Climate change and child malnutrition: A Nigerian perspective☆

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Highlights

- We study the effects of climate change on children's nutrition in Nigeria.
- Temperature directly affects child malnutrition while precipitation has an indirect effect.
- Climate change has a higher adverse effect in rural areas compared to urban areas.
- Progress made to reduce malnutrition can be lost due to the effect of climate change.

Abstract

Erratic temperatures and precipitation influence nutrition, human capital investment, and living standards, particularly for children. This study investigates the effect of climate change (changes in the monthly maximum average near-surface temperature and total monthly precipitation) on children's health outcomes, particularly stunting and underweight, in Nigeria. We combine Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) data with high resolution gridded climate data. We find that the rise in temperature is associated with higher levels of stunting – even more so in rural areas. The paper's findings highlight the need for climate-friendly policies to mitigate the long-term effect of climate change on malnourishment. Without such policies, climate change could reverse years of progress in lowering children's malnutrition.

JEL classification: Q54; I12; I15

Keywords: Climate change; Malnutrition; Stunting; Underweight; Spatial analysis

1. Introduction

Sub-Saharan Africa accounts for one-third of all malnourished children globally, highlighting that malnutrition among children under 5 years remains a major health concern in the region (Akombi et al., 2017, Onyango et al., 2019). Although the prevalence of undernourishment among children under 5 years of age has declined since 2000, there has been an increase in undernourishment since 2015, in part associated with climate change and extreme events (Niles et al., 2021, FAO, 2019b). Food production in Sub-Saharan African countries is dependent on rainfall and natural resources. These countries face the risk of declining food availability as current food systems are threatened by climate variables, including extreme weather events, seasonality and changes to ecosystems, biodiversity, and natural resources (Alderman et al., 2006a).

Adverse health outcomes for children such as stunted growth and being underweight are a typical result of food insecurity (Grace et al., 2012a). When unmet nutritional and caloric needs negatively impact a child's natural growth trajectory, a child's growth and brain development slows, which negatively impacts children's adulthood outcomes such as education, productivity, and income (Arthur et al., 2015, Alderman et al., 2006b). The effects of malnutrition can also be intergenerational: malnutrition can cause individuals to remain in poverty across generations (Yitbarek and Beegle, 2019, Pena and Bacallao, 2002). In addition, malnourished girls are more likely to experience complications during delivery and to deliver lower birth-weight babies (Grace et al., 2012a; Alderman et al., 2006a).

Environmental and climate factors such as rising temperatures and droughts negatively affect the welfare and nutrition of young children (Grace et al., 2015). Ahdoot et al. (2015) notes that humans are vulnerable to climate change because of its adverse effects on physical and mental health, such as increased stress and decreased air and water quality. Disease patterns, the increased probability of extreme weather events, agricultural productivity, and food security are all affected by climate change. Through their impact on these key factors, erratic temperatures and precipitation influence nutrition, human capital investment, and living standards, particularly for children (Davenport et al., 2017, Lobell and Field, 2007). Children are more vulnerable to the adverse effect of climate change due to their dependence on caregivers and their immature physiology. Children in households that are dependent on agriculture are most susceptible to chronic malnutrition resulting from climate change (Brown and Funk, 2008).

While several studies explore the relationship between child malnutrition and agroecological, geographic, socioeconomic, and demographic factors (Galway et al., 2018, Johnson et al., 2013), the empirical evidence linking climate change and children's health outcomes is scant, especially in Africa. This study uses nationally representative panel data from Nigeria to investigate the impact of changing temperature and precipitation on child malnutrition (specifically, stunting and being underweight).

The relationship between climate change and children's nutritional outcomes is complex. First, changes in climate affect malnutrition through an agroecosystems pathway with an adverse impact on food production; for instance, by affecting crop output, crop growth, diseases, and pests (Reddy et al., 2019, Niles et al., 2021). As a result, climate change could affect food security and diet diversity by changing the availability and quality of food sources. Climate change effects on food security and diet diversity could occur over the short-term (e.g., due to extreme weather events such as heatwaves and floods) and longer-term (e.g., increasing temperatures and decreasing precipitation). Second, climate change can affect nutritional outcomes indirectly through heat effects on pregnant women and their children's health outcomes such as low birth weight and preterm birth (Zhang et al., 2017). Finally, climate change may reduce food security through changes in food prices and market-related shocks and stressors (Brown et al., 2017).

The study is not the first to consider the effects of climate change on children's health outcomes in Africa. Child stunting has been associated with decreases in rainfall in Rwanda (Akresh et al., 2011). Temperature irregularities have also been found to be associated with child stunting in Ethiopia (Hagos et al., 2014). However, these studies use predictive changes in temperature and rainfall to forecast health outcomes. We instead combine household survey data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) with actual weather data (temperature and precipitation) to form a panel dataset that allows us to investigate how actual changes in temperature and precipitation impact contemporary children's health outcomes.

Our results indicate that increasing temperatures and decreasing precipitation lead to a higher probability of malnutrition (stunting and being underweight) among children, supporting the notion that temperature has a direct effect on child malnutrition and precipitation an indirect effect (Ahdoot et al., 2015, Cooper et al., 2019). These effects are more prominent in rural areas than in urban areas. We find that a one-unit (°C) increase in temperature

increases the likelihood of a child being stunted by 0.53% and 0.71% per year in urban and rural areas, respectively. Overall, results suggest that climate change is threatening to undo the progress made in Nigeria to reduce childhood malnutrition.[1] From a policy perspective, results point to the need for climate-friendly policies that can avert the effect of climate change on malnutrition, especially among children. Improvements to public infrastructure (Bassolé et al., 2007), access to electricity (Davenport et al., 2017), food aid and subsidies supporting agricultural research and services (Mary et al., 2020), as well as improved educational and social institutions (Grace et al., 2012b) are some mechanisms shown to be effective against climate change, thereby improving population health. For countries like Nigeria, where most of the population depends on subsistence agriculture, promoting climate-smart agricultural practices can also reduce child malnutrition and increase human capital accumulation (Tesfaye and Tirivayi, 2018, Tesfaye and Tirivayi, 2020).

The rest of this paper is set out as follows. Section 2 summarizes the literature on child malnutrition and climate change. Section 3 describes the data used and presents the descriptive statistics. Section 4 presents the estimation strategy. Section 5 sets out the empirical results with regards to temperature, precipitation, as well as the combined effect. Section 6 offers discussion points and policy implications. Section 7 concludes.

2. Literature review

Nelson et al. (2009) links the adverse effects of climate change on human well-being and agriculture. Their estimate suggests that $7.1-$7.3 billion investment is required to mitigate the effect of climate change on child malnutrition. The author also stresses the need to improve agricultural productivity to meet future food security demands in the face of climate change. In addition, other research has shown that long-term improvement of economic development, such as higher human capital and economic growth in Africa, may hinge, at least partially, on decreasing child malnutrition (Davenport et al., 2017).

Chronic malnutrition leads to stunting in a third of all children under 5 years of age born in developing countries (Costello et al., 2009, Beegle and Christiaensen, 2019). Developing countries are more vulnerable to climate change due to a lack of resources and their dependence on subsistence agriculture (Balk et al., 2005). Sub-Saharan Africa is especially prone to malnutrition in children as it already has a history of chronic food insecurity, poor health outcomes and, more recently, increased temperatures and decreased rainfall (Davenport et al., 2017).

Phalkey et al. (2015) conducts a systematic literature review to identify the pathways in which climate variability leads to undernutrition among subsistence farming households. Extreme weather (floods and droughts), seasonality, and rise in temperature reduce crop yields, affecting household income, food prices, and food affordability that can negatively affect children's health outcomes. However, the impact of climate change on nutrition is uncertain, mainly due to a limited understanding of interacting pathways. Myers et al. (2017) stresses the influence of climate change on food quality and quantity coupled with equitable distribution. Their result indicates that increased CO_2 leads to nutrient losses. Rice, wheat, barley, and potatoes exhibit 7%–15% protein reduction, where cereals, grains, and legumes exhibit 3%–11% reductions in zinc and iron coupled with 5%–10% reductions in "phosphorus, potassium, calcium, sulfur, magnesium, copper, and manganese".

Datar et al. (2013) found that exposure to a natural disaster within the past year increased the likelihood of child stunting and being underweight by 7% in India. Hagos et al. (2014) investigate the impact of weather variables – temperature and rainfall – on child undernutrition for three agroecological zones in Ethiopia. Their estimate shows that one standard deviation increase in rainfall led to a 0.242 standard deviation increase in stunting. Results indicated that wasting is unrelated to rainfall and temperature; however, a positive relationship exists between rainfall square, suggesting a non-linear relationship. Berkhout et al. (2019) investigate the link between malnutrition and soil quality in selected Sub-Saharan African countries. The authors found evidence that increased micronutrients in the soil significantly reduce the prevalence of child mortality, stunting, wasting, and underweight only in rural areas.

While growing empirical studies explore the relationship between child malnutrition and agroecological, geographic, socioeconomic, and demographic factors, the empirical evidence linking climate change and children's health outcomes is scant, especially in Africa. The current analysis uses various malnutrition measures–stunting and underweight–to understand the effects of climate change on children's malnutrition and extend the findings of two studies in Africa. Akresh et al. (2011) and Hagos et al. (2014) study the effect of climate change on children stunting in Rwanda and Ethiopia, respectively. However, both studies use predictive temperature and rainfall changes to forecast children's health outcomes. We instead combine national representative survey data from Nigeria with actual weather data to form a panel dataset and investigate the effect of actual changes in temperature and precipitation on children's health outcomes, stunting, and underweight.

Although Black et al. (2008) found that poor children are often at considerable risk of malnutrition and stunting, in agriculture-dependent countries like Nigeria, all children are susceptible. Given Nigeria's economic composition, we expect urban as well as rural children to be vulnerable to climate change since households are dependent on low-cost and locally grown foods (Davenport et al., 2017). In Nigeria, the cornerstone of the economy remains agriculture regardless of the availability of oil. Agriculture employs 36.5% of the entire labour force (World Bank, 2019) and contributes roughly a quarter of Nigeria's GDP (African Development Bank, 2019). Moreover, around 88% of farmers in Nigeria are subsistence farmers (World Bank, 2019) and half of Nigeria's population live in rural areas (FAO, 2019c), suggesting that malnutrition will become an even more substantial concern in Nigeria with a changing climate.

