CLIMATE VARIABILITY AND CHILD HEALTH OUTCOMES IN THE SOUTH ASIAN REGION

by

PRAYASH PATHAK CHALISE

(Under the Direction of Genti Kostandini)

ABSTRACT

Extreme weather variations, chronic food insecurity, and lack of coping mechanisms place children in South Asia at a high risk. While there is a large body of literature documenting the effect of precipitation extremes on child health in this region, there is a lack of research work focusing on temperature- related extremities and analyzing differential vulnerabilities among various socio-demographic groups. This study examines the effect of climate variability on birth and early childhood health parameters by combining high-resolution climate data with child anthropometry and demographic data from four South Asian countries (India, Pakistan, Bangladesh, and Nepal). We find temperature and precipitation anomalies to be strong negative predictors of child health outcomes with their effects concentrated mostly in-utero period. We further expand on our findings by looking at how these effects differ across groups based on economic, gender and social vulnerabilities.

INDEX WORDS: Climate change, Child health outcomes, South Asia, Pre-natal climate anomalies, Differential vulnerabilities

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DEDICATION

I dedicate my thesis to my family and friends.

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CHAPTER 1

INTRODUCTION AND BACKGROUND

The manifestation of climate change in the form of changing variation in global temperature and precipitation has been well recognized in the past few decades and has sparked the discussion of how climate change affects human health (UNICEF, 2014). A report of the Intergovernmental Panel on Climate Change (IPCC) published in 2007 identified the effect of climate variation on food security and undernutrition of developing countries as the largest single most detrimental effects of climate variation on health (Hales & Akhtar, 2007). Those suffering the greatest from climate variations are the poorest and most vulnerable sub-groups of world population like pregnant women and children belonging to the marginalized communities because of their limited adaptive capacity, higher dependence on climate sensitive resources and direct exposure to climate change effects. However the extent of these effects is still unclear (WFO, 2009). With further projections of disruptions in food supply systems due to worldwide changes in climate patterns worldwide, the vulnerability of at-risk populations to the effect of climate change is a critical research topic (Thiede, 2019; McMahon & Gray, 2021).

This study investigates the level to which exposure to climate variation affects early childhood health parameters of children from four developing South Asian countries. Despite of various previous studies, there are many identified research gaps which have not been fully addressed fully. First, most of these studies lack a specific focus on child group populations; they study relationship between climate and human health while including children as a subgroup of analysis. Second only, few of these articles try to dig deeper by differentiating the analysis based on various vulnerability categories like sex, age, caste, and others. Third, lack of quantitative research restricts a comprehensive understanding of the climate-child health relationships (Sheffield & Landrigan, 2011). Finally, most of these studies are focused only on high-income countries in Europe and North America even though the effect on children varies largely based on the prevailing inequalities both within and between countries (Helldén et al., 2021). Disadvantaged children of developing countries suffer from a disproportionately higher unjust burden of climate change impacts which further exacerbates the inequalities in income and health status (Stephenson et al., 2010). Mendelsohn et al. (2006) links this vulnerability to the location of the poor countries, followed by the reasoning that these countries lying in low latitudes already start with higher temperatures meaning more increase in temperature adds on to the effects seen in climate-sensitive economic sectors.

Coupled with the insufficiency in technology, wealth, and overall mitigation strategies studies on the effect of climate change on human health needs to be focused on low-income developing countries of the world, however there is limited knowledge and research on identifying which regions suffers the most from the effect of climate change (Rylander et al., 2013).

Our study deviates from the previous literatures and makes the following contributions. First, we provide a comprehensive summary of climate and child health relationship by quantifying the impact of temperature and precipitation variation, measured as deviations from locations specific historic norms, on both childbirth weight and child nutritional indicators. Previous literature focus only on either one of the climate variables or one of the child health parameters. Second, identification of vulnerable periods in first 1000 days of child's life to such exogenous (assumed) effects of climate variation is done. To do so, we divide these 1000 days of exposure into different time like prenatal (in-utero) period[1], first year and second year of child life so that we can identify the period of highest vulnerability. Third, we test of differential level of vulnerability among various socio-demographic groups to identify populations at highest risk of exposure. Finally, we add to the scarce literature on climate vulnerability and health in the South Asian region and identify potential mitigating measures that affect this vulnerability.

To explore the relationship between climate variation and child health, we first link the socio-demographic and health data of each individual child, obtained from Demographic and Health Survey (DHS), with their location specific climate data, taken from publicly available Climate Research Unit Time Series (CRU TS) data. DHS surveys provide rich information not only on our main dependent variables: childbirth weight and child anthropometric measures (like height-for-age, weight-for-height, and weight-for-age) but also specify socio-demographic variables which are essential to be used as controls. Based on the Global Positing System (GPS) information we can identify the geographic locations (latitude and longitude) of each survey clusters which is then linked with its respective monthly climate data from CRU TS. Then, based on child's birth date and detailed spatial information, we construct our main explanatory variables (i.e., deviations of time specific climate variables from long-run average of total climate variables) for each individual child clusters[2].

Using exogenous variation in temperature or precipitation deviation from long term local average to which the child was exposed, we reach the following findings. First, both temperature and precipitation variability are important predictors of early child health outcomes, with precipitation anomalies displaying comparatively stronger negative effects in case of nutritional

[1] In case of birth weight, we further divide the prenatal period into four different trimesters of pregnancy.
[2] The word "time-specific" here refers to what the variable of interest is, for example if we are looking at prenatal temperature anomalies then our calculation time is 9 months, similarly if we are looking at anomalies in first year of child's life then our calculation time is 12 months.

indicators while temperature variability doing so in case of birthweight measures. Second, in-utero exposure to these climate anomalies seem to significantly affect child health parameters as compared to exposure during other first 1000 days of child's life. Third, socio-demographic characteristics also play a highly significant role on either buffering the child against such shocks or adding on to the pre-existing vulnerabilities of the economically and socially disadvantaged groups. Finally, we find that mitigative measures like basic awareness on cleanliness and hygiene, access to improved toilet and drinking water, promoting maternal education and development of human capital can help mitigate the detrimental impacts of climate variation on child health outcomes in South Asia region.

The remainder of the thesis is organized as follows: Chapter 2 provides a literature review. Chapter 3 describes our data source and summary statistics, following this Chapter 4 explains the empirical methods. Chapter 5, then reports the estimated result which is discussed in more detail in Chapter 6. Finally, Chapter 7 provides a conclusion of the thesis along with limitations and recommendation for future research.

CHAPTER 2

LITERATURE

2.1. Climate variability and vulnerability of South Asia

The climate of South Asia can be characterized by strong seasonal variations, high temperature and humidity, and seasonal monsoon with heavy precipitation (Janes et al., 2019) which can also be seen in the graphs plotted in figure 1 and 2. A recent increase in occurrence of extreme weather events in different parts of this region is now seen as an evidence of climate change. For example, during the period of 1990 to 2010 Afghanistan experienced the highest temperature increase of 0.27^{0}C and Maldives the smallest temperature increase of 0.07^{0}C (Tiwari et al., 2022). Similarly, from 2005 to 2016, the region experienced a total of 481 climatic disasters in the form of landslides, droughts, wildfires, cyclone, and floods which are also projected to increase (Tiwari et al., 2022). Researchers have reached a common consensus of projected increase in temperature and heavy intense annual precipitation across various South Asian countries by the end of 21^{st} century (Kumar et al., 2013; Philip et al., 2019).

Despite an improvement in economic conditions, many countries in South Asia still report high rate of child and maternal mortality (Alimohamadi et al., 2019). South Asia is home to over 600 million children, and among them it bears the burden of $2/3^{rd}$ of the global malnutrition and 34% of the global child death with an estimated half of the global maternal deaths (Bhutta et al., 2004). Global stunting rates decreased by more than 40% since the past two decades, but still almost 37% of South Asian children continue to suffer from stunting with higher increase rates among poor rural children (UNICEF, 2016). Malnutrition is a major public health issue in South

Asia leading to cases of wasting, underweight and stunting, all of which have been recognized to cause serious economic distress among at-risk populations (Akhtar, 2016). Similarly, South Asia also reports 21-28%, the highest rate of low-birth-weight incidences (i.e., birthweight less than 2500g) in the world (UN, 2009).

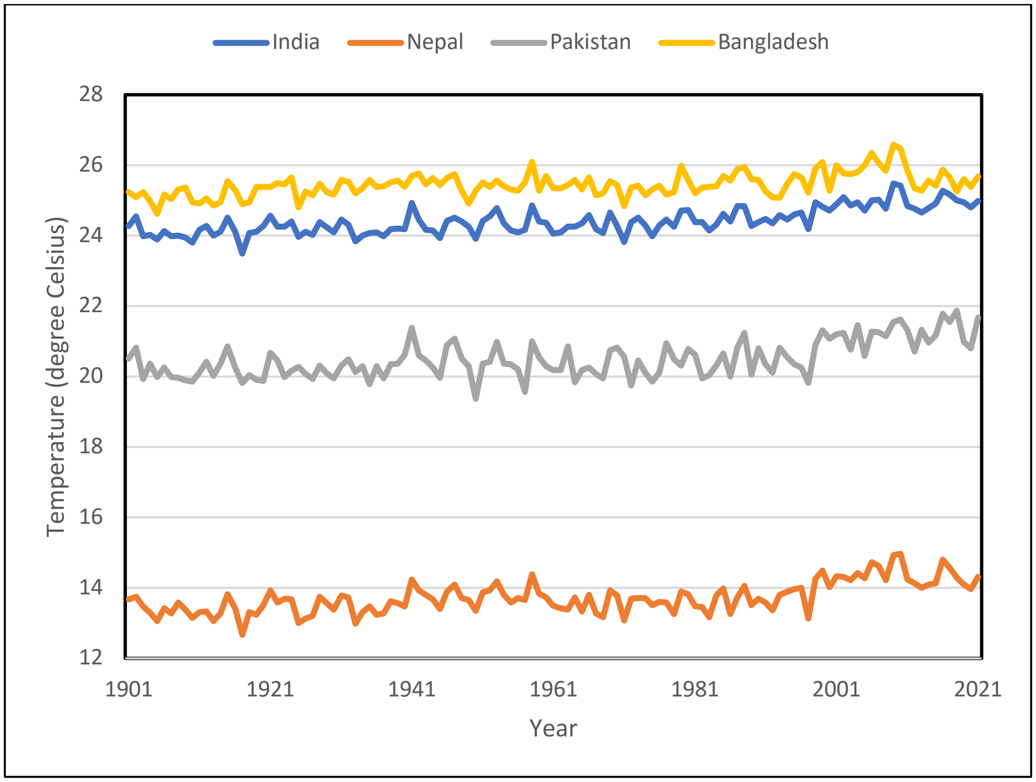

Figure 1. Annual average temperature variation in South Asia
Source: Self constructed from the CRU TS database

Coupled with an unprecedented rate of natural resource degradation, high rate of population increases, and continuing growth in levels of food insecurity and poverty, these effects of climate change make South Asia a highly vulnerable region (Sivakumar & Stefanski, 2011). By 2050, projections have shown an increase in moderate stunting of 1-29% along with an estimated increase in rate of severe stunting in South Asia by 62% because of climate change (Llyod et al., 2011). UNICEF (2021) published its first ever child focused “Children’s Climate Risk Index (CCRI)” where it ranked four South Asian countries namely, India, Pakistan, Afghanistan, and Bangladesh at an extremely high risk of climate crisis impacts with calls for immediate investment in education, nutrition, and child health.

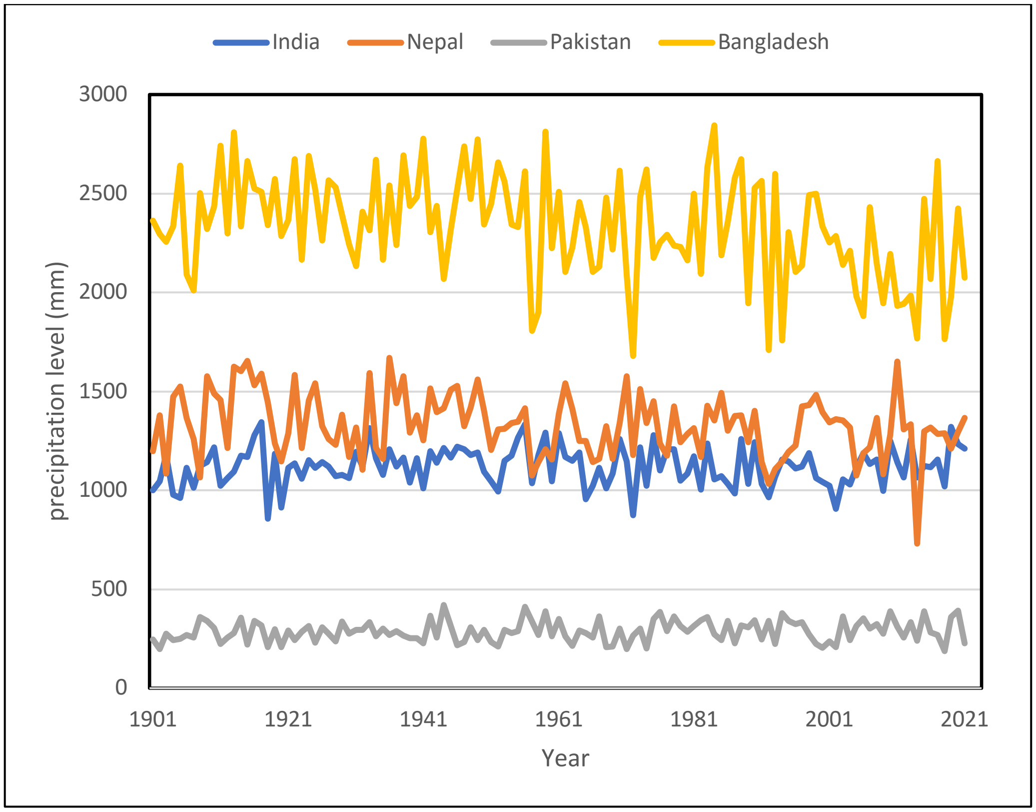

Figure 2. Annual average precipitation variation in South Asia
Source: Self constructed from the CRU TS database

Figure 3 shown below is a state-wise representation of the low birth and stunting prevalence in four countries of South Asia- India, Pakistan, Bangladesh, and Nepal. This figure was plotted from the child health data obtained from DHS for the most recent survey years of each country. Color coding is done to identify states with highest rate of child health depravities. It is evident from the figure, that most of these states display high rate of child health depravity in terms of percentage of children stunted (as high as 31.57%) and born with low birthweight (as high as 26.66%).

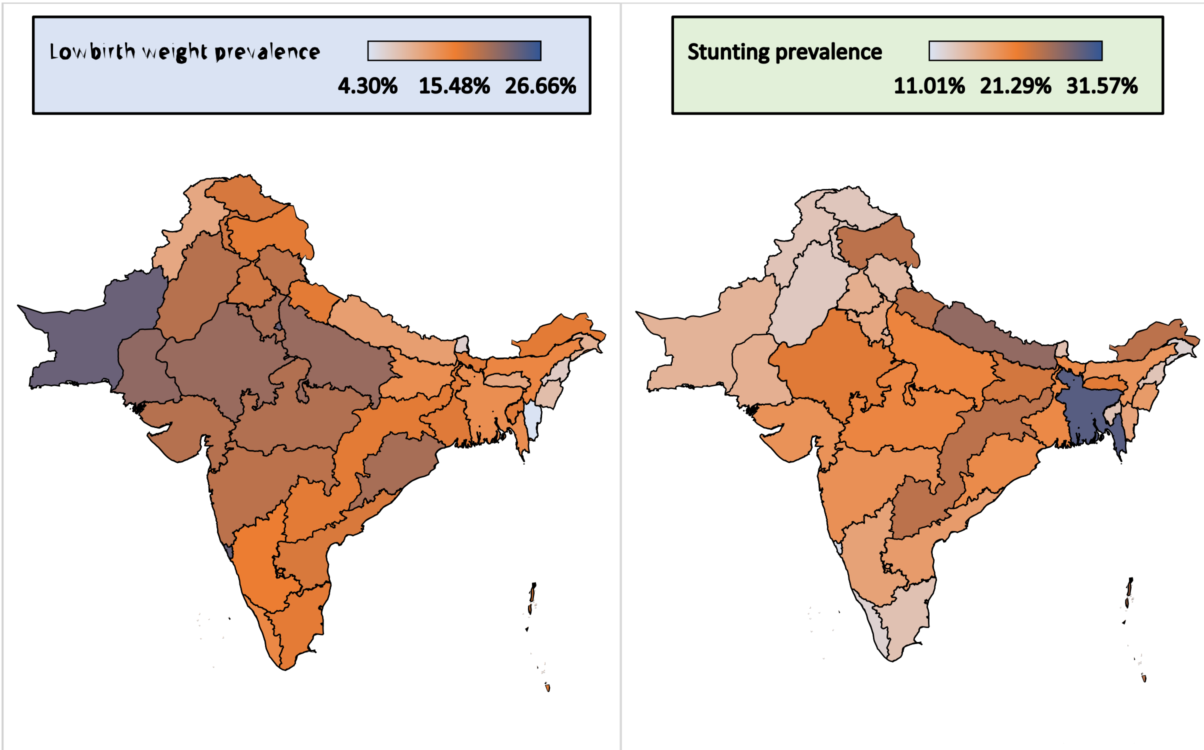

Figure 3. Study area plotted with low-birth-weight indicator (left) and stunting indicator (right)
Source: Self constructed from the DHS database

2.2.Relationship between climate variation and child health

A rich body of literature has already established that climate change acts through various pathways to negatively affect the health and well-being of children (Ebi & Paulson, 2007; O'Neill & Ebi, 2009; Seal & Vasudevan, 2011; Philipsborn & Chan, 2018; Helldén et al., 2021). In general, studies agree that children are more exposed to the consequences of climate change because of their developing physiology and the probability of long-term exposure (Bunyavanich et al., 2003; Patz et al., 2007; Helldén et al., 2021). Bust and Pedro (2022) identify the first 1000 days of child's life as the most vulnerable period of exposure in South Africa where the effects are manifested directly or indirectly through mechanisms like heat stress, extreme weather events, food insecurity or mass migration (Patz et al., 2005; Kim et al., 2014).

Generally, three pathways are commonly explored when trying to understand the climate-child health relationship: heat stress, infectious disease transmission and agricultural livelihood

(Randell et al., 2020; Bratti et al., 2021). Prolonged exposure to high temperatures causes heat stress that has proven to lead to significant impairments in fetal development (Ravanelli et al., 2019). Also, most of the developing countries depend on favorable temperature and rainfall conditions to improve food security and household income through abundant livestock and crop harvest (Kotir, 2011). Finally, adverse weather conditions also exacerbate cases of water borne diarrheal diseases or vector-borne malarial diseases considered highly detrimental to the health of young children and pregnant mothers (McMicheal, 2015).

These above effects can be described as either direct or indirect. Direct effects act through pathways like heatwaves, flooding and droughts. Heatwaves have been reported to evidently increase the risk of child mortality, more strongly among infants and older age populations in low- or middle-income households (Nathalie et al., 2015; Philipsborn & Chan, 2018). Similar effect has been seen because of flooding or extreme precipitation where the damages get further amplified over long term because of nutritional insecurity and spread of communicable diseases (Zhang et al., 2019). Similarly, in case of indirect effects, studies report alterations in distributions of vectors and pathogen transmissions because of climate change extracting heavy toll on children (UNICEF, 2008). Climate change in the form of frequent and extreme weather events has also been linked with increase in mental health illness with higher level of emotional distress among young people (Ojala, 2012). Recent literature has now focused on studying the effect of in-utero and early life exposure to climate change. Empirical studies have shown detrimental effects of climate change on child nutrition, though the interaction between climate change and under/overnutrition is less understood and complex (Swinburn et al., 2019). Likewise, studies have also associated temperature change during pregnancy with preterm birth, and low precipitation and extreme temperature with cases of lower birthweight and pregnancy complications (Carolan-Olah & Frankowska, 2014; Ngo & Horton, 2016).

Several climate and child health relationships in low-income country context have been examined in the previous literature, however most of them tend to focus specifically on Sub-Saharan African countries (SSA). The literature on climate change and child anthropometrics is growing but at a relatively small rate (Freudenreich et al., 2022) and since, different countries face different levels of climate exposures and employ country-specific mitigation measures it makes sense to focus on relatively new study regions like South Asia.

There are previous studies in SSA, Thiede and Strube (2020) studied the effect of climate variability on child nutrition in 18 SSA countries. Using linear regression models, the authors reported positive relationship between child weight reduction and high temperature and low precipitation anomalies, and high temperatures to increase the risk of wasting. Davenport et al. (2017) conducted an extensive study of child health outcomes in SSA by studying the relationship between child malnutrition and low birth weight with projected scenarios of climate change differing between various socio-economic development conditions revealing possible mitigation of the negative effect of drying and warming on child stunting through increased access to electricity and educational level of mother. The authors also reported relatively small changes in birth weights because of projected warming and drying scenarios which could not be mitigated by similar positive trends in socio-economic developments.

