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Effect of extreme weather events on child health in rural Uganda

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Abstract

Children in rural farming households across the developing countries are often vulnerable to a multitude of risks, including health risks associated with climate change and variability. This study empirically traced the effect of extreme weather events on nutritional health outcomes among rural children in Uganda, while accounting for households' behavioural responses. We combined four waves of the Uganda National Panel Survey (UNPS) for the period 2009-2014, with long-term rainfall and temperature datasets and study the effect of extreme weather shocks on child health. We find that droughts and heat waves worsened child anthropometrics, particularly child chronic undernutrition. Exposure to drought significantly lowered height-for-age scores (HAZ) of up to -0.57 standard deviations. The main causal transmission channels were through lower crop production and increased frequency of child diseases. We highlight on the importance of ex-ante resilience building against extreme weather events particularly when compared to ex-post relief actions.

Keywords: Child health, droughts, Uganda

JEL Codes: I13, I15, I18, J0

1 Introduction

The intensity and frequency of extreme weather events have increased globally over the recent years (National Research Council, 2020). For instance, 2016 was the hottest year on record while the last five years since 2015 were the warmest years in a series, and 2010-2019 was recognized as the warmest decade on record (WMO, 2019, 2020). It is estimated that 712 extreme weather events occurred in 2017 (Watts et al., 2018), and approximately 160 million and 500 million children were residing in areas experiencing high severity of drought and extreme floods in 2015, respectively (Ghani, Zubair, & Nissa, 2017; UNICEF, 2015). Future climate change projections indicate warmer years, and more extreme weather events (Watts et al., 2018; Yobom, 2020), potentially posing severe risks to human well-being and health (Filippelli et al., 2020; Sellers, 2020; Watts et al., 2019). The negative health effects such as injuries, illnesses and deaths resulting from extreme weather events and climate variability are already evident (Filippelli et al., 2020). Watts et al. (2019) indicate that children born today are likely to experience a warmer world (at least 4°C above the historical average), facing associated climate related health impacts in all stages of their lives. Compared to other age-groups, children bear a higher health burden because of their susceptibility to under-nutrition and infectious diseases (such as diarrhoea and malaria), and also due to their incomplete development, immature metabolism and physiology (Ahdoot & Pacheco, 2015; Burke & Lobell, 2010; Smith et al., 2014; Watts et al., 2019; World Health Organization, 2009). In fact, Bhutta, Aimone, and Akhtar (2019) estimate that nearly 88% of the disease burden arising from climate change and variability is borne by children.

Under-nutrition in particular, is recognized as a major health impact due to climate change and variability (Cooper et al., 2019; Sellers, 2020). Under-nutrition is also a risk factor for other infectious diseases, respiratory diseases and child mortality (Hasegawa, Fujimori, Takahashi, Yokohata, & Masui, 2016; Troeger et al., 2018) thus, creating "under-nutrition- infections vicious cycle" (Maleta, 2006). Disease burden estimation of at least 50% of years lived with disability (YLD) in children under four years is attributed to nutritional deficiencies (Ebi & Bowen, 2016; Vos et al., 2012). These health effects have severe consequences on children's physical and cognitive development and hence future educational, economic productivity and income levels given that some of them are irreversible (Phalkey, Aranda-Jan, Marx, Höfle, & Sauerborn, 2015; World Health Organization, 2009).

Worldwide, about 151 million and 51 million of the 2.2 billion under-five children were stunted and wasted in 2017, respectively (Development Initiatives, 2018). The number of undernourished children is projected to increase by 20-25 million due to climate change impacts in 2050 comparing with and without climate change A2 scenarios, with high proportion primarily in developing countries (Al-Delaimy, Ramanathan, & Sorondo, 2020; Phalkey et al., 2015). High dependence on rain fed agriculture is one of the major factors that make households in the Sub-Saharan Africa (SSA) more vulnerable to negative effects of climate change and variability (Codjoe, Atidoh, & Burkett, 2012; Radeny et al., 2019; Yobom, 2020). Furthermore, households lack access to sufficient quantities of good quality water for good hygiene and drinking, in addition to the lack of safety nets and adequate health care (Hanna & Oliva, 2016).

Vulnerability of child health to impacts of climate change and variability does not only start after their birth but also while still in the utero. The exposure of pregnant women to weather extremes and anomalies results in maternal under-nutrition, food insecurities, respiratory illnesses, heat related diseases, stress and poverty that can consequently lead to high risk of pre-term birth and low birth weight of children (Pacheco, 2020) These negative effects on child development can be both short-term and long-term. For example, Hu and Li (2019) found that heat stress experienced during pregnancy had long-term negative effects on height of born individuals in their later life. Deschênes, Greenstone, and Guryan (2009) reported a negative relationship between extremely high temperatures and birth weight on a global sample of 37.1 million births. The latter study further predicted that extremely high temperatures experienced during pregnancy will decrease average birth weights by end of 21st century, with high impacts among Africans (Deschênes et al., 2009). Other related studies documented a decrease in birth weight due to maternal exposure to increases in temperature in Andean region (Molina & Saldarriaga, 2017), high temperatures and low rainfall in 19 African countries (Grace, Davenport, Hanson, Funk, & Shukla, 2015) and lower weight-for-height z-scores (WHZ) under maternal drought exposure in India (Kumar, Molitor, & Vollmer, 2016).

Child stunting (low height for age) is one form of under-nutrition resulting from long-term nutritional changes. The recent empirical literature on climate and health has revealed that stunting is very sensitive to shocks related to climate and weather anomalies (Cooper et al., 2019). Therefore, continued increases in climate related negative events could not only retard progress towards "a world with food security for all" (von Braun, 2020) but also reverse the gains achieved globally in stunting reduction (Cooper et al., 2019) Some studies have linked precipitation extremes (droughts and floods or extreme wetness) with stunting and other forms of under-nutrition, while considering different periods of early child life. Shively (2017) found a positive relationship between height-for-age z-scores (HAZ) and weight-for-height z-scores (WHZ), and rainfall experienced during growing seasons of the birth year, preceding survey year and also while in the utero, for children in Uganda and Nepal.

Apart from the aforementioned study, a strand of literature has used Standardized Precipitation–Evapotranspiration Index (SPEI) to assess the relationship between precipitation extremes and stunting. Using data from 53 countries, Cooper et al. (2019) found that increase in child stunting (low HAZ scores) was associated with precipitation extremes. Similarly, Muttarak and Dimitrova (2019) using SPEI found that floods or abnormally wet conditions increased stunting and wasting likelihood of under five children in Kerala, India. In contrast, Nsabimana and Mensah (2020) revealed that wet shocks did not have distinct effects on child stunting in Tanzania. However, the latter study found positive and significant impact of dry shocks on stunting.

Bauer and Mburu (2017) and Johnson and Brown (2014) used normalized difference vegetation index (NDVI) as a drought indicator in Kenya and in four West Africa countries, respectively. They found mixed results on stunting and mid-upper arm circumference (MUAC). While Bauer and Mburu (2017) found a negative relationship between NDVI z-score and the probability of child malnourishment as measured by MUAC, Johnson and Brown (2014) reported that NDVI for child's birth year was inconsistently associated with stunting, positively with wasting and negatively with the mortality risk. Other studies exploring the linkages between climate or weather variables and their proxies on under nutrition with mixed results are as follows; Grace, Davenport, Funk, and Lerner (2012) found a significant positive impact of rainfall on the HAZ scores of under five children in Kenya. Conversely, Hagos, Lunde, Mariam, Woldehanna, and Lindtjørn (2014) revealed that increases in rainfall and temperature resulted into increase and decrease in moderate stunting, respectively.

A set of studies that found positive correlation between drought and stunting or negative effect on the HAZ and height include; Bahru, Bosch, Birner, and Zeller (2019) reporting low HAZ scores on children in Dercon and Porter (2014) , where children who were below 3 years at the 1984 drought incidence peak had lower height- difference of 5cm as compared to older ones. Jankowska, Lopez-Carr, Funk, Husak, and Chafe (2012) found association between stunting with water balance index in Mali. Conversely, Hirvonen, Sohnesen, and Bundervoet (2020) documented that 2015 drought did not significantly lead to under-nutrition (stunting or low HAZ) but poor road network interaction with drought was a mediating factor for under-nutrition in 43 clusters of Ethiopia. Rodriguez-Llanes, Ranjan-Dash, Mukhopadhyay, and Guha-Sapir (2016) focusing on flood argued that there was no correlation between flooding and stunting in Eastern India.

With regards to wasting and underweight, Rodriguez-Llanes et al. (2016) found significant association between flooding, wasting and underweight. Similarly, Omiat and Shively (2020) reported significant associations between precipitation and low child WHZ in Uganda. Jankowska et al. (2012) revealed that underweight and anemia variables were not associated with water balance index. Ledlie, Alderman, Leroy, and You (2018) found no consistent relationship between wasting for children aged 0-24 months and the rainfall shock in Ethiopia. Hirvonen et al. (2020) and Hagos et al. (2014) confirmed the same in Ethiopia; wasting (WHZ) was unrelated to rainfall or drought and temperature except for severe wasting which was positively related with rainfall quadratic term as reported by the latter study.

While the aforementioned studies focused on the current nutritional impacts, a distinct set of studies explored future impacts considering different climate change scenarios. A global study by Lloyd, Sari Kovats, and Chalabi (2011) developed a model that predicted future increases in stunting due to climate change in all regions by 30-50% for severe stunting, though with higher levels in South Asia and SSA. Davenport, Grace, Funk, and Shukla (2017)showed that in 13 African countries the risk of increased child low birth weight was lower as compared to risk of child stunting considering warming and drying conditions.

Even though climate change and weather extremes have been shown to have adverse effects on under-nutrition, there is evidence of potential impact reduction through adaptation activities. Controlling for adaptation covariates, (Bahru et al., 2019; Davenport et al., 2017; Shively, 2017) consistently found that good access to socio-economic conditions, transport and health infrastructure, and productive safety nets helps to smooth out the adverse effects of precipitation and temperature extremes on under-nutrition.

The outlined literature and evidence above suggest that there are still significant research gaps on how extreme weather events affect the health and physical development of children. The results and predictions are consistent with Phalkey et al. (2015) review which indicated the relevance of under-nutrition and recommended further research priorities on the same. They further noted that even though children under-nutrition was due to complex and multiplex inter-linkages and factors, most of the mediating factors were climate sensitive revealing that weather and climate variables played a vital role. However, most studies that evaluated the links between extreme weather and child health did not explicitly unpack the multiple causal mechanisms between climate variables and under-nutrition. This paper seeks to contribute to filling these critical gaps in the current knowledge. Another key added value of this study is that it uses panel data on children's anthropometric measures, thus applying a more rigorous causal identification strategy. Most previous studies in this strand of research relied on repeated cross-sections of demographic and household surveys (DHS) and focused on either one or two under-nutrition measures. The current study also combines the survey data with other rich, high-quality data from multiple sources in order to control for a wide range of factors that could possibly affect the health outcomes. We combine weather information and inter-annual household and individual level (child) information that is nationally representative for Uganda to address the following research questions:

1. How do extreme weather events (droughts and heat waves) affect children nutritional and health outcomes?

2. What are their causal transmission mechanisms?

3. What solutions do households use to minimize the negative effects of weather extremes?

Uganda is selected for this study because it is a least developed country with at least two thirds of its population residing in rural areas. The country is also highly dependent on rain fed agriculture, vulnerable to weather anomalies and prone to infectious diseases, food and nutritional insecurities (FAO, 2020). Furthermore, child under-nutrition levels and mortality rates are relatively high thus a key challenge to sustainable development. For instance, a third of the total child population in the country (2.4 million) are stunted and 250,000 deaths of young children that occurred from 2013-2015 were due to under-nutrition (MGLSD & UNICEF, 2015). Thus, malnutrition is still a contributory risk factor to both disability and premature death in the country. The lessons learnt from Uganda are, thus, also highly useful for other developing countries as well.

Our results show strong, significant and negative effect of the heat waves experienced in the different seasons of different time periods with HAZ scores-a reduction of between -0.03 to -0.15 standard deviations, given an increase in one heat event. Consistently, significant and negative results were still observed on HAZ scores of both boys and girls with exposure to extreme dry conditions – a higher effect size of up to -0.57 standard deviations. Generally, negative associations were also reported on some extreme weather variables on WAZ and WHZ, even though the effects were not consistently significant. Further evidence indicate that problems related to child illnesses such as diarrhoea, fever and reductions in household crop output that escalate with weather extremes might explain the above-mentioned results. However, with proper adaptation strategies such as precautionary savings and use of improved farm technologies, the negative effects of different weather shocks are smoothed. The rest of the paper is organized as follows: section two outlines materials and methods, section three presents' empirical results, and relevant discussions and finally section four concludes.

