 5: Soil Moisture			Model 6: NDVI			Model 7: Soil Moisture			Model 8: NDVI		
Independent Variables	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
DHS survey cluster level												
Average climate measures 1-3 months before survey month	-0.05	0.05	0.36	0.01	0.04	0.88	-0.02	0.03	0.40	0.02	0.02	0.17
Urban (ref)												
Rural	**-0.19**	**0.07**	**0.01**	**-0.20**	**0.07**	**0.01**	**-0.14**	**0.04**	**0.00**	**-0.13**	**0.04**	**0.00**
Child level												
Male (Ref)												
Female	0.10	0.06	0.07	0.10	0.06	0.07	0.05	0.03	0.12	0.05	0.03	0.13
Birth order	**-0.05**	**0.02**	**0.02**	**-0.05**	**0.02**	**0.02**	**-0.06**	**0.02**	**0.00**	**-0.06**	**0.02**	**0.00**
Age (months)	-0.01	0.01	0.30	-0.01	0.01	0.29	**-0.02**	**0.00**	**0.00**	**-0.02**	**0.00**	**0.00**
Not current breastfeeding (ref)												
Current breastfeeding	-0.02	0.12	0.86	-0.02	0.12	0.87	**-0.25**	**0.08**	**0.00**	**-0.26**	**0.08**	**0.00**
Breastfeeding not recorded	-0.06	0.13	0.65	-0.06	0.13	0.67	-0.46	0.50	0.35	-0.48	0.50	0.33
Recent fever	**-0.19**	**0.06**	**0.00**	**-0.19**	**0.06**	**0.00**	**-0.15**	**0.03**	**0.00**	**-0.15**	**0.03**	**0.00**
Recent diarrhea	-0.01	0.07	0.88	-0.01	0.07	0.93	**-0.22**	**0.06**	**0.00**	**-0.21**	**0.06**	**0.00**
Mother level												
Age (years)	**0.01**	**0.01**	**0.05**	**0.01**	**0.01**	**0.05**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**
No education (Ref)												
Primary education	**0.15**	**0.08**	**0.05**	**0.15**	**0.08**	**0.05**	**0.11**	**0.05**	**0.04**	**0.11**	**0.05**	**0.03**
Secondary education	**0.29**	**0.12**	**0.02**	**0.29**	**0.12**	**0.02**	**0.35**	**0.05**	**0.00**	**0.36**	**0.05**	**0.00**
Household level												
Natural floor (Ref)												
Rudimentary floor	-0.40	0.73	0.58	-0.40	0.73	0.58	0.12	0.31	0.71	0.15	0.31	0.64
Finished floor	0.09	0.06	0.14	0.10	0.06	0.13	**0.18**	**0.04**	**0.00**	**0.18**	**0.04**	**0.00**

Table 3: *Estimates of linear regression models considering the effect of soil moisture and NDVI averaged 3 months prior to the DHS on WHZ in Senegal and Bangladesh.*

Table 4

	Senegal						Bangladesh					
	Model 9: Soil Moisture			Model 10: NDVI			Model 11: Soil Moisture			Model 12: NDVI		
Independent Variables	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
DHS survey cluster level												
Average climate measures 1-2 months before survey month	-0.05	0.06	0.37	0.01	0.03	0.87	-0.03	0.03	0.20	0.02	0.02	0.23
Urban (ref)												
Rural	**-0.19**	**0.07**	**0.01**	**-0.20**	**0.07**	**0.01**	**-0.14**	**0.04**	**0.00**	**-0.13**	**0.04**	**0.00**
Child level												
Male (Ref)												
Female	0.11	0.06	0.07	0.11	0.06	0.07	0.05	0.03	0.13	0.05	0.03	0.12
Birth order	**-0.05**	**0.02**	**0.02**	**-0.05**	**0.02**	**0.02**	**-0.06**	**0.02**	**0.00**	**-0.06**	**0.02**	**0.00**
Age (months)	-0.01	0.01	0.29	-0.01	0.01	0.29	**-0.02**	**0.00**	**0.00**	**-0.02**	**0.00**	**0.00**
Not current breastfeeding (ref)												
Current breastfeeding	-0.02	0.12	0.86	-0.02	0.12	0.89	**-0.25**	**0.08**	**0.00**	**-0.26**	**0.08**	**0.00**
Breastfeeding not recorded	-0.06	0.13	0.64	-0.06	0.13	0.67	-0.46	0.50	0.36	-0.48	0.50	0.33
Recent fever	**-0.19**	**0.06**	**0.00**	**-0.20**	**0.06**	**0.00**	**-0.15**	**0.03**	**0.00**	**-0.15**	**0.03**	**0.00**
Recent diarrhea	-0.01	0.07	0.89	-0.01	0.07	0.93	**-0.21**	**0.06**	**0.00**	**-0.21**	**0.06**	**0.00**
Mother level												
Age (years)	**0.01**	**0.01**	**0.05**	**0.01**	**0.01**	**0.05**	**0.02**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**
No education (Ref)												
Primary education	**0.15**	**0.08**	**0.05**	**0.15**	**0.08**	**0.05**	**0.11**	**0.05**	**0.04**	**0.11**	**0.05**	**0.03**
Secondary education	**0.29**	**0.12**	**0.02**	**0.29**	**0.12**	**0.02**	**0.35**	**0.05**	**0.00**	**0.36**	**0.05**	**0.00**
Household level												
Natural floor (Ref)												
Rudimentary floor	-0.40	0.73	0.59	-0.40	0.73	0.58	0.10	0.31	0.74	0.14	0.31	0.64
Finished floor	0.09	0.06	0.15	0.10	0.06	0.13	**0.18**	**0.04**	**0.00**	**0.18**	**0.04**	**0.00**