Grace et al. (2015) studied the relationship between temperature and precipitation on birth weight outcomes in 19 African countries by matching birth weight and socio-demographic data from DHS surveys from 1986 to 2010 with gridded climate dataset from CRU time series. The results suggested that decreasing precipitation and an increase in number of hot days positively correlated with lower birth weight and increase the probability of low birth weight (LBW). The authors also allowed the observed effect of weather variables to vary across different livelihood zones to test different level of vulnerability among population with different covariates. Finally, the authors conclude increasing women's education and household electricity access as possible control mechanisms. Baker and Anttila-Hughes (2020) quantified the relationship between increase in ambient temperature and child nutrition by combining anthropometric data for 192,000 children from 30 African countries with historical temperature data. The authors first established strong negative relationship between temperature increase in months leading to survey, year leading to survey and child's lifetime with decline in acute malnutrition measures. Then, predicted an increase (as high as 37%) in prevalence of wasting by 2100 based on local temperature projections.

Looking individually at Nigeria, van der Merwe et al. (2022) used LSMS (Living Standards Measurement Study) dataset to report higher probability of malnutrition among children exposed to decreasing precipitation and increasing temperature with the observed effect concentrated more in rural areas. More specifically, one unit increase in previous year temperature seemed to increase the probability of a child being stunted in urban area by 0.53% and by 0.71% in rural areas. For countries like Nigeria with majority of population subsisting through agriculture, the authors suggest policies promoting climate-smart agricultural practices to reduce these detrimental effects.

Thiede et al. (2022) studied the relationship between temperature and precipitation variability on plausible changes in probabilities of childbearing combining high resolution global gridded climate dataset with birth histories data from DHS across 23 SSA countries. The authors reported mothers who experienced spells of precipitation and temperature anomalies showing reductions in fertility probability in the following year. In another study, focused on analyzing the relationship between women's reproductive goals and climate variability in SSA, Eissler et al. (2019) used 40 rounds of DHS survey collected between 1990 to 2015 to estimate statistical relationship between temperature and precipitation anomalies with women's Ideal Family Size (IFS) and fertility preferences. One S.D. increase in temperature anomalies 12 and 60 months prior to survey time was associated with respective reduction in IFS by greater then 0.042 and 0.101 children. Similarly, a women exposed to high temperatures had decreased preference of wanting a first or additional child meaning environmental stress can lead to expected fertility decline the reasoning behind it being entry of women into labor force and increase in incidence of intra-household conflict. In contrast precipitation anomalies during the 60 months prior period seemed to positively increase IFS which the authors attribute to generation of favorable agricultural condition leading to need for additional household labor force.

Blom et al. (2022) studied the cumulative effects of exposures to different bins of temperature on child nutrition in six different SSA countries linking 15 rounds of DHS surveys with gridded weather dataset from Princeton Terrestrial Hydrology Research Group. Restricting their study to children within 3-36 months of age, the authors found significant increase in prevalence of chronic and acute malnutrition because of lifetime exposure to temperatures above 35^0C and recent exposures to temperature of 30-35^0C respectively. These extreme temperature range were also related to a 18% and 16% increase in prevalence of stunting and wasting, respectively. Deviating slightly from this, Bratti et al. (2021) studied the effects of prenatal exposure of heat waves among children in SSA. Using Heat Wave Magnitude Index, as an indicator of heat wave, the authors investigated the effect of in-utero exposure to heat waves on child health variables like Height-for-age z scores (HAZ), Weight-for-age z scores (WAZ), undernutrition and severe undernutrition, stunting and severe stunting, anemia, birth weight and low birth weight. The second and third trimester of pregnancy were identified to be highly vulnerable to heat waves of higher intensity. Also, the overall detrimental effects were calculated to be most severe in increasing the probability that the child is stunted because of these exposures. Unlike previous research, the authors reported no significant role of adaptation mechanisms like electricity, improved water, and housing on mitigating these negative impacts, at least in the case of SSA countries.

Looking at a different region, Molina and Saldarriaga (2017) studied the effects of in utero exposure of temperature variability (measured as fluctuate=ions from historical mean) on different birth outcome variables focusing on three developing countries in the Andean region. The authors reported exposure to temperature anomalies one S.D. above the historical mean during pregnancy reduced birth weight by 20 grams while increasing the probability of low birth weight in child by 0.7 percentage points. They also explored potential channels explaining their derived results and identified decrease in health care and increase in food insecurity for pregnant mother as the major pathway variables. Similarly, being focusing on Kyrgyzstan, a country predicted to suffer from extreme future scenarios of weather events and climate change, Freudenreich et al. (2022) analyzed the effect of three types of weather shocks (cold winters, droughts, and extreme rainfall events) on the probability of being stunted among children of 0-60 month of age. Employing fixed effect regression models by controlling for household, children, mother, year and state fixed effects, the authors reported cold shocks experience in winter to be highly detrimental for children under 20 months of age with the effects being more pronounced for households depending on electricity for indoor heating. Excessive rainfall in autumns were also seen to be more harmful which the authors attribute to the geographical delineation of Kyrgyzstan citing majority of its population to be vulnerable to flooding and landslides which frequently abrupt health care access and increases food prices.

With respect to studies focused within South Asian region, McMahon and Gray (2021) combined high resolution climate dataset with socio-demographic dataset from DHS to calculate the effect of climate change on child nutrition in four South Asian countries (India, Nepal, Pakistan, and Bangladesh). Along with monthly measures of climate exposures the authors supplemented their climate variable by including data on daily maximum and minimum precipitation and temperature rate for each survey unit. The authors reported child growth in these four South Asian countries are undermined severely by unusually wet days on first year of child's life and extreme temperature exposure during the first two year of life with these effects being severely concentrated among resource poor households with low rate of maternal education and access to electricity. Likewise, Le and Nguyen (2021) studied how does in-utero rainfall shock affects child health by combining DHS and CRU, TS dataset for 55 low-income countries. Assuming long run deviations of in-utero rainfall exposures as exogenous shocks, the authors first conclude adverse early childhood health outcomes because of increased rainfall variability. Then, by grouping children of similar age brackets, they report comparatively stronger effects during first year of child's life and in some cases the harmful effects lasting till later years. Finally, using heterogeneity analysis, the authors identify severe detrimental effects among socially disadvantaged population groups.

Focusing on one South Asian country, Tiwari et al. (2016) analyzed the seasonal agriculture of Nepal and timing of rainfall shocks to figure out the effect of precipitation variability on early anthropometric measures of children in rural places of Nepal. The authors report excess monsoon rainfall in second year of child life to significantly impact male and female stature linking this vulnerability to the transitional period of shift towards family diet. However, they do mention this effect to be only transitory, disappearing completely by the time the child turns 5 years of age while also identifying food insecurity as the major pathway variable. Finally, the authors conclude a 0.13 S.D. increase in weight for height for children aged 0-60 months who experienced a 10% increase in rainfall as compared to historic means.

Similarly, Dimitrova and Bora (2020) studied the detrimental effects of monsoon weather shocks on early childhood undernutrition in India. Using multivariate logistic regression, the authors reported increased risk of child undernutrition because of exposure to climate anomalies during in-utero and infancy period. Diving a bit deeper into various topographical setting, they found elevated risk of stunting among children residing in tropical wet and sub-tropical humid regions, whereas reduced risk of stunting for those in mountainous regions. Finally, the authors identify water-transmittable disease like diarrhea as the channel connecting excessive rainfall with stunting.

Focusing on the socio-economic settings of South Asia and its relation to child health variables, Krishna et al. (2018) studied the socio-economic disparities in child stunting rates among four South Asian countries-India, Bangladesh, Nepal, and Pakistan. Using logistic regression model to study the relationship between probability of stunting and three groups of disadvantages (social, economic, and dietary), the authors recorded high rate of stunting across all countries which seem to increase with increase in socio-economic adversities. More specifically, stunting was found to be concentrated among households which displayed all types of adversity i.e., poor dietary diversity, low or no maternal education and weak economic status. Likewise, Sathi et al. (2022) analyzed socioeconomic disparities in low birth weight (LBW) in South Asia and reported wealth and educational inequalities to be negatively related with LBW among under-five children in South Asia. The study also revealed significant adverse effect of multiple birth, female gender, lack of health seeking behavior and early childbearing- common occurrences in South Asia- on birth weight of newborn babies.

Similarly, Fikree and Pasha (2004) also talk about gender-based health disparity in South Asia. Gender based discrimination starting right from birth is found to contribute significantly to various health inequalities, sex selective abortions, neglect of girl child, reproductive mortality and poor or no health care access. Likewise, Aguayo and Menon (2016) focus on how economic growth alone is not sufficient to solve the issues of child malnutrition and stunting in South Asia. The authors first identify poor diets of children, insufficient nutrition of mother during and before pregnancy and unsanitary household practices as important factoring affecting child stunting in South Asia, then go on to suggest potential strategies to reducing stunting by focusing within these problems.

CHAPTER 3

DATA

3.1. Health and socio-demographic data

This study is based on nationally representative cross-sectional data taken from the Demographic and Health Surveys (DHS) funded by the U.S. Agency for International Development (USAID) (accessible through IPUMS-DHS) combined with high-resolution gridded weather dataset taken from the Climate Research Unit (CRU) a project running under the University of East Anglia. DHS collects periodic data on health and population in more than ninety low- and middle-income countries (LMICs). DHS respondents are selected through a multi-stage sampling process, with geographical areas first being randomly selected followed by a systematic sampling of 20-30 households chosen randomly from a complete list of household dwellings collected for each selected region (Corsi et al., 2012). DHS surveys have been extensively used for demographic and health research and are among the highest quality population health surveys among LMICs (Theide, 2019). Additionally, recent DHS survey also provide high resolution geographic identifiers needed to link it with climate dataset. To be able to integrate demographic data with weather data, we used only those DHS surveys which provided GPS location of the enumeration areas, hence totaling to 13 rounds of DHS surveys including five rounds in Bangladesh (2004, 2007, 2011, 2014, 2017), four rounds in Nepal (2001, 2006, 2011, 2016), and two rounds each in India (2015 and 2020) and Pakistan (2006 and 2017). Clustered level geocodes allow us to link individual survey dataset with gridded temperature and precipitation dataset from

CRU. A sample figure of how these clusters is spread across the surveyed country is given in Figure A1 in the appendix.

We focus our study on two key variables of child health outcomes: childbirth weight and child anthropometric variables. In the case of childbirth weight, we construct two study variables from the DHS dataset which provides detailed information on various indicators of neo-natal health (delivery method, birth weight, birth size, birth complication) for children under five years of age. First, we restrict the sample to remove mothers who were not permanent resident of the enumeration area and were just visiting during the survey time. Similarly, we remove children from multiple births (duplets, triplets, etc.) because twinning is related to low birth weight (Kramer, 1987). Also, we exclude mothers younger than 15 years of age or older than 45 years, so that health condition of the studied children is not in any way affected by mother's age (Kramer, 1987).We also exclude observations with birth weight below 500 gm or above 6500 gm, since they are out of the normal range as defined by the medical literatures (Molina & Saldarriaga, 2017). Based on this dataset, we construct two dependent variables measuring fetal health: a) birth weight of child, a continuous variable containing child weight at birth in grams (gm) and, b) low birth weight, a dummy variable that takes a value of one if the birth weight of the child is less than 2500gm (WHO, 2013). We also construct a dummy independent variable called "birthweight recall" that takes a value of 1 if the reported birthweight was collected from health card or 0 if it was collected from mother's memory.

Similarly, the main dependent variable representing the child nutritional outcomes were the standardized z-scores calculated from the anthropometric height and weight measures of children in relation to sex and age of a reference population. Specifically, three such measures were calculated: height-for-age Z score (HAZ), weight-for-age Z score (WAZ) and weight-for-height Z score (WHZ) and based on them we constructed six more indicator variables based on World Health Organization (WHO, 2006) specifications. For example, from our study if we consider one child of a specific age then first, we calculate their HAZ score by subtracting that child's height from a reference height (De Onis et al., 2004) based on the child's age and then divide this by a reference standard deviation. Now, a child with a HAZ score equal to or less than -2 (two or more standard deviations form a reference mean population) is labelled as "stunted", and "severely stunted" if the z score is equal to or less than -3. Similarly, we compute WHZ score and from it "wasting" and "severe wasting" if WHZ is less than or equal to -2 and -3 respectively. The same approach is used to compute WAZ score and from it "underweight" and "severe underweight" dummy variables if WAZ is less than or equal to -2 and -3 respectively. Through this process, we end up with three continuous and six dummy variables representing child nutritional status. Similarly, we remove biologically implausible observations based on the cut-off score published by WHO (2006). We remove observations for which the child's HAZ score is below -6 or above +6, WAZ score is below -6 or above +5 and WHZ score is below -5 or above +5. A visual representation of our main variables is given in figure 4.

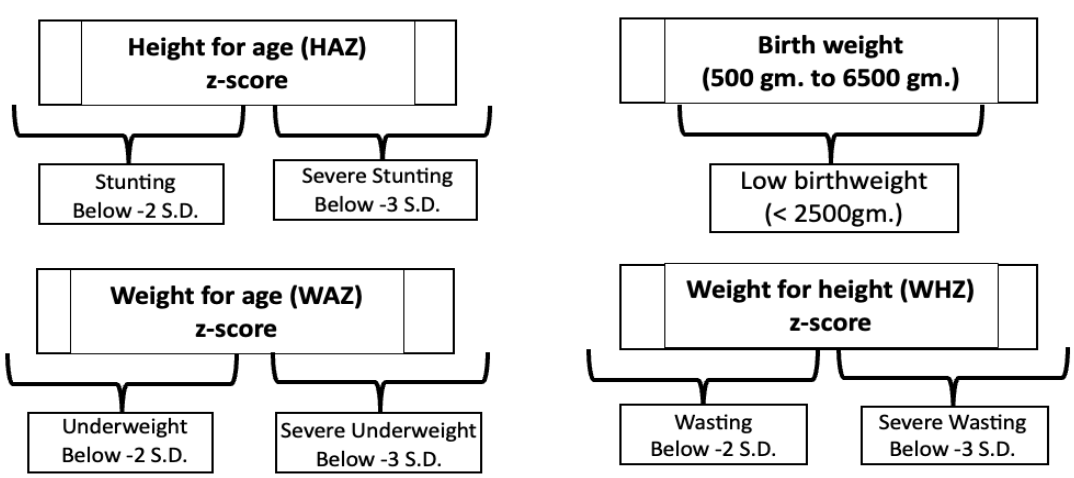

Figure 4. Visual representation of our main study variables
Source: Self constructed

3.2. Climate data

Information on temperature and precipitation is taken from the University of East Anglia Climate Research Unit (CRU). CRU is a global dataset of monthly climate variables like temperature, precipitation, wind velocity, humidity, etc, that is widely used in population-environment research (Randell & Grey, 2019; Theide, 2019). It offers gridded climate dataset at 0.5^{o} X 0.5^{0}-degree resolution (approximately at 56 km at the equator) that can then be linked to the GPS location of DHS surveyed households(Harris et al., 2020). For our study, we extract temperature and precipitation records from 1991 to 2020 for each grid cells the survey location falls in and based on historic deviation calculate climate anomalies for each survey cluster as described below.

To measure temperature and precipitation anomalies, we measure deviations from the long-term average conditions within each cluster of the DHS surveys. Using the geo-codes/GPS location, we first extract 30 year (1991 to 2020) monthly temperature and precipitation records for each surveyed cluster. Then, we define climate anomalies based on fluctuations from historic mean temperature or total precipitation during a given time "t" (Scherrer et al., 2005). To put it simply, these are z-scores that represent standard deviations of temperature/precipitation in a community during the time period *t* and in reference to long term mean and standard deviation of temperature/precipitation in that community for all *t* periods from 1991 to 2020.

The time period (t) with respect to which the anomaly is calculated differs based on the dependent variable of study. If it is child birthweight, then we calculate two kinds of climate anomalies. The first represents pre-natal climate anomaly for which $t=9$ and the other represents climate anomalies during the three trimesters of pregnancy for each of which $t=3$. For instance, if pre-natal temperature anomaly indicates the number of standard deviations during the pre-natal period (9 months) before the child's date of birth with respect to the cluster's historical temperature mean. For a child born in cluster c in year y and month t, where t = {1, 2, ...,12}, it can be represented as follows:

$$SD_{cyt} = [\tfrac{1}{9} \sum_{T=t-8}^{t} (\text{temp}_{cyT} - \overline{\text{temp}_c})] / \sigma_m$$

Here, SD_{cyt} measures the temperature anomaly experienced by the child in utero. The variable temp_{cyT} is the average monthly temperature in the cluster for the T^{th} month before the birth month of the child, $\overline{\text{temp}_c}$ is the cluster's historical temperature mean for 30 years (1991 to 2020) and σ_m is the standard deviation if temperature for this time. A visual representation of time specific climate anomalies calculated for this study is given in figure 5.

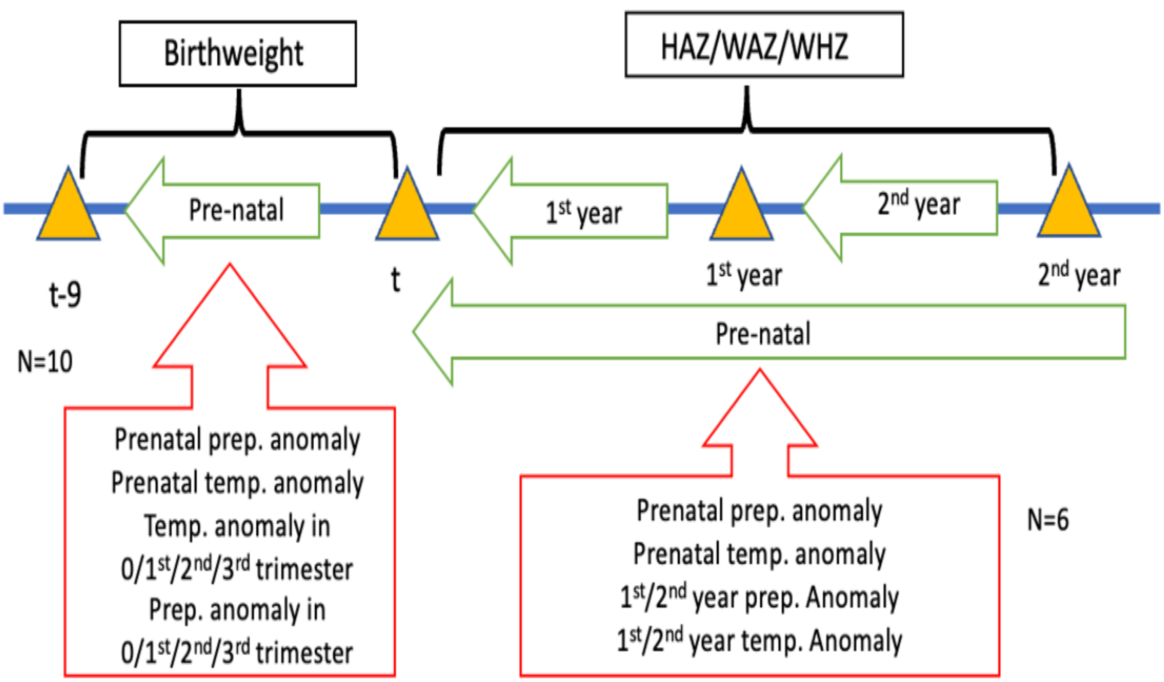

Figure 5. Visual representation of climate anomalies time specific calculation
Source: Self constructed

Similarly, analysis can be done to calculate pre-natal precipitation anomalies. However, if our dependent variable is one of the nine nutritional status indicators, then we calculate three kind of climate anomalies. The first of which is the pre-natal climate anomalies measured just like we explained above. The second one is the climate anomaly measured during the first year of child's life for which *t*= 12 months after birth and the third one if the climate anomaly measured during the second year of child's life for which *t*= 12 months after the first year of birth. The temporal sequence in which the climate variables are calculated is also illustrated in Figure 6. These standardized climate variables provide a comparatively more meaningful deviations from local conditions and can be interpreted as exogenous shocks and are a stronger predictor than raw climate values (McMahon & Gray, 2021).

The compiled dataset is finally divided into two components: those containing data on child birthweight parameters and the other on child nutritional outcomes. These are then cleaned to form a uniform data. We also restrict our sample to include children aged only 24-59 months. This is done to focus on climate exposures within the prenatal period of the children and the two years of life to cover the first 1000 days of child's life which is considered the most vulnerable and key period in child development (Schwarzenberg & Georgieff, 2018) and exposure during these times is shown to be a strong representation of health and development till adulthood (Ramakrishnan et al., 2012). Table 1 provides weighted summary statistics for child nutritional and birthweight parameters. After thorough cleaning and assumed restrictions, we end up with an estimation sample of 81,211 for child nutritional parameters and 87,635 for childbirth weight parameters. The unevenness in size between these two samples can be attributed to incomplete survey information from different survey waves. Table A1 in the appendix provides the country-wise survey year list used to derive out final estimation sample which gives a brief glance of dataset used for this study. In order to link the DHS dataset with calculated climate anomalies we only use those surveys which provide geographic information of enumeration area.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Child nutritional indicators (A)			Child birthweight indicators (B)		
Dependent variables					
HAZ	-1.437	1.613	Birth weight	2813.524	555.040
WAZ	-1.504	1.224	Low birth weight	0.167	0.373
WHZ	-0.896	1.389	-	-	-
Stunting	0.230	0.421	-	-	-
Severe stunting	0.135	0.342	-	-	-
Under weight	0.234	0.424	-	-	-
Severe under weight	0.098	0.298	-	-	-
Wasting	0.110	0.312	-	-	-
Severe wasting	0.067	0.250	-	-	-
Independent variables					
Demographics-Child					
Child is a girl	0.481	0.500	Child is a girl	0.480	0.500
Childs' age (month)	41.765	10.295	Childs' age (month)	36.570	13.960
Child's birth order	2.035	1.211	Child's birth order	2.026	1.203
Demographics-Mother					
Age of mother	27.881	4.729	Age of mother	27.334	4.784
Marital status	0.004	0.066	Marital status	0.013	0.115
Education status of mother					
None (reference)	0.189	0.392	None (reference)	0.193	0.394
Primary	0.132	0.338	Primary	0.122	0.327
Secondary	0.533	0.499	Secondary	0.531	0.499
Higher	0.146	0.354	Higher	0.155	0.362
Employment status	0.033	0.179	Employment status	0.033	0.180
Children ever born	2.378	1.244	Children ever born	2.335	1.235
Household characteristics					
Total household members	6.267	2.688	Total household members	6.166	2.630
Number of children under 5 in household	1.691	0.843	Number of children under 5 in household	1.709	0.833
Male household head	0.869	0.337	Male household head	0.855	0.352
Rural residence	0.454	0.498	Rural residence	0.656	0.475
Wealth quantile of the family					
Poorest	0.209	0.407	Poorest	0.218	0.413
Poorer	0.221	0.415	Poorer	0.214	0.410
Middle	0.202	0.401	Middle	0.204	0.403
Richer	0.199	0.399	Richer	0.199	0.399
Richest	0.170	0.375	Richest	0.165	0.371
WASH variables					

Water location (not on premise)	0.273	0.289	Water location (not on premise)	0.280	0.449
Sanitation (unimproved)	0.339	0.445	Sanitation (unimproved)	0.346	0.479
Hygiene (poor)	0.240	0.477	Hygiene (poor)	0.236	0424
Historical climate trend					
Historical monthly prep., SD	130.731	79.926	Historical monthly prep., SD	125.153	73.371
Historical monthly prep., mean	101.641	61.746	Historical monthly prep., mean	100.553	56.643
Historical monthly temp., SD	4.446	1.541	Historical monthly temp., SD	4.345	1.547
Historical monthly temp., mean	25.975	2.063	Historical monthly temp., mean	26.035	2.094
Main independent variables					
Prenatal temperature anomaly	0.086	0.327	Temp. anomaly in zero trimester	-0.008	0.856
Temperature anomaly in first year of life	0.080	0.101	Temp. anomaly in first trimester	-0.007	0.867
Temperature anomaly in second year of life	0.048	0.093	Temp. anomaly in second trimester	0.126	0.851
Prenatal precipitation anomaly	0.013	0.323	Temp. anomaly in third trimester	0.124	0.824
Precipitation anomaly in first year of life	0.020	0.127	Prep. anomaly in zero trimester	-0.016	0.799
Precipitation anomaly in first year of life	0.014	0.152	Prep. anomaly in first trimester	-0.067	0.797
-	-	-	Prep. anomaly in second trimester	0.008	0.811
-	-	-	Prep. anomaly in third trimester	0.093	0.841
Observations	81,211		Observations	87,635	

As we can see, on average, children of our sample have HAZ, WAZ and WHZ scores of roughly -1.44, -1.5 and -0.89 standard deviations correspondingly with 23% of entire sample suffering from stunting and under-weight, and 11% of them suffering from wasting. Similarly, the average birthweight of children in our sample is 2813.53 grams which is very close to the benchmark of being classified as a low birthweight case (i.e., 2500 grams). Likewise, the negative measures (below the reference of median population) of our main nutritional variables also indicate that our sample consist of children from low- and middle-income countries. Several socio-demographic characteristics of the survey sample also points to high prevalence of deprivation and poverty in our data set. For example, about 19% of the mother population received no education at all, with only about 15% reporting higher level of education. Similarly, only 3.3% of the mother population are employed and almost 90% of the households are headed by a male. Likewise, most of the study population reside in rural areas (as high as 65%), with 28% of them not having drinking water within their household premises and 34% of them falling under unimproved hygiene category.

CHAPTER 4

METHODS

4.1. Conceptual framework

Our analysis expands on the conceptual relationship developed by UNICEF in 1990 that explores the underlying causes of child malnutrition so that local governments or organizations can pinpoint effective areas of interventions. This multi-dimensional framework primarily identifies the immediate, underlying, and basic causes of child nutrition and how these factors interact or interconnect with each other. To sum it up, briefly, food and nutrient intake, and disease exposure are identified as immediate causes of child malnutrition which are further influenced by socio-economic resources of the household like food availability and feeding practice, sanitation, hygiene, and health care use. Following these are the basic causes that affect capital use and distribution like social norms and cultures, economic systems, governance, and institutions (UNICEF, 2014). Exposure to climate, though not included in this basic model, was later identified as a key factor that affects and exacerbates all these causes (Tirado et al., 2013; Dimitrova & Muttarak, 2020; Le & Nguyen, 2021). Primarily, climate variability influences child nutrition through the underlying causes of undernutrition, like maternal and childcare, food access and feeding practices, health care facilities and household health factors (sanitation, drinking water, hygiene) (Tirado et al., 2013). Based on this framework, we investigate the effect of climate variation on several child health parameters.

4.2. Baseline model

In our baseline model we exploit the exogenous variation in climate experienced by the child during the study period relative to the cluster specific normal climate trend for the same period to identify the plausible impacts of climate variation on child health outcomes with the basic assumption that the observed deviations in temperature and precipitation compared to the long-term means are random within and across clusters. This follows the framework employed by similar previous studies (Dimitrova & Muttarak, 2020; Le & Nguyen, 2021).

We use multivariate regression models to study the association between climate anomalies and child health status. When the dependent variable is a continuous measure (birth weight or z-scores) we use ordinary least squares (OLS) regressions and if it is a dummy variable then a logistic regression model is used. Sampling weights, provided by DHS survey design are applied to all models. All the standard errors are clustered at cluster level of enumeration areas.

With data for child *i* born in cluster *c* during year *y* and month *t*, we estimate the following model:

$$h_{icyt} = \beta_o + \beta_1 \mathrm{W_{icyt}} + \gamma X'_{icyt} + \delta_c + \sigma_y + \mu_t + \varepsilon_{icyt} \qquad (1)$$

Where, h_{icyt} represents our main variable of interest, δ_c, σ_y and μ_t represents state, birth year and month fixed effects, respectively. These fixed effects account for the health and seasonality at birth. W_{icyt} represents our calculated climate variable. X_{icyt} is a vector for controls to account for individual, maternal and household variables that are known to affect our child health outcomes. Child controls include age in months[3], sex and birth order to account for biological factors that influences child health (Shrimpton et al., 2001). Similarly, maternal controls include age of mother at childbirth, marital status, education level, work status and total number of child ever born, while household controls include total number of household members, number

[3] All age variables are also squared to account for non-linearity.

of kids under 5 years, sex of household head, wealth quantile and urban/rural status. The last two controls account for allocation and availability of household resources (de Silva & Sumarto, 2018).

4.3. Differential vulnerabilities

Next, we examine the potential differential vulnerabilities across subgroups of populations by including an interaction term between the climate measure and specific sociodemographic measures of interest. The main socio-demographic variables that we are interested in are gender of the child, urban-rural residence, wealth quantile of the household, mother's level of education and WASH (Water, Sanitation and Hygiene indicators) variables.

$$Y_{icyt} = \beta_o + \beta_1 \mathrm{W}_{\mathrm{icyt}} + \beta_2 D_{icyt} + \beta_3 (W * D)_{icyt} + \delta_c + \sigma_y + \mu_t + \varepsilon_{icyt} \quad (2)$$

Table 1 also includes the summary statistics for these variables. The five classes of wealth quantiles listed were constructed based on information on building materials and assets of the households. Similarly, from the DHS dataset we also construct three types of indicators commonly grouped as WASH variables. First, water availability is classified as the presence or absence from the household premise based on location of drinking water. Second, sanitation facilities are classified as improved or unimproved based on the type of toilet facilities. Improved sanitation includes facilities like flushed toilet, sewer system or other safe toilets that do not contaminate the surrounding. Unimproved sanitation includes facilities like absence of toilet, pit latrines, and other unsafe facilities. Third, we construct indicators for high and low hygiene based on how the mother disposes child's stool. Hygiene classified as high indicates proposal disposal of stool either in toilet or by burial. However, low hygiene indicators identify improper disposal of stool like in a ditch or garbage or left in open. All these variables were constricted following the specification of Dimitrova and Muttarak (2020).

To ensure our analysis is easily interpretable, we focus only on one climate and child health variable. We restrict our dependent variable to either indicate the probability of being stunted or the probability of low birth weight while our independent climate measure represents a single temperature or precipitation variable summed up for the entire vulnerable period of exposure. The availability of all these records across every wave of DHS country wise survey is quite hard to find or focused only on specific sub-sections of populations which also leads to a subsequent reduction of our estimation sample size.

CHAPTER 5

RESULTS

5.1. Baseline model

The estimated impact of climate variability on child health parameters is reported in Tables 2-4. Starting with Table 2, each three column headings represent the estimated OLS coefficients for the main three dependent variable of interest. Then, Table 3 represents the logistic regression table with calculated odds ratio for the six-indicator nutritional variables derived from these three dependent variables. In general, the results display that early childhood exposure to climate variation does have a significant negative impact on child health with effects being more pronounced in cases of precipitation variability. Although, few estimates are statistically significant in case of temperature variability, the negative sign of the estimates does indicate negative effects to child health parameters and we should also notice that the effects get reversed in some period of exposure, meaning higher heat benefits child health outcomes.

Interpreting some of the derived results in Table 2. (Column 1), estimates show that one standard deviation increase in precipitation variability during pre-natal period (in-utero exposure) reduces child's HAZ score by 0.027 standard deviations at an alpha of 0.01. Likewise, a one standard deviation increases in precipitation anomaly during the prenatal, first and second year of child's life significantly decreases WAZ score by 0.043, 0.095 and 0.1 standard deviations respectively at 0.01 level of significance. Similar significances were not seen in case of temperature variability. Likewise in case of WHZ score, 1 S.D. increase in precipitation anomaly in first and second year of life reduces it by 0.165 and 0.141 S.D. respectively at an alpha of 0.001.

Table 2. Fixed effect regression for child nutritional indicators[4]

Variables	HAZ (Height for age z scores) (1)	WAZ (Weight for age z scores) (2)	WHZ (Weight for height z scores) (3)
Prenatal temperature anomaly	-0.005	0.005	0.012
	(0.046)	(0.034)	(0.039)
Temperature anomaly in first year of life	-0.063	-0.199*	-0.346
	(0.164)	(0.114)	(0.156)
Temperature anomaly in second year of life	-0.040	-0.080	-0.039
	(0.156)	(0.113)	(0.149)
Prenatal precipitation anomaly	-0.027**	-0.043**	-0.051**
	(0.032)	(0.020)	(0.024)
Precipitation anomaly in first year of life	0.048	-0.095**	-0.165***
	(0.064)	(0.045)	(0.053)
Precipitation anomaly in second year of life	0.026	-0.100**	-0.141***
	(0.062)	(0.043)	(0.048)
Observations	81,211	81,211	81,211
All controls	*Yes*	*Yes*	*Yes*
Fixed effects	*Yes*	*Yes*	*Yes*

Likewise, the results of Table 3 can be interpreted in form of odds ratio. For instance, a one standard deviation increase in precipitation anomaly in first year of life (column 1) increases the log odds of stunting by 1.139, severe stunting by 0.865, wasting by 1.208 and severe wasting by 1.492 respectively. Likewise, temperature anomaly in first year of child life increases the log odds of wasting and severe wasting by 1.560 and 0.511 respectively.

[4] Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Fixed effects include state, birth month and birth year fixed effects.

Table 3. Logistic regression for child nutrition parameters[5]

Variables	Stunting (1)	Severe stunting (2)	Underweight (3)	Severe underweight (4)	Wasting (5)	Severe wasting (6)
Prenatal temperature anomaly	0.984	0.978	1.008	0.926	0.919	0.937
	(0.058)	(0.086)	(0.028)	(0.078)	(0.074)	(0.058)
Temperature anomaly in first year of life	0.913	0.767	0.905	0.941	1.560*	0.511**
	(0.173)	(0.187)	(0.164)	(0.245)	(0.373)	(0.174)
Temperature anomaly in second year of life	1.192	1.183	1.158	1.230	1.279	0.437***
	(0.205)	(0.274)	(0.196)	(0.286)	(0.271)	(0.136)
Prenatal precipitation anomaly	1.007	0.948	0.970	1.129**	1.079*	1.052
	(0.040)	(0.046)	(0.039)	(0.063)	(0.049)	(0.055)
Precipitation anomaly in first year of life	1.139**	0.865*	1.037	1.071	1.208**	1.492***
	(0.075)	(0.074)	(0.068)	(0.104)	(0.108)	(0.189)
Precipitation anomaly in second year of life	1.077	1.069	1.128*	1.119	1.120	1.169
	(0.067)	(0.082)	(0.070)	(0.098)	(0.095)	(0.136)
Observations	81,211	81,211	81,211	81,211	81,211	81,211
All controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Similarly looking at column 6 we can say that at 99.9% confidence interval, a one standard deviation increase in temperature anomaly in second year of life increases logs odds of the child being severely wasted by 0.437.

[5] Note: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Fixed effects include state, birth month and birth year fixed effects.

Following this, we now move on to our next variable of interest: the effect of climate variability on birth weight of the child. Estimates for this variable are presented in Table 4 and 5 which includes three columns each representing both the estimated results for the fixed and logistic effect regression respectively. Column (1) of each table is then followed by the method of data collection, if the birth weight of the surveyed child was recalled by mother's memory or by a health card. Thus, the sample of Column (1) of each table is split in two samples, one if birthweight was recalled by the mother (i.e., Column (2)) and the other if recalled by a health card (i.e., Column (3)). Also, each table consist of two panels, the first one representing results for entire prenatal period and the second one representing result divide by trimester of pregnancy.

Table 4. Fixed effect regression for birth weight parameters

Variable	**Birth weight** (For all sample) **(1)**	**Birth weight** **(**Recalled by health card) **(2)**	**Birth weight** (Recalled by mother's memory) **(3)**
Prenatal precipitation anomaly	-15.256	-10.686	-15.740
	(11.988)	(14.502)	(23.075)
Prenatal temperature anomaly	4.155	14.799	-24.831
	(17.032)	(19.643)	(33.049)
Prep. anomaly in zero trimester	4.203	-5.984	18.338
	(6.620)	(8.068)	(11.894)
Prep. anomaly in first trimester	2.320	-5.287	15.411
	(6.491)	(7.697)	(12.356)
Prep. anomaly in second trimester	-7.424	-13.280	5.292
	(6.697)	(8.214)	(12.149)
Prep. anomaly in third trimester	8.372	2.362	14.657
	(6.159)	(7.497)	(11.514)
Temp. anomaly in zero trimester	-22.694	-35.200*	11.180
	(12.542)	(14.738)	(25.561)

Temp. anomaly in first trimester	-5.424	-12.834	14.407
	(13.618)	(15.916)	(26.352)
Temp. anomaly in second trimester	-24.749^{*}	-36.612^{**}	8.510
	(12.082)	(14.004)	(26.116)
Temp. anomaly in third trimester	-17.163	-32.373^{*}	27.283
	(13.179)	(15.442)	(25.356)
Observations	87,635	51,902	35,733
All controls	*Yes*	*Yes*	*Yes*
Fixed effects[6]	*Yes*	*Yes*	*Yes*

In general, we see statistically significant result when the birth weight is recalled by a health card which makes sense considering the accuracy of these data source as compared to those recalled through mother's memory years after childbirth. Likewise, in case of birthweight parameter, we see temperature variability to be a significant predictor of child health outcomes, with effects distributed throughout various trimester of pregnancy.

Table 5. Logistic effect regression for birth weight parameters

Variable	**Low birth weight** (For all sample) **(1)**	**Low Birth weight (**Recalled by health card) (2)	**Low Birth weight** (Recalled by mother's memory) **(3)**
Prenatal precipitation anomaly	1.039	0.999	1.100
	(0.045)	(0.055)	(0.078)
Prenatal temperature anomaly	0.891^{*}	0.836^{**}	1.027
	(0.051)	(0.058)	(0.102)
Prep. anomaly in zero trimester	0.975	1.004	0.945
	(0.023)	(0.030)	(0.036)
Prep. anomaly in first trimester	0.971	0.969	0.984
	(0.022)	(0.028)	(0.038)

[6] Fixed effects include state, birth month and birth year fixed effects.

Prep. anomaly in second trimester	1.021	1.020	1.030
	(0.023)	(0.030)	(0.037)
Prep. anomaly in third trimester	0.972	0.990	0.951
	(0.022)	(0.029)	(0.035)
Temp. anomaly in zero trimester	1.048	1.053	1.036
	(0.044)	(0.054)	(0.080)
Temp. anomaly in first trimester	0.948	0.951	0.950
	(0.041)	(0.049)	(0.075)
Temp. anomaly in second trimester	1.035	1.016	1.074
	(0.045)	(0.053)	(0.085)
Temp. anomaly in third trimester	0.993	0.995	0.981
	(0.043)	(0.053)	(0.076)
Observations	87,635	51,902	35,733
All controls	*Yes*	*Yes*	*Yes*
Fixed effects[7]	*Yes*	*Yes*	*Yes*

We see reduction in birth weight and increase in odds ratio of the child being low birth weight, though significant effects are seen only in case of temperature variability as compared to precipitation variability. For instance, temperature anomaly in-utero period increases the log odds of the child being born with a low birth weight by 0.891 at an alpha of 0.01. Likewise, a one standard deviation increase in temperature anomaly during second trimester of pregnancy decreases the birthweight of a child by 24.749 grams for overall birthweight measure and by 36.612 grams when the birthweight is recorded in a health card.

Most of the socio-demographic variables included in the model as explained in equation (1) also show significant relationship with the dependent variables. This has been shown for HAZ scores and birthweight measures in Table A2 of the appendix (col. 1 and 2., respectively). To

[7] Fixed effects include state, birth month and birth year fixed effects.

briefly explain these results, on average boys have lower HAZ scores and birthweight compared to girls. Also, children born from educated mother have higher HAZ scores and birthweight as compared to mother with no formal education and the rate of increase seems to be proportional with increases in level of education. Likewise, children from wealthier households have higher HAZ scores and birthweight compared to the poorer reference group, with similar proportional increase as wealth quantile increases.

5.2. Differential vulnerabilities:

Table 6. Mean HAZ scores and birthweight summarized for each socio-demographic groups.

Variables	**Child nutritional indicators (A)**		**Child birthweight indicators (B)**	
	Mean HAZ	% stunted	Mean Birthweight	% of low birthweight
Sex of child				
Female	-1.426	23.2%	2775.36	18.2%
Male	-1.447	22.8%	2843.27	15.4%
Residence				
Urban	-1.177	18.7%	3036.57	12.7%
Rural	-1.764	29.6%	3007.5	15.1%
Education				
No	-1.786	26.1%	2768.57	18.6%
Primary	-1.661	27.8%	2774.44	18.6%
Secondary	-1.388	22.7%	2813.56	16.6%
Higher	-0.962	15.8%	2900.03	12.9%
Wealth quantiles				
Poorest	-1.814	27.8%	2752.3	19.6%
Poorer	-1.606	25.7%	2789.64	17.9%
Middle	-1.460	24.2%	2819.61	16.0%
Richer	-1.226	19.8%	2844.14	15.3%
Richest	-0.972	16.0%	2880.88	13.5%
Water location				
Not on premise	-1.590	24.7%	2789.63	17.9%
On premise	-1.379	22.4%	2822.82	16.2%
Sanitation				
Unimproved	-1.685	26.4%	2782.48	15.9%
Improved	-1.308	21.2%	2830.63	18.0%
Hygiene				
Low	-1.677	26.7%	2786.82	17.6%

High	-1.522	24.0%	2826.33	16.3%

Table 6. shows the mean table for HAZ scores and birthweight calculated separately for each of the socio-demographic classes. It is evident that HAZ is lower for more socially deprived groups with higher percent of stunted children and children with lower birth weight. For instance, with increase in either wealth status of the family or educational level of mother, we see a decrease in HAZ scores and birthweight and increase in prevalence of stunting and low birth weight.

Similarly, Table 7 shows the interaction effect calculated individually for each of the socio-demographic variables. In case of HAZ scores, we look at the interaction effect on prenatal climate anomalies and climate anomalies over the entire first two years of child life. Similarly, for birthweight we look at the interaction effect of climate anomalies during in-utero period.

First, significant differences between boys and girls were seen only in case of two years temperature anomalies, where boys seem to benefit by having a 0.581 S.D. (Column 4) increase in HAZ scores as compared to boys who were not exposed to these anomalies. Second, children in rural areas appear to be suffering the most from climate anomalies as compared to children from urban areas.

Third, in case of every WASH variable, children with improved sanitation, high hygiene and water on premise are almost entirely protected from climate anomalies in any given period with the effects being significantly stronger for HAZ scores during the two-year anomaly's exposure. Likewise, children with no maternal education (another indicator of depravity) are suffering the most from climate anomalies in case of both HAZ and birthweight. With an increase in mother's level of education, the negative effects seem to go down and we even see positive association for mothers with higher level of education. The trend seems to continue for wealth quantiles, with children from poorer families suffering the most. Children from richer families seem to benefit from the positive effects of climate across all developmental periods. A generalization can be made from the observed values that higher the level of depravity in the observed population group, more concentrated are the negative effect of climate variabilities.

Table 7. Interaction effects of socio-demographic variables with climate anomalies.

Interaction term	HAZ scores				Birth weight	
	Prenatal anomalies		**2 years anomalies**		**Prenatal anomalies**	
	Prep. **(1)**	Temp. **(2)**	Prep. **(3)**	Temp. **(4)**	Prep. **(5)**	Temp. **(6)**
Sex of child						
Boy	-0.031	-0.048	-0.112	0.581^{**}	-2.298	10.73
Girl	0.031	0.048	-0.263	0.368	1.167	-11.20
Residence						
Urban	-0.110	-0.122^{***}	0.118	-0.466	-3.602	32.51^{*}
Rural	-0.124^{***}	-0.195^{***}	-0.791^{***}	-1.296^{***}	6.386	-37.46^{***}
WASH variables						
High hygiene	0.076	0.130	-0.116	-0.841^{*}	23.81	21.92
Low hygiene	-0.005	-0.042	-1.525^{***}	-2.136^{***}	-5.243	-6.884
Improved sanitation	0.028	0.069	0.255	0.156	6.912	2.954
Unimproved sanitation	-0.025	-0.071	-1.029^{***}	-2.258^{***}	-9.112	-9.036
Water on premise	0.0257	0.046	0.308^{*}	-0.239	5.624	11.26
Water not on premise	-0.025	-0.046	-1.314^{***}	-1.496^{***}	-5.624	-11.26
Educational status of mother						
No	-0.047	0.0942	-1.548^{***}	-2.954^{***}	-49.27^{*}	-24.35
Primary	0.021	-0.111	-0.977^{**}	-2.687^{***}	3.018	-9.253
Secondary	0.012	-0.107^{*}	0.0001	-0.292	29.75	3.274
Higher	0.078	0.036	1.404^{***}	1.578^{***}	6.789	-6.209
Wealth quantiles						
Poorest	-0.200^{**}	-0.108	-1.985^{***}	-3.551^{***}	-16.45	-14.61
Middle	0.067	-0.129	0.160	-0.945^{**}	21.25	-37.95

Richest	0.165*	0.061	1.288***	2.362***	13.10	23.23

CHAPTER 6

DISCUSSION

South Asia covers a significant burden of global child health disparities having the largest percentage of stunted children (33.3%) under 5 years, second highest population of children with low cognitive and early development scores, and one-fourth of the low-birth-weight cases (26%) of the world (Lee et al., 2013; McCoy et al., 2016; UNICEF, WHO, & World Bank group, 2018). South Asia is also home to the highest proportion of children worldwide at risk of poor development because of extreme poverty exposure and stunting risk (Lu et al., 2020). Following this, in this study we focus on how severe the effect of early childhood climate variability exposure is to the already suffering children population of South Asia as well as explore some potential mechanisms to mitigate these effects.

First, we show that temperature and precipitation variability experienced during in utero and early child's life does play a significant role in child health outcomes in South Asia and the effects seem to add on to the pre-existing vulnerabilities of various health inequities that are already present there. We find that precipitation (as compared to temperature) is a strong predictor of child nutrition indicator when the study parameter is child nutritional indicator, whereas temperature variability in case of childbirth weight parameters. Prenatal precipitation anomaly was found to decrease child's HAZ, WAZ and WHZ score by 0.027, 0.043 and 0.051 respectively, and in case of WAZ and WHZ the effects seem to continue till second year of child's life. Likewise, precipitation anomaly in first year of life increases the log odds of stunting by 1.139, severe stunting by 0.865, wasting by 1.208 and severe wasting by 1.492 respectively. Similar findings have been reported by other studies (Tiwari et al., 2016; Molina & Saldarriaga, 2017; Baker & Anttila-Hughes, 2020; Thiede & Strube, 2020; McMahon & Gray, 2021; Blom et al., 2022; Freudenreich et al., 2022; van der Merwe et al., 2022), though the severity and timing of impacts does seem to vary based on study areas.

Our results seem to be in line with some previous studies who highlight the importance of safe in-utero condition to early health parameters (Cornwell & Inder, 2015; Randell et al., 2020; Dimitrova and Bora, 2020). In accordance with these previous works, we deduct that nutritional deprivation and mother's health condition during the intrauterine growth period detrimentally affects child's initial health shocks which, in some cases, even gets resonated to later phases. Similarly, Dimitrova and Muttarak (2020) also identify in-utero period as the most critical period of exposure and cite their reasoning to the hypothesis of developmental origin given by Mandy and Nyirenda (2018) which states that environmental conditions before and shortly after birth have a long-lasting impact on health during childhood.

However, in case of nutritional indicators, some of the previous literature literatures report precipitation extreme during first year of life as the major determinant of decreasing HAZ scores and increasing stunting (McMahon & Gray, 2021) which we do not find in this study. As compared to these detrimental impacts of precipitation, the negative effects of temperature anomaly seem to be less pronounced in case of nutritional indicators. We even find positive association of temperature variability in some cases. Similar cases were also reported by (McMahon & Gray, 2021; Nicholas et al., 2021) who argue that considering the agricultural dependence of the studied countries initial warming may prove to be beneficial for local agricultural conditions. However, the thing to consider is that a causal relationship between climate variation and health parameters is quite hard to find. Bakhtsiyarava et al. (2018) provides two reasoning for this firstly, small health effects of climate variation that cannot be easily detected due to various indirect pathways affecting this relationship and secondly issues with data availability and quality which has been briefly discussed at the end.

But, talking about birthweight parameters, we see significant relationship only in case of temperature variability which explains why previous similar studies only reported association between temperature anomalies and birthweight (Molina & Saldarriaga, 2017). Like the authors, we do not see a statistically stronger effect of a particular term of gestational period which leads us to conclude that the effect of temperature variability on childbirth outcomes is likely driven by the overall variability experienced throughout the period of pregnancy.

Similarly, we see that socio-demographic factors play a significant role in determining the interaction between climate anomalies and child health outcomes in South Asian countries. We add to the previous literatures which emphasize that the effects of exposure to climate anomalies hit the hardest when the exposed population is socially and economically disadvantaged (Tiwari et al., 2017; Krishna et al., 2018; Dimitrova & Muttarak, 2020; McMahon & Gary, 2021; Le & Nguyen, 2021).

The effects are more concentrated among poorer families of the communities who in turn have less access to drinking water, practice poor hygiene practices like disposal of baby’s stool and/or do not have access to improved toilet facilities. These findings are also in accordance with previous studies from (Victora et al., 2003; Pappachan & Choonara, 2017; Omidakhsh & von Ehrenstein, 2021) who identify poverty, sanitation, and nutritional insecurity as major drivers of child health disparities in South Asia. Following this, Aguayo and Menon (2016) conclude that along with economic growth it is also equally important to make investment in improving child and women’s nutrition and household hygiene and sanitation.

Finally, we highlight the importance of mother's education in safeguarding the children from the detrimental effect of climate exposure. Krishna et al. (2018) report similar findings and reported largest decline in stunting among South Asian children who had mothers with higher educational status. Likewise, Sathi et al. (2022) reported significant relationship between lower levels of maternal education and rise in cases of low birth weight (LBW). This also points out to the fact that better education can buffer against the effect of climate exposure by improving awareness on dietary intake and sanitary behaviors during pregnancy and child rearing (Khan et al., 2020; Tessema et al., 2021)

To summarize, we find that increasing access to basic resources like education, toilet, and water along with spreading awareness about simple hygiene and cleanliness condition are mechanisms that can substantially protect against the negative impacts of climate variabilities. However, these interactions are significant only within South Asia as studies in other regions e.g. (Thiede &Strube, 2020; Nicholas et al., 2021) do not seem to follow the same patterns of socio-demographic analysis.

CHAPTER 7

CONCLUSION

The discussion on the effects of climate change on human health has primarily been focused within human health of more developed countries or adult sub-populations. The study of the relationship between climate variability and the effects of its exposure to infants and young children of developing countries has received less attention. In this study, we aim to shed light on this topic by focusing our estimation sample to children aged 5 years or younger belonging to one of the four South Asian countries under study – India, Nepal, Pakistan, and Bangladesh. We further expand on our findings by looking at how the effects of climate exposure differs based on different socio-demographic groups varying in terms of economic, gender and social vulnerabilities and focus on potential mitigation mechanisms.

First combine the health and socio-demographic data from Demographic and Health Surveys (DHS) with global gridded high resolution monthly climate dataset from Climate Research Unit (CRU TS). Assuming climate variations as exogenous factors, we then empirically analyze the effect of temperature and precipitation variability on two kinds of child health parameters (child birthweight and child nutritional indicators).

Our results shows that both precipitation and temperature variabilities are strong predictors of early childhood health parameters. More specifically, we find strong relationship between prenatal climate anomalies and precipitation anomalies spread over the first 1000 days of child's life. We find that 1 S.D. increase in temperature and precipitation variability during pre-natal period decreases child's HAZ score by 0.005 and 0.027 S.D., respectively. Likewise, 1 S.D.

increases in precipitation anomaly during the prenatal, first and second year of child's life decreases WAZ score by 0.043, 0.095 and 0.1 S.D., respectively. We also find that a 1 SD increase in prenatal temperature and precipitation anomaly decreases the odds of child being stunted by 15.3% and increases the odds of child being stunted by 4.5% respectively. Similar results were found in case of child birthweight parameters. In case of precipitation anomalies experienced by the child during various stages of pregnancy, we find a reduction in birth weight and increase in odds ratio of the child being low birth weight. In comparison, the effects of temperature anomaly on birth weight seems to be less pronounced or even opposite in some cases (meaning positive effects of heat exposure on child birthweight). Overall, we find in-utero period to be the most vulnerable time of climate exposure and conclude that with projections of strong climate extremities health and nutritional interventions should be targeted within pregnant mothers and infants.

Finally, we interreact different socio-demographic groups with climate anomalies to identify the level of vulnerabilities and ways we can protect and improve child health conditions. The set of results suggests that child health outcomes not only depend on climate exposures but also on the existence and severity of socio-demographic vulnerabilities. Children born in economically and socially disadvantaged households seem to suffer the most from the effect of climate variations. We also identify mechanisms like promoting mother's education, improving hygiene and sanitation awareness, providing access to drinking water within household premise and improved toilet infrastructure, and investment in human capital as adaptive measures that can strengthen resilient capacity of at-risk groups against the detrimental effects of climate anomalies.

We acknowledge several potential limitations in our study which could not be accounted because of restrictions in data availability and choice of empirical modelling. First the use of cross-sectional data limits our ability to directly establish a causal relationship between child health variables and climate anomalies. Second, the selectivity issue because of in-utero mortality and selection into parenthood. In-utero mortality refers to the possibility that climate variabilities become so extreme such that it causes in-utero mortality which then excludes such children from our estimation sample. Similarly, selection into parenthood refers to the possibility that educated parents may choose the option of delaying conception till the projected climate extreme scenarios pass away. We were not able to address these issues because of our data restriction (i.e., DHS dataset does not distinguish between stillbirth, miscarriage and abortion or reasons for terminated pregnancies) or because of social desirability bias which may exist during reporting of fetal loss. Finally, all our control variables are self-reported during the DHS survey which means there is possibility of mis-reporting bias in our sample which we are not able to control.

Future research can build upon this work by expanding the temporal dimension of the calculated climate anomalies. In this study, we look at climate anomalies calculated at monthly period but given the availability of suitable data it would be interesting to see the effects estimated at daily climate anomalies. Likewise, it is quite hard to obtain data on direct (heatwaves) and indirect (food insecurity, infectious disease) effects of climate change based on the DHS dataset, however a study to identify these effects would also be interesting. Finally, given that we concentrated on only one country, it will also be interesting to see how effective intervention measures have been to mitigate the effects of climate variation on child health outcomes.

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APPENDIX

Table A1. List of country and each wave of DHS survey

Country	Survey year	Country	Survey year
Child nutritional indicator		Child birthweight indicator	
Bangladesh	2000	Bangladesh	2018
	2004	India	2015
	2007		2020
	2011	Nepal	2001
	2014		2006
India	2015		2011
	2020		2016
Nepal	2001	Pakistan	2006
	2006		2017
	2011		
	2016		
Pakistan	2017		

Table A2. Regression result for control variables

Variable	HAZ (OLS)	Birthweight (OLS)
Demographics-Child		
Child is a girl (ref=male)	0.001	-63.145***
	(0.015)	(6.117)
Childs' age (month)	-0.026***	-1.141**
	(0.008)	(0.462)
Child's age squared	0.000***	0.023***
	(0.000)	(0.008)
Child's birth order	-0.151***	19.511***
	(0.017)	(5.486)
Demographics-Mother		
Age of mother	0.067***	21.148***
	(0.012)	(3.604)
Age of mother squared	-0.001***	-0.338***
	(0.000)	(0.062)
Marital status	0.102*	26.987
	(0.062)	(17.760)
Education status of mother (ref= no formal education)		
Primary	0.074***	5.896
	(0.022)	(7.434)
Secondary	0.235***	35.248***
	(0.020)	(6.024)
Higher	0.450***	91.243***
	(0.033)	(8.912)
Employment status	0.038	-5.295
	(0.030)	(11.135)
Children ever born	0.067***	5.075
	(0.016)	(5.563)
Household characteristics		
Total household members	0.008***	0.009
	(0.003)	(0.922)
Number of children under 5 in household	-0.111***	5.753*
	(0.012)	(3.398)
Male household head	0.011	5.785
	(0.018)	(5.031)
Rural residence	-0.007	19.675***
	(0.021)	(6.004)
Wealth quantile of the family (ref=poorest)		
Poorer	0.170***	20.907***
	(0.020)	(6.750)
Middle	0.301***	54.382***
	(0.024)	(7.482)

Richer	0.459***	73.468***
	(0.028)	(8.125)
Richest	0.675***	128.293***
	(0.034)	(10.274)
Observations	81,211	87,635

Table A3. Results for range specific climate anomalies

Variability range	Temperature				Precipitation			
	Trimester zero	1st trimester	2nd trimester	3rd trimester	Trimester zero	1st trimester	2nd trimester	3rd trimester
<-1.5σ	-16.18	7.659	-11.76	-12.45	-68.56	-137.4	-33.80	-0.866
	(-0.60)	(0.35)	(-0.40)	(-0.78)	(-1.07)	(-1.47)	(-0.41)	(-0.01)
[-1.5 σ, -0.5 σ)	-19.09	44.94	22.14	26.57	3.790	-20.36	-31.85	-94.84
	(-1.05)	(2.52)	(1.41)	(1.50)	(0.15)	(-0.31)	(-0.76)	(-3.98)
[-0.5 σ, 0.5 σ]	-5.556	15.80	-30.56	-21.14	-24.43	-69.68	12.91	-18.63
	(-0.19)	(0.94)	(-1.01)	(-1.76)	(-1.17)	(-1.90)	(0.71)	(-1.17)
(0.5 σ, 1.5 σ]	25.31	0.872	37.31	-9.610	53.15*	26.91	-0.171	-4.234
	(1.23)	(0.05)	(1.37)	(-0.34)	(1.24)	(0.83)	(-0.00)	(-0.18)
>1.5 σ	-56.28*	-51.50*	-0.788	-51.95	-17.59	-23.95	-30.52	7.254
	(-1.33)	(-1.18)	(-0.02)	(-1.35)	(-0.58)	(-1.29)	(-1.46)	(0.36)

Estimates in Table A3 compare the effect of five different classes of climate anomalies on child birthweight. Though, significance results were not quite evident, generally they point out that stronger and positive anomaly (i.e., 1.5 deviation above the mean) have more severe effect on birthweight variable. Similar analysis could not be conducted for nutritional indicator variables because of lack of needed diversification among climate anomalies.

Table A4. Sensitivity analysis for birthweight results

Variable	OLS/coef.			Logit/OR		
	1 Birth wt.	2 Mother's memory	3 Health Card	4 Low birth wt.	5 Mother's Memory	6 Health Card
Prenatal precipitation anomaly	-30.322	2.819	-82.655*	1.142*	1.037	1.297**
	(19.056)	(24.632)	(32.186)	(0.074)	(0.090)	(0.134)
Prep. anomaly in zero trimester	-0.857	-5.952	7.151	1.025*	1.044*	1.002
	(4.204)	(5.181)	(7.150)	(0.015)	(0.020)	(0.022)
Prep. anomaly in first trimester	8.707	-5.218	30.989*	0.947*	0.976	0.914*
	(8.012)	(10.281)	(13.218)	(0.026)	(0.035)	(0.039)
Prep. anomaly in second trimester	-0.273	-14.116	23.520	0.996	1.034	0.950
	(7.660)	(9.643)	(12.982)	(0.026)	(0.036)	(0.039)
Prep. anomaly in third trimester	6.734	3.924	7.862	0.977	1.008	0.940**
	(5.443)	(6.884)	(9.491)	(0.019)	(0.026)	(0.028)
Prenatal temperature anomaly	-4.244	30.450	-97.644	1.009	0.971	1.131
	(26.305)	(30.140)	(51.521)	(0.097)	(0.116)	(0.188)
Temp. anomaly in zero trimester	-0.259	-8.186	20.011	1.023	1.010	1.029
	(7.993)	(9.823)	(13.751)	(0.028)	(0.035)	(0.046)
Temp. anomaly in first trimester	12.158	-3.584	52.427*	0.973	0.977	0.938
	(12.373)	(14.961)	(22.854)	(0.043)	(0.054)	(0.070)
Temp. anomaly in second trimester	1.620	-16.798	51.084*	1.006	0.992	0.994
	(11.991)	(14.424)	(22.231)	(0.044)	(0.054)	(0.074)
Temp. anomaly in third trimester	3.477	-8.978	36.699*	0.977	0.956	0.984
	(9.441)	(11.750)	(16.315)	(0.032)	(0.040)	(0.053)
Observation	87635	51902	35733	87635	51902	35733

Note: We test for another model by using different sets of fixed effects. We replace birthyear and month with interview year with the reasoning that climate exposure before birth should not be affected by after birth factors.

Table A5. Sensitivity analysis for nutritional indicator results

Variables	HAZ (1)	WAZ (2)	WHZ (3)	Stunting (4)	Severe Stunting (5)	Underweight (6)	Severe Underweight (7)	Wasting (8)	Severe Wasting (9)
	OLS coef.			Odds ratio					
Prenatal temperature anomaly	0.064**	0.065***	0.040	1.008	0.846***	0.932**	0.821***	1.021	1.075
	(0.024)	(0.019)	(0.021)	(0.028)	(0.030)	(0.025)	(0.031)	(0.041)	(0.059)
Temperature anomaly in first year of life	-0.140	0.168	0.346*	0.965	0.864	0.754	0.715	1.489	0.416**
	(0.150)	(0.098)	(0.136)	(0.160)	(0.185)	(0.124)	(0.171)	(0.350)	(0.140)
Temperature anomaly in second year of life	-0.082	-0.163	-0.140	1.459*	1.068	1.146	1.283	1.249	0.472*
	(0.129)	(0.094)	(0.120)	(0.218)	(0.207)	(0.175)	(0.263)	(0.265)	(0.148)
Prenatal precipitation anomaly	-0.013	-0.039*	-0.048*	0.992	1.041	0.987	1.124**	1.004	0.973
	(0.022)	(0.018)	(0.020)	(0.026)	(0.034)	(0.026)	(0.041)	(0.036)	(0.048)
Precipitation anomaly in first year of life	0.012	-0.051	-0.067	1.123	0.967	0.992	1.053	1.161	1.412**
	(0.060)	(0.043)	(0.050)	(0.071)	(0.078)	(0.062)	(0.099)	(0.103)	(0.176)
Precipitation anomaly in second year of life	0.033	-0.084*	-0.124**	1.073	1.054	1.116	1.131	1.111	1.188
	(0.060)	(0.042)	(0.048)	(0.065)	(0.079)	(0.067)	(0.096)	(0.093)	(0.135)
Observation	81211	81211	81211	81211	81211	81211	81211	81211	81211

Note: We test for a different model with fixed effects set at interview year of the compiled survey.

Figure A1. Country wise survey clusters in DHS