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Child health outcomes in sub-Saharan Africa: A comparison of changes in climate and socio-economic factors

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A R T I C L E I N F O

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A B S T R A C T

We compare changes in low birth weight and child malnutrition in 13 African countries under projected climate change versus socio-economic development scenarios. Climate scenarios are created by linking surface temperature gradients with declines in seasonal rainfall sea along with warming values of 1 °C and 2 °C. Socio-economic scenarios are developed by assigning regionally specific changes in access to household electricity and mother's education. Using these scenarios, in combination with established models of children's health, we investigate and compare the changes in predicted health outcomes. We find that the negative effects of warming and drying on child stunting could be mitigated by positive development trends associated with increasing mothers' educational status and household access to electricity. We find less potential for these trends to mitigate how warming and drying trends impact birth weights. In short, under warming and drying, the risk of more malnourished children is greater than the risk of more children with low birth weights, but increases in child malnutrition could be averted in regions that increase access to educational resources and basic infrastructure.

1. Introduction

Many in the scientific community are actively trying to determine the impact of a warming and drying planet on individual health and wellbeing (Brooks et al., 2005; Burke et al., 2015; McMichael, 2013). However, the evidence suggests that climate change has already begun to impact people in dramatic and measurable ways (Funk and Brown, 2009; McMichael, 2013; Morton, 2007). Increases in extreme weather events like droughts and floods, as well as wildfires, have all been linked to climate change (Allen et al., 2010; Flannigan et al., 2009). These events are likely to cause long lasting damage, including economic struggles, loss of life, and chronic impacts on overall health and development (Asseng et al., 2015; Brown and Funk, 2008; Dellink et al., 2017; Jones and Thornton, 2003; Moore and Diaz, 2015; Parry et al., 2004). There is also increasing evidence of negative health impacts associated with warming and drying trends among some of the very youngest people – newly born infants and very young children (Grace et al., 2015; McMichael, 2013). The relationship between warming, drying, and child health is especially pronounced in sub-Saharan Africa (SSA) – a region with a history of chronic food insecurity, poor health outcomes and, more recently, increased temperatures and decreased rainfall (Funk et al., 2008b).

Warming temperatures, decreasing rainfall and increasing variability in rainfall and temperature are associated with low birth weights and child stunting (a measure of malnutrition), both of which are related to chronic health issues in SSA (Funk and Brown, 2009; Funk et al., 2008b; Grace et al., 2012, 2015; Verdin et al., 2005). Prior research suggests that low birth weights and stunted growth result from combined exposure to poverty along with both extremes and variability in temperature and rainfall (Balk et al., 2005; Grace et al., 2012, 2015). The relationship between child health and weather stems from the combined influences of in utero heat stress along with undernutrition from crop and livestock loss related to rainfall shortages and inconsistent seasonal patterns. Chronic seasonal crop and livestock loss is a serious concern in SSA as subsistence and small-scale farming dominate the food systems of most SSA countries (Jones and Thornton, 2003; Morton, 2007). Overall the evidence suggests that if SSA gets warmer and dryer, the region may see increases both in the number of babies born with low birth weight and in the number of children suffering from chronic malnutrition (Balk et al., 2005; Grace et al., 2012, 2015).

On the other hand, it is possible that the increases in low birth weights and child malnutrition induced by warming, drying, and climatic variability might be mitigated by positive socio-economic development trends. Increased access to basic infrastructure could provide

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relief from heat and water stress and weather instability. More educational opportunities can broaden labor force participation beyond subsistence agriculture. However, the mitigating impacts of development trends across and within SSA countries have been mixed: not all areas are improving and areas that are getting better are not doing so at the same rate. Places that experience extreme weather events and increased variability along with decreased access to infrastructure and education are at increased risk of poor health outcomes. *If positive development trends continue, will they compensate for the negative health outcomes induced by warming and drying and within-season variation? If development trends reverse and people lose access to infrastructure and educational resources, how might this exacerbate low birth weights and child malnutrition in areas that are becoming warmer and dryer? How will these effects vary across urban and rural populations? Will populations dependent primarily on crop production for their livelihoods fare the same as those dependent on livestock?*

The goal of this paper is to begin to answer these questions by using empirical models to generate combined climate and development scenarios. We use these scenarios to explore the relative effects of socioeconomic development and climate trends on household-level child health outcomes. Using household survey data from 13 SSA countries we examine spatially explicit child health outcomes under varying degrees of warming, drying, and socio-economic development. Specifically, we examine how joint changes in the mother's education and access to electricity influence birth weights and child stunting. We examine these changes under warming and drying scenarios, and we compare results across countries and livelihood zones. By examining changes in predicted values under various scenarios we quantify the differential impacts of investment in climate change mitigation versus factors associated with development. We note that our goal of using a scenario-based approach, consistent with the historical use of scenarios, is to establish a sense of the range of our outcome variables and the related uncertainty in human response (Bradfield et al., 2005; Moss et al., 2010). A scenario approach allows for an investigation of the potential impacts of *changes* in certain factors that already have an established link to the outcomes under study (Moss et al., 2010). We *do not intend to predict future outcomes*, but instead wish to provide a perspective on the relative influence of probable future changes in development versus climate factors as they impact children's health.

The next section of the paper (Section 2) summarizes prior research on the relationships among climate, weather, development, and health outcomes and then outlines our scenario analysis approach. Sections 3 and 4 present the data, methods, and results. The following section (Section 5) summarizes and concludes and the two supporting appendices provide more detailed information regarding our precipitation scenarios and empirical results.

2. Background

2.1. Climate, weather, development, and health outcomes

We focus on the ways that climate and development scenarios influence health outcomes in some of the poorest and most climatically sensitive places on the planet. Specifically, we investigate how birth weight and child stunting vary as a response to different scenarios across thirteen of the poorest sub-Saharan African countries. These outcomes are selected for two reasons: (1) prior research has already established a link between low birth weight, stunting occurrence, and climate related stress in selected African countries (Grace et al., 2012, 2015); and (2) Low birth weights and stunted growth can lead to impaired health and productivity in adulthood (Alderman et al., 2002; Hoddinott et al., 2008; Jamison, 1986). As an example, children who were born low birth weight or who experience stunting are less likely to attend school and achieve the income earning levels of their peers (Alderman et al., 2006; Black et al., 2008). The developmental challenges faced by low birth weight babies and undernourished children are considered a leading cause of intergenerational poverty transmission (Grantham-McGregor et al., 2007). Given the multi-generational effects of low birth weight and stunting, reducing the rates of these mostly preventable conditions is vital to the long-term economic development of poor countries.

2.1.1. Socio-economic factors and child health

Because there is already an expansive and detailed literature addressing the correlates or causes of these conditions in sub-Saharan Africa, we can select a suite of independent variables with known relationships to birth weight and child stunting. For example, more educated mothers, relative to their country-norms, who are in the middle of their childbearing years, and space their children around three years apart are less likely to have low birth weight or stunted children (Grace et al., 2015).

Increased education is linked to positive maternal and child health outcomes for a variety of reasons. Among the theorized links is the increased understanding of nutrition (Glewwe, 1999; Engle et al., 1999; Barrera, 1990), increased household income, or strengthened maternal bargaining power that may accompany higher education (Frost et al., 2005), as well as the possibility that more time spent in a formal educational setting contributes to a greater maternal understanding of public institutions related to health and aid procurement (Joshi, 1994). Given the varying levels of development within the countries under study in this investigation, the role of and access to education may be somewhat relative within country. In other words, secondary education may be attainable to most urban dwellers in Kenya but much less attainable to those urban dwellers in Mali.

Increased access to public infrastructure, specifically electricity, is also found to benefit the most malnourished children, although this effect varies from urban to rural areas (Bassole, 2007). Electricity may serve as a proxy measure of household income. Electricity could also serve as a way for people to reduce their risk of heat stress through fan/air conditioner use and ownership or provide greater access to information if it is used to power televisions (see, Fay et al., 2005).

2.1.2. Warming, drying and child health

The relationship between climate change and low birth weight and stunting is both direct, likely because of heat stress and dehydration, and indirect, likely connected through food production failures.

The research linking birth weights with climate focuses on developed-world births (Cooperstock and Wolfe, 1986; Keller and Nugent, 1983; Rayco-Solon et al., 2005). Of the investigations focused on low-income communities, Rousham and Gracey (1998) found a connection between very low birth weight babies (those weighing less than 1500 g) and the wet season, but did not find a connection among larger low birth weight infants. In studies focused on African infants, agricultural production and food insecurity seems to primarily explain incidence of low birth weight (Grace et al., 2015; Rayco-Solon et al., 2005). Without consideration of food and agricultural production, ambient temperature has been linked to LBW as pregnant women are theorized to face increased emotional and physical strain due to high ambient temperatures (Prentice, 1989; Wells and Cole, 2002). However, Strand et al. (2011) suggest that because low temperatures may also have a negative impact on birth weight outcomes, extreme temperatures may be at the root of the link between temperature and birth weight. LBW is also associated with preterm birth, which may also result from extreme weather (Basu et al., 2010; Rousham and Gracey, 1998; Wang et al., 2013).

