WORKING PAPER SERIES
ISSN 2785-1079

Number 21

FEBRUARY 2022

ARIDIFICATION, AGRICULTURE, AND INFANT HEALTH: EVIDENCE FROM SOIL POTENTIAL EVAPOTRANSPIRATION

Jacopo Lunghi

Maurizio Malpede

Marco Percoco

Università Bocconi
GREEN
Centre for Geography, Resources, Environment, Energy and Networks

Aridification, Agriculture, and Infant Health: Evidence from Soil Potential Evapotranspiration

Jacopo Lunghi*, Maurizio Malpede*, and Marco Percoco*

*GREEN, Bocconi University, Milan, Italy

February 14, 2022

Abstract

This study explores how aridity (proxied with a measure of soil potential evapotranspiration) impacts agricultural productivity and child wellbeing in Sub-Saharan Africa. Climate conditions, crop yield, and infant health measures are collected over approximately 4,000 grid cells of 0.5 x 0.5 in 34 countries. The results indicate that cells with higher soil aridity suffer from lower agricultural productivity, and infants born in arid areas are comparatively more likely to be underweight at birth and in the early years. Additionally, the aridity measure in this study captured a large share of the effect on crop yields and child health imputed to precipitations alone. The findings are applied to model projections of future climate conditions to emphasize the importance of accounting for aridity, alongside precipitations, when assessing the economic impact of climate.

Keywords: Climate, aridification, agricultural productivity, potential evapo-transpiration, child mortality, infant health, climate damages

JEL Classification: J1, J13, I15, Q54, Q56, O15

1 Introduction

The effects of climate change and global warming have been a central issue in the recent scientific and economic literature. Studies have found strong evidence of a relationship between the evolution of weather factors and economic welfare, both at the micro and macro level (Dell et al. 2008, 2012, Burke et al. 2015, Zhang et al. 2017, Peri & Sasahara 2019). Yet, while climate change is now irrefutable due to empirical evidence, the nature of the aforementioned relationship remains unclear. The consequences of this accelerating process for the planet and its inhabitants are still a matter of great discussion, and relatively little consensus has been reached.

Among the numerous implications of climate change, water access for people worldwide is a key concern. The availability of a reliable water source is crucial for developing sustainable human settlements as well as agricultural and economic systems, and water availability is strongly influenced by precipitation and its intensity. According to current predictions, global rainfall is expected to rise in the next few decades due to climate change. Panel A in Figure 1 illustrates the upcoming trend in rainfall using five of the most commonly used Earth System Models (ESM) for the periods 2040– 2079 and 2060–2099: all models predict a consistent increase in global precipitation levels, roughly between 5.7% and 12.2%.

Most of the economic literature has examined the separate action of rainfall and temperatures as key determinants of the amount of water available to individuals in developing countries. Maccini & Yang (2009) use early-life precipitations in Indonesia to show how fluctuations in agricultural output have a long-lasting impact on women's health, schooling, and socioeconomic status. Kudamatsu et al. (2012) used rainfall and temperature to determine how a period of relative drought affects infant mortality in Africa, finding that in-utero drought exposure increases babies' risk of death. In both these papers, nutrition and malnutrition (experienced either by a mother or an infant during early life) constitute the primary channel through which climate conditions affect individuals. Conversely, Jayachandran (2006) used rainfall shocks in underdeveloped rural India to explain the impact of productivity shocks to agriculture on wages, migration, and credit constraints.

Based on these findings, rainfall can be thought to have, to a degree, a positive impact on human development in rural settings, primarily through its beneficial effect on the agricultural sector. While this consideration is supported by substantive evidence,

precipitations alone do not capture actual soil water availability, which also depends on concurring factors such as land quality, solar radiation, temperature, air humidity, and wind speed. As climate change accelerates and temperatures rise globally, the stability of the relationship between precipitations and water availability could be questioned. This is not a mere technicality but rather has relevant implications in discussing the forthcoming impact of climate change. If one fails to recognize the role of other critical determinants of water availability, one may superficially believe that climate change could imply enhanced water access. Thus, this paper reassesses the role of precipitations when matched with a measure of soil water retention. It combines data on temperature and rainfall defined on a 0.5° X 0.5° (ca. 56km X 56 km at the equator) earth grid with an original measure of soil aridification, namely potential evapotranspiration (PET), which considers the combination of two sources of soil water loss: soil surface evaporation (i.e., the process whereby liquid water is converted to water vapor and removed from the evaporating surface) and reference crop transpiration (the vaporization of liquid water contained in plant tissues and the vapor removal to the atmosphere; Allen et al. 1998). Following environmental research on the topic, we assume PET as an indication of aridity of an area (Rind et al. 1990, Cherlet et al. 2018). We study the differential impact of our measures on agriculture and infant wellbeing in Africa, where the increase in precipitations is projected to take place similarly to the rest of the world (Figure **??**, Panel B).

The study proceeds in two steps. First, drawing from previous research identifying agriculture as the primary mechanism through which rainfall impacts socioeconomic development, this work aims to clarify whether a relationship exists between precipitations, PET, and agricultural output. Data is gathered on crop suitability, production, harvested land, and yield for a sample of 21 crops, covering 3,896 cells in 32 African countries. Agricultural data from the Food and Agriculture Organization (FAO) is combined with precipitations, PET, and temperatures. Moreover, climate variables are constructed, calculated using the entire solar year or only the cell-specific growing season months. In this study, a mostly negative relationship is observed between PET and crop yield, although the ultimate effect depends on the composition of agricultural output in the area. Moreover, precipitation alone is found to be insufficient to explain variations in agricultural productivity and becomes even a second-order factor when PET is considered.

Second, the study directly analyzes how PET influences the role of precipitations in human development. Consistently with previous contributions in the literature, the focus of the study is on the core indicators of infant health as a proxy for economic wellbeing

(Aber et al. 1997, Benshaul-Tolonen 2018). Geolocalized data is combined from nationally representative demographic and health surveys; across four survey waves, information is obtained regarding women and children in 34 countries between 1992 and 2018, with a primary focus on neonatal mortality, self-reported by women in the survey. On a subsample of individuals, the study also documents the joint effect of rainfall and PET on body mass index (BMI) at the time of interview and size at birth in children under five years old. The study's findings suggest that the tendency retrieved for agricultural productivity reflects infant health. Indeed, children in more arid lands tend to be smaller at birth and have systematically lower BMI values by the time of interview. The results prove robust for redefining the primary outcome variables with comparable measures, such as weight-to-height ratio. Aridity also exacerbates infant mortality, but the results are somewhat unclear. Yet, an important finding is that the inclusion of PET absorbs part of the effect previously imputed to precipitations.

This paper contributes to the economic and environmental literature on the effects of weather conditions and climate changes in several ways. First, by using the most com prehensive spatial data on PET and exploiting temporal and cross-sectional variation, the study constructs a map of desertification in the African continent. Furthermore, this work demonstrates how agricultural productivity tends to suffer from increasing evapotranspiration, and the role of precipitations in boosting crop yields appears to be reduced when soil aridity is considered . In this regard, the paper adds to the literature on rainfall's effect on agricultural productivity (Jayachandran 2006, Brückner 2012, Rosenzweig & Udry 2014, Amare et al. 2018). In addition, as the results emphasize the importance of aridity in evaluating the consequences of climate change, this paper links to the current environmental economics debate concerning adequate statistical measures to study the future of global warming (Dell et al. 2014, Almer et al. 2017, Harari & Ferrara 2018).

Second, with further evidence, this research complements the relationship between precipitations and human wellbeing, thus adding to the literature on the effect of rainfall and climate change in low-income countries on child health (Kudamatsu et al. 2012, Rabassa et al. 2014, Bharadwaj et al. 2020) and other economic outcomes (Rose 1999, Barrios et al. 2010, Brückner & Ciccone 2011, Björkman-Nyqvist 2013, Rocha & Soares 2015).

The remainder of the paper is organized as follows: Section 2 summarizes the debate on the future of precipitations and presents the data. In Section 3, we study the relationship between rainfall, PET, and agricultural productivity. In Section 4, we transpose our research design to study the impact of weather conditions on child health. In Section 5, we discuss our findings and list some of the caveats of our approach. Section 6 concludes.

2 Background and Data Description

2.1 The Geography of Desertification

There is an ongoing debate about the near-term evolution of global precipitation levels among the several implications of rising temperatures and the changing composition of earth, land, and sea. It was initially posited that climate change could lead to a wet-get-wetter and dry-get-drier pattern (Held & Soden 2006) due to atmospheric moisture convergence and divergence. Nonetheless, due to a lack of consistent empirical evidence, this hypothesis has seemingly been replaced by a contrasting view: mean precipitations are expected to increase at high- and mid-latitudes, but they will likely not decrease in subtropical regions (Kirtman et al. 2013, Donat et al. 2016). In turn, average rainfall at the global level is expected to increase in the coming years (Cherlet et al. 2018).

The premises alone suggest that the amount of water available to an individual in developing countries for productive use, or even for simple subsistence, may increase in the short and medium term and that, to the extent that higher levels of precipitations could help prevent drought and boost agricultural productivity, rural communities may benefit from weather modifications. Climate change could even have positive implications for rural households in the upcoming decades, something that, possibly unexpectedly, could buck the trend of the current discourse on future environmental threats. However, the latter conclusion is potentially flawed and shortsighted. It fails to consider progressive soil aridification parallel to changes in rainfall. As temperatures are expected to rise sharply in the next few years, they are predicted to increase the rate of soil moisture loss, resulting in mounting evapotranspiration rates. The World Atlas of Desertification (WAD) estimates that drylands, defined as areas with a ratio of precipitations over PET less than 0.65[1], are expected to increase between 10% and 21% by 2100 (Cherlet et al. 2018). This complicates predictions regarding the impact of climate change on land productivity and well-being.

This study reconsiders the focus on environmental factors by taking soil aridity into account. It assesses the direct effect of soil evapotranspiration on crop productivity and in-

[1] In the WAD, this ratio is referred to as Aridity Index (AI) $\left[AI = \sum_{i=1}^{30} \left(\frac{PET_i}{Prec_i}\right)\right]$.

fant health measures and the role of rainfall in light of PET. To this aim, the study accesses publicly available data collected by the Climate Research Unit (CRU), established at the University of East Anglia and funded by the UK National Centre for Atmospheric Science (NCAS). The CRU TS4.04 dataset contains gridded time-series data on month-by-month variations in climate over the period 1901–2019, provided on high-resolution (0.5 \times 0.5 degree) grids[2]. To harmonize the different data sources on climatic factors, crop, and infant health in this paper, the focus is on an area covering almost 40% of the entire African continent. Moreover , as the study's measure of infant mortality records some births taking place up to the early 1950s, this work focuses on weather conditions between 1951 and 2019 and considers three measures of climate variation: PET (mm/month), precipitations (mm/month), and monthly mean temperature (°C). PET represents the amount of water lost from a cropped reference surface that is not short of water (a hypothetical grass reference crop with specific characteristics). As such, this measure estimates the evaporative demand of the atmosphere independently of crop type, crop development, and management practices. PET estimates are calculated using a variant of the Penman-Monteith method, which is briefly summarized in Section A.1.1 in Appendix.

We report the evolution of our environmental measures over the sample period in Table 1. 1. The mean yearly averages of each variable are included in time windows of 15 years each. The predictions about increasing rainfall cannot be confirmed using historical data and a limited sample period; however, the study's series points in that direction. Indeed, the level of average precipitations appears on a reverting trend, decreasing at first and then rising again in the early 2000s. Conversely, average PET and temperatures are on a stable, increasing path. Additionally, the process of aridification and rising temperatures seems to accelerate starting from the 80s .