3. Data

Three waves of the Nigerian Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) data are used to investigate temperature and precipitation's effect on children's health outcomes. The LSMS-ISA is a multi-topic, nationally representative household panel survey focusing on agriculture-related data. It is collected by the World Bank's Development Data Group in collaboration with the Nigerian National Bureau of

Statistics (NNBS) in three rounds; 2010–2011, 2012–2013, and 2015–2016. All the surveys collect detailed information on socioeconomic characteristics, health (including anthropometric measurements for children under 5), consumption expenditure, assets ownership, and access to services. In addition, the agriculture module collects data on land ownership and agricultural inputs use, crop production, livestock ownership, and access to agricultural extension services. In all waves, households are georeferenced using a global positioning system (GPS) that allows combining the survey data with historical temperature and precipitation data.

The LSMS-ISA data is sampled in two stages: the post-planting stage, which occurs between August and October, and the post-harvest stage, which occurs between February and April. To measure the panel-effect of climate change, we use data of children that stay in the sample for at least two consecutive waves and are below the age of 5.

3.1. Outcome variables

We construct health outcome variables (stunting and underweight), following the World Health Organization (WHO) standards for all children under 5 years of age whom we observe in two consecutive waves. First, we calculate height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height (WHZ) z-scores. The z-scores represent the number of standard deviations by which the child's anthropometric measurements deviate from the median child growth standard of WHO (World Health Organization, 2010). Second, a z-score cut-off point of −2 is used to generate a binary indicator for stunting, underweight, and wasting. A z-score of less than −2 identifies children who have low height-for-age or stunted children, low weight-for-age or underweight children, and low weight-for-height or wasted children (World Health Organization, 1995). We exclude children with incomplete or implausible anthropometry data from the analysis.[2]

Stunting represents long-term, life-threatening health outcomes. Stunting can arise due to poor nutrition in-utero and early childhood, which could worsen due to poor sanitation, unsafe drinking water, and lack of hygiene (Grace et al., 2017). Children who suffer from stunting may never reach their full possible height and may have suboptimal brain development that negatively affects children's cognitive development, educational attainment, and economic productivity during adulthood (UNICEF et al., 2020, Beegle and Christiaensen, 2019, Feinstein, 2003). Existing empirical evidence suggests that taller siblings from the same mothers perform better on cognitive tests and have better health, economic, and educational outcomes (Case and Paxson, 2010, Glewwe and Jacoby, 1995). Stunting can also cause decades of harmful effects and can undermine the development of a country; for developing countries, the average per capita income penalty from stunting is about 7% (Galasso and Wagstaff, 2019).

Wasting is a short-term indicator of acute malnutrition that results from poor nutrition or disease, and children suffer from weakened immunity and have an increased risk of death when wasting is severe (UNICEF et al., 2020). On the other hand, the underweight measure is a composite indicator of stunting and wasting. The effects of malnutrition vary but, it can undermine health and development, limit learning ability, diminish immune systems, reduce adult work performance and productivity, and increase the chance of giving birth to underfed babies (Jankowska et al., 2012). Therefore, malnutrition has adverse effects on a country's health and the development of its population, both in the short and long term.

In our sample, 37.7%, 19.1%, and 30.5% of children are stunted in the first, second, and third waves, respectively.[3] We note a decline in the rate of stunting between the first and second wave but a deterioration between the second and third wave. Although the prevalence of underweight children in the sample is less than stunting, the pattern is similar. It is important to note that the decline in the prevalence of stunting and underweight could be partly data-driven. The analysis relies on children under the age of 5 that stayed in our sample for two consecutive waves, which might underestimate the prevalence of stunting and underweight in the second wave. Although our identification strategy could underestimate the prevalence of child malnutrition, we note that the full sample of children under 5 follows a similar pattern in prevalence of stunting and underweight with 39%, 19.3% in the first, and 33.9% and 27.1% in the second, 10.5%, and 18.2% in the third waves. This observation suggests that the decline in the prevalence of stunting and underweight in the second wave might be due to an increase in the sample in the same wave. Nevertheless, the total number of stunted and underweight children remained almost unchanged.

Nigeria has made some progress reducing child malnutrition over the last decades (Nwosu and Ataguba, 2020). However, stunting prevalence is increasing in some parts of Nigeria; for instance, in North West, stunting in children aged 24–59 months increased from 52.6% in 2008 to 54.9% in 2013 to 56.9% in 2018 (Ezeh et al., 2021). It is worth mentioning that the decrease in the prevalence of malnutrition in the second wave coincides with colder temperatures and more precipitation in 2012/2013 (survey year of the second wave) and the year preceding it. Overall, malnutrition of children improves in our sample, but the persistent nature of stunting is alarming.

3.2. Measures of climate variability

Temperature and precipitation data are from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia (Harris et al., 2014).[4] The temperature and precipitation variables measure average near-surface maximum temperature in degree Celsius and total precipitation in millimeters, respectively.

The temperature and precipitation data are gridded monthly time-series that cover the period 1960–2018 with a spatial resolution of 2.5 min which is roughly 21 km^2. The households in the LSMS-ISA dataset have GPS coordinates that we associate with each grid in the climate data, and we create a buffer with a radius of 5 kilometers around each household. We create the buffer because the GPS coordinates are offset randomly, so this allows with relative certainty that the specific household point is in that buffer zone.[5] Then, we merge the climate data with the buffer for each household. Merging these two data sets at the relevant spatial and temporal scales is crucial to ensure a thorough analysis of household health and climate changes (Grace et al., 2012b). However, very few studies adopt this approach.

Both the temperature and precipitation are calculated at monthly averages. The monthly average for each survey was taken from July (post-planting) the previous year of the survey to June (post-harvesting), the year of the survey for temperature, and similarly for precipitation except at 4 years and 3-year intervals from July to June. These periods allow capturing the climate variability span of both the post-planting and post-harvesting stages of the LSMS-ISA dataset.

Cooper et al. (2019) find that precipitation's effect on children's health outcomes takes longer. We, therefore, investigate the effects of $\text{precipitation}_{t-3}$'s on child health outcomes.[6] On the other hand, change in temperature is the main contributor to the direct consequences of climate change, such as heat stress, diseases, and air quality that directly affect health outcomes (Ahdoot et al., 2015). Thus, we focus on temperature_{t-1}.

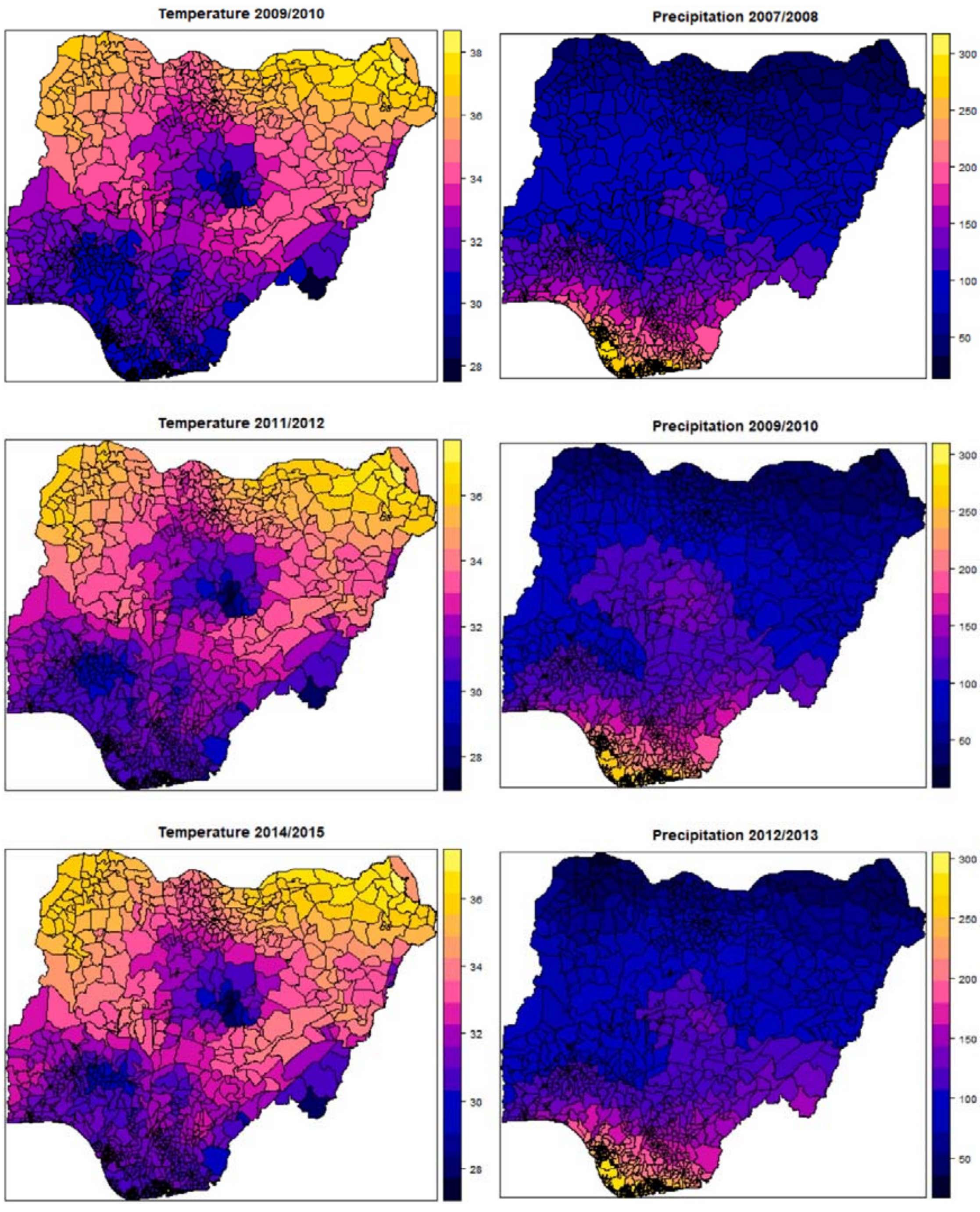

Fig. 1. Maps of temperature and precipitation.

Note: Temperature_{t-1} and $\text{precipitation}_{t-3}$ used in the analysis are shown for each wave.

The different climate zones across Nigeria are presented in Fig. 1. The northern part of the country is typically dryer, experiencing less precipitation, and has higher average temperatures than the South. The south-most point is the concentration point of precipitation.[7] We note an increase in the average maximum temperatures and a decrease in the average total precipitation over time.[8] The patterns in our sample are similar to the climate changes of Nigeria noted by the World Bank (2020).

We also investigate differences in temperature and precipitation across urban and rural households. We note differences in temperature and precipitation patterns across these two areas; the rural areas appear to experience warmer temperatures than urban areas. On average, urban households experience more precipitation (See Table B.2, Table B.3 in Appendix B.)