With regard to child malnutrition, prior evidence suggests that agricultural production and food insecurity are among the main mechanisms linking climate and child health. Children who are at the highest risk of increased rates of chronic malnutrition induced by warming and drying tend to be those dependent on regional and rainfed dependent agricultural food production to meet caloric requirements (Brown et al., 2014, 2015; Shively et al., 2015). Because poor urban and peri-urban children are also dependent on low cost foods and sometimes locally grown foods, climate stress can cause failures in their ability to access and afford available food, making the link between children's health and the environment relevant in communities that are not always thought of as vulnerable. Stunting reflects a child's long-term exposure to inadequate nutrition which can result from issues related to water/sanitation or hygiene as well as inadequate caloric intake, or a combination of these factors (Balk et al., 2005; Brown et al., 2015; Grace et al., 2017; Smith et al., 2000). Poor children, regardless of where they live, are often at greatest risk for malnutrition, including stunting (Black et al., 2008). Research focusing on individual-level exposures to climate stressors may help to isolate the differential contribution of environmental factors versus development and health factors as well (Black et al., 2008).

2.2. Scenarios analysis

Guided by the work of the Intergovernmental Panel on Climate Change (IPCC), we develop our analysis of health outcomes under different scenarios building on the Shared Socio-economic Pathways (SSPs) (O'Neill et al., 2014). SSPs are constructed to broadly describe a set of "plausible alternative trends in the evolution of society and natural systems at the level of the world and large world regions" (O'Neill et al., 2014, p. 389). They are used in combination with climate scenarios to help identify and describe future society-climate situations (O'Neill et al., 2014). SSPs contain no information on climate change or climate policies, rather they are focused on population and development to allow flexibility in use with different climate scenarios (O'Neill et al., 2014). Because our research is focused at the individual-level, the expansive and general SSPs are not ideally suited to our needs. Our approach can be considered a country-specific downscaling of the SSPs (Gaffin et al., 2004; van Vuuren et al., 2007). We construct country and livelihood specific development and climate scenarios based on recent country-specific trends and household level observations.

We use these scenarios to explore how simultaneous changes in climate and two key socio-economic variables change predicted health outcomes. Our objective is to examine changes in birth weight and child stunting resulting from combined warming/drying and socio-economic development scenarios. The process of using changes in predictive values to compare relative effect sizes is formally described in Gelman and Pardoe (2007). We expand on that process by framing predictive comparisons under different scenarios, examining outcomes resulting from simultaneous changes to multiple variables, and by using country specific socio-economic trends to define the degree of change across observations.

The list of scenarios are shown in Table 1. In the baseline scenario ('0. Warming and Drying'), we examine changes in health outcomes resulting from warming and drying but we do not make any changes to mothers education and access to electricity. We use this scenario to establish a baseline change in birth weights and stunting that would result from warming and drying. In each scenario we examine how health outcomes change when average daily maximum temperature increases 1 °C or 2 °C coupled with region specific precipitation scenarios.

The climate trend scenarios used here are based primarily on observation data developed to support trend analyses for the US Agency for International Development (Funk et al., 2012). The rates of warming are similar to those observed over Africa, and consistent with projections from climate change simulations (Funk et al., 2015c). The observed precipitation changes across the Sahel are thought to be related to a stronger north–south Atlantic sea surface temperature gradient (Cook, 2008; Folland et al., 1986a; Giannini et al., 2003). Observed declines across east Africa, on the other hand, are thought to be related to an increased west-to-east tropical Pacific sea surface temperature gradient (Funk and Hoell, 2015; Funk et al., 2014a,b). We develop region specific precipitation scenarios by empirically linking rainfall in our target regions to relevant sea surface temperature (SST) gradients and then examine plausible drought-inducing changes in these gradients and resulting national level rainfall values. These scenarios would therefore be consistent with reasonable low frequency changes in SST gradients that increased aridity in the target countries. This approach is described in detail in Appendix A, while the country specific rainfall scenarios are shown in Table 2. However, the likelihood of a specific event occurring is currently very difficult to ascertain, given uncertainties in the climate change simulations, thus we emphasize that these represent plausible scenarios, rather than concrete predictions.

Table 1
List of scenarios: This table summarizes the scenarios we use to frame our analysis. The scenario names refer to specific changes in variables and are referenced when we present the results in Figs. 2 and 3. Changes to variables are divided between changes to climate variables, households in urban areas, and households in rural areas. Changes to climate variables are held constant in each scenario while changes to socio-economic variables (access to electricity and the mother's educational status) either stay the same, improve, or worsen.

Scenario name	Changes to variables		
	Climate	Urban	Rural
0. Baseline Warming an Drying	% change in Precip (Table 2) +1°/2 °C	Stay the same	Stay the same
1. Urban and Rural Areas Improve	% change in Precip (Table 2) +1°/2° C	Improve[a]	Improve[a]
2. Only Urban Areas Improve	% change in Precip (Table 2) +1°/2° C	Improve[a]	Stay the same
3. Urban Areas Improve and Rural Areas Worsen	% change in Precip (Table 2) +1°/2° C	Improve[a]	Worsen[b]

[a] No formal education → completed primary education or higher. No electricity → electricity.
[b] Completed primary education or higher → no formal education. Electricity → electricity.

The subsequent scenarios (1–3) then examine how the negative impacts of warming and drying might be mitigated or exacerbated by changes in access to electricity and mother's education. The change parameters are based on country specific trends from the period 2000–2010. These changes are shown, along with other key summary statistics, in Table 2. For example, the last row of the column '**Δ in households with elec.**' in Table 2 shows that from 2000–2010, the percent of the urban population in Senegal with access to electricity increased by 20%. In the urban improvement scenario for Senegal we would then randomly select 20% of urban households that do not have electricity and 'give' them electricity by changing the values in the data. In the scenarios where rural areas worsen we reverse the trends. Continuing with the example from Senegal, we select 15% of rural households that have electricity and change the status to not having electricity. In this way we can keep the permutated values within a realistic range based on recent trends. However, the mother's education trends from the World Bank Development Indicators are not stratified by urban/rural so we apply the sampling percentages in the scenarios to both urban and rural populations. We repeat this sampling and re-assignment process 1000 times and then compare average predicted changes across all simulations within a certain scenario.

In the first scenario ('1. Urban and Rural Areas Improve') we assume that positive trends seen from 2000–2010 continue in both urban and rural areas. All subsequent scenarios assume that urban areas continue to see positive changes consistent with the rate shown from 2000–2010. The other scenarios examine changes to rural populations, as these tend to be the most vulnerable to climate change. In the second scenario ('2. Urban Areas Improve and Rural Areas Stay the Same') we assume that rural areas do not improve. In the final scenario (3) we assume that the changes in rural areas from 2000–2010 reverse and follow a negative development trend.

We use the variables of household access to electricity and whether

Table 2
Summary table showing sample sizes ($N(bw)$), mean birth weight ($\mu(bw)$), and mean HAZ ($\mu(haz)$). The 'years' column indicates DHS (Demographic and Health Survey) sample years for each country. Sample sizes and means are calculated across survey years for by country and urban/rural status. Column labels *not* in bold face are calculated from the DHS. Column labels in names in boldfaces are from the World Bank Development Indicators and describe percent changes in access to electricity and mother's educational status from the period 2000–2010. We use these percent changes to guide the sampling frequencies when generating the scenarios. The Δ *in Precip*. column shows precipitation changes used in the scenarios. These changes are based on the relationship between sea surface temperature gradients and observed precipitation trends. Note that for Kenya and Ethiopia different change values were used for the Eastern and Western portions of those countries. A full description of the methodology used for the precipitation patterns is presented in Appendix B.

Region	Country	Years	Type	$N(bw)$	$\mu(bw)$	$N(haz)$	$\mu(haz)$	Households with elec.	**Δ in households with elec.**	Mothers with primary or higher educ.	**Δ in mothers with primary or higher educ.**	Δ *in Precip.*
East	Ethiopia (ET)	2000, 2005	Rural	167	3396	39	−1.56	16%	4%	20%	26%	−25% (East); −5% (West)
			Urban	1047	3312	264	−1.03	94%	16%	66%	26%	−25% (East); −5% (West)
East	Kenya (KE)	2003, 2008	Rural	2277	3370	462	−1.35	7%	4%	57%	2%	−17% (East); −3% (West)
			Urban	1293	3295	248	−0.71	61%	16%	75%	2%	−17% (East); −3% (West)
East	Madagascar (MG)	1997, 2008	Rural	3373	3063	301	−2.4	6%	3%	31%	34%	−1%
			Urban	1543	3171	135	−1.99	62%	0%	69%	34%	−1%
East	Malawi (MW)	2000, 2004, 2010	Rural	11,817	3284	2081	−2.11	2%	2%	19%	14%	−3%
			Urban	1596	3262	367	−1.54	27%	10%	44%	14%	−3%
East	Rwanda (RW)	2005	Rural	1210	3480	210	−1.93	3%	3%	23%	43%	−15%
			Urban	628	3528	99	−1.18	31%	1%	43%	43%	−15%
East	Uganda (UG)	2000, 2006	Rural	1863	3414	385	−1.6	4%	3%	29%	1%	−4%
			Urban	695	3347	144	−1.06	43%	13%	58%	1%	−4%
East	Zimbabwe (ZW)	1999, 2005	Rural	3095	3153	456	−1.27	7%	5%	62%	5%	−12%
			Urban	1493	3109	139	−1.08	91%	−10%	91%	5%	−12%
West	Burkina Faso (BF)	1999, 2003	Rural	1925	3004	768	−1.85	1%	1%	8%	42%	−12%
			Urban	1643	3003	662	−1.1	45%	9%	37%	42%	−12%
West	Guinea (GN)	2005	Rural	1187	3362	231	−1.62	5%	1%	5%	36%	−21%
			Urban	833	3360	159	−0.97	63%	3%	22%	36%	−21%
West	Mali (ML)	2001, 2006	Rural	2035	3198	675	−1.71	7%	1%	6%	28%	−21%
			Urban	3167	3199	1059	−0.96	52%	−12%	27%	28%	−21%
West	Niger (NE)	1998	Rural	180	2968	78	−2.1	0%	1%	7%	29%	−19%
			Urban	720	3060	300	−1.69	42%	5%	33%	29%	−19%
West	Nigeria (NG)	2003, 2008	Rural	1302	3225	424	−1.11	58%	7%	82%	0%	−2%
			Urban	2079	3305	640	−0.95	94%	−6%	90%	0%	−2%
West	Senegal (SN)	1997, 2005	Rural	2490	3085	198	−0.98	25%	17%	8%	32%	−30%
			Urban	2837	3171	190	−0.57	75%	20%	28%	32%	−30%

or not the mother has had a primary education in our scenarios for several reasons. First, as discussed earlier, they are consistently identified in both the empirical and theoretical literature as being correlated with child health outcomes. Second among the various socio-economic factors associated with child health, access to electricity and educational status are the most consistently measured across countries and datasets. However, we fully acknowledge that it may not be these particular factors that are ultimately at play when determining child health. For example, access to electricity may be proxy measure of overall access to infrastructure while a mother's education may be representative of either labor force participation or simply a mother's ability to navigate the main institutions in her country. Thus we interpret the results not as the direct impacts of electricity and a mother's education on child health but rather as the impact of overall development trends on child health.