Table 1 reports summary statistics and correlations between the climate variables used in this research. To interpret cross-sectional variability across grids, the average level of yearly precipitations and PET throughout the sample period is plotted in Figure 2. While PET shows steady but little volatility over time, the sample retains substantial cross-sectional variation, ranging from areas with almost no evapotranspiration to cells where this measure even exceeds the average level of precipitations.[3]

[2]As it is usually the case for model-computed weather data, the choice of the CRU database comes with partial concerns regarding the quality of data. We justify the suitability of this dataset for our purpose in Section A.1.3 in Appendix.

[3]When PET exceeds actual precipitation, it is an indication that the soil may eventually dry out, unless

2.2 Measures of Agricultural Productivity

One of the aims of the present paper is to verify the existence of a relationship between PET, precipitations, and agriculture. To this end, this study collects data on crop and agricultural productivity from the Global Agro-Ecological Zones (GAEZ) v4 database, which defines the cultivation potentials for approximately 50 crops for each location of the globe. It is assembled based on grids, with a resolution of 30 arc-seconds (about 0.9 km x 0.9 km at the equator) and five arc-minutes (about 9 km x 9 km). For Africa, all necessary information can be retrieved for a total of 22 crops, which represent a consistent share of agricultural output in the area: on average, these crops account for roughly 75% of the total harvested land in the cell. To compare the data with the climate variables in this study, the cell size is harmonized to meet the structure of the CRU TS4.04. This implies computing the average value (e.g., yield) or the total (e.g., harvested area) in the corresponding wider cell.

From GAEZ, cell- and crop-specific data on the harvested area (thousands of hectares) and crop yield (tons/ha) is retrieved. This information is available for two unique points in time: 2000 and 2010. In addition, a suitability index (SI) is calculated using historical climate between 1981 and 2010. This measure is a weighted sum of the component soil or terrain suitability rating factors4 [4].

Figure 3 plots the spatial distribution of the prominent crop family (i.e., the family with the widest harvested area in the cell) across the grid in this study, averaging 2000 and 2010 values. The figure illustrates that agriculture on the African content is highly reliant on cereals (e.g., maize and millet) and root-tuber crops (e.g., potato and cassava). To confirm this evidence, a complete list of the available crops is included in Table 2, which reports the average share of area devoted to each crop over the cultivated surface instead of absolute quantities. According to the table, cereals such as maize and millet, tubers such as cassava and yam, and olives account, on average, for a high share of the cultivated areaa in each cell. Moreover, while the cultivable area devoted to each crop remains, from 2000 to 2010, the average yield grows for almost all crops. This is explained by a progressive improvement in crop management techniques, for example mechanization,

irrigation is used to outset the loss. However, that the effective amount of water dispersed depends also on the type of plants cultivated on the land.

[4] Extensive details on the methodology employed to compute the indicators reported can be found in Fischer et al. (2021).

optimal applications of nutrients and chemical pesticides , and disease and weed control Fischer et al. (2021).

Furthermore, we provide a measure of gross energy (kcal/kg of dry matter) of the raw product for each crop[5]. This indicator is used to quantify yield in terms of caloric power using tons produced. While this is only a proxy for the actual potential nutritional intake related to each crop, it represents a measure of comparability among crops with vastly different yields in terms of dry matter production. A study observation is that staple crops in the sample tend to have similar gross energy values, although rice and cassava provide less energy than cereals such as maize, millet, or sorghum.

2.3 Measures of infant health

This study combines data on weather factors and agricultural production with information on child health from the Demographic and Health Surveys (henceforth DHS) database. The program collects nationally representative data on health and population in developing countries, compensating for the lack of high-quality infant health statistics, particularly in Sub-Saharan Africa. In the present study, a dataset is constructed using up to four survey waves, conducted between 1992 and 2018, for 34 countries. The survey is stratified into clusters, which are geolocalized with displacement up to 2 km for urban and 10 km for rural points[6]. Data from the Individual Recode dataset and the Child Recode dataset is utilized. The former contains data on every eligible woman, including individual socioeconomic characteristics, birth history, pregnancy, and postnatal care; the latter comprises some core child health indicators for children under five years and their mothers. Here, the study sample is restricted to women who experienced at least one completed pregnancy. Table 3 summarizes descriptive statistics on mothers and infant mortality across the sample period[7]. We obtained 468,873 women aged 13 to 50, corresponding to more than 2 million birth entries between 1955 and 2019. However, wealth and education characteristics and records on size at birth and BMI are available only for a subsample of individuals. These leave us with a final sample of roughly 1.7 million births and more than 400,000 children under five. The number of available children under five is instead almost 700,000.

[5]This information is retrieved through *Feedipedia*, an open access information system on that provides information on nature, occurrence, chemical composition, nutritional value and safe use of nearly 1400 worldwide livestock and human feeds. Further details in Section A.1.2 in Appendix.

[6]The geographical distribution of clusters available in at least one wave is plotted in Figure A.1.

[7]All variables relevant for our study are described in Section A.1.2.

Since this study considers a large number of countries and a variety of developing settings, women in the sample are heterogeneous in terms of education and economic wealth scores. Average schooling is relatively low: women in the sample, on average, have attended school for less than four years, with almost 50% declaring having received no formal education. Moreover, roughly 70% to 75% of the sample comprises women living in rural households. As extensively highlighted in previous literature, fertility appears to be high in the sample, with an average of more than five births per woman. These measures tend to remain homogeneous across different survey waves.

The first outcome variable is infant mortality, retrieved from a woman's reporting of completed pregnancies. The variable is a binary indicator taking a value of 1 if a woman reports the child to have died within 12 (60) months from the declared date of birth. This methodology of computing infant mortality has already been adopted in the literature employing DHS data (Kudamatsu et al. 2012, Benshaul-Tolonen 2018). As Table 3 indicates, despite a steady decrease, the average probability of a pregnancy resulting in a child's death ranges from 8.4% (12%) to 6.2% (8.9%) across the survey waves. However, infant mortality is highly volatile across the sample, with large standard deviations common to all rounds. Moreover, there seems to be only a negligible difference between the mortality rate of male and female children in the sample.

In addition to child mortality, other infant health indicators are analyzed in this study to provide further evidence of the mechanism discussed in the paper. This study considered a measure of BMI calculated using the new Child Growth Standards (CGS) from WHO at the time of interview and a categorical variable indicating whether the child's size at birth was below or above average[8]. These measures allow us to understand better whether aridity could also affect the health of those who survive. These indicators have been collected irregularly throughout the DHS waves; hence they are only available for a subset of children under five years of age. From Table 3, we notice that kids in our sample display consistently below-average weight/height ratio (the average child falls in the left tail of the weight/height distribution, around the 40th percentile), while for BMI this appears only towards the last waves survey collection. Unsurprisingly, this is not captured in our measure of size at birth, given that the average size of a child is determined by mothers

[8]Later in the analysis, we check the robustness of our findings using a slight variation of our outcome measures. We focus on five years mortality, and the ratio of weight over height, expressed in standard deviations and again calculated using the CGS method.

through comparison with their peers. All three measures retain strong volatility across the sample.

To explore the link between crop productivity and human development, a positive relationship is documented in Figure 4 wwhere the cross-sectional correlation between average crop yield and the mean value of the health measures is plotted. As this figure illustrates, average yield at the cell level is negatively correlated with child mortality and positively correlated with BMI, weight-to-height ratio, and size at birth.

3 Aridification and Crop Productivity

The attempt to predict the impact of climate change on crop production is rarely retrieved in the economic literature , but it has been a highly debated topic in environmental sciences (e.g., Vermeulen et al. 2012, Asseng et al. 2013, Challinor et al. 2014). While no definitive consensus has been reached, researchers have highlighted how the effects of global heating and weather modifications may be heterogeneous, depending mainly on the predominant agricultural output in a region and the population's ability to foresee and adapt to climate shocks (Kandlikar & Risbey 2000, Lema & Majule 2009, Juana et al. 2013).

Economists often indicate agricultural productivity as a primary mechanism through which precipitations affect socioeconomic development. Indeed, especially in low-income countries and rural areas, agriculture directly supplies food and nutrition to and constitutes a significant source of income for individuals. Still, relatively little is known about the relationship between crop productivity and PET . On the one hand, one may expect a rising trend in PET to negatively impact agricultural output, given the exacerbated soil water loss, which subtracts nutrients from growing plants. However, it is well understood that rainfall is a vital determinant of cultivation potential. On the other hand, as PET partially reflects higher temperatures and more intense solar radiation, its increase may benefit crops requiring long sun exposure to reach maturity. Moreover, there is no evidence of the role of PET when compared to precipitations. The evidence presented in this section corroborates the belief that an increase in PET may constitute a potential threat to crop productivity in this study's sample.

3.1 Methodological Approach

Studying the effects of aridification is especially cumbersome because, differently from other forms of weather shocks, it encompasses a gradual change over a long period. To meet the characteristics of the available data sources, this study focuses on the yearly realization of precipitations and PET and their impact on agricultural output. This approach does not directly assess the effect of the slow deterioration of soil's capability to retain water. However, it allows one to highlight the importance of soil evapotranspiration on crop productivity relative to other environmental factors. Together with the abovementioned projections on the evolution of climate conditions in the upcoming decades, the results can thus indirectly contribute to the debate on the long-term effects of raising PET.

The following baseline specification is thus estimated:

$$\log(Y)_{c,k,t} = \sum_{r=0}^{1} \alpha_{1,r} PRE^{g}_{c,t-r} + \sum_{r=0}^{1} \alpha_{2,r} PET^{g}_{c,t-r} + \gamma X_{k,c,t} + \delta_{k(c)(t)} + \varepsilon_{k,c,t} \qquad (1)$$

where $\log(Y)_{c,k,t}$ represents the natural logarithm of the yield of crop k at time t in cell c. In this section, the time dimension comprises only two years, 2000 and 2010. $PRE_{c,t}$ and $PET_{c,t}$ are respectively the levels of precipitations and potential evapotranspiration at time t in cell c. The superscript g indicates whether the variable is measured over the entire year or only considering the cell's growing season months. To explore the time dependency of agricultural output with water availability, we also include a one-period lag of both variables. $X_{c,t,k}$ comprises of a set of crop- and cell-specific controls. Among those, to make sure PET is not merely acting as a proxy for temperature, we control for it at time t in cell c. In addition, given that environmental conditions in a cell are inevitably correlated with the typology of crops cultivated and that different crops may be more or less resilient to climatic fluctuations, we add a Suitability Index of crop k in cell c (the index is time-invariant, and calculated over the 30-year period between 1981 and 2010). Finally, $\delta_{k,(c,t)}$ represents three sets of crop, cell and time fixed effects.

To cope with potential attenuation bias in the main coefficients deriving from measurement error in precipitations and PET, in the spirit of Maccini & Yang (2009), in addition to our linear model we estimate an instrumental variable regression, in which actual rainfall and evapotranspiration in year t and cell c is instrumented using the average of the corresponding measure in up to eight neighbouring cells in the same year[9]. With this methodology, we obtain highly correlated instruments for precipitations and PET (correlation between the environmental measure and its corresponding instrument computed in neighboring cells is always more than 85%). The validity of this approach relies on the assumption that measurement error is orthogonal across neighboring cells and uncorrelated with the error of the instrumented variable.