2 Materials and methods

2.1 Study area

Uganda is among the countries vulnerable to climate change and climate variability (MAAIF, 2018). Growing impacts of droughts and other climatic hazards such as floods, heat waves, landslides and associated diseases and pests are becoming evident (MAAIF, 2018; The World Bank, 2019). Devereux and Nzabamwita (2018) showed that the 2015/2016 drought event in Uganda was responsible for increasing the poverty rate to 27% from 19% in 2012. Hunger situation in the country is critical with the country being ranked in position 87 out of the total 118 countries in 2016 with the hunger index score of 26 (Devereux & Nzabamwita, 2018). This situation worsened in 2018, as the hunger score rose to 31.2 and Uganda fell to rank 105 out of 119 countries. Each year, approximately 200,000 and 500,000 people are affected by drought and flood events, respectively, and at least 7% of the farming households are prone to flooding (MAAIF, 2018; The World Bank, 2019). These extreme events are most often experienced in poverty-stricken areas along the cattle corridor stretching from mid Northern, Eastern, Central and south-western Uganda (MAAIF, 2018; The World Bank, 2019). Location of Uganda in Africa and the sampled households in the four regions of Uganda are shown in (Supplemental materials Figure.S1)

Generally, the country experiences an average annual rainfall of 1200mm ranging from 500mm-2800mm, and monthly temperature range of °C with an annual mean of 22.40°C (The World Bank Group, 2020). Figure.1 indicates the historical annual temperature and rainfall amounts in Uganda from 1901 to 2016, and further the average monthly rainfall and temperature from 1901 to 2016. Concerning temperature variability, (Caffrey et al., 2013) reported a significant temperature increases of about 0.5 – 1.2 °C experienced in the country for time periods 1981-2010 and 1951-1980, while Funk, Rowland, Eilerts, and White (2012) reported an increase in temperature of up to 1.5°C.

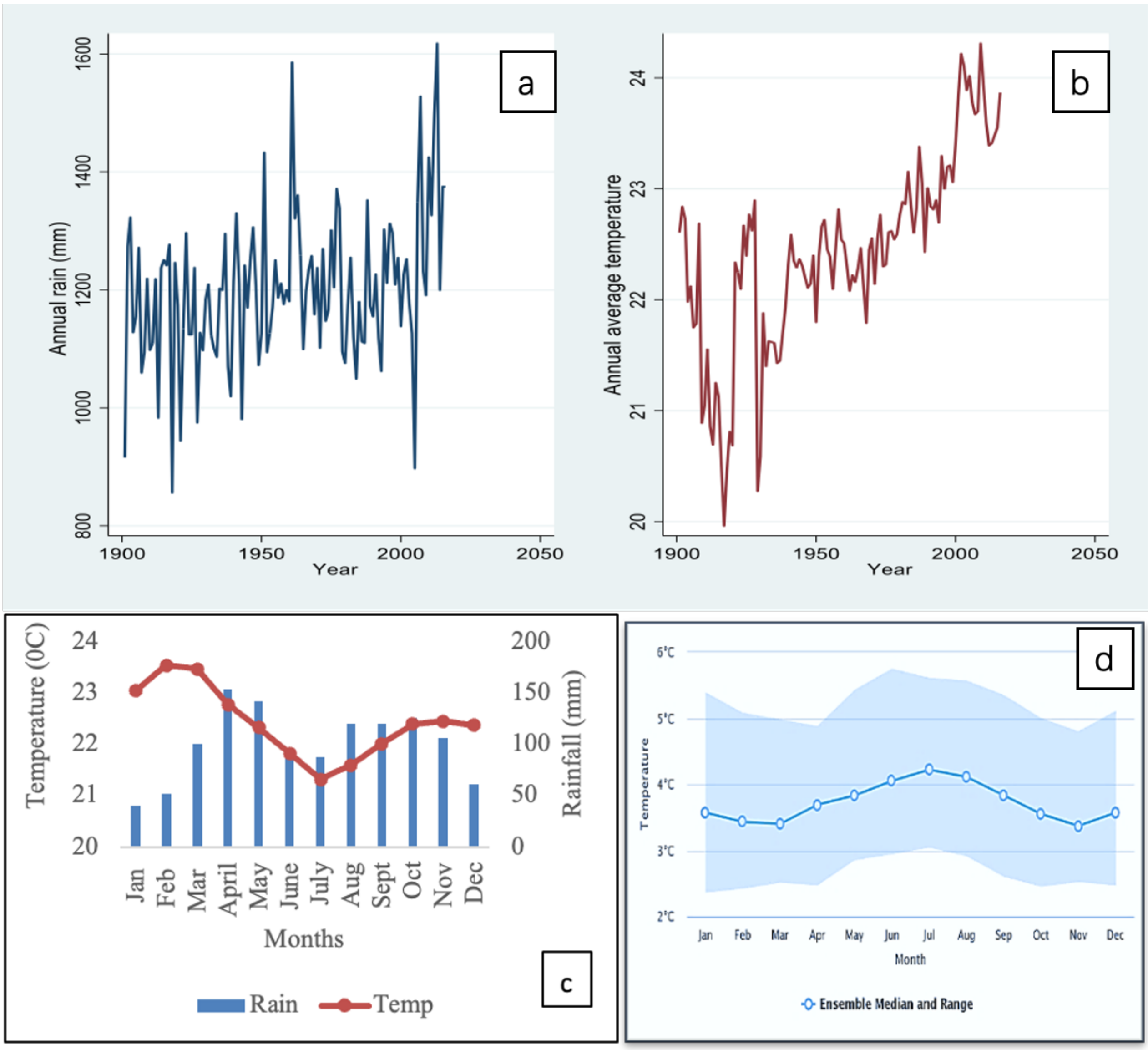

Figure 1: Rainfall and temperature trends in Uganda from 1901 to 2016 (A & B), average monthly rainfall and temperature of Uganda from 1901-2016 (C), and projected change in monthly temperature for 2080-2099 compared to 1986-2005 (D)
Source: adapted from the World Bank data

Annual mean temperature are further projected to increase with an average of 2.5°C to 4.4°C, and 4.5°C to 6.0°C in some areas in the near future (2021-2050), and in mid-century respectively, relative to 1981-2010 average under the Intergovernmental Panel on Climate Change (IPCC) special report on emission scenarios (SRES) A2 (Nimusiima et al., 2014). Addition-ally, the World Bank temperature projections in Figure1(D) reveal that the change in monthly temperature will be highest in the historical cold months (May-July), with an increase of up to 40C in 2080-2099 compared to 1986-2005, under the RCP8.5 Scenario. While most of the temperature projections are consistent indicating an increase in near surface temperature, future rainfall trends are not clear. For instance, Nsubuga and Rautenbach (2018) reports an expected decrease in precipitation in most parts of the country while Nimusiima et al. (2014) forecast wetter conditions as a result of increase in rainfall, especially for the second season rains and the previously dry months ranging from December to February.

2.2 Data Sources

Uganda National Panel Survey (UNPS)

The study uses the four waves (2009-2014) of the Uganda National Panel Survey (UNPS), a national representative survey conducted and funded by Government of Uganda through Uganda Bureau of Statistics (UBOS) and World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS –ISA) in Uganda. This study used two questionnaires. The household (HH) level and agriculture questionnaires, which were administered once and twice per year, respectively (UBOS, 2007, 2014). Household questionnaire consisted of 17 sections covering information on all possible household socio-economic information including individual health shocks, children's anthropometry, weather shocks, consumption expenditure, food security and other welfare indicators. Agriculture questionnaire comprised of a total of 10 modules capturing information on household land holdings, crops grown, input and technology use, quantities of agricultural produce and livestock information.

These datasets were selected because of their representativeness at national level with the samples drawn from all regions (East, West, North and Central) of Uganda, and in both urban and rural areas. However, this study targeted rural sampled households only since they are the most vulnerable to climatic shocks and depend on agriculture for their livelihoods. An important feature of this dataset is that households' geographical locations were geo-referenced. This enabled us to match households within a given enumeration area with weather specific information. Furthermore, the households and individuals in the different waves were linked through unique, household identifiers and individual identifiers since tracking was not only done at household level but also at individual level.

Sampling was done through two stage stratified cluster sampling and the survey design in the different waves was maintained as the same. A third of the total households sampled (i.e. 3, 123) from the baseline panel 2005/06 were tracked, followed and re-interviewed in subsequent waves to ensure consistency (UBOS, 2014). However, due to attrition rates of 15-25% and sample refresh that was introduced in 2013/2014 wave Moreover, since our sample is composed of children aged 7-59 months, a child automatically dropped out of the sample if she/he became older than 59 months. The anthropometric measures were not taken for older children beyond 59 months. Children with z scores beyond the required World Health Organization (WHO) limit also dropped automatically during computation due to the fact that the measures were not biologically feasible for the different under-nutrition measures.

Nonrandom attrition is of concern in the panel data and may potential lead to biased results. We conducted t-tests of differences in mean in WAZ, HAZ and WHZ z scores of children who dropped in the subsequent waves and those who retained and we found no significant differences of the of children that appeared in waves 1, 2 and 3 except for those in the 4 waves. However, the number of children in the four waves was negligible. We therefore assumed that attrition was random and used unbalanced datasets since there is loss of substantial efficiency if observations are dropped to make balanced datasets (Biørn, 2004). Additionally, Mátyás and Lovrics (1991) indicate that unbalanced panels are consistent and unbiased under reasonable and general conditions. This study used data from 3794 distinct children with approximately 1500 children observations appearing in either three or four waves thus translating into cumulative observations at least 5000 children.

Weather data

Rainfall datasets comprise the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) data version 2 ranging from 1981 to present and measured in millimetres (Funk et al., 2015). The CHIRPS product was developed by the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center scientists. The product provides up-to-date, reliable and complete data sets for drought monitoring and trend analysis. The CHIRPS is also advantageous for its high spatial resolution $(0.05°C \times 0.05°C)$ (Funk et al., 2015; Poméon, Jackisch, & Diekkrüger, 2017). Additionally, it is the only long-term high spatial rainfall dataset with both satellite and in-situ rainfall station data(Funk et al., 2015; Haile, Signorelli, Azzarri, & Johnson, 2018).

Monthly surface temperature dataset was retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS). Spatial and temporal extent of the datasets is global, from 2000 to present and values are also in the same 0.05°C longitude/latitude climate modelling grid (Hooker, Duveiller, & Cescatti, 2018; Wan, Hook, & Hulley, 2015), matching the rainfall dataset. These datasets were developed by National Aeronautics and Space Administration (NASA) in collaboration with USGS. The downloaded monthly temperature (2000-2014) and rainfall datasets (1981-2014) were processed in QGIS software and used to construct weather indices described in the next section. Self-reported drought measure from the survey was also used to enable comparison of results with those estimated from objective measures.