Looking at the correlation between temperature and precipitation, we note an inverse relationship between temperature_{t-1} and $\text{precipitation}_{t-3}$ in Fig. 2, indicating warm seasons tended to be dryer in Nigeria.

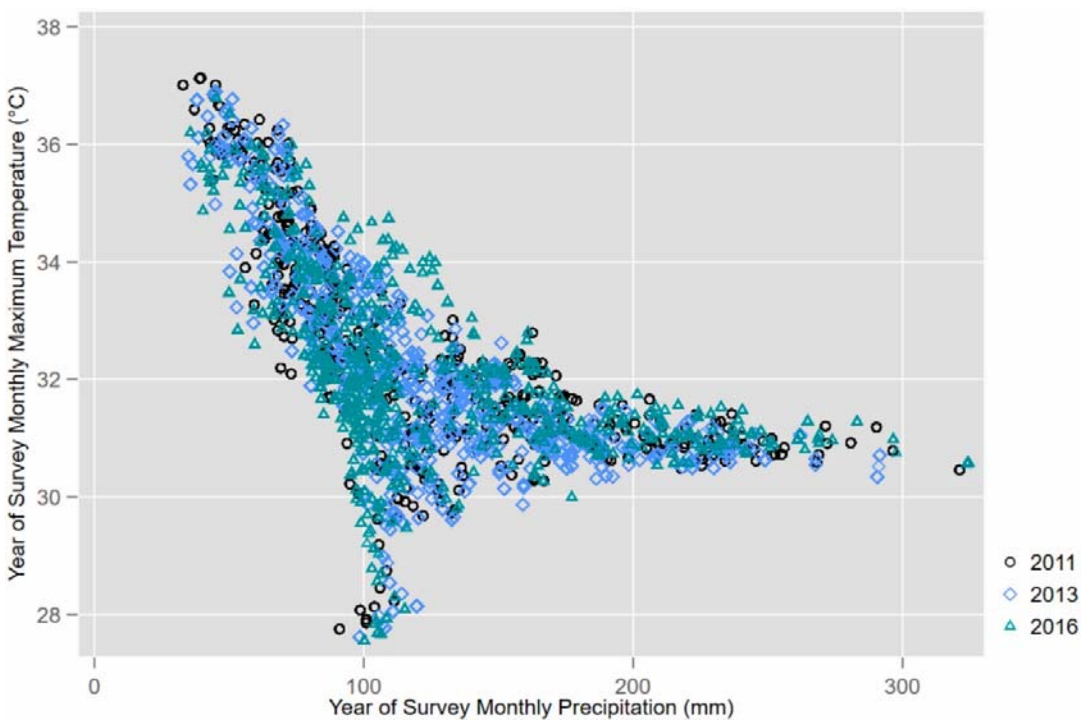

Fig. 2. Temperature and precipitation.

Panel (a) of Fig. 3 plots the distribution of temperature for stunted and non-stunted children. The figure shows that one-year lagged monthly maximum average near-surface temperature (temperature_{t-1}) distribution for stunted children is tilted toward the right and has a lower peak compared to the distribution for non-stunted peers, suggesting a positive relationship between warmer temperatures and stunting. On the other hand, the distribution of three-year lagged total average monthly precipitation ($\text{precipitation}_{t-3}$) for stunted children is tilted to the left, suggesting less precipitation is associated with worse child nutrition (Panel (b) of Fig. 3).

We document a similar distribution of temperature, precipitation, and underweight in Panel (a) and (b) of Fig. 4, respectively.

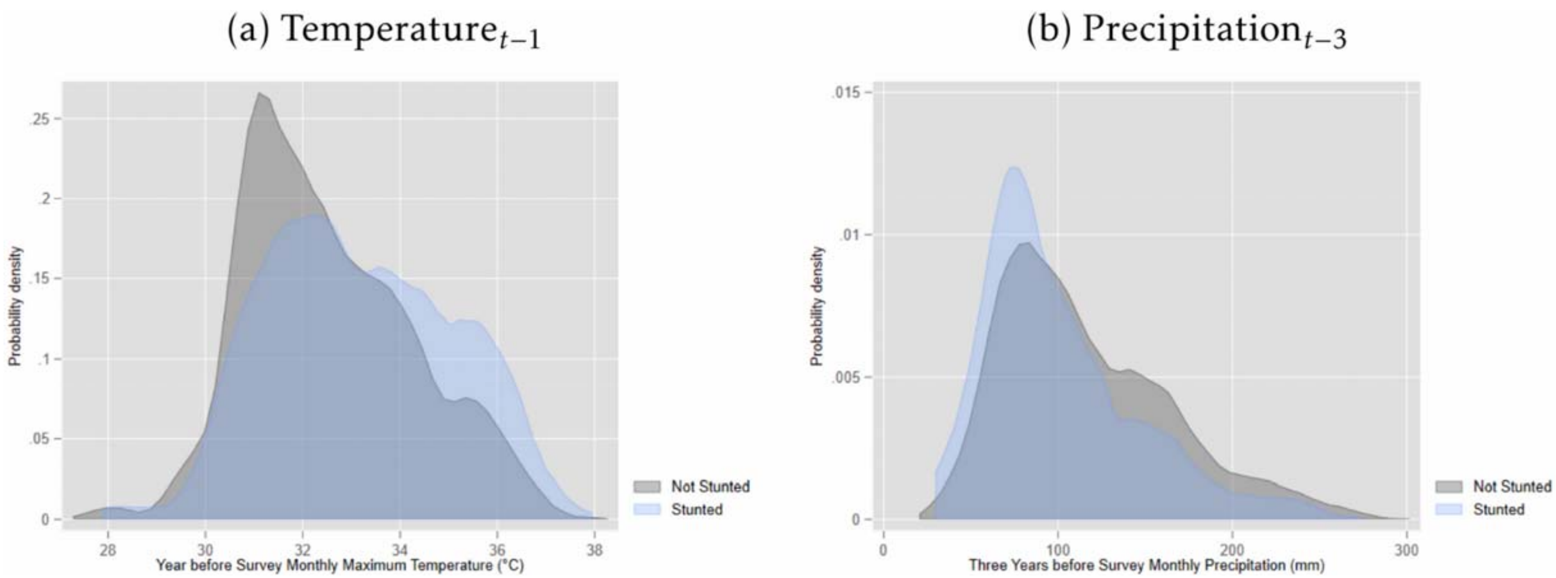

Fig. 3. Relationship between stunting and temperature/precipitation.

Note: temperature$_{t-1}$ (left) and precipitation$_{t-3}$ (right) for stunting.

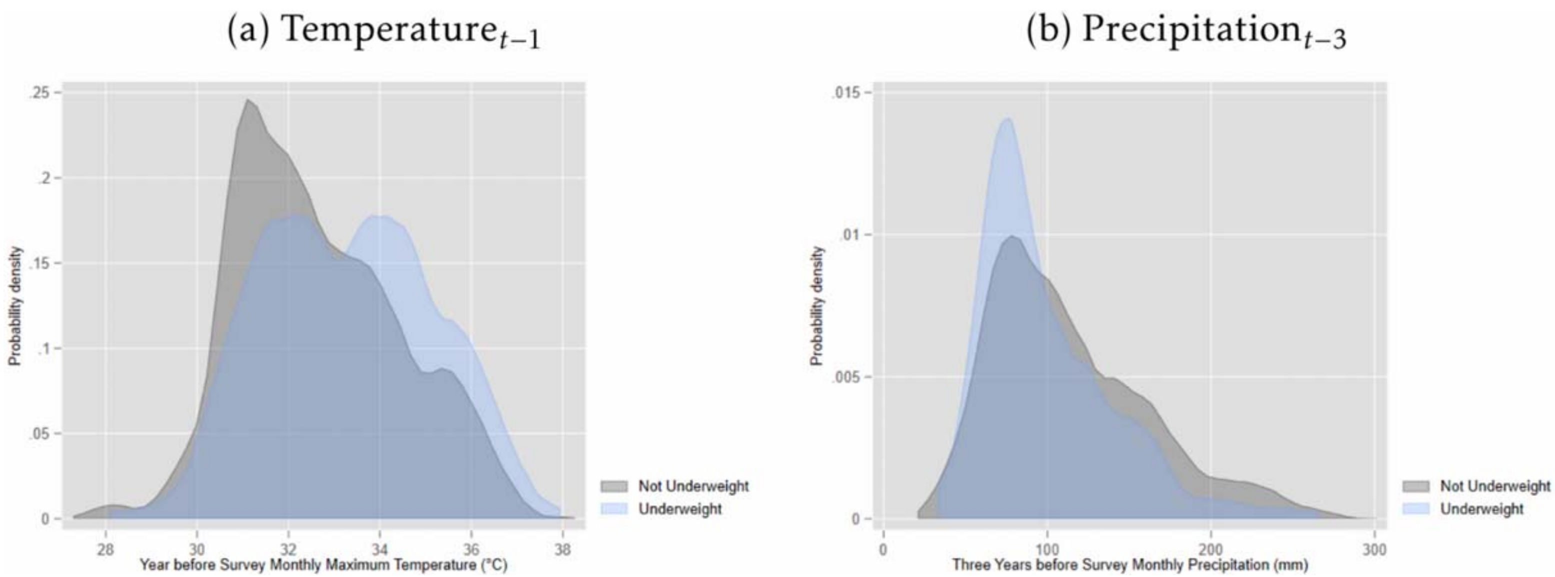

Fig. 4. Relationship between underweight and temperature/precipitation.

3.3. Control variables

The variables included in the regressions were selected based on related literature.[9] These variables control for geographical information (distance to freshwater, cities, and markets), family characteristics (the number of meals to children, access to electricity, household head education), child characteristics (age and gender), household wealth (asset ownership and consumption), agriculture characteristics (aggregate plot size, soil quality, tropical livestock unit), and household access to services (agriculture extension services and access to credit or loans).[10] Household size, educational attainment, and gender of household head control taste, preference, and income-related heterogeneity between children.