While Equation 1 captures the average effect of precipitations and PET in a cell that harvests multiple crops, it is informative to look separately at the impact on each cultivation, to assess the existence of important heterogeneity. We thus estimate Equation 1 separately for each crop $k \in I$, (with $\dim(I) = 22$), thus obtaining a set of coefficients:

$$\log(Y)_{c,k,t} = \alpha PRE^{g}_{c,t} + \alpha_{2,k} PET^{g}_{c,t} + \gamma X_{c,k,t} + \delta_{c(t)} + \varepsilon_{c,k,t} \tag{2}$$

As highlighted above, the sign of the set of $\boldsymbol{\alpha}$ coefficients is ultimately an empirical question. It is also unclear whether the inclusion of PET could influence the effect of precipitations. Indeed, if one considers precipitations and soil evapotranspiration as two entirely independent processes, using PET may increase the model's explanatory power but leave almost unaltered considerations on precipitations. Conversely, to the extent that meteorological factors may determine some non-negligible correlation between these two measures, adding PET into the equation may resolve some omitted variable bias and hence help to reconsider the role of rainfall in the literature.

3.2 Empirical findings

The estimates of Equation 1 are reported in Table 4. To ease interpretation, both environmental measures are standardized. Following standard practice in the literature, we focus on the five major crops by harvested area (Jayachandran 2006)

The results demonstrate the fundamental impact of PET on crop yield compared to precipitations. When rainfall is included alone as the primary explanatory variable, its effect on crop yield is positive and strongly significant: one standard deviation increase in precipitations raises yield by 6.15% (Column 1). The inclusion of PET in the regression

[9]Given data availability in our grid, not all cells have environmental measures for all surrounding neighbours. The average number of cells used to compute the instrument is 7, with a minimum of 2 and a maximum of 8.

has a two-fold implication. First, evapotranspiration appears to impact agricultural yield significantly: when PET increases by one standard deviation, yield is expected to decrease by 32.67% (Column 2). Second, the effect imputed to precipitations is almost three times lower than that in the previous regression and is still strongly significant. The inclusion of lagged terms for precipitations and PET (Column 3) and the use of the study's instrument for potential measurement error (Column 4) only marginally affect the magnitude of the main coefficients of interest, while the significance is partially lost only for precipitations [10].

In Panel B, we report the estimates of Equation 1 using as main independent variables climate conditions calculated using uniquely growing season months in the cell[11]. TThe tendency highlighted in Panel A seems to persist. Yet, the magnitude of the coefficients is considerably lower, particularly for PET. One standard deviation increase in growing season evapotranspiration decreases crop yield by between 0.37% and 5.6%, with scattered significance. Similar considerations could be made for the effects of precipitations in the growing season, although it is still evident that accounting for PET captures part of the previously attributed to rainfall. It seems that weather conditions even outside growing season months affect agricultural productivity. This can be easily explained by the fact that farmers may not comply with model-derived harvesting periods, since the latter consider the average crop composition in the cell.

Furthermore, this study explores the possibility of heterogeneous responses to fluctuations in rainfall and PET levels depending on the specific crop, followed by an iterative estimation of Equation 2. We obtain a set of 22 coefficients for each climate measure; to enhance visualization, we focus here on PET and plot the coefficients in Figure 5. As it emerges from the graph, some crops appear to benefit from greater evapotranspiration (e.g., olive, banana). Nonetheless, focusing on those products that account for the average highest shares of cultivated land in the cell (whose coefficients are plotted with a darker shade), higher levels of PET appear to reduce yield systematically.

While the estimates in Table 4 reveal a drop in productivity suffered by African staple crops due to high PET, the actual implications of such yield loss might be hard to quantify, as crops entail significantly different amounts of dry mass production. To better understand

[10] First stage coefficients for the estimates in Column 4 are reported in Table A.3 in Appendix

[11] Data on the growing season in each cell are available through the GAEZ v4 database, starting from 1960. Growing season is calculated using the beginning date of the earliest growing period and total number of growing period days. Further details are provided in Appendix A.1.2.

the impact of aridity and rainfall, we thus newly estimate Equation 1, this time using our data on dry-mass caloric intake to express crop yield in terms of kcal/m^2. The results are report in Appendix, Table A.1. The results are very similar to those presented in Table 4, and the trend in the coefficients is unchanged. Focusing on yearly values of precipitations and PET (Panel A), when precipitations are the main explanatory variable, one standard deviation increase implies an expected yield gain of 6%. The predicted increase is three times lower when PET is brought into the picture. Conversely, PET maintains a robust negative impact on caloric yield: one standard deviation increase in PET implies between a 32% and 45% kcal/mˆ{2} loss, with all coefficients maintaining strong significance. The inclusion of environmental controls during the growing season (Panel B) again significantly reduces the magnitude of the coefficients, with very similar coefficients to what was observed for yield in dry mass.

It appears that aridity can substantially impact agricultural productivity, leading to a significant loss in dry product mass and caloric intake of the overall production. Yet, while the average effect appears to be strongly negative, each area could be affected differently depending on the production mix adopted in the agricultural sector. As such, whether an average productivity loss may have health implications for inhabitants remains an open question, which this study attempts to address in Section 4.

4 Precipitations, PET and Infant Health

As seen so far, soil evapotranspiration could influence crop productivity and lead to a sensitive loss in agriculture yield, depending on the characteristics of the cultivated land. In an area such as Sub-Saharan Africa, where most of the population lives in rural areas, agriculture has historically accounted for more than 50% of the gross domestic product (GDP) until the beginning of the 90s (Diao et al. 2007), and agricultural productivity has been key. Even at the time of writing, in the 34 countries in the sample, in 2020 agriculture, forestry, and fishing accounted for an average of 21.4% of the GDP, with some countries even exceeding 50% [12]. As such, by impacting agricultural productivity, aridity could affect human development through the channels analyzed in the literature on rainfall.

[12]Source: World Development Indicators, The World Bank Group: Agriculture, forestry, and fishing, value added (% of GDP). Data for Comoros, Cote d'Ivoire, Mozambique, are available from 2019. Data for Zimbabwe are available from 2018.

This section quantifies the effect of PET on health indicators that can serve as proxies for economic well-being.

Once again, a linear fixed-effects panel data model is employed, exploiting exogenous variation in weather conditions in each year and across cells to identify the effects of rainfall and PET on the infant health indicators in this study. To compare the impact of PET and precipitations, an unbalanced panel dataset is assembled using the DHS.

The following equation is estimated:

$$Y_{i,m,q,c,t} = \sum_{r=0}^{1} \beta_{1,r} PRE^{g}_{c,t^*-r} + \sum_{r=0}^{1} \beta_{2,r} PET^{g}_{c,t^*-r} + \rho X_{i,m,c} + \sigma_{trend} + \phi_{q(t^*)} + \epsilon_{i,m,q,c,t} \tag{3}$$

where Y_{i,m,q,c,t^*} now represents our measure of infant health for child i born from mother m in cluster q, in cell c. $t \in \{t^*, \tilde{t}\}$ can represent either a child's year of birth (t^*) or the year of interview ($\tilde{t}$). As main regressand, we consider a measure of infant mortality (mortality at one year), BMI in standard deviations recorded at the time of interview and size at birth. We also assess the robustness of our results on a different yet comparable set of outcome variables (mortality at five years and weight/height ratio).

In our baseline specification, the reference model for the binary outcome variable of infant mortality is a linear probability model (LPM). Using a linear estimator eases the interpretation of the coefficients and allows for immediate comparisons between the different specifications. Moreover, this choice is deemed to be preferable given the ample set of fixed effects included in the regression[13].

The primary environmental measures of rainfall and PET are defined as in Equation 1, and calculated at a child's year of birth (t^*). Lagged terms are still included, which, in this case, have a slightly different interpretation. Levels of precipitations and PET may impact infant health by impinging a mother's physical wellbeing or ability to effectively take care of her child. Thus, the study controls for weather conditions one year before childbirth, which more clearly isolates a potential effect on the mother that is not directly linked to the child's health.

[13]While it is possible to estimate non-linear models through iterative algorithms, such as Iteratively Reweighted Least Squares (IRLS), some theoretical challenges exist regarding the existence of a solution to the algorithm or whether relevant parameters are identifiable.

$X_{i,m,c}$ includes a set of covariates at birth, woman, and grid level. Since information was obtained on each child's year and month of birth, the year is taken as the time dimension, but the study accounts for the month of birth as a control. This approach allows for seasonality in precipitations and PET to be smoothened out, while accounting for infant health may be influenced by exposure to weather conditions both in utero and immediately after childbirth. Moreover, the study controls for a mother's education and self-reported wealth index, the main source of water supply in the household, and again for temperature in the grid at time t or in the corresponding growing season, for the same reason as above. Moreover, $\phi_{c(t)}$ includes two sets of time and cluster fixed effects [14]. Lastly, the term σ_{trend} captures country trends.

Based on previous findings and the existing literature, PET and precipitations are expected to have opposite effects on infant health. Once again, however, it is an empirical question whether controlling for PET in the estimation can also affect the impact of rainfall, as observed for crop productivity.

4.1 Baseline Results

Table A.2 reports the estimates of the impact of precipitations and PET from Equation 3. As in previous sections, in Panel A, weather variables are computed over the entire year of reference, while in Panel B, they are calculated in the corresponding growing season. PET and precipitation variables are standardized to ease comparison. By first examining Panel A, in Column (1), the effect of precipitations alone on infant mortality within one year can be estimated. Higher rainfall seems to prevent infant mortality partially: one standard deviation increase reduces mortality by 0.26%. The coefficient of the lagged term also reveals that some of the effects of precipitations on mortality could already be in place in utero, as one standard deviation increase in rainfall in the year before birth decreases mortality by 0.14%, with a 5% significance level. When adding PET into the regression (Column 2), however, the effect of precipitations drops to 0.15% in the year of birth and approaches 0 one year before (Column 2). The effect also appears to be stronger compared to rainfall, as one standard deviation increase in PET increases expected mortality by 0.63%. Conversely, PET displays positive coefficients, suggesting a detrimental effect of increased PET on infant mortality. However, significance is not reached in OLS estimates,

[14] Adding cluster FEs consitutes a more conservative approach compared to cell FEs, as a cell in our grid contains at least one cluster.

while the coefficient for PET_{t-1} is significant at a 5% level in our IV specification (Column 3).

A similar tendency can be observed for BMI (Columns 4 to 6): when precipitations are included alone, one standard deviation increase raises BMI by 0.0746 standard deviations in the year of birth and 0.0331 standard deviations in the previous year. When PET is brought into the regression, the joint effect of the two terms is roughly halved. Conversely, PET appears to harm BMI, which again becomes strongly significant when instrumenting weather measures: one standard deviation increase in PET decreases BMI by 0.136 standard deviations in the year of birth and by 0.1246 standard deviations in the previous year (Column 6). Finally, examination of the size at birth reveals a similar tendency, although the effect of aridity is not always significant.

Panel B reports the same estimates, with only growing season months, with environmental measures computed. Most of the coefficients remain comparable in terms of both magnitude and significance, but the effect of the main regressors generally appears smaller across specifications, as highlighted in Table 4. It thus appears again that, while the discrepancy between the estimates in the two panels is now lower, environmental conditions can impact child health even outside growing season months.

As Table A.2 indicates, the results observed for infant health are robust when substituting the outcome variables adopted with similar measures of health and mortality. Indeed, repeating the estimation with mortality within five years and weight-to-height ratio in standard deviations returns remarkably similar coefficients, both in magnitude and in significance.

From the analysis performed in this section, a similar tendency emerges to that depicted for agricultural productivity. First, the effect of precipitations and PET tends to move in opposite directions. More importantly, whenever PET is introduced in the analysis, the explanatory power of rainfall systematically decreases. The remainder of the paper addresses some potential endogeneity concerns when testing the results' robustness and explaining the findings' implications.