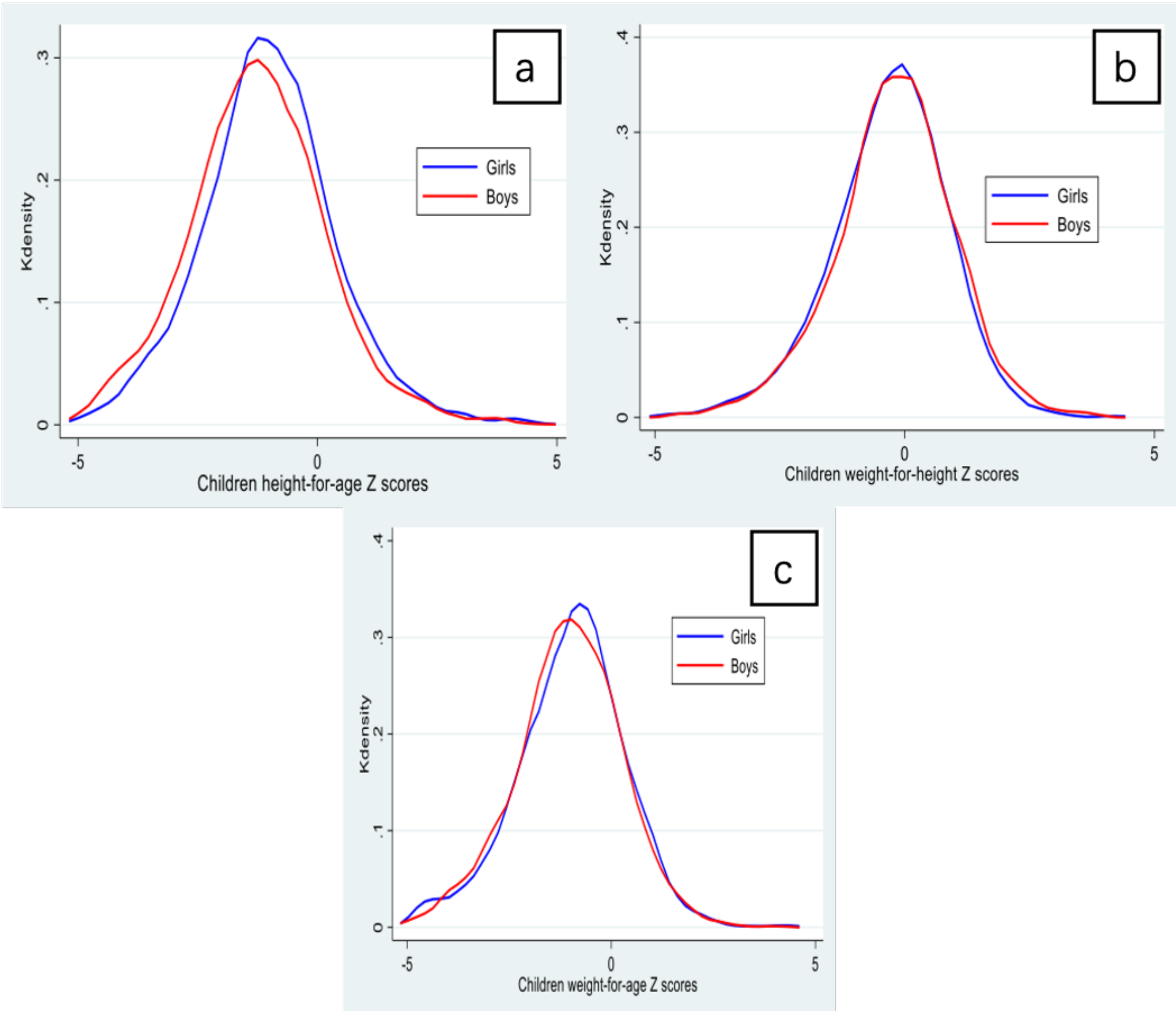

Figure 2: Distribution of child mean HAZ (a), WAZ (b) and WHZ (c) among boys and girls

2.3 Data variables

Outcome variables

The main dependent variables in studying the effect of weather variables on child nutritional outcomes were the standardized z scores derived from the anthropometric measures of body height and weight in relation to sex and age of children aged 7 to 59 months old. Specifically, three measures: the height-for-age z-scores (HAZ), weight-for-height z- scores (WHZ) and weight-for-age z sores (WAZ) were used. These indicators were created by comparing age, sex, height and weight of the sampled children with reference data for 'healthy' children for the US population, as recommended for international comparisons by the WHO (O'Donnell, van Doorslaer, Wagstaff, & Lindelow, 2007). The three outcomes measures both short-term or current status of nutrition (WHZ), long-term (HAZ) nutritional status changes and a mixture of both (WAZ) (O'Donnell et al., 2007). From our sampled children, correlations between HAZ and WAZ, WAZ and WHZ were evident while no correlations were found between WHZ and HAZ (*see supplemental materials* Figure.S2). The HAZ is usually related to past chronic or frequent illness and nutritional deficiencies and represents cumulative linear growth, with the extreme scores in comparison to the standard reference group denoting stunting (O'Donnell et al., 2007). Wasting and underweight are usually measured by low WHZ and WAZ respectively with cut-offs of -2. However, in the regression model the respective z scores were used as continuous variables in STATA 14 analysis software. The distributions of HAZ, WAZ and WHZ scores between boys and girls are presented in Figure.2. The means of the HAZ and WAZ scores were greater for girls as compared to the boys.

Explanatory variables

The main explanatory variables in this study were the different weather extreme variables. Since the impacts of extreme weather events on child health will unfold over several seasons and with lags, several weather indices including the lagged variables and cumulative ones were created. Statistical z scores were used in construction for both rainfall and temperature indicators to enhance comparability. The formula used for z-scores is represented as follows;

$$z_{it} = \frac{X_{it} - \bar{X}_{it}^{LTM}}{\sigma_{it}^{LT}} \tag{1}$$

Where X_{it} is the monthly temperature or seasonal rainfall amounts (sum of rainfall received in the four months) recorded in an enumeration area/ household/child i in year t, $\bar{X}_{it}^{LTM}$ is the historical monthly average temperature or seasonal rainfall averages corresponding the specified months that fall within respective seasons for household/child i in year t and σ_{it}^{LT} is the long-run standard deviation (SD) of household/child i in year t. Thus, the scores are interpreted as the standard deviation number by which a given weather data point of an individual is above or below the value of the long-term mean rainfall or temperature, assuming normal distribution. A z-score of 0 implied that the data point value was equal to the mean.

For precipitation we developed z scores of the total seasonal rainfall amounts (in mm) received during the main planting and growing season (first season), and second season separately, over the long-term mean of the same time periods starting 1981 to the respective panel years. We then adopted z-scores cut-offs from World Meteorological Organization (WMO) Standardized Precipitation Index (SPI) with slight modifications to create a rainfall categori-cal variable of 5 categories instead of 7 (WMO, 2012). Specifically, z scores of -2 and less denoted extreme dry spell, -1.99 to -1 moderately dry, -0.99 to 0.99 near normal, 1 to 1.99 moderately wet and z scores greater than 2 represented extremely wet spell conditions.

The distribution of HAZ scores under different rainfall regimes are shown in Figure.3a below. Lower average HAZ scores were consistently recorded on children exposed to extreme dry spells. However, higher average HAZ scores were observed on children who experienced extreme wet conditions, than the rest of the four rainfall regimes. Similar distribution was observed on WAZ and WHZ where lower means were recorded under extreme dry conditions. Therefore, this study focused on extreme dry spell category of rainfall only and not extreme wet spell or any other rainfall regimes in the respective regressions. Other studies using alternative rainfall shock measure SPEI on different outcome variables include; Kubik and Maurel (2016) who did not assign any threshold, while Cooper et al. (2019) used a categorical variable to focus on the effects of drought and normal rainfall conditions on HAZ.

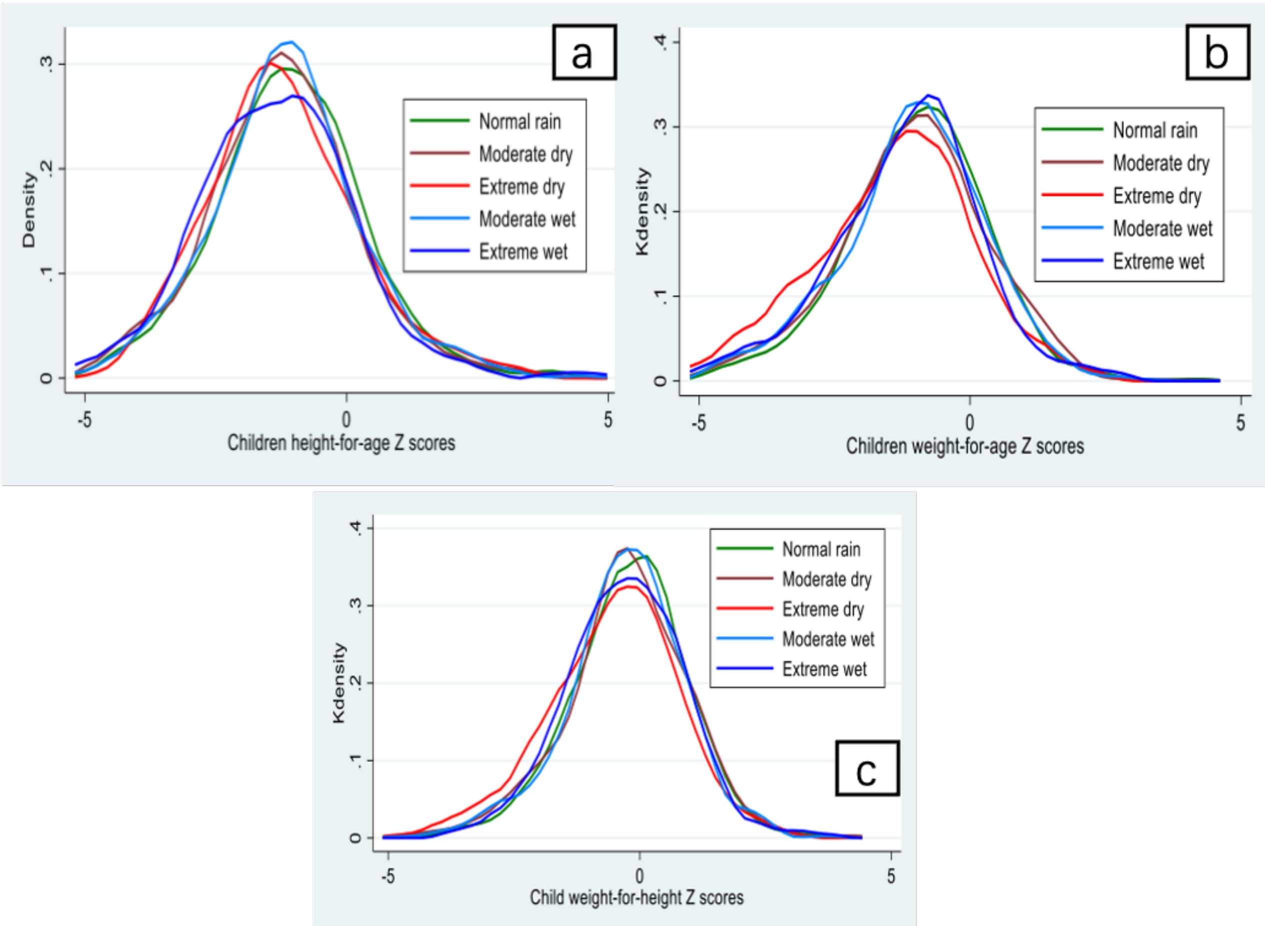

Figure 3: Distribution of child mean HAZ (a), WAZ (b) and WHZ (c) among boys and girls.

With regards to temperature, heat wave months, a proxy of heat wave was created by counting number of months in the both planting and growing seasons of the year (first season march – June) and second season (august –November) separately, where the z-scores were equal to or greater than 1. The respective monthly temperatures with more than 1 standard deviation (SD) above the mean had an average temperature of at least 29°C (84.2 °F). This temperature cutoff is consistent with most previous studies definition of detrimental temperatures. For instance, Heal and Park (2013) indicated that several studies in labor productivity, economics and health defined hot days by temperatures of about 25°C (78 °F) and above. Similarly, Traore and Foltz (2018) interpreted high temperature as the number of days with mean temperatures of at least 27°C which was 1.77SD above the historical average. Hu and Li (2019) and 34°C considered temperatures of above 85oF and 34°C respectively to define their growing degree days variable. The concept of heat wave months was adapted from Haile et al. (2018)

Specifically, one- and five-time lags of the abovementioned weather indicators were created. Thai and Falaris (2014) argued that a given rainfall shock at a given time point may have lagged effects on nutrition and income. Therefore, since the long-term health outcomes such as stunting and underweight are usually a result of past shocks and nutritional deficiencies, the current weather changes in respective panels may not have an immediate effect on the anthropometrics measures except for WHZ and perhaps WAZ which respond to short-term effects. Apart from lagged variables, we also developed count variables for extreme dry spell and heat wave months over a five-year period which were reported alongside the previous year seasonal rainfall effects on nutritional outcomes (HAZ and WAZ). Famine early warning systems network (FEWS NET) seasonal calendar for a typical year in Uganda was used to define the four respective months in first and second planting and growing seasons, and the eight months for the one in the Northern region.

Spatial and temporal distribution of heat waves of the sampled areas and households constructed are shown in Figure 4. Heat-waves were consistently experienced in the Karamoja (Northeastern sub-region) for all time periods. It is also important to note the increase of heat-wave events in 2010 (Fig 4b) especially in the Southwestern region. Given that heat events exacerbate drought occurrences or sometimes occur simultaneously, more heat events recorded in 2010 is consistent with The World Bank (2019) who reported drought events in 2010. Furthermore, graphical representation shows that stunting rate in the sampled children was highest in 2010, a period where the frequency of heat waves in the previous year was also equally high (*See supplemental materials* Figure.S3). Other sub-regions which experienced more months of heat waves include Teso, Lango and West-Nile.

