Food Security
https://doi.org/10.1007/s12571-021-01211-6

ORIGINAL PAPER

Heat shocks, maize yields, and child height in Tanzania

S. Block[1] · B. Haile[2] · L. You[2,3] · D. Headey[2]

Received: 2 October 2020 / Accepted: 18 August 2021

Abstract
This paper advances previous literature that has posited a climate-nutrition link without identifying a specific pathway via agriculture. We measure the specific effects of exposure to extreme heat on maize yields in Tanzania, and then test whether prenatal heat-induced yield losses predict subsequent child growth outcomes. In the first stage we find that substituting one full day (24 h) exposure to 39 °C for a day at 29 degrees reduces predicted yield for the entire growing season by 6–11%. In the second stage we find that in utero exposure to growing degree days greater than 29 °C predicts lower postnatal HAZ scores for Tanzanian boys 0–5 years of age, but not girls. Consistent with a maternal malnutrition mechanism, we also find a negative association between maize yields and women's body mass. Insofar as climate change is likely to increase the incidence of heat shocks in much of sub-Saharan Africa, our results suggest a significant risk of adverse nutritional impacts.

Keywords Yield · Heat · Maize · Nutrition · Tanzania

1 Introduction

For the millions of African farm households that primarily depend on rainfed agriculture or livestock for their livelihoods, climatic shocks constitute a serious threat to their food, water and nutrition security. One significant concern is that these shocks erode human capital of the next generation through undernutrition in early childhood, particularly its manifestation in inadequate linear growth, commonly referred to as stunting. A substantial body of research demonstrates that stunting in early childhood is a strong predictor of later-life health problems, poor schooling attendance and lower grades, and lower adult wages and cognitive test scores (Hoddinott et al., 2008, 2013; Kang et al., 2009; Maluccio et al., 2009). Hence, climate-based shocks to child nutrition could have important impacts on human capital in the long run.

✉ S. Block
steven.block@tufts.edu

[1] Fletcher School, Tufts University, Medford, MA 01742, USA

[2] International Food Policy Research Institute, Washington, DC 20005, USA

[3] Macro Agriculture Research Institute, College of Economics and Management, Huazhong Agricultural University, Wuhan 430070, Hubei, China

The potentially harmful effects of climate shocks on child nutrition are of particular concern in Africa for two reasons. First, the region is predicted to experience significant warming and increased frequency of climate shocks (IPCC, 2014). Second, child stunting rates are much higher among Africa's vast numbers of predominantly rainfed agricultural households than they are among other livelihood groups (Headey & Masters, 2021).

Despite the hypothesized linkage between climate shocks, agriculture and nutrition, empirical research has typically stopped short of identifying specific agricultural mechanisms linking climate and nutrition (Deschênes et al., 2009; Hoddinott & Kinsey, 2001; Lohmann & Lechtenfeld, 2015; Maccini & Yang, 2009; Rocha & Soares, 2015; Rojas-Downing et al., 2017). Indeed, while it is clear that weather shocks could easily translate into production, income and dietary shocks for the many poor African households highly dependent on rainfed agriculture, there are also plausible non-agricultural "health" mechanisms that could account for associations between climate shocks and child nutrition or health. Higher temperatures may increase infections among infants and children by expanding the range of vector-borne diseases, with one meta-analysis showing that long term warming promotes the geographic expansion of several infectious diseases (Wu, et al., 2016). Still other studies—including several from non-farm populations

Published online: 20 September 2021

in high income countries—show that heat stress during pregnancy can lead to worse birth or child health outcomes (Cil & Cameron, 2017; Isen et al., 2017; Kudamatsu et al., 2012; Levy et al., 2016; Wilde et al., 2017).

This ambiguity in the mechanisms linking climate shocks to child health or nutrition is clearly problematic from a policy perspective: should policymakers focus on agricultural interventions and social protection to de-link climate, yields and nutrition, or should they instead focus on public health interventions?

In light of this ambiguity, this paper attempts to identify a specific agricultural mechanism linking climate shocks to child nutrition outcomes via a well-established and specific non-linear relationship between ambient temperature and crop yields. Simple measures of temperature and precipitation averages in the growing season can explain up to 30% of the yearly variation on yields for staple crops, including wheat, maize, and barley in a diverse array of agroecologies (Lobell & Field, 2007). When crops are exposed to temperatures above a certain crop-specific threshold, they lose their ability to create seeds and fruits (Porter & Semenov, 2005). For example, Schlenker and Roberts (2009) find that US maize yields increase gradually with temperatures up 29 °C, beyond which yields decline sharply. The same study shows different temperature kink points for other crops (30 °C for soybeans and 32 °C for cotton), while many other studies confirm these well-defined kinks (see further references below).

Temperature threshold effects create an opportunity to identify a testable crop-specific mechanisms linking temperature shocks to nutrition through yield effects, provided that: (1) a crop-specific temperature threshold explains variation in yields of the corresponding crop (i.e., a 29 °C accounts for yield loss in maize) and (2) crop-specific temperature thresholds do not explain variation in other factors that could influence child health and nutrition, such as malaria or diarrheal pathogens, or maternal heat stress.

The context of our study is Tanzania, which is highly dependent on a maize-based rainfed agricultural system that has become increasingly exposed to higher ambient temperatures in recent years. Figure 1 demonstrates an accelerating trend in mean temperature between 2000 and 2015, during which time annual mean temperature rose from 22.7 to 23.7 °C. Given these temperature trends, it is likely that extreme heat events in Tanzania will be increasingly frequent and severe (Rowhani et al., 2010; Russo et al., 2019). In addition to direct consumption effects from reduced food supply, shocks to maize production may reduce real incomes through either direct income losses to maize-producing households, or by adversely affecting consumers through higher maize prices. Previous research finds that real income shocks might reduce dietary diversity more than calorie intake, because income losses induce households into switching to cheaper sources of calories to maintain overall calorie intake and avert hunger (Block et al., 2004). This suggests that maize shocks may chiefly affect dietary quality through reduced intake of foods rich in micronutrients and high-quality protein. Income shocks may also affect non-food expenditures relevant to nutrition, particularly on health services. However, we also hypothesized that these shocks may have their greatest impact in

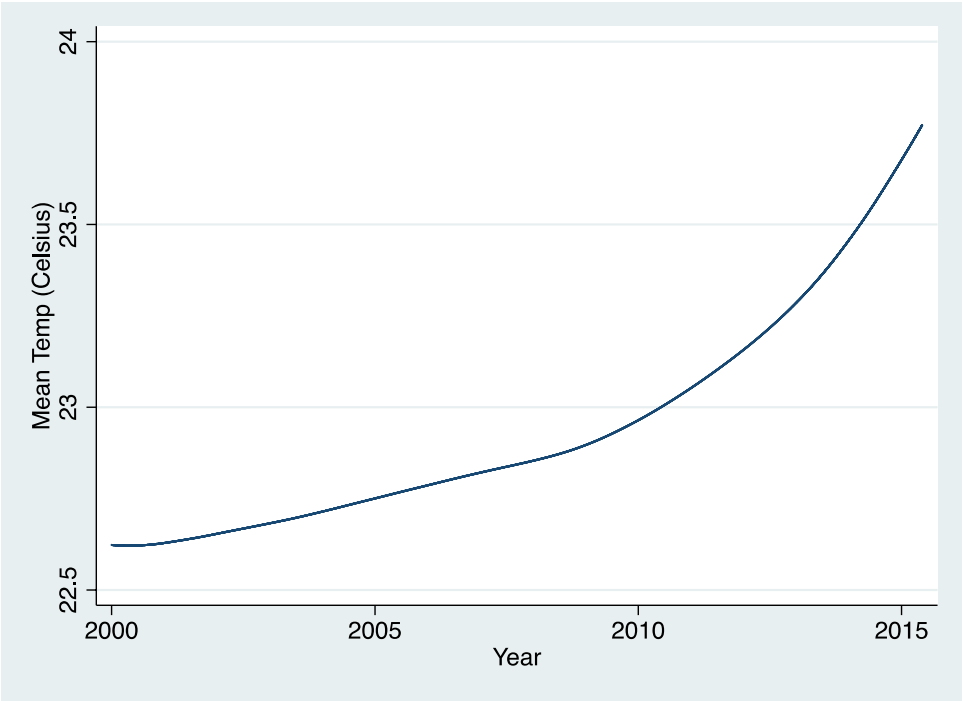

Fig. 1 Nonparametric relationship between mean temperature and time in Tanzania based on daily temperature observations. Source: NASA/Goddard Institute for Space Studies surface temperature data

Table 1 Descriptive statistics for the indicators used in this study

Variable	N	Mean	sd	Min	Max
Maize yield (kg/ha)	3980	772.95	1097.88	3.29	32,947.39
Growing degree days (8–28 °C)	3980	2396.69	459.37	1448.03	6091.61
Growing degree days (> 29 °C)	3980	20.02	15.28	0	82.19
Total rainfall for the growing season (millimeters)	3980	630.41	252.52	145.74	1713.32
Household labor	3980	2.7	1.68	0	25
Age of household head (years)	3980	48.29	16.07	18	102
Average adult education (years)	3980	4.56	2.71	0	16
Land size operated by the household (ha)	3980	2.02	2.19	0.01	34.4
Inorganic fertilizer used (kg)	3980	51.88	1609.25	0	92,664.53
Organic fertilizer used (kg)	3980	219.16	2122.49	0	123,552.71
Durable agricultural assets (index)	3980	0.37	1.39	− 9.97	12.84
Per capita household consumption expenditure (PPP)	3980	631.69	464.6	0	5650.56
Child age (months)	1829	31.99	16.76	0	60
HAZ (boys)	847	− 1.75	1.52	− 5.83	4.99
HAZ (girls)	982	− 1.57	1.41	− 5.71	5.46

Sample sizes are determined by regression samples

the prenatal period through transmission of poor maternal nutrition to fetal development. Prior research has found this to be the case in low-income settings, although much of this research has found stronger impacts for male children (Mulmi et al., 2016), consistent with the so-called male fragility hypothesis (Kraemer, 2000). Hence, we test for separate impacts of climatically-induced maize yield shocks on the nutrition outcomes of male and female children.

2 Materials and methods

2.1 Data

The data needed for linking climate shocks to yields and to subsequent child growth are stringent, requiring household panel data with information on child anthropometrics, yields of major crops and geocoded cluster locations to incorporate GIS-based climate data.

2.2 Household data

Household data for this study come from three rounds of the Tanzania National Panel Survey (NPS) conducted in 2008/09 (round 1), 2010/11 (round 2) and 2012/13 (round 3). The NPS sample covers all the 26 first-level administrative divisions (regions) of Tanzania and is designed to be representative at the national and urban/rural level, as well as that of major agro-ecological zones (National Bureau of Statistics, Tanzania). NPS sample summary by survey round, area of residence (rural versus urban), and commonly grown crops is shown in Table 7. in the Appendix A while supplementalFig. 4 shows the spatial distribution of NPS panel households. Table 1 provides descriptive statistics for the key indicators used in this study.

Given that maize was grown by approximately half of the rural survey households, our analysis focuses on maize yields and the sub-sample of NPS households that reported growing maize at each round. Maize yield was computed based on self-reported total maize harvest and area allocate for maize production. When maize is grown on intercropped plots, we use self-reported share of total plot area allocated to different crops to partition plot area into different crops.

Crop yield data are prone to measurement error. Wineman et al. (2019) use the Tanzanian NPS surveys to explore this issue with particular focus on the calculation of area planted (i.e., the denominator used to calculate yield from survey questionnaires) in multi-cropped plots. Comparing four alternative methods, Wineman et al., find large differences in yield estimates. In the present paper we first use yield as the dependent variable when estimating the effect of heat shocks, but then use yield as an independent variable when estimating the effects of yield on child nutrition. In the first stage, measurement error merely adds noise to the estimates, however random measurement error in an independent variable may lead to attenuation bias in the estimates. In addition to detailed general household information, such as household food and non-food expenditure, the NPS collected detailed crop-specific agricultural data. While agricultural data were collected for both the long and short rainy season, this study analyzes maize yield data for the long rainy season. Mean maize yield for the long rains decreased from 1188 kg/ha in 2008/09 to 805 kg/ha in 2010/11, and still further to 770 kg/ha in 2012/13, with the distribution in each case skewed towards lower-yielding households.

NPS also collected anthropometric data of household members at least 6 months old who were at home, not too ill, and who consented to provide these data. We use the 2006 World Health Organization (WHO) Child Growth Standards Group (WHO, 2006) to construct standardized age- and sex-specific z scores for child height for age (HAZ) for children 6–59 months of age. HAZ is a measure of chronic or cumulative nutrition that can be influenced by nutritional insults in utero, infancy or early childhood. Mean HAZ for children aged 6–60 months in our sample across all three waves was a very low − 1.64. Mean HAZ for girls was − 1.36 as compared with − 1.56 for boys—a statistically significant difference at the 0.01-level. These results, including worse HAZ scores for boys, are typical for Sub-Saharan Africa (Headey et al., 2018), for example, found a mean of − 1.73 for a sample of 23 countries in the region and worse scores for boys). Children in the Tanzanian NPS also follow the typical age path of HAZ, with a steep decline up to age 20 months followed by a moderate increase until leveling off at approximately − 1.5 by age 50 months.

In this study, as in others in the literature, we hypothesized that prenatal nutritional insults were likely to have the most impact on current HAZ status. Thus, while the reported maize growing seasons are for the survey years listed above, we used information on child birth dates to identify children who were in utero during the relevant maize growing seasons.

2.3 Weather data

We use NPS Global Positioning System coordinates to link individual and household NPS data to environmental weather conditions, particularly rainfall and temperature. The daily rainfall is from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), which was downloaded from http://chg.geog.ucsb.edu/data/chirps/ as daily 0.05 degree resolution grids. The daily minimum and maximum temperature data are from the Global Land Data Assimilation System (GLDAS), which generates satellite- and ground-based observational data products using advanced land surface modeling and data assimilation techniques (Rodell et al., 2004). Temperature data are in 0.25 degree resolution and range from February 24th of 2000 to the end of the study period. The temporal resolution is every 3 h, and we calculate the daily minimum and maximum temperatures from the 8 temperature observations within 24 h. Based on the modified GPS coordinates of survey households, we identified the corresponding grid cell of the above climate grid and extract the relevant values. Data on the months of the maize growing period corresponding with the available GPS values are obtained from Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2019). Depending on the region, maize planting months range between September and January while months of harvest range between November and April.

Although rainfall, soil conditions and other factors clearly influence crop production, temperature variability has been shown to be highly influential for a range of crops. Here we follow a large agronomics literature in focusing on growing degree days (GDD), a construct used to specifically assess crop development during the growing season (Snyder, 1985). The basic concept is that crop development will only occur if the temperature exceeds some minimum crop-specific base temperature (e.g. cereal and forage crops show little growth or development when average temperatures are below 5 °C), but will also be seriously hampered if temperature exceeds a temperature ceiling (e.g. 34 °C). In the absence of these extreme conditions (or others such as drought or disease), plants grow in a cumulative stepwise manner that is strongly influenced by the ambient temperature. Empirically, daily growing degree day values are added together from the beginning of the season, providing an indication of the cumulative energy suitable for plant growth.

In this study GDD are defined as follows. First, GDD are defined as the number of days in the growing season in which mean daily temperature (average of daily maximum and minimum temperatures) is within the useful range for maize growth (taken by Schlenker and Roberts (2009) to be temperatures above 8 °C and below 34 °C,), where each mean daily temperature value above 8 °C adds a degree day. That is, a day of 9 °C contributes 1 degree day, a day of 10 °C contributes 2 degree days, and so on up to a temperature of 34 °C. Growing days at 34 °C and above all contribute 26 degree days. We thus calculate degree days based on heat (h) as:

$$g(h) = \begin{cases} 0 & h \leq 8\,^{\circ}\mathrm{C} \\ h - 8 & 8\,^{\circ}\mathrm{C} < h \leq 34\ ^{\circ}\mathrm{C} \\ 26 & h > 34\,^{\circ}\mathrm{C} \end{cases} \tag{1}$$

Following Snyder (1985), we assume a sine curve distribution of temperature within a day and calculate the growing degrees as the sum of truncated degrees between two temperature bounds, 8 °C and 34 °C as specified above.

The choice to model the discontinuity in maize yields at 29 °C is validated by numerous previous studies in addition to Schlenker and Roberts (2009). Related studies that use US data to test this discontinuity threshold include Burke and Emerick (2016), as well as a series studies by Butler and Huybers (2013, 2015)—who dramatically refer to GDDs > 29 °C as "killing degree days"—as well as Butler et al. (2018), Ortiz-Bobea (2012), Roberts et al. (2013), and Xu et al. (2016), who model a threshold of 30 °C. Similarly, two cross-country studies of maize yields in Sub-Saharan Africa (Steward et al.,

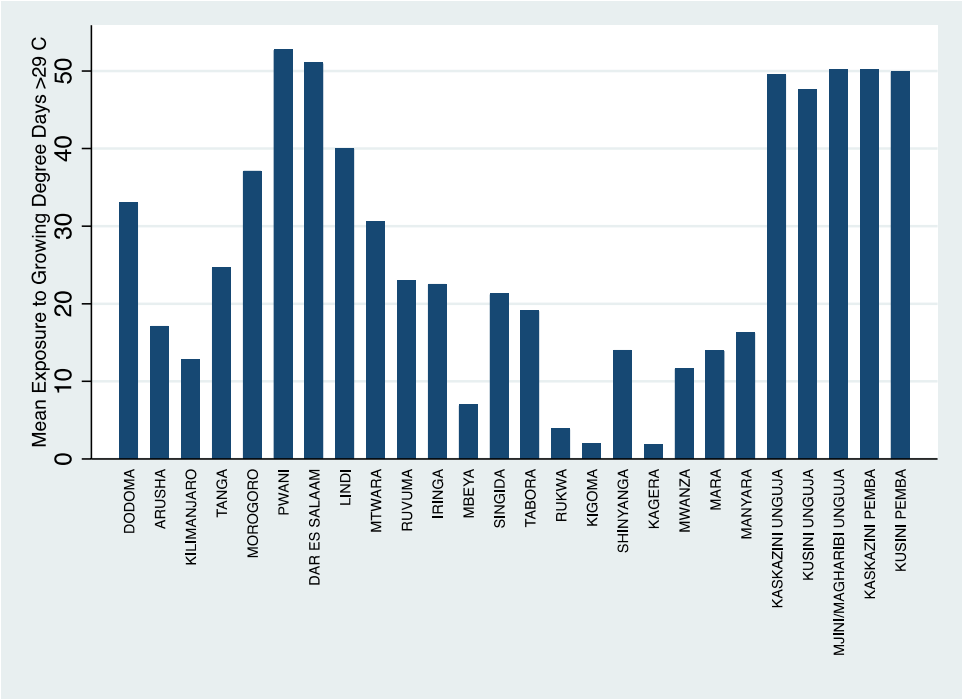

Fig. 2 The mean number of growing degree days > 29 °C by Region

2018; Lobell et al., 2011) model a discontinuity at 30 °C. We follow these models in always flexibly controlling for rainfall and other regional characteristics.

The mean number of degree days > 29 °C was 28.6 during the 2008/09 growing season, 30.2 in the 2010/11 season, and 28.1 during 2012/13. Figure 2 illustrates the geographical variation in mean number of GDDs > 29 °C across Tanzania's primary administrative regions.

2.4 Statistical analyses

We explore the linkages between climate, crop yields and subsequent child growth in two steps. First, we estimate the non-linear relationship between yields and growing degree days as per previous research from US maize, but also provide quantile regression results as a means of exploring heterogeneous impacts of climate shocks across the yield distribution. Then we link maize yields in the season prior to birth to child height observed at a later period, since child growth is a cumulative process.

The core regression strategy estimates maize yields as the cumulative effect of exposure to given temperature levels, as measured by degree days. As Schlenker and Roberts (2009) explain and validate, this approach assumes that the yield effect of exposure to growing season temperature levels are the same and additively substitutable. In its most general form, the regression equation proposed by Schlenker and Roberts (2009) to capture this cumulative effect of heat, *h,* on yield growth *g(h)* in region *I* in growing season *t* is given in Eq. (2):

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)dh + z_{it}\delta + c_i + \varepsilon_{it} \tag{2}$$

where y is log yield for the long rainy season and $\phi_{it}(h)$ is the time distribution of heat over the growing season.

Our specific implementation of this approach aggregates the range of degree day exposures into two categories, modeling *g(h)* as a piecewise linear function with a kink at 29 °C, as per Schlenker and Roberts (2009) and Burke and Emerick (2016) among others. We therefore estimate a piecewise specification via ordinary least squares (OLS):

$$y_{it} = \alpha + \beta_1 DD_{it;h\in[8,29]} + \beta_2 DD_{it;h\in(29,\infty]} + z_{it}\delta + c_i + \varepsilon_{it} \tag{3}$$

where z is a matrix of regressors including a quadratic function of log total rainfall, farm and household characteristics, and fixed effects for survey round, and region. Standard errors are adjusted for spatial correlations between locations as per Conley (1999), using "acreg" command in Stata. Interdependencies among households that share similar agro-ecological and economic conditions will cause interdependence among their unobservables violating ordinary least squares' assumption of independent error terms and resulting in biased standard errors. The Conley adjustment models dependencies between households (i.e., economic distance) using GPS data and estimates error covariance matrices nonparametrically, and is shown to be consistent even when economic distance may not be defined precisely.

In this specification, α indicates predicted yield for temperatures below the lower bound of 8 °C; β_1 estimates the change in predicted yield for each additional degree day of exposure between 8 and 29 °C; and, β_2 estimates the effect of each additional degree day of exposure to temperatures greater than 29 °C. We estimate this model on a sample that is limited to rural maize-growing households.

To connect our findings for the effect of extreme heat on maize yields to child nutrition outcomes, we estimate the following equation:

$$HAZ_{ijt} = \alpha + \beta_1 MzYield_{t=b} + Child_{ijt}\lambda + Hhld_{ijt}\zeta + z_{jt}\gamma + \varepsilon_{ijt} \tag{4}$$

where HAZ_{ijt} is the height-for-age Z-score of child i in region j at time t, $MzYield$ is the log of the maize yield in the growing season prior to each child's birth (time period b), $Child$ is a vector of child characteristics including gender and a cubic function of age in months, $Hhld$ is a vector of household characteristics including parental education and household size, Z is a vector of additional controls including rainfall and average maximum temperature by trimester in utero and during the first year post-birth as well as dummy indicators for month and year of birth, region, and survey wave. These additional environmental controls help to distinguish the effect of maize yield from potential weather-related confounders. Standard errors are again adjusted for spatial autocorrelation.

The posited functional linkage from maize yield in the growing season prior to birth to later HAZ is maternal nutrition during pregnancy and its effect on birthweight. We do not have direct observations of maternal nutrition during pregnancy but conjecture that yield shocks adversely affect household income (through direct income effects, but perhaps also through effects on local maize prices), and lead to deteriorations in diet. It is well-established that maternal nutrition during pregnancy is a central determinant of child birth weight (Abu-Saad & Fraser, 2010; Amosu & Degun, 2014; Verma & Shrivasta, 2016) and that low birth weight is a critical risk factor for later stunting (Admassu et al., 2017; Christian et al., 2013; de Silva Lopes et al., 2017).

The linkage we thus propose is that extreme heat reduces maize yields, which in turn harms maternal nutritional status during pregnancy, leading to low birth weight and subsequently reduced HAZ. We summarize this chain of reasoning as

$$HAZ = f\left(X, maize\ yield\left(X, DD29_{+}\right)\right) \tag{5}$$

where X represents the control variables described above.

In this case, the effect of a single degree day > 29 °C on HAZ can be estimated as

$$\frac{\partial HAZ}{\partial DD29_{+}} = \frac{\partial HAZ}{\partial MzYield}\frac{\partial MzYield}{\partial DD29_{+}} \tag{6}$$

We apply Eq. (6) to derive an order of magnitude for the effect of a single degree growing day > 29 °C on HAZ, and then scale that estimate up based on the actual number of such days experienced to estimate the magnitude of the total effect of extreme heat on HAZ specifically as channeled through the pathway described above.

3 Results

3.1 Baseline results linking yields to growing degree days

Table 2 presents least squares regression results linking rural households' maize yields to growing degree days.[1] The baseline specification in column (1) indicates a flat function of yield with respect to heat up to 29 °C, followed by a strong decline in maize yield at degree days > 29 °C, consistent with US-based results cited above. The effect in our baseline specification is large: each full day of exposure to temperatures greater than 29 °C reduces predicted maize yield by 1%.[2] Stated differently, substituting one day with mean temperature of 39 °C for a day at 29 °C reduces predicted yield for the entire growing season by 10%.

Controlling for a quadratic function of log rainfall during the growing season reduces the rate of yield loss to degree days > 29 °C from 1 to 0.8% per day. The remaining specifications in Table 2 demonstrate the robustness of these estimates by progressively adding controls for farm and household characteristics, region fixed effects (column 5) and survey wave-region effects. Results using all controls suggest that substituting one day with mean temperature of 39 °C for a day at 29 °C reduces predicted yield for the entire growing season by 6%.

Figure 3 translates the degree day coefficients from Eq. (2) into normalized predicted maize yields as a function of the piecewise linear function of individual degrees. The discontinuity at 29 °C is sharp and clearly statistically significant. We explore heterogeneity in the effects of temperature shocks in Appendix B, finding suggestive evidence that households with lower maize

[1] Growing degree days (as detailed above) measure the cumulative heat exposure of crops during the growing season, defined as the number of days in the growing season in which mean daily temperature is within the useful range for maize growth.

[2] Using a threshold of 30C (instead of 29C) in a multi-country study of maize yields in Africa, Lobell et al. (2011) also estimate a reduction of 1% of yield per GDD above the kink.

Table 2 Baseline results for maize yields as a function of growing degree days, rainfall and other controls

	1	2	3	4
Growing degree days between 8 and 29 °C	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Growing degree days temperature was > 29 °C	− 0.010***	− 0.008***	− 0.006***	− 0.006***
	(0.003)	(0.002)	(0.002)	(0.002)
Log total rainfall in growing season	− 5.133***	− 4.959***	− 0.880	− 0.717
	(1.159)	(1.149)	(0.869)	(0.873)
Log total rainfall in growing season	0.430***	0.417***	0.080	0.066
	(0.095)	(0.094)	(0.070)	(0.071)
Survey wave dummies	X	X	X	X
Household controls[a]		X	X	X
Region dummies			X	X
Survey wave*region dummies				X
Number of observations	4669	4669	4669	4669
R2	0.053	0.100	0.152	0.169

Results are based on least squares regressions. Spatially adjusted Conley standard errors are reported in parenthesis. ***p<0.01, **p<0.05, *p<0.10; Sample is limited to rural maize-growing households

[a]Household controls include land operated (hectares), total inorganic fertilizer, total organic fertilizer, agricultural wealth index, family size, age of the household head, and average education among adult members

yields suffer greater losses from high heat during the growing season, although the differences are not statistically significant.

3.2 Maize yields in early childhood and subsequent height attainment

Do maize yields in early childhood predict subsequent linear growth of children? Table 3 explores this possibility by testing the height-for-age Z score effects of yields in the growing season before birth versus the effect of yields in the season following each child's birth. Consistent with our hypothesis outlined above, in utero effects are dominant. However, Table 4 also separates results by gender, only to find that boys in utero appear to be substantially more vulnerable than girls to yield shocks. Specifically, a 1% increase in yields in the season prior to a boy's birth predicts a 0.156 standard deviation improvement in that boy's subsequent height, while the respective coefficient for girls is smaller by a third and not significantly different from zero. We consider this point estimate to be an upper bound, as unobserved and excluded covariates may well bias this estimate upwards.

Table 4 explores the yield-HAZ associations with a richer set of specifications, maintaining the gender separation begun in Table 3.[3] Estimates for the full sample (columns 1, 4, 7) would appear to suggest small and insignificant effects of in utero maize on HAZ. However, disaggregating by gender reveals quite a different story. Maize yields in the season prior to birth continue to have no predictive power for girls' subsequent HAZ, but the subsequent HAZ of boys is consistently sensitive to yields. The fully specified model includes controls for year/month of birth child age, weather (measured by rainfall as well as both the mean temperature and the difference between mean and maximum temperature) for each prenatal

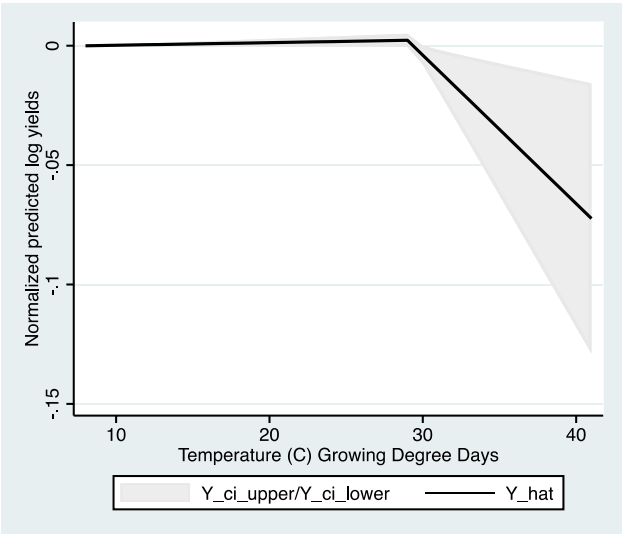

Fig. 3 Effect of an additional degree day of exposure to temperatures on predicted maize yield (based on specification 3 of Table 2)

[3] All regressions for HAZ exclude children resident in the major urban hub of Dar es Salaam, where domestic yield shocks will be less relevant given the availability of imported cereals.

Table 3 Associations between child HAZ scores and maize yields before and after birth, by gender

	1 Full sample	2 Boys only	3 Girls only
log of maize yield in season prior to birth	0.143**	0.156*	0.103
	(0.061)	(0.088)	(0.071)
log of maize yield in season following birth	− 0.012	0.074	− 0.118
	(0.078)	(0.085)	(0.083)
Year and month of birth dummies	X	X	X
Year x month of birth dummies	X	X	X
Survey wave dummies	X	X	X
Region dummies	X	X	X
Child age (cubic function of months)	X	X	X
Number of observations	1863	907	956
R2	0.188	0.244	0.254

Results are based on pooled least squares regressions. Spatially adjusted Conley standard errors are reported in parenthesis. ***p<0.01, **p<0.05, *p<0.10

trimester, and a set of additional household characteristics, yet still indicates that a 10% reduction in maize yield in the growing season prior to birth reduces later height for boys by nearly 1.4 standard deviations, with little apparent effect on girls. Hence, while it is possible that extreme temperature conditions might have direct effects on maternal health/nutrition via heat stress or disease during pregnancy, generic measures of warmer temperatures are neither individually nor jointly significant in explaining HAZ. Likewise, rainfall measures—which could affect malaria or diarrhea incidence—are also not statistically different from zero at conventional levels. This does not fully rule out non-agricultural mechanisms linking climate conditions to child nutrition, but the significant connections between the specific 29 °C temperature threshold and yields, and between yields in utero and subsequent HAZ for boys, does lend weight to a yields-based mechanism at work.

To assess the implied effect of temperature shocks during the growing season prior to birth on subsequent HAZ, we apply Eq. (6) using the relevant parameters from Table 5 (the HAZ-maize yield coefficient) and Table 2 (the yield response to a single degree growing day > 29 °C on HAZ) to estimate the magnitude of the marginal effect of extreme heat on HAZ as channeled through the yield pathway.

Taking a point estimate of 0.14 as a representative point estimate for the effect of maize yields on HAZ

Table 4 The sensitivity of associations between child HAZ and maize yields prior to birth to environmental and household controls

	1 All	2 Boys	3 Girls	4 All	5 Boys	6 Girls	7 All	8 Boys	9 Girls
log of maize yield in season prior to birth	0.052	0.136**	− 0.028	0.056	0.161**	− 0.029	0.027	0.139**	− 0.060
	(0.038)	(0.065)	(0.047)	(0.038)	(0.065)	(0.046)	(0.038)	(0.066)	(0.048)
Year and month of birth dummies	X	X	X	X	X	X	X	X	X
Year x month of birth dummies	X	X	X	X	X	X	X	X	X
Child age (cubic fn of months)	X	X	X	X	X	X	X	X	X
Survey wave dummies	X	X	X	X	X	X	X	X	X
Region dummies	X	X	X	X	X	X	X	X	X
Difference between maximum and average temperature and rain by prenatal trimester				X	X	X	X	X	X
Household controls[a]							X	X	X
Number of observations	1829	847	982	1829	847	982	1,829	847	982
R2	0.176	0.156	0.246	0.183	0.254	0.256	0.197	0.267	0.267

Results are based on pooled least squares regressions. Spatially adjusted Conley standard errors are reported in parenthesis

***p < 0.01, **p < 0.05, *p < 0.10

[a]Household controls include years of education of household head, and indicator for agricultural wealth (assets)

Table 5 Associations between women's body mass index and maize yields in the season prior to BMI measurement (women aged 16–45)

	1	2	3	4
log of Maize Yield in Season Prior to interview date	0.121*	0.150**	0.137**	0.10
	(0.064)	(0.066)	(0.066)	(0.065)
Survey wave dummies	X	X	X	X
Region dummies	X	X	X	X
Maternal age, age-squared		X	X	X
Maternal education (years)			X	X
Household expenditure				X
Number of observations	4,256	4,256	4,256	4,256
R2	0.030	0.065	0.074	0.090

Results are based on pooled least squares regressions. Spatially adjusted Conley standard errors are reported in parenthesis. ***p<0.01, **p<0.05, *p<0.10. All specifications include dummy variables for region and survey wave

scores for boys, and the estimate − 0.6 for the percent reduction in maize yield per degree growing day greater than 29 °C, we can approximate the effect of a single degree growing day greater than 29 °C on HAZ as being on the order of − 0.08 standard deviations. For context and scale, the average across regions of the standard deviation of GDDs > 29 °C is 7.6. This suggests that as a broad order of magnitude, a one standard deviation increase in such exposure in utero (on average across regions) would reduce boys' subsequent HAZ by 0.64 standard deviations.[4] For all children, the point estimate for the effect of maize yield on HAZ was .027 (albeit not statistically different from zero). Applying similar calculations to this point estimate suggests a mean reduction of 0.12 standard deviations in HAZ, given an increase of the average 1 s.d. exposure.

3.3 Extensions

Further evidence in support of our hypothesis that maize yield shocks in utero may be transmitted via effect on maternal nutritional status is presented in Table 5.[5] Ideally, we would want to establish a relationship between maize yields and maternal weight during pregnancy, but the economic survey used in this study has no information on which women are pregnant. In Table 6 we therefore focused on the sensitivity of body mass among women of childbearing age (16–45 years) in the sample to yields from the most recent agricultural season. These specifications demonstrate a robust positive relationship between maize yields and women's body mass index (BMI). This association is robust to the inclusion of individuals' characteristics, including age and education (though including per capita household expenditure pushes the t-statistic on yield to .12, and hence not statistically significant at accepted levels). Hence these results lend indirect support to the prenatal nutrition mechanisms discussed above.

As noted above, it is possible that temperature and rainfall could affect postnatal nutrient through child disease incidence, which has been implicated in retarded linear growth. Table 6 reports results exploring whether the various climate variables explain fever or diarrhea incidence in the past 2 weeks. Growing degree days greater than 29 °C, which demonstrably reduce predicted maize yields, have no significant effects on morbidity incidence. Interestingly, however, rainfall is weakly statistically associated with diarrhea incidence, albeit non-linearly (with the partial derivative with respect to rainfall becoming statistically different from zero at the .10-level for rainfall levels above the 85th percentile

Table 6 Tests for significant associations between weather conditions in the most recent growing season and the prevalence of fever or diarrhea among children in the past two weeks

	1 Fever	2 Diarrhea
Growing degree days between 8 and 29 °C	− 0.000	0.000
	(0.000)	(0.000)
Growing degree days temperature was > 29 °C	0.002	− 0.000
	(0.001)	(0.001)
Log total rainfall in growing season	− 0.729	− 0.547**
	(0.615)	(0.234)
Log total rainfall in growing season, squared	0.066	0.044**
	(0.052)	(0.019)
Survey wave dummies	X	X
Region dummies	X	X
Household controls[a]	X	X
Number of observations	1356	5394
R2	0.065	0.036

Results are based on pooled least squares regressions. Spatially adjusted Conley standard errors are reported in parenthesis

***p < 0.01, ** p < 0.05,*p < 0.10

[a]Household controls include working age household size, age of the household head, average years of education of household members 15 years and older, and total land operated (hectares)

[4] Applying Eq. (6), we multiply the point estimate for the effect of log maize yield on HAZ times the effect of a single GDD > 29C on yield to obtain the effect of a single GDD > 29C on HAZ, and then scale that product by the mean number of such days: 0.14 × (− 0.6) × 7.6 = − 0.64 for boys.

[5] Our data do not distinguish mothers from other women. To at least partially address this measurement issue, we limit the sample of women here to those between the ages of 16 and 45.

of the rainfall distribution). This is consistent with a recent meta-analysis finding high diarrhea incidence after heavier rainfall (Levy et al., 2016).

4 Discussion

In this study we show that extreme temperature shocks can severely reduce cereal yields in a developing country setting, and that yield losses in the season prior to birth are strongly predictive of reduced height attainment among boys. We also show that reductions in maize yields are predictive of lower body mass among women, but not predictive of diarrhea or fever incidence in children. Together, these results suggest that maternal malnutrition during pregnancy is a key pathway linking heat shocks to agricultural production and subsequent child growth.

This study builds on an extensive literature establishing the predictive power of climate shocks in early childhood on subsequent health and economic outcomes and often assumes an underlying agricultural mechanism linking climate to child health (Bratti et al., 2021; Cil & Cameron, 2017; Deschênes et al., 2009; Geruso & Spears, 2018; Isen et al., 2017; Kudamastsu et al., 2012;Miller, 2017; Wilde et al. 2017). However, only a limited literature establishes more direct evidence of an agricultural mechanism. Burgess et al. (2014) find that heat shocks in India reduce both agricultural yields and real wages, resulting in substantial increases in rural mortality, while Banerjee and Maharaj (2020) find effects of heat-induced reductions in agricultural yields on nutrition in utero and later adverse health outcomes.

In a series of papers using data from rural Burkina Faso, Belesova et al. (2017, 2018, 2019) finds strong associations between low cereal yields in children's birth year, poor nutritional status (measured by middle-upper arm circumference, MUAC), and increased child mortality. Moreover, as in our findings, Belesova et al. (2017) find stronger adverse impacts on boys.[6] These findings lend support to the "male fragility" literature, indicating that male fetuses and newborns are more vulnerable to a wide range of health and nutritional insults (DiPietro & Vogeltine, 2017; Kraemer, 2000; Mulmi et al., 2016; Rosenfeld, 2015).

Whilst this research takes an important further step in establishing an agricultural mechanism linking temperature shocks to child malnutrition in poor rural settings, more research is needed on precisely how yield shocks affect maternal and child nutrition. This is especially important given predicted changes in the magnitude, intensity and frequency of weather variability and extreme weather events in Africa, a region for which temperature is projected to rise faster than the global average in the 21st century (Niang, 2014). Unfortunately, agricultural surveys—such as the one used in this study—do not typically collect individual dietary data or other health inputs, nor extensive information on maternal health outcomes. Longer term panel data could also be used to identify temporal variation in shocks, rather than the predominantly spatial variation used herein. Clearly, furthering our understanding of these linkages is a daunting challenge, but an important one to overcome in the context of warming climates in highly agrarian economies in which malnutrition is already widespread, and extremely costly. This line of research clearly indicates a potential nutritional rationale for curbing the worst agricultural impacts of climate change in vulnerable populations. Potential interventions include nutrition-sensitive safety nets (e.g. maternal and child cash transfers, including during pregnancy), nutrition-specific interventions (e.g. supplements targeting pregnant women), agricultural weather insurance, climate-smart agricultural R&D and extension services, improved early warning systems and monitoring systems, and longer-term policies to encourage out-migration from regions highly vulnerable to climate change.

Appendix A

(see Table7; Figs.4,5).

Table 7 Distribution of Tanzania National Panel Survey sample by survey round, area of residence, and share of maize growers

NPS wave	Wave 1 (2008/09)	Wave 2 (2010/11)	Wave 3 (2012/13)
Sample households-ALL	3265	3924	5010
Sample households-rural	1991	2526	3219
Sample of maize growers-all	1305	1523	1937
Sample of maize growers-rural	1125	1287	1647
Sample of paddy growers-all	411	536	651
Sample of paddy growers-rural	358	444	535
Sample of beans growers-all	445	489	641
Sample of beans growers-rural	396	440	569
Sample of groundnut growers-all	311	281	419
Sample of groundnut growers-rural	280	251	364

[6] In addition, these studies raise the possibility that the data used here reflect a degree of selection bias, as children must have survived in utero and infancy to appear in our data, although Alderman et al. (2011) generally expect such bias to be small.

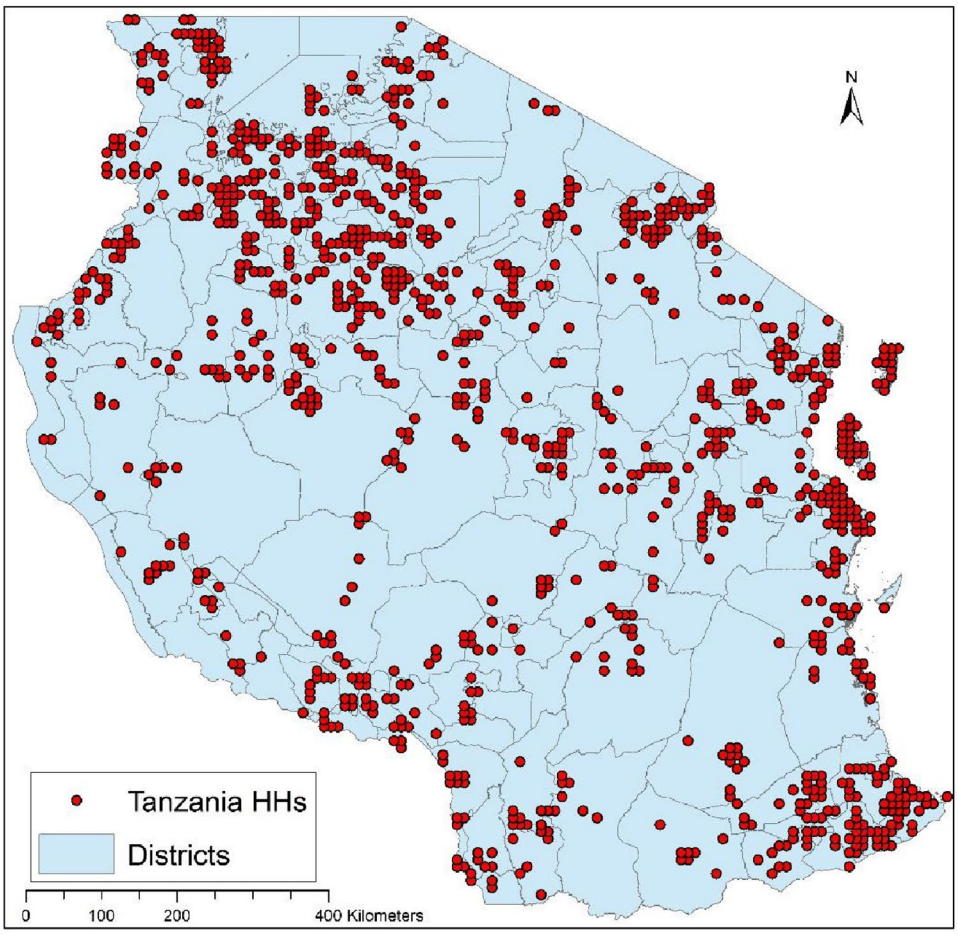

Fig. 4 Spatial distribution of Tanzania's National Panel Survey GPS data

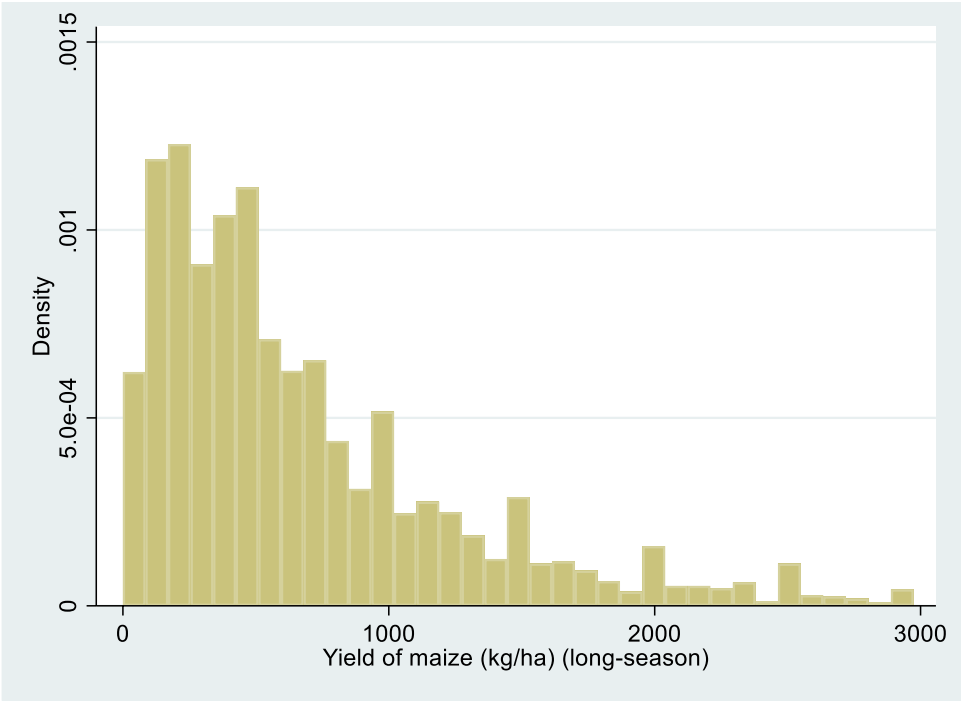

Fig. 5 The distribution of long-season maize yields in Tanzania across all rounds

Additional details about the weather data

The Climate Research Unit Time Series Grid Version 3.23 (CRU TS v. 3.23) at the University of East Anglia provides a monthly 0.5 degree spatial resolution gridded weather product from 1901 to 2014. Among the available climate variables, are maximum (max) and minimum (min) temperature, which reflects average daily max and min temperature for the month in °C. In addition, total monthly rainfall is reported in millimeters. Data from over 4000 weather stations are used to assign the temperature and rainfall grid values [1].

The CRU temperature and rainfall data from 1981 to 2014 were downloaded and processed as.netcdf files [2]. Once data were downloaded, a point shapefile of the household clusters for Tanzania were used to generate the value of each point for each monthly temperature and rainfall pixel it intersects with. Points that fall into a pixel with missing data were moved to the nearest pixel with data.

The output is a.csv table of every date and the temperature and rainfall values of the points for each household coordinate point for every month.

The final data was converted to a Stata file. Five columns were added as the first five columns of the original survey data table: (1) FID- the ID of the point shapefile, which can be linked back to the shapefile created to map. (2) cru_temp_min -The daily average minimum temperature for the month in °C. (3) cru_temp_max -The daily average maximum temperature for the month in °C. (4) cru_rain_mm -The total monthly rainfall in millimeters. 5) date- time is in the following format: YYYY_M or YYYY_MM.

Daily rainfall data

CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) was downloaded from http://chg.geog.ucsb.edu/data/chirps/ as daily 0.05 degree resolution grids for all of Africa. The years 2000-present were selected.

A point shapefile of households were used to generate the value of each point for each daily rainfall pixel it intersects with. The output is a.csv table of every date and the rainfall values of the points for each household coordinate point.

Some of the coordinates in Tanzania do not intersect with the rainfall data for any day. These coordinates are near water and the rainfall pixels do not have data when the majority of pixel contains water. To compensate, the points were moved to the nearest pixel and given the value of the nearest pixel to which they were moved.

The final data was converted to a Stata file with three columns added to the first three columns of the original survey data table: (1) fid—the id of the point shapefile, which can be linked back to the shapefile created to map. (2) CHIRPS_daily_mm—The daily rainfall values in milimeters. A value of 0 simply means no rainfall for that day. (3) date—time is in the following format: YYYY.MM.DD.

If interested python script for data generation, minus the movement of the coordinates to the nearest pixel, can be found at: https://github.com/timpjohns/python-pandas/blob/master/CHIRPS_extraction_daily.py. Please contact for any questions.

Daily temperature data

The Noah 2.7.1 model in the Global Land Data Assimilation System (GLDAS) has several simulated land surface parameters. The data are in 0.25 degree resolution and range from February 24, 2000 to present. The temporal resolution is 3-h. The simulation was created by: "combination of NOAA/GDAS atmospheric analysis fields, spatially and temporally disaggregated NOAA Climate Prediction Center Merged Analysis of Precipitation (CMAP) fields, and observation based downward shortwave and longwave radiation fields derived using the method of the Air Force Weather Agency's AGRicultural METeorological modeling system (AGRMET)"(39).

The data are located on the OPENDAP NASA web server as GRIB and netcdf files. 22 land surface parameters are available, our interest for now was just the "near surface air temperature" parameter in Kelvins.

Once data were downloaded. A point shapefile for Tanzania were used to generate the value of each point for each 3-hourly temperature pixel it intersects with. The output is a.csv table of every date and the temperature values of the points for each household coordinate point for every 3-h.

Several of the household coordinates do not intersect with the temperature data for any day. These coordinates are near water and the temperature pixels do not have data when the majority of pixel contains water. To compensate, the points were moved to the nearest pixel and given the value of the nearest pixel to which they were moved.

The final data was converted to a Stata file. There are 8 temperature points of the 3-hourly data for each day. We take the minimum and the maximum among the eight data points as daily minimum and maximum temperatures, the average of the eight data points is the daily temperature. Five columns were added as the first three columns of the original survey data table: (1) fid- the id of the point shapefile, which can be linked back to the shapefile created to map. (2) dailyMin- The daily minimum temperature values in Kelvins. (3) dailyMax- The daily maximum temperature values in Kelvins. (4) dailyTemp- The daily average temperature values in Kelvins. (5) day- time is in the following format: YYYYDDD. The last column is "Data", where 0 is when the household coordinate was moved to nearest pixel.

Table 8 Quantile regressions of log maize yield at the 25th, 50th, 75th percentiles of the yield distribution with interquartile differences

	q25 (1)	q50 (2)	q75 (3)	q75–q25 (4)	q25 (5)	q50 (6)	q75 (7)	q75–q25 (8)
Growing degree days between 8 and 29 °C	0.000***	0.000**	0.000**	− 0.000	0.000*	0.000***	0.000	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growing degree days temperature was > 29 °C	− 0.008***	− 0.007***	− 0.006**	0.002	− 0.007**	− 0.006***	− 0.004**	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Log total rainfall in growing season	− 1.141	0.674	0.102	1.243	− 0.676	0.561	− 0.432	0.244
	(1.305)	(1.304)	(1.095)	(1.392)	(1.251)	(1.203)	(1.035)	(1.457)
Log total rainfall in growing season, squared	0.094	− 0.051	− 0.011	− 0.105	0.057	− 0.045	0.029	− 0.027
	(0.105)	(0.104)	(0.087)	(0.111)	(0.099)	(0.095)	(0.082)	(0.116)
Survey wave dummies	X	X	X	X	X	X	X	X
Region dummies	X	X	X	X	X	X	X	X
Household controls					X	X	X	X
Number of observations	3980		3980		3980		3980	

***p < 0.01, **p < 0.05, *p < 0.10. All specifications include dummies for survey round and region. Household controls include household size, age of household head, average adult years of education, fertilizer applications, and agricultural wealth index. Sample is limited to rural maize-growing households

Appendix B

Heterogeneity of heat shock effects on maize yields

The yield impacts of temperature shocks may be more severe for lower productivity farmers because of lower levels of inputs, lower quality inputs (e.g. soil) or poorer management practices. To explore this possibility we employ quantile regressions, which allows us to explore the full distribution of yield data. Table 3 presents simultaneous quantile regressions at the 25th, 50th, and 75th percentiles (q25, q50, and q75, respectively), and tests the difference between q75 and q25. We find a statistically significant yield discontinuity at all three points along the yield distribution, controlling for rainfall and region in columns (1–3). Households at the 25th percentile of the yield distribution appear to suffer greater

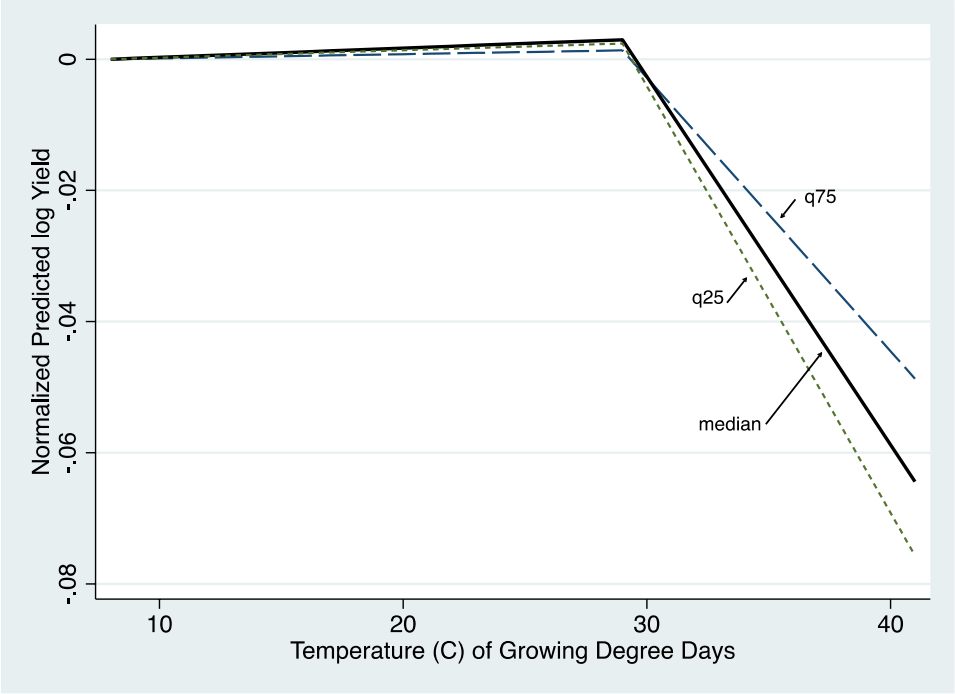

Fig. 6 Effect of an additional degree day of exposure to temperatures on predicted maize yield at the 25th, 50th, and 75th Percentiles of the Maize Yield Distribution

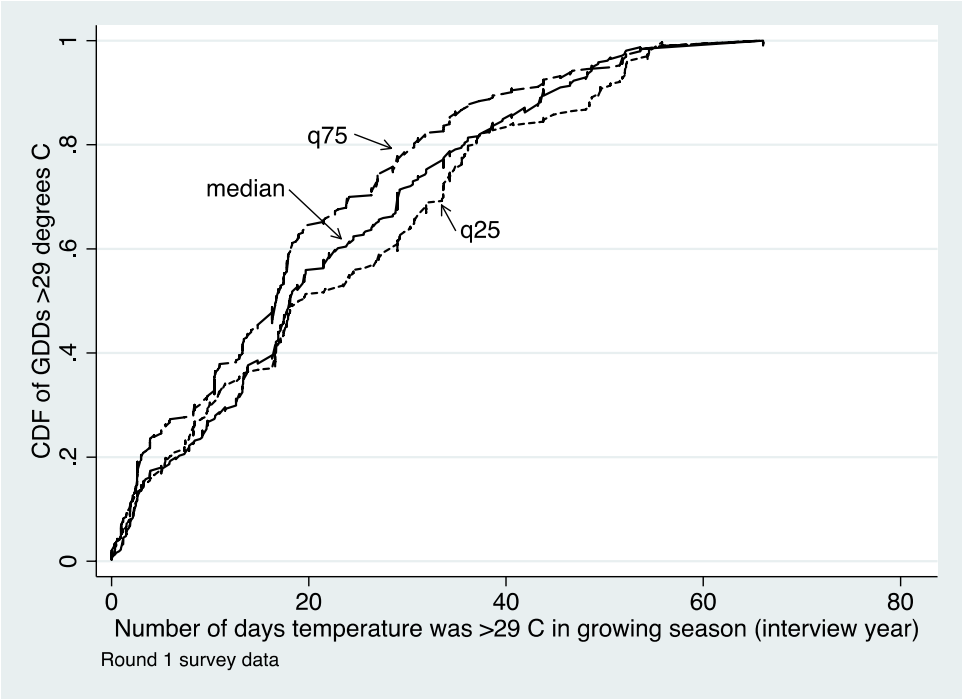

Fig. 7 Cumulative distribution functions of exposure to degree days > 29 °C, by quartile of the yield distribution (q25 (q75) indicates the 25th (75th) percentile of the yield distribution, median is q50

effect of high heat than more productive households (e.g., those at the 75th percentile), though the difference (column 4) is not statistically significant. Adding controls for household characteristics (columns 5–7) somewhat increases the difference in point estimates between the 25th percentile and 75th percentile households, though the difference remains statistically insignificant. The point estimates suggest, however, that households at the 25th percentile of yield lose 0.7% of maize yield for each GDD > 29C, as compared with a loss of 0.4% for households at the 75th percentile. Figure 4 illustrates these differences as a function of additional days at given temperatures over the relevant range.

(See Table8).

(See Fig.6).

These differences across quantiles relate directly to the role of cross-sectional geographic effects as the source of identifying variation to the extent that lower-yielding versus higher-yielding households may live in different places that vary by exposure to high heat. Figure 5 explores this by comparing the cumulative distribution functions of degree days > 29 °C across quartiles of the yield distribution for data pooled across three survey rounds. The differences across quartiles with respect to heat exposure are striking. As reflected in both the cumulative density functions and the kernel densities, the lower-yielding households (q25) have much greater exposure to extreme heat than the higher-yielding households (q75). Thus lower-yielding households both face greater exposure to high heat and suffer greater losses in yield for each hot day. Our reliance on geographic variation, however, fails to preclude the existence of potential unobserved confounding factors and thus limits a causal interpretation of these results.

(See Fig.7).

Acknowledgements Authors are grateful to Kyle Emerick (Tufts University) and Avery Cohn (ex-Tufts University) as well as Kalle Hirvonen (IFPRI) for their guidance on the relevant literature and techniques on the measurement of weather variability. We thank Wahid Quabili (IFPRI) for his support during the weather data processing. This research was supported by a grant from the Bill and Melinda Gates Foundation to IFPRI in support of the Advancing Research on Nutrition and Agriculture (ARENA) project.

Author contributions LY constructed the datasets. SB lead the statistical analysis with support from BH and DH. All authors participated in writing.

Funding The work presented here was supported by a project led at IFPRI on Advancing Research in Nutrition and Agriculture (ARENA) funded by the Bill & Melinda Gates Foundation as OPP1177007 through the International Food Policy Research Institute (project number 301052.001.001.515.01.01).

Data availability All data and replication files will be available on request from the authors.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

References

Abu-Saad, K., & Fraser, D. (2010). Maternal nutrition and birth outcomes. *Epidemiologic Reviews, 32*(1), 5–25.

Admassu, B., et al. (2017). Body composition at birth and height at 2 yrs: A prospective cohort study among children in Jimma, Ethiopia. *Pediatric Research, 82*, 209–214.

Alderman, H., Lokshin, M., & Radyakin, S. (2011). Tall claims: Mortality selection and the height of children in India. *Economics & Human Biology, 9*(4), 393–406.

Amosu, A. M., & Degun, A. M. (2014). Impact of maternal nutrition on birth weight of babies. *Biomedical Research, 25*(1), 75–78.

Banerjee, R., & Maharaj, R. (2020). Heat, infant mortality, and adaptation: Evidence from India. *Journal of Development Economics, 143*, 102378.

Basu, R., Malig, B., & Ostro, B. (2010). High ambient temperature and the risk of preterm delivery. *American Journal of Epidemiology, 172*(10), 1108–1117. https://doi.org/10.1093/aje/kwq170

Belesova, K., Gasparrini, A., Sié, A., Sauerborn, R., & Wilkinson, P. (2017). Household cereal crop harvest and children's nutritional status in rural Burkina Faso. *Environmental Health, 16*, 65.

Belesova, K., Gornott, C., Milner, J., Sié, A., Sauerborn, R., & Wilkinson, P. (2019). Mortality impact of low annual crop yields in a subsistence farming population of Burkina Faso under the current and a 1.5 °C warmer climate in 2100. *Science of the Total Environment, 691*, 538–548.

Belesova, K., Gasparrini, A., Sié, A., Sauerborn, R., & Wilkinson, P. (2018). Annual crop-yield variation, child survival, and nutrition among subsistence farmers in Burkina Faso. *American Journal of Epidemiology, 187*(2), 242–250.

Block, S., Kiess, L., Webb, P., Soewarta, K., Moench-Pfanner, R., Bloem, M., & Timmer, C. P. (2004). Macro shocks and micro outcomes: Child nutrition during Indonesia's crisis. *Economics and Human Biology, 2*(2), 21–44.

Bratti, M., Frimpong, P. B., & Russo, S. (2021) "Prenatal Exposure to Heat Waves and Child Health in Sub-saharan Africa". IZA Institute of Labor Economics Discussion Paper No. 14424

Burgess, R., Deschenes, O., Donaldson, D., & Greenstone, M. (2014). *The unequal effects of weather and climate change: Evidence from mortality in India*. London School of Economics.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy, 8*(3), 106–140.

Butler, E. E., & Huybers, P. (2015). Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase. *Environmental Research Letters, 10*(3), 034009.

Butler, E., Mueller, N. D., & Huybers, P. (2018). Peculiarly pleasant weather for US maize. *Proceedings of the National Academy of Sciences USA, 115*(47), 11935–11940.

Butler, E., & Huybers, P. (2013). Adaptation of US maize to temperature variations. *Nature Climate Change, 3*, 68–72.

Christian, P., Lee, S. E., Angel, M. D., Adair, L. S., Arifeen, S. E., Ashorn, P., Barros, F. C., Fall, C. H. D., Fawzi, W. W., Hao, W., Hu, G., Humphrey, J. H., Huybregts, L., Joglekar, C. V., Kariuki, S.K., Kolsteren, P., Krishnaveni, G.V., Liu, E., Martorell, R., Osrin, D., Persson, L-A., Ramakrishnan, U., Richter, L., Roberfroid, D., Sania, A., Ter Kuile, F. O., Tielsch, J., Victora, C. G., Yajnik, C. S., Yan, H., Zeng, L., & Black, R. E. (2013). Risk of childhood undernutrition related to small-for-gestational age and preterm birth in low- and middle-income countries. *International Journal of Epidemiology, 42*(5), 1340–55.

Cil, G., & Cameron, T. A. (2017). Potential climate change health risks from increases in heat waves: Abnormal birth outcomes and adverse maternal health conditions. *Risk Analysis, 37*(11), 2066–2079.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics, 92*(1), 1–45.

Danaei, G., Andrews, K. G., Sudfeld, C. R., Fink, G., McCoy, D. C., Peet, E., Sania, A., Smith Fawzi, M. C., Ezzati, M., & Fawzi, W. W. (2016). Risk factors in childhood stunting in 137 developing countries: A comparative risk assessment at global, regional, and city levels. *PLOS Medicine, 13*(11), e1002164.

Deschênes, O., Greenstone, M., & Guryan, J. (2009). Climate and birth weight. *American Economic Review: Papers & Proceedings, 99*(2), 211–217.

da Silva Lopes, K., Ota, E., Shakya, P., Dagvadorj, A., Balogun, O. O., Peña-Rosas, J. P., De-Regil, L. M., & Mori, R. (2017). Effects of nutrition interventions during pregnancy on low birth weight: An overview of systematic reviews. *BMJ Global Health, 2*(3), e000389.

DiPietro, J. A., & Vogeltine, K. M. (2017). The gestational foundation of sex differences in development and vulnerability. *Neuroscience, 342*(7), 4–20.

Geruso, M., & Spears, D. (2018). Heat, humidity, and infant mortality in the developing world. National Bureau of Economic Research, Working Paper 24870. July. Cambridge, MA

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 dataset. *International Journal of Climatology, 34*, 623–642. https://doi.org/10.1002/joc.3711

Headey, D., & Masters, W. A. (2021). Agriculture and nutrition. In K. Otsuka & S. Fan (Eds.), *Agricultural development: New perspectives in a changing world*. IFPRI.

Headey, D., Stifel, D., You, L., & Guo, Z. (2018). Remoteness, urbanization, and child nutrition in sub-Saharan Africa. *Agricultural Economics, 49*(6), 765–775.

Hoddinott, J., Alderman, H., Behrman, J., Haddad, L., & Horton, S. (2013). The economic rationale for investing in stunting reduction. *Maternal and Child Nutrition, 9*(Suppl 2), 69–82.

Hoddinott, J., & Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics, 63*(4), 409–436.

Hoddinott, J., Maluccio, J., Behrman, J., Flores, R., & Martorell, R. (2008). Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults. *The Lancet, 371*, 411–416.

Hoogenboom, G., Porter, C. H., Boote, K. J., Shelia, V., Wilkens, P. W., Singh, U., White, J. W., Asseng, S., Lizaso, J. I., Moreno, L. P., Pavan, W., Ogoshi, R., Hunt, L. A., Tsuji, G. Y., & Jones, J. W. (2019). The DSSAT crop modeling ecosystem. In K. J. Boote (Ed.), *Advances in crop modeling for a sustainable agriculture* (pp. 173–216). Burleigh Dodds Science Publishing. https://doi.org/10.19103/AS.2019.0061.10

Intergovernmental Panel on Climate Change (IPCC). (2014). 5th assessment report. United Nations Environment Program

Isen, A., Rossin-Slater, M., & Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Science (PNAS) 114*(51), 13447–13452. https://doi.org/10.1073/pnas.1702436114

Kang, Y., Khan, S., & Ma, X. (2009). Climate change impacts on crop yield, crop water productivity and food security—a review. *Progress in Natural Science, 19*(12), 1665–1674. https://doi.org/10.1016/j.pnsc.2009.08.001

Kraemer, S. (2000). The fragile male. *British Medical Journal, 321*(7276), 1609–1612.

Kudamatsu, M., Persson, T., & Strömberg, D. (2012). Weather and infant mortality in Africa, CEPR Discussion Papers 9222, C.E.P.R. Discussion Papers

Levy, K., Woster, A. P., Goldstein, R. S., & Carlton, E. J. (2016). Untangling the impacts of climate change on waterborne diseases: A systematic review of relationships between diarrheal diseases and temperature, rainfall, flooding, and drought. *Environmental Science and Technology, 50*(10), 4905–4922.

Lobell, D. B., & Field, C. B. (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters, 2*(1), 014002.

Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear hear effects on African maize as evidenced by historical yield trials. *Nature Climate Change, 1*, 42–45.

Lohmann, S., & Lechtenfeld, T. (2015). The effect of drought on health outcomes and health expenditures in rural Vietnam. *World Development, 72*, 432–448.

Maccini, S., & Yang, D. (2009). Under the weather: health, schooling, and economic consequences of early-life rainfall. *American Economic Review, 99*(3), 1006–1026.

Maluccio, J., Hoddinott, J., Behrman, J., Martorell, R., Quisumbing, A., & Stein, A. (2009). The impact of nutrition during early childhood on education among Guatemalan adults. *Economic Journal, 119*, 734–763.

Miller, R. (2017). Childhood health and prenatal exposure to seasonal food scarcity in Ethiopia. *World Development, 99*, 350–376.

Mulmi, P., Block, S., Shively, G., & Masters, W. (2016). Climatic conditions and child height: Sex-specific vulnerability and the protective effect of sanitation and food markets in Nepal. *Economics and Human Biology, 23*, 63–75.

National Bureau of Statistics (NBS). (2017). *Government of Tanzania, Dodoma, Tanzania*. National Panel Survey 2008-2009, Wave 1.

Niang, I., Ruppel, O. C., Abdrabo, M. A., Essel, A., Lennard, C., Padgham, J., & Urquhart, P.` (2014). Africa. In V. R., Barros, C. B., Field, D. J., Dokken, M. D., Mastrandrea, K. J., Mach, T. E., Bilir, M., Chatterjee, K. L., Ebi, Y. O., Estrada, R. C., Genova, B., Girma, E. S., Kissel, A. N., Levy, S., MacCracken, P. R., Mastrandrea, & L. L., White (Eds.) Climate change 2014: Impacts, adaptation, and vulnerability. Part B: Regional aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1199–1265

Ortiz-Bobea, A., & Just, R. (2012). Modeling the structure of adaptation in climate change impact assessment. *American Journal of Agricultural Economics, 95*, 244–251.

Porter, J. R., & Semenov, M. A. (2005). Crop responses to climatic variation. *Philosophical Transactions of the Royal Society B, 360*, 2021–2035.

Roberts, M. J., Schlenker, W., & Eyer, J. (2013). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics, 95*(2), 236–243.

Rocha, R., & Soares, R. R. (2015). Water scarcity and birth outcomes in the Brazilian semiarid. *Journal of Development Economics, 112*, 72–91.

Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J. K., Walker, J. P., Lohmann, D., & Toll, D. (2004). The global land data assimilation system. *Bulletin of the American Meteorological Society, 85*(3), 381–394.

Rojas-Downing, M. M., Nejadhashemi, A. P., Harrigan, T., & Woznicki, S. A. (2017). Climate change and livestock: Impacts, adaptation, and mitigation. *Climate Risk Management, 16*, 145–163.

Rosenfeld, C. (2015). Sex-specific placental responses in fetal development. *Endocrinology, 156*(10), 3422–3434.

Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2010). Climate variability and crop production in Tanzania. *Agricultural and Forest Meteorology, 151*, 449–460.

Russo, S., Sillmann, J., Sippel, S., Barcikowska, M. J., Ghisetti, C., Smid, M., & O'Neill, B. (2019). Half a degree and rapid socioeconomic development matter for heatwave risk. *Nature Communications, 10*, 136.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences USA, 106*(37), 15594–15598. and Appendix.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and Forest Meteorology, 35*, 353–358.

Steward, P. R., Dougill, A. J., Thierfelder, C., Pittelkow, C. M., Stringer, L. C., Kudzala, M., & Shackelford, G. E. (2018). The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. *Agriculture, Ecosystems & Environment, 251*, 194–202.

Verma, S., & Shrivastava, R. (2016). Effect of maternal nutritional status on birth weight of babies. *International Journal of Contemporary Medical Research, 3*(4), 943–945.

WHO Multicentre Growth Reference Study Group. (2006). *WHO child growth standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development*. World Health Organization.

Wilde, J., Apouey, B. H., & Jung, T. (2017). *The effect of ambient temperature shocks during conception and early pregnancy on later life outcomes*. University of South Florida.

Wineman, A., Anderson, C., Reynolds, T., & Biscaye, P. (2019). Methods of crop yield measurement on multi-cropped plots: Examples from Tanzania. *Food Security*. https://doi.org/10.1007/s12571-019-00980-5

Wu, X., Lu, Y., Zhou, S., Chen, L., & Xu, B. (2016). Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. *Environment International, 86*, 14–23. https://doi.org/10.1016/j.envint.2015.09.007

Xu, H., Twine, T. E., & Girvetz, E. (2016). Climate change and maize yield in Iowa. *PLoS ONE, 11*(5), e0156083. https://doi.org/10.1371/journal.pone.0156083

S. Block is Professor of International Economics at the Fletcher School, Tufts University, where he teaches courses on development economics, food policy, and political economy. He is co-author of *Economics of Development* (7th edn., with Perkins, Radelet, and Lindauer). He received his PhD in Political Economy and Government from Harvard University.

B. Haile is a Research Fellow in the Environment and Production Technology Division of the International Food Policy Research Institute, in Washington, D.C. She is a development economist with over ten years of experience in policy relevant applied microeconomic research to sustainably improve food and nutrition security in Sub-Saharan Africa. Her research focuses on determinants and effects of agricultural technology adoption, linkages between agriculture and nutrition, and resilience to weather variability. She received her PhD in Economics from Columbia University.

L. You , a senior scientist, joined IFPRI in 2000 to conduct research on agricultural science and technology policy. Liangzhi earned a B.S. in hydraulic engineering from Tsinghua University, Beijing, and an M.S. in environmental economics and Ph.D. in civil and environmental engineering from Johns Hopkins University. Before joining IFPRI, Liangzhi was a research assistant at Johns Hopkins University. Liangzhi is a citizen of China.

D. Headey is a Senior Research Fellow in the Poverty, Health and Nutrition Division at the International Food Policy Research Institute (IFPRI), where he has worked since 2008. A development economist, his research chiefly focuses on agricultural development and nutrition, though he has also works on economic growth, food security and poverty reduction issues. He is the principal investigator for the Advancing Research on Nutrition and Agriculture (ARENA, 2013–2021), funded by the Bill and Melinda Gates Foundation. He received his PhD in Economics from the University of Queensland, Australia.