5 Robustness and Additional Evidence

5.1 Farmers' adaptation

Despite the inclusion of high-dimensional fixed effects and the intrinsic exogeneity of weather conditions, farmers' endogenous adaptation to climate change could affect the estimates. On the basis of the hypothesis that farmers can foresee the evolution of soil evapotranspiration and temperature, possibly by observing decreasing yields through time, they may revert to crops that benefit from a warmer climate and require a lower amount of water throughout the growing period. Under this assumption, the impact of evapotranspiration on agricultural productivity may be underestimated.

This potential concern is confronted in two ways in this study. First, the limited change in cell-specific crop composition is highlighted between 2000 and 2010. The average absolute variation in the harvested area devoted to each crop is roughly 0.2 hectares, corresponding to 1.8 percentage points of relative harvested share. Therefore, on average, more than 40% of cultivated area in a cell is devoted to a single crop, while the four major crops sum up to roughly 80%; such slight variation implies no dramatic conversion in the composition of harvested land.

Furthermore, to raise endogeneity concerns, the change in crop composition should be non-orthogonal to the variation in precipitations and PET, thus reflecting farmers' adaptation to climate change. If this were the case, one might observe that farmers reorganize agricultural production toward plants that are generally more suitable to the evolving climate conditions. The index of suitability is exploited to explore this instance. A suitability score (SSc) is calculated for each cell c in 2000 and 2010, according to the following expression:

$$SSc_{c,t} = \sum_{k}^{K} SI_{k,c} \cdot Har_{k,c,t} \tag{4}$$

where $K \in \{2, 3, ..., dim(I)\}$ and $t \in \{2000, 2010\}$. We then compute the score differential between 2010 and 2000 for each cell (ΔSSc). We plot the distribution of the resulting ΔSSc in Figure 6. Two considerations are in place. Firstly, the probability density function of ΔSSc appears symmetric and centered around zero, with limited variability (the average gain in suitability score is 3.6 points, with 231.7 standard deviations). This sustains the belief that there is no systematic direction in crop substitution, which instead appears relatively randomic. In addition, even relaxing the previous assumption, the average SSc gain (when ΔSSc in indeed positive) is negligible provided that the average score is around 2000 points.

Despite little descriptive evidence of the endogenous adaptation of farmers, this study also proposes a more analytical strategy to further alleviate this concern.

The unexpected variation in precipitations and PET in a given year is computed and used as the main predictor of agricultural yields. Under the assumption of endogenous adaptation to increasing aridity, much of the effect observed in the paper should indeed be captured by the unpredictable component of PET volatility, to which farmers fail to adjust. Farmers' expectations regarding future weather conditions must hence be modeled. The literature exploring their decision-making process has observed that farmers tend to form predictions and carry out harvesting operations based on a heuristic connecting past climate conditions Guido et al. (2020), seemingly looking back to up to three years Zaveri et al. (2020). Thus, we model farmers' expectations using an exponentially decaying weighted average, in which historical weather conditions up to N years in the past are weighted by a discount factor ρ, according to the following equation:

$$\mathbb{E}[V]_t = \sum_{i=1}^{N} \frac{\rho^{i-1} V_{t-i}}{\rho^{i-1}} \tag{5}$$

and use expected values to estimate Equation 1 with unexpected variation in precipitations and PET as main regressors, i.e.:

$$\log(Y)_{c,k,t} = \sum_{r=0}^{1} \alpha_{1,r} \widehat{PRE}^{g}_{c,t-r} + \sum_{r=0}^{1} \alpha_{2,r} \widehat{PET}^{g}_{c,t-r} + \gamma X_{k,c,t} + \delta_{k(c)(t)} + \varepsilon_{k,c,t} \tag{6}$$

where $\widehat{V}_t = V_t - \mathbb{E}\left[V_t\right]$, and other terms are defined as in Equation 1. We estimate the coefficients for two values of N ($N \in \{3, 5\}$) and four values of ρ ($\rho \in \{0, 0.5, 0.7, 1\}$). These value of the two parameters include the scenario of fully adaptive expectations, i.e. farmers inferring current rainfall and PET looking uniquely at values in the previous year ($\mathbb{E}[V]_t = V_{t-1}$).

We report the coefficients of interest in Table 6. While the effect of unexpected variation in precipitations is fuzzy, with coefficients switching sign and generally high standard errors, unexpected PET appears on a more stable path: the coefficients are systematically negative and always strongly significant. However, it is reassuring to notice that the magnitude of the coefficients is considerably lower than those estimated in Table 4, in an order of magnitude of roughly 0.1 to 0.2. This, in turn, implies that the effect of PET cannot be imputed uniquely to its unexpected component, reinforcing even further the belief that limited adaptation, if at all, is not enough to obfuscate significantly our findings.

5.2 Migration

If one assumes that climate change may push people to move toward more productive regions based on some non-random characteristics, the results could again suffer from endogeneity. Another concern may pertain to endogenous migratory flows. Two primary considerations are in place.

First, based on the visual representation of the sample's precipitations and PET levels in Figure 2, these climate factors show some spatial correlation. As such, migration would be of higher concern if one hypothesizes that people displace non-randomly to considerably different climatic areas. It can anecdotally be argued that, given the preeminently internal nature of migration in Sub-Saharan Africa, one may not expect this to be the case often.

Second, the information contained in the sample can be used to strengthen the study's claim. Indeed, for around 60% of women in the sample, information has been retained regarding the number of years they have lived in their current residence. More than 80% of those women had been living in the same place of residence for more than 15 years at the time of the interview. Estimates of Equation 3 are thus repeated, limiting the sample to these individuals. This threshold is chosen to balance the tradeoff between the loss of observations and the impossibility of households relocating following an evaluation of climate conditions. As such, this study assumes that migrations that occurred more than 15 years in the past are uncorrelated with the climate conditions at time t.

Observing significant discrepancies with the study's baseline estimates would support the hypothesis that individuals tend to react to climate change by relocating endogenously, and the study's coefficients would not capture the true effect of precipitations and PET. However, the results reported in the Appendix (Table A.4) seem to alleviate this concern. First, the loss of information (roughly 25% of the overall sample) translates into a partial loss of significance. Yet, the order of magnitude and general trend in the coefficients appear to be mostly unchanged. Such evidence offers reassurance that the coefficients capture the true effect of yearly rainfall and aridity on child health.

6 Calculation of Aridification Losses

Throughout the analysis, standardized coefficients were presented for all climate variables of interest to compare the contribution of precipitations and PET in explaining crop yield variability and child health. While these estimates serve, at best, the narrative of the present paper, they provide no information on whether the impact of aridity is economically relevant for policymakers. To determine the degree to which the process of aridification could impact the measures of agricultural productivity and socioeconomic development employed in this paper, unstandardized coefficients are estimated, and a short back-of-the-envelope calculation is performed[15]. This study emphasizes that the average PET across the grid has steadily increased since the 1980s. Since then, average PET across the grid has increased by roughly 40 mm/year (around 1.8 mm when considering growing season months uniquely). The yearly marginal estimates in Table A.6, suggest that the evolution of the African climate since 1980 is responsible of an average yield loss between 4.4% and 6%, in addition to a decrease in children BMI by between roughly 0.015 and 0.0175 standard deviations and a 0.008-unit drop in the average size at birth class. Despite some evidence that mortality could have been affected, the estimates do not allow for a precise inference of this effect.

While progressing aridity appears to have contributed to harming agricultural productivity and the health of African children throughout the sample period, neglecting the role of PET has especially crucial implications if one focuses on climate simulations for the next century. To this end, this study obtains projections of future levels of PET and rainfall over two time horizons (2040–2079 and 2060–2099) for the sample grid from five different ESMs[16] over two representative concentration pathway (RCP) scenarios. RCPs represent pathways for greenhouse gas concentration trajectories and vary depending primarily on a set of assumptions about the human response to the climate emergency. The study fo-

[15] The estimates can be found in Table A.5 and Table A.6 in Appendix.

[16] The time series at $0.5^\circ \times 0.5^\circ$ grid resolutions are produced by five ESMs: GFDL-ESM2M, HadGEM2-ES, IPSL-CM54-LR, MIROC-ESM-CHEM, NorESM1-M. These are all part of the Coupled Model Intercomparison Project Phase 5 (CMIP5). More information about the nature and specificities of these models can be found in Noce et al. (2020).

cuses on RCPs 4.5 – often addressed as an “intermediate” and more likely scenario, which foresees a peak in emissions between 2010 and 2030, followed by a decline throughout the 21st century – and 8.5, a “worst-case” scenario under which the emissions curve does not flatten in the next 100 years.

We report the sample average of the simulated levels in Table 7, which shows that the RCP scenarios differ most significantly in PET predictions, while rainfall projections remain relatively stable. Moreover, the discrepancy intensifies as predictions extend further into the future. The estimated coefficients are then applied to the simulated series to quantify the importance of controlling for PET. First, the net effect of the increase in precipitations is calculated using only estimates from the specifications that do not include PET. The projected precipitations are considered relative to the observed 2010–2019 average level. Under RCP 4.5, all else equal, the increase in precipitations is expected to boost crop yield by 0.77 to 1.72 percentage points and raise children's BMI and size at birth by 0.0097 to 0.022 standard deviations and 0.008 to 0.017 points, respectively. However, when PET is included, the net effect of the climate's projected evolution changes dramatically . The net impact on crop yield oscillates from a 1.9% gain to an 8.5% loss. The same applies for BMI and size at birth, which stand between +0.013 and -0.0311 and between +0.008 and -0.02 points, respectively. Notably, only those models that do not foresee a sizable increase in evapotranspiration still allow for positive predictions regarding the impact of climate change on water availability.

Under the RCP 8.5 scenario, accounting for PET projections has even more substantial implications. Predicted gains in crop yield (+0.83% to 2.39%), children's BMI (+0.01 to +0.03), and size at birth (+0.008 to +0.024) turn into considerable losses (-5.8 to -45.89% for crop yield, -0.01 to -0.12 for BMI, and -0.007 to -0.057 for size at birth). While this is a less likely scenario, it provides a negative benchmark on how aridity could dramatically impact African households in the next decades

7 Conclusion

This paper reconsiders the role of precipitations as soil aridification subsists, adding to the current debate on the effects of climate change on human development. The impact of precipitations and PET on crop productivity and child health are examined on a grid of more than 4,000 cells of 0.5 x 0.5 in Sub-Saharan Africa.

When considered alone, higher rainfall has, on average, a positive effect on crop yields, although this result is conditional on the composition of the area harvested in the cell. One standard deviation increase in precipitations increases the average yield of the five most cultivated crops by 6%. However, when PET is considered, the effect of precipitations fades, offset by the strong negative impact of PET on yield: one standard deviation increase implies a yield loss between 31.9% and 45.6%.

Furthermore, the study investigates the effect of water availability on child health indicators. A similar pattern is observed: the inclusion of PET not only harms health (reducing a child's size at birth and BMI at the time of interview) but also reduces the impact of rainfall. These results have important policy implications. Enhancing agricultural productivity and ensuring the food security of rural communities emerge as crucial points on the agenda of policymakers, given the future rise in temperatures and soil evapotranspiration.

However, these findings are not final. Future research should focus on understanding farmers' ability to adapt to the challenges of global warming and the ways in which planting substitution could counter the negative impact of aridification. Furthermore, new avenues for investigation should analyze how evolving societies and climate change impact the transmission mechanism between agricultural productivity and human development.

References

Aber, J. L., Bennett, N. G., Conley, D. C. & Li, J. (1997), 'The effects of poverty on child health and development', *Annual review of public health* **18**(1), 463–483.

Allen, R. G., Pereira, L. S., Raes, D., Smith, M. et al. (1998), 'Crop evapotranspiration-guidelines for computing crop water requirements-fao irrigation and drainage paper 56', *Fao, Rome* **300**(9), D05109.

