The Impact of Climate Change on Children's Nutritional Status in Coastal Bangladesh*

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Abstract

This paper studies the impact of climate change on the nutritional status of very young children between the ages of 0 – 3 years by using weather data from the last half century merged with rich information on child, mother, and household characteristics in rural coastal Bangladesh. We evaluate the health consequences of rising temperature and relative humidity and varying rainfall jointly employing alternate functional forms. Leveraging models that control for annual trends and location-specific seasonality, and that allow the impacts of temperature to vary non-parametrically while rainfall and humidity have flexible non-linear forms, we find that temperatures that exceed 25 ^{o}C (the "comfortable" benchmark) in the month of birth exert negative effects on children's nutritional status as measured by mid upper arm circumference. Humidity has a positive impact which persists when child, mother and household controls are included. We find that exposure to changing climate *in utero* also matters. Explanations for these results include consequences of weather fluctuations on the extent of pasture, cropland, and rainfed lands planted with rice and other crops, and on mother's age at first marriage. Our results underline that climate change has real consequences for the health of very young populations in vulnerable areas.

Key Words: Climate Change, Temperature, Humidity, Rainfall, Bangladesh, Children, Mid Upper Arm Circumference, Non-Parametric

JEL Codes: Q54, I15, O15, Q56, J13

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1. Introduction

Climate change is especially salient in Bangladesh. Although researchers have considered the implications of changing climate on adult and child health in this country, most studies have focused on natural disasters such as floods and cyclones attributable to extreme weather, or the incidence of (self-reported) diseases such as malaria, dengue and diarrhea that are triggered by variations in temperatures or rainfall (Kabir et al. 2016, Khan et al. 2011, Thiede and Gray 2020, Wu et al. 2014). In a scoping review of the literature on climate change and child health, Hellden et al. (2021) notes that temperature variations, rainfall, floods, and droughts may directly alter crop yields, thus causing malnutrition. While there may be direct effects on mortality, morbidity and migration, changes in ecosystems and disease vectors wrought by climate extremes may indirectly influence these outcomes as well. However, the existing literature has mostly not considered the correlation between - and possible joint impacts of – temperature and rainfall, or evaluated how humidity may mediate their effects on child health. We address this gap in our research by studying the simultaneous consequences of changing temperatures, rainfall, and humidity on the nutritional status of young children in rural coastal Bangladesh, adopting a more comprehensive framework for documenting the impacts of climate change than, to the best of our knowledge, has been undertaken before.

A sizable proportion of rural households in Bangladesh is involved in agriculture, and land is an important livelihood asset. Ahmed et al. (2012) notes that in terms of production, up to 43 % of rural women devote their time to aquaculture and agriculture which are spheres likely to be affected by weather variability. If yield from cultivating land and from fisheries is at risk, reductions in output may translate into nutritional deficiencies for vulnerable individuals. In particular, such deficits are likely to have serious health consequences for those who are very young. Further, resulting income declines may have implications for women’s agency, dietary quality, and assets (Malapit et al. 2018, Quisumbing et al. 2021), with concomitant decreases in child health. Utilizing weather data from half a century, we investigate the consequences of rising temperature and changing patterns in precipitation and relative humidity on children's nutritional status as measured by mid upper arm circumference (MUAC), a commonly used indicator of wasting in this region (Haque et al. 2021, Hossain et al. 2017, Hossain et al. 2021).

We find that climate has changed in coastal Bangladesh. Results using non-parametric techniques for modeling data on temperature, rainfall and humidity show that average monthly temperature, both in levels and in deviations from the long run means, has been trending upwards since the early 1970s. Similarly, monthly relative humidity has risen in the fifty-year time span from 1970 – 2020. Although patterns in rainfall are less consistent, the variability of monthly rainfall has increased particularly at higher precipitation levels. Using a saturated fixed-effects model that flexibly controls for annual variations and location-specific seasonality, our empirical approach leverages random fluctuations in weather parameters while conditioning on child, mother and household characteristics to identify causal impacts.

In our preferred specification and in the full sample of rural children aged 0 – 3 years, we find that relatively high temperatures in the month of birth have detrimental effects on child MUAC measures. Compared to children born in the comfortable monthly temperatures of 20 – 25 ^{o}C, those who happen to be born in the next higher bin of 25 – 30 ^{o}C have MUAC measures that are a little over 1.5 millimeter (mm) lower. This represents a 1.1 % decline relative to mean MUAC. Humidity, especially when allowed to vary non-linearly, has a positive impact on MUAC up to a certain threshold. When we condition on child, mother and household characteristics, the temperature impacts are no longer measured with precision while the effects of humidity persist. Among controls, mother's age and years of schooling are found to have beneficial effects for children's nutritional status. Land owned by the household, a proxy for household wealth, is also found to have strong positive effects on children's MUAC.

We next analyze consequences of exposure in the month of birth on different age-groups post-birth. In general, the negative impacts of temperature and the non-linear effects of humidity are evident up to the first 1000 days. We then shift the window of time to investigate whether impacts of changing climate are evident from exposure *in utero* and find that in general, relatively high temperatures in the third trimester have harmful impacts with some indication that exposure in the second trimester matters beneficially, especially at lower temperature ranges. Rainfall and humidity have positive effects in the third trimester although these are insignificant.

In terms of mechanisms, we find that relatively high temperatures hasten the decrease in cropland area, total area planted with rice, and area planted with rainfed rice. Rising temperature also reduces soil oxygen availability, an important measure of soil quality and soil health, consistent with the literature on the impact of temperature on soil respiration – the amount of carbon dioxide released from the soil that originates from the decomposition of organic matter by microbes and from plant respiration (Bond-Lamberty and Thomson 2010). Rainfall is found to have some positive consequences in increasing the area of pasturelands. Interestingly, higher relative temperatures decrease mother's age at first marriage. This is consistent with Ahmed et al. (2019) and Carrico et al. (2020) which show that vulnerable households use early marriage of daughters as a means of coping with climate shocks. We find little evidence that weather variations affect the incidence of miscarriage in our sample of mothers, supporting the fact that the sample of children we study is representative. We undertake a series of specification checks and present falsification tests to demonstrate the robustness of our results.

We contribute to the literature in several ways. First, given evidence in our data that weather parameters are correlated, we study climate change in a developing country context that jointly evaluates the impacts of varying temperature, rainfall and humidity over time. Considering these parameters in isolation or in restricted combinations may render the estimated coefficients biased. To demonstrate robustness, we undertake the joint estimation using alternate empirical functional forms. Second, we evaluate implications of climate change on an outcome for very young children – MUAC – that is a commonly used measure of nutritional deprivation in children in South Asia (Huq et al. 2021, Rabbi et al. 2021, Saville et al. 2021), which also has the advantage of being very responsive to short-term stresses as captured in monthly climate shocks as compared to height-for-age for example (Hoddinott et al. 2020, Pinchoff et al. 2021). Moreover, MUAC is easy to measure accurately even in young populations, reducing the possibility of measurement errors. Finally, we use weather data spanning half a century in order to accurately analyze consequences of changing climate in a part of the world that is especially susceptible.

2. Conceptual Framework

How might exogenous weather fluctuations *in utero* or at the time of birth influence the nutritional status of children aged 0 – 3 years? We hypothesize that mechanisms for this include changes in crop yields that may influence food availability affecting children indirectly in their *in utero* stages of development by reducing mother's nutrient intake. Zhang et al. (2017) shows that relatively high temperatures and insufficient rainfall reduces crop yields. Relatively higher levels of humidity on the other hand, raises yields (Zhang et al. 2017). The negative impacts of weather shocks on child health persist at the time of birth and in infancy when children are dependent on mothers for nourishment. As children age, weather shocks may now have direct effects by jeopardizing food intake over and above the lasting consequences on health from initial exposure to environmental insults *in utero* and at the time of birth (Almond et al. 2018, Aguilar and Vicarelli 2022, Andalon et al. 2016, Barker 2007, Currie and Vogl 2013, Edwards 2017, Le and Nguyen 2021, Thai and Falaris 2014, and Tiwari et al. 2017).