Apart from the extreme weather measures, other additional weather variables used in different regressions consisted of annual rainfall, annual average temperature, temperature and rainfall experienced in the month prior to the surveys, and coefficient of variation. The latter variable is an indicator of climate risk and seasonal rainfall variability, used to explore the agriculture mechanisms. This standard measure shows the degree of variability in relation to the mean (the standard deviation divided by the mean) (Chattopadhyay & Kelley, 2016).

The rest of the explanatory variables used in the study were guided by literature and theory. Some of the socio-economic variables controlled for in the different model specifications include; tropical livestock units (TLU), asset index, water sanitation and hygiene (WASH) index. All the three mentioned indices were continuous variables with the latter two constructed through statistical multivariate technique; the principal component analysis (PCA) that enables reduction of the number of variables into smaller dimensions of the datasets (Vyas &

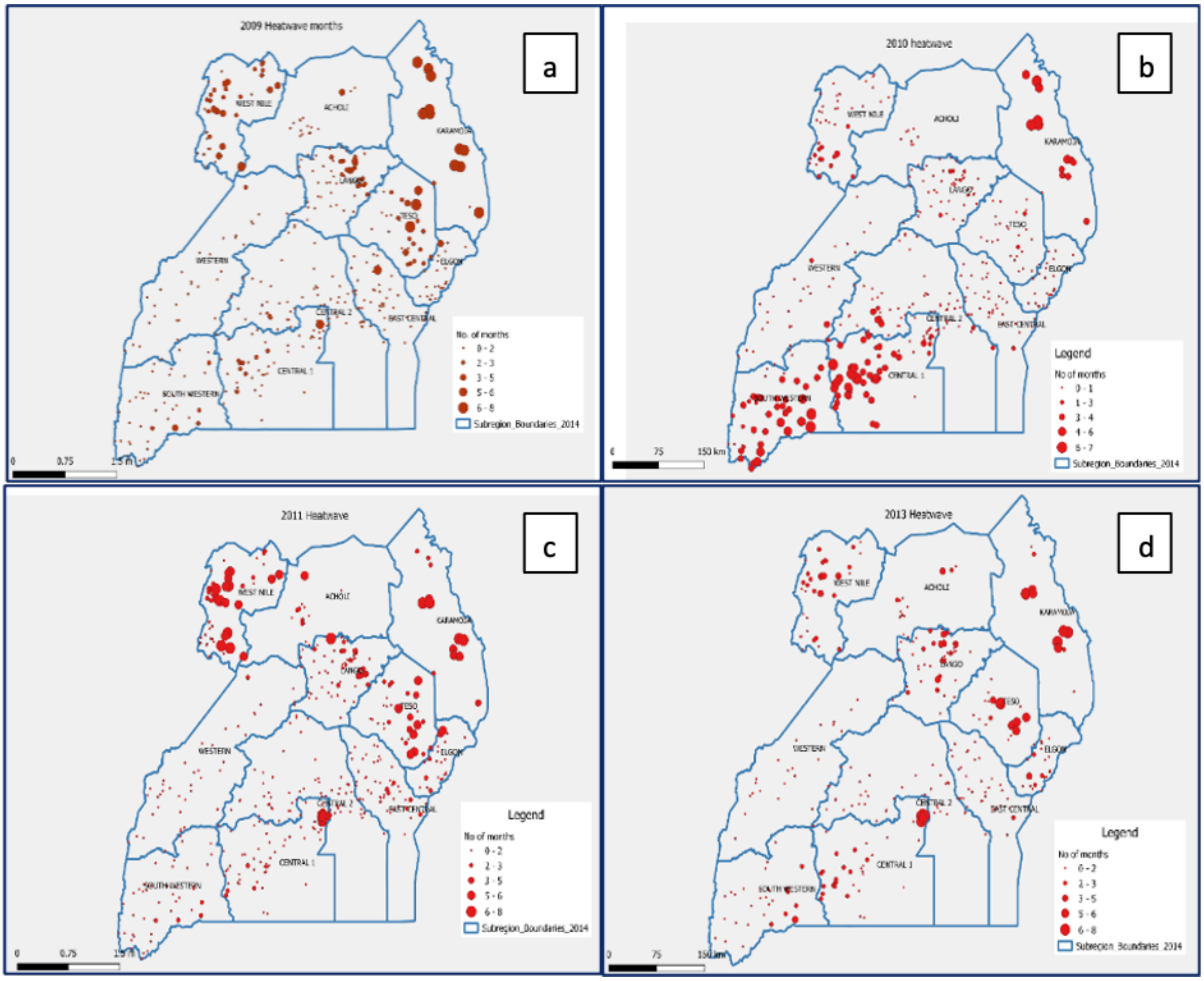

Figure 4: Maps showing the frequency of heat waves (Number of heat wave) months for survey years 2009, 2010, 2011 and 2013 respectively for the sampled households.

Kumaranayake, 2006).. WASH index and asset index were derived separately with different combination of relevant variables related to household assets and water, sanitation and hygiene defined in ‘‘ Section 9A; Housing conditions, water and sanitation of the UNPS as well as the Section 14 ‘’Household assets”.

2.4 Analytical Framework

In absence of controlled experimental data for economic research, panel data provides more accurate, reliable and efficient estimates as compared to a one-time cross-sectional data. In this study we took advantage of World Bank sponsored LSMS study in Uganda to explore the effects of weather extremes on children health outcomes. According to K. H. Hsiao, Hsiao, and Yan (2014) panel data has time (T) and cross section (N) dimensions and combines both the inter-individual and intra-individual dynamics enabling analysis of critical and complex questions with less assumptions that would not be possible with one cross section. The large sample sizes are known to provide more variability and less collinearity among data variables and degrees of freedom are increased (Baltagi, 2020; K. H. Hsiao et al., 2014). Importantly, the ability of panel data to control for omitted variable bias, individual and time heterogeneity improves validity of estimates (Baltagi, 2020; K. H. Hsiao et al., 2014). In order to estimate the total effect of extreme weather events on child health, we adopted panel fixed effects estimation approach, which focuses on the within group variation and thus is not affected by heterogeneity bias (Bell & Jones, 2015; C. Hsiao, 2007). The fixed effects estimation used in this study is expressed in the reduced form equation as follows;

$$Y_{it} = \beta_0 + \beta_{1_{it}} W_{it} + \beta_{2_{it}} Ch_{it} + \beta_{3_{it}} CS_{it} + \beta_{4_{it}} X_{it} + \varepsilon_{1_{it}} \quad (2)$$

Where Y_{it} is the main outcome variable - a continuous variable of child health represented by either HAZ, WAZ or WHZ scores for child i aged between 7-59 months in year t. Outcome variables are explained by our main treatment variables, the extreme weather events (W_{it}) experienced by child $i$in year t. Main coefficient of interest is denoted by $\beta_{1_{it}}$. The extreme weather events are assumed to be exogeneous and random, thus no correlation of weather variables with the time varying factors is expected. This enables us to infer causality on changes in child health outcome to changes in extreme weather events.

Since the weather extremes fluctuates from year to year, and some of the different undernutrition measures are due to the lagged weather effects, weather extremes used in the respective regressions include both dummies as well as count variables over specified periods of time. For precipitation extremes we use dummy variables for extremely low rainfall in the main agricultural season of the interview year (t), previous year $(t-1)$, the fifth lag $(t-5)$ and counts of dry spell events in the previous five years. With regards to temperature, counts of heat wave events in particular seasons are used. These count variables include; counts of heat wave events in the previous 5 years, counts of heatwave events in the survey year, previous year and the fifth lag count variable. Lagged weather variables are used in the HAZ and WAZ models and not in WHZ since the latter is a short-term measure of current nutritional deficiencies, thus responsive to the weather extremes experienced in the interview year.

We also controlled for additional covariates such as child factors (Ch_{it}) that have a direct effect on child health such as sex, age and the quadratic term of age. Since nutritional and health outcomes are also as a result of differences in household socio-economic conditions, we controlled for these factors by including a vector of covariates (X_{it}). These variables include: asset index, age and sex of household head, age, sex and education of the mother or female head, whether the biological mother was living in the household, household farm size and number of under-five years children in a household. We also controlled for household coping strategies that help smooth the negative effects of weather extremes. These strategies are dummy variables for savings, government assistance, involuntary change of diet, relatives and friends' assistance, non-farm work, access to credit and sell of assets.

In equation (2) we did not add covariates for potential transmission mechanisms through which extreme weather events affect child health. This is in order to avoid biased results because the mechanism variables are also affected by the weather extremes (Meierrieks, 2021). We therefore estimate separate regressions in order to establish the effect of weather extremes on the respective potential pathways (child diarrhoea that define the disease environment, household crop output and livestock tropical livestock units that define the agricultural pathways) using the following regression;

$$M_{it} = \alpha_0 + \alpha_{1_{it}} W_{it} + \alpha_{2_{it}} AS_{it} + \alpha_{3_{it}} W_{it} * AS_{it} + \alpha_{4_{it}} X_{it} + \varepsilon_{2_{it}} \tag{3}$$

Where M_{it} is the pathway variable - either a dummy variable indicating if child $i$suffered from diarrhoeal diseases in the past 30 days in year t, or a continuous variable for crop output harvested, measured in kilograms and transformed into a logarithm value, or the weighted TLU measure for child household i in year t. W_{it} is a vector of temperature and rainfall extremes experienced in the interview year. Additional weather variables added to the respective regressions include; coefficient of variation in crop output and TLU regressions. Rainfall and temperature of the month prior to the interview and annual weather measures were included in the diarrhoea equations. In the crop output model, we also controlled for adaptation strategies (AS_{it}) used by households such as organic and inorganic fertilizer, improved seed use, number of crops planted, use of pesticides, irrigation and water harvesting technologies. The interaction term $W_{it} * AS_{it}$ enabled us to assess whether the adaptation strategies mitigate the negative effects of extreme weather events on crop output. The (AS_{it}) was only controlled for in crop output model and not in the TLU and disease models. X_{it} is a vector of other covariates affecting respective mechanisms variables. The covariates in the diarrhoea mechanism model include; water, sanitation and hygiene conditions, child age and sex, mothers age and education and household head education. Other explanatory variables used in crop output pathway include; household age, sex, education, wealth index, plot area and soil characteristics. Household covariates were also used in the livestock pathway model.

3 Results and discussion

3.1 Descriptive statistics

Table S1 in the supplemental materials summarizes the descriptive statistics of children aged between 7-59 months, extreme weather events and other covariates for mother/female/head and children households. In general, children had lower HAZ, WAZ and WHZ scores averaged at -1.13, -1.02 and -0.25 respectively. Approximately 27 % of children were stunted, 21% underweight and only 7 % were wasted. Children were 32 months of age on average, and half of them were female. Fever was the most common symptom reported in approximately a third of the total children. However, only 9% of the sampled children experienced diarrhoea episodes. Children were from relatively poor households, given that the asset index was averagely -0.77, and the tropical livestock units (TLU) was 2.31 units. Moreover, household's access to water, sanitation and hygiene (WASH) conditions was generally poor with a mean index of -0.54. The average farm size of households was 2.47 acres.

Extreme dry conditions were experienced by approximately 5% of the sampled children households, even though 39% of the households subjectively indicated to have experienced drought in the year preceding the interview. This substantial difference could be attributed to the fact that only extreme values of low rainfall (less than -2 standard deviations from the value of the long-term mean rainfall) were considered in the objective extreme dry spell variable. Heat waves were also experienced by some of the sampled children. On average, children experienced one month of heat in the first, and second seasons.

Due to the negative effects of extreme weather events, households of sampled children engaged in different coping strategies; both anticipatory as well as reactive. Undesirable coping strategies such as involuntary change of the diet was the most common strategy used by 22% of the respondents, followed by savings (an *ex-ante* strategy) practiced by 20% of total respondents. Households also engaged in multiple practices such as receiving aid/help from the government, friends and relatives and more off –farm work. With regards to farm technology use, majority of households (30%) used water harvesting technologies, 20% used improved seed, 12% organic fertilizers and pesticides while only 4 % used organic fertilizers. Detailed descriptive statistics are in Supplementary Materials Table S1.