Allen, R., Smith, M., Perrier, A. & Pereira, L. S. (1994), 'An update for the definition of reference evapotranspiration', *ICID bulletin* **43**(2), 1–34.

Almer, C., Laurent-Lucchetti, J. & Oechslin, M. (2017), 'Water scarcity and rioting: Disaggregated evidence from sub-saharan africa', *Journal of Environmental Economics and Management* **86**, 193–209. Special issue on environmental economics in developing countries.
URL: *https://www.sciencedirect.com/science/article/pii/S0095069617303650*

Amare, M., Jensen, N. D., Shiferaw, B. & Cissé, J. D. (2018), 'Rainfall shocks and agricultural productivity: Implication for rural household consumption', *Agricultural Systems* **166**, 79–89.
URL: *https://www.sciencedirect.com/science/article/pii/S0308521X18302440*

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D. et al. (2013), 'Uncertainty in simulating wheat yields under climate change', *Nature climate change* **3**(9), 827–832.

Barrios, S., Bertinelli, L. & Strobl, E. (2010), 'Trends in rainfall and economic growth in africa: A neglected cause of the african growth tragedy', *The Review of Economics and Statistics* **92**(2), 350–366.

Benshaul-Tolonen, A. (2018), 'Local Industrial Shocks and Infant Mortality', *The Economic Journal* **129**(620), 1561–1592.
URL: *https://doi.org/10.1111/ecoj.12625*

Bharadwaj, P., Fenske, J., Kala, N. & Mirza, R. A. (2020), 'The green revolution and infant mortality in india', *Journal of health economics* **71**, 102314.

Björkman-Nyqvist, M. (2013), 'Income shocks and gender gaps in education: Evidence from uganda', *Journal of Development Economics* **105**, 237–253.
URL: *https://www.sciencedirect.com/science/article/pii/S0304387813001120*

Brückner, M. (2012), 'Economic growth, size of the agricultural sector, and urbanization in africa', *Journal of Urban Economics* **71**(1), 26–36.

Brückner, M. & Ciccone, A. (2011), 'Rain and the democratic window of opportunity', *Econometrica* **79**(3), 923–947.

Burke, M., Hsiang, S. M. & Miguel, E. (2015), 'Global non-linear effect of temperature on economic production', *Nature* **527**(7577), 235–239.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S., Smith, D. & Chhetri, N. (2014), 'A meta-analysis of crop yield under climate change and adaptation', *Nature Climate Change* **4**(4), 287–291.

Cherlet, M., Hutchinson, C., Reynolds, J., Hill, J., Sommer, S. & Von Maltitz, G. (2018), *World atlas of desertification: Rethinking land degradation and sustainable land management*, Publications Office of the European Union.

Couttenier, M. & Soubeyran, R. (2014), 'Drought and civil war in sub-saharan africa', *The Economic Journal* **124**(575), 201–244.

Dell, M., Jones, B. F. & Olken, B. A. (2008), Climate change and economic growth: Evidence from the last half century, Technical report, National Bureau of Economic Research.

Dell, M., Jones, B. F. & Olken, B. A. (2012), 'Temperature shocks and economic growth: Evidence from the last half century', *American Economic Journal: Macroeconomics* **4**(3), 66–95.

Dell, M., Jones, B. F. & Olken, B. A. (2014), 'What do we learn from the weather? the new climate-economy literature', *Journal of Economic Literature* **52**(3), 740–98.

Diao, X., Hazell, P. B., Resnick, D. & Thurlow, J. (2007), *The role of agriculture in development: Implications for Sub-Saharan Africa*, Vol. 153, Intl Food Policy Res Inst.

Donat, M. G., Lowry, A. L., Alexander, L. V., O'Gorman, P. A. & Maher, N. (2016), 'More extreme precipitation in the world's dry and wet regions', *Nature Climate Change* **6**(5), 508–513.

Ekström, M., Jones, P. D., Fowler, H. J., Lenderink, G., Buishand, T. A. & Conway, D. (2007), 'Regional climate model data used within the swurve project: projected changes in seasonal patterns and estimation of pet', *Hydrology and Earth System Sciences* **11**(3), 1069–1083.
URL: *https://hess.copernicus.org/articles/11/1069/2007/*

Fischer, G., Nachtergaele, F. O., van Velthuizen, H., Chiozza, F., Francheschini, G., Henry, M., Muchoney, D. & Tramberend, S. (2021), 'Global agro-ecological zones (gaez v4)-model documentation'.

Guido, Z., Zimmer, A., Lopus, S., Hannah, C., Gower, D., Waldman, K., Krell, N., Sheffield, J., Caylor, K. & Evans, T. (2020), 'Farmer forecasts: Impacts of seasonal rainfall expectations on agricultural decision-making in sub-saharan africa', *Climate Risk Management* **30**, 100247.

Harari, M. & Ferrara, E. L. (2018), 'Conflict, climate, and cells: a disaggregated analysis', *Review of Economics and Statistics* **100**(4), 594–608.

Harris, I., Osborn, T. J., Jones, P. & Lister, D. (2020), 'Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset', *Scientific data* **7**(1), 1–18.

Held, I. M. & Soden, B. J. (2006), 'Robust responses of the hydrological cycle to global warming', *Journal of climate* **19**(21), 5686–5699.

Jayachandran, S. (2006), 'Selling labor low: Wage responses to productivity shocks in developing countries', *Journal of political Economy* **114**(3), 538–575.

Juana, J. S., Kahaka, Z. & Okurut, F. N. (2013), 'Farmers' perceptions and adaptations to climate change in sub-sahara africa: A synthesis of empirical studies and implications for public policy in african agriculture', *Journal of Agricultural Science* **5**(4), 121.

Kandlikar, M. & Risbey, J. (2000), 'Agricultural impacts of climate change: if adaptation is the answer, what is the question?', *Climatic change* **45**(3-4), 529.

Kirtman, B., Power, S. B., Adedoyin, A. J., Boer, G. J., Bojariu, R., Camilloni, I., Doblas-Reyes, F., Fiore, A. M., Kimoto, M., Meehl, G. et al. (2013), 'Near-term climate change: projections and predictability'.

Kudamatsu, M., Persson, T. & Strömberg, D. (2012), Weather and infant mortality in africa, Technical report, CEPR Discussion Papers N. DP9222. Available at: `https://ssrn.com/abstract=2210191`.

Lema, M. A. & Majule, A. E. (2009), 'Impacts of climate change, variability and adaptation strategies on agriculture in semi arid areas of tanzania: The case of manyoni district in singida region, tanzania', *African Journal of Environmental Science and Technology* **3**(8), 206–218.

Maccini, S. & Yang, D. (2009), 'Under the weather: Health, schooling, and economic consequences of early-life rainfall', *American Economic Review* **99**(3), 1006–26.

Noce, S., Caporaso, L. & Santini, M. (2020), 'A new global dataset of bioclimatic indicators', *Scientific data* **7**(1), 1–12.

Peri, G. & Sasahara, A. (2019), The impact of global warming on rural-urban migrations: Evidence from global big data, Technical report, National Bureau of Economic Research.

Rabassa, M., Skoufias, E. & Jacoby, H. (2014), 'Weather and child health in rural nigeria', *Journal of African Economies* **23**(4), 464–492.

Rind, D., Goldberg, R., Hansen, J., Rosenzweig, C. & Ruedy, R. (1990), 'Potential evapotranspiration and the likelihood of future drought', *Journal of Geophysical Research: Atmospheres* **95**(D7), 9983–10004.

Rocha, R. & Soares, R. R. (2015), 'Water scarcity and birth outcomes in the brazilian semiarid', *Journal of Development Economics* **112**, 72–91.
URL: *https://www.sciencedirect.com/science/article/pii/S0304387814001096*

Rose, E. (1999), 'Consumption smoothing and excess female mortality in rural india', *The Review of Economics and Statistics* **81**(1), 41–49.
URL: *http://www.jstor.org/stable/2646784*

Rosenzweig, M. R. & Udry, C. (2014), 'Rainfall forecasts, weather, and wages over the agricultural production cycle', *American Economic Review* **104**(5), 278–83.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.104.5.278*

Vermeulen, S. J., Aggarwal, P. K., Ainslie, A., Angelone, C., Campbell, B. M., Challinor, A. J., Hansen, J. W., Ingram, J., Jarvis, A., Kristjanson, P. et al. (2012), 'Options for support to agriculture and food security under climate change', *Environmental Science & Policy* **15**(1), 136–144.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. (2010), 'A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index', *Journal of climate* **23**(7), 1696–1718.

Zaveri, E., Russ, J. & Damania, R. (2020), 'Rainfall anomalies are a significant driver of cropland expansion', *Proceedings of the National Academy of Sciences* **117**(19), 10225–10233.

Zhang, P., Zhang, J. & Chen, M. (2017), 'Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation', *Journal of Environmental Economics and Management* **83**, 8–31.

Tables

Table 1: Summary statistics - Climate variables

	1951-1965	1966-1980	1981-1995	1996-2010	2010-2019	Avg growth
Prec	1064.9	1032.9	965.6	1006.1	1016.9	-0.3%
	(545.99)	(527.67)	(523.01)	(520.64)	(516.55)	
	[1.67 ; 3,194.77]	[2.44 ; 3,110.26]	[2.09 ; 3,107.39]	[2.07 ; 3,102.73]	[0.89 ; 2,959.36]	
PET	1402.1	1396.6	1412.0	1431.9	1435.7	0.07%
	(315.89)	(314.28)	(310.26)	(318.03)	(310.12)	
	[809.00 ; 2,664.20]	[811.60 ; 2,680.00]	[823.20 ; 2,704.00]	[822.20 ; 2,794.80]	[836.67 ; 2,713.33]	
Temp	23.231	23.243	23.555	23.905	23.993	0.07%
	(3.58)	(3.61)	(3.58)	(3.58)	(3.56)	
	[8.76 ; 29.68]	[8.90 ; 29.¡93]	[9.35 ; 30.15]	[9.51 ; 30.65]	[9.99 ; 30.68]	

Correlations

	Prec	PET	Prec	PET	Prec	PET	Prec	PET	Prec	PET
PET	-0.58	.	-0.62	.	-0.63	.	-0.63	.	-0.61	.
Tmp	0.21	0.39	0.13	0.41	0.13	0.41	0.13	0.42	0.13	0.40

Notes: summary statistics are shown on a sample of 4,052 grid cells. Precipitations and PET show the total millimetres of rain and water lost by the soil in the year, averaged throughout the indicated period, while temperature is an yearly average (°C). Standard deviations are reported in parentheses; minimum and maximum values are reported in brackets. The average growth column is calculated as $\Delta = 1/T \sum_t^T (X_{t+1} - X_t)/X_t$, where T is the entire sample period (68 years).