3. Data

We use a combination of household level demographic surveys, country level data on socio-economic trends, and gridded estimates of rainfall and temperature. Each of these datasets is described below.

3.1. Child health and socio-economic variables

Our measures of individual physical and socio-economic variables come from Demographic and Health Surveys (DHS). The DHS records contain detailed anthropometric data on children under 5 years of age at the time of the survey. The anthropometrics measures of birth weight and height-for-age *Z* score are the child health outcomes that we model. The height-for-age *Z* score (HAZ) is a common measure of child stunting. HAZ is calculated by first measuring the child's height, then subtracting a reference height based on the child's age in months, and then dividing that amount by a reference standard deviation. The reference height and standard deviations are determined by the World Health Organization and based on findings from the Multicenter Growth Reference Study (MGRS) (WHO, 2004). A child with a HAZ score of less than or equal to -2 (two or more standard deviations away from the reference mean) is considered 'stunted' and to suffer from chronic malnutrition. Among children under five years of age, stunting represents a culmination of experiences reflecting, in utero exposure to stress (including food stress) malnutrition and inadequate care and represents a chronic rather than an acute condition (Black et al., 2008; Danaei et al., 2016; Grace et al., 2016; Sweeney et al., 2013). This is the standard measure of child malnutrition used in the majority of empirical studies and is more robust to seasonal bias than measures of acute malnutrition (Wright et al., 2012).

The DHS also provides several measures of individual-, household- and community-level resources and living conditions and also contain the key socio-economic indicator variables of mother's educational attainment and household access to electricity.

The countries and DHS sampling locations used in the analysis are shown in Fig. 1. Fig. 1 also shows livelihood zones in each of the countries we examine. Livelihood zones refer to areas where the majority of the population living in a given region gain their livelihoods from a specific activity – for example agriculture or crop production, pastoralism, fishing, et cetera. The livelihood zones data are compiled by the Famine Early Warning System Network (FEWSNET) to inform food security planning and response. We use livelihood zones in this paper to summarize and interpret our results. We report changes in birth weights and child stunting by livelihood (and country) because populations living in different livelihood zones might respond to climate stresses in different ways (Adger, 2000; Brooks et al., 2005). The livelihood zones also allow us to summarize the data beyond the country level and potentially identify, both within and across countries, which types of populations may be more or less threatened from warming and drying trends.

We also use country level trends on rates of electricity access and women's education to inform the sampling regime in our scenarios exercise. Country level trends come from World Bank Development Indicators which are compiled from a variety of survey and census data, and in some cases include the Demographic and Health Surveys. Those data and how we use them in the scenario exercises are described in more detail in Section 2.2.

3.2. Climate variables

3.2.1. Precipitation

When modeling birth weights we measure precipitation in the period one year prior to the child's birth and when modeling malnutrition we measure precipitation from one year prior to the date of birth up to the day when the child's stunting (HAZ) score was recorded. We use 0.05° (~5 km) gridded precipitation data generated from combined in situ and remotely sensed observations (Funk et al., 2015b).

These precipitation data come from the Climate Hazards Group (CHG) Infrared Precipitation with Stations (CHIRPS) dataset. CHIRPS is a 1981–present, quasi-global (50°S–50°N) archive that combines a high quality high resolution background climatology (Funk et al., 2015d), with precipitation estimates from geostationary satellite observations and in situ gauge observations (Funk et al., 2015b). CHIRPS has been explicitly designed to support drought analysis in food insecure regions. In Africa, CHIRPS also benefits from additional gauge data not available in global archives (Funk et al., 2015a).

Each grid cell in the CHIRPS data contains the total precipitation (in mm) for a given month at that location. The precipitation records for each child are generated by averaging grid cells from a 10 km radius around the child's DHS sampling cluster. We chose the 10 km buffer for two reasons. First because the point location given for the DHS sampling clusters have been randomly offset by 10 km for rural areas and 2 km for urban areas. Second, the buffer is meant to provide a rough aggregation of environmental conditions in the area and smooth out any hyper-local precipitation or temperature patterns.

When birth weights are the dependent variable, average precipitation around the sampling cluster is calculated for every month in the one year period before the child's birth date. Monthly precipitation values are then summed over trimesters to create a measure of total precipitation during each 3 month period one year before the child's birth. We use rainfall values of one year, rather than nine months, prior to birth to capture what the rainfall conditions were in the time leading up to conception and during gestation. Additionally, using growing calendar information, we sum the rain per trimester that falls within the growing season. For example, if the first trimester of the pregnancy contains only one month of the prime rainy season for that region, then only the precipitation during that rainy season month is counted. For example, let $rain_{(y,m,c)}$ be the rainfall in a 10 km area around a DHS sampling cluster (c) in a given month (m) and year (y). Then our measure of growing season rainfall for a given 3 month period (trimester) prior to birth is:

$$R_{tri} = \sum_1^3 (\mathrm{rain}_{y,m,c} \times I_m)$$

$$\text{where } I_m = \begin{cases} 1 & \text{if } m \text{ is a growing season month} \\ 0 & \text{if } m \text{ is not a growing season month} \end{cases}$$

In this way, we can examine the relationship between precipitation and birth weight and explicitly focus on the role that rainfall plays in local subsistence level food production. We perform a similar calculation when child stunting is the dependent variable. As with the low birth weights model, we calculate the spatial average of precipitation grid cells around the sampling cluster. We then average precipitation from one year prior to child's birth date up through the month when the child's height for stunting score was recorded. For child stunting we use the average, rather than the total (as we do for birth weights) because the length of treatment differs for every child: for birth weights every

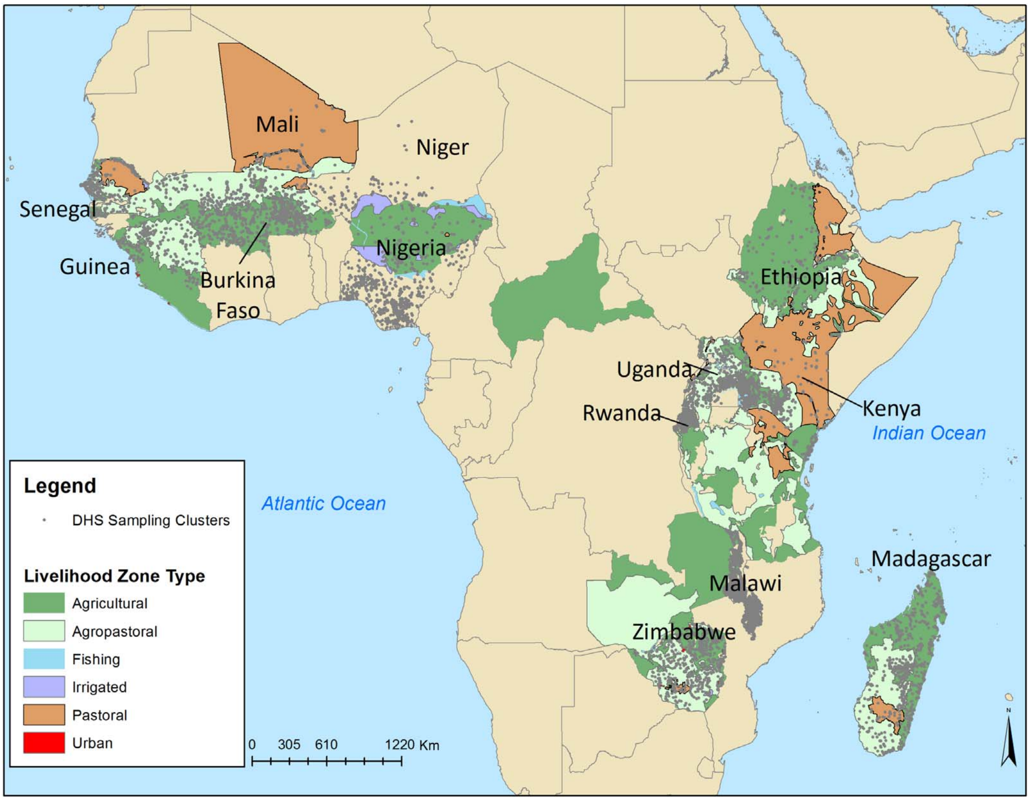

Fig. 1. Countries included in this study (labeled), DHS sampling locations (dots), and livelihood zones. Sampling locations that fall outside known livelihood zones are classified as 'unknown'. DHS surveys cover the period of 1997–2010 (see Table 2).

child has had up to 1 year of exposure in utero (and prior to conception) but for stunting, the length of exposure ranges from birth to the date of the interview, and thus varies for each child.