3.2 Fixed effects regression results on children anthropometrics

The estimated effects of both objective weather variables and households' self-reports of extreme weather events, and other covariates on children HAZ scores are presented in Table 1 , for all children and a sub-sample of children in at-least three waves. Different time periods of weather indicators were also considered given that HAZ is a measure of recurrent or chronic under-nutrition. These time periods include, first lag, fifth lag and cumulative five-year counts measures of extreme weather events. Results in column 1, 2 and 3 of Table 1 indicate that heat waves experienced in the first seasons were negatively and significantly associated with HAZ at different levels of significance. Holding other factors constant, a one event of heat wave in the first season of the previous year, and over the previous five years reduced the HAZ scores in a range between 0.03 and 0.11 standard deviations. Relatively higher effects of heat waves on HAZ reduction of up to 0.15 standard deviation were recorded on a subsample of children in at least 3 waves, as shown in columns 8. Worst significant HAZ scores were observed on children exposed to extremely dry conditions (columns 4 and 12), especially in the previous five years on a sub-sample analysis (a significant reduction of up to 0.57 standard deviations). Self-reported drought shock variable also had similar results - significant and negative effects on the HAZ scores of about 0.22 to 0.24 as shown in columns 14 and 7 respectively. The effect sizes of both the objective extreme dry spell and subjective drought shock variables were similar at -0.24 standard deviation. The sign effect on most of the variables remained unchanged on the sub-sample analysis of children in at least three waves. Extreme weather events had negative and significant effects on HAZ scores of both boys and girls as shown in Table S2, even though the magnitude of the effect of heat extremes was higher for girls. On the contrary, the effect sizes of rainfall extremes were higher for boys HAZ scores as compared to the effect on girls HAZ.

Regression estimates using weather variables in the second season for the same time periods remained the same in terms of the expected signs, with diminishing magnitude sizes and significance levels as compared to Table 1. For instance, the effect of heat waves in the prior year of the interview on HAZ was consistently significant and negative though the coefficients were smaller, ranging from 0.05 to 0.10 standard deviations *(see supplemental materials* Table S3). In a nutshell, the above results revealed that exposure to both extreme heat and extreme dry spell or drought conditions had detrimental effects on children HAZ scores, and this is consistent with most of the previous findings; Nsabimana and Mensah (2020); Cooper et al.(2019); Bahru et al. (2019); Shively (2017); Dercon and Porter (2014); Grace et al. (2012).

Table 1: Effects of weather extremes and children HAZ scores

Variable	All children							Children in at least 3 waves						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Heat wave main season (t-1)	-0.113***							-0.156***						
	(0.030)							(0.040)						
Heat wave main season (t-5)		-0.105**							-0.122**					
		(0.045)							(0.057)					
Heat wave (5-year count)			-0.033*							-0.051**				
			(0.017)							(0.022)				
Extreme dry main season (t-1)				-0.246**							-0.229			
				(0.115)							(0.156)			
Extreme dry main season (t-5)					-0.306							-0.572**		
					(0.194)							(0.286)		
Extreme dry (5-year counts)						-0.001							-0.127	
						(0.136)							(0.195)	
Drought (subjective)							-0.235***							-0.216*
							(0.086)							(0.115)
R-squared	0.078	0.073	0.072	0.072	0.071	0.070	0.074	0.112	0.102	0.102	0.099	0.101	0.095	0.010
Mean HAZ	-1.13	-1.13	-1.13	-1.13	-1.13	-1.13	-1.13	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19
Sample size	4,921	4,921	4,921	4,921	4,921	4,921	4,921	1,381	1,381	1,381	1,381	1,381	1,381	1,381

Standard errors in parenthesis. ***, **, *Difference in significance at 1%, 5% and 10% levels respectively. Models 1-7 are for all children and Models 8-14 are for balanced panel of children appearing in all three rounds. All models include child level covariates (age, age squared, gender) household covariates (number of children, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household, access to credit, changing diet, savings, government aid, non-farm work, farm work and assistance from friends and relatives.

Despite the negative effects of weather extremes on HAZ, household employed different strategies to reduce these deleterious effects. For instance, households that engaged in *ex-ante* strategies such as precautionary savings were associated with better HAZ scores while involuntary change of diet (*ex-post*) was associated with poorer scores as shown in Table 1 and Table S3. In addition, government aid was positively associated with better HAZ scores and of higher magnitude than the other coping strategies, even though the effect was insignificant. Other coping strategies such as informal safety nets from friends/ relatives, non-farm work, sell of assets and credit access were controlled for in the respective regressions. However, their effects were mixed and insignificant. Children in wealthier households recorded better HAZ scores of at least 0.10 standard deviations.

With regards to WAZ, significant and negative associations were only observed on heat wave variables in the year of the interview, heat wave in the previous five years as well as the subjective drought measure as shown in columns 1, 3 and 9 for the whole children sample (*see supplemental materials* Table S4). The significant negative effects of extreme weather events on WAZ ranged from 0.075 to 0.174 with higher effect size on the subjective drought variable. Only prior year heat wave had a significant effect on WAZ on a subsample of children in at least 3 waves. Effect of coping strategies on WAZ were consistent to those reported earlier in HAZ models.

Table 2: Effect of weather extremes on children WHZ.

	All children			Children in at least 3 waves		
Variable name	1	2	3	4	5	6
Heat wave (t) (main season)	-0.120***			-0.111***		
	(0.027)			(0.037)		
Extreme dry spell (t) main season		-0.134			-0.038	
		(0.119)			(0.185)	
Drought (subjective)			-0.137*			-0.136
			(0.079)			(0.109)
R-squared	0.143	0.129	0.127	0.143	0.129	0.131
Mean WHZ	-0.25	-0.25	-0.25	-0.26	-0.26	-0.26
Sample size	3,870	3,870	3,870	1,140	1,140	1,140

Standard errors in parenthesis. ***, **, *Difference in significance at 1%, 5% and 10% levels respectively. Models 1-7 are for all children and Models 8-14 are for balanced panel of children appearing in all three rounds. All models include child level covariates (age, age squared, gender) household covariates (number of children, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household, access to credit, changing diet, savings, government aid, non-farm work, farm work and assistance from friends and relatives.

Given that WHZ is a measure of acute under-nutrition resulting from current or the recent past nutritional deficiencies, associations were sought using the previous season weather measures of the interview year only, and not previous year or five-year time period variables as used in WAZ and HAZ models. The results in Table 2 indicate the negative effect of heat waves on WHZ scores for all categories of children. Specifically, a one event of heat wave led to a 0.11

to 0.12 standard deviations reduction in WHZ as presented in columns 1 and 4. The subjective drought measure was also negatively associated with WHZ, a reduction of about 0.137 standard deviations as shown in column 3. Most of the weather variables were negative as expected, however, they were mostly statistically insignificant in the subsample analysis. The effect of other covariates and the different coping strategies on WHZ measure were mostly mixed and statistically non-significant. Both boys and girls WHZ scores were affected by extreme weather events even though girls WHZ were more sensitive to the heat as compared to the effect of heat on boys WHZ as shown in Table S5.

3.3 Transmission channels on children health outcomes

Following the research findings between different extreme weather indicators and children anthropometrics scores in the previous sub-section, we explored the potential mechanisms that may be responsible for these effects. In particular, we tested for four mechanisms: crop output and livestock holdings that constitute agriculture pathways and whose effect is through food and income. Presence of illnesses such as diarrhoea and fever that inhibit uptake, absorption and retention of nutrients represented the disease pathways.

We chose to investigate crop output as a linking channel because rural smallholder farmers are highly dependent on agricultural production for both food and income access. It is apparent that the two are major determinants of good nutritional status. For instance, IFAD (2014) states that *"good nutrition begins with food and agriculture"*. Substantial literature reveal the effect of rainfall and temperature and their extremes on crop production (Hatfield & Prueger, 2015; Hu & Li, 2019). Since the study datasets (LSMS) contained information on crop production of all crops grown in two seasons, this enabled us to explore the agricultural channel. Furthermore, the effect of agricultural technologies such as improved seed in reducing the negative effects of heat stress or drought on production were tested by interacting the respective extreme weather variables with improved seed, water harvesting and use of organic fertilizers. Contrary to nutritional outcomes, the weather variables were for the specific time seasons over the long-term mean and not lagged weather variables since crops are more affected with the weather shocks during the respective current or immediate seasons. Apart from seasonal rainfall amounts, an additional indicator of seasonal rainfall variability- coefficient of variation (CV) was added to the fixed effect regression since rainfall variability affects crop production.

Table 3 presents the fixed effects results of the direct effect of weather extremes and variations on crop output after controlling for farm characteristics, adaptations and household head characteristics. Extreme dry conditions had strong negative and significant effects on crop output as clearly illustrated in columns 3,4, 8 and 9. These results are consistent with the negative effect of dry spell on the nutritional outcomes reported earlier (especially HAZ), even though the effect sizes on crop output are quite high. Likewise, reductions in crop output by at least 20% were recorded on alternative rainfall measures i.e. subjective drought shock measure and rainfall variability in columns 5, 6 and 7. Rainfall is crucial for agricultural production especially during the planting and growing periods of the crops. High rainfall in absence of floods therefore translates into availability of abundance and variety of food basket for a household thus good nutritional status.

Extremely high temperatures also significantly and negatively affected total crop output by about 18% to 29%, holding another factors constant. Heat stress is one of the major limiting factors in crop production. Siebert and Ewert (2014) argued that high temperatures results into seed abortion, leaf senescence due to decreased photosynthesis, low pollen production and viability thus low production. Consistently Hu and Li (2019), and Letta, Montalbano, and Tol (2018) documented that high temperatures have adverse effects to crops yields.

Table 3: Effect of weather extremes and variability on total crop output

Variable name	1	2	3	4	5	6	7	8	9
Heat wave (main season)	-0.265***	-0.282***						-0.293***	-0.189***
	(0.044)	(0.093)						(0.091)	(0.046)
Extreme dry (main season)			-1.407***	-1.234**				-1.313***	-1.073***
			(0.171)	(0.501)				(0.171)	(0.183)
Rainfall coefficient of variation					-1.408***			-1.465***	-1.887***
					(0.410)			(0.399)	(0.416)
Drought (subjective)						-0.202***	-0.404**		
						(0.072)	(0.194)		
Improved seed	0.289***	0.082	0.262***	0.288***	0.257***	0.240**	0.284**	0.089	
	(0.097)	(0.122)	(0.096)	(0.098)	(0.098)	(0.098)	(0.125)	(0.119)	
Number of crops	0.235***	0.249***	0.249***	0.260***	0.244***	0.245***	0.229***	0.244***	
	(0.026)	(0.029)	(0.025)	(0.026)	(0.026)	(0.026)	(0.031)	(0.029)	
Organic fertilizer	0.029	0.088	0.062	0.002	0.024	0.028	0.059	0.109	
	(0.120)	(0.130)	(0.119)	(0.119)	(0.121)	(0.121)	(0.147)	(0.127)	
Inorganic fertilizer	0.238	0.145	0.259	0.255	0.293	0.287	0.483**	0.182	
	(0.184)	(0.204)	(0.182)	(0.185)	(0.186)	(0.186)	(0.242)	(0.199)	
Pesticides	0.330***	0.345**	0.345***	0.319***	0.325***	0.315***	0.270*	0.363***	
	(0.120)	(0.140)	(0.119)	(0.119)	(0.122)	(0.121)	(0.154)	(0.137)	
Good soil	0.080	0.070	0.075	0.067	0.012	0.036	0.036	0.061	
	(0.072)	(0.071)	(0.071)	(0.070)	(0.073)	(0.072)	(0.072)	(0.071)	
Water harvesting technology	0.408***	0.271***	0.392***	0.342***	0.369***	0.405***	0.324***	0.237**	
	(0.081)	(0.094)	(0.080)	(0.080)	(0.082)	(0.082)	(0.106)	(0.092)	
Improved seed * extreme weather		0.206***		-0.039			-0.101	0.208 ***	
		(0.069)		(0.474)			(0.183)	(0.067)	
Water harvesting* extreme weather		0.207***		1.145***			0.207	0.194***	
		(0.066)		(0.389)			(0.160)	(0.065)	
Organic fertilizer * extreme weather		-0.151		1.344***			-0.067	-0.154	
		(0.143)		(0.459)			(0.216)	(0.140)	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.118	0.130	0.113	0.151	0.151	0.102	0.105	0.167	0.046
Observations	4,782	4,782	4,782	4,782	4,782	4,782	4,782	4,782	5,532

Standard errors in parenthesis. ***, **, * Difference in significance at 1%, 5% and 10%levels respectively. Other controls include plot area, irrigation use, good soil, wealth index, sex, age and education of the household head

Despite the negative effects of high temperatures, drought shock and rainfall variability, results indicate that adoption of different adaptation strategies such as use of improved seed reduced the negative effect of heat stress on crop production. This is evidenced by the positive sign of the interaction term between heat wave and improved seed, water harvesting and organic fertilizer in columns 2, 4 and 8 of Table 3. Moreover, other adaptation strategies such as pesticide use and crop diversification were associated with improved crop output.