4. Estimation strategy

Let the *m* be an indicator for childhood malnutrition where superscripts and represent stunting and underweight, respectively. Let be a vector of the control variables defined in Section 3.3 and listed in A.4. In order to assess the effect of temperature, precipitation and their interaction on child health outcomes, we specify separate regressions as follows:

$$m_{it}^{s,u} = \alpha + \delta_1 Temperature_{t-1} + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it} \tag{1}$$

$$m_{it}^{s,u} = \alpha + \delta_2 Precipitation_{t-3} + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it}. \tag{2}$$

$$\begin{aligned} m_{it}^{s,u} &= \alpha + \delta_3 Temperature_{t-1} + \delta_4 Precipitation_{t-3} \\ &\quad + \theta \left(Temperature_{t-1} \times Precipitation_{t-3}\right) + \beta X_{it} + \gamma \bar{X}_i + r_i + \varepsilon_{it} \end{aligned} \tag{3}$$

We estimate Eqs. (1)–(3) using a logit model with panel techniques where $\bar{X}_i$ is the time-average variable for and allows for the estimation of the correlated random effects (CRE) model as described by Wooldridge (2012). We use the CRE logit model for two reasons: (1) our interest lies in the marginal effects, and (2) the heterogeneous marginal effects across sectors (rural and urban areas). The conditional logit fixed effects do not estimate the individual effects, r_1 in our model. Thus, the marginal effects based on the conditional logit fixed effects model would assume the individual effects are equal to 0, which would bias our marginal (partial) effect of the variable of interest (Wooldridge, 2012).[11] There is still a possibility of endogeneity in our preferred model if there are unmeasured time-varying confounders. This unobserved heterogeneity could be related to seasonal patterns that are correlated with temperature and precipitation and influence child stunting and underweight prevalence.

5. Empirical results

We present the results in three stages. First, we present the effects of temperature on stunting and underweight for all children under 5 years of age. Second, we discuss the effects of precipitation on stunting and underweight. Lastly, we present the interaction effect of temperature and precipitation on children's health outcomes for a robustness check. For brevity, we present and discuss the marginal effects at the means of the CRE logit estimation in Tables 1, 2, and 3 for temperature, precipitation, and their interaction, respectively.[12] To understand the differential effect of climate change on children's health outcomes in rural and urban areas, we estimated the marginal effects at the means by areas of residence. Results are reported in Panel B of Tables 1, 2, and 3 for temperature, precipitation, and their interaction, respectively.

5.1. Effects of temperature

Table 1 displays the marginal effects of the average monthly maximum lagged temperature on child malnutrition, with stunting in Panel A and underweight in Panel C. The first column only includes temperature$_{t-1}$ and uses CRE techniques. Then columns 2–7 gradually add additional regional, location, and household demographics controls.

In Panels A and C of Table 1, temperature has a positive effect on both stunting and underweight, and the results are more robust to adding household demographics and regional characteristics. In Panel A, a one-unit (°C) increase in temperature$_{t-1}$ will increase the probability of child stunting by between 18.6% (column 5) and 22.3% (column 7). Increases in temperature in Nigeria has been approximately per decade from 1981–2021 (NOAA National Centers for Environmental Information, 2021). This is an average change of 0.03°C per year. Focusing on Column 7, this amounts to an increase in the probability of a child stunting by approximately 0.67% per year.[13] This positive correlation implies that the increase in temperature has a detrimental effect on human capital accumulation in Nigeria. Of policy concern, low human development of children that can be manifested in the form of stunting at an early age can result in a poverty trap when remediation of child stunting is partly or mostly irreversible (Beegle and Christiaensen, 2019, Barrett et al., 2016).

Focusing on Panel C in Table 1, the probability of a child being underweight increases by between 7.9% (column 1) and 15.2% (column 7) with a one-unit (°C) increase in temperature$_{t-1}$. Again, with an average change of 0.03°C per year, the probability of a child underweight increases by 0.46% per year, Column 7. Although this effect is smaller in magnitude than the effects we note on stunting, underweight children are less productive and have higher mortality rates (Jankowska et al., 2012).

Following the same argument as above, relying on estimates on Panel B and Column 7, the probability of a child being stunted increases by 0.525% and 0.714% per year in urban and rural areas, respectively. Similarly, the probability of a child underweight increases by 0.369% and 0.489% in urban and rural areas, respectively.[14] Our results suggest that children in rural areas are more susceptible to higher temperatures.[15]

Our findings on the associations between higher temperatures and children's malnutrition are consistent with prior studies; however, there is limited empirical evidence on the pathways through which higher temperatures might have a heterogeneous effect in rural and urban areas. To our knowledge, our analysis is novel. Higher temperatures can affect children's health in rural areas through an agroecosystems pathway with an adverse impact on food production (Reddy et al., 2019, Niles et al., 2021). On the other hand, climate change could affect food security and diet diversity in urban areas by changing the availability and quality of food sources through changes in food price and market-related shocks (Brown et al., 2017, Myers et al., 2017).

Table 1
Marginal effects — Temperature$_{t-1}$.

Panel A: Marginal Effect of Temperature$_{t-1}$ (°C) on Stunting							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature$_{t-1}$ (°C)	0.042	0.026	0.048	0.192***	0.186***	0.197***	0.223***
	(0.044)	(0.044)	(0.044)	(0.056)	(0.056)	(0.056)	(0.062)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel B: Marginal Effect of Temperature$_{t-1}$ (°C) on Stunting by Area of Residence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban	0.041	0.025	0.040	0.165***	0.164***	0.157***	0.175***
	(0.043)	(0.043)	(0.037)	(0.048)	(0.050)	(0.045)	(0.050)
Rural	0.043	0.026	0.051	0.191***	0.193***	0.210***	0.238***
	(0.044)	(0.045)	(0.046)	(0.055)	(0.058)	(0.059)	(0.066)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel C: Marginal Effect of Temperature$_{t-1}$ (°C) on Underweight							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature$_{t-1}$ (°C)	0.079**	0.053	0.080**	0.134***	0.121***	0.135***	0.152***
	(0.033)	(0.033)	(0.033)	(0.038)	(0.038)	(0.038)	(0.043)
Observations	3886	3886	3886	3565	3565	3565	2936
Panel D: Marginal Effect of Temperature$_{t-1}$ (°C) on Underweight by Area of Residence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban	0.076**	0.052	0.066**	0.109***	0.106***	0.105***	0.123***
	(0.032)	(0.033)	(0.028)	(0.032)	(0.034)	(0.031)	(0.036)
Rural	0.080**	0.053	0.085**	0.143***	0.127***	0.146***	0.163***
	(0.034)	(0.034)	(0.035)	(0.041)	(0.040)	(0.041)	(0.046)
Observations	3886	3886	3886	3565	3565	3565	2936
Geographical Information	No	No	No	Yes	Yes	Yes	Yes
Family Characteristics	No	No	No	Yes	Yes	Yes	Yes
Child Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Wealth	No	No	No	Yes	Yes	Yes	Yes
Agriculture Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Assistance	No	No	No	Yes	Yes	Yes	Yes
Education	No	No	No	No	No	No	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Controls	No	Yes	No	No	Yes	No	No
Urban/Rural Controls	No	No	Yes	No	No	Yes	Yes
Survey Year Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All marginal effects are at the mean values of the explanatory variables. Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2

Marginal effects — Precipitation$_{t-3}$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Marginal Effect of Precipitation$_{t-3}$ (mm) on Stunting							
Precipitation$_{t-3}$ (mm)	−0.003*	−0.002*	−0.003*	−0.004**	−0.004**	−0.004**	−0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel B: Marginal Effect of Precipitation$_{t-3}$ (mm) on Stunting by Area of Residence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban	−0.002*	−0.002*	−0.002*	−0.003**	−0.003**	−0.003**	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	−0.003*	−0.003*	−0.003*	−0.004**	−0.004**	−0.004**	−0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel C: Marginal Effect of Precipitation$_{t-3}$ (mm) on Underweight							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Precipitation$_{t-3}$ (mm)	0.001	0.001	0.001	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3886	3886	3886	3565	3565	3565	2936
Panel D: Marginal Effect of Precipitation$_{t-3}$ (mm) on Underweight by Area of Residence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban	0.001	0.001	0.001	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural	0.001	0.001	0.001	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3886	3886	3886	3565	3565	3565	2936
Geographical Information	No	No	No	Yes	Yes	Yes	Yes
Family Characteristics	No	No	No	Yes	Yes	Yes	Yes
Child Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Wealth	No	No	No	Yes	Yes	Yes	Yes
Agriculture Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Assistance	No	No	No	Yes	Yes	Yes	Yes
Education	No	No	No	No	No	No	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Controls	No	Yes	No	No	Yes	No	No
Urban/Rural Controls	No	No	Yes	No	No	Yes	Yes
Survey Year Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All marginal effects are at the mean values of the explanatory variables. Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

5.2. Effects of precipitation

Table 2 reports the marginal effects of precipitation$_{t-3}$ on children malnutrition with Panel A displaying effect on children stunting and Panel C on underweight.[16] Table 2 Column 1 presents the regression result with only precipitation$_{t-3}$ and the relative CRE techniques while Columns 2–6 add additional regional, location, and household demographics controls.

The results indicate that increasing precipitation$_{t-3}$ has a negative effect on the probability of children stunting. This effect remains robust to the different specifications. From Panel A of Table 2, results indicate that a one-unit (1 mm) decrease in the precipitation$_{t-3}$, increases the probability of children stunting by 0.2%(column 1) and 0.4% (column 4, 5 & 6). According to World Bank (2020), average precipitation per year has decreased significantly in Nigeria, by approximately 3.5 mm per month per decade between 1960–2006. This is a decrease in precipitation of 0.35 mm per year on average. Therefore, focusing on Column 7, a decrease in precipitation$_{t-3}$ of 0.35 mm will increase the probability of child stunting by 0.105% per year.[17]

Our findings support the notion that precipitation has an indirect effect on child nutrition and corroborate with the empirical evidence documented by Skoufias and Vinha (2012). As noted by Phalkey et al. (2015), the effect of precipitation works through many demographic and economic variables. The indirect effect of precipitation implies that changing patterns of rain, drizzle, or any other forms of precipitation take time to affect the nutritional status of children. More specifically, water availability from dams or nearby water sources causes the impact of dry seasons to take time to influence crop production and food security.

Regardless of the small magnitude, we again note heterogeneous effects between urban and rural areas (Panel B of Table 2). Rural areas are affected more severely than urban areas; a one-unit (mm) decrease in precipitation$_{t-3}$ leads to an increase in the probability of child stunting by 0.3% and 0.4% in urban and rural areas, respectively, when focusing on Column 7. More relevant, a decrease in precipitation$_{t-3}$ of 0.35 mm will increase the probability of a child suffering from stunting by 0.105% in urban areas and 0.14% in rural areas per year.