3.2.2. Temperature

We also measure heat stress occurring prior to and during the pregnancy as well as during the child's life (when stunting is the dependent variable). The daily temperature maximum data used in this analysis comes from the global gridded (0.5° × 0.5° spatial resolution) dataset generated by (Sheffield et al., 2006). This dataset has been widely used in various global studies (Sheffield and Wood, 2008a,b; Shukla et al., 2013) and also supports Princeton University's African Food and Drought Monitor. Sheffield et al. (2006) provide a detailed background on this dataset which we summarize here.

Due to the lack (especially in Africa) of long-term spatially and temporally consistent in situ observational record of temperature, this dataset is primarily derived from the National Center for Environmental Prediction's reanalysis (Kalnay et al., 1996; Kistler et al., 2001). A reanalysis is a computer model simulated record of atmospheric and surface variables (e.g. air temperature, radiations, precipitation, wind speed, sea-level pressure and sea-surface temperature) and is generated by assimilating a long-term quality controlled database of land, oceanic, and atmospheric observations when/where available. To remove bias in this dataset the monthly mean temperature values are matched to the monthly temperature values of the Climate Research Unit's 0.5° gridded temperature data (New et al., 1999, 2000) by first calculating the difference in both monthly values and then adjusting the daily values in the raw dataset by that difference.

For the birth weights model, we count the number of days in each trimester where the maximum daytime temperature exceeds 37.7 °C (100 °F). We use this threshold as this is a common threshold for measuring extreme heat stress and is used in prior models of heat and child health (Grace et al., 2015). Let $tmax_{(y,d,c)}$ be the maximum daily temperature surrounding DHS sampling cluster c in a given calendar day, the measure of heat exposure for a 3 month period prior to birth is:

$$T_{tri} = \sum_{1}^{3} (tcount_{(y,d,c)})$$

$$tcount_{(y,d,c)} = \begin{cases} 1 & \text{if } tmax_{(y,d,c)} \geq 37.7\,^{\circ}\text{C} \\ 0 & \text{if } tmax_{(y,d,c)} < 37.7\,^{\circ}\text{C} \end{cases}$$

Again we use a similar approach when modeling child malnutrition. However, in this case we count the number of days where maximum daytime temperature exceeds 37.7 °C and divide this amount by the number of days from one year prior to the child's birth date to the date of the DHS interview. As with the precipitation data, child records are joined to temperature data by calculating the daily average maximum temperature in a 10 km radius surrounding the associated sampling cluster.

4. Methods and results

4.1. Empirical models

Our starting point is a regression model of infant birth weight as a function of climate and household level socio-economic factors. We also construct a similar model for child malnutrition. The model specifications are based on theory and prior empirical work (Balk et al., 2005; Grace et al., 2012, 2015; Smith et al., 2000; Sweeney et al., 2013). In each case we model the conditional mean of either birth weight or child stunting (HAZ) as a function of characteristics of region, household, mother, and child along with measurements of local rainfall and temperature characteristics. Let $m_{(i)}$ represent a vector of controls used in modeling both birth weights and child stunting for a given child$_{(i)}$,

$$m_{(i)} = \beta_0 + N_{(n)} + M_{(m)} + S_{(rs)} + X\theta_{(k)} + \beta_1 Elec + \beta_2 Educ$$

where $N_{(n)}$, $M_{(m)}$, and $S_{(rs)}$ are indicators (dummy variables) for the country, birth month, and whether or not the child was born in the rainy season. These are all meant to control for unobserved influence of the country and timing of birth. The *n by k* matrix X includes additional controls such as the mother's characteristics (age, height, and marital status) and additional characteristics of the sampling cluster, such as whether the sampling cluster is classified as urban or rural. Two other key variables, whether or not the household has access to electricity and the educational status of the mother, are listed separately simply because those are the key socio-economic variables used in our scenarios. As noted in the discussion of the climate variables (Section 3.2), the birth weights model separates out precipitation and temperature terms by trimester while the child malnutrition model uses average rainfall and temp over the course of the child's life span. The model for birth weights is

$$birthweight_{(i)} = m_i + W\Omega + R\alpha_{(tri)} + T\gamma_{(tri)} + \varepsilon_{(i)},$$

where W contains additional variable specific to modeling birth weights (such as how the birth weight was recorded) and the environmental variables R and T store precipitation and maximum daily temperature data for the three month periods 1 year before birth (as discussed in Section 3.2). The model for child stunting is

$$HAZ_{(i)} = m_i + H\Delta + \overline{R}_i\alpha + \overline{T}_i\gamma + \overline{T}_i^2\omega + \varepsilon_{(i)},$$

where $\overline{R}$ and $\overline{T}$ are average rainfall (during rainy seasons) and proportion of days that are over 37.7° C during the period from the child's conception to the date of the interview. We chose the 10 km buffer for two reasons. First because the point location given for the DHS sampling clusters have been randomly offset by 10 km for rural areas and 2 km for urban areas. Second, the buffer is meant to provide a rough aggregation of environmental conditions in the area and smooth out any hyper-local precipitation or temperature patterns. The matrix H contains additional measures specific to malnutrition, including the birth weight of the child. Both models contain a heteroskedastic error term ($\varepsilon_{(i)}$) and the standard errors are clustered on the sampling units (clusters) (Wooldridge, 2003), a method that allows error terms to have arbitrary correlation within a sampling cluster but assumes independence across sampling clusters.

We also expand on the basic model specification by fitting flexible models, wherein the coefficients of electricity and mothers education vary by country. We also fit models wherein the coefficients for the environmental variables vary by household access to electricity and the mother's educational status. We do this to allow for the fact that the marginal benefits of increased education and access to electricity are not uniform across countries and may also vary across climatic regimes.

We frame our analysis by examining changes in predicted values on models with and without coefficients that vary by country or climate variables and then report the mean predicted change across models. Evidence from prior research shows that averaging predictive values across model specifications generally produces more accurate results than those from a single model and also out performs more complex model selection and weighting processes (Clemen, 1989; Jose and Winkler, 2008; Makridakis, 1983). This approach relaxes the assumption that there is 'one true model' and is robust to over fitting (based on model selection criteria) or extreme values that can result from using a single model specification.

Table 3 shows estimated coefficients for the key variables for the models with and without spatially varying coefficients. The estimated coefficients for these key variables (mother's education, electricity, rainfall, and temperature) shape the results our scenarios analysis. We present them here briefly.

Focusing first on birth weights, Table 3 shows that on average, the baby of a mother with a primary education will be 19 g (*m_educprimary* = 19.1) heavier than the baby of mother without primary education. Likewise a baby born into a house with electricity will be 30 g (*electricity_yes* = 30.4) heavier than a baby born into a house without electricity. The variables have similar effects on child stunting, but the relative magnitude is larger. Mothers with primary education have children with height for age scores that are 0.12 standard deviations higher than mothers without a primary education. Children living in a household with access to electricity will, on average, have height for age scores that are 0.16 standard deviations higher than those living in houses without electricity.

In the birth weights model, our environmental covariates are growing-season precipitation and the number of days over 100 °F during each trimester. As discussed earlier in this paper, among the climatic influences, temperature rather than rainfall tends to have the dominant effect on birth weights. Our results show that every day over 37.7° C in the first trimester will reduce birth weight by 0.7 g (*tmax100.t1* = −0.72) and every day over 100 °F in the second trimester will reduce birth weight by 0.9 g (*tmax100.t2* = −0.86). When the child stunting is the dependent variable, we use average growing season rainfall and average number of days over 37.7 °C from the child's birth until the date of the interview. Rainfall has the dominant effect on stunting with an extra 10 mm of rainfall during the growing season increasing child's height-for-age by about 0.1 standard deviations.

The relative magnitude and direction of these relationships has already been established in prior work (discussed above). Our goal is to extend the analyses beyond isolated marginal effects by examining how rainfall, temperature, access to electricity, and mother's education jointly impact child health outcomes under a set of empirically plausible warming/drying and socio-economic scenarios.

4.2. Scenario results

We run scenarios for both the low birth weight and child stunting models and then examine the resulting changes in the average birth weights and stunting scores by livelihood zones and by countries. The results highlight regions and populations that are at increased risk of negative child health outcomes from warming and drying trends and also show where these risks can be potentially mitigated with increased access to key infrastructure and resources.

We focus our results on the percent change of birth weights and child stunting that can be induced by simultaneous patterns of warming, drying, and socio-economic development. The distribution of changes across livelihoods is presented in the boxplots shown in left panels of Figs. 2 and 3. The solid red vertical line in the boxplots indicates 0% change, values to the left of this are where health outcomes might worsen and to the right of that are where health might improve. The wider the box, the greater the range of potential change. Changes across countries are shown in the right panels of the same figures.

In general we find that warming and drying induces small changes to birth weights but that these changes would not be mitigated by positive socio-economic development trends. The change in predicted outcomes for child stunting are larger than the changes seen for birth weights. However, unlike the birth weight outcomes, the results suggest that negative stunting outcomes induced by warming and drying could be mitigated by positive socio-economic changes. Overall we find that the gains and losses in health scores are not homogenous across all livelihood zones and countries. For example, across all scenarios we found that pastoralists tend to have the widest range of changes in birth weights but not in child stunting. We expand on the results for changes in birth weights and child stunting in the next two sections.