Livestock is the second transmission channel that we tested, given that it plays a significant role in rural household livelihoods and welfare in terms of food, income, asset, source of credit, insurance protection and also act as safety net for the poor. Alonso, Dominguez-Salas, and

Grace (2019) documents the importance of livestock products on children nutrition in the early life (first 1000 days). Since some farmers were agro-pastoralists and highly dependent on livestock for their livelihoods, we decided to investigate this mechanism using TLU as our dependent variable.

Results in Table S6 (*see supplemental materials*) showed that majority of the weather variables did not have a significant effect on TLU. Unlike in the other analysis, high temperatures did not have a significant effect on TLU despite having the expected sign. These results are consistent with Letta et al. (2018) who found that temperature shocks did not have a significant effect on TLU used as a measure of asset growth in their study. A possible explanation would be that perhaps most of the livestock were indigenous and adaptable to hot conditions. Sejian, Gaughan, Baumgard, and Prasad (2015) indicates that animals are more adaptable to hot weather and climates, thus the direct effect of heat can be observed through milk and meat production. Extreme dry spell had an unexpected positive and significant effect on TLU as presented in column 5 and 9. It is not clear what could be driving such positive associations since the study expected a negative association.

Under-nutrition resulting from infections that causes diarrhoea have been documented by Humphrey (2009). Müller and Krawinkel (2005) indicate that chronic and severe infections related to diarrhoea are the second major causes of malnutrition after inadequate supply of food nutrients. Apart from direct loss of nutrients through frequent diarrhoea episodes, other underlying pathways include; reduced micronutrients uptake (von Braun, 2020), general reduction in food intake due to anorexia, impairment of nutrients absorption and metabolic requirement increases (Müller & Krawinkel, 2005). Humphrey (2009) however noted that the contribution of diarrhoea and WASH interventions to under-nutrition are still unresolved. Controlling for WASH index and other factors, our probit analysis margins results on all children are in Table 4. The probability of diarrhoea occurrence increased by 1.4 percentage points given an increase of one heatwave event as shown in column 1. These results are consistent with other previous studies. For example, Akil, Anwar Ahmad, and Reddy (2014) noted that *Salmonella* and *Vibrio cholera*, which are some of the food and waterborne pathogens responsible for diarrhoea infections were positively correlated with high temperatures. Additionally, bacterial pathogens like *Escherichia coli* e.t.c are linked with diarrhoea and have been found to be associated with high temperatures, which facilitates faster replication and survival extension in external environment (Azage, Kumie, Worku, Bagtzoglou, & Anagnostou, 2017).

An increase in diarrhoea likelihood of about 4 percentage points was also recorded on the objective extreme dry spell variable as shown in columns 2. Emont, Ko, Homasi-Paelate, Ituaso-Conway, and Nilles (2017) noted that low quantities and quality of drinking water and reduced intensity and frequencies of hygiene practices increased diarrhoea risk during drought periods. Furthermore, contamination of water and subsequent increase in diarrhoea is also experienced after events of heavy rainfall (Azage et al., 2017). However, this study does not find a positive and significant effect of high rainfall on probability of diarrhoea increase.

Results further showed consistently that the likelihood of diarrhoea was higher in younger children as opposed to older children at 1% level of significance in all regressions. Additionally, the probability of diarrhoea was higher for children with illiterate mothers while good water, sanitation and hygiene conditions significantly decreased the probability of diarrhoea.

Table 4: Effect of weather variables on probability of child diarrhoea (average marginal effects)

Variable name	1	2	3	4	5
Heat wave	0.014***				
	(0.003)				
Extreme dry		0.038**			
		(0.017)			
Drought (subjective)			0.004		
			(0.008)		
Log month rainfall				-0.012	
				(0.033)	
Log rainfall squared				0.003	
				(0.004)	
Month temperature				-0.007	
				(0.010)	
Log temperature squared				0.000	
				(0.000)	
Log annual total rain					0.008
					(0.829)
Log annual total rain squared					0.001
					(0.058)
Annual average temp (0C)					-0.042**
					(0.019)
Annual average temp squared					0.001**
					(0.000)
WASH index	-0.005	-0.010***	-0.010***	-0.008**	-0.003
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Mother/female head Illiteracy	0.031***	0.0310***	0.031***	0.033***	0.030***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Child age	-0.004***	-0.003***	-0.004***	-0.004***	-0.004***
	(0.0003)	(0.000)	(0.000)	(0.000)	(0.000)
Child sex	0.008	0.008	0.008	0.008	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Other controls	Yes	Yes	Yes	Yes	Yes
N	5100	5100	5100	5,100	5100

Standard errors in parenthesis. ***, **, * represents significance levels at at 1%, 5% and 10% respectively. Other controls include, sex, gender of the household head, household size, age of the mother.

Lastly, malaria is one of the illnesses responsible for morbidity and deaths among young children aged 6-59 months (Kateera et al., 2015). One of the major symptoms of malaria is fever, experienced by at least a third of the interviewed children. The results in Table 5, columns 1, 4 and 5 shows a positive effect of temperature increase on the likelihood of child fever. Specifically, an increase in heatwave event increased the probability of fever by 1.6 per-centage points, while a unit change in temperature of the month before the interview and annual temperature also increased fever occurrence. The temperature quadratic terms were significant and negative while rainfall variables and their quadratic terms did not have a significant effect on fever as illustrated in column 4 and 5. Previous literature indicate associations between malaria and under-nutrition (Kateera et al., 2015) , and further associations between temper-ature variables with malaria (Kateera et al., 2015). Malaria in early years of childhood years may lead to lasting under-nutrition and long-term health (Gone, Lemango, Eliso, Yohannes, & Yohannes, 2017).

Table 5: Effect of weather variables on probability of child fever (average marginal effects)

Variable name	1	2	3	4	5
Heat wave	0.016***				
	(0.006)				
Extreme dry		0.008			
		(0.033)			
Drought (subjective)			0.033**		
			(0.013)		
Log month rainfall				0.038	
				(0.056)	
Log rainfall squared				-0.002	
				(0.007)	
Month temperature (°C)				0.106**	
				(0.020)	
Temperature squared				-0.001***	
				(0.000)	
Log annual total rain					0.577
					(1.504)
Log annual total rain squared					-0.042
					(0.106)
Annual temperature (0C)					0.133***
					(0.039)
Annual temp squared					-0.002***
					(0.000)
WASH index	-0.010**	-0.015***	-0.014***	-0.015***	-0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Child age	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Child sex	-0.016	-0.017	-0.012	-0.009	-0.011
	(0.020)	(0.020)	(0.013)	(0.013)	(0.013)
Other controls	Yes	Yes	Yes	Yes	Yes
N	5100	5100	5100	5100	5100

Standard errors in parenthesis. ***, **, * represents significance levels at at 1%, 5% and 10% respectively. Other controls include, sex, gender of the household head, household size, age of the mother.

4 Conclusion

The study investigated whether extreme weather events had an effect on children health outcomes, and the possible transmission mechanisms. Children health outcomes were measured by HAZ, WAZ and WHZ. Uganda National Panel Survey was used in combination with gridded rainfall and temperature data.

Fixed effects result consistently showed evidence of significant effect of rainfall and temperature extreme indicators on children health outcomes, after controlling for other important factors such as assets. Temperature extremes had negative and significant effects on HAZ, WAZ and WHZ, while objective rainfall extremes significantly affected child HAZ scores. Similarly, subjective drought shock was observed to have significant negative effect on HAZ scores and to some extent WAZ and WHZ. Household crop output, child diarrhoea and fever occurrence in children were the major channels through which weather extremes affected children nutritional outcomes, given the significant associations of these pathway variables with both temperature and rainfall.

The results further showed that children in households which engaged in *ex-post* harmful coping strategies such as change of diet shocks had poor health outcomes especially for HAZ and WAZ. On the contrary, households engaged in *ex-ante* coping strategies such as precautionary savings, consistently registered positive child anthropometrics and those practicing good agronomic practices registered higher crop output. In addition, the coefficients of improved seed and water harvesting technologies interactions with extreme weather on crop output were positive. These results indicate that right adaptation strategies have the capacity to increase crop output and minimize health effects resulting from climate change, rural households should be sensitized of the same. Furthermore, policy makers should advocate for the right approaches - *ex-ante* or anticipatory based measures that improve crop output, nutrition and protect households from other climate related health risks given future projections of increasing climate extreme events. Future studies should consider more long-term socio-economic panels and up-to date data in the analysis, and further experimental analysis.

Our study had the following limitations: first, considering that the secondary household data was collected for other purposes other than our research objectives, some key variables were lacking thus not included in the regressions. For instance, information on breastfeeding, complementary feeding of all children, child birth weight, mother's anthropometrics, households' access to nutritional information and health insurance. Second, even though the weather products provided long-term information on rainfall and temperature, the household surveys were a short-run five-year panel, and anthropometrics not collected for children beyond the age of five thus limiting study of long-term effects of weather effects on the different outcomes and use of balanced panels. The datasets did not provide mortality and disability information thus we were unable to examine the mortalities effects arising from weather extremes.

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Supplemental Materials

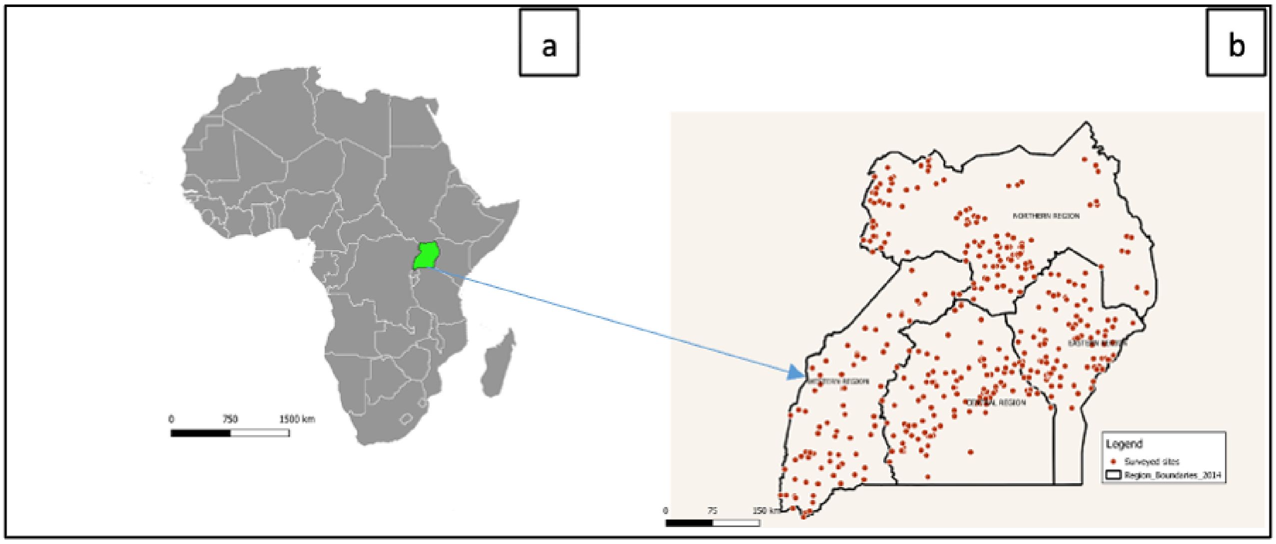

Figure S1: Map showing the study country location in Africa (a) and sampled sites in different regions of Uganda (b).
Source: Author, Uganda National Panel Survey data