Table 2: Summary statistics - Agricultural outcomes and productivity

	Harvested share (% tot)*		Yield** (avg, t/ha)		Suitability Index***	Water req**** (avg, mm/ha)	Gross energy (avg, kcal/kg)
	2000	2010	2000	2010	1980-2010		
Maize	0.22	0.24	1.46	1.77	3082.66	650	4466.42
	(0.20)	(0.19)	(1.08)	(1.42)	(1,729.77)		
Olive	0.16	0.17	1.51	2.55	89.32	500	4920.23
	(0.20)	(0.18)	(1.57)	(2.01)	(515.27)		
Cassava	0.15	0.14	7.82	9.13	3575.96	550	4012.61
	(0.14)	(0.12)	(3.23)	(4.71)	(2,060.48)		
Millet	0.12	0.10	0.71	0.75	892.95	550	4227.57
	(0.17)	(0.16)	(0.36)	(0.47)	(1,482.21)		
Sorghum	0.10	0.10	0.94	1.01	3267.54	550	4514.19
	(0.11)	(0.12)	(0.90)	(0.89)	(2,076.29)		
Rice	0.10	0.11	1.67	1.96	1548.43	575	3893.19
	(0.17)	(0.17)	(1.44)	(1.61)	(1,355.12)		
Yam	0.09	0.09	6.15	6.95	2996.28	.	4132.03
	(0.11)	(0.12)	(3.10)	(4.76)	(1,858.26)		
Wheat	0.08	0.08	2.96	2.63	1482.51	550	4418.65
	(0.14)	(0.14)	(2.25)	(2.05)	(1,610.57)		
Pulses	0.08	0.09	0.23	0.25	3107.48	675	4370.88
	(0.07)	(0.08)	(0.12)	(0.14)	(1,580.30)		
Barley	0.08	0.07	1.86	2.31	193.50	550	4442.53
	(0.13)	(0.13)	(1.71)	(1.58)	(886.96)		
Coffee	0.07	0.07	0.91	0.90	2424.94	425	4657.50
	(0.13)	(0.13)	(0.91)	(0.75)	(1,946.88)		
Groundnut	0.06	0.07	0.88	0.92	2464.53	600	4633.61
	(0.08)	(0.08)	(0.51)	(0.52)	(1,628.93)		
Cotton	0.05	0.03	0.86	0.98	2570.88	1000	5684.53
	(0.08)	(0.06)	(0.54)	(0.74)	(1,402.07)		
Vegetables	0.03	0.03	1.28	1.47	1911.59	433	.
	(0.04)	(0.05)	(0.86)	(1.10)	(1,162.70)		
Sugarcane	0.03	0.02	54.41	54.16	2890.75	2000	4394.76
	(0.05)	(0.05)	(31.02)	(32.87)	(1,877.00)		
Potato	0.02	0.03	6.02	7.61	785.99	600	4012.61
	(0.03)	(0.03)	(5.18)	(7.03)	(1,254.33)		
Sunflower	0.02	0.03	0.80	0.79	2071.86	800	6854.88
	(0.05)	(0.05)	(0.51)	(0.36)	(1,946.71)		
Banana	0.02	0.02	9.64	13.39	1828.20	1700	4108.15
	(0.03)	(0.03)	(9.69)	(12.51)	(1,683.12)		
Sugarbeet	0.02	0.02	51.31	55.77	128.36	650	4036.50
	(0.03)	(0.03)	(9.24)	(10.17)	(644.53)		
Soybean	0.01	0.02	1.11	1.08	3050.71	575	4347.00
	(0.02)	(0.04)	(0.60)	(0.58)	(1,790.60)		
Tobacco	0.01	0.01	0.96	0.88	2507.20	500	.
	(0.01)	(0.02)	(0.55)	(0.58)	(1,563.73)		
Rapeseed	0.01	0.01	0.71	1.16	972.40	.	5063.53
	(0.02)	(0.01)	(0.33)	(0.47)	(1,577.97)		

Notes: mean values over a grid of 3,896 cells are reported.
*Harvested area for each crop is reported as a share of the total area cultivated.
** Crop yield is expressed in tons per hectare of area cultivated.
*** Suitability Index (SI) is defined on a scale 0-10000.
**** Water requirements indicate water yield and water requirements are expressed respectively in tons and millimetres per hectare of area cultivated.

Table 3: Summary statistics - Mothers and children

	All sample	Wave III	Wave IV	Wave V	Wave VI	Wave VII	Min	Max
	Count							
*Sample characteristics**								
N. countries	32	3	14	13	28	12		
N. clusters	36842	859	7885	6433	16010	5655		
Mothers	468873	11277	120289	110359	186949	89867		
Births	2358849	46343	511967	501581	979807	319151		
Births u5	697710	12237	132073	149913	296656	106831		
	Mean (sd)							
Mother's characteristics								
Age	35.254	35.630	36.041	35.083	35.061	34.796	15	50
	(8.07)	(8.02)	(8.02)	(8.15)	(8.03)	(8.05)		
Education	3.451	2.469	2.852	3.806	3.558	3.669	0	27
	(4.18)	(3.99)	(4.12)	(4.00)	(4.23)	(4.29)		
Wealth**	2.796	.	2.822	2.804	2.790	2.781	1	5
	(1.40)	.	(1.42)	(1.39)	(1.40)	(1.40)		
Rural household	0.279	0.263	0.266	0.230	0.296	0.330	0	1
	(0.45)	(0.44)	(0.44)	(0.42)	(0.46)	(0.47)		
Births	5.402	5.724	5.673	5.694	5.226	5.004	1	19
	(2.75)	(2.67)	(2.78)	(2.81)	(2.70)	(2.65)		
Age of first birth	18.784	18.225	18.915	18.402	18.883	18.976	3	47
	(3.64)	(3.52)	(3.57)	(3.51)	(3.72)	(3.66)		
Children under 5	1.550	1.694	1.386	1.546	1.623	1.576	0	24
	(1.32)	(1.39)	(1.28)	(1.22)	(1.40)	(1.26)		
N. of living children	4.560	4.494	4.584	4.652	4.543	4.438	0	16
	(2.24)	(2.19)	(2.24)	(2.29)	(2.22)	(2.20)		
Infant morality								
1 year	0.084	0.120	0.103	0.097	0.073	0.062	0	1
	(0.28)	(0.33)	(0.30)	(0.30)	(0.26)	(0.24)		
5 years	0.120	0.172	0.144	0.140	0.105	0.089	0	1
	(0.33)	(0.38)	(0.35)	(0.35)	(0.31)	(0.28)		
1 year - boys	0.090	0.126	0.110	0.104	0.079	0.068	0	1
	(0.29)	(0.33)	(0.31)	(0.30)	(0.27)	(0.25)		
5 years - boys	0.127	0.177	0.151	0.148	0.111	0.096	0	1
	(0.33)	(0.38)	(0.36)	(0.35)	(0.31)	(0.30)		
Infant nutrition-health								
BMI (SD)***	0.57	.	.	1.82	1.22	-2.72	-500	500
	(142.94)	.	.	(156.37)	(144.29)	(119.50)		
Weight/Height (SD)***	-12.38	.	.	-12.88	-11.83	-13.20	0	99.8
	(140.44)			(152.18)	(140.38)	(124.27)		
Size at birth (cat) ****	2.22	2.45	2.08	2.32	2.23	2.25	0	4
	(0.99)	(0.99)	(0.95)	(0.98)	(0.99)	(1.00)		

Notes: the DHS surveys employed are conducted between 1992 and 2019.
* The number of countries, clusters, mothers and generic births refers to the data available from the Individual Recode DHS survey. The number of births under 5 refers to the data available from the Child Recode DHS survey.
** Wealth is a categorical index spanning from 1 (very poor) to 5 (very rich).
*** The measures are presented with two implied decimal places; the actual value is obtained by dividing the variable by 100.
**** Size at birth is a categorical variable spanning from 0 (very small) to 4 (very large)

Table 4: Precipitations, PET and crop productivity in Africa

Yield (ton/ha)	(1) OLS	(2) OLS	(3) OLS	(4) IV
		[A] Yearly values		
Prec $_t$	0.0615***	0.0239***	0.0118*	0.0135**
	(0.0065)	(0.0066)	(0.0062)	(0.0066)
PET $_t$		-0.3267***	-0.4560***	-0.3185***
		(0.0201)	(0.0210)	(0.0215)
Observations	38,520	38,520	38,520	38,520
R^2	0.8968	0.8971	0.8973	
		[B] Growing season		
Prec GS $_t$	0.0165***	0.0155**	0.0081	-0.0094
	(0.0052)	(0.0072)	(0.0074)	(0.0070)
PET GS $_t$		-0.0037	-0.0559***	-0.0248
		(0.0146)	(0.0169)	(0.0166)
Observations	34,208	34,208	34,208	34,208
R^2	0.8952	0.8952	0.8954	
Controls	Y	Y	Y	Y
Lags	N	N	Y	N
Crop FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cell FE	Y	Y	Y	Y
F-stat. (excl.)				83.42

Notes: Panel [A] shows the estimates using yearly values of precipitations and PET. In Panel [B], precipitations and PET are calculated using only growing season months. The sample comprises on the five major crops in each cell by harvested area. These account on average for roughly 80% of the total harvested area in the cell. Environmental variables are standardized. Robust standard errors are clustered at cell level, with significance levels at 10, 5, and 1 percent.

Table 5: Impact of Precipitations and PET on infant health

	Mort (1y)			**BMI (SD)**			**Size at birth**		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
[A] Yearly values									
Prec_t	-0.0026***	-0.0015**	0.0004	7.4652***	5.1982***	4.1962***	0.0363***	0.0222***	0.0303***
	(0.0006)	(0.0007)	(0.0008)	(1.2166)	(1.2941)	(1.5804)	(0.0064)	(0.0067)	(0.0078)
$\text{Prec}_{(t-1)}$	-0.0014**	-0.0003	0.0014*	3.3141***	1.2999	-0.0667	0.0308***	0.0172***	0.0212***
	(0.0006)	(0.0007)	(0.0008)	(1.1741)	(1.2384)	(1.5083)	(0.0059)	(0.0063)	(0.0074)
PET_t		0.0020	0.0020		-9.6136*	-13.5959**		0.0139	-0.0217
		(0.0024)	(0.0027)		(5.1651)	(6.0826)		(0.0266)	(0.0314)
$\text{PET}_{(t-1)}$		0.0029	0.0063**		-1.3564	-12.4924**		-0.0754***	-0.0348
		(0.0024)	(0.0026)		(5.1662)	(5.9796)		(0.0266)	(0.0312)
Observations	2,059,719	2,059,719	2,059,719	266,469	266,469	266,469	518,591	518,591	518,591
R^2	0.0352	0.0353		0.1999	0.2000		0.1331	0.1332	
[B] Growing season									
Prec GS $_t$	-0.0016***	0.0005	0.0000	3.4957***	2.4391**	2.6218**	0.0173***	0.0080	-0.0018
	(0.0006)	(0.0007)	(0.0009)	(1.0977)	(1.1367)	(1.3315)	(0.0059)	(0.0062)	(0.0075)
Prec GS $_{(t-1)}$	-0.0005	0.0001	-0.0009	3.2944***	2.2290**	1.5798	0.0117**	0.0046	-0.0051
	(0.0006)	(0.0007)	(0.0009)	(1.0955)	(1.1369)	(1.3352)	(0.0058)	(0.0059)	(0.0072)
PET GS $_t$		0.0016	0.0021		-4.5811*	-2.0338		-0.0416***	-0.0651***
		(0.0021)	(0.0030)		(2.7278)	(3.6986)		(0.0147)	(0.0201)
PET GS $_{(t-1)}$		-0.0012	0.0011		-4.5907*	-15.0802***		-0.0137	-0.0247
		(0.0020)	(0.0030)		(2.7214)	(3.7126)		(0.0146)	(0.0200)
Observations	1,721,409	1,721,391	1,721,384	227,786	227,786	227,786	432,729	432,729	432,729
R^2	0.0349	0.0198		0.1833	0.1835		0.1287	0.1289	
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat. (excl.)			1833			674.4			457.9

Notes: the table presents the estimates of β_1 and β_2. Long controls include woman's education in single years, wealth index of the household, kid's month of birth, main source of water, cell temperature in the corresponding time period. Columns (1) to (3) are based on a sample of 33 countries and 22,757 clusters. Columns (4) to (9) are based on a sample of 34 countries and 22,909 clusters. In Panel [A], precipitations and PET are computer over the entire year; in Panel [B], only growing season months are considered. Robust standard errors are clustered at DHS cluster level, with significance levels at 10, 5, and 1 percent.