4.2.1. Birth weight

We see relatively small absolute changes in birth weight across all scenarios with overall changes averaging around 0.5%. However even under the most optimistic scenarios, the negative changes from warming and drying are generally not mitigated by socio-economic development trends. One exception is Madagascar, which sees net positive changes under the 'Urban and Rural Areas Improve' scenario. This is likely due to the low baseline of mother's education in that country (31% for rural areas) relative to the large increase in mother's education seen from 2000–2010 (34% increase). The boxplots in Fig. 2 show the range of changes in birth weight across countries, by livelihood zone. Pastoralists tend to have the widest range of changes compared to the other livelihoods. The hotter, drier countries in West Africa tend to have the largest negative changes as these are among the warmest and least developed countries examined in this analysis.

Table 3
This table shows regression coefficients for mothers education, access to electricity, precipitation, and temperature. The columns marked 'Yes' for Spatially Varying also include interaction terms between country and mothers education and country and access to electricity. The columns marked 'Yes' for Climate Varying include interaction terms between the environmental variables and mother's education and between the environmental variables and access to electricity. Interaction terms and country fixed effects are omitted from these tables. Standard errors (in parenthesis) are clustered on DHS sampling clusters. Full regression tables with estimated coefficients for all variables are shown in Appendix B.

Dep. variable	Birth Wt.	Birth Wt.	Birth Wt.	HAZ	HAZ	HAZ
Spatially Varying	No	Yes	No	No	Yes	No
Climate Varying	No	No	Yes	No	No	Yes
Educ(m_educprimary)	19.138*	−5.027	2.545	0.125***	0.213*	0.040
	(7.606)	(27.136)	(14.908)	(0.036)	(0.102)	(0.079)
Educ(m_educsecondary and beyond)	9.187	−55.009	−58.077**	0.301***	0.630**	0.354**
	(12.759)	(83.503)	(22.063)	(0.057)	(0.223)	(0.110)
Elec(electricity_yes)	30.451**	56.553*	−12.664	0.165***	0.402***	0.088
	(9.914)	(25.364)	(17.168)	(0.045)	(0.111)	(0.096)
$R_{tri=0}$(rseasonprecip.t0)	0.006	0.006	−0.036			
	(0.019)	(0.019)	(0.023)			
$R_{tri=1}$(rseasonprecip.t1)	0.019	0.018	−0.007			
	(0.019)	(0.019)	(0.023)			
$R_{tri=2}$(rseasonprecip.t2)	0.027	0.026	−0.027			
	(0.019)	(0.019)	(0.023)			
$R_{tri=3}$(rseasonprecip.t3)	0.045*	0.045*	0.019			
	(0.020)	(0.020)	(0.024)			
$T_{tri=0}$(tmax100.t0)	−0.488^	−0.476^	−0.570^			
	(0.271)	(0.271)	(0.320)			
$T_{tri=1}$(tmax100.t1)	−0.725**	−0.699**	−0.809*			
	(0.266)	(0.266)	(0.331)			
$T_{tri=2}$(tmax100.t2)	−0.868**	−0.816**	−1.011**			
	(0.268)	(0.269)	(0.329)			
$T_{tri=3}$(tmax100.t3)	−0.325	−0.291	−0.514			
	(0.266)	(0.268)	(0.320)			
R(r.season.precip.mn)				0.116***	0.113***	0.093**
				(0.029)	(0.030)	(0.035)
T(tmax100_mn)				−0.001	−0.004	−0.002
				(0.019)	(0.019)	(0.019)
T^2(tmax100_mn2)				0.000	0.000	0.000
				(0.001)	(0.001)	(0.001)
N	60,577	60,577	60,577	12,752	12,752	12,752
R^2	0.039	0.042	0.040	0.137	0.142	0.137
adj. R^2	0.038	0.040	0.039	0.134	0.136	0.134
Resid. sd	700.991	700.387	700.843	1.473	1.471	1.473

Robust standard errors in parentheses.
* Significant at $p < 0.05$.
** Significant at $p < 0.01$.
*** Significant at $p < 0.001$.
^ Significant at $p < 0.10$.

4.2.2. Stunting (HAZ)

Shifting attention to the results for child stunting (HAZ), the boxplots in Fig. 3 suggest that the absolute changes are larger than those for the birth weight outcomes, with average negative changes of around −4% and positive changes of approximately 5%. Unlike the birth weight outcomes, we do see more potential for positive socio-economic development trends to mitigate the negative effects of warming and drying. The boxplots in Fig. 3 also show a wider range of results for agriculturalists, even under the most optimistic scenario ('1 Urban and Rural Areas Improve'). This is likely explained by the fact that agriculturalists are more vulnerable to rain induced food shocks and, unlike birth weights, rainfall tends to have more influence than temperature on HAZ scores. The Urban and Rural Areas Improve Scenario also shows stronger potential for climate mitigation socio-economic development in Western Africa. We believe that this again relates to the dominant effect that rainfall (compared with temperature) has on stunting scores.

A notable outlier in West Africa is Guinea (GN), where average change in HAZ is negative in every scenario (Fig. 3). The results for Guinea are driven by high reduction in rainfall (−21%) coupled with relatively small changes in access to electricity (rural = 1%; urban = 3%). Contrast the results in Guinea, with neighboring Senegal (SN), where the drying is more severe (−30%) but where there were substantial increases in access to electricity (rural = 17%; urban = 20%). In Senegal, the average change in HAZ was positive in every scenario. The contrast between Guinea and Senegal highlights the influence that positive development trends may have on mitigating the negative effects of even the most severe drying trends.

5. Discussion and conclusion

5.1. Discussion

In this paper, we examined how simultaneous changes in key climatic and socio-economic variables change child health outcomes. We frame these changes under a number of different socio-economic scenarios while holding climate effects constant. We found that while the effects of warming and drying on low birth weights and child malnutrition are small, they are similar in magnitude to corresponding changes in the key variables of mothers education and electricity access. However, in the case of birth weights the negative effects of warming and drying (while small) are not counteracted by positive socio-economic trends. When compared with birth weights, the impacts of warming and drying on child malnutrition were larger, but we found that these effects could (potentially) be mitigated by positive socio-economic development trends. However, as noted in the introduction, we *do not intend to predict future outcomes*. Rather our goal is to provide a perspective on the potential range of child health outcomes under a set of plausible development and climate scenarios.

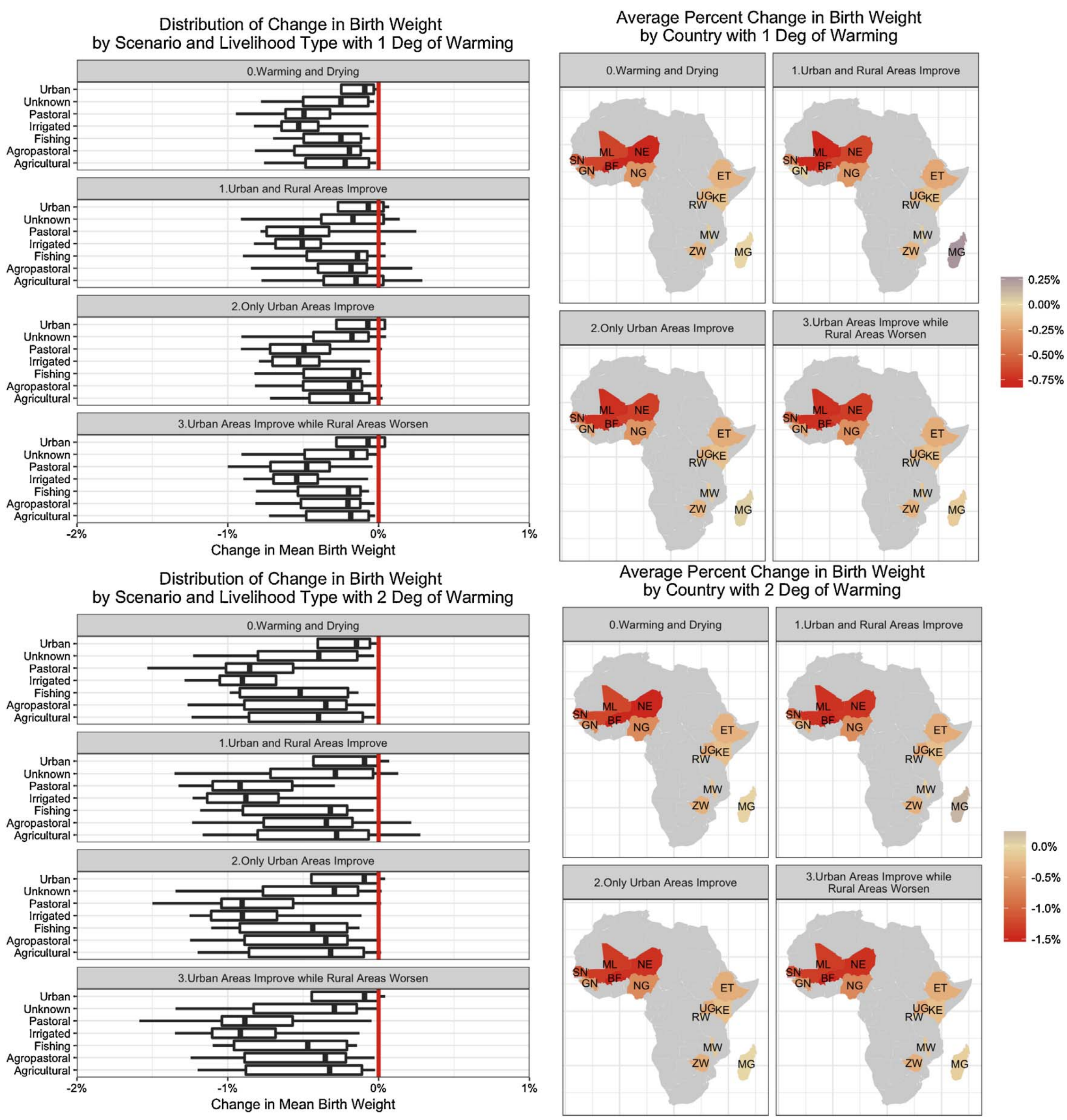

Fig. 2. Low birth weight scenarios. Top row shows 1° warming. Bottom row shows 2° warming. Boxplot on the left shows the range of predicted outcomes by Livelihood type. Maps on the right show results averaged across countries. Scenarios are described in Section 2.2 and summarized in Table 1.

Overall, the results suggest that substantial changes in rainfall or temperature can have as large an impact on birth weights and child stunting as key societal indicators such as educational attainment and access to electricity. In addition, improvements in access to education and basic infrastructure may mitigate the detrimental impacts on child malnutrition resulting from a warmer, dryer climate. However a similar mitigation may not be possible with birth weight outcomes. Finally, this pattern of increased rates in lower birth weights but potentially less instances of stunting – given positive socio-economic development trends – is most pronounced in West Africa. Among the West African countries in our study, Burkina Faso, Niger, and Mali are among the poorest countries in the world. The results seem to indicate that even modest increases in development may have great potential for improving health.

As with any empirical analysis, our results are only as strong as the underlying data. While the DHS uses established survey instruments, the sampling process is notoriously under-representative of nomadic populations (Randall, 2015). Our results likely reflect this sampling bias. Because nomadic peoples may be among the poorest and also live in the hottest and most remote regions of SSA, our results may underestimate the overall impacts of warming and drying as well as the potential gains that could be made from increased rural development. In addition, we may be overly optimistic in assuming positive trends in urban areas, especially if rural-urban migration radically outpaces the infrastructure necessary to support it. We are also forced to make assumptions about past and present socio-economic development trends. Our scenarios are guided by recent trends, but the political economy of SSA is notoriously volatile and we may be assuming more political stability than is warranted. It is also difficult to forecast the rates at which climatic and socio-economic changes will occur. The slower the climate changes occur the more time populations will have to adapt.

Another potential weakness of the study is the fact that increased access to electricity may also increase green house gas emissions. While some analysts suggest that the future energy resources in Africa will stem from hydro and solar power (Karekezi, 2002), fossil fuels will likely remain a substantial part of the African energy portfolio. We currently assume that increased access to electricity will keep carbon emissions static, but future studies could try to accommodate this potentially endogenous relationship.

There are more avenues for future work. The evidence in this paper suggests that increased access to educational resources and electricity

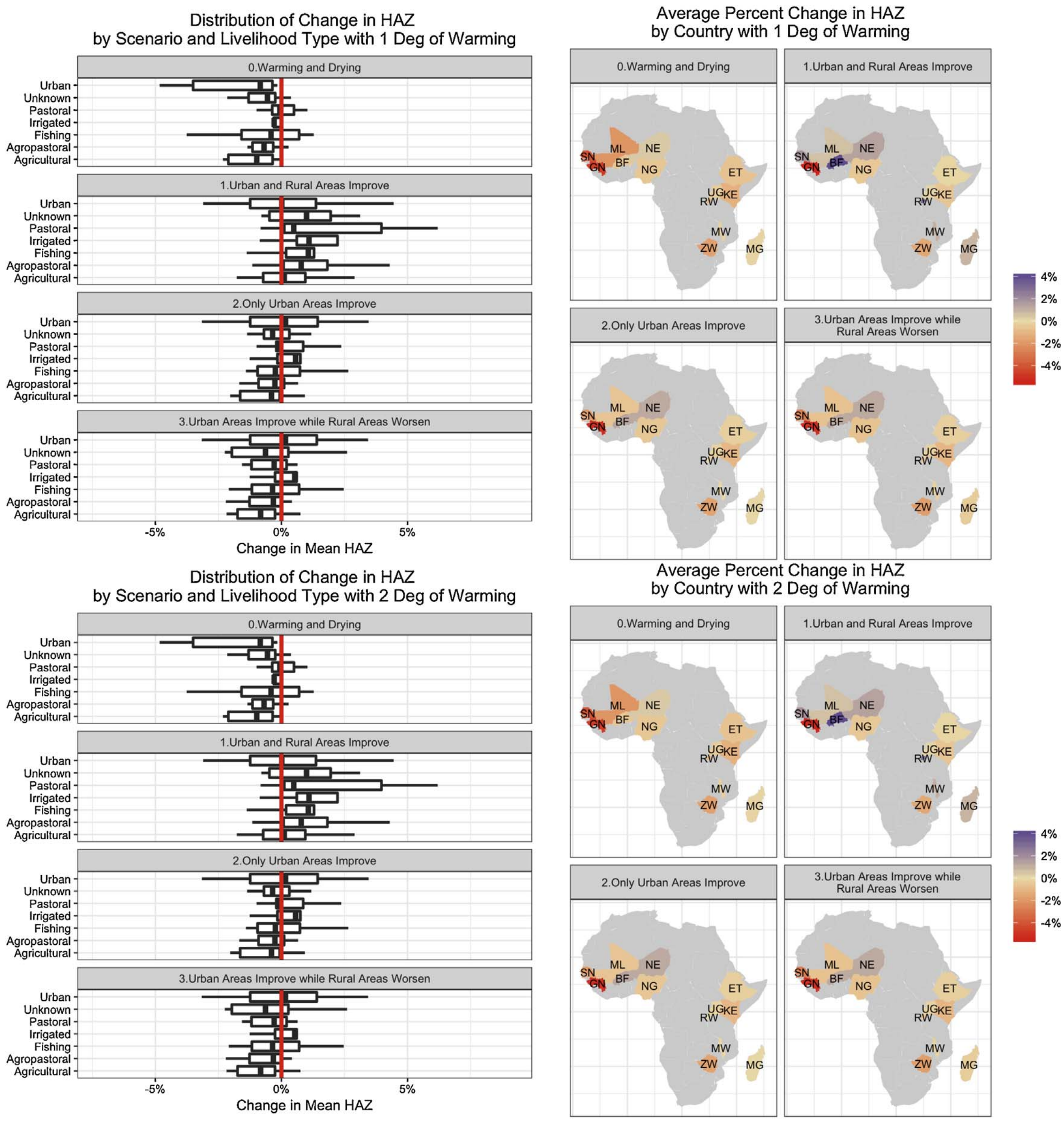

Fig. 3. Child stunting scenarios. Top row shows 1° warming. Bottom row shows 2° warming. Boxplot on the left shows the range of predicted outcomes by Livelihood type. Maps on the right show results averaged across countries. Scenarios are described in Section 2.2 and summarized in Table 1.

(or components correlated with them) might mitigate the negative impacts of climate change. The logical follow up research would analyze the costs, benefits, and trade offs of investing in education, infrastructure, or some other form of climate mitigation across SSA. The overall effectiveness of investments in education in developing countries is difficult to estimate (Psacharopoulos and Patrinos, 2004). However, the small but growing base of field experiments examining the effectiveness of development policies could provide some baseline with which to measure the efficacy of various intervention strategies (Banerjee et al., 2013; Tewari and Shah, 2003).

Another avenue would be to incorporate the joint relationship between low birth weights and child malnutrition. Babies born with low birth weight are more likely to be malnourished. We do not account for this in our current model, but the birth weights interventions might be more beneficial than our results suggest if they also contributed to lower rates of malnutrition.

5.2. Conclusion

In this paper we attempt to quantify how climate change and varying development trends simultaneously impact low birth weight and chronic malnutrition across countries and livelihood zones. Overall the impacts vary by *country and livelihood strategy* and our results suggest that pastoralists may have the most potential for either positive or negative changes in child health, depending on the nature of the development scenario. We find that warming and drying scenarios produce relatively small changes in birth weights but that these changes would not be mitigated by positive trends in socio-economic development. We also find that warming and drying increase child stunting rates more than they decrease birth weights. However unlike the birth weight outcomes, the results suggest that negative changes to child stunting outcomes induced by warming and drying could be mitigated by positive socio-economic development trends.

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Appendix A. Precipitation scenarios

Here we present the basis of our precipitation scenarios. From the outset, we would like to emphasize that these represent plausible scenarios, not predictions. The approach taken here is to link, empirically, rainfall in our target regions to relevant sea surface temperature (SST) gradients, and then to examine plausible drought-inducing changes in these gradients and national level rainfall values. It is well known that African rainfall can vary dramatically on decadal scales, with different patterns of variability in Western, Eastern and Southern Africa (Nicholson, 2000). We describe our analysis of each region below. The SST anomalies discussed below are based on a 1900–2014 baseline. Rainfall for western and southern Africa is drawn from the Global Precipitation Climatology Center archive, version 7 (Becker et al., 2013). Eastern Africa precipitation variations are represented by the Centennial Trends dataset (Funk et al., 2015a).

A.1 West Africa

Decadal rainfall variability in West Africa has received extensive analysis, due to the large reduction in rainfall there from peak values found in the 1960s. While it was originally postulated that this decline had resulted from land cover and surface albedo changes (Charney, 1975), it was later established that the Sahel drying was due to north–south (meridional) Atlantic SST gradients (Folland et al., 1986b) with decadal fluctuations of West African rainfall co-varying with the Atlantic Meridional Oscillation (AMO) (Giannini et al., 2003). While there has been a recovery of Sahel rainfall, in general precipitation levels remain lower there than they were in the 1950s (Nicholson, 2005). Substantial uncertainty surrounds the future state AMO and the Atlantic SST gradient. Over the past century Southeastern Atlantic (30–15°W, 20–40°S, SEA) increased abruptly in 1980s

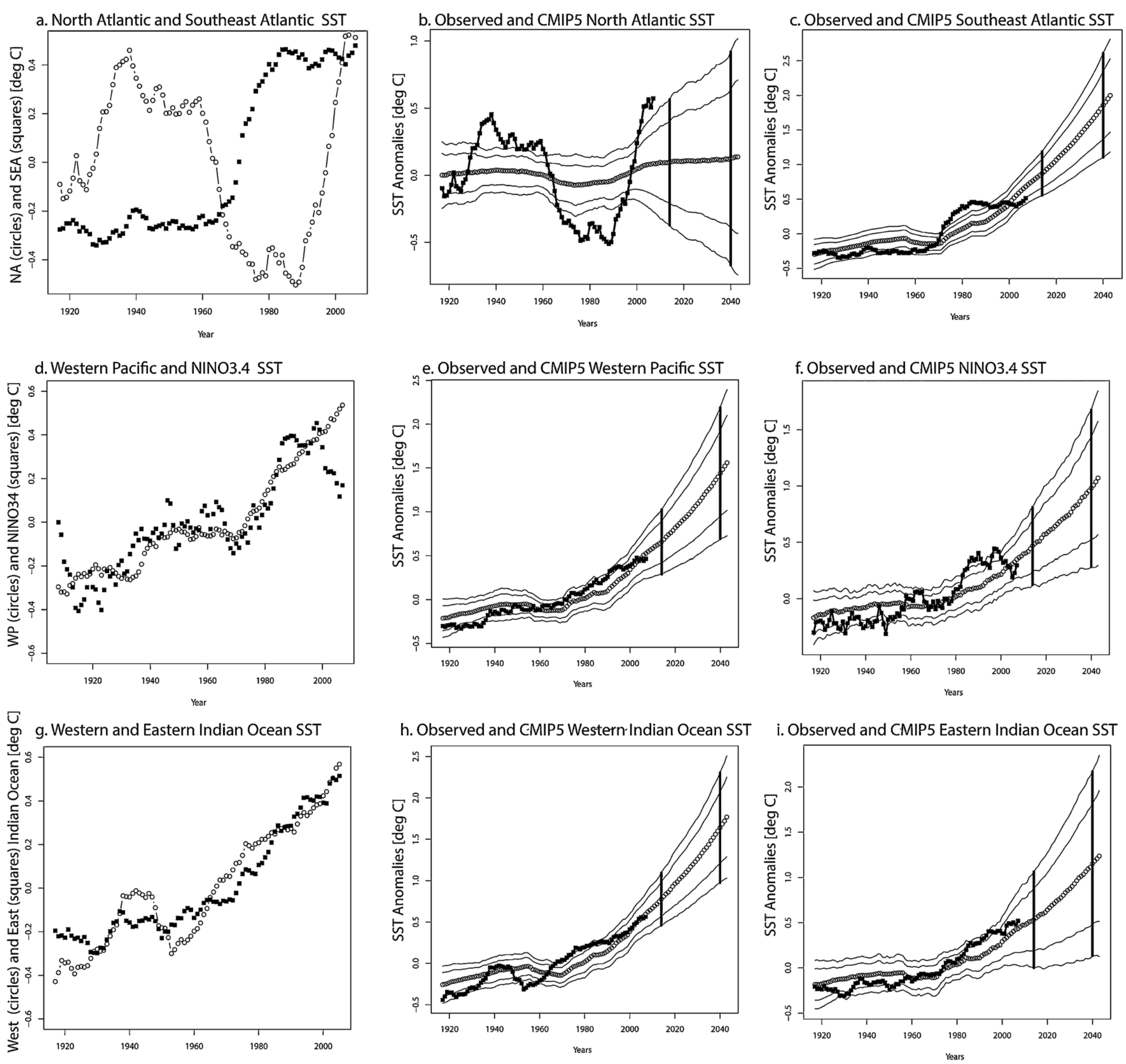

Fig. A1. (a) Observed NOAA reconstructed version 4 June–September 15-year SST from the North and Southeast Atlantic. (b) Observed (black squares) and CMIP5 ensemble average (white circles) 15-year SST from the North Atlantic. Thin lines in (b) correspond to the lower 20th and 5th and upper 80th and 95th percentiles from the 74-member CMIP5 ensemble. (c) Same for the Southeast Atlantic. (d–f) Same but for the equatorial West Pacific and NINO3.4 region. (g–i) Same but for the equatorial Western and Eastern Indian Ocean.

and then remained relatively constant (Fig. A1a). Over the same time period North Atlantic (45–15°W, 55–65°N, NA) SST oscillated upwards in the 1940–50s and late 1990s (Fig. A1a). While ensembles of coupled atmosphere-ocean models (Taylor et al., 2011) indicate a coherent warming of SEA region (Fig. A1b), the outlook of the models for the NA indicates a wide spread of uncertainty (Fig. A1b). One plausible scenario of future drought-inducing SST change between the past 15 years and 2040 could involve a rapid warming of the SEA region (+1.2°, in line with the ensemble average from the climate change simulations), combined with a modest warming of the NA (+0.5°). Using regressions between 15-year SEA and NA observed SST (Huang et al., 2015) and regional Global Precipitation Climatology Centre (Becker et al., 2013) rainfall time series were used in conjunction with these SST changes to develop the rainfall variations in Table 2. While Nigerian rainfall was found to be invariant, the other countries exhibited rainfall reductions on the order of 10–30%. Decadal variations in the Sahel were well fit by our models (R^2 values of more than 70%).

A.2 East Africa

Over the past few decades East African rainfall has exhibited substantial declines (Funk et al., 2008a; Liebmann et al., 2014; Lyon, 2014; Lyon and DeWitt, 2012; Verdin et al., 2005; Williams and Funk, 2011). While some studies suggest that these declines are tied to anthropogenic warming in the Indo-Pacific Warm Pool (Funk et al., 2008a; Funk and Hoell, 2015; Mantua and Hare, 2002; Williams and Funk, 2010), others studies (Lyon, 2014; Lyon and DeWitt, 2012; Yang et al., 2014) suggest that the East African drying is primarily due to natural variability associated with the El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) (Mantua and Hare, 2002). These studies agree, however, that Indo-Pacific SST gradients modulate the strength of the Walker Circulation, which is inversely related to the magnitude of East African precipitation, in areas situated near the equator and Indian Ocean. Building on empirical work (Funk et al., 2014) relating East African rainfall to SST in the West Pacific and ENSO, we model 15-yr variations in East African precipitation as function of WP and NINO3.4 SSTs. Kenya and Ethiopia are divided longitudinally, because Western Kenya (longitude less than 36°E) and Western Ethiopia (longitude < 39°E) are not strongly influenced by Pacific SST gradients. Between the early 1900s and 1980s, WP and NINO3.4 SSTs covaried strongly, then diverged in the 1990s and 2000s (Fig. A1d), possibly due to an emergent climate change influence associated with preferential warming of the Western Pacific. For our East African drought scenario, we regress observed WP and NINO3.4 SSTs with climate change ensemble SSTs for these regions (Fig. A1e–f). Between 2000–2014 and 2040 the WP is estimated to warm by +1.1 °C and the NINO3.4 region is estimated to warm by +0.7 °C. Under this scenario, Eastern Ethiopia, Eastern Kenya, and Rwanda would dry by 15–26%, while Western Ethiopia, Western Kenya and Uganda would experience little change (Table X). Decadal variations in the Eastern Ethiopia, Eastern Kenya, Uganda and Rwanda were reasonably well fit by our models (R^2 values of more than 40%).

While some research has linked Southern African precipitation to ENSO-related (Reason and Rouault, 2002) SST variations, exploratory analysis suggested that our Southern African countries were most closely related to variations in the western and eastern Indian Ocean, though even these models had low R^2 values. Hence, these scenarios were based on the difference between western equatorial Indian Ocean (10°S–10°N, 50–70°E) and eastern equatorial Indian Ocean (10°S-Eq, 90–110°E) SSTs. These correspond to the western and eastern nodes of the Indian Ocean Dipole (Saji et al., 1999). Our southern African rainfall time series have been fairly stationary, however, and western and eastern Indian Ocean SSTs have been pretty similar since the early 1900s (Fig. A1g). Zimbabwe and Malawi precipitation is modestly enhanced when western (eastern) Indian Ocean SST are increased (decreased). Madagascar rainfall in enhanced when the Eastern Indian Ocean warms more than the western Indian Ocean. For Zimbabwe and Malawi potential drought scenarios were explored by projecting more rapid 2040 warming in the eastern Indian Ocean as opposed to the western portion of the basin. This produced an estimated 11% decrease in Zimbabwe precipitation and a −3% change for Malawi. For Madagascar the opposite warming pattern was assumed, these assumptions were associated with a −1% decrease in Madagascar rainfall.