Table S1: Descriptive statistics

Variable	Variable definition	Mean	SD
Children outcome variables			
HAZ	Height for age Z scores of children aged 7-59 months	-1.13	(1.42)
WAZ	Weight for age Z scores of children aged 7-59 months	-1.02	(1.32)
WHZ	Weight for height Z scores of children aged 7-59 months	-0.25	(1.18)
Other children variables			
Child fever	A dummy variable (1=Yes) if a child had last month fever and 0 otherwise	0.30	(0.456)
Child diarrhoea	A dummy variable (1=Yes) if a child had diarrhoea last and 0 otherwise	0.09	(0.279)
Sex of child	A dummy variable, 1 if child is male and 0 if female	0.50	(0.502)
Age of child	Child age in complete months	32.4	(15.04)
Household variables including coping strategies			
Sex of HHs head	A dummy variable, 1 if household head is male and 0 if female	0.80	(0.402)
Age of the Head	Household head age in complete years	41.3	(12.99)
Asset Index	Asset Index constructed from PCA	-0.77	(1.987)
WASH Index	Water, Sanitation and hygiene index constructed from PCA	-0.54	(1.350)
TLU	Tropical Livestock Units	2.31	(6.70)
Number of children	Number of children in a household aged 0-59	1.92	(0.833)
Household size	Number of people in the household	7.32	(2.93)
Mother living in the Household	A dummy variable (1= if biological mother of the child was living in the household), 0 if otherwise	0.89	(0.305)
Mother/female head age	Age of the mother of the child or the female head of the household	35.2	(11.88)
Mother/female school in attendance	A dummy variable (1= if mother or female head never attended school)	0.22	(0.413)
Change diet	A dummy variable (1= if household involuntarily changed diet to cope with weather extremes e.g drought), 0 if otherwise	0.22	(0.410)
Savings	A dummy variable (1= if household used savings to cope with weather extremes)	0.20	(0.401)
Received Govt aid	A dummy variable (1=if household received government aid to cope with weather extremes)	0.01	(0.098)
Relatives & friends	A dummy variable (1= if household received assistance from friends and relatives to cope with weather extremes)	0.09	(0.292)
Non-farm work	A dummy variable (1= if household engaged in more non-farm work during weather extremes)	0.13	(0.335)
Change crops	A dummy variable (1= if household engaged changed crops grown to cope with weather extremes)	0.05	(0.22)
Farm area	Household total crop farm size in acres	2.47	(3.63)
Number of crops	Continuous variable on number of crops planted by a household	4.08	(1.77)
Improved seed use	A dummy variable if household used improved seed (1= yes, 0 otherwise)	0.20	(0.40)
Organic fertilizer use	A dummy variable if household used organic fertilizers (1= yes, 0 otherwise)	0.12	(0.32)
Inorganic fertilizer use	A dummy variable if household used inorganic fertilizers (1= yes, 0 otherwise)	0.04	(0.21)
Pesticide use	A dummy variable if household used pesticide (1= yes, 0 otherwise)	0.12	(0.33)
Water harvesting	A dummy variable if household used water harvesting technology (1= yes, 0 otherwise)	0.30	(0.46)
Weather variables both objective and subjective			
Drought shock (subjective)	A dummy variable (1= if households experienced drought shock prior year), 0 if otherwise)	0.39	(0.488)
Extreme dry spell SN 1	A dummy variable (1= if rainfall amounts in the first season of the interview year were <-2 SD, 0 if otherwise)	0.04	(0.192
Extreme dry spell SN1 (t-1)	A dummy variable (1= if rainfall amounts in the first season of the prior year were <-2 SD, 0 if otherwise)	0.05	(0.211)
Extreme dry spell SN1 (t-5)	A dummy variable (1= if rainfall amounts in the first season of the fifth lag were <-2 SD, 0 if otherwise)	0.03	(0.157)
Extreme dry spell SN (5 year)	Counts of extreme dry spell events for the first season over a 5-year period prior to interview)	0.18	(0.518)
Extreme dry spell SN2	A dummy variable (1= if rainfall amounts in the second season of the interview year were <-2 SD, 0 if otherwise)	0.05	(0.215)
Extreme dry spell SN2 (t-1)	A dummy variable (1= if rainfall amounts in the second of the first lag year were <-2 SD, 0 if otherwise)	0.05	(0.225)
Extreme dry spell SN2 (t-5)	A dummy variable (1= if rainfall amounts in the second of the fifth lag year were <-2 SD, 0 if otherwise)	0.03	(0.156)
Extreme dry spell SN2 (5 year)	Counts of extreme dry spell events for the first season over a 5-year period prior to interview)	0.21	(0.569)
Extreme dry spell(5yr)	Counts of extreme dry spell events for both seasons over a 5-year period prior to interview)	0.39	(1.14)
Rainfall coefficient of variation	Rainfall annual coefficient of variation	0.37	(0.096)
Heat wave SN1	Monthly counts in the first season of the interview year with temperature values >1SD	0.75	(1.162)
Heat wave counts SN2	Monthly counts in the second season of interview year with temperature values >1SD	0.65	(1.10
Heat wave SN1 (t-1)	Monthly counts in the first season of the prior year with temperature values >1SD	0.69	(1.13)
Heat wave SN2 (t-1)	Monthly counts in the second season of the prior year with temperature values >1SD	0.63	(1.048)
Heat wave SN12 (t-1)	Monthly counts in the both seasons of the prior year with temperature values >1SD	1.33	(1.86)
Heat wave SN12(five year)	Monthly counts in the both seasons over five-year period with temperature values >1SD	6.13	(8.085)
Heat wave counts SN1 (t-5)	Monthly counts in the first season of the fifth lag year with temperature values >1SD	0.51	(1.02)
Heat wave counts SN2 (t-5)	Monthly counts in the second season of the fifth lag year with temperature values >1SD	0.62	(1.056)
Heat wave SN1 (5 year)	Monthly counts in the both seasons over 5 years with temperature values >1SD	3.22	(4.88)

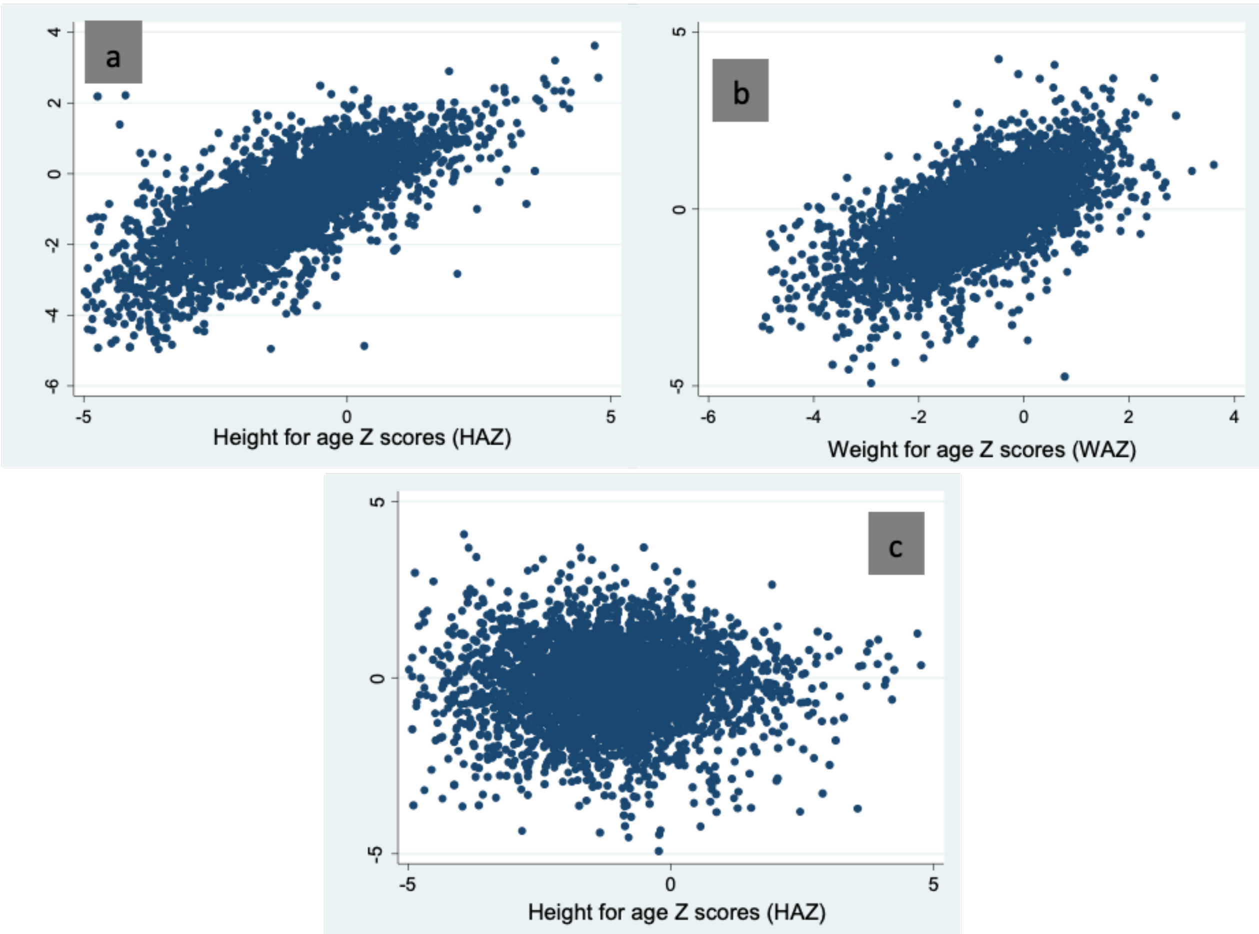

Figure S2: Two-way scatter plots on correlations between different child anthropometric measures; HAZ and WAZ (a), WAZ and WHZ (b) and, HAZ and WHZ (c)

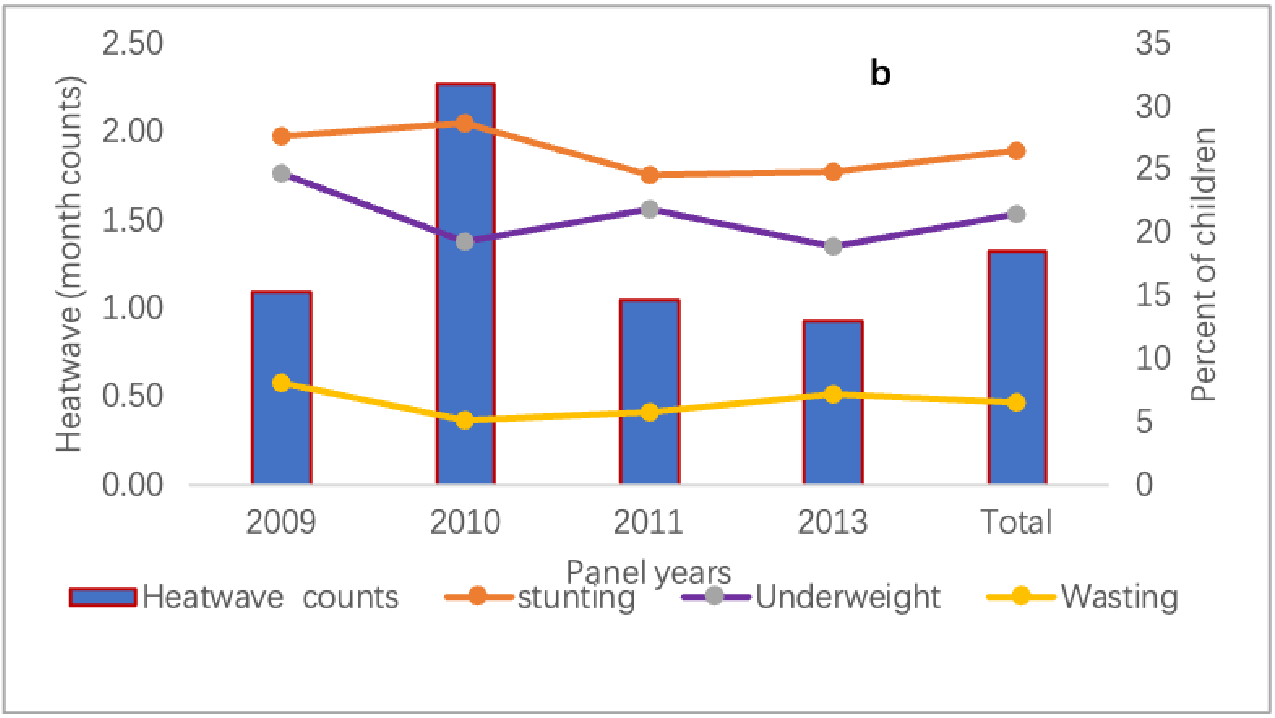

Figure S3: Relationship between heat wave (t-1) and stunting, wasting and underweight in in the respective four panel years

Table S2: Fixed effect regression results on the effect of weather extremes in the first season on children HAZ by gender of the child