5.3. Interaction effect of temperature and precipitation

In the literature it is noted that temperature and precipitation work in tandem to influence child nutrition outcomes (Davenport et al., 2017, Grace et al., 2012b). For robustness, we have interacted temperature$_{t-1}$ and precipitation$_{t-3}$ in the regressions.[18]

Table 3 presents the marginal effects of the interaction model. From all the panels of Table 3 it is clear that the effect of temperature$_{t-1}$ dominates for both stunting and underweight.[19]

The precipitation$_{t-3}$ does not significantly affect the probability of a child being underweight in this specification. However, these two variables work in tandem as higher temperatures and less precipitation increase the probability of children being stunted or underweight.

Comparing this combined effect with temperature alone, the marginal effects of temperature on underweight are similar, but the marginal effects on stunting are smaller. From Panel A and C in Table 3, we get that a one-unit (°C) increase in temperature increases the probability of child stunting by 16.7% and being underweight by 18.9%. Following the same logic as in Section 5.1, with an average change of 0.03 °C in precipitation$_{t-3}$ per year, the probability of child stunting increases by 0.501% per year, and the probability of a child being underweight

Table 3

Marginal effect — Interaction effect of temperature and precipitation.

Panel A: Marginal Effect on Stunting							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature$_{t-1}$ (°C)	−0.015	−0.023	−0.012	0.138**	0.129**	0.145**	0.167***
	(0.046)	(0.046)	(0.046)	(0.059)	(0.058)	(0.059)	(0.064)
Precipitation$_{t-3}$ (mm)	−0.002	−0.002	−0.003*	−0.002	−0.001	−0.002	−0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel B: Marginal Effects on Stunting by Area of Residence							
Urban (Temperature$_{t-1}$ (°C)	−0.015	−0.023	−0.010	0.128**	0.122**	0.123**	0.143***
	(0.046)	(0.046)	(0.041)	(0.053)	(0.053)	(0.049)	(0.053)
Rural (Temperature$_{t-1}$ (°C)	−0.013	−0.021	−0.010	0.150**	0.144**	0.158**	0.188***
	(0.047)	(0.048)	(0.049)	(0.061)	(0.061)	(0.062)	(0.069)
Urban (Precipitation$_{t-3}$ (mm)	−0.002	−0.002	−0.002*	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Rural (Precipitation$_{t-3}$ (mm)	−0.003*	−0.003*	−0.003*	−0.002	−0.002	−0.002	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3511	3511	3511	3212	3212	3212	2662
Panel C: Marginal Effect on Underweight							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature$_{t-1}$ (°C)	0.101**	0.092**	0.102**	0.167***	0.161***	0.170***	0.189***
	(0.040)	(0.041)	(0.040)	(0.047)	(0.047)	(0.047)	(0.052)
Precipitation$_{t-3}$ (mm)	0.002	0.002	0.002	0.002	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3886	3886	3886	3565	3565	3565	2936
Panel D: Marginal Effects on Underweight by Area of Residence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban (Temperature$_{t-1}$ (°C)	0.093**	0.086**	0.083***	0.145***	0.146***	0.138***	0.158***
	(0.036)	(0.038)	(0.032)	(0.039)	(0.041)	(0.037)	(0.042)
Rural (Temperature$_{t-1}$ (°C)	0.097**	0.086**	0.103***	0.173***	0.167***	0.179***	0.199***
	(0.038)	(0.038)	(0.040)	(0.046)	(0.046)	(0.047)	(0.052)

Urban (Precipitation$_{t-3}$ (mm)	0.002*	0.002	0.002*	0.002*	0.002	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rural (Precipitation$_{t-3}$ (mm)	0.002*	0.002	0.002*	0.002*	0.002*	0.002*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	3886	3886	3886	3565	3565	3565	2936
Geographical Information	No	No	No	Yes	Yes	Yes	Yes
Family Characteristics	No	No	No	Yes	Yes	Yes	Yes
Child Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Wealth	No	No	No	Yes	Yes	Yes	Yes
Agriculture Characteristics	No	No	No	Yes	Yes	Yes	Yes
Household Assistance	No	No	No	Yes	Yes	Yes	Yes
Education	No	No	No	No	No	No	Yes
CRE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Controls	No	Yes	No	No	Yes	No	No
Urban/Rural Controls	No	No	Yes	No	No	Yes	Yes
Survey Year Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All marginal effects are at the mean values of the explanatory variables. Delta-Method Standard Errors in Parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

increases by 0.567% per year, from Column 7. We do not find any significance of precipitation$_{t-3}$ on stunting but we do find a small positive effect on underweight that is marginally significant depending on control variables included in the regression.

As documented earlier, where we investigate the separate effect of temperature and precipitation, we note a heterogeneous effect of precipitation and temperature on rural and urban areas. Children in rural areas are more susceptible to increases in temperatures as the probability that these children are either stunted or underweight is higher than those in urban areas. More relevant and focusing on Column 7, a 0.03 °C increase in temperature$_{t-1}$, increases the probability of a child suffering from stunting by 0.429% per year in urban areas and by 0.564% in rural areas. For underweight, these figures are 0.474% and 0.597% per year in urban and rural areas, respectively.

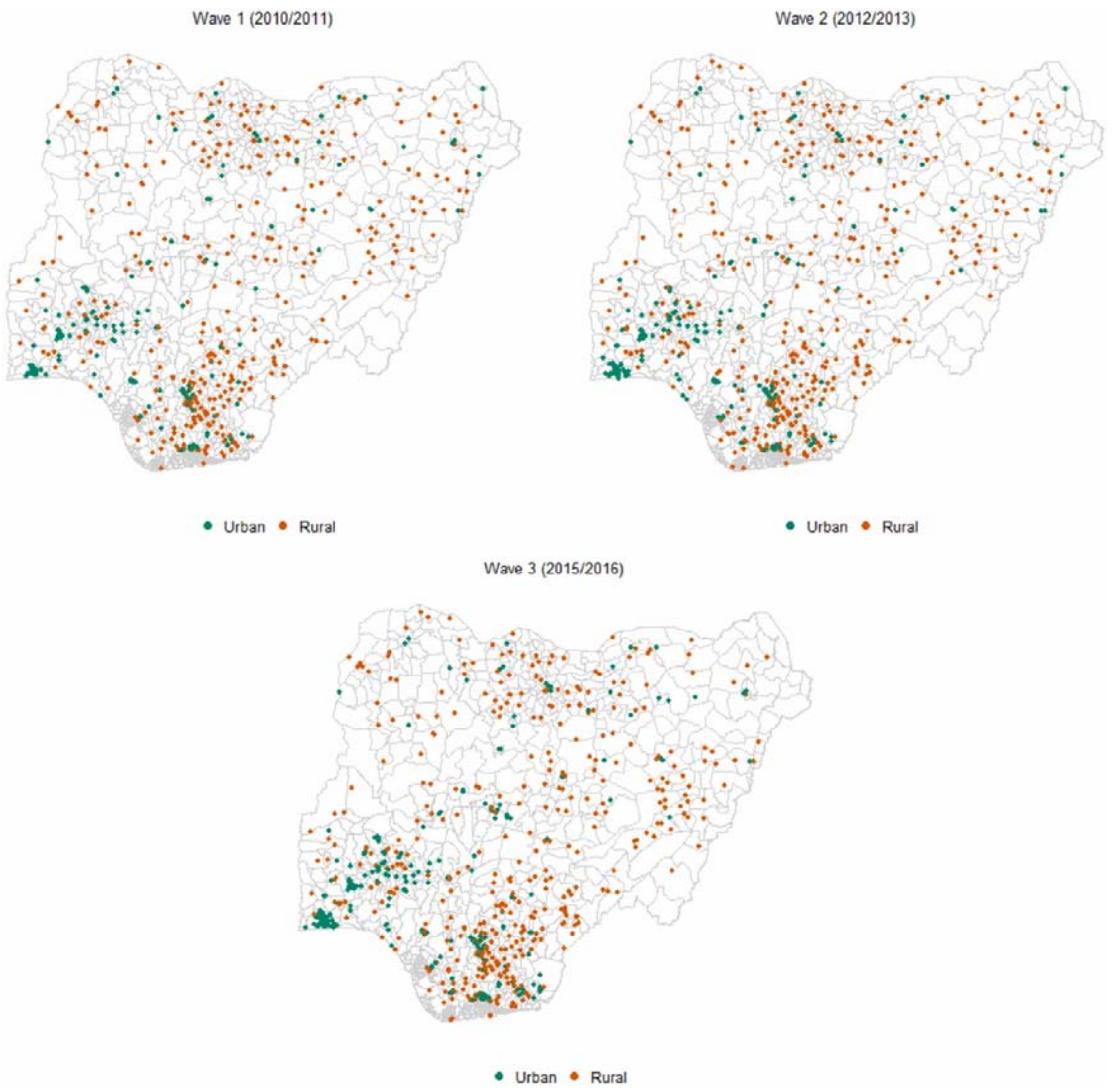

Fig. B.1. Maps of urban and rural split.

Table B.1
Temperature and precipitation across waves.

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016
n (%)	1528 (30.5)	2391 (47.8)	1088 (21.7)
{Temperature}			
Temperature$_t$ (°C), mean (sd)	32.78 (1.80)	32.67 (1.76)	32.65 (1.59)
Temperature$_{t-1}$ (°C), mean (sd)	33.20 (1.97)	32.59 (1.73)	32.76 (1.65)
Temperature$_{t-2}$ (°C), mean (sd)	32.90 (1.93)	32.79 (1.76)	32.84 (1.64)
Temperature$_{t-3}$ (°C), mean (sd)	32.40 (1.71)	33.22 (1.94)	32.71 (1.73)
Temperature$_{t-5}$ (°C), mean (sd)	32.97 (1.90)	32.79 (1.76)	32.82 (1.73)
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.96 (1.90)	32.68 (1.75)	32.75 (1.63)
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.74 (1.81)	32.84 (1.81)	32.72 (1.66)
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.23 (1.09)	25.22 (1.08)	25.20 (1.11)
{Precipitation}			
Precipitation$_t$ (mm), mean (sd)	113.61 (52.50)	110.54 (45.73)	107.91 (45.60)
Precipitation$_{t-1}$ (mm), mean (sd)	110.50 (48.70)	110.18 (52.67)	101.21 (50.52)
Precipitation$_{t-2}$ (mm), mean (sd)	117.55 (53.93)	112.39 (51.18)	99.01 (47.32)
Precipitation$_{t-3}$ (mm), mean (sd)	112.19 (51.02)	109.32 (47.94)	106.83 (43.13)
Precipitation$_{t-5}$ (mm), mean (sd)	107.32 (51.10)	110.73 (50.23)	108.38 (47.51)
Three Year Average Monthly Precipitation (mm), mean (sd)	113.89 (51.46)	111.04 (49.65)	102.71 (47.37)
Five Year Average Monthly Precipitation (mm), mean (sd)	113.95 (51.64)	111.70 (49.81)	104.20 (46.77)
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	234.00 (65.09)	232.07 (63.71)	227.18 (59.49)
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	217.61 (49.03)	215.01 (45.80)	206.11 (42.62)

Average temperature in the wettest quarter, monthly precipitation in the wettest quarter, and monthly rainfall in the wettest quarter are taken from the LSMS-ISA dataset.