Lacking data on yield, we proxy for it by using changes in areas of pastures, cropland, area planted with the main staple crop rice, and measures of soil quality. Other factors that might also link weather fluctuations to the nutritional status of very young children include household migration patterns in response to climate shocks as well as changes in the age of first marriage of mothers. If relatively richer households migrate from the region leaving the poorer households in the sample, then weather shocks may be linked to nutritional indicators mechanically as poorer children likely have worse health. In terms of age of first marriage, the literature notes that marrying off daughters at younger ages is a household coping mechanism in times of distress (Ahmed et al. 2019, Carrico et al. 2020). The literature also notes that children of younger mothers have precarious health (Brainerd and Menon 2015). We explore all these factors below.

In this context, MUAC is a particularly well-suited measure of children's nutritional status which is commonly used in the South Asian context (Hoddinott et al. 2020, Rabbi et al. 2021, Saville et al. 2021). In particular, children's MUAC is an indicator of wasting which is sensitive to age (we control for child's age) and positively correlated with their weight for height z-scores (Zaba et al. 2020). It is reflective of mother's health and nutritional status during pregnancy (Harding et al. 2018), and given its responsiveness to immediate conditions such as those caused by monthly weather shocks (the focus of this research), an appropriate indicator of short-term child health which is relevant in our context.

We end this section by noting that although we jointly evaluate random fluctuations in temperature, rainfall and humidity that have become more prevalent with changing climate, there are other factors such as cyclones or floods, a common problem in Bangladesh, that we do not explicitly consider. The main reason is data constraints – we do not have information on these measures. However, in so far as cyclones (and consequent flooding) are caused by the three weather “primitives” we do evaluate (Albert et al. 2021), we believe our study analyzes several of the main measures associated with climate change upheavals in Bangladesh.

3. Evidence of Changing Climate

We use data from the International Center for Diarrheal Disease Research, Bangladesh (ICDDR,B) health monitoring station in Chakaria upazilla (sub-district) located in Chittagong division. Figure 1 is a map of Bangladesh with the centroid of Chakaria highlighted in the southeast corner slightly towards the interior of the country. ICDDR,B has been involved in community-initiated health care projects in the Chakaria region since the early 1990s. In order to understand the efficacy of ICDDR,B’s outreach in this area, a health station was established in a subset of villages in the Chakaria region that has been involved in monitoring conditions since 1999. Additional details are discussed below.

We use weather variables obtained from the Bangladesh Meteorological Department’s monitoring station in Cox’s Bazaar, which is the closest station to Chakaria (at a distance of about 40 kilometers or 25 miles). The second point on the coastline in Figure 1 is the weather station at Cox’s Bazaar. We have monthly information from 1970 to 2020 from this weather monitor on average temperature in degrees Centigrade, average rainfall in millimeters, and average relative humidity in percent. Relative humidity is defined as a ratio where the numerator is the amount of water vapor in the air and the denominator is the maximum water vapor that the air can hold at a certain temperature (Zhang et al. 2017). Hence relative humidity is correlated to both temperature and rainfall (the correlation coefficient between temperature and humidity is 0.661, between rainfall and humidity is 0.802, and between temperature and rainfall is 0.470, all significant at the 5 % level). This underlines the needs to estimate their impacts jointly in order to avoid bias (Barreca 2012, Zhang et al. 2017). While these climate variables are correlated, relative humidity can have different impacts beyond those exerted by temperature and rainfall. For instance, while propitious levels of temperature and precipitation are beneficial for crop growth, suboptimal levels of humidity (conditional on precipitation and temperature) can influence the water content of crops, leaf growth, photosynthesis, pollination, and cause the growth of fungal spores that lead to plant diseases and insect pests (Zhang et al. 2017). In terms of human impacts, low humidity may cause dehydration and aid in the spread of air-borne pathogens such as the influenza virus, while high humidity worsens heat stress by inhibiting the body's ability to cool itself through sweating and causes diseases by propagating bacteria and fungi (Barreca 2012). We refer to "relative humidity" as "humidity" in the paper.

Figure 2 shows non-parametric (bin) forms for these variables where Panel A denotes patterns in average monthly temperature, and Panels B and C depict patterns for monthly rainfall and monthly humidity, respectively. The y-axis in each case indicates the total number of months over the fifty years that the weather variables fell in these ranges. The framework of Figure 2 follows techniques developed in Barreca (2012) and Graff Zivin and Neidell (2014). Focusing on Panel A, there is evidence that since the 1970s, there has been an increase in the number of months with relatively high temperatures. For instance, focusing on the 25 ^{o}C and above temperature bins that are considered to be "above comfortable," there were 82 months in the 1970 – 1979 time period. By the 2010s, there were 95 months in this range.

Panel B focuses on rainfall. Unlike the variations evident in temperature, rainfall patterns in this region of Bangladesh appear to be relatively stable over the fifty years we analyze (the consistency of rainfall patterns are similar to those noted in Dell et al. (2012)). There is an increase in the number of months with rainfall less than 5 mm (from 62 to 68) from 1970-1979 to 2010-2020, but the number of months with the highest level of rainfall (greater than 45 mm) has increased only from 2 to 3 across decades. Patterns in Panel C for humidity resonate a little more with the variations evident for temperature. The number of months with oppressively high levels of humidity that exceed 75 % increased from 82 months in 1970-1979 to 101 months in the most recent decade.

Figure 3 plots the kernel densities for the weather variables for the first and the last decade of the fifty-year time span we consider. Consistent with Zhang et al. (2017) and trends in Figure 2, climate change shifts the distribution of temperature to the right in Panel A of Figure 3. Panel B suggests that higher levels of precipitation are more evident in the 2010-2020 decade as compared to the earliest decade. Panel C indicates that climate change has altered the distribution of humidity as well. In particular, the bimodal distribution of humidity in the 1970s with peaks around 75 % and 85 % has experienced a right shift to peaks that are somewhat closer to 80 % and 90 % fifty years later (these bimodal patterns in the humidity kernel densities are similar to those noted in Zhang et al. (2017) for China).

4. Empirical Methodology

4.1. Preferred specification

Our main specification estimates models of the following form:

$$y_{ihv} = \sum_{B} \beta^{B} Temp_{mt}^{B} + \gamma Rain_{mt} + \delta Humid_{mt} + \theta X_{ihv} + \sigma_m + \alpha_t + \mu_v + (\sigma_m * \mu_v) + \varepsilon_{ihv} \qquad (1)$$

where i denotes a child, h denotes a household, v is village, and m and t are month and year of birth, respectively. The dependent variable y_{ihv} is the mid upper arm circumference (MUAC) for child i in household h in village v at the time of the survey. The vector β^{B} are the coefficients on the monthly temperature bins ($Temp_{mt}^{B}$) in a non-parametric form, where similar to Zhang et al. (2017), we include dummy variables for each 5 °C interval. The β coefficients are interpreted relative to the excluded bin

(20 – 25 ^{o}C or 68 – 77 ^{o}F, which is considered "comfortable"). We follow the most recent literature in casting temperature in its non-parametric form (Burke et al. 2015). Rainfall in the month and year of birth and its quadratic are included in $Rain_{mt}$. We estimate the impacts of humidity in $Humid_{mt}$ in both its linear and quadratic form similar to Zhang et al. (2017).

Equation (1) controls for child, mother and household characteristics in X_{ihv}. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether she has had a miscarriage. Household characteristics include amount of land owned in decimals (100 decimals equals one acre), and whether the household migrated from the area. In our main estimates, we add these sequentially to understand how they moderate the influence of temperature, rainfall and humidity. Similar to Barreca (2012) and Geruso and Spears (2018), Equation (1) includes disaggregated region (in our case, village) fixed-effects μ_v, month of birth fixed-effects σ_m, and their interactions. The interactions control for village-specific (local) seasonality that could, in their absence, lead to the endogeneity of weather and the composition of births with possible resulting implications on the dependent variable y_{ihv}. The parameters α_t are year of birth fixed-effects as in Zhang et al. (2017), and ε_{ihv} is the error term. We cannot include year of birth fixed-effects interacted with month of birth fixed-effects as our weather variables are measured at the month and year level. In this empirical framework, the impacts of temperature, rainfall and humidity may be interpreted as "presumably random" monthly deviations from their long-run averages (Deschenes and Greenstone 2007). That is, the identifying assumption is that conditional on normal weather and location specific seasonality, the actual profile of weather realizations is random.