	Outcome variable: child HAZ													
Variable	Boys							Girls						
	1	2	3	4	5	6	7	8	9	10	11	12	12	14
Heat wave	-0.075*							-0.143***						
main season (t-1)	(0.043)							(0.042)						
Heat wave		-0.116*							-0.122*					
main season (t-5)		(0.063)							(0.065)					
Heat wave			-0.073***							-0.001				
(5-year count)			(0.023)							(0.025)				
Extreme dry				-0.121							-0.356**			
main season (t-1)				(0.167)							(0.160)			
Extreme dry					-0.573**							-0.032		
main season (t-5)					(0.261)							(0.291)		
Extreme dry						-0.159							0.050	
(5-year counts)						(0.214)							(0.179)	
Drought(subjective)							-0.263**							-0.221*
							(0.119)							(0.125)
HHs and mother /female variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other coping	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.075	0.076	0.083	0.073	0.078	0.072	0.078	0.1147	0.105	0.100	0.107	0.101	0.100	Yes
Mean HAZ	-1.246	-1.246	-1.246	-1.246	-1.246	-1.246	-1.246	-1.011	-1.011	-1.011	-1.011	-1.011	-1.011	-1.011
Sample size	2,474	2,474	2,474	2,474	2,474	2,474	2,474	2,447	2,447	2,447	2,447	2,447	2,447	2,447

Standard error in parenthesis. ***, **, * ***, **, * for significance of 1%, 5% and 10% levels respectively. Other covariates in include child age squared, number of children in a household, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household and other coping strategies such as access to credit, non-farm work, farm work and assistance from friends and relatives

Table S3: Fixed effect regression results on the effect of weather extremes in the second season on children HAZ

	Outcome variable: child HAZ											
Variable name	**All Children**						**Children in at least 3 waves**					
	1	2	3	4	5	6	7	8	9	10	11	12
Heat wave SN2 (t-1)	-0.054* (0.031)						-0.095** (0.042)					
Heat wave SN2 (t-5)		-0.090** (0.038)						-0.140*** (0.050)				
Heat wave SN2 (5-year count)			-0.065** (0.025)						-0.097*** (0.034)			
Extreme dry SN2 (t-1)				-0.014 (0.145)						-0.245 (0.195)		
Extreme dry SN2 (t-5)					-0.085 (0.128)						-0.105 (0.173)	
Extreme dry SN 2 (5-year counts)						0.119 (0.156)						0.184 (0.203)
Asset Index	0.104*** (0.038)	0.104*** (0.037)	0.106*** (0.037)	0.101*** (0.037)	0.102*** (0.037)	0.103*** (0.037)	0.123*** (0.047)	0.116** (0.047)	0.132*** (0.047)	0.122** (0.047)	0.121** (0.047)	0.123*** (0.047)
Child age	-0.069*** (0.007)	-0.069*** (0.007)	-0.070*** (0.007)	-0.068*** (0.007)	-0.069*** (0.007)	-0.068*** (0.007)	-0.083*** (0.010)	-0.086*** (0.010)	-0.084*** (0.010)	-0.084*** (0.010)	-0.085*** (0.010)	-0.084*** (0.010)
Child sex	-0.112 (0.536)	-0.148 (0.535)	-0.120 (0.535)	-0.150 (0.520)	-0.149 (0.520)	-0.146 (0.520)	-0.352 (0.669)	-0.378 (0.669)	-0.368 (0.668)	-0.335 (0.641)	-0.333 (0.641)	-0.323 (0.641)
Change diet	-0.115* (0.065)	-0.117* (0.065)	-0.126* (0.065)	-0.107* (0.065)	-0.105 (0.064)	-0.102 (0.065)	-0.182** (0.085)	-0.188** (0.085)	-0.198** (0.086)	-0.177** (0.085)	-0.172** (0.085)	-0.015 (0.057)
Savings	0.069 (0.066)	0.074 (0.066)	0.072 (0.066)	0.070 (0.066)	0.068 (0.066)	0.068 (0.066)	0.157* (0.086)	0.161* (0.086)	0.154* (0.086)	0.162* (0.086)	0.161* (0.086)	-0.165* (0.085)
Government aid	0.191 (0.321)	0.189 (0.321)	0.179 (0.321)	0.197 (0.322)	0.199 (0.321)	0.207 (0.321)	0.238 (0.519)	0.247 (0.518)	0.179 (0.518)	0.193 (0.520)	0.201 (0.521)	0.159* (0.086)
Other child variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HHs and Mother/female variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other coping	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.072	0.073	0.0738	0.070	0.070	0.070	0.099	0.102	0.103	0.0961	0.094	0.095
Mean HAZ	-1.13	-1.13	-1.13	-1.13	-1.13	-1.13	-1.19	-1.19	-1.19	-1.19	-1.19	-1.19
Sample size	4,921	4,921	4,921	4,921	4,921	4,921	1,381	1,381	1,381	1,381	1,381	1,381

Standard error in parenthesis. ***, **, * ***, **, * for significance of 1%, 5% and 10% levels respectively. Other covariates in include child age squared, number of children in a household, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household and other coping strategies such as access to credit, non-farm work, farm work and assistance from friends and relatives

Table S4: Fixed effect regression results on the effect of weather extremes in the main season on children WAZ[4]

	Outcome Variable: child WAZ																	
Variable	All children									Children in at least 3 waves								
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Heat wave SN1 (t)	-0.075***									-0.024								
	(0.026)									(0.034)								
Heat wave SN1 (t-1)		-0.009									-0.059*							
		(0.026)									(0.034)							
Heat wave SN1 (t-5)			-0.076*									-0.042						
			(0.039)									(0.048)						
Heat wave (5-year count)				0.029									0.018					
				(0.024)									(0.030)					
Extreme dry main season (t)					-0.096									-0.104				
					(0.103)									(0.143)				
Extreme dry SN1 (t-1)						0.019									0.030			
						(0.096)									(0.125)			
Extreme dry SN1 (t-5)							-0.106									-0.275		
							(0.155)									(0.212)		
Extreme dry (5-year counts)								0.103									0.171	
								(0.112)									(0.157)	
Drought (subjective)									-0.174**									-0.124
									(0.074)									(0.095)
Asset index	0.031	0.038	0.040	0.036	0.041	0.041	0.041	0.041	0.044	0.046	0.046	0.049	0.047	0.047	0.047	0.046	0.047	0.049
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)
Child age	0.007	0.008	0.008	0.008	0.007	0.007	0.007	0.007	0.006	0.012	0.012	0.012	0.012	0.012	0.013	0.012	0.012	0.011
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Child sex	0.215	0.266	0.267	0.254	0.218	0.202	0.201	.220	0.186	-0.174	-0.154	-0.155	-0.169	-0.184	-0.208	-0.212	-0.162	-0.220
	(0.479)	(0.480)	(0.479)	(0.479)	(0.465)	(0.465)	(0.465)	(0.465)	(0.464)	(0.587)	(0.586)	(0.586)	(0.587)	(0.561)	(0.560)	(0.559)	(0.561)	(0.559)
Change diet	-0.112**	-0.123**	-0.114**	-0.116**	-0.123**	-0.128**	-0.126**	-0.123**	-0.044	-0.163**	-0.165**	-0.160**	-0.161**	-0.161**	-0.167**	-0.163**	-0.160**	-0.039
	(0.055)	(0.055)	(0.055)	(0.056)	(0.055)	(0.055)	(0.055)	(0.055)	(0.065)	(0.070)	(0.070)	(0.071)	(0.071)	(0.070)	(0.070)	(0.070)	(0.070)	(0.047)
Savings	0.082	0.073	0.073	0.073	0.075	0.076	0.073	0.075	0.156**	0.146	0.139*	0.145**	0.143**	0.144**	0.145**	0.142**	0.142**	-0.110
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.066)	(0.072)	(0.072)	(0.072)	(0.072)	(0.071)	(0.071)	(0.071)	(0.071)	(0.083)
Government aid	0.025	0.017	0.019	0.020	0.018	0.013	0.037	0.012	0.069	-0.168	-0.146	-0.162	-0.174	-0.172	-0.175	-0.122	-0.194	0.203**
	(0.230)	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)	(0.233)	(0.231)	(0.231)	(0.329)	(0.329)	(0.329)	(0.329)	(0.328)	(0.330)	(0.330)	(0.329)	(0.084)
Othercontrols	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.072	0.067	0.070	0.068	0.068	0.067	0.067	0.068	0.070	0.116	0.118	0.117	0.116	0.116	0.116	0.118	0.117	0.118
Mean WAZ	-1.02	-1.02	-1.02	-1.02	-1.02	-1.02	-1.02	-1.02	-1.02	-1.06	-1.06	-1.06	-1.06	-1.06	-1.06	-1.06	-1.06	-1.06
Sample size	4,963	4,963	4,963	4,963	4,963	4,963	4,963	4,963	4,963	1,412	1,412	1412	1,412	1,412	1,412	1,412	1,412	1,412

Standard error in parenthesis. ***, **, * ***, **, * for significance of 1%, 5% and 10% levels respectively. Other covariates in include child age squared, number of children in a household, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household and other coping strategies such as access to credit, non-farm work, farm work and assistance from friends and relatives

[4]We include the current year weather extremes as well as the lags because WAZ is a both short and long-term measure.

Table S5: Fixed effect regression results on the effect of children weather extremes on children WHZ by gender of the child.

	Outcome variable: child WHZ					
	Boys			Girls		
	1	2	3	4	5	6
Heat wave (main season)	-0.064* (0.038)			-0.183*** (0.039)		
Extreme dry spell main season		-0.241 (0.166)			-0.062 (0.175)	
Drought (subjective)			-0.107 (0.111)			-0.181 (0.118)
Other child variables	Yes	Yes	Yes	Yes	Yes	Yes
HHs and Mother/female variables	Yes	Yes	Yes	Yes	Yes	Yes
Other coping	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.152	0.151	0.150	0.185	0.149	0.152
Mean WHZ						
Sample size	1,981	1,981	1,981	1,889	1,889	1,889

Standard error in parenthesis. ***, **, * for significance of 1%, 5% and 10% levels respectively. Other covariates in include child age squared, number of children in a household, land size, sex and age of household head, mother/female illiteracy and age, mother living in the household and other coping strategies such as access to credit, non-farm work, farm work and assistance from friends and relatives

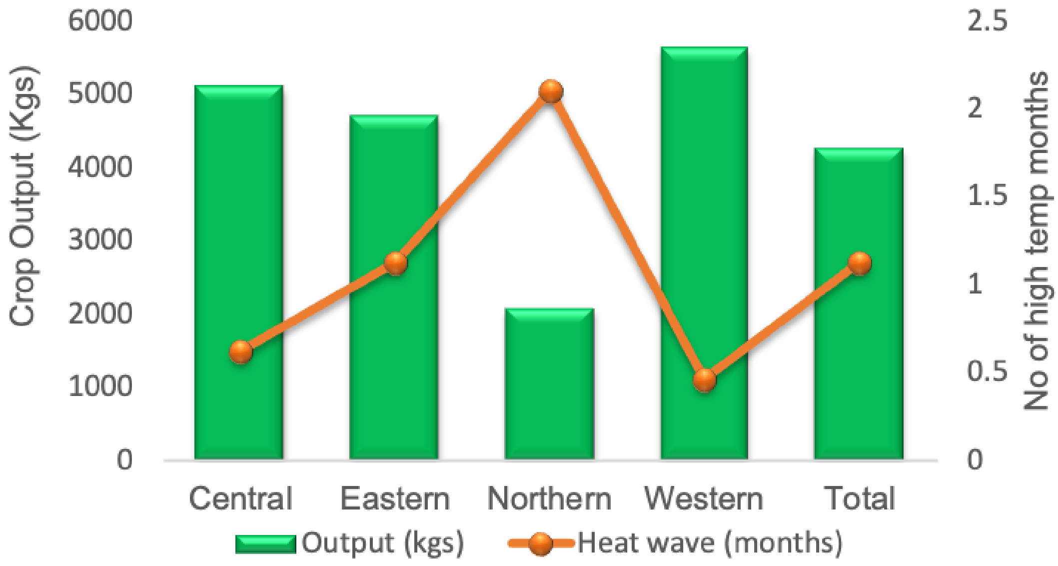

Figure S4: Relationship between average crop output and number of heat wave months in the different sampled regions of Uganda

Table S6: Effect of weather extremes on Household TLU

	Outcome variable: Tropical livestock units								
Variable name	1	2	3	4	5	6	7	8	9
Heat wave (t)	0.026 (0.125)								
Heat wave (t-1)		-0.204 (0.127)							
Heat wave (t-5)			-0.092 (0.184)						
Heat wave counts (5 year)				-0.034 (0.072)					
Extreme dry (t)					0.918* (0.492)				
Extreme dry (t-1)						0.417 (0.468)			
Extreme dry (t-5)							-0.461 (0.731)		
Extreme dry counts (5 year)								-0.252 (0.528)	
Drought (subjective)									0.386* (0.201)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.008	0.008	0.007	0.007	0.009	0.007	0.007	0.007	0.007
N	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846

*Figure in parenthesis is standard error. ***, **, *Difference in significance at 1%, 5% and 10% levels respectively*