Table B.2

Temperature and precipitation across waves in urban areas.

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016
n (%)	411 (31.4)	634 (48.4)	264 (20.2)
{Temperature}			
Temperature$_t$ (°C), mean (sd)	32.40 (1.77)	32.30 (1.71)	32.31 (1.52)
Temperature$_{t-1}$ (°C), mean (sd)	32.74 (1.94)	32.22 (1.68)	32.42 (1.59)
Temperature$_{t-2}$ (°C), mean (sd)	32.45 (1.91)	32.42 (1.71)	32.51 (1.57)
Temperature$_{t-3}$ (°C), mean (sd)	32.04 (1.69)	32.76 (1.89)	32.31 (1.68)
Temperature$_{t-5}$ (°C), mean (sd)	32.52 (1.88)	32.42 (1.71)	32.42 (1.68)
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.53 (1.87)	32.31 (1.70)	32.41 (1.56)
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.35 (1.79)	32.43 (1.77)	32.35 (1.60)
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.19 (1.10)	25.20 (1.09)	25.14 (1.10)
{Precipitation}			
Precipitation$_t$ (mm), mean (sd)	123.97 (52.65)	117.96 (45.49)	111.48 (45.82)
Precipitation$_{t-1}$ (mm), mean (sd)	116.68 (47.13)	118.10 (52.19)	114.25 (49.94)
Precipitation$_{t-2}$ (mm), mean (sd)	128.37 (54.04)	123.23 (51.45)	106.32 (47.31)
Precipitation$_{t-3}$ (mm), mean (sd)	124.29 (50.79)	116.54 (46.22)	115.51 (43.44)
Precipitation$_{t-5}$ (mm), mean (sd)	112.49 (49.95)	123.33 (50.03)	119.76 (48.24)
Three Year Average Monthly Precipitation (mm), mean (sd)	123.01 (51.00)	119.76 (49.51)	110.68 (47.16)
Five Year Average Monthly Precipitation (mm), mean (sd)	123.14 (51.02)	120.68 (49.36)	112.54 (46.71)
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	232.95 (67.64)	232.37 (65.77)	227.54 (62.60)
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	212.68 (44.40)	210.97 (39.39)	202.96 (35.24)

Average temperature in the wettest quarter, monthly precipitation in the wettest quarter, and monthly rainfall in the wettest quarter are taken from the LSMS-ISA dataset. Note that sample is from children under 5 that are present in at least two consecutive surveys.

Table B.3
Temperature and precipitation across waves in rural areas.

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016
n (%)	1117 (30.2)	1757 (47.5)	824 (22.3)
{Temperature}			
Temperature$_t$ (°C), mean (sd)	32.92 (1.79)	32.80 (1.76)	32.76 (1.60)
Temperature$_{t-1}$ (°C), mean (sd)	33.37 (1.95)	32.73 (1.73)	32.87 (1.66)
Temperature$_{t-2}$ (°C), mean (sd)	33.07 (1.91)	32.92 (1.76)	32.95 (1.65)
Temperature$_{t-3}$ (°C), mean (sd)	32.53 (1.70)	33.38 (1.93)	32.83 (1.73)
Temperature$_{t-5}$ (°C), mean (sd)	33.13 (1.88)	32.92 (1.76)	32.95 (1.73)
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	33.12 (1.88)	32.81 (1.75)	32.86 (1.63)
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.89 (1.80)	32.98 (1.81)	32.83 (1.66)
Average Temperature in the Wettest Quarter (°C), mean (sd)	25.24 (1.09)	25.23 (1.08)	25.21 (1.11)
{Precipitation}			
Precipitation$_t$ (mm), mean (sd)	109.79 (51.95)	107.87 (45.53)	106.77 (45.50)
Precipitation$_{t-1}$ (mm), mean (sd)	108.23 (49.09)	107.32 (52.57)	97.04 (50.02)
Precipitation$_{t-2}$ (mm), mean (sd)	113.57 (53.36)	108.48 (50.53)	96.66 (47.11)
Precipitation$_{t-3}$ (mm), mean (sd)	107.74 (50.40)	106.72 (48.30)	104.05 (42.68)
Precipitation$_{t-5}$ (mm), mean (sd)	105.42 (51.41)	106.19 (49.53)	104.73 (46.72)
Three Year Average Monthly Precipitation (mm), mean (sd)	110.53 (51.25)	107.89 (49.34)	100.16 (47.19)
Five Year Average Monthly Precipitation (mm), mean (sd)	110.57 (51.48)	108.47 (49.59)	101.53 (46.50)
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	234.39 (64.15)	231.96 (62.97)	227.07 (58.49)
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	219.42 (50.53)	216.47 (47.83)	207.12 (44.70)

Average temperature in the wettest quarter, monthly precipitation in the wettest quarter, and monthly rainfall in the wettest quarter are taken from the LSMS-ISA dataset. Note that sample is from children under 5 that are present in at least two consecutive surveys.

Table B.4
Temperature and precipitation across zones.

Columns by: zone	(1) North-Central	(2) North-East	(3) North-West	(4) South-East	(5) South-South	(6) South-West
n (%)	882 (17.6)	1134 (22.6)	1325 (26.5)	605 (12.1)	612 (12.2)	449 (9.0)
{Temperature}						
Temperature$_t$ (°C), mean (sd)	32.13 (1.46)	34.00 (1.37)	33.82 (1.44)	31.41 (0.67)	31.00 (0.46)	31.25 (0.83)
Temperature$_{t-1}$ (°C), mean (sd)	32.23 (1.48)	34.24 (1.44)	33.96 (1.49)	31.45 (0.68)	31.03 (0.47)	31.28 (0.84)
Temperature$_{t-2}$ (°C), mean (sd)	32.23 (1.46)	34.24 (1.41)	33.99 (1.45)	31.48 (0.67)	31.06 (0.45)	31.30 (0.81)
Temperature$_{t-3}$ (°C), mean (sd)	32.24 (1.50)	34.30 (1.47)	34.08 (1.51)	31.42 (0.69)	31.00 (0.48)	31.29 (0.86)
Temperature$_{t-5}$ (°C), mean (sd)	32.24 (1.47)	34.28 (1.39)	34.02 (1.46)	31.47 (0.67)	31.06 (0.45)	31.30 (0.82)
Three Year Average Monthly Maximum Temperature (°C), mean (sd)	32.20 (1.46)	34.16 (1.40)	33.92 (1.45)	31.44 (0.67)	31.03 (0.46)	31.28 (0.82)
Five Year Average Monthly Maximum Temperature (°C), mean (sd)	32.18 (1.46)	34.19 (1.38)	33.93 (1.44)	31.42 (0.67)	31.01 (0.45)	31.25 (0.82)
Average Temperature in the Wettest Quarter (°C), mean (sd)	24.88 (1.18)	25.27 (0.97)	25.46 (1.33)	25.13 (0.75)	25.21 (0.56)	25.16 (1.15)
{Precipitation}						
Precipitation$_t$ (mm), mean (sd)	106.35 (15.10)	79.56 (20.80)	75.21 (16.61)	158.53 (18.21)	198.32 (42.58)	121.08 (21.48)
Precipitation$_{t-1}$ (mm), mean (sd)	106.23 (16.63)	70.79 (18.77)	71.18 (19.84)	160.91 (19.40)	200.66 (44.21)	120.24 (16.71)
Precipitation$_{t-2}$ (mm), mean (sd)	105.45 (16.48)	72.60 (18.16)	74.74 (16.50)	162.24 (19.71)	205.90 (44.27)	128.17 (25.07)
Precipitation$_{t-3}$ (mm), mean (sd)	110.12 (13.78)	72.67 (19.17)	74.84 (18.58)	157.55 (16.87)	195.05 (40.80)	124.01 (19.84)
Precipitation$_{t-5}$ (mm), mean (sd)	106.66 (14.39)	71.05 (18.24)	72.84 (15.04)	159.77 (18.32)	199.83 (41.62)	125.98 (23.74)
Three Year Average Monthly Precipitation (mm), mean (sd)	106.01 (15.26)	74.31 (18.31)	73.71 (17.21)	160.56 (18.77)	201.62 (42.99)	123.16 (19.71)
Five Year Average Monthly Precipitation (mm), mean (sd)	107.57 (14.58)	74.54 (18.57)	74.20 (17.31)	160.90 (18.65)	202.11 (42.75)	124.33 (18.99)
Monthly Precipitation in the Wettest Quarter (mm), mean (sd)	223.79 (29.82)	196.13 (34.77)	201.16 (35.60)	281.30 (27.53)	344.35 (65.17)	205.59 (44.19)
Monthly Rainfall in the Wettest Quarter (mm), mean (sd)	210.65 (33.42)	190.87 (36.88)	190.41 (30.25)	262.24 (23.83)	275.12 (47.84)	198.83 (16.18)

Average temperature in the wettest quarter, monthly precipitation in the wettest quarter, and monthly rainfall in the wettest quarter are taken from the LSMS-ISA dataset. Note that sample is from children under 5 that are present in at least two consecutive surveys.

Table B.5
Control variables at household level.