4.2. Alternate specifications

We consider two alternate specifications in order to ascertain the robustness of our results. First, we allow humidity also to vary non-parametrically as in Barreca (2012). This leads to Equation (2) of the following form:

$$y_{ihv} = \sum_{B} \beta^{B} Temp_{mt}^{B} + \gamma Rain_{mt} + \sum_{B} \delta^{B}\, Humid_{mt}^{B} + \theta X_{ihv} + \sigma_m + \alpha_t + \mu_v + (\sigma_m * \mu_v) + \epsilon_{ihv} \qquad (2)$$

The interpretation of the variables remain similar to those in Equation (1) but now the δ coefficients are interpreted relative to the excluded humidity bin (humidity less than 65% which is the lowest value in our data, usually 30-50% humidity levels are considered to be "comfortable"). We also considered the interaction of the highest temperature bin with humidity measured linearly as in Barreca (2012), but the results were insignificant. Consistent with Barreca (2012), Geruso and Spears (2018) and Zhang et al. (2017), and because Figures 2 and 3 do not indicate sizable measurable shifts in the non-parametric or kernel densities over the years we consider, precipitation is modeled parametrically (non-linear quadratic form).

Second, we construct weather shocks as deviations relative to historical mean values adjusted by historical standard deviation. As noted in Dell et al. (2014), Feng et al. (2010) and Ibanez et al. (2021), these may be interpreted as random draws from the respective underlying weather distributions. We define a weather shock between 2011 and 2020 (the year of birth of children in our data) as the standardized value of weather equal to or exceeding two standard deviations (SD) above its historical average (1970 – 2007). Hence, a temperature shock occurred in a month if the temperature realization in that month (relative to historical mean and historical standard deviation) was equal to or greater than 2 SDs. Similarly for rainfall and humidity. We incorporate these measures in Equation (1) in two steps. We begin by replacing only the non-parametric form of temperature with this shock equivalent given the focus on temperature in the climate change literature (Aragon et al. 2021, Carleton and Hsiang 2016, Jessoe et al. 2016). This leads to:

$$y_{ihv} = \beta TempShock_{mt} + \gamma Rain_{mt} + \delta Humid_{mt} + \theta X_{ihv} + \sigma_m + \alpha_t + \mu_v + (\sigma_m * \mu_v) + \vartheta_{ihv} \qquad (3)$$

We then investigate shocks to all three measures of weather we consider in a related specification of the following format:

$$y_{ihv} = \beta TempShock_{mt} + \gamma RainShock_{mt} + \delta HumidShock_{mt} + \theta X_{ihv} + \sigma_m + \alpha_t + \mu_v + (\sigma_m * \mu_v) + \omega_{ihv} \qquad (4)$$

Results from these alternate models are presented below.

5. Data and Summary Statistics

Data for this study are from the Chakaria Health and Demographic Surveillance System (HDSS), which, since 2011, has collected comprehensive information on a variety of indicators for 49 randomly chosen villages in the Chakaria in conjunction with the International Center for Diarrheal Disease Research, Bangladesh (ICDDR, B). As noted above, Chakaria is ICDDR, B's health monitoring station in the southeast of the country near Cox's Bazaar (the inland point in Figure 1). The original site has existed for close to twenty years, surveying about 20,000 households (about 118,000 residents). More information may be obtained from the Chakaria HDSS Annual Report (various years). We focus on the most recently available (2020) malnutrition module that collected information on children's MUAC measure for 19,357 children (3 years of age and below) of 12,398 mothers from 13,197 households on a monthly basis from 2011 to early 2020. Our sample consists of children born between January 2011 and March 2020 when data collection had to be halted because of the pandemic.

The closest weather station to the households in our survey is situated in Cox's Bazaar. Since our sample is from the sub-district of Chakaria, there is little variation in the distance of each household in the sample from the weather station to exploit (most households are at the same average distance). We have information on average monthly temperature, on average monthly rainfall, and on average monthly humidity from 1970 to 2020. We construct the non-parametric and standardized forms of the weather variables and merge them with the child sample by month and year of birth. In subsequent analysis, we shift time windows to consider impacts of exposure in the month of conception and by trimesters *in utero*. For purposes of the summary statistics discussion, we focus on the sample constructed by merging information at the month and year of birth levels.

We combine four additional data sets to the child health and weather sample. The first includes incidence of miscarriage suffered by mothers (merged with the main sample on the basis of mother's ID and as of early 2020), and the second includes information on households that were surveyed in 2011 but then out-migrated from the region in the 2011-2020 time window (merged with the main sample on the basis of household ID). Haque et al. (2019) notes that climate change has resulted in the displacement of people in Bangladesh. Controlling for these households is thus important from the viewpoint of accounting for possibly selective attrition. We also include satellite-sourced information in square kilometers (kms) from 2017 on changes from 1990 to 2017 in pasture area, in cropland (arable land and permanent crops) area, in total area planted with rice, in total rainfed rice area, and in total rainfed other crops (no rice) area, from the Historical Database of the Global Environment (HYDE 3.2) data source (Goldewijk et al. 2017). We merge these variables with the Chakaria HDSS data using the GIS location codes of households in the sample to test whether they explain the impacts of changing climate on child MUAC. We supplement these variables with satellite data from 2012 on soil oxygen availability obtained from FAO's Harmonized World Soil Database (FAO 2012).

Other characteristics that were initially included are change in area of the Sundarbans (to measure land lost due to either rise in the sea level or excessive salinity from rising ocean waters) and causes of mortality and morbidity (pneumonia, tuberculosis, diarrheal diseases). These were available only at the annual level and thus their impacts could not be separately identified since our models condition on year fixed-effects.

Table 1 provides the descriptive statistics of the sample. Panel A (children's and mother's statistics) reports that the mean child MUAC is 138.7 millimeters. The threshold for being well nourished in this age group is 135 millimeters, and so the average child is barely above this benchmark. In estimates not reported, 25 % of children is at risk for acute malnutrition, and 6.4 % suffer moderate acute malnutrition. About 0.6 % of children experience severe acute malnutrition. Other estimates in Panel A show that 51 % of the sample is male and 12 % are infants. The average age in days of children in the sample is 557 (1.5 years). Average year of birth of mothers in the sample is 1989 (average age is 31 years). Age at first marriage of mothers is 18 years. The mean level of mother's schooling is about 5 years, which indicates that most mothers in the sample have not completed primary school. Approximately 11 % of mothers report having had at least one miscarriage in the past.

Panel B (household sample) shows that average land ownership among these households is low at 0.3 decimals, about 9 percent of households migrated from the area in the years of the survey, and pasture, cropland, total rice, rainfed rice, and rainfed non-rice crop areas have all decreased between 1990 and 2017. Soil quality measures range from 0 (low) to 7 (high) and the mean value of oxygen availability indicates that soil quality is low.

Panel C (children's sample) notes the summary statics for the weather variables. Considering the temperature bins, most children are born in months of the year when temperature ranges between 25 – 30 ^{o}C (77 – 86 ^{o}F) on average, and temperature shocks are evident on average for around 5.3 % of the months from 1970 to 2020. The mean of average monthly rainfall in this region (total monthly rainfall divided by number of days in a month) is around 10 mm, and approximately 6.6 % of months have experienced a rainfall shock. The final weather-related measures involve humidity where the constructed bins indicate that the largest proportion of months experience relatively high humidity levels of 75 % and higher, also reflected in the mean value of average humidity (80 %).