Table 6: Unexpected variation in precipitations and PET and crop productivity

		Yield (ton/ha)		Yield (kcal/m3)	
		$\widehat{PRE}$	$\widehat{PET}$	$\widehat{PRE}$	$\widehat{PET}$
		(1)	(2)	(3)	(4)
	$\rho = 0$	-0.0066	-0.0379	-0.0067	-0.0384
		(0.0018)	(0.0025)	(0.0010)	(0.0025)
N=3					
	$\rho = 1$	0.0016	-0.0432	0.0011	-0.0437
		(0.0021)	(0.0020)	(0.0007)	(0.0021)
	$\rho = 0.7$	-0.0019	-0.0434	-0.0023	-0.0440
		(0.0020)	(0.0020)	(0.0007)	(0.0020)
	$\rho = 0.5$	-0.0041	-0.0429	-0.0045	-0.0437
		(0.0019)	(0.0020)	(0.0008)	(0.0021)
N=5					
	$\rho = 1$	0.0098	-0.0473	0.0100	-0.0473
		(0.0022)	(0.0021)	(0.0000)	(0.0022)
	$\rho = 0.7$	0.0033	-0.0457	0.0034	-0.0459
		(0.0021)	(0.0021)	(0.0005)	(0.0021)
	$\rho = 0.5$	-0.0016	-0.0442	-0.0017	-0.0447
		(0.0020)	(0.0020)	(0.0007)	(0.0021)

Notes: the table presents the estimates of Equation 6. All coefficients are estimated through OLS. The five major crops in each cell are considered for the calculation of yield. Each row assigns a different value of the parameter that enter in the calculation of the regressors of interest. Controls include unexpected variation in temperature and suitability index in cell c at time t, year and cell fixed effects. Robust standard errors clustered at cell level are reported in parentheses.

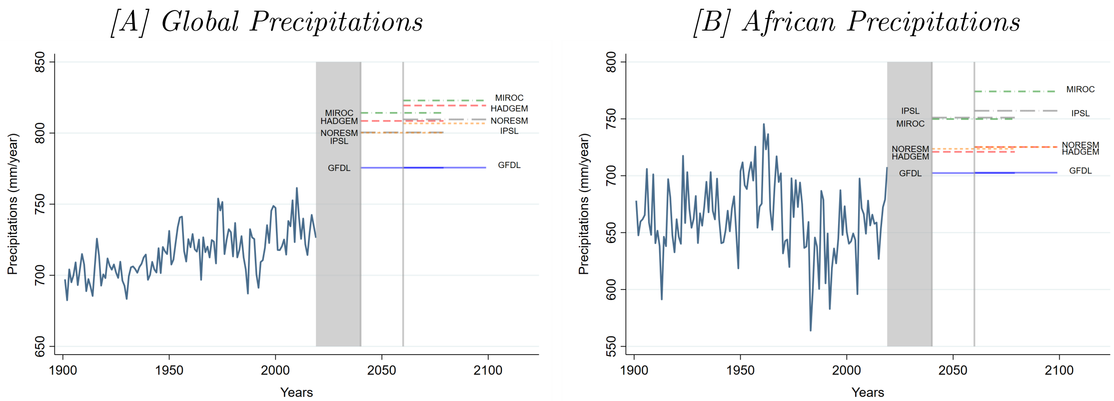
Table 7: Precipitations and PET projections - sample average

	RCP 4.5				RCP 8.5			
	Rainfall		PET		Rainfall		PET	
	2040-79	2060-99	2040-79	2060-99	2040-79	2060-99	2040-79	2060-99
GFDL	1094.3	1098.4	1437.5	1458.7	1099.7	1105.2	1520.6	1600.6
HadGEM2	1117.4	1123.7	1524.2	1566.7	1116.7	1114.1	1627.9	1743.6
IPSL	1176.0	1189.0	1500.6	1533.6	1222.3	1255.6	1608.7	1730.0
MIROC	1150.9	1180.3	1458.6	1488.6	1183.7	1224.0	1547.1	1547.1
NorESM1	1107.0	1113.4	1419.4	1441.1	1111.9	1128.0	1496.6	1578.9

Notes: the table presents the projections for yearly precipitations and PET (mm/year) averaged over our sample grid from five ESMs (GFDL-ESM2M, HadGEM2-ES, IPSL-CM54-LR, MIROC-ESM-CHEM, NorESM1-M) for the time intervals 2040-2079 and 2060-2099. Data is displayed for two RCP scenarios: 4.5 (decreasing "intermediate" emission levels by 2100) and 8.5 (non-decreasing "worst-case" emission levels by 2100). Source: CMCC-BioClimInd dataset.

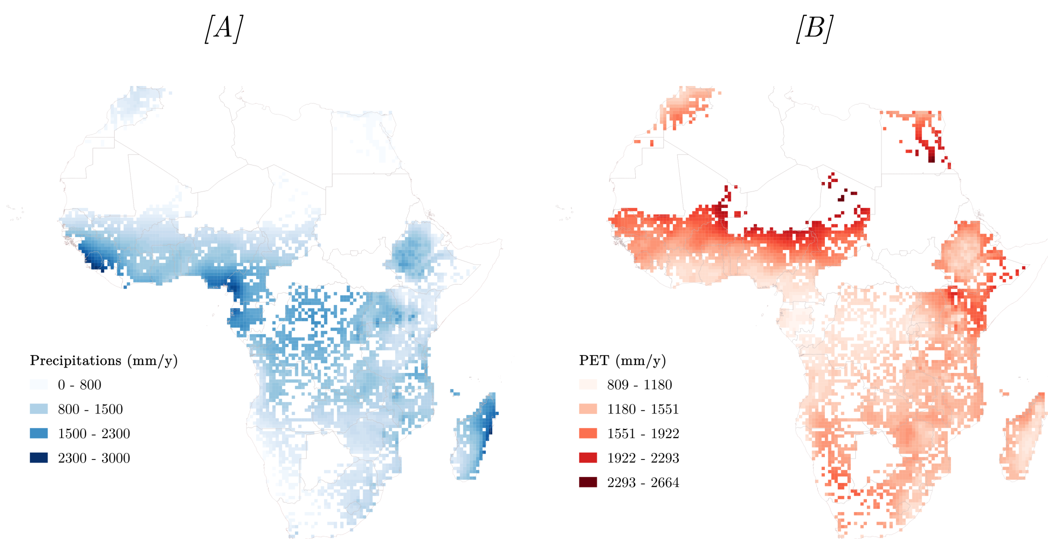
Figures

Figure 1: Historical trend and future projections in yearly precipitation, 1901-2099



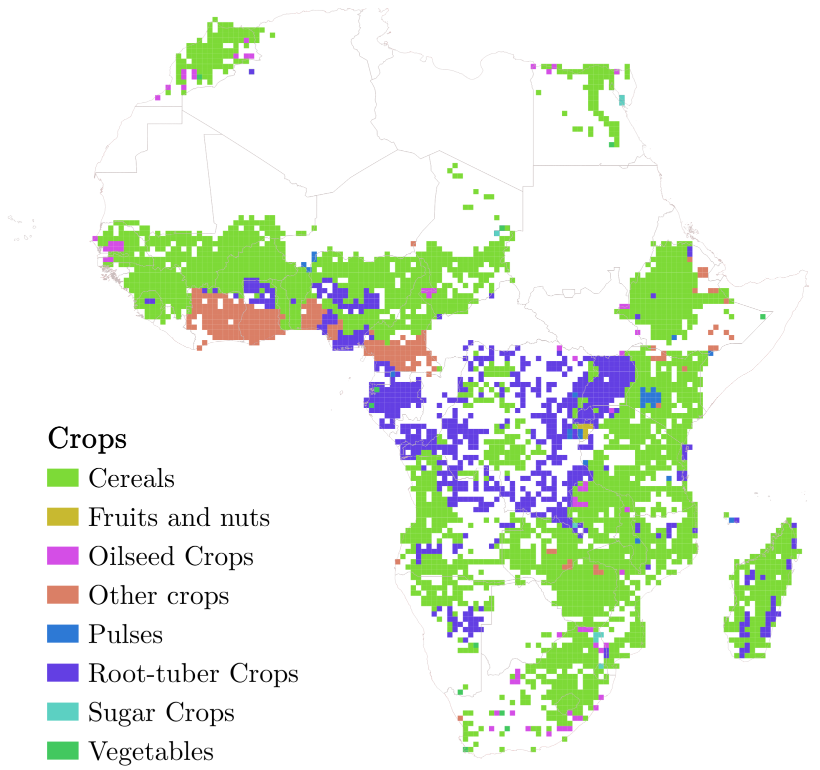
Notes: the figure depicts the trend in yearly precipitations (mm/year) starting form 1901. The series between 1901 and 2019 is computed from the CRU TS4.04 dataset. Projections for two time horizons (2040-2079 and 2060-2099) are accessed from five commonly employed Earth System Models (ESMs): GFDL-ESM2M, HadGEM2-ES, IPSL-CM54-LR, MIROC-ESM-CHEM, NorESM1-M. Bias-corrected projections are plotted under the Representative Concentration Pathway (RCP) 4.5, a greenhouse gas concentration trajectory which possibly constitutes the most probable baseline scenario taking into account the exhaustible character of non-renewable fuels. Panel [A] plots average global precipitations levels; panel [B] focuses on the African continent. Source: CMCC-BioClimInd dataset.

Figure 2: Geographical variation in Precipitations and PET (1951-2018)



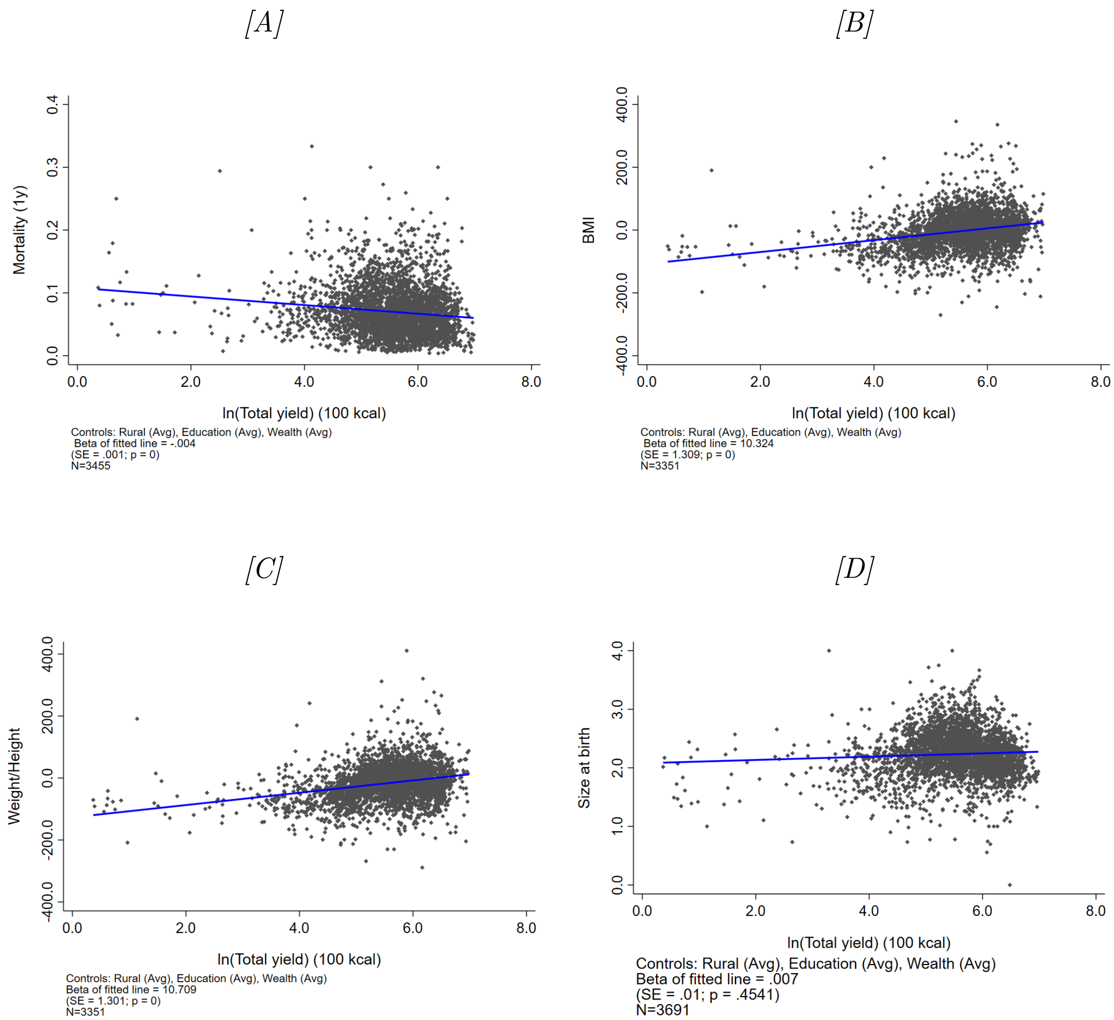
Notes: Panel [A] depicts precipitations (mm/year) over the sample grid. Panel [B] shows PET (mm/year) in the same cells. In Panel [A], lighter cells identify areas of scarce precipitations. In Panel [B], darker cells identify arid regions.