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016
n (%)	1528 (30.5)	2391 (47.8)	1088 (21.7)
{Varying Control Variables}			
Distance to Closest Water Source (km), mean (sd)	4.41 (2.99)	4.43 (3.04)	4.49 (3.07)
Distance to Closest Market (km), mean (sd)	69.81 (44.06)	70.45 (43.48)	72.32 (43.05)
Distance to Closest City (km), mean (sd)	22.93 (21.87)	19.45 (15.45)	27.55 (21.43)
Log of Education Expenditure, mean (sd)	4.83 (3.51)	5.24 (3.43)	6.18 (3.11)
Log of Consumption per Capita, mean (sd)	11.03 (0.68)	11.09 (0.62)	11.25 (0.63)
Number of People in Household, mean (sd)	7.35 (3.13)	7.86 (3.57)	8.26 (3.30)
Number of Children in HH (Less than 5 Years of age), mean (sd)	3.33 (1.18)	3.53 (1.04)	3.59 (2.19)
Number of Meals to Children, mean (sd)	3.58 (1.57)	3.71 (2.00)	3.50 (1.09)
Restricted Meals so Children can Eat, mean (sd)	0.45 (1.06)	0.50 (1.24)	0.42 (1.03)
Household Asset Index, mean (sd)	3.01 (1.84)	3.17 (1.74)	3.44 (1.55)
Number of different Production Shocks Reported, mean (sd)	0.14 (0.42)	0.15 (0.38)	0.10 (0.33)
Number of different Market Shocks Reported, mean (sd)	0.12 (0.44)	0.13 (0.41)	0.18 (0.46)
Log of Aggregate Plot Size, mean (sd)	8.58 (1.54)	8.66 (1.28)	8.69 (1.36)
Tropical Livestock Units as of the time of survey, mean (sd)	3.79 (54.24)	1.27 (5.84)	1.34 (4.80)
Soil Workability (constraining field management) (mean), mean (sd)	1.50 (0.68)	1.50 (0.70)	1.51 (0.72)
Soil Nutrient availability (mean), mean (sd)	1.82 (0.79)	1.80 (0.78)	1.77 (0.78)
{Binary Control Variables}			
Borrow Food, or Rely on Friend/Relative? (Yes), n (%)	181 (12.4)	192 (8.3)	105 (9.7)
Borrow from Microfinance/Credit Associations/Bank (Yes), n (%)	53 (3.5)	121 (5.1)	56 (5.2)
Borrow from Friends/Relatives/Money Lenders (Yes), n (%)	494 (32.4)	739 (31.2)	114 (10.5)
Borrow from Informal Institution (Yes), n (%)	284 (18.7)	431 (18.2)	33 (3.0)
Has Non-Farm Enterprise (Yes), n (%)	761 (49.8)	1461 (61.1)	666 (61.2)
Agri-extension (Government/Private Sector) (Yes), n (%)	77 (5.0)	62 (2.6)	33 (3.0)
Government Assistance (food/cash/otherwise) (Yes), n (%)	25 (1.6)	102 (4.3)	39 (3.6)
Does HH have Electricity in Dwelling? (Yes), n (%)	674 (44.2)	1122 (47.0)	483 (44.5)
Gender of Household Head, n (%)			
Female	65 (4.3)	102 (4.3)	62 (5.8)
Male	1462 (95.7)	2286 (95.7)	1013 (94.2)

sector, n (%)			
Urban	411 (26.9)	634 (26.5)	264 (24.3)
Rural	1117 (73.1)	1757 (73.5)	824 (75.7)
{Categorical Control Variables}			
Ordered Level of Household Head's Completed Education, n (%)			
None/Less than Primary	487 (37.9)	759 (39.1)	365 (42.3)
Primary School Complete	438 (34.1)	585 (30.1)	244 (28.3)
Secondary School Complete	294 (22.9)	467 (24.1)	205 (23.8)
University or Higher Education Complete	65 (5.1)	130 (6.7)	48 (5.6)
zone, n (%)			
North-Central	280 (18.3)	414 (17.3)	188 (17.3)
North-East	358 (23.4)	543 (22.7)	233 (21.4)
North-West	358 (23.4)	623 (26.1)	344 (31.6)
South-East	190 (12.4)	293 (12.3)	122 (11.2)
South-South	203 (13.3)	299 (12.5)	110 (10.1)
South-West	139 (9.1)	219 (9.2)	91 (8.4)

Note that sample is from children under 5 that are present in at least two consecutive surveys.

Table B.6
Variables for children in the sample.

Columns by: Year of Survey	2010/2011	2012/2013	2015/2016
n (%)	1528 (30.5)	2391 (47.8)	1088 (21.7)
{Continuous Variables}			
Age in Months, mean (sd)	17.73 (11.12)	30.30 (18.24)	38.36 (18.71)
Weight (kg), mean (sd)	9.60 (7.03)	12.02 (4.83)	15.24 (3.60)
Length (cm), mean (sd)	68.23 (26.88)	84.67 (19.63)	97.60 (10.23)
Length/height-for-age Z-score, mean (sd)	−1.05 (2.71)	−0.63 (1.88)	−0.99 (2.00)
Weight-for-age Z-score, mean (sd)	−0.77 (2.20)	−0.48 (1.42)	−0.51 (1.44)
Weight-for-Height/Length Z-score (WHO), mean (sd)	0.05 (1.86)	−0.15 (1.39)	0.03 (1.47)
{Binary Variables}			
Gender, n (%)			
Female	715 (46.8)	1132 (47.3)	509 (46.8)
Male	813 (53.2)	1259 (52.7)	579 (53.2)
Is Child Stunted?, n (%)			
No	526 (62.3)	1453 (80.9)	606 (69.5)
Yes	318 (37.7)	343 (19.1)	266 (30.5)
Is Child Underweight?, n (%)			
No	807 (72.7)	1696 (89.2)	776 (88.6)
Yes	303 (27.3)	205 (10.8)	100 (11.4)
Does HH have Electricity in Dwelling?, n (%)			
No	851 (55.8)	1267 (53.0)	603 (55.5)
Yes	674 (44.2)	1122 (47.0)	483 (44.5)
Gender of Household Head, n (%)			
Female	65 (4.3)	102 (4.3)	62 (5.8)
Male	1462 (95.7)	2286 (95.7)	1013 (94.2)
{Categorical Variables}			
Ordered Level of Household Head's Completed Education, n (%)			
None/Less than Primary	487 (37.9)	759 (39.1)	365 (42.3)
Primary School Complete	438 (34.1)	585 (30.1)	244 (28.3)
Secondary School Complete	294 (22.9)	467 (24.1)	205 (23.8)
University or Higher Education Complete	65 (5.1)	130 (6.7)	48 (5.6)

Note that sample is from children under 5 that are present in at least two consecutive surveys.

6. Discussion and policy implications

Ensuring food and nutrition security in rural Nigeria is an important policy goal since households are vulnerable to food shortages, unbalanced diets, poor quality of food, and insufficient amounts of food (Akinyele, 2009). Since the turn of the millennium, several programs and policies have effectively reduced the prevalence of stunting and being underweight in children in the country. Some of these programs include the Food and Nutrition Policy (FNPN), the National Plan of Action for Food and Nutrition, Accelerated Child Survival and Development, and The Agriculture Nutrition Advantage (TANA) (Awoyemi et al., 2012). These community and country-level programs and policies were introduced to combat malnutrition. Furthermore, they are in place to mitigate risk, address the causes of malnutrition, achieve zero hunger, and contribute to sustainable national food security.

The results set out in Section 5 highlight the potential dangers of climate change that could overturn decades of progress made to reduce child malnutrition in Nigeria. As climate change models project increasing temperatures and decreasing precipitation in Nigeria, child malnutrition could worsen in the absence of interventions that reduce the effects of climate change, especially in rural areas. Our findings indicate that a one-unit (°C) increase in temperature$_{t-1}$ increases the probability of a child being stunted by 0.525% and 0.714% per year in urban and rural areas, respectively. Similarly, the likelihood of a child being underweight increases by 0.369% in urban areas and 0.489% in rural areas. Therefore, children in rural areas are more likely to suffer from adverse climate-changing conditions. Malnutrition and low human capital accumulation can lead to a vicious cycle of the human development trap (Yitbarek and Beegle, 2019, Hoddinott et al., 2013). That is, increases in childhood malnutrition can reduce the ability of those children to improve their living standards when they reach adulthood.

From a policy perspective, the results point to a need for climate-friendly policies that can avert the effect of climate change on malnutrition among children. Key policy priorities relevant to mitigating the effect of climate change on children's malnutrition include improvements in public infrastructure, access to electricity, improved educational and social institutions, as well as upscaling climate-smart agricultural practices — all of which would generally have positive spillover impacts on human capital accumulation and development (Bassolé et al., 2007, Grace et al., 2012b, Davenport et al., 2017, Tesfaye and Tirivayi, 2018, Tesfaye and Tirivayi, 2020).

7. Conclusion

There is an urgent need to develop and scale-up radically improved solutions addressing the fundamental drivers of malnutrition in developing countries. However, the underlying drivers of malnutrition are complex and vary across regions and contexts. Therefore, empirical evidence on variables associated with child malnutrition can improve policy actions. This study provides empirical evidence highlighting the need to address climate change to alleviate childhood malnutrition. We use the LSMS-ISA panel data to investigate the effect of actual changes in the average monthly maximum temperature (°C) and average monthly total precipitation (mm) patterns on children's malnutrition, specifically stunting and being underweight.

We document that increases in the monthly average maximum temperature raise the probability of stunting and being underweight among children in Nigeria. In contrast, an increase in the average monthly precipitation decreases the likelihood of child malnourishment. The study also illustrates that an increase in temperature has a more immediate and direct impact on the prevalence of stunting and being underweight than changes in precipitation. Direct effects of temperature increases include heat stress, decreases in air and water quality, lower agriculture productivity, and more frequent extreme weather events (Ahdoot et al., 2015). On the other hand, effects of changes in precipitation occur mainly through indirect channels such as water scarcity, displacement, and uncertainty (Myers and Bernstein, 2011). The indirect effect of precipitation might be due to the current rich water sources in Nigeria (Ngene et al., 2021). Lastly, we document that the effects of climate change are more pronounced in rural areas than in urban areas.

Overall results indicate that leaps and bounds made to combat malnutrition can be lost without further policy interventions that tackle the effects of changing temperature and precipitation. Therefore, the first step to mitigating the effect of climate change on childhood malnutrition is to ensure that child-orientated policies are in place (Lawler and Patel, 2012). In addition, improvements in public infrastructure, as well as aid supporting the agricultural sector and promoting climate-smart agricultural practices, can also play an important role in reducing the effect of climate change on child malnutrition (Bassolé et al., 2007; Grace et al., 2012b; Tesfaye and Tirivayi, 2018; Tesfaye and Tirivayi, 2020).

CRediT authorship contribution statement

Eduard van der Merwe: Data curation, Investigation, Writing – original draft. **Matthew Clance:** Data curation, Visualization, Methodology, Validation, Writing – review & editing. **Eleni Yitbarek:** Conceptualization, Supervision, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of competing interest document has not been provided; hence, we have just used the first option in the standard form, as this section is a requirement. Please confirm if this is correct.

Appendix A. Technical Appendix

A.1. Climate data

Temperature and precipitation data are from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia (Harris et al., 2014).[20] This version is a gridded time-series dataset that covers the period 1960–2018. The spatial resolution is 2.5 min which is roughly 21 km^2. The variables available are average near-surface minimum temperature (°C), average near-surface maximum temperature (°C) and total precipitation (mm). For this paper, we focus on the effects that changes in the average monthly maximum near-surface temperature (°C) and the average monthly total precipitation (mm) has on child nutrition.