6. Results for Impacts on MUAC

6.1. Exposure in month and year of birth

Table 2 reports results for impacts of temperature, rainfall and humidity in month and year of birth on children's MUAC. The first three columns (Model 1) correspond to Equation (1) where humidity is measured only in its linear form. Model 2 encompasses columns (4) through (6) where the impact of humidity is allowed to vary non-linearly with a quadratic model. Columns (1) and (4) condition on only the saturated fixed-effects in Equation (1), while columns (2) and (5) add the child and mother characteristics. Columns (3) and (6) include household characteristics. We report only the weather-related variables in Table 2. The full set of results for all variables is shown in Appendix Table 1 and discussed briefly below.

Estimates in column (1) indicate that as compared to children born in the comfortable monthly temperatures of 20 – 25 ^{o}C, those born in the next higher bin of 25 – 30 ^{o}C have MUAC measures that are a little over 1.5 mm lower. Since the mean MUAC in the sample is 138.7 mm, this represents a 1.1 % decline relative to the mean. Similarly, those born when temperatures exceed 30 ^{o}C have MUAC measures that are 2.2 mm lower, a 1.6 % decline relative to the mean.

Columns (2) and (3) add the child, mother and household variable sequentially and while the negative impact of the greater than 25 ^{o}C bins are still evident, these are not measured with significance.

Focusing on columns (4) – (6) in Table 2, again, relatively higher temperature leads to declines in children's MUAC but now the linear measure of humidity has a positive impact while its square term has a negative impact. Hence, humidity has a positive impact on child health, but there is an optimal level beyond which these impacts decline. These signs are consistent with the non-linear effects of humidity in Zhang et al. (2017). Improvements in crop yields with rising humidity (as documented in Zhang et al. 2017) is a channel that may explain the beneficial effect on child MUAC. As before, adding child, mother and household characteristics absorbs the significance of temperature. However, the humidity variables continue to be significant in column (6). Permutation inference for these models where children are matched to randomly assigned village-level climate variables yield similar results, indicating that power is less of a concern (Hahn and Shi 2017).

We briefly discuss the impacts of the child, mother and household characteristics in the full model of Equation (1) reported in Appendix Table 1. Male children have relatively higher MUAC measures than female children, while infants have lower MUAC measures as compared to older children in the 0-3 years age group. Older mothers have children with better health, and mother's years of schooling have positive effects on her children's MUAC. Households that own land (and so potentially richer) have children with relatively higher MUAC values. The sign and significance of the household out-migration indicator suggests that population displacement has a negative effect on child MUAC measures. A possibility here is that the relatively richer households (with better child health) are more likely to leave the area and thus the average level of MUAC among children who remain is comparatively lower. The significance of this variable underlines the importance of controlling for displacement of this nature as we do here.

6.2. Impacts on different age groups post-birth

We disaggregate children by age post-birth in order to analyze whether exposure has differential impacts over time. Results are reported in Table 3 where column (1) and (5) focus on children who are six months old or younger, and columns (2) and (6) focus on children who are one year old or younger. There is some indication that relatively higher temperatures are beneficial for the youngest age group, echoing findings in Babalola et al. (2018), but we are less confident of these results given the reduced sample size. Relative temperature impacts are absent when we extend the window to those who are a year old or younger while humidity has impacts only in Model 2 that allows its more flexible form. While temperature and humidity have the expected signs in Model 1 for those who are 24 months or younger (column (3)) and those in the first 1000 days of life (column (4)), there are few results that are statistically significant except for a consistent indication that being born in relatively cooler months (15 – 20 ^{o}C) is beneficial. This is true for the corresponding columns under Model 2 as well in terms of temperature (columns (7) and (8)) with humidity remaining significant in its linear and quadratic terms. We conclude that overall, disaggregation by ages reduces sample sizes such that statistical precision in the weather variables is apparent primarily in samples that include the older age groups.

6.3. Exposure in month of conception

We next consider exposure in the month of conception. Focusing on this time-period is helpful since, as noted in Brainerd and Menon (2014), it is often the time when a mother is unaware that she is pregnant, thus minimizing the effect of any adaptive behaviors that might render the impact of weather endogenous (for example, limiting exposure to heat by curtailing hours of work to the extent possible, or as noted in Dankelman et al. (2008), adapting agricultural practices by switching to easily marketable but possibly less-nutrient crops, or moving from raising poultry to raising relatively more labor intensive ducks with a view to increasing savings). These results are reported in Appendix Table 2 and show that conditional on child, mother and household characteristics, none of the weather variables are significant. The month of conception is often not a time when pregnant women are gaining weight, and thus shocks to mother's nutrition from detrimental impacts on yield from weather fluctuations as we hypothesize, are less likely to be relevant.

6.4. Exposure by trimester

The final window of time we consider is exposure in the complete *in utero* period. We focus on individual trimesters and then adopt the most flexible form that conditions on all three trimesters simultaneously and report results in Table 4. Conditioning on all covariates and focusing on the specification in column (4), coefficients indicate that the largest harmful impacts of relatively high temperatures result from exposure in the third trimester mostly, with some evidence that exposure in the second trimester matters beneficially, especially at the lowest temperature range. Rainfall has (negative) effects mainly in the first and second trimesters, while humidity has similar effects to those documented above in the third trimester although these are not significant.

The first trimester is when the fetus develops rapidly both neurologically and physically. This progresses into the second trimester; the fetus begins to gain weight near the end of the second trimester and through the third trimester. The results in Table 4 indicate differential impacts of weather during these timespans with temperature exerting negative effects mainly during the weight gain stage, suggesting that declines in mother's nutrition matters at this point in time. The positive impacts of rainfall and humidity in the third trimester support this possibility (the rainfall coefficients are significant in trimester 3 as noted in column (3) of Table 4), further underlining the Fetal Origins hypothesis attributed to Barker (2007) and developed more recently in Edwards (2017) that nutritional deprivation prenatally has long-lasting effects.

In sum, relatively higher temperatures have negative effects and humidity has positive effects on MUAC at the time of birth, in the larger samples that include older children in the 0 – 3 year age group, and during the third trimester where rainfall too has beneficial impacts.

7. Mechanisms

7.1. Impacts of weather on migration, changes in pasture, cropland and rainfed rice and non-rice areas, and soil oxygen availability

In order to understand possible mechanisms underlying the effects of changing weather on child's health, we analyze impacts on household indicators including whether the household out-migrated, changes between 2017 and 1990 in the extent of pastures, cropland, total area planted with rice, total area planted with rainfed rice, total area planted with rainfed crops other than rice, and the health of soil in the region as measured by oxygen availability. We focus on these crop area variables as we do not have data on crop yield which is hypothesized to be the channel through which weather impacts children's nutrition and health. It is likely that if total area planted with rice has decreased over time, rice yield has declined correspondingly. Other studies that proxy for yield using area planted and provide evidence that area planted is important in contexts where climate has changed measurably include Anderson et al. (2017), Anderson et al. (2013) and Aragon et al. (2021). These results are reported in Table 5.

Column (1) of Table 5 shows that while there are few measurable impacts on out-migration from the area, rainfall in column (2) has had a non-linear influence on the area of pastures between 1990 and 2017 (these are the earliest start and end points of time for the available HYDE 3.2 data from these localized regions). The summary statistics presented in Table 1 showed that pastures have shrunk in this time span, and the coefficients in column (2) provide (weak) evidence that declines in rainfall has been a contributory factor. In terms of cropland area in column (3) (where cropland measures arable land and permanent crops), relatively higher temperatures have led to more declines (mean cropland area has decreased over these years). Columns (4) and (5) provide additional evidence that relatively higher temperatures have decreased total areas planted with rice, the staple food grain, and total area planted with rainfed rice. Rice is among the least water efficient cereals, utilizing over 1,600 liters of water per kilogram of production, most of which has to be rainfed in Bangladesh, and there is evidence that planting alternate crops such as maize or sorghum can drastically reduce water demand in South Asia

(Davis et al. 2018). Correspondingly, relatively higher temperatures have somewhat increased areas planted with crops other than rice (although the data do not allow us to pinpoint which these are exactly). Finally, higher relative temperatures decrease the oxygen availability of soils, perhaps by their negative impact on soil respiration. The results in Table 5 underline that temperature in particular may influence child health by altering agricultural landscapes with resulting effects on household nutritional intake.