Table 4: *Estimates of linear regression models considering the effect of soil moisture and NDVI averaged 2 months prior to the DHS on WHZ in Senegal and Bangladesh.*

Table 5

	Senegal						Bangladesh					
	Model 13: Soil Moisture			Model 14: NDVI			Model 15: Soil Moisture			Model 16: NDVI		
Independent Variables	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
DHS survey cluster level												
Average climate measures 1 month before survey month	-0.04	0.05	0.36	0.01	0.03	0.88	**-0.05**	**0.02**	**0.04**	0.02	0.02	0.38
Urban (ref)												
Rural	**-0.20**	**0.07**	**0.01**	**-0.20**	**0.07**	**0.01**	**-0.14**	**0.04**	**0.00**	**-0.13**	**0.04**	**0.00**
Child level												
Male (Ref)												
Female	0.11	0.06	0.07	0.10	0.06	0.07	0.05	0.03	0.13	0.05	0.03	0.11
Birth order	**-0.05**	**0.02**	**0.02**	**-0.05**	**0.02**	**0.02**	**-0.06**	**0.02**	**0.00**	**-0.06**	**0.02**	**0.00**
Age (months)	-0.01	0.01	0.29	-0.01	0.01	0.29	**-0.02**	**0.00**	**0.00**	**-0.02**	**0.00**	**0.00**
Not current breastfeeding (ref)												
Current breastfeeding	-0.02	0.12	0.86	-0.02	0.12	0.86	**-0.25**	**0.08**	**0.00**	**-0.27**	**0.08**	**0.00**
Breastfeeding not recorded	-0.06	0.13	0.65	-0.06	0.13	0.67	-0.45	0.50	0.36	-0.50	0.50	0.31
Recent fever	**-0.19**	**0.06**	**0.00**	**-0.19**	**0.06**	**0.00**	**-0.14**	**0.03**	**0.00**	**-0.15**	**0.03**	**0.00**
Recent diarrhea	-0.01	0.07	0.90	-0.01	0.07	0.93	**-0.21**	**0.06**	**0.00**	**-0.21**	**0.06**	**0.00**
Mother level												
Age (years)	0.01	0.01	0.07	**0.01**	**0.01**	**0.05**	**0.02**	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**
No education (Ref)												
Primary education	**0.15**	**0.08**	**0.05**	**0.15**	**0.08**	**0.05**	**0.11**	**0.05**	**0.03**	**0.11**	**0.05**	**0.03**
Secondary education	**0.29**	**0.12**	**0.02**	**0.29**	**0.12**	**0.02**	**0.35**	**0.05**	**0.00**	**0.36**	**0.05**	**0.00**
Household level												
Natural floor (Ref)												
Rudimentary floor	-0.40	0.73	0.58	-0.40	0.73	0.58	0.10	0.31	0.75	0.15	0.31	0.64
Finished floor	0.09	0.06	0.15	0.10	0.06	0.13	**0.18**	**0.04**	**0.00**	**0.18**	**0.04**	**0.00**

Table 5: *Estimates of linear regression models considering the effect of soil moisture and NDVI averaged 2 months prior to the DHS on WHZ in Senegal and Bangladesh.*