A.2. Agriculture and geographical factors

Soil quality data is from the Harmonized World Soil Database version 1.2. This dataset is a 30 arc-second (about 1 km^2) raster database with over 15 000 different soil mapping units that combine existing regional and national updates of soil information worldwide with the information contained within the 1 : 5000000 scale FAO-UNESCO Soil Map of the World (Fischer et al., 2008). The variables used to measure the soil quality is the "Nutrient availability", "Nutrient retention capacity", "Rooting conditions", "Oxygen availability to roots", "Excess salts", "Toxicity", and "Workability (constraining field management)" of the soil. These vary on a scale from 0–7 where 0 - Ocean, 1 - No or slight limitations, 2 - Moderate limitations, 3 - Severe limitations, 4 - Very severe limitations, 5 - Mainly non-soil, 6 - Permafrost area, and 7 - Waterbodies.

The first source of freshwater data is from the Global Lakes and Wetlands Database (Lehner and Döll, 2004). This database draws on a variety of existing data to create a global scale of large lakes, reservoirs, waterbodies, and wetlands. This paper utilizes freshwater in the form of lakes, reservoirs, rivers, freshwater marshes, floodplains, and intermittent wetlands or lakes. A second source used for freshwater data is AQUAMAPS. AQUAMAPS is a global spatial database on water and agriculture which is produced by the Food and Agriculture Organization of the United Nations (FOA). From this database, freshwater sources include water bodies, rivers, and dams in Africa (FAO, 2019a).

A.3. Combining the demographic and climate data

The households in the LSMS-ISA dataset have GPS references which are offset by two kilometers in urban areas, five kilometers in rural areas and in extreme rural cases (1%) are offset by ten kilometers. We used the households' GPS references to create a five-kilometer buffer around each of these points. This buffer allows us to assume, with relative certainty, that the specific household point is in that buffer zone without the zone being too big. We then used these five-kilometer buffer and georeferencing techniques to merge the climate data in this buffer with each specific household.

Merging these two data sets at the relevant spatial and temporal scales is crucial to ensure a thorough analysis of household health and climate changes (Grace et al., 2012b). Very few studies adopt this approach and, by utilizing this approach, this paper contributes to the literature. Furthermore, this method of combination ensures we capture the individual-level effects across our panel data and ensures consistency throughout.

Given that the spatial resolution of the climate data is 21 km^2, households are combined with their GPS locations to the specific climate conditions ascribed by the resolution. Since the maximum distance a household is offset by is ten kilometers, we can assign these households climate conditions with relative confidence that those will be the climate conditions the household experience. Although households close to each other can experience different climate conditions, this barely happens and depends on the breakdown of the grid that contains the climate data.

A.4. Control variables

Controls for geographical information include the following: (1) distance to the closest freshwater source (km); (2) distance to the closest (km) market; (3) distance to closest city (km)

- with a population of twenty thousand or more people; and (4) whether there is a market in the community or not. Access to freshwater, markets, and cities are shown to be determinants of child malnutrition. The expectation is that access to these sources reduces malnutrition rates.

Controls for family characteristics include the following: (1) number of people in the household; (2) number of meals to children; (3) number of times adults restrict meals so children can eat; (4) number of production shocks; (5) number of market shocks; (6) gender of household head; (7) whether a household has access to electricity; and (8) whether a household has a non-farm enterprise. Columns 7–9 also controls for the household head's education. Given the importance of the parent's education, we expect the household head to influence the level of malnutrition of the children due to the prominent role of the household head. The education level is in four categories: no education, completed primary education, completed secondary education, and completed tertiary or higher education. Since the expectation is that mothers are more nurturing than their male counterparts, there is a control for the gender of the household head. Furthermore, electricity can be a proxy for different social infrastructures and is important to control for.

Controls for child characteristics include (1) their age (in months); and (2) the gender of the child. Household wealth controls include: (1) log of education expenditure; (2) an asset index; and (3) log of household consumption per capita. A household's asset index compromise of whether they have a bicycle, motorcycle, car/other vehicles (vans), tractor, computer, telephone, cellular, radio, television, refrigerator, and stove. Therefore, this asset index ranges from zero to eleven, where eleven indicates a household that owns all of the assets. A control for education expenditure is necessary, as the literature expect more education reduces the chance of malnutrition.

Controls for agriculture characteristics include the following: (1) tropical livestock units; (2) log of aggregate plot size; (3) soil workability (mean); and (4) soil nutrient availability (mean). The livestock of households determines the tropical livestock unit for each household (Otte and Chilonda, 2002). Calculations of this unit of measurement are for the beginning of the period (post-planting stage), and the end of the year (post-harvesting stage). Due to the correlation, we only use the TLU at the end of the survey period. Since the plot size of a household influences agriculture production, a control for the aggregate plot size of each household is necessary. We use the log form of plot size and assign a value of zero (log (1)) to those households who do not have a plot.

Furthermore, agriculture productivity depends on soil quality. Hence, it is beneficial to control for the mean of soil workability and nutrient availability of the soil. Each household has a five-kilometer buffer while the soil quality is approximately on a 1 km^2 grid. Therefore, the mean of these indications of soil quality in the five-kilometer buffer is the closest approximation to the household's actual level of soil quality. A high mean value of these soil quality indicators implies better soil quality, as previously discussed.

Controls for household assistance include the following: (1) borrowing from a microfinance institute/credit association/bank; (2) borrow from friends/relatives/money lenders; (3) borrow food, or rely on friend/relative; (4) government assistance (food/ cash/otherwise); and (5) agri-extension services (government or private). The financial status or assistance a household receive can influence the nutritional status of children.

Lastly, the columns alternate between no regional or sectoral dummies, regional dummies, and sectoral dummies. The use of dummies for the regions of Nigeria controls for regional fixed effects. The motivation being the dispersion seen in Fig. B.1. These regions are North-Central, North-West, North-East, South-South, South-East, and South-West. The sectoral dummy consists of whether the household is classified as urban or rural. Since we investigate the effects of climate change across these areas, it is important to account for different urban and rural fixed effects.

Appendix B. Descriptive statistics

This section present the descriptive statistics for the sample.

Appendix C. Supplementary data

The following is the Supplementary material related to this article.

MMC S1. Supplementary appendix to Climate Change and Child malnutrition, a Nigerian Perspective.

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Notes

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[1] The Food and Nutrition Policy (FNPN), The Home-Grown School Feeding and Health Program, and the National Special Program for Food Security (NSPFS) are some examples of programs that have reduced malnutrition prevalence among children in Nigeria (Akinyele, 2009, Awoyemi et al., 2012).
[2] Biologically implausible values for HAZ are those > 6 SDs above or below, and for WHZ are > 5 SDs above or below the median z score of the reference population (World Health Organization, 2010).
[3] See Table B.6 in Appendix B.
[4] The downscaled version that corrects for bias, which is produced by WorldClim (Fick and Hijmans, 2017), is used.
[5] Note that each cluster's GPS coordinates in the LSMS-ISA data are offset by up to 2 km in urban areas and 5 km in rural areas, randomly. Only (1%) of clusters in the rural areas are offset by a1round 10 km.

[6] We also check the effect of precipitation$_{t-1}$, results are available on request. We find small positive effects for precipitation$_{t-1}$.

[7] Table B.4 in Appendix B shows climate variables by zone.

[8] See Table B.1 in Appendix B.

[9] A full list and explanation of control variables are available in Appendix A.4 of Appendix A. Additionally, descriptive statistics for control variables are presented in Table B.5, Table B.6 of Appendix B.

[10] The data for distance to freshwater is from the Global Lakes and Wetlands Database (Lehner and Döll, 2004) and AQUAMAPS (FAO, 2019a), respectively. We consider freshwater as water in the form of lakes, reservoirs, rivers, freshwater marshes, floodplains, and intermittent wetlands or lakes. More information on data sources and merging are available in Appendix A.

[11] To check the robustness of our estimates, we also used a Linear Probability Model (LPM), and the conclusions remain unchanged. Results are available from authors.

[12] The CRE logit model coefficients (full tables) are in the online Appendix Tables 1 and 2 for stunting and underweight, respectively. The coefficient signs can discern the increasing or decreasing effects, but the marginal effects are more informative. The average marginal effect for each variable of interest is similar to the results in Tables 1, 2, and 3. The difference between the two marginal effect calculations is less than 0.015 or 1.5%.

[13] 0.03 is 3 hundredths of 1 °C. Therefore, 3 hundredths of 22.3% is 0.67%. Over a decade, the probability of a child suffering from stunting increases by 6.7%.

[14] These marginal effects are calculated over the means of households in urban and rural areas.

[15] Movement of households across areas (internal migration) may affect the results. However, we could not verify using the available data. In our data, only 2 percent of households moved from urban to rural areas, making it empirically impossible to estimate the effect of internal migration on our results.

[16] Tables 3 and 4 in the online Appendix present the full CRE logit results for precipitation$_{t-3}$ on stunting and underweight for all children under 5 years of age whom we observe in two consecutive waves. The results for precipitation$_{t-1}$ is available on request and provides support for the results found by Skoufias and Vinha (2012) and mentioned in Phalkey et al. (2015). Comparison of the results of precipitation$_{t-1}$ and precipitation$_{t-3}$ support research that precipitation has an indirect effect on child nutrition.

[17] 0.35 hundredths of 0.3% is 0.105%. Furthermore, over a decade, a decrease in precipitation of 3.5 mm will increase the probability of child stunting by 1.05%.

[18] When we include the interaction between temperature$_{t-1}$ and precipitation$_{t-1}$, the results for stunting remain similar. The lagged temperature still dominates the effect of children suffering from stunting. Notwithstanding, the impact on children suffering from underweight is different when looking solely at the regression tables. The precipitation$_{t-1}$ is negative and significant, while temperature$_{t-1}$ is positive but insignificant. However, the picture changes when looking at the marginal effects at the means. An increase in temperature$_{t-1}$ leads to a significant change in the probability of a child being underweight. A change in precipitation$_{t-1}$ does not significantly affect the probability that a child suffers from being underweight.

[19] Tables 1.5 and 1.6 in the online Appendix present the full CRE logit results for the model specified in Eq. (3) on stunting and underweight for all children under 5 years of age whom we observe in two consecutive waves.

[20] The downscaled version that corrects for bias, which is produced by WorldClim (Fick and Hijmans, 2017), is used.