Appendix B. Regression tables

Table B1
Regression table for low birth weight models. All models include fixed effects for countries and calendar month of birth. Model 5 includes interaction terms between country and electricity and country and mother's education. Model 6 includes interaction between the environmental variables (precip and temp) and electricity and the environmental variables and mother's education. Clustered standard errors are calculated based on DHS sampling cluster.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Precip. Variables	*No*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Temp. Variables	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Spatially Varying	*No*	*No*	*No*	*No*	*Yes*	*No*
Climate Varying	*No*	*No*	*No*	*No*	*No*	*Yes*
(Intercept)	2799.956***	2776.678***	2872.449***	2851.758***	2853.566***	2889.918***
	(39.26)	(40.16)	(42.52)	(43.98)	(44.68)	(45.10)
sex (Male)	117.507***	117.449***	117.415***	117.341***	117.504***	117.121***
	(5.71)	(5.71)	(5.71)	(5.71)	(5.70)	(5.71)
m_age	(1.19)	(1.18)	−1.319$^{\wedge}$	−1.301$^{\wedge}$	−1.334$^{\wedge}$	−1.260$^{\wedge}$
	(0.73)	(0.73)	(0.73)	(0.73)	(0.74)	(0.73)
birth_order	22.504***	22.526***	22.709***	22.700***	22.760***	22.594***
	(2.29)	(2.29)	(2.29)	(2.29)	(2.31)	(2.29)
marital_status (married)	57.558***	58.391***	58.341***	58.887***	59.433***	59.497***
	(9.23)	(9.23)	(9.24)	(9.24)	(9.24)	(9.23)
Educ(m_educprimary)	21.247**	20.688**	19.346*	19.138*	(5.03)	2.55
	(7.61)	(7.61)	(7.61)	(7.61)	(27.14)	(14.91)
Educ(m_educsecondary and beyond)	11.21	10.09	9.84	9.19	(55.01)	−58.077**
	(12.79)	(12.76)	(12.78)	(12.76)	(83.50)	(22.06)
took_malaria_drugs (not_recorded)	(1.25)	(0.98)	(1.94)	(1.76)	(4.16)	(4.14)
	(16.60)	(16.64)	(16.64)	(16.67)	(16.47)	(16.63)
took_malaria_drugs (unsure)	33.59	33.77	34.57	34.83	39.05	35.10

(continued on next page)

Table B1 *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(45.56)	(45.46)	(45.50)	(45.40)	(45.25)	(45.27)
took_malaria_drugs (yes)	12.68	12.58	12.68	12.57	7.46	9.42
	(9.15)	(9.15)	(9.14)	(9.14)	(9.20)	(9.15)
prenatal_visits_at_least_one (notrecorded)	39.63	38.08	38.38	37.42	38.63	38.63
	(34.16)	(34.20)	(34.16)	(34.19)	(34.03)	(34.16)
prenatal_visits_atleast_one (one or more)	9.06	8.57	7.70	7.53	10.91	8.64
	(31.02)	(31.04)	(30.99)	(31.00)	(30.92)	(30.99)
birth weight recall (notrecorded)	82.123**	82.940**	65.422*	67.349*	68.068*	68.713*
	(29.75)	(29.65)	(29.75)	(29.64)	(29.92)	(29.80)
birth weight recall (recall)	48.160***	47.500***	47.110***	46.844***	47.141***	46.550***
	(7.10)	(7.11)	(7.10)	(7.11)	(7.12)	(7.11)
urban_rural (Urban)	(1.03)	(0.96)	(2.83)	(2.65)	(2.45)	(1.43)
	(9.36)	(9.33)	(9.29)	(9.27)	(9.42)	(9.30)
Elec(electricity_yes)	31.895**	31.773**	30.496**	30.451**	56.553*	(12.66)
	(9.95)	(9.93)	(9.92)	(9.91)	(25.36)	(17.17)
floor_material (natural)	−16.271*	−16.080*	−14.514^	−14.644^	−21.158**	−15.541^
	(8.12)	(8.11)	(8.10)	(8.11)	(8.18)	(8.11)
floor_material (not recorded)	29.34	32.23	33.61	35.37	36.05	34.34
	(96.50)	(96.29)	(96.61)	(96.36)	(96.66)	(96.13)
floor_material (other)	47.44	49.06	52.07	52.77	59.40	52.70
	(78.42)	(78.39)	(78.18)	(78.16)	(79.51)	(78.88)
floor_material (unfinished wood)	−53.920^	−56.788^	−53.110^	−54.847^	−61.205^	−53.745^
	(31.42)	(31.45)	(31.42)	(31.42)	(31.79)	(31.63)
month of birth in rainy season (yes)	−17.742**	−21.411*	−14.504*	−19.005^	−19.827*	−18.687^
	(6.18)	(9.39)	(6.90)	(9.78)	(9.76)	(9.82)
$R_{tri=0}$(rseasonprecip.t0)	0.02		0.01	0.01	(0.04)	
		(0.02)		(0.02)	(0.02)	(0.02)
$R_{tri=1}$(rseasonprecip.t1)	0.034^		0.02	0.02	(0.01)	
		(0.02)		(0.02)	(0.02)	(0.02)
$R_{tri=2}$(rseasonprecip.t2)	0.039*		0.03	0.03	(0.03)	
		(0.02)		(0.02)	(0.02)	(0.02)
$R_{tri=3}$(rseasonprecip.t3)	0.055**		0.045*	0.045*	0.02	
		(0.02)		(0.02)	(0.02)	(0.02)
$T_{tri=0}$(tmax100.t0)		−0.569*	−0.488^	−0.476^	−0.570^	
			(0.27)	(0.27)	(0.27)	(0.32)
$T_{tri=1}$(tmax100.t1)		−0.611*	−0.725**	−0.699**	−0.809*	
			(0.26)	(0.27)	(0.27)	(0.33)
$T_{tri=2}$(tmax100.t2)		−0.915***	−0.868**	−0.816**	−1.011**	
			(0.27)	(0.27)	(0.27)	(0.33)
$T_{tri=3}$(tmax100.t3)		−0.551*	(0.33)	(0.29)	(0.51)	
			(0.26)	(0.27)	(0.27)	(0.32)
N	60,577.00	60,577.00	60,577.00	60,577.00	60,577.00	60,577.00
R^2	0.04	0.04	0.04	0.04	0.04	0.04
adj. R^2	0.04	0.04	0.04	0.04	0.04	0.04
Resid. sd	701.23	701.15	701.03	700.99	700.39	700.84

Robust standard errors in parentheses.
* Significant at $p < 0.05$.
** Significant at $p < 0.01$.
*** Significant at $p < 0.001$.
^ Significant at $p < 0.10$.

Table B2
Regression table for child stunting models. All models include fixed effects for countries and calendar month of birth. Model 5 includes interaction terms between country and electricity and country and mother's education. Model 6 includes interaction between the environmental variables (precip and temp) and electricity and the environmental variables and mother's education. Clustered standard errors are calculated based on DHS sampling cluster.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Precip. Variables	*No*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Temp. Variables	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Spatially Varying	*No*	*No*	*No*	*No*	*Yes*	*No*
Environmentally Varying	*No*	*No*	*No*	*No*	*No*	*Yes*
(Intercept)	−7.971***	−8.169***	−7.910***	−8.188***	−8.187***	−8.145***
	(0.44)	(0.45)	(0.45)	(0.46)	(0.46)	(0.46)
sex (Male)	−0.166***	−0.166***	−0.166***	−0.166***	−0.166***	−0.166***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
bw	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
c_age	0	0	0	0	(−0.001)	0
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
birth_order	−0.052***	−0.053***	−0.052***	−0.053***	−0.052***	−0.053***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

(continued on next page)

Table B2 *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
marital_status (married)	0.05	0.05	0.05	0.05	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
m_age	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
m_height	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	–	–	–	–	–	–
Educ(m_educprimary)	0.127***	0.125***	0.126***	0.125***	0.213*	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)	(0.08)
Educ(m_educsecondary and beyond)	0.314***	0.302***	0.312***	0.301***	0.630**	0.354**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.22)	(0.11)
urban_rural (Urban)	0.187***	0.188***	0.186***	0.188***	0.194***	0.189***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Elec(electricity_yes)	0.169***	0.165***	0.167***	0.165***	0.402***	0.09
	(0.05)	(0.04)	(0.05)	(0.05)	(0.11)	(0.10)
water_source (unprotected well)	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.07)
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
water_source (well)	0.05	0.05	0.05	0.05	0.07	0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
water_source (protected well)	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.05)
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
water_source (vendor/truck)	0.00	0.01	0.01	0.01	0.06	0.01
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
water_source (piped)	0.04	0.05	0.05	0.05	0.07	0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
water_source (not recorded)	(0.20)	(0.18)	(0.20)	(0.18)	(0.13)	(0.18)
	(0.30)	(0.30)	(0.30)	(0.30)	(0.29)	(0.30)
floor_material (natural)	0.294^	0.268^	0.293^	0.267^	0.27	0.271^
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.16)
floor_material (not recorded)	0.283***	0.278***	0.281***	0.279***	0.274***	0.279***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
floor_material (other)	(0.08)	(0.09)	(0.09)	(0.09)	(0.19)	(0.07)
	(0.27)	(0.27)	(0.27)	(0.27)	(0.25)	(0.27)
floor_material (unfinished wood)	0.43	0.45	0.43	0.45	0.49	0.44
	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
month of birth in rainy season (yes)	0.01	0.01	0.01	0.01	0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R(r.season.precip.mn)		0.110***		0.116***	0.113***	0.093**
		(0.03)		(0.03)	(0.03)	(0.04)
T(tmax100_mn)			(0.01)	(0.00)	(0.00)	(0.00)
			(0.01)	(0.02)	(0.02)	(0.02)
T^2(tmax100_mn2)				–	–	–
				(0.00)	(0.00)	(0.00)
N	12,752.00	12,752.00	12,752.00	12,752.00	12,752.00	12,752.00
R^2	0.14	0.14	0.14	0.14	0.14	0.14
adj. R^2	0.13	0.13	0.13	0.13	0.14	0.13
Resid. sd	1.47	1.47	1.47	1.47	1.47	1.47

Robust standard errors in parentheses.

* Significant at $p < 0.05$.

** Significant at $p < 0.01$.

*** Significant at $p < 0.001$.

^ Significant at $p < 0.10$.

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