7.2. Impacts of weather on mother's age at first marriage and incidence of miscarriage

As is well understood, child health is importantly influenced by mother's characteristics. We focus on the measures that are available to us in this realm and study the consequences of changing climate on mother's age at first marriage and the incidence of miscarriage. We consider these indicators given the literature that shows that children of younger mothers have worse health (Brainerd and Menon 2015), and because younger mothers are at greater risk of experiencing a miscarriage. Considering results in column (2) of Table 6 that includes all controls, there is evidence that relatively higher temperatures decreases age at first marriage. These patterns reflect impact of changing weather on household security and (agricultural) wealth with subsequent implications on the early marriage of daughters as a coping mechanism in the face of climate shocks (Ahmed et al. 2019, Carrico et al. 2020). Results in column (4) show that there are essentially very few measurable impacts of changing weather on miscarriages reported by mothers (some evidence that relatively lower temperatures reduce miscarriages). We also considered impacts on miscarriage of weather in the month of conception and three and six months prior to conception where the results were insignificant. This gives us additional confidence that the sample of children we study is not selected along this dimension. Even with selection of this nature, we would have a conservative bias in our results. This is because if climate change increased the risk of miscarriage, then the sample of births is likely to be positively selected, as the strongest fetuses would survive to term. Hence, our coefficients would underestimate the true (negative) impacts of weather fluctuations on children's health.

8. Alternate Specifications and Falsification Tests

We report the results of the alternate empirical frameworks in Equations (2), (3) and (4) in Table 7. In this table, Model 3 corresponds to Equation (2) which now includes non-parametric measures for humidity in the month and year of birth of the child. Focusing on column (1) that includes only the fixed-effects, negative impacts of relatively high temperature is still evident but relative excessive humidity also exerts harmful effects on children's MUAC. The significance of both temperature and humidity measured non-parametrically (with rainfall measured parametrically) is similar to results in Barreca (2012). However, coefficients in column (2) indicate that these impacts are no longer significant when child, mother and household characteristics are included.

Results in columns (3) and (4) correspond to Model 4, which is Equation (3). Here rainfall and humidity are measured in their quadratic forms while the temperature variable is in its shock form denoting a standardized monthly level that is 2 SDs above the historical mean. Results indicate the expected negative impact of such temperature shocks on child MUAC; however, the coefficient is insignificant (in the 50-year time span we consider, there are relatively few months with temperature shocks of this size). On the other hand, humidity continues to exert similar significant effects as reported in Table 2 for Equation (1).

We end the discussion of estimates in Table 7 by noting that the last two columns report results for Model 5 (Equation (4)). While the temperature and humidity shocks have the expected detrimental impacts on child MUAC in column (6), these are both measured with error. A rainfall shock however has large positive and significant consequences on children's health as measured by MUAC. Many of these findings echo those from our preferred specification in Equation (1) that relatively higher temperatures have negative effects, while humidity and rainfall have positive effects in Tables 2 – 4.

We undertake falsification tests to check the robustness of our results. In order to do this, we consider the impact of weather three months before the month of conception and in a separate set of runs, six months before the month of conception. If the results in our preferred specification in Table 2 are due to omitted variables that are simultaneously correlated with the outcome and the weather measures, or if the model is mis-specified, then temperature, rainfall and humidity will have significant effects on children's MUAC even before conception. Table 8 reports the results of these falsification tests for Models 1 and 2 that include all controls. The overall lack of significance in this table provides re-assurance that omitted variables are not a cause for concern.

9. Conclusions and Policy Implications

This study undertakes a careful analysis of the joint effects of temperature, rainfall and humidity on the nutritional status of young children in rural coastal Bangladesh. We document that children's health (as measured by mid upper arm circumference) is at risk from exposure in the month of birth from rising temperatures in particular, while variable rainfall and humidity exert milder more beneficial impacts. Male children are less affected, and mother's years of schooling and land ownership protect children's nutritional well-being. There is some evidence that exposure *in utero* also matters, especially in the third trimester. Some channels that explain these findings include the detrimental impact of excessive heat on croplands and total rainfed areas planted with rice, the staple crop in Bangladesh. Further, there is evidence that temperature variations reduce mother's age at first marriage. Specification and robustness checks underline the validity of our estimates. The data from this study is from the Chakaria sub-district of southeast Bangladesh supplemented with satellite information on agriculture and land use in this region.

The results of our study offer clear thinking on how to alleviate some of the impacts of changing climate on populations who are unprotected. Evidence indicates that particular attention needs to be paid to the agricultural resources of households, damage to which may have long-lasting implications on the extent of cultivable lands, changes to crop choice and input mixes, and may result in declining agricultural productivity, with subsequent threats to rural livelihoods. Focusing on protecting the health of vulnerable groups such as young children is a direct implication of our work. Creative thought that guides design on policies, solutions, and possible adaptations, may help circumvent some of the negative consequences on those who are especially susceptible. Since environmental insults can have long-run consequences on child and adult health (Barker 2007, Currie and Vogl 2013, Edwards 2017), this issue deserves serious consideration in current debates on the deleterious effects of climate change.

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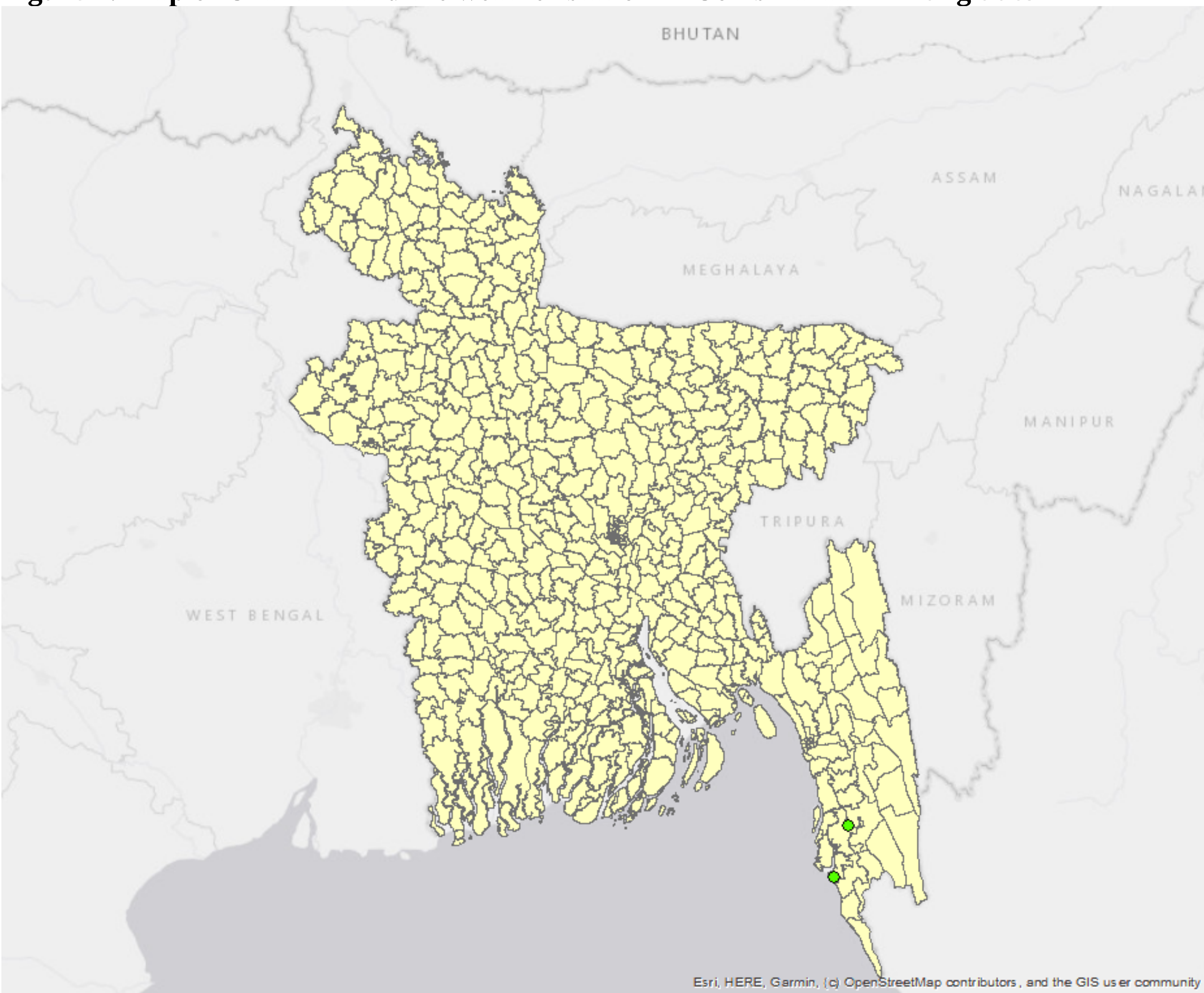
Figure 1: Map of Chakaria and the weather station in Cox's Bazaar in Bangladesh