Figure 3: Most frequently harvested crop family per cell - average (2000; 2010)



Notes: the figure reports the crop family with the widest relative harvested area in each cell. Families are defined by the following crops: cereals (barley, maize, millet, rice, sorghum, wheat); fruits and nuts (banana); oilseed crops (groundnut, olive, rapeseed, soy, sunflower); pulses; root-tuber crops (cassava, potato, yam); sugar crops (sugar cane, sugar beet); vegetables; other (coffee, cotton, tobacco).

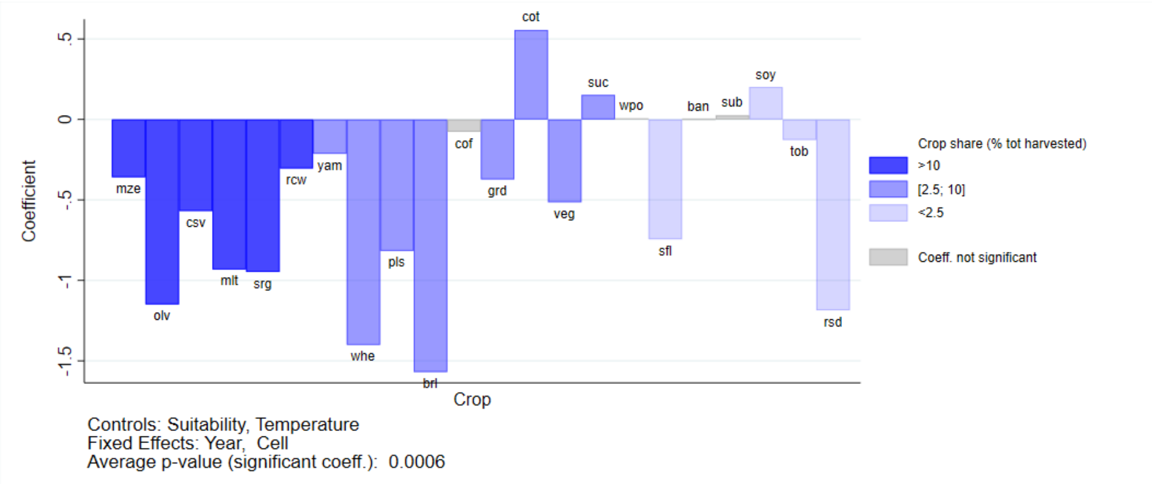
Figure 4: Geographical variation in Precipitations and PET (1951-2018)



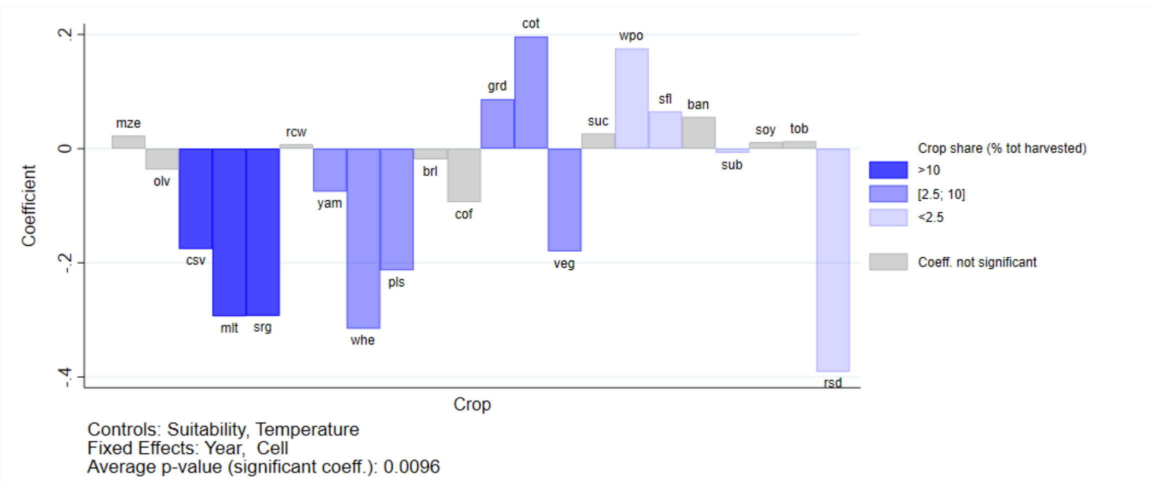
Notes: the figure reports the correlation across cells between child's health and crop yield. Fitted lines are obtained through of a linear regression of the the mean cell value of mortality [A], BMI [B], Weight/Height [C], and Size at birth [D] on the average crop yield between 2000 and 2010. Cell average of rural area, education and wealth index are added as controls. We only consider children born after year 2000 to match the period of our crop dataset.

Figure 5: PET and crop yield - single crop regressions coefficients

[A] Yearly values

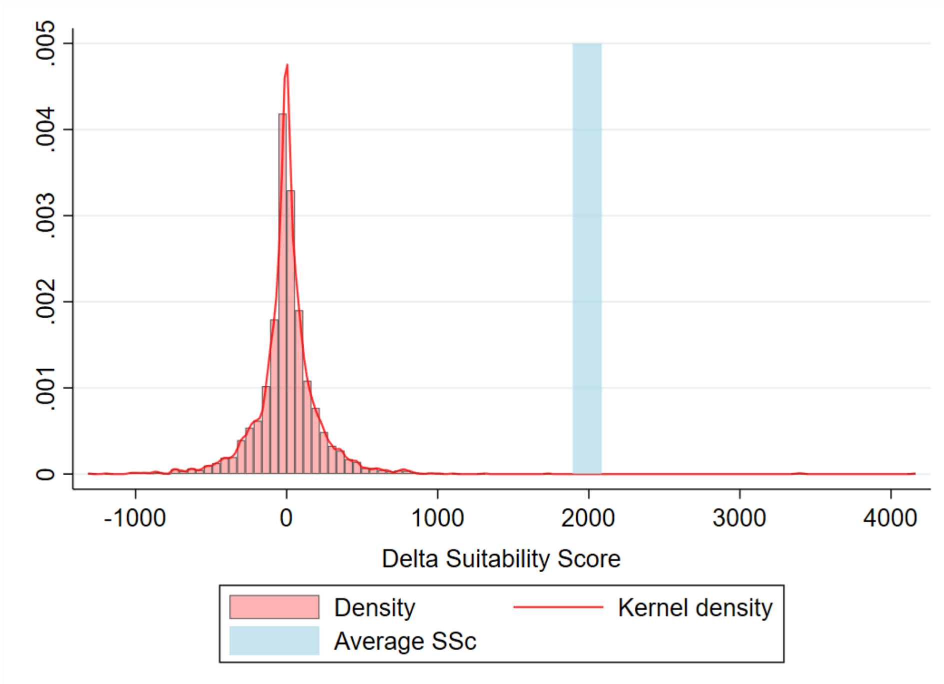


[B] Growing Season



Notes: the figure reports the set of coefficients obtained from of Equation 2. Panel A estimates Equation 2 using yearly values of precipitations and PET. In Panel B, these variables are calculated in growing season months. Bars coloured with darker shades represent a higher average share of the total harvested area in the cell. Grey bars are plotted when the coefficient is not significant.

Figure 6: Distribution of the variation in Suitability Score between 2000 and 2010



Notes: the figure reports the set of coefficients obtained from of Equation 2. Panel A estimates Equation 2 using yearly values of precipitations and PET. In Panel B, these variables are calculated in growing season months. Bars coloured with darker shades represent a higher average share of the total harvested area in the cell. Grey bars are plotted when the coefficient is not significant.

A.1 Data Appendix

A.1.1 Computation of Potential Evapotranspiration

We access a measure for potential evapotranspiration from the CRU TS.04 dataset. This is calculated using a modelling scheme based on climate simulations, developed by the Hadley Centre (HadRM3H). A full description of the relevant regional climate models can be found in Ekström et al. (2007). Here, we report a short summary explaining the computation of PET.

The estimates for PET are provided using a variant of the Penman-Monteith method, as proposed by FAO. This indicator is addressed as *potential* since it employs a grass reference crop [17] PET is computed according to the following equations:

$$PET = \frac{0.408\Delta\left(R_n - G\right) + \gamma + \frac{900}{T+273.16}U_2\left(e_a - e_d\right)}{\Delta + \gamma\left(1 + 0.34U_2\right)} \tag{7}$$

where R_n represent net radiation at crop surface (MJ m^{-2} per day), G is soil heat flux (MJ m^{-2} per day), T is mean temperature, U is wind speed ($\frac{m}{s}$), $(e_a - e_d)$ and Δ are respectively vapour pressure deficit and the relative slope of the vapour pressure curve ($\frac{kPa}{oC}$), and γ is a psychrometric constant. While wind speed and temperature are direct outputs from the HadRM3H, the other constants in the formula are calculated using model data.

As it appears from Equation 7, while temperature is indeed relevant in the computation of PET (which justify an average positive correlation of around 40% between PET and temperature), it is only part of the story. As such, by controlling for yearly average temperature in our main specifications, we are able to isolate the effect of soil water availability, without capturing potential noise coming from heat volatility.

A.1.2 Datasets and Variables description

Feedipedia: Feedipedia is a joint project of INRAE (formerly INRA-Institut National de la Recherche Agronomique, French National Institute for Agricultural Research), CIRAD (Centre de Coopération Internationale en Recherche Agronomique pour le Développement, French Agricultural Research Center for International Development, AFZ (Association Française de Zootechnie, French Association for Animal Production) and FAO (Food and Agriculture Organization of the United Nations).

FAO crop database: Crop based information provided by FAO is the resulting combination of Crop Ecological Requirements Database (ECOCROP), WCA infoNET (Internet-based integrated information platform managed by the International Programme for Technology and Research in Irrigation and Drainage (IPTRID), and FAOSTAT dataset.

Precipitations (PRE): total, mm /year

Potential evapotranspiration (PