CLIMATE VARIABILITY AND CHILD UNDERNUTRITIION IN ETHIOPIA

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Professional Studies in Global Development

by

Addis Abera Ayalew

August, 2023

ABSTRACT

Extreme climate events are increasing the susceptibility of children's health and nutrition. This study focuses on the link between varying levels of precipitation and temperature and the occurrence of child undernutrition in Ethiopia. By combining data from nationwide demographic and health surveys with hourly weather observations of a high-resolution geographic scale, the study reveals that experiencing dry weather is linked to an 8 percent rise in stunting levels. Additionally, exposure to higher temperatures is associated with a 13 percent increase in wasting levels. Furthermore, the study offers suggestive evidence that highlights agriculture and infectious diseases as the primary pathways connecting different weather exposures to child undernutrition.

BIOGRAPHICAL SKETCH

Addis is a graduate candidate in the Master of Professional Studies program in Global Development with a concentration in Economic Development and Policy. Prior to joining Cornell, he has worked for over a decade in the public sector in Ethiopia. Most notably, he has served in key public institutions, such as the Ethiopia Commodity Exchange and the Ethiopian Agricultural Transformation Institute, where he participated in multiple development projects across a wide range of areas, including market infrastructure, rural financial services, digital technologies, and private sector development.

Addis holds a bachelor's degree in economics from Haramaya University and a master's degree in economics from the Swedish University of Agricultural Sciences. He is also an alumnus of the Mandela Washington Fellowship of the Young African Leaders Initiative. He has research interests in development economics and public policy.

ACKNOWLEDGMENTS

I extend my heartfelt gratitude to my supervisor, Professor John Hoddinott, for his invaluable guidance and consistent encouragement throughout the study period. I am also grateful to Abenezer Zeleke for his constructive suggestions at various stages of the research work. Furthermore, I would like to take this opportunity to express my profound appreciation to the Institute for African Development at Cornell University for generously funding my graduate study.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Addressing the challenges associated with child undernutrition remains one of the central issues within the sphere of global development. Child undernutrition, taking on varied forms, contributes to 45 percent of all child deaths globally (Black et al., 2013). It also holds the potential for a lasting adverse impact on both health and socioeconomic outcomes in children's later life (Alderman et al., 2006; Hoddinott et al., 2013; Victora et al., 2008). Studies also indicate that the rising frequency and intensity of extreme climate events are contributing to an elevated risk of child health and nutritional outcomes (Helldén et al., 2021; Romanello et al., 2022). Presently, an estimated 22 percent of children under the age of five worldwide are stunted (low height-for-age), and 7 percent are wasted (low weight-for-height) (FAO, 2022).

Ethiopia stands out as a notable example of a country vulnerable to climate-induced risks. Located in the Horn of Africa, one of the world's most drought-prone regions, the country has witnessed escalating temperatures and heightened drought risks in recent times (FEWSNET, 2022; Funk et al., 2023). In parallel, the country contends with higher rates of child undernutrition. Its population under the age of five is approximately 13 million (nearly 16 percent of the total population), of which 35 percent are stunted, and 7 percent are affected by wasting (FAO, 2022; UNICEF, 2023).

This study examines the impacts of exposures to varying weather conditions on child nutrition outcomes in Ethiopia. Specifically, it addresses two primary research questions. Firstly, it investigates the effect of exposure to different precipitation and temperature levels on the prevalence of chronic undernutrition (stunting) among children aged between 6 to 36 months, born between 1989 and 2011. The study's focus on this specific age group is motivated by a methodological preference to explore the climatic effects during the children's crucial age, a period when they are notably susceptible to underlying nutrition-related factors and health risks (Alderman & Headey, 2018; Shrimpton et al., 2001; Victora et al., 2010). Secondly, it explores a similar effect on acute undernutrition (wasting) level within the same age-group and timeframe. The WHO height-for-age (HAZ) and weight-for-height (WHZ) standard scores are employed to measure child stunting and wasting levels, respectively.

The study integrates data from demographic and health surveys with historical weather data, using a spatial resolution of 0.1 degrees, which is around 11-kilometer scale. This approach enables the categorization of weather conditions observed within the spatial grid-cells where the sampled children were located. Accordingly, the precipitation and temperature levels at each grid-cell are classified into three exposure intensities. Subsequently, the study calculates the precipitation and temperature exposure amounts by summing the monthly hours during which a child is exposed to the three exposure levels across two distinct time windows.

These exposure windows correspond to the two outcome variables: chronic and acute undernutrition. To assess acute undernutrition, a condition associated with short-term nutritional deficiencies, the study examines the recent exposure period spanning three months before the survey interview date. To assess the impact on chronic malnutrition, the entire lifetime exposure is analyzed. The analytical approach of measuring the exposure levels largely builds on the method used by (Blom et al., 2022).

Three major findings emerge from the study using a fixed-effect cross-sectional estimation approach. Firstly, chronic undernutrition is primarily influenced by exposure to arid weather. The estimation result indicates that a 100-hour increase in children's mean monthly lifetime exposure to precipitation below 0.5 mm, compared to the middle exposure bin, [0.5 – 4] mm, is associated with approximately an 8 percent decline from the sample mean HAZ score. Secondly, acute malnutrition appears to be more sensitive to varying levels of exposure, with warm temperatures (above 26 °C) having a particularly pronounced impact. In terms of the sample mean, this effect translates to an approximate 13 percent decline in WHZ score and an 11 percent worsening in the prevalence of wasting, compared to the effects of the middle exposure bin, [16 – 26] °C. Thirdly, the study offers suggestive evidence regarding agriculture and infectious diseases as the two primary underlying pathways that potentially link various levels of weather exposure to the incidence of acute and chronic undernutrition.

The study finding concerning the relationship between precipitation exposure and stunting, along with the associated underlying impact pathways, closely aligns with the outcomes of existing research. However, the study's other findings, highlighting the absence of a noteworthy effect from warm temperature exposure on child stunting, and likewise, the lack of a significant impact from arid weather exposure on child wasting, deviate from conclusions drawn in previous studies in Ethiopia (Dimitrova, 2021; Hagos et al., 2014; Randell et al., 2020).

Furthermore, the study's primary contribution to the current body of literature revolves around the methodology for assessing weather exposure, an approach previously lacking in Ethiopian weather-nutrition studies. This method, which measures hourly weather exposure at a high-resolution geographic scale, significantly enhances the precision of weather pattern assessment compared to conventional approaches that rely on mean monthly or seasonal data at a broader geographic scale or administrative units. The study's findings will also contribute to a deeper understanding of the intricate interconnections between climate variability and child nutritional outcomes.

The rest of the study is organized as follows. Section 2 provides a concise conceptual framework, Section 3 outlines the empirical methodology, Section 4 presents the main findings, Section 5 provides a general exploration of the mechanisms that explain the main findings, and section 6 concludes.

2. CONCEPTUAL FRAMEWORK

This section outlines the primary factors contributing to child undernutrition, thus providing a basis for formulating hypotheses regarding the potential pathways through which climate variability may impact child undernutrition in Ethiopia. Subsequently, the hypotheses will be judiciously integrated into the development of the study's empirical methodology.

The study depends on the conceptual framework of maternal and child undernutrition, originally developed by UNICEF and expounded in (Black et al., 2008, 2013). This framework establishes a hierarchy of three interrelated levels that impact child nutrition. The first level consists of two immediate determinants, namely child's adequate dietary intake and health status. These immediate factors are mutually dependent and, in turn, are determined by three key underlying factors: household food security status, adequate care for mother and child, and household access to health environment and services. At the third level, there are basic determinants that manifest at broader geographical levels and directly influence the underlying determinants. The basic determinants encompass a range of factors, including economic, demographic, environmental, and infrastructural elements.

The interplay of the determinants at the three levels is manifested in the short-term and long-term consequences of child nutrition outcomes. The short-term consequences of child undernutrition, often referred to acute malnutrition (wasting), include thin physical stature and a weakened immune system, leading to an increased risk of disease and mortality (Black et al., 2013). On the other hand, the long-term consequences of inadequate dietary intake and recurrent diseases result in chronic malnutrition (stunting) – the condition of being too short for one's age. Stunted children are exposed to a lifetime of possibly irreversible consequences, including poor cognitive development, reduced school attainment, diminished intellectual capabilities, and lower labour productivity as adults (Alderman et al., 2006; Hoddinott et al., 2013; Victora et al., 2008)

Within this conceptual framework, the impact of climate variability on child nutrition outcomes primarily occurs through its influence on the underlying causes, operating through interconnected pathways (Helldén et al., 2021; Romanello et al., 2022). Some of these pathways involve direct effects, which are triggered by changes in temperature and precipitation levels. For instance, extreme heatwaves (Ortiz-Bobea et al., 2019) or droughts can directly affect agricultural productivity, leading to food shortages and reduced access to nutrition (Bahru et al., 2019; Isabel et al., 2021). Additionally, the indirect effects of climate variability are associated with a wide range of changes in the ecosystem. These changes can affect water quality (Bandyopadhyay et al., 2012; Levy et al., 2018), air pollution (Sun et al., 2017), and disease transmission (Siraj et al., 2014), ultimately impacting child nutrition and health (Helldén et al., 2021; Swinburn et al., 2019).

Furthermore, the impact of climate variability on child undernutrition can be influenced by basic determinants, such as economic conditions, demographic trends, and infrastructural development. As a result of this intricate interplay, identifying specific causes of child undernutrition due to climate variability often becomes challenging. For instance, the interaction of these multiple factors may have a mitigating role on the positive side or an amplifying role on the negative side. Consequently, understanding the specific contributions of climate variability to child undernutrition demands careful consideration of the broader context of various influencing elements within the settings of a given study area.

This leads to an inquiry into the possible impact pathways of precipitation and temperature exposures on child nutrition outcomes in Ethiopia. I identify two major pathways given the existing literature. Firstly, weather conditions and variability may have an effect through their impact on agriculture production and household food security, subsequently affecting child dietary intake (Hagos et al., 2014; Randell et al., 2020). Almost the entire Ethiopian agricultural production relies on a rain-fed agriculture system, making it highly vulnerable to weather variability. Secondly, climatic conditions can contribute to the prevalence and transmission of various waterborne and vector-borne pathogens that frequently impact child health in Ethiopia. For instance, inadequate hygiene and sanitation practices leading to diarrhea, coupled with malaria infections, remain notable factors contributing to child mortality and morbidity rates in Ethiopia (Ahmed et al., 2020).

3. EMPIRICAL METHODOLOGY

This section begins by describing the data utilized. In the second part, it explains the model variables, with a particular focus on the classification methods used to quantify precipitation and temperature exposures. Subsequently, the identification strategy is discussed.

3.1 Data

A. Demographic and health survey

The study draws data from five waves of nationally representative demographic and health surveys (DHS), conducted between 1993 and 2014[1]. These surveys were conducted at approximately five-year intervals, with new enumeration areas (EAs) being resampled each time. The DHS employs a two-stage cluster design to determine its sample. In the first stage, a random sample of enumeration areas (EAs) at the sub-district level is selected. In the second stage, households are chosen from each of the EAs. Then within each household, all women of reproductive health age (15 to 49 years) are interviewed. Consequently, the child data is organized in such a way that there is one record for every child of the interviewed women who were born in the five years preceding the survey.

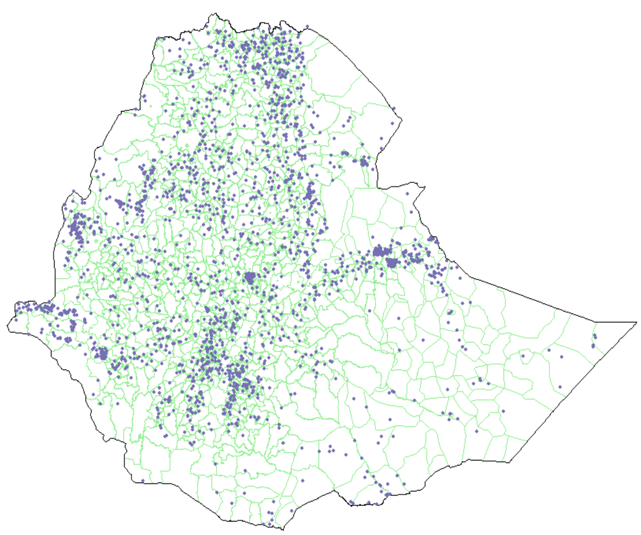

Figure 1. DHS cluster locations and wereda boundaries
Note: Wereda is the third-level administrative unit, following region and zone. Map is draws at a scale of 0.1 degrees.

[1] *These are the years of the survey interviews, distinct from the reporting years.*

The surveys altogether covered all regional and zonal administrations, and nearly half of the weredas (districts) in the country. On the other hand, The DHS geo-location reference is at the EA level. Approximately 3% of the EAs lack geo-location information and have therefore been excluded from our sample. Figure 1 illustrates the wide coverage and representativeness of the surveys.

From this representative sample, I specifically focus on children aged 6 to 36 months. This age group is of particular interest because it commonly observes growth faltering patterns especially in developing countries (Victora et al., 2010). In other words, during their early ages, typically spanning up to three years, children's anthropometric measures often exhibit a rapid decline followed by recovery. This phenomenon can be attributed to heightened vulnerability of children to underlying nutrition-related factors and health risks (Alderman & Headey, 2018; Shrimpton et al., 2001; Victora et al., 2010). Thus, the study aims to investigate the climatic impacts on child nutritional outcome during this critical period.

And finally, after excluding any missing and unrealistic child anthropometric measurements, the final sample consists of 17,950 children. Table 1 presents a summary of the child anthropometric outcomes by survey rounds. The overall average of the sample reveals a HAZ score of -1.71 and a WHZ of -0.65. Over the course of the study period, there was a remarkable decline in the prevalence of stunting, decreasing by 18% from 55% in 2000. Additionally, the prevalence of stunting wasting showed a decline of 7%, down from 16%.

Table 1. Child anthropometric outcomes by survey round

Year	Sample	HAZ		Stunted		WHZ		Wasted	
		mean	*sd*	*pct*	*sd*	*mean*	*sd*	*pct*	*sd*
2000	4,373	-2.14	1.67	0.55	0.50	-0.80	1.29	0.16	0.37
2005	1,917	-1.82	1.90	0.49	0.50	-0.50	1.46	0.14	0.35
2011	4,611	-1.69	1.77	0.44	0.50	-0.69	1.25	0.13	0.34
2016	4,418	-1.40	1.72	0.38	0.48	-0.61	1.26	0.13	0.34
2019	2,586	-1.48	1.53	0.37	0.48	-0.48	1.14	0.09	0.29
Total	**17,905**	**-1.71**	**1.74**	**0.45**	**0.50**	**-0.65**	**1.28**	**0.13**	**0.34**

B. Weather data

The study uses the 'ERA5-land' dataset obtained from the Copernicus Climate Change Services. This dataset provides hourly reanalysis weather data at a spatial resolution of 0.1 degrees. By utilizing this dataset, Figure 2 and Figure 3 depict the temporal and spatial variations - respectively, of precipitation and temperature levels in Ethiopia.

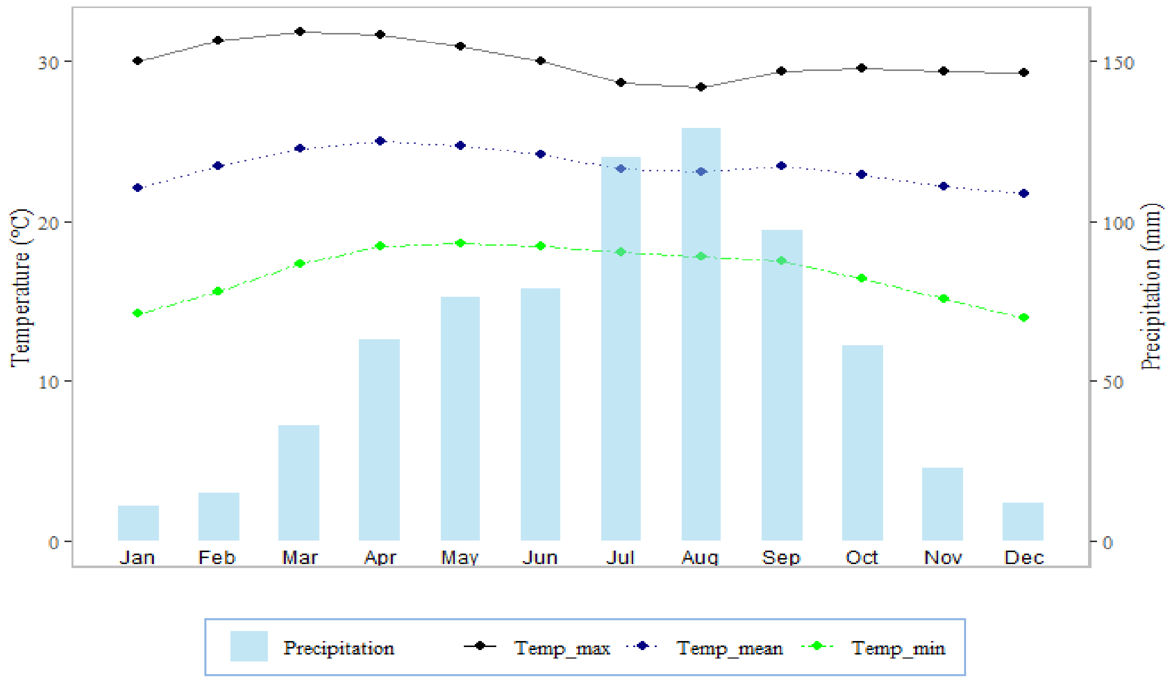

Figure 2. Temporal climatology of Ethiopia

Note: the data cover years ranging from 1985 to 2014. The temperature (shown in a line graph) indicates the monthly average in degrees Celsius, while precipitation (depicted in a bar graph) represents the monthly total in millimeters.

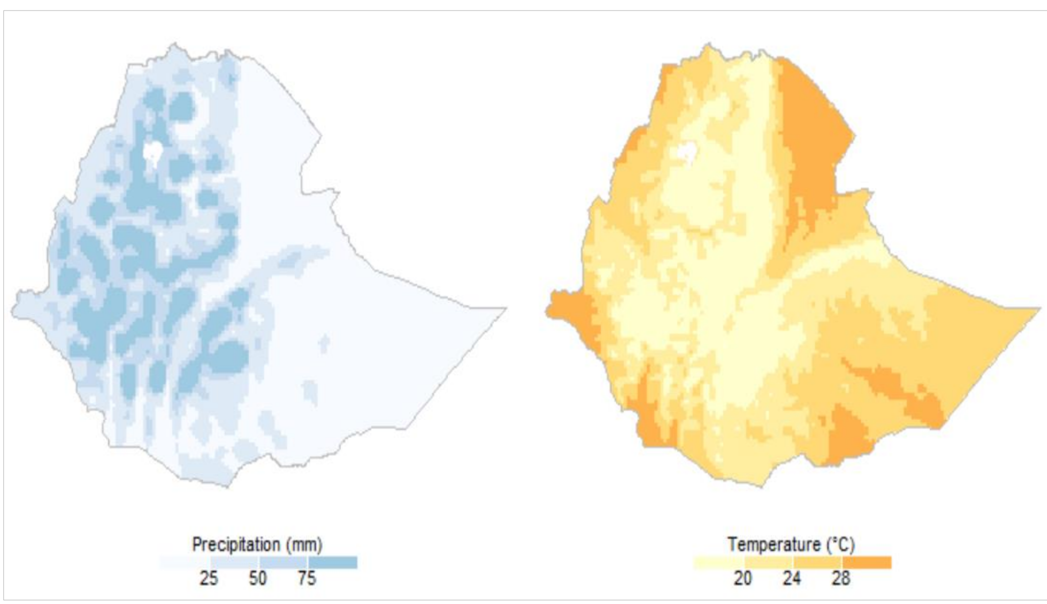

Figure 3. Spatial climatology of Ethiopia

Note: the data cover years ranging from 1985 to 2014. Precipitation (left) represents the monthly total in millimeters; while temperature (right) represents the monthly average in degrees Celsius. Maps are draws at a scale of 0.1 degrees.

Three important insights can be derived from the weather distributions. Firstly, precipitation stands out as a major factor, displaying noteworthy spatiotemporal disparities. The main rainy season spans from June to September, contributing to more than two-thirds of the annual rainfall (Segele & Lamb, 2005). Prior to this, a brief rainy season is experienced in the majority of the highlands, occurring between February and May. On average, the annual precipitation ranges up to 500 mm in the lowland region to 1200 mm in the highlands. Secondly, the country predominantly experiences a tropical climate, with mean annual temperatures ranging from 15°C in the highlands to 25°C in the lowlands. Additionally, there are noticeable temperature variations across regions, with intra-day variation being relatively higher in the lowlands. Thirdly, a large part of the western half of the country gets more rain and lower temperatures. This sub-region constitutes the primary rain-fed agricultural area, inhabiting more than 90 percent of the total population (Wakjira et al., 2021). The geographical concentration of survey clusters in Figure 1 notably aligns with this sub-region.

3.2 Model variables

A. Outcome variables

The study examines two outcome variables: chronic undernutrition and acute undernutrition. Chronic undernutrition captures the impact of prolonged nutritional deficiency or repeated illness. It is measured by child anthropometric measurements for stunting using the height-for-age (HAZ) score. On the other hand, acute undernutrition represents the impact of short-term consequence of insufficient food intake or incidence of diseases. It is measured by child anthropometric measures for wasting using the weight-for-height (WHZ). Children are classified as stunted or wasted if their HAZ or WHZ scores, respectively, fall more than two standard deviations below the WHO Child Growth Standards median. A three standard deviation threshold implies severe undernutrition for both forms.

Table 2. Child undernutrition distribution across agro ecological zones

Variable	Tropical (n=6125)		Subtropical (n=8756)		Temperate (n=3024)	
	Mean	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*
HAZ	-1.57	1.82	-1.8	1.69	-1.77	1.69
Stunted (1/0)	0.41	0.49	0.47	0.50	0.46	0.50
WHZ	-0.84	1.29	-0.6	1.26	-0.39	1.23
Wasted (1/0)	0.17	0.38	0.13	0.33	0.09	0.29
Monthly precipitation (mm)	37.33	29.3	62.45	38.89	95.39	48.84
Monthly temperature (°C)	25.06	2.75	18.71	1.72	14.77	1.62
Altitude (m)	973.28	377.44	1878.4	202.77	2542.16	213.89

Note: The agro-ecology classification is primarily based on (MoA, 1998). Subtropical zones span altitudes from 1500 to 2300 meters above sea level, with the lower and upper ranges corresponding to tropical and temperate regions, respectively.

Table 2 presents the distribution of stunted and wasted children across agro ecological zones in our sample. These ecologies mainly depend on altitude, where tropical, subtropical, and temperate regions roughly match lowland, midland, and highland areas, respectively. While there is no prima facie association between stunting and agro ecologies, we do notice a relatively higher prevalence of wasting in tropical regions, where there is higher temperature and lesser precipitation distribution.

B. Precipitation exposures

Precipitation exposure measures the hourly amount of precipitation experienced in the grid cells where the children were located. The exposure is categorized into three ranges: absence of precipitation (below 0.5 mm), light to moderate rainfall (0.5-4 mm), and heavy to intense rainfall (above 4 mm). To establish the exposure categories, I initially take into account the average daily rainfall during the main rainy season (June to September), which usually amounts to about 3.5 mm. In addition, the overall daily average rainfall is approximately 2.0 mm. Subsequently I set rule-of-thumb thresholds to distinguish between instances of no precipitation and heavy rainfall. It's important to note that daily precipitation events frequently transpire within specific hours rather than spanning an entire day. Therefore, this study adopts an hourly approach to more effectively capture intra-day variations in precipitation frequency and intensity[2].

Then, I calculate the levels of precipitation exposure within two different time frames for the two outcome variables. For acute undernutrition, which is associated with short-term undernutrition events, I calculate the recent exposure period spanning three months prior to the survey interview date. This duration is considered adequately sufficient to observe the effects on children's wasting measures before their recovery.[3] The lifetime exposure period, covering from birth to interview dates, is calculated to capture the impact on chronic undernutrition.

Figure 4 illustrates the distribution of average monthly exposure hours by child. In Panel I, the recent exposure period shows a dense concentration of children from the sample in the lower exposure range – below 0.5 mm. The median exposure to this particular range is 422 hours out of the total 720 hours in a month (30 days' x 24 hours). Similarly, in Panel II, for the lifetime exposure period, the median exposure in the lower range is 502 hours.

2 *A sensitivity analysis is included for daily basis exposure in section 4.3.*

3 *For instance, according to UNICEF, approximately 90 percent of severely wasted children can achieve full recovery in approximately six weeks. A sensitivity analysis for scenarios of one to five months confirms the robustness of the three-month exposure window.*

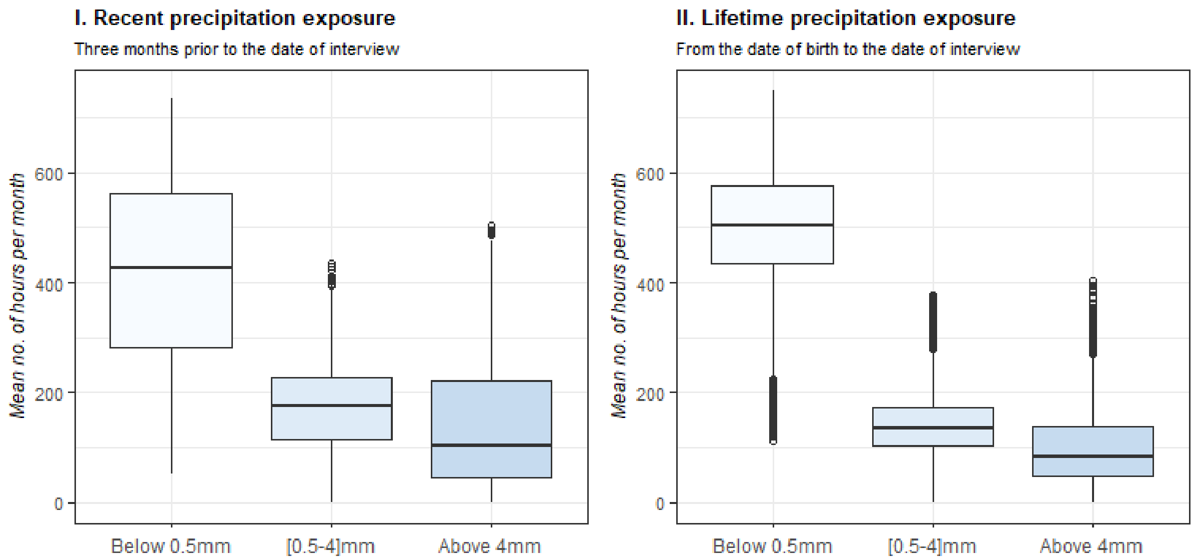

Figure 4. Mean monthly precipitation exposure by child

Note: the box plots show the distribution of mean monthly hours of exposure in each precipitation range during recent and lifetime exposure periods. I calculate this by adding the number of hours a child is exposed to a given precipitation level during recent exposure window (three months prior to the date of the survey interview) and the after-birth exposure window (entire lifetime period). For comparison purposes, I then normalize the total exposure hours by dividing three months for recent exposure and by age of the child (in months) for after-birth exposure. The outlier values shown, a minimal in number, have been excluded in the regression analysis to improve the overall representativeness of the sample.

The major assumption here is that precipitation exposures primarily affect child undernutrition through agricultural pathways. Specifically, arid regions with heightened exposure to lower precipitation levels (below 0.5 mm) endanger household food security and subsequently impacting child dietary intake. Conversely, excessive precipitation in the form of heavy rainfall and flooding (above 4 mm) may intensify water contamination, thereby positively correlating with increased diarrhea cases.

C. Temperature exposures

Temperature exposure measures the hourly temperature experienced in the grid cells where the children were located. The exposure is divided into three ranges: cold (below 16°C), cool (16 to 26°C), and warm (above 26°C). This classification is primarily based on the temperature levels commonly observed in the three major agro ecological zones. Furthermore, careful consideration is given to how different temperature ranges are associated to the growth and survival of pathogens and vectors that potentially affect child health.

The temperature exposure timeframes and calculation follow the same procedure with the precipitation case. Figure 5 illustrates the distribution of average monthly temperature exposure hours by child. In Panel I, the recent exposure period shows a dense concentration of children in the middle exposure range – [16 to 26] °C.

The median exposure to this particular range is 426 hours out of the total 720 hours in a month (30 days' x 24 hours). In the same way, in Panel II, for the lifetime exposure period, the median exposure in the middle range is 417 hours.

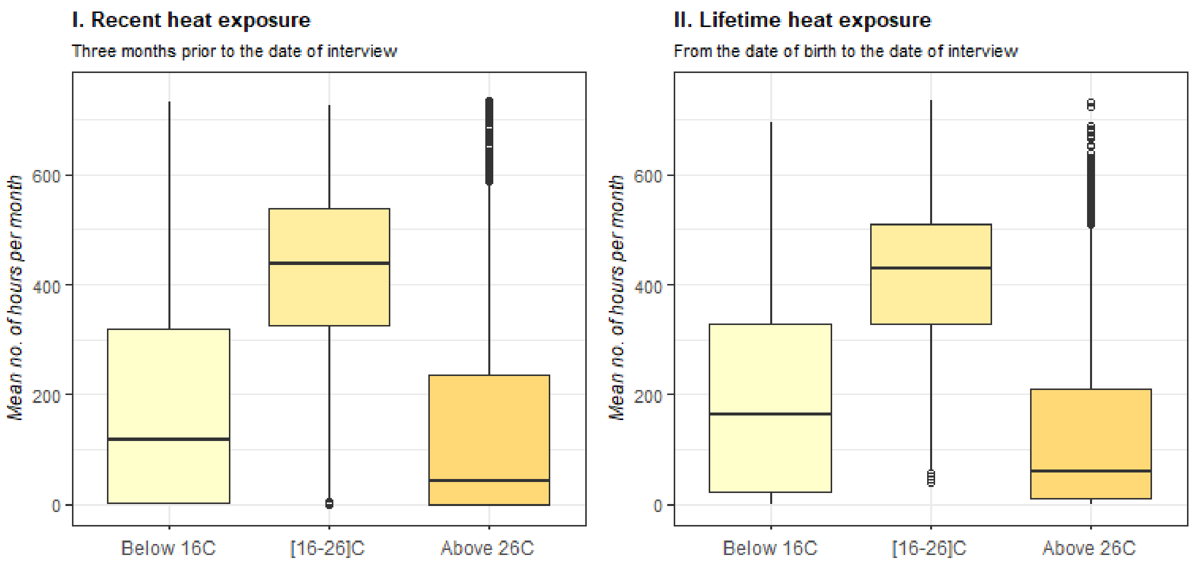

Figure 5. Mean monthly temperature exposure by child

Note: the box plots show the distribution of mean monthly hours of exposure in each temperature range during recent and lifetime exposure periods. We calculate this by adding the number of hours a child is exposed to a given temperature level during recent exposure window (three months prior to the date of the survey interview) and the after-birth exposure window (entire lifetime period). For comparison purposes, we then normalize the total exposure hours by dividing three months for recent exposure and by age of the child (in months) for after-birth exposure. The outlier values shown, a minimal in number, have been excluded in the regression analysis to improve the overall representativeness of the sample.

Here the assumption is the higher temperature range (above 26°C) has a more adverse impact on child nutritional outcomes compared to the lower temperature ranges. Specifically, our hypothesis is grounded in the potential link between warmer temperatures and the spread of various pathogens that can undermine child health. For instance, temperatures falling below approximately 18°C and 15°C, respectively, are known to impede the development of Plasmodium falciparum and P. vivax parasites, which are responsible for the majority of malaria cases in Ethiopia (Lyon et al., 2017). In contrast, the optimal conditions for the highest proportion of the malaria vector survival during the incubation period lie within the temperature range of 28°C to 32°C (Teklehaimanot et al., 2004). However, it is important to note that this assumption is contingent on other climatic factors that influence the prevalence and distribution of malaria vectors, such as altitude and rainfall patterns. Furthermore, studies indicate a correlation between higher temperatures and waterborne as well as foodborne child illnesses, including cases of diarrhea (Ahmed et al., 2020).

D. Precipitation anomalies

The precipitation and temperature categories discussed quantify the degree of weather exposures. The precipitation anomalies on the other hand aim to account for deviations from normal climatic patterns. In the context of the agricultural system, timing – specifically the onset and cessation of rainfall during cropping seasons – is a critical factor in determining production outcomes. Particularly, the precipitation anomaly gains significant relevance in Ethiopia's agricultural setting, which heavily relies on rain-fed systems (Segele & Lamb, 2005; Wakjira et al., 2021). Strong evidence suggests that irregularities in precipitation timing can have adverse effects on agricultural production, ultimately resulting in diminished food security.

In our model, the precipitation anomaly is calculated (scaled in thousands of millimeters) as the average deviation of monthly total precipitation from the historical levels observed between 1985 and 2014 in the specific grid-cell where the children were located. Appendix A illustrates the distribution of exposures to monthly precipitation anomalies during both the recent and lifetime exposure periods. As can be observed, the median exposure across months is largely negative, implying that a majority of the children in our sample experienced lower precipitation exposure compared to historical weather conditions.

E. Demographic factors

The demographic factors include determinants of child nutrition outcome at child, mother and household levels. Table 3 presents the summary statistics of these variables. Among the total children in the sample, 49 percent are female, aged above 20 months, and of medium birth size. Of these children, 19% are first-born in their families. Turning to the characteristics of the mothers, the average age is above 28 years old, and their height averages at 163 centimeters. A small proportion of the mothers, just 8%, have completed more than 9 grades of education. Household access to clean drinking water and sanitation facilities follows the DHS program standard for 'improved' access. Accordingly, access to improved drinking water and sanitation facilities stands at 42% and 17%, respectively. Lastly, a majority of these households fall below the third wealth quantile.

Table 3. Summary statistics by key demographic variables

Variable	Mean	Sd
Child is female (1/0)	0.49	0.50
Child's age (months)	20.57	9.02
Child birth size[4]	3.10	1.35
Eldest child (1/0)	0.19	0.40
Mother's age (years)	28.62	6.47
Mother's education (9+ years)	0.08	0.27
Mother's height (cm)[5]	163.62	70.38
Improved drinking water (1/0)	0.42	0.49
Improved latrines (1/0)	0.17	0.38
Wealth quantile	2.70	1.52

3.3 Identification strategy

Our main data source, the DHS, introduced new EAs and households with each new wave. This consideration primarily influences the choice of our estimation model. As a result, I employ the appropriate, fixed-effect cross-section model, represented by the following equation.

$$\mathbf{Y} = \text{Precipitation}\boldsymbol{\beta} + \text{Temperature}\boldsymbol{\gamma} + \text{Weather\_anomaly}\boldsymbol{\delta} + \text{Weather\_controls}\boldsymbol{\eta} + \text{Demographic\_controls}\boldsymbol{\theta} + \boldsymbol{\alpha}_{\boldsymbol{R}} + \boldsymbol{\alpha}_{\mathbf{T}} + \boldsymbol{\varepsilon} \qquad \textbf{(1)}$$

Where Y is a column vector of outcome variable, chronic child undernutrition (HAZ score or stunting level) for child i, in grid-cell g, with birth-date d, birth-month m and birth-year y.

Precipitation represents the mean monthly precipitation exposure of child_igdmy, in hundred-hours, across lower (< 0.5 mm) and upper (> 4 mm) precipitation ranges during the lifetime exposure window. The middle range [0.5 – 4] mm serves as the reference (omitted) category variable in the model. Thus, β denotes the effects of a 100-hour increase per month in children's exposure within a given lower or upper precipitation range compared to the reference exposure range.

[4] *Child birth size as reported by mother, ranges from 1 (very large) to 5 (very small)*

[5] *Missing mother's height values, which amount to 8% of the total sample are replaced with the median value.*

In the same way, temperature refers to the mean monthly temperature exposure of child_igdmy, in hundred-hours, across lower (< 16 °C) and upper (> 26 °C) temperature ranges during the lifetime exposure window. The intermediate range [16 – 26] °C serves as the reference (omitted) category variable. Thus, γ represents the effects of a 100-hour increase per month in children's exposure within lower or upper temperature ranges compared to the reference temperature range.

Weather anomaly represents the mean monthly precipitation anomalies in grid-cell g, where child_idmy was located during the lifetime exposure window. Thus δ measures the effects on chronic undernutrition for each monthly average deviation (scaled in thousands mm) from historical observed levels.

Weather controls contain as set variables that include precipitation exposure, temperature exposure and weather anomalies during prenatal period. The prenatal weather exposure calculation and timeframe coincides with the after-birth exposures. On the other hand, the demographic controls refer to determinants of child nutrition outcome at child, mother and household levels. The model further incorporates region-specific fixed effects (α_R), along with distinct time fixed effects (α_{T}) for months and years relevant to both the survey interview and the birth period.

Finally, in order to estimate the effect on acute undernutrition, equation (2) is adopted to accommodate distinct factors from the chronic undernutrition case. The exposure window now spans three months prior to the interview date, excluding prenatal weather exposures. As result, the time fixed effects also exclude the birth month control.

$$\mathbf{Y} = \text{Preciptation}\boldsymbol{\beta} + \text{Temperature}\boldsymbol{\gamma} + \text{Weather\_anomaly}\boldsymbol{\delta} + \text{Demographic\_controls}\boldsymbol{\theta} + \boldsymbol{\alpha}_{\boldsymbol{R}} + \boldsymbol{\alpha}_{\mathbf{T}} + \boldsymbol{\varepsilon} \qquad \mathbf{(2)}$$

4. RESULTS

In this section, I present the main results on the effects of weather exposures on child nutrition outcomes using the outlined identification strategies.

4.1 Effect on chronic undernutrition

Table 3 presents the results of the effects of lifetime weather exposures on chronic child undernutrition, as measured by HAZ score and associated binary indictors of child stunting prevalence: stunted (HAZ < -2) and severely stunted (HAZ < -3). The table columns represent alternative model results of Equation (1) using different sets of control variables.

Table 4. Effects of lifetime weather exposures on HAZ and stunting

	HAZ				Stunted	Sev_stunted
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation < 0.5 mm	0.030	0.437***	−0.147**	−0.133**	0.028	0.006
	(0.026)	(0.061)	(0.065)	(0.067)	(0.018)	(0.015)
Precipitation > 4 mm	−0.0003	0.150	−0.145	−0.154	0.028	−0.021
	(0.040)	(0.107)	(0.105)	(0.122)	(0.035)	(0.027)
Temperature < 16 °C	0.002	0.246***	−0.005	−0.011	−0.014	0.008
	(0.012)	(0.049)	(0.052)	(0.053)	(0.015)	(0.013)
Temperature > 26 °C	0.054***	0.048	0.033	0.041	−0.0001	0.003
	(0.014)	(0.044)	(0.044)	(0.045)	(0.012)	(0.010)
Constant	−1.938***	−1.877***	−0.648	−0.540	0.149	−0.036
	(0.162)	(0.287)	(1.578)	(1.582)	(0.460)	(0.367)
Controls:						
Region FE	N	Y	Y	Y	Y	Y
Prenatal weather	N	Y	Y	Y	Y	Y
Survey-time FE (Y, M)	N	Y	Y	Y	Y	Y
Demographic factors	N	N	Y	Y	Y	Y
Birth-time FE (Y, M)	N	N	Y	Y	Y	Y
Prcp anomaly	N	N	N	Y	Y	Y
Mean of dep. var.	-1.71	-1.71	-1.71	-1.71	0.45	0.22
Observations	17,836	17,836	17,835	17,835	17,835	17,835
Adjusted R^2	0.003	0.073	0.197	0.199	0.151	0.102

Note: This table reports the OLS estimates of the effects of lifetime weather exposures on HAZ and stunting. The after-birth (lifetime) exposure period spans from birth to the survey interview dates, while the prenatal exposure period encompasses three years preceding the birthdate for precipitation, and the standard gestation period of 40 weeks for temperature. The coefficients of the weather bins indicate the effects of a 100-hour increase per month in children's exposure within a given bin compared to their respective middle bins, [0.5 – 4] mm for precipitation and [16 – 26] °C for temperature. 'Prcp anomaly' is the average deviation of monthly total precipitation from the historical levels observed between 1985 to 2014 in the specific grid-cell where the children were located. Demographic controls refer to child, mother and household characteristics. Standard errors are clustered at the region level. See Appendix B for the complete regression result. Significance levels: *p<0.1; **p<0.05; ***p<0.01

Our preferred model, Table 3 (4), indicates that after-birth exposure to arid weather (i.e., precipitation < 0.5 mm) has a statistically significant negative association with HAZ score. This result aligns with our initial assumption that arid weathers could possibly contribute to a prolonged nutritional stress. The result can be interpreted as a 100-hour increase in children's exposure to arid weather is associated with a decrease of HAZ by 0.113 points compared to the effects on the exposure of the reference bin, [0.5 – 4] mm. Given the mean HAZ score of our sample, which is -1.71, this effect is approximately an 8% decline.

However, as reported in Table 3 (5) and (6), we do not find evidence supporting the idea that prolonged exposure to arid weather affects the prevalence of stunting, despite the correlations aligning with our expectations. Additionally, we find no statistically significant associations between other weather exposure categories and both the HAZ score and the prevalence of stunting. On the other hand, regarding the effects of precipitation anomalies, a deviation in monthly precipitation level (scaled in thousands mm) from the normal weather pattern (i.e., the historical average) has a negative effect on HAZ score, as assumed, but it is not statistically significant. This effect is mainly observed during the major rainy months, which run from June through September. However, for most of dry months, the association direction is positive, and statistically significant. This effect of monthly precipitation anomalies is further illustrated in Figure 6.

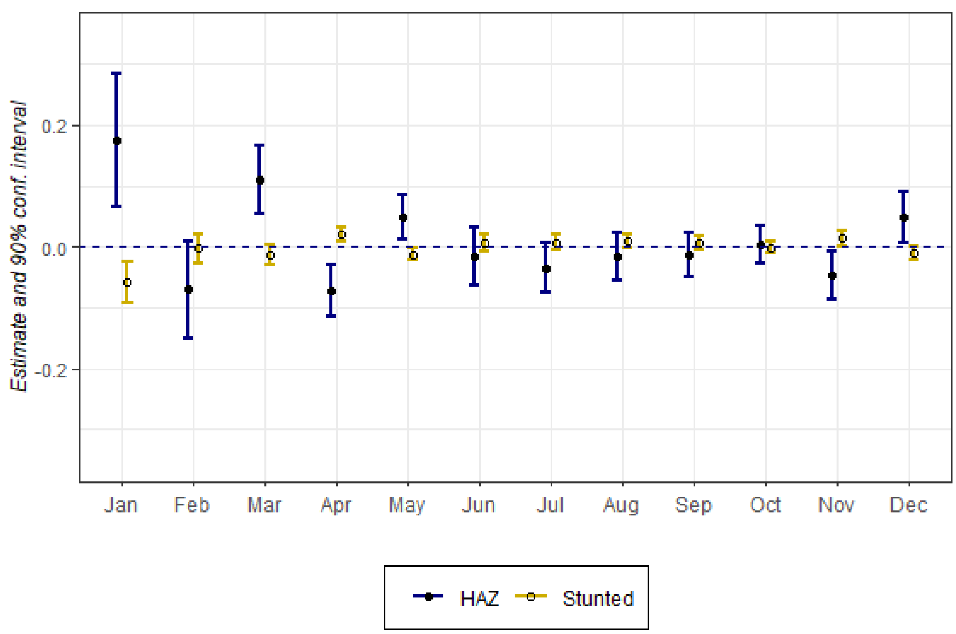

Figure 6. Effects of monthly precipitation anomalies on HAZ and stunting
Note: This figure illustrates the coefficient estimates of monthly precipitation anomalies derived from the main model results for chronic undernutrition. The anomaly is calculated (scaled in thousands mm) as the average deviation of monthly total precipitation from the historical levels observed between 1985 to 2014 in the specific grid-cell where the children were located. Standard errors are clustered at the regional level. See Appendix C for complete regression result.

Coming back to the results of exposure to arid weather condition, the age and location-specific effects are illustrated in Figure 7. Panel (I) shows the age-specific effect, which aligns with the growth faltering patter expectation, indicating that children in the sample are most vulnerable to climatic shocks before they turn two years of age. As can be seen, this impact is highest on children aged between 18 and 23 months, gradually decreasing afterward. Given the mean HAZ score -2.0 and stunting prevalence 0.52 of this particular age group, the effect is over 13 percent decline and approximately 11 percent increase, respectively.

Additionally, panel (II) indicates that the impact of exposure to arid weather is more pronounced on children located in subtropical and temperate zones, where relatively higher precipitation levels are observed on average compared to tropical areas. Tropical regions, which already have longer dry seasons, do not show notable differences in response to arid weather exposure when the precipitation remain below 0.5 mm.

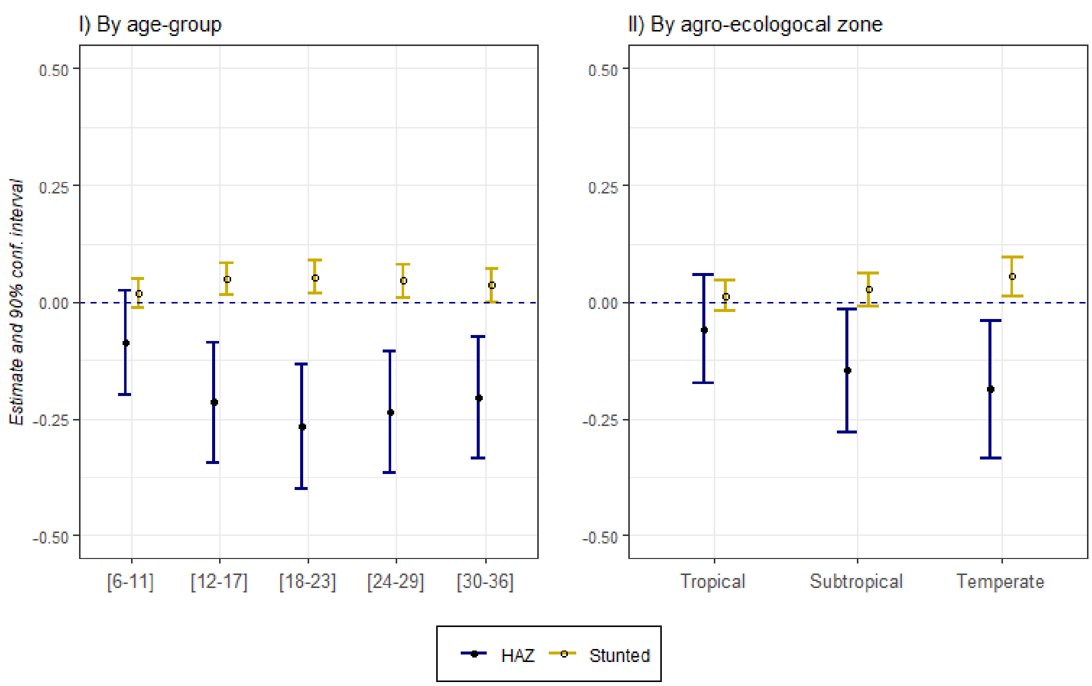

Figure 7 Age and location specific effects of lifetime exposure to arid weather
Note: panel I and II illustrate the coefficients of age and location-specific estimates from the main model – table 4 (4-5), respectively. Both panels represent different model results, in which age and ago-ecology groups are separately interacted with the lower precipitation range (< 0.5 mm). The regression results are reported in appendices E and F.

4.2 Effect on acute undernutrition

Table 5 presents the results of the effects of recent weather exposures on acute child undernutrition, as measured by WHZ score and wasting prevalence. Column (4) is the preferred model as it is specified with the full set of control variables. The results show that WHZ and wasting prevalence are sensitive to the different levels of weather exposures, except for the higher precipitation range.

Table 5. Effects of recent weather exposures on WHZ and wasting

	WHZ				Wasted	Sev_wasted
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation < 0.5 mm	0.006	0.029	0.038**	0.043**	−0.008*	0.002
	(0.014)	(0.018)	(0.018)	(0.018)	(0.005)	(0.003)
Precipitation > 4 mm	−0.039**	−0.018	−0.013	−0.009	−0.0001	0.005
	(0.018)	(0.021)	(0.021)	(0.021)	(0.006)	(0.003)
Temperature < 16 °C	0.045***	0.027***	0.020***	0.020***	−0.004*	−0.002**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.002)	(0.001)
Temperature > 26 °C	−0.079***	−0.085***	−0.083***	−0.083***	0.014***	0.004**
	(0.008)	(0.011)	(0.011)	(0.011)	(0.003)	(0.002)
Constant	−0.586***	−0.031	−0.169	−0.200	0.149	−0.097
	(0.078)	(0.131)	(0.438)	(0.438)	(0.130)	(0.164)
Controls:						
Region FE	N	Y	Y	Y	Y	Y
Survey-time (Y, M)	N	Y	Y	Y	Y	Y
Demographic controls	N	N	Y	Y	Y	Y
Birth-time (Y)	N	N	Y	Y	Y	Y
Prcp anomaly	N	N	N	Y	Y	Y
Mean of dep. var.	-0.65	-0.65	-0.65	-0.65	0.13	0.04
Observations	17,905	17,905	17,904	17,904	17,904	17,904
Adjusted R^2	0.020	0.043	0.096	0.096	0.047	0.020

Note: This table reports the OLS estimates of the effects of recent weather exposures on WHZ and wasting. The coefficients of the weather bins indicate the effects of a 100-hour increase per month in children's exposure within a given bin compared to their respective middle bins, [0.5 – 4] mm for precipitation and [16 – 26] °C for temperature. 'Prcp anomaly' is the deviation of monthly total precipitation from the historical levels observed between 1985 to 2014 in the specific grid-cell where the children were located. Demographic controls refer to child, mother and household characteristics. Standard errors are clustered at the region level. See Appendix C for the complete regression result. Significance levels: *p<0.1; **p<0.05; ***p<0.01

I emphasize the impact of exposure to higher temperature (> 26 °C), considering the higher possibility of this specific exposure category as a significant factor leading to acute child undernutrition. In particular, the assumption is based on the potential correlation between warmer temperatures and various pathogens that can have adverse effects on child health.

The findings also highlight this particular temperature range as having the highest magnitude when compared to other exposure ranges. The estimation result indicates that compared to the effects of exposure in the reference bin [16 – 26] °C, a 100-hour increase in children's exposure to warm weather is associated with a decrease of 0.083 points in WHZ and a 1.4% increase in the prevalence of wasting. Considering the sample mean, this effect translates to an approximate 13% decline in WHZ score and an 11% worsening in the prevalence of wasting.

Figure 7 illustrates age and location specific effects of recent exposure to warm temperature on acute undernutrition. Panel (I) indicates a heightened vulnerability of infants aged 6 to 11 months to the consequences of climatic shocks, as compared to their older counterparts. This impact can be quantified as a decline of more than 13 percent and increase around 8 percent, respectively, based on the mean HAZ score (-0.79) and the prevalence of stunting (0.22) for the specific age group. This observation aligns with previous research indicating an imminent risk of increased child wasting, preceding the potential occurrence of stunting in later stages (Rieger & Trommlerová, 2016). Furthermore, panel (II) illustrate the location-specific effect, in which the impact of exposure to arid-weather is significantly pronounced on children located in in tropical zones.

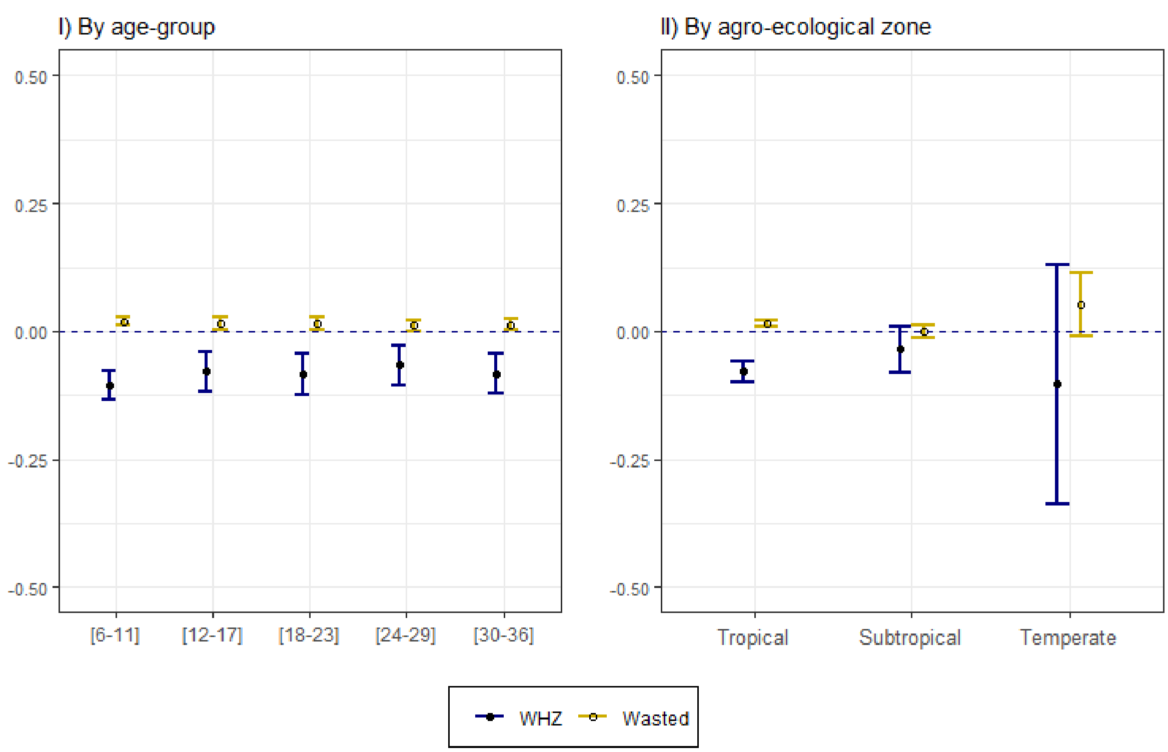

Figure 8. Age and location specific effects of recent exposure to warm temperature

Note: panel I and II illustrate the coefficients of age and location-specific estimates from the main model – table 5 (4), respectively. Both panels represent different model results, in which age and ago-ecology groups are separately interacted with the higher temperature range (> 26 °C). The regression results are reported in appendices E and F.

Regarding the impact of monthly precipitation anomalies on acute malnutrition, it is important to note that the surveys were conducted in specific months. As a result, the calculation of recent exposure, which covers the three-month period preceding the survey interviews, primarily falls between April and July. Despite this, we observe similar impact trends during these months, where the rainy months (June and July) exhibit a negative association with HAZ score (see Appendix B for full regression result).

4.3 Robustness check

This section highlights the major tests conducted to assess the overall robustness of the study's main findings. The initial step involves verifying the plausibility of weather exposure estimates using a set of alternative control variables. Thus, as a first step, the analysis is systematically performed, progressing from the grid-cell level to various cluster levels. The results at lower cluster levels and with time fixed effect interaction terms hide much of the identifying spatiotemporal variations necessary for the model estimation. In comparison, the preferred specification at the regional cluster level leads to overall improved estimation results. Nevertheless, the alternative specifications reveal a consistent correlation between weather exposure bins and the outcome variables, despite differences in significance levels. Moreover, the final estimation result emerges after addressing potential model endogeneity problems, such as seasonality issues, by including monthly anomalies and accounting for omitted covariates through the inclusion of major demographic controls that determine child undernutrition.

Table 6. Effects of daily mean weather exposure

	HAZ	Stunted	WHZ	Wasted
	(1)	(2)	(3)	(4)
Precipitation < 0.5 mm	−0.013	0.001	0.009***	−0.002**
	(0.010)	(0.003)	(0.002)	(0.001)
Precipitation > 4 mm	−0.017	0.001	0.0005	−0.0002
	(0.016)	(0.005)	(0.002)	(0.001)
Temperature < 16 °C	−0.004	−0.001	0.004***	−0.001***
	(0.006)	(0.002)	(0.001)	(0.0003)
Temperature > 26 °C	0.010	−0.0002	−0.013***	0.003***
	(0.007)	(0.002)	(0.002)	(0.001)
Constant	−0.808	0.308	−0.189	0.144
	(1.534)	(0.445)	(0.431)	(0.127)
FE	Y	Y	Y	Y
Observations	17,904	17,904	17,904	17,904
Adjusted R^2	0.198	0.150	0.096	0.048

Note: The coefficients of the weather bins indicate the impact of an additional day's exposure per month compared to the respective reference bins, [0.5 – 4] mm for precipitation and [16 – 26] °C for temperature.

In the subsequent phase, I perform two sensitivity analyses concerning the categorization of weather bins. The initial test involves examining weather exposure on a daily basis rather than hourly. Table 6 presents the resulting test outcomes, revealing that the overall correlations between the new estimates and the outcome variables remain consistent. These coefficients representing daily mean weather exposure can be interpreted as the impact of an additional day's exposure per month in the lower or upper temperature and precipitation bins, relative to the respective reference bins. However, these estimates exhibit a relatively lesser magnitude in comparison to the hourly exposure. This difference could potentially be attributed to the assumption that the alternative hourly method might more effectively capture intra-day variations in terms of exposure frequency and intensity[6]. Furthermore, Table 7 presents the results of a sensitivity analysis conducted for recent exposure window scenarios, ranging from one to five months, thereby confirming the robustness of the three-month exposure window. Notably, column (3) demonstrates a larger impact when compared to the other scenarios.

Table 7. Sensitivity analysis of recent exposure periods on WHZ

	Exposure period: (months)				
	(1)	(2)	(3)	(4)	(5)
Precipitation < 0.5 mm	0.0002	0.0004**	0.043**	0.0005*	0.0004*
	(0.0001)	(0.0002)	(0.018)	(0.0002)	(0.0002)
Precipitation > 4 mm	−0.0002	−0.00003	−0.009	−0.0003	−0.0003
	(0.0002)	(0.0002)	(0.021)	(0.0003)	(0.0003)
Temperature < 16 °C	0.0002***	0.0004***	0.020***	0.0002**	0.0001
	(0.0001)	(0.0001)	(0.008)	(0.0001)	(0.0001)
Temperature > 26 °C	−0.001***	−0.002***	−0.083***	−0.001***	−0.001***
	(0.0001)	(0.0002)	(0.011)	(0.0001)	(0.0001)
Constant	−0.115	−0.191	−0.200	−0.155	−0.113
	(0.436)	(0.437)	(0.438)	(0.447)	(0.446)
FE	Y	Y	Y	Y	Y
Observations	17,717	17,717	17,904	17,883	17,883
Adjusted R^2	0.096	0.096	0.96	0.097	0.097

Note: each column corresponds to recent exposure period in months from the surveys interview date.
Column (3) is the preferred model, representing the three-month exposure period.

[6] *The estimates in the main model represent an additional 100-hour exposure effect per month, while the estimates in Table 6 represent an additional daily (24-hour) exposure effect per month.*

5. MECHANISMS

The main findings of the study indicate that chronic undernutrition is predominantly influenced by exposure to arid weather. On the other hand, acute malnutrition appears to be more sensitive to varying levels of exposure, with warm temperatures having a particularly pronounced adverse impact. Thus, this section provides a general exploration of the underlying pathways that explain these findings.

First I examine the agricultural channel through how adverse weather environments affect chronic child undernutrition. The DHS data lacks information on agricultural production and income to directly evaluate this pathway. Therefore, I focus on investigating maternal employment within the agricultural sector. The underlying rationale is that women's participation in employment has the potential to augment the total household income and increase the share of income managed by women. On the contrary side, maternal employment might also influence the allocation of time, which could potentially impact maternal childcare responsibilities. Consequently, increased vulnerability to adverse weather conditions could potentially exacerbate challenges in both agriculture and childcare aspects.

Table 8. Effects by maternal employment in the agricultural sector

	HAZ	Stunted	HAZ	Stunted
	(1)	(2)	(3)	(4)
Precipitation < 0.5 mm	−0.121	0.035	−0.182*	0.040
	(0.075)	(0.022)	(0.102)	(0.029)
Precipitation > 4 mm	−0.168	0.032	−0.259	0.050
	(0.134)	(0.039)	(0.184)	(0.053)
Temperature < 16 °C	−0.021	−0.017	−0.020	−0.022
	(0.058)	(0.017)	(0.080)	(0.023)
Temperature > 26 °C	0.017	0.002	0.021	0.003
	(0.048)	(0.014)	(0.070)	(0.020)
Mother in agriculture	0.432***	−0.064	0.222	−0.046
	(0.159)	(0.046)	(0.234)	(0.068)
Father in agriculture			−0.138**	0.033*
			(0.058)	(0.017)
Arid-weather*mother_in_agri	−0.091***	0.015*	−0.059	0.012
	(0.032)	(0.009)	(0.047)	(0.013)
Constant	0.683	−0.216	−2.565	0.944
	(1.855)	(0.539)	(2.377)	(0.688)
FE	Y	Y	Y	Y
Mean of dep. var.	-0.65	0.13	-0.65	0.13
Observations	15,257	15,257	7,910	7,910
Adjusted R^2	0.207	0.155	0.195	0.151

Note: This regression result extends the findings of the main model from Table 4 (4). "Arid-weather" represents the lower precipitation exposure range (< 0.5 mm). Standard errors are clustered at the regional level. Significance Levels: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8 presents effects by maternal employment in the agricultural sector. The result shows a positive correlation between maternal on-farm work and HAZ score. Specifically, mothers engaged in the agricultural sector exhibit an additional HAZ score of 0.432 compared to those involved in non-agricultural employment or without any employment. Additionally, when considering the interaction between maternal employment and adverse weather conditions (precipitation below 0.5 mm), the result reveals a negative effect, implying that mothers with on-farm work are adversely affected by 0.09 HAZ points (or 14 percent from sample mean) more than the others. Furthermore, Table 8 (3-4) presents the model results with the inclusion of the partially available paternal employment data. These directions of impact remain consistent even after accounting for paternal employment. Certainly, this preliminary exploratory analysis highlights a future research area of work. A more comprehensive and robust model could be developed by considering household decision-making dynamics, off-farm employment and the influence of paternal involvement.

Secondly, I investigate the impacts of climate variability on acute undernutrition through disease pathways. Diarrhea and fever incidences observed in the last two weeks from the survey dates serve as proxy indicators for the prevalence infectious diseases. As depicted in Table 9 (1-2), a significant positive correlation exists between the upper temperature exposure range and the prevalence of these incidences. Considering the sample mean of the occurrence of both cases, the effect is approximately 7.5 percent for diarrhea and 6.5 percent for fever.

Building upon this observation, Table 9 (3-4) sheds light on the influence of warm temperatures on water, hygiene, and sanitation aspects linked to acute undernutrition. The result generally underscores how children from households with improved access to drinking water and sanitation remain less vulnerable to the adverse climate effects of warmer temperatures. Specifically, given the sample mean, these children from household with improves waster access are with 9 percent less likely to be affected by wasting, and similarly the latrines are 8 percent less likely to be wasted. However, the results also uncover a negative direct correlation between access to drinking water and both WHZ and wasting prevalence. This phenomenon could potentially be attributed to scenarios where the impact of water contamination or related diseases is influenced by other cofounding factors, such as household behavior. For instance, Table 9 (5-6) demonstrates that this relationship become statistically insignificant when accounting for access to improved latrines and weather specific effects.

The study also investigated the potential impact of malaria on acute undernutrition through an assessment of favorable months and rainfall distribution of the weather data. However, these analyses did not yield significant results. This could possibly be due to the necessity for a more comprehensive spatial identification model, capable of accurately pinpointing malaria transmission-favorable areas while accounting for various geographic factors. These findings highlight a potential area of future research.

Table 9. Effects by access to improved drinking water and latrines

	Diarrhea	Fever	WHZ	Wasted	WHZ	Wasted
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation < 0.5 mm	−0.030***	−0.003	0.043**	−0.008*	0.042**	−0.009*
	(0.007)	(0.007)	(0.018)	(0.005)	(0.018)	(0.005)
Precipitation > 4 mm	−0.026***	0.011	−0.009	−0.0003	−0.010	−0.0004
	(0.008)	(0.008)	(0.021)	(0.006)	(0.021)	(0.006)
Temperature < 16 °C	0.002	0.002	0.021***	−0.004**	0.020***	−0.004*
	(0.003)	(0.003)	(0.008)	(0.002)	(0.008)	(0.002)
Temperature > 26 °C	0.017***	0.017***	−0.102***	0.021***	−0.080***	0.016***
	(0.004)	(0.004)	(0.012)	(0.004)	(0.011)	(0.003)
Improved drink'water	−0.004	−0.010	−0.080***	0.027***	−0.025	0.009
	(0.018)	(0.009)	(0.029)	(0.008)	(0.024)	(0.007)
Improved latrines	−0.020	−0.014	0.124***	−0.027***	0.147***	−0.014
	(0.023)	(0.012)	(0.029)	(0.007)	(0.036)	(0.008)
Warm-temp**impr_drink'water*			0.034***	−0.012***		
			(0.011)	(0.003)		
Warm-temp**impr_latrines*					−0.015	−0.010***
					(0.014)	(0.004)
Constant	0.571***	0.339**	−0.142	0.129	−0.210	0.143
	(0.131)	(0.136)	(0.439)	(0.130)	(0.439)	(0.130)
FE	Y	Y	Y	Y	Y	Y
Mean of dep. var.	0.23	0.26	-0.65	0.13	-0.65	0.13
Observations	15,318	15,318	17,904	17,904	17,904	17,904
Adjusted R^2	0.048	0.045	0.097	0.048	0.096	0.048

Note: This regression result extends the main model's findings from Table 5 (4). "Warm-temp" represents the upper temperature range (> 26 °C). Standard errors are clustered at the regional level. Significance Levels: *p < 0.1; **p < 0.05; ***p < 0.01.

6. CONCLUSION

This paper highlights the relationship between different levels of rainfall and temperature and the prevalence of child undernutrition in Ethiopia. The study focuses on ages 6 to 36 months, a critical period when children are especially susceptible to underlying nutrition-related factors and health risks. Three major findings emerge from the study.

Firstly, chronic undernutrition is mainly influenced by arid weather. For every 100-hour increase in children's monthly exposure to less than 0.5 mm of precipitation over their lifetime, their HAZ score drops by 0.113 points compared to moderate exposure of [0.5 – 4] mm. This represents an 8 percent reduction from the average HAZ score in our sample. This effect is most pronounced until the age of two years and then gradually decreases. Additionally, the impact of dry weather is more significant on children in subtropical and temperate areas, where average precipitation levels are relatively higher compared to tropical regions.

Secondly, acute malnutrition is more responsive to different exposure levels, especially with higher temperatures having a stronger negative effect. The results indicate that a 100-hour rise in recent exposure to warm temperatures above 26°C, compared to the moderate range of [16 – 26] °C, results in a decrease of 0.083 points in WHZ and a 1.4 percent rise in wasting prevalence. On average, this corresponds to roughly a 13 percent decrease in WHZ score and an 11 percent increase in wasting prevalence. This effect is most pronounced on children aged 6 to 11 months. Moreover, the impact of dry weather on acute child undernutrition is particularly significant for children in tropical zones.

Thirdly, the study suggests that agriculture and infectious diseases are the main pathways connecting different weather exposures and child undernutrition. Children with mothers working in agriculture exhibit a higher HAZ score of 0.432 compared to those with non-agricultural working mothers or those without jobs. However, children whose mothers engage in on-farm work are more affected by adverse weather conditions than the others. Additionally, there's a clear link between children's recent exposure to warm temperatures above 26°C and the incidence of fever and diarrhea. The findings also indicate that children with access to improved water and sanitation are less vulnerable to the negative effects of adverse weather.

Overall, the study's finding regarding the positive impact of rain on stunting, and the related pathways, align with existing research. However, the study doesn't find evidence of a significant effect of warm temperatures on stunting, nor does it indicate a notable impact from arid weather on wasting. Complementing these results of the study with the existing research findings will contribute to a deeper understanding of the intricate connections between climate variability and child nutritional outcomes.

Finally, two key limitations of this study point toward future research directions. The first pertains to the method of recent weather exposure used to investigate the impact on acute malnutrition. The second relates to the methods employed to assess the impact pathways of agriculture and infectious disease. In both instances, comprehensive and high-frequency data on agricultural income, household decision-making, and child health could strengthen the causal implications of the findings. Additionally, combining this data with an improved spatial identification model capable of better identifying areas conducive to disease transmission could further enhance the study's validity.

APPENDIX

A. Precipitation anomalies

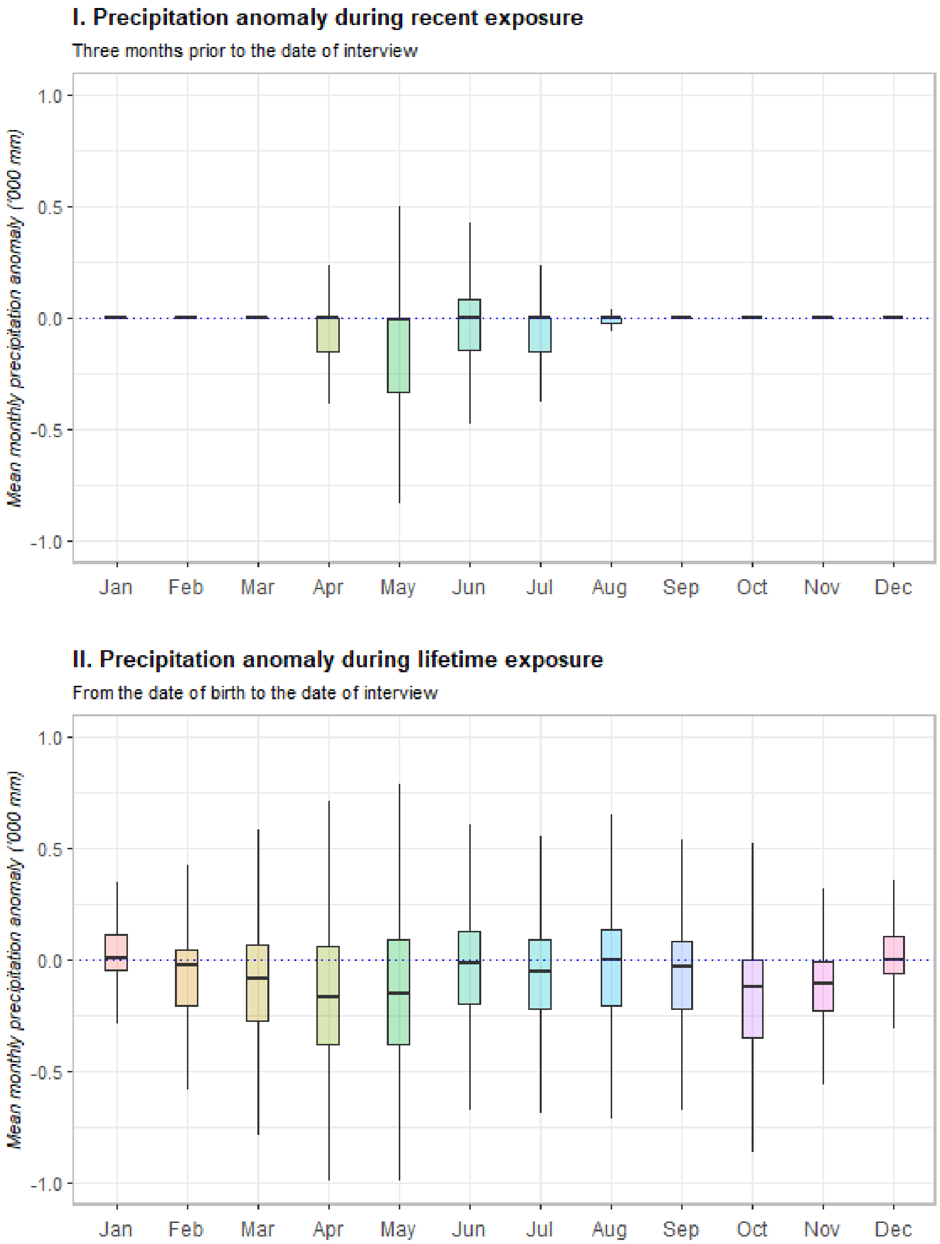

Figure 9. Mean monthly precipitation anomalies by child

Note: the box plots show the distribution of mean monthly precipitation anomalies during recent and lifetime weather exposure periods. Precipitation anomaly is calculated (scaled in thousands mm) as the average deviation of monthly total precipitation from the historical levels observed between 1985 to 2014 in the specific grid-cell where the children were located. The surveys were conducted in specific months, and thus the calculation of recent exposure - the three-month period preceding the survey interviews, predominantly falls between April and July.

B. Full regression report

	HAZ	Stunted	Sev_stunted	WHZ	Wasted	Sev_wasted
Precipitation $<$ 0.5 mm	-0.133^{**}	0.028	0.006	0.043^{**}	-0.008^{*}	0.002
	(0.067)	(0.018)	(0.015)	(0.018)	(0.005)	(0.003)
Precipitation $>$ 4 mm	-0.154	0.028	-0.021	-0.009	-0.0001	0.005
	(0.122)	(0.035)	(0.027)	(0.021)	(0.006)	(0.003)
Temperature $<$ 16 °C	-0.011	-0.014	0.008	0.020^{***}	-0.004^{*}	-0.002^{**}
	(0.053)	(0.015)	(0.013)	(0.008)	(0.002)	(0.001)
Temperature $>$ 26 °C	0.041	-0.0001	0.003	-0.083^{***}	0.014^{***}	0.004^{**}
	(0.045)	(0.012)	(0.010)	(0.011)	(0.003)	(0.002)
Prcp anomaly: Jan	0.174^{***}	-0.058^{***}	-0.030^{*}			
	(0.067)	(0.020)	(0.017)			
Prcp anomaly: Feb	-0.070	-0.003	-0.001			
	(0.049)	(0.015)	(0.013)			
Prcp anomaly: Mar	0.110^{***}	-0.015	-0.008			
	(0.034)	(0.010)	(0.008)			
Prcp anomaly: Apr	-0.071^{***}	0.021^{***}	0.008	0.001	0.008^{*}	0.001
	(0.025)	(0.007)	(0.006)	(0.020)	(0.005)	(0.003)
Prcp anomaly: May	0.049^{**}	-0.012^{*}	-0.008	0.038^{**}	-0.005	0.002
	(0.022)	(0.006)	(0.005)	(0.016)	(0.004)	(0.002)
Prcp anomaly: Jun	-0.016	0.006	0.014^{*}	-0.025	0.009	0.010^{**}
	(0.029)	(0.009)	(0.007)	(0.023)	(0.007)	(0.004)
Prcp anomaly: Jul	-0.035	0.008	0.006	-0.036^{*}	0.010^{*}	-0.001
	(0.025)	(0.008)	(0.006)	(0.020)	(0.006)	(0.004)
Prcp anomaly: Aug	-0.017	0.009	-0.002			
	(0.023)	(0.007)	(0.006)			
Prcp anomaly: Sep	-0.013	0.007	0.009^{*}			
	(0.022)	(0.007)	(0.005)			
Prcp anomaly: Oct	0.004	-0.001	-0.002			
	(0.018)	(0.006)	(0.004)			
Prcp anomaly: Nov	-0.046^{*}	0.015^{*}	0.012^{***}			
	(0.024)	(0.008)	(0.005)			
Prcp anomaly: Dec	0.049^{*}	-0.010	-0.010^{**}			
	(0.026)	(0.007)	(0.005)			
Child is female	0.211^{***}	-0.054^{***}	-0.048^{***}	0.168^{***}	-0.037^{***}	-0.012^{***}
	(0.024)	(0.007)	(0.006)	(0.018)	(0.005)	(0.003)
Eldest child	0.084^{**}	-0.010	-0.027^{***}	0.095^{***}	-0.012^{*}	-0.010^{***}
	(0.033)	(0.010)	(0.008)	(0.026)	(0.007)	(0.004)
Single birth	0.570^{***}	-0.124^{***}	-0.077^{***}	0.202^{***}	-0.039^{*}	-0.017
	(0.083)	(0.027)	(0.024)	(0.063)	(0.020)	(0.012)
Birth size: small	-0.064	-0.008	-0.013	-0.123^{***}	0.009	0.009
	(0.050)	(0.014)	(0.012)	(0.038)	(0.010)	(0.005)
Birth size: Medium	-0.162^{***}	0.032^{***}	0.007	-0.209^{***}	0.016^{**}	0.009^{**}
	(0.043)	(0.012)	(0.010)	(0.032)	(0.008)	(0.004)
Birth size: Large	-0.332^{***}	0.073^{***}	0.059^{***}	-0.374^{***}	0.036^{***}	0.018^{***}
	(0.053)	(0.015)	(0.013)	(0.040)	(0.011)	(0.006)
Birth size: Very large	-0.473^{***}	0.113^{***}	0.071^{***}	-0.523^{***}	0.076^{***}	0.033^{***}
	(0.049)	(0.014)	(0.012)	(0.037)	(0.010)	(0.006)
Mother age (years)	0.008^{***}	-0.002^{**}	-0.001	-0.004^{**}	0.001^{**}	0.0003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.0005)	(0.0003)
Mother height (log cm)	0.554^{***}	-0.114^{***}	-0.068^{**}	-0.038	0.010	-0.004
	(0.131)	(0.032)	(0.028)	(0.076)	(0.023)	(0.012)
Mother education (Above 8th)	0.454^{***}	-0.130^{***}	-0.064^{***}	0.224^{***}	-0.031^{***}	-0.003
	(0.045)	(0.013)	(0.009)	(0.038)	(0.008)	(0.004)
Improved drink'water	-0.042	0.001	-0.004	-0.026	0.008	0.003
	(0.031)	(0.009)	(0.008)	(0.024)	(0.007)	(0.004)
Improved latrines	0.144^{***}	-0.038^{***}	-0.035^{***}	0.126^{***}	-0.028^{***}	-0.009^{**}
	(0.038)	(0.012)	(0.009)	(0.029)	(0.007)	(0.004)

…continued on the following page

	HAZ	Stunted	Sev_stunted	WHZ	Wasted	Sev_wasted
Wealth quantile: 2nd	−0.0004	−0.001	−0.005	0.005	−0.011	0.001
	(0.037)	(0.011)	(0.010)	(0.029)	(0.008)	(0.005)
Wealth quantile: 3rd	0.092**	−0.022*	−0.019*	0.039	−0.006	−0.001
	(0.038)	(0.011)	(0.010)	(0.029)	(0.009)	(0.005)
Wealth quantile: 4th	0.168***	−0.051***	−0.050***	0.153***	−0.036***	−0.012**
	(0.040)	(0.012)	(0.010)	(0.031)	(0.008)	(0.005)
Wealth quantile: 5th	0.325***	−0.109***	−0.075***	0.231***	−0.056***	−0.015**
	(0.054)	(0.016)	(0.014)	(0.042)	(0.011)	(0.006)
Location (rural)	−0.036	0.009	0.005	−0.090**	−0.001	−0.001
	(0.049)	(0.015)	(0.012)	(0.039)	(0.011)	(0.006)
Prenatal Prcp $<$ 0.5 mm	0.164**	−0.023	−0.011			
	(0.075)	(0.021)	(0.017)			
Prenatal Prcp $>$ 4 mm	0.297**	−0.046	−0.009			
	(0.129)	(0.037)	(0.029)			
Prenatal Temp $<$ 16 °C	−0.033	0.027*	0.004			
	(0.052)	(0.015)	(0.013)			
Prenatal Temp $>$ 26 °C	0.003	−0.009	−0.007			
	(0.043)	(0.012)	(0.010)			
Prenatal Prcp anomaly: Jan	−0.282**	0.033	0.067**			
	(0.121)	(0.035)	(0.031)			
Prenatal Prcp anomaly: Feb	−0.007	0.021	0.002			
	(0.056)	(0.017)	(0.015)			
Prenatal Prcp anomaly: Mar	−0.026	0.008	−0.009			
	(0.043)	(0.013)	(0.011)			
Prenatal Prcp anomaly: Apr	−0.0004	−0.0003	−0.003			
	(0.033)	(0.010)	(0.009)			
Prenatal Prcp anomaly: May	0.034	−0.003	0.008			
	(0.030)	(0.009)	(0.008)			
Prenatal Prcp anomaly: Jun	0.126***	−0.037***	−0.038***			
	(0.041)	(0.013)	(0.011)			
Prenatal Prcp anomaly: Jul	0.023	−0.006	−0.016			
	(0.035)	(0.011)	(0.010)			
Prenatal Prcp anomaly: Aug	0.086**	−0.010	−0.011			
	(0.035)	(0.011)	(0.010)			
Prenatal Prcp anomaly: Sep	−0.010	0.006	0.005			
	(0.036)	(0.011)	(0.010)			
Prenatal Prcp anomaly: Oct	0.033	−0.006	−0.011			
	(0.031)	(0.010)	(0.008)			
Prenatal Prcp anomaly: Nov	−0.003	−0.008	−0.007			
	(0.067)	(0.019)	(0.016)			
Prenatal Prcp anomaly: Dec	−0.088	0.029	0.027			
	(0.094)	(0.028)	(0.023)			
Constant	−0.540	0.149	−0.036	−0.200	0.149	−0.097
	(1.582)	(0.460)	(0.367)	(0.438)	(0.130)	(0.164)
FE	Y	Y	Y	Y	Y	Y
Observations	17,835	17,835	17,835	17,904	17,904	17,904
Adjusted R^2	0.199	0.151	0.102	0.096	0.047	0.020

Table 10. Full regression report

Note: The table reports the regression results of the effects of lifetime weather exposures on HAZ and stunting (for Table 3); and of the effects of recent weather exposures on WHZ and Wasting (for Table 4). The full set of fixed effects are listed in the summary result tables. In addition, child age is controlled through a set of 31 fixed effects, accounting for each month of age between 6 and 36. Standard errors are clustered at the region level. Significance levels: *p<0.1; **p<0.05; ***p<0.01

C. Age-specific effects of adverse weather conditions

	HAZ	Stunted	WHZ	Wasted
	(1)	(2)	(3)	(4)
Precipitation < 0.5 mm	−0.088	0.019	0.043**	−0.008*
	(0.068)	(0.020)	(0.018)	(0.005)
Precipitation > 4 mm	−0.155	0.030	−0.009	−0.0003
	(0.122)	(0.036)	(0.021)	(0.006)
Temperature < 16 °C	−0.034	−0.009	0.020***	−0.004*
	(0.053)	(0.016)	(0.008)	(0.002)
Temperature > 26 °C	0.063	−0.005	−0.106***	0.019***
	(0.043)	(0.013)	(0.015)	(0.004)
Age [6-11] months	−0.923	0.222	−0.159	0.140
	(1.551)	(0.456)	(0.426)	(0.117)
Age [12-17] months	−2.853**	0.641*	−0.176	0.125
	(1.185)	(0.349)	(0.421)	(0.116)
Age [18-23] months	−3.626***	0.823***	0.030	0.059
	(1.000)	(0.294)	(0.416)	(0.114)
Age [24-29] months	−4.536***	1.021***	−0.036	0.073
	(0.831)	(0.244)	(0.416)	(0.114)
Age [30- 36] months	−5.342***	1.232***	0.001	0.049
	(0.669)	(0.197)	(0.410)	(0.113)
Adverse-weather**Age [12-17] months*	−0.126***	0.030***	0.026*	−0.004
	(0.037)	(0.011)	(0.016)	(0.004)
Adverse-weather**Age [18-23] months*	−0.178***	0.034***	0.021	−0.005
	(0.042)	(0.012)	(0.018)	(0.005)
Adverse-weather**Age [24-29] months*	−0.147***	0.026**	0.039**	−0.008*
	(0.039)	(0.011)	(0.016)	(0.004)
Adverse-weather**Age [30- 36] months*	−0.116***	0.016	0.022	−0.007
	(0.040)	(0.012)	(0.017)	(0.005)
FE	Y	Y	Y	Y
Observations	17,835	17,835	17,904	17,904
Adjusted R^2	0.594	0.530	0.281	0.176

Table 11. Effects of exposure to adverse weather conditions across age groups

Note: This regression result extends the main model's findings. Adverse weather represents precipitation < 0.5 mm for HAZ and stunting columns, and temperature > 26 °C for WHZ and wasting columns. The total age-specific effects are calculated as β1 + β2, where β1 is the coefficient for adverse weather in the age group of 6 to 11 months, and β2 is the coefficient for the associated age-specific interaction term for the rest of the age groups. Standard errors are clustered at the regional level.

Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

D. Location-specific effects of adverse weather conditions

	HAZ	Stunted	WHZ	Wasted
	(1)	(2)	(3)	(4)
Precipitation < 0.5 mm	−0.058	0.013	0.031*	−0.006
	(0.071)	(0.021)	(0.018)	(0.005)
Precipitation > 4 mm	−0.163	0.033	−0.018	0.002
	(0.123)	(0.036)	(0.021)	(0.006)
Temperature < 16 °C	−0.020	−0.012	0.014	−0.003
	(0.054)	(0.016)	(0.012)	(0.003)
Temperature > 26 °C	−0.007	0.012	−0.079***	0.014***
	(0.045)	(0.013)	(0.012)	(0.003)
Tropical-zones	−0.926	0.224	−0.186	0.145
	(1.553)	(0.457)	(0.425)	(0.117)
Subtropical-zones	−0.606	0.191	−0.169	0.147
	(1.556)	(0.458)	(0.427)	(0.117)
Temperate-zones	−0.458	0.072	−0.106	0.132
	(1.571)	(0.462)	(0.430)	(0.118)
Adverse-weather* *Subtropical*	−0.089**	0.013	0.043*	−0.014**
	(0.037)	(0.011)	(0.024)	(0.007)
Adverse-weather* *Temperate*	−0.129**	0.042**	−0.025	0.038
	(0.055)	(0.016)	(0.114)	(0.031)
FE	Y	Y	Y	Y
Observations	17,835	17,835	17,904	17,904
Adjusted R^2	0.593	0.530	0.281	0.176

Table 12. Effects of exposure to adverse weather conditions across agro ecological zones

Note: This regression result extends the main model's findings. Adverse weather represents precipitation < 0.5 mm for HAZ and stunting columns, and temperature > 26 °C for WHZ and wasting columns. The total agroecology-specific effects are calculated as β1 + β2, where β1 is the coefficient for adverse weather in the age group of 6 to 11 months, and β2 is the coefficient for the associated agroecology-specific interaction term for the rest of the age groups. Standard errors are clustered at the regional level.
Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

REFERENCES

Ahmed, K. Y., Page, A., Arora, A., Ogbo, F. A., & collaboration (GloMACH), G. M. and C. H. R. (2020). Associations between infant and young child feeding practices and acute respiratory infection and diarrhoea in Ethiopia: A propensity score matching approach. *PLOS ONE*, *15*(4), e0230978. https://doi.org/10.1371/journal.pone.0230978

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

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers*, *58*(3), 450–474. https://doi.org/10.1093/oep/gpl008

Bahru, B. A., Bosch, C., Birner, R., & Zeller, M. (2019). Drought and child undernutrition in Ethiopia: A longitudinal path analysis. *PLOS ONE*, *14*(6), e0217821. https://doi.org/10.1371/journal.pone.0217821

Bandyopadhyay, S., Kanji, S., & Wang, L. (2012). The impact of rainfall and temperature variation on diarrheal prevalence in Sub-Saharan Africa. *Applied Geography*, *33*, 63–72. https://doi.org/10.1016/j.apgeog.2011.07.017

Black, R. E., Allen, L. H., Bhutta, Z. A., Caulfield, L. E., De Onis, M., Ezzati, M., Mathers, C., & Rivera, J. (2008). Maternal and child undernutrition: Global and regional exposures and health consequences. *The Lancet*, *371*(9608), 243–260. https://doi.org/10.1016/S0140-6736(07)61690-0

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., de Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R., & 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

Blom, S., Ortiz-Bobea, A., & Hoddinott, J. (2022). Heat exposure and child nutrition: Evidence from West Africa. *Journal of Environmental Economics and Management*, *115*, 102698. https://doi.org/10.1016/j.jeem.2022.102698

Dimitrova, A. (2021). Seasonal droughts and the risk of childhood undernutrition in Ethiopia. *World Development*, *141*, 105417. https://doi.org/10.1016/j.worlddev.2021.105417

FAO. (2022). *The State of Food Security and Nutrition in the World 2022*. FAO. https://doi.org/10.4060/cc0639en

FEWSNET. (2022). *Ethiopia—Food Security Outlook Update: Thu, 2022-08-04 | Famine Early Warning Systems Network*. https://fews.net/east-africa/ethiopia/food-security-outlook-update/august-2022

Funk, C., Harrison, L., Segele, Z., Rosenstock, T., Steward, P., Anderson, C. L., Coughlan de Perez, E., Maxwell, D., Endris, H. S., Koch, E., Artan, G., Teshome, F., Aura, S. M., Galu, G., Korecha, D., Anderson, W., Hoell, A., Damerau, K., Williams, E., … Hughes, D. (2023). Tailored Forecasts Can Predict Extreme Climate Informing Proactive Interventions in East Africa. *Earth's Future*, *11*(7), e2023EF003524. https://doi.org/10.1029/2023EF003524

Hagos, S., Lunde, T., Mariam, D. H., Woldehanna, T., & Lindtjørn, B. (2014). Climate change, crop production and child under nutrition in Ethiopia; a longitudinal panel study. *BMC Public Health*, *14*(1), 884. https://doi.org/10.1186/1471-2458-14-884

Helldén, D., Andersson, C., Nilsson, M., Ebi, K. L., Friberg, P., & Alfvén, T. (2021). Climate change and child health: A scoping review and an expanded conceptual framework. *The Lancet Planetary Health*, *5*(3), e164–e175. https://doi.org/10.1016/S2542-5196(20)30274-6

Hoddinott, J., Alderman, H., Behrman, J. R., Haddad, L., & Horton, S. (2013). The economic rationale for investing in stunting reduction. *Maternal & Child Nutrition*, *9 Suppl 2*(Suppl 2), 69–82. https://doi.org/10.1111/mcn.12080

Isabel, M., K, B., J, B., I, T., P, W., I, D., & R, S. (2021). The Impact of Rainfall Variability on Diets and Undernutrition of Young Children in Rural Burkina Faso. *Frontiers in Public Health*, *9*. https://doi.org/10.3389/fpubh.2021.693281

Levy, K., Smith, S. M., & Carlton, E. J. (2018). Climate Change Impacts on Waterborne Diseases: Moving Toward Designing Interventions. *Current Environmental Health Reports*, *5*(2), 272–282. https://doi.org/10.1007/s40572-018-0199-7

Lyon, B., Dinku, T., Raman, A., & Thomson, M. C. (2017). Temperature suitability for malaria climbing the Ethiopian Highlands. *Environmental Research Letters*, *12*(6), 064015. https://doi.org/10.1088/1748-9326/aa64e6

MoA. (1998). *Agro-ecological zones of Ethiopia*. MoA.

Ortiz-Bobea, A., Wang, H., Carrillo, C. M., & Ault, T. R. (2019). Unpacking the climatic drivers of US agricultural yields. *Environmental Research Letters*, *14*(6), 064003. https://doi.org/10.1088/1748-9326/ab1e75

Randell, H., Gray, C., & Grace, K. (2020). Stunted from the start: Early life weather conditions and child undernutrition in Ethiopia. *Social Science & Medicine*, *261*, 113234. https://doi.org/10.1016/j.socscimed.2020.113234

Rieger, M., & Trommlerová, S. K. (2016). Age-Specific Correlates of Child Growth. *Demography*, *53*(1), 241–267. https://doi.org/10.1007/s13524-015-0449-3

Romanello, M., Di Napoli, C., Drummond, P., Green, C., Kennard, H., Lampard, P., Scamman, D., Arnell, N., Ayeb-Karlsson, S., Ford, L. B., Belesova, K., Bowen, K., Cai, W., Callaghan, M., Campbell-Lendrum, D., Chambers, J., Van Daalen, K. R., Dalin, C., Dasandi, N., … Costello, A. (2022). The 2022 report of the Lancet Countdown on health and climate change: Health at the mercy of fossil fuels. *The Lancet*, *400*(10363), 1619–1654. https://doi.org/10.1016/S0140-6736(22)01540-9

Segele, Z. T., & Lamb, P. J. (2005). Characterization and variability of Kiremt rainy season over Ethiopia. *Meteorology and Atmospheric Physics*, *89*(1), 153–180. https://doi.org/10.1007/s00703-005-0127-x

Shrimpton, R., Victora, C. G., de Onis, M., Lima, R. C., Blössner, M., & Clugston, G. (2001). Worldwide Timing of Growth Faltering: Implications for Nutritional Interventions. *Pediatrics*, *107*(5), e75. https://doi.org/10.1542/peds.107.5.e75

Siraj, A. S., Santos-Vega, M., Bouma, M. J., Yadeta, D., Ruiz Carrascal, D., & Pascual, M. (2014). Altitudinal changes in malaria incidence in highlands of Ethiopia and Colombia. *Science (New York, N.Y.)*, *343*(6175), 1154–1158. https://doi.org/10.1126/science.1244325

Sun, F., Dai, Y., & Yu, X. (2017). Air pollution, food production and food security: A review from the perspective of food system. *Journal of Integrative Agriculture*, *16*(12), 2945–2962. https://doi.org/10.1016/S2095-3119(17)61814-8

Swinburn, B. A., Kraak, V. I., Allender, S., Atkins, V. J., Baker, P. I., Bogard, J. R., Brinsden, H., Calvillo, A., De Schutter, O., Devarajan, R., Ezzati, M., Friel, S., Goenka, S., Hammond, R. A., Hastings, G., Hawkes, C., Herrero, M., Hovmand, P. S., Howden, M., … Dietz, W. H. (2019). The Global Syndemic of Obesity, Undernutrition, and Climate Change: The Lancet Commission report. *The Lancet*, *393*(10173), 791–846. https://doi.org/10.1016/S0140-6736(18)32822-8

Teklehaimanot, H. D., Lipsitch, M., Teklehaimanot, A., & Schwartz, J. (2004). Weather-based prediction of Plasmodium falciparum malaria in epidemic-prone regions of Ethiopia I. Patterns of lagged weather effects reflect biological mechanisms. *Malaria Journal*, *3*, 41. https://doi.org/10.1186/1475-2875-3-41

UNICEF. (2023). *Children in Ethiopia | UNICEF Ethiopia*. https://www.unicef.org/ethiopia/children-ethiopia

Victora, C. G., Adair, L., Fall, C., Hallal, P. C., Martorell, R., Richter, L., Sachdev, H. S., & Maternal and Child Undernutrition Study Group. (2008). Maternal and child undernutrition: Consequences for adult health and human capital. *Lancet (London, England)*, *371*(9609), 340–357. https://doi.org/10.1016/S0140-6736(07)61692-4

Victora, C. G., De Onis, M., Hallal, P. C., Blössner, M., & Shrimpton, R. (2010). Worldwide Timing of Growth Faltering: Revisiting Implications for Interventions. *Pediatrics*, *125*(3), e473–e480. https://doi.org/10.1542/peds.2009-1519

Wakjira, M. T., Peleg, N., Anghileri, D., Molnar, D., Alamirew, T., Six, J., & Molnar, P. (2021). Rainfall seasonality and timing: Implications for cereal crop production in Ethiopia. *Agricultural and Forest Meteorology*, *310*, 108633. https://doi.org/10.1016/j.agrformet.2021.108633