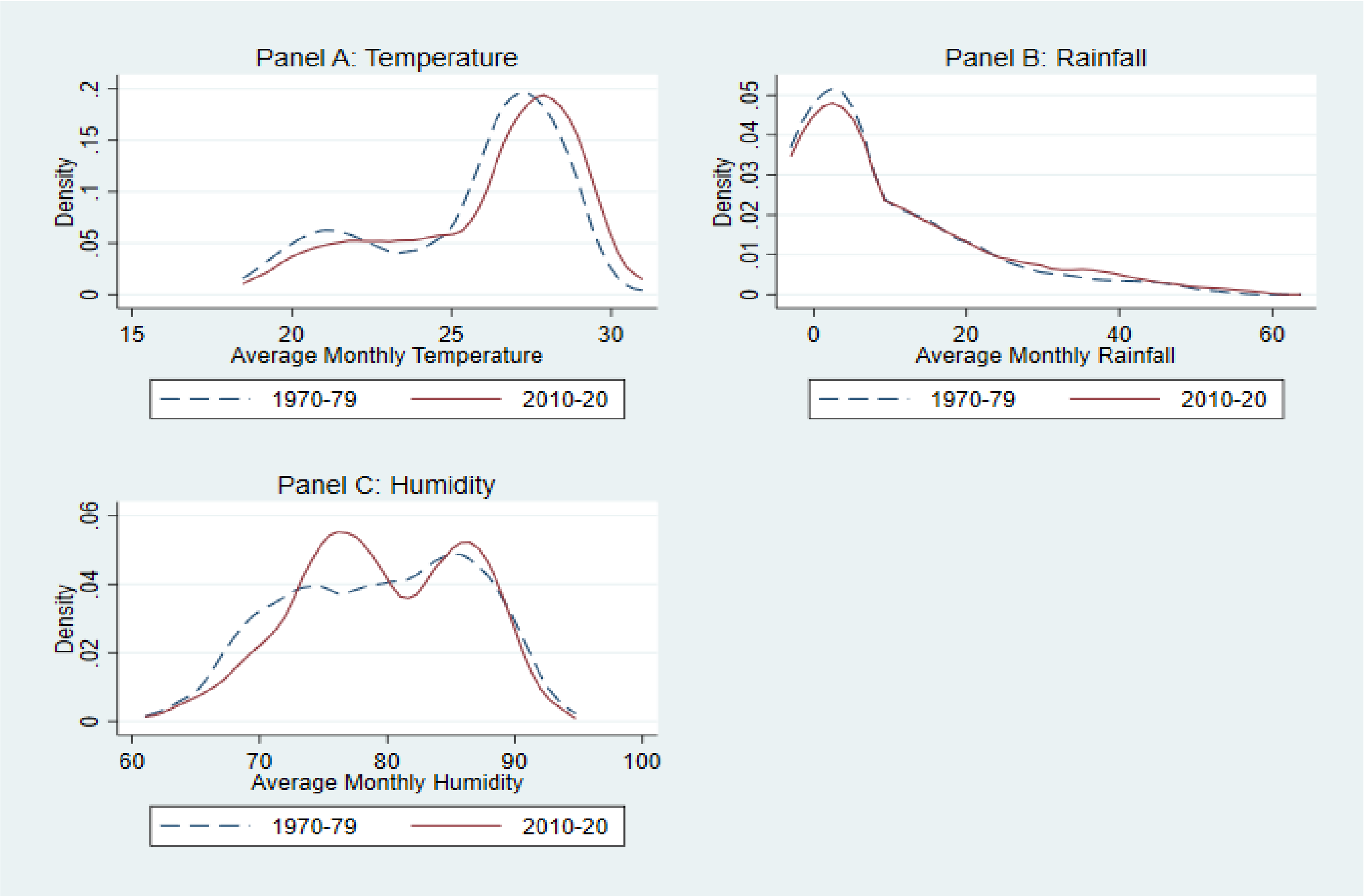


Notes: Authors' calculations. Boundaries denote upazillas (sub-districts) in Bangladesh.

Figure 2: Non-parametric measures of temperature, rainfall and humidity 1970-2020

Notes: Author's calculations using meteorological data from the Cox's Bazaar weather station.

Figure 3: Kernel densities of temperature, rainfall and humidity 1970-2020



Notes: Author's calculations using meteorological data from the Cox's Bazaar weather station.

Table 1: Summary statistics for the sample

Variable	Mean	Standard Deviation	Observations
Panel A: Child and mother related			
Outcome: Mid upper arm circumference (MUAC)	138.687	9.796	19,357
Male	0.507	0.500	19,357
Infant	0.116	0.320	19,357
Age in days	557.128	307.491	19,357
Month of birth	6.513	3.487	19,357
Year of birth	2015.232	2.688	19,357
Mother's Year of birth	1989.632	6.469	12,392
Mother's Age at first marriage	18.116	2.994	12,198
Mother's Years of schooling	4.828	3.712	12,385
Whether mother has had a miscarriage	0.109	0.311	8,210
Panel B: Household related			
Land owned in decimals	0.267	1.262	12,407
Whether migrated from the area	0.087	0.282	12,408
Change in pasture area (km^2) between 1990 and 2017	-0.039	0.094	10,614
Change in cropland (arable land and permanent crops) area (km^2) between 1990 and 2017	-8.067	1.748	10,614
Change in total rice area (km^2) between 1990 and 2017	-6.807	6.981	10,614
Change in total rainfed rice area (km^2) b/w 1990 and 2017	-47.835	22.290	10,614
Change in total rainfed other crops (no rice) area (km^2) between 1990 and 2017	-7.057	18.229	10,614
Soil oxygen availability	1.465	0.722	10,614
Panel C: Weather related			
15 – 20 ºC	0.038	0.191	19,357
20 – 25 ºC	0.254	0.436	19,357
25 – 30 ºC	0.700	0.458	19,357
> 30 ºC	0.008	0.087	19,357
Temperature >= 2SD above historical mean (1970 – 2007)	0.053	0.224	19,357
Rainfall (mm)	10.234	12.930	19,357
$Rainfall^2$ (mm)	271.907	539.278	19,357
Rainfall >= 2SD above historical mean (1970 – 2007)	0.066	0.248	19,357
< 65 %	0.010	0.099	19,357
65 – 70 %	0.072	0.259	19,357
71 – 75 %	0.160	0.367	19,357
76 – 80 %	0.309	0.462	19,357
81 – 85 %	0.170	0.375	19,357
86 – 90 %	0.271	0.444	19,357
91 – 95 %	0.008	0.091	19,357
Humidity (%)	79.797	6.522	19,357
$Humidity^2$ (%)	6410.035	1031.227	19,357
Humidity >= 2SD above historical mean (1970 – 2007)	0.008	0.088	19,357

Notes: Weather is average temperature, average rainfall and average humidity. Sample in Panels A and C includes all children. Sample in Panel B includes households.

Table 2: Impact of temperature, rainfall and humidity in month and year of birth on children's MUAC

	Model 1			Model 2		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
15 – 20 ºC	0.320	0.570	0.550	0.331	0.570	0.549
	(0.413)	(0.429)	(0.432)	(0.409)	(0.426)	(0.430)
25 – 30 ºC	-1.533***	-0.635	-0.593	-1.595***	-0.719	-0.677
	(0.398)	(0.480)	(0.480)	(0.399)	(0.473)	(0.472)
> 30 ºC	-2.154**	-0.807	-0.798	-2.150**	-0.830	-0.821
	(0.843)	(1.038)	(1.033)	(0.843)	(1.034)	(1.029)
Rainfall	-0.009	0.011	0.011	0.024	0.046	0.046
	(0.041)	(0.036)	(0.036)	(0.041)	(0.038)	(0.037)
Rainfall^2	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	-0.045	-0.038	-0.037	1.174***	1.190**	1.200**
	(0.028)	(0.032)	(0.032)	(0.423)	(0.521)	(0.519)
Humidity^2				-0.008***	-0.008**	-0.008**
				(0.003)	(0.003)	(0.003)
Observations	19,354	13,813	13,813	19,354	13,813	13,813
R-squared	0.233	0.257	0.259	0.234	0.257	0.260
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓	✓	✓
Child and mother characteristics	×	✓	✓	×	✓	✓
Household characteristics	×	×	✓	×	×	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 3: Impact of temperature, rainfall and humidity in month and year of birth on children's MUAC by age groups

	Model 1				Model 2			
	<=6m	<=1y	<=24m	<=1000d	<=6m	<=1y	<=24m	<=1000d
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
15 – 20 ºC	2.865	0.799	1.087*	0.877*	2.958	0.657	1.042*	0.874*
	(1.820)	(1.078)	(0.606)	(0.474)	(2.097)	(1.109)	(0.606)	(0.473)
25 – 30 ºC	-2.187	-0.811	-0.854*	-0.573	-2.241	-0.887	-0.947*	-0.647
	(2.261)	(0.991)	(0.481)	(0.489)	(2.301)	(0.996)	(0.474)	(0.479)
> 30 ºC	8.676**	-2.980	-2.160	-0.641	8.527**	-2.863	-2.156	-0.648
	(4.222)	(2.354)	(1.340)	(1.002)	(4.158)	(2.358)	(1.342)	(1.002)
Rainfall	-0.179	-0.018	-0.029	0.011	-0.211	0.030	0.012	0.042
	(0.290)	(0.086)	(0.053)	(0.039)	(0.307)	(0.091)	(0.057)	(0.041)
Rainfall^2	-0.001	0.000	0.001	-0.000	-0.001	0.000	0.001	-0.000
	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
Humidity	-0.025	-0.054	-0.008	-0.046	-0.765	2.091*	1.542*	1.038*
	(0.275)	(0.075)	(0.044)	(0.037)	(3.842)	(1.219)	(0.771)	(0.592)
Humidity^2					0.005	-0.015*	-0.010**	-0.007*
					(0.026)	(0.008)	(0.005)	(0.004)
Observations	1,170	4,122	8,945	12,408	1,170	4,122	8,945	12,408
R-squared	0.530	0.355	0.287	0.268	0.530	0.355	0.287	0.268
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓	✓	✓	✓	✓
Child and mother characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child, mother and household characteristics are the same as in Table 2. Models report robust standard errors clustered at the village level. Columns (1) and (5) consider children less than or equal to six months old, columns (2) and (6) consider children less than or equal to a year old, columns (3) and (7) are children less than or equal to two years old, and columns (4) and (8) consider children in the first 1000 days of life. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 4: *In utero* impacts of temperature, rainfall and humidity on children's MUAC

Variable	Trimester 1 (1)	Trimester 2 (2)	Trimester 3 (3)	All Trimesters (4)
First trimester: 15 – 20 ºC	-0.219			-3.675
	(0.437)			(3.254)
First trimester: 25 – 30 ºC	0.544			1.052
	(0.627)			(1.649)
First trimester: > 30 ºC	0.531			3.528
	(1.091)			(3.802)
Second trimester: 15 – 20 ºC		-0.014		6.496**
		(0.433)		(2.858)
Second trimester: 25 – 30 ºC		0.104		0.549
		(0.582)		(2.811)
Second trimester: > 30 ºC		-0.389		2.889
		(0.994)		(4.849)
Third trimester: 15 – 20 ºC			0.015	-3.419
			(0.449)	(2.552)
Third trimester: 25 – 30 ºC			0.237	-1.447
			(0.576)	(1.700)
Third trimester: > 30 ºC			-0.153	-6.493***
			(1.078)	(2.372)
First trimester: Rainfall	-0.093			-0.192*
	(0.090)			(0.099)
First trimester: Rainfall^2	0.001			0.003*
	(0.001)			(0.001)
Second trimester: Rainfall		-0.336***		-0.425***
		(0.064)		(0.084)
Second trimester: Rainfall^2		0.004***		0.006***
		(0.001)		(0.001)
Third trimester: Rainfall			0.209***	0.113
			(0.072)	(0.078)
Third trimester: Rainfall^2			-0.003***	-0.001
			(0.001)	(0.001)
First trimester: Humidity	0.243			-0.784
	(0.730)			(0.920)
First trimester: Humidity^2	-0.001			0.006
	(0.005)			(0.006)
Second trimester: Humidity		-0.961		-0.785
		(0.916)		(1.042)
Second trimester: Humidity^2		0.008		0.007
		(0.006)		(0.007)
Third trimester: Humidity			0.338	1.306
			(0.879)	(1.166)
Third trimester: Humidity^2			-0.003	-0.010

			(0.006)	(0.008)
Observations	13,807	13,807	13,807	13,807
R-squared	0.261	0.262	0.261	0.263
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓
Child and mother characteristics	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓

Notes: The excluded category for temperature across trimesters is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 5: Impact of temperature, rainfall and humidity in month and year of birth on mechanisms

Variable	HH out migration (1)	Change in pasture area (2)	Change in cropland area (3)	Change in total rice area (4)	Change in rainfed rice area (5)	Change in rainfed non-rice area (6)	Soil oxygen availability (7)
15 – 20 ºC	-0.021	-0.001	0.017	0.139	0.169	-0.017	0.002
	(0.015)	(0.001)	(0.019)	(0.250)	(0.198)	(0.229)	(0.005)
25 – 30 ºC	-0.019	-0.003	0.052*	0.670*	0.556*	-0.701*	-0.009*
	(0.017)	(0.002)	(0.027)	(0.390)	(0.326)	(0.364)	(0.005)
> 30 ºC	-0.053	-0.008	0.132**	1.428**	1.304	-1.021	0.001
	(0.036)	(0.006)	(0.060)	(0.701)	(0.876)	(0.632)	(0.018)
Rainfall	0.001	-0.000	0.001	0.014	0.008	-0.006	0.001
	(0.002)	(0.000)	(0.001)	(0.011)	(0.009)	(0.010)	(0.001)
Rainfall^2	0.000	0.000*	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Humidity	0.034	-0.001	0.007	0.123	0.076	-0.110	-0.000
	(0.024)	(0.001)	(0.009)	(0.130)	(0.117)	(0.123)	(0.001)
Humidity^2	-0.000	0.000	-0.000	-0.001	-0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	12,400	10,604	10,604	10,604	10,604	10,604	10,604
R-squared	0.088	0.956	0.970	0.693	0.980	0.960	0.983
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓	✓	✓	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes households. Household characteristics include land owned in decimals, and whether the household out-migrated (latter is excluded in column (1)). Models report robust standard errors clustered at the village level. Area measured in square kilometers, change is measured as (2017 – 1990). Soil oxygen availability is measured in 2012. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 6: Impact of temperature, rainfall and humidity on mother's outcomes

	Age at first marriage		Miscarriage	
Variable	(1)	(2)	(3)	(4)
15 – 20 ºC	0.117	0.107	-0.063**	-0.062**
	(0.197)	(0.191)	(0.030)	(0.030)
25 – 30 ºC	-0.407**	-0.372*	-0.016	-0.014
	(0.192)	(0.196)	(0.024)	(0.024)
> 30 ºC	-0.483	-0.570	-0.025	-0.019
	(0.382)	(0.357)	(0.035)	(0.034)
Rainfall	-0.026	-0.032**	0.000	0.000
	(0.017)	(0.015)	(0.002)	(0.002)
Rainfall^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Humidity	0.018	-0.047	0.009	0.005
	(0.214)	(0.198)	(0.026)	(0.026)
Humidity^2	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Observations	12,186	12,175	8,191	8,104
R-squared	0.080	0.151	0.093	0.095
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓
Mother characteristics	✗	✓	✗	✓
Household characteristics	✗	✓	✗	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes mothers. Mother characteristics include age and years of schooling in column (2), also includes mothers' years of schooling in column (4). Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 7: Impact of temperature, rainfall and humidity in month and year of birth on children's MUAC in alternate specs.

	Model 3		Model 4		Model 5	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Temperature measures						
15 – 20 ºC	0.308	0.563				
	(0.431)	(0.447)				
25 – 30 ºC	-1.476***	-0.544				
	(0.401)	(0.482)				
> 30 ºC	-2.115**	-0.751				
	(0.849)	(1.052)				
Temperature >= 2SD above historical mean			-0.281	-0.284	-0.278	-0.285
			(0.230)	(0.296)	(0.224)	(0.280)
Rainfall measures						
Rainfall	0.051	0.061	0.028	0.048		
	(0.045)	(0.048)	(0.042)	(0.038)		
Rainfall^2	-0.001	-0.001	0.000	-0.000		
	(0.001)	(0.001)	(0.001)	(0.001)		
Rainfall >= 2SD above historical mean					0.412	0.668***
					(0.258)	(0.246)
Humidity measures						
65 – 70 %	0.522	1.126*				
	(0.667)	(0.601)				
71 – 75 %	0.072	0.724				
	(0.720)	(0.716)				
76 – 80 %	0.157	0.613				
	(0.623)	(0.641)				
81 – 85 %	-0.632	0.125				
	(0.782)	(0.780)				
86 – 90 %	-1.632*	-0.648				
	(0.913)	(0.954)				
91 – 95 %	-0.690	0.425				
	(1.405)	(1.547)				

Humidity			1.137***	1.197**		
			(0.418)	(0.515)		
Humidity^2			-0.008***	-0.008**		
			(0.003)	(0.003)		
Humidity >= 2SD above historical mean					-1.900*	-1.378
					(1.060)	(0.973)
Observations	19,354	13,813	19,354	13,813	19,354	13,813
R-squared	0.234	0.260	0.233	0.260	0.233	0.259
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓	✓	✓
Child and mother characteristics	✗	✓	✗	✓	✗	✓
Household characteristics	✗	✓	✗	✓	✗	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." The excluded category for humidity is < 65 % (30-50 % is considered "comfortable"). Historical means include data from 1970 to 2007. Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Table 8: Impact of temperature, rainfall and humidity in three and six months before conception on children's MUAC (falsification)

Variable	Three months before conception (1)	(2)	Six months before conception (3)	(4)
15 – 20 ºC	0.400	0.402	0.779**	0.786**
	(0.536)	(0.536)	(0.378)	(0.382)
25 – 30 ºC	-0.255	-0.274	0.237	0.242
	(0.487)	(0.489)	(0.505)	(0.510)
> 30 ºC	-1.152	-1.146	-0.305	-0.307
	(0.951)	(0.949)	(0.911)	(0.909)
Rainfall	-0.025	-0.016	0.027	0.025
	(0.037)	(0.037)	(0.038)	(0.040)
Rainfall^2	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	0.051	0.600	-0.037	-0.136
	(0.036)	(0.468)	(0.041)	(0.460)
Humidity^2		-0.004		0.001
		(0.003)		(0.003)
Observations	13,812	13,812	13,812	13,812
R-squared	0.261	0.262	0.263	0.263
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓
Child and mother characteristics	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

ONLINE APPENDIX

Appendix Table 1: Impact of temperature, rainfall and humidity in month and year of birth on children's MUAC (full set of results)

	Model 1			Model 2		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
15 – 20 ºC	0.320	0.570	0.550	0.331	0.570	0.549
	(0.413)	(0.429)	(0.432)	(0.409)	(0.426)	(0.430)
25 – 30 ºC	-1.533***	-0.635	-0.593	-1.595***	-0.719	-0.677
	(0.398)	(0.480)	(0.480)	(0.399)	(0.473)	(0.472)
> 30 ºC	-2.154**	-0.807	-0.798	-2.150**	-0.830	-0.821
	(0.843)	(1.038)	(1.033)	(0.843)	(1.034)	(1.029)
Rainfall	-0.009	0.011	0.011	0.024	0.046	0.046
	(0.041)	(0.036)	(0.036)	(0.041)	(0.038)	(0.037)
$Rainfall^2$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	-0.045	-0.038	-0.037	1.174***	1.190**	1.200**
	(0.028)	(0.032)	(0.032)	(0.423)	(0.521)	(0.519)
$Humidity^2$				-0.008***	-0.008**	-0.008**
				(0.003)	(0.003)	(0.003)
Male		2.770***	2.764***		2.770***	2.763***
		(0.134)	(0.136)		(0.134)	(0.136)
Infant		-3.860***	-3.878***		-3.825***	-3.842***
		(0.312)	(0.319)		(0.314)	(0.321)
Mother's year of birth		0.077***	0.077***		0.077***	0.078***
		(0.017)	(0.017)		(0.017)	(0.017)
Mother's age at first marriage		0.044	0.038		0.044	0.039
		(0.032)	(0.032)		(0.032)	(0.032)
Mother's years of schooling		0.157***	0.140***		0.156***	0.140***
		(0.026)	(0.027)		(0.026)	(0.026)
Whether mother has had a miscarriage		-0.331	-0.303		-0.336	-0.307
		(0.273)	(0.272)		(0.272)	(0.272)
Land owned by household in decimals			0.427***			0.426***

			(0.086)			(0.086)
Whether household migrated from the area			-0.674*			-0.688*
			(0.357)			(0.356)
Observations	19,354	13,813	13,813	19,354	13,813	13,813
R-squared	0.233	0.257	0.259	0.234	0.257	0.260
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓	✓	✓
Child and mother characteristics	✗	✓	✓	✗	✓	✓
Household characteristics	✗	✗	✓	✗	✗	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Appendix Table 2: Impact of temperature, rainfall and humidity in month of conception on children's MUAC

	Model 1		Model 2	
Variable	(1)	(2)	(3)	(4)
15 – 20 ºC	0.356	-0.037	0.358	-0.041
	(0.420)	(0.437)	(0.420)	(0.437)
25 – 30 ºC	0.998*	0.707	1.002*	0.699
	(0.531)	(0.593)	(0.530)	(0.593)
> 30 ºC	0.700	0.850	0.693	0.853
	(1.030)	(1.173)	(1.029)	(1.171)
Rainfall	-0.024	0.001	-0.028	0.005
	(0.043)	(0.047)	(0.043)	(0.045)
Rainfall^2	0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	0.066	0.043	-0.097	0.247
	(0.042)	(0.049)	(0.455)	(0.438)
Humidity^2			0.001	-0.001
			(0.003)	(0.003)
Observations	19,353	13,812	19,353	13,812
R-squared	0.241	0.263	0.241	0.263
Year, village, month FEs, village FEs x month FEs	✓	✓	✓	✓
Child and mother characteristics	✗	✓	✗	✓
Household characteristics	✗	✓	✗	✓

Notes: The excluded category for temperature is 20 – 25 ºC (68 – 77 ºF), which is considered "comfortable." Models include a constant term. Sample includes children. Child characteristics include age and gender. Mother characteristics include age, years of schooling, age at first marriage, and whether has had a miscarriage. Household characteristics include amount of land owned in decimals, and whether the household migrated from the area. Models report robust standard errors clustered at the village level. *** Denotes significance at the 1% level, ** at the 5% level and * at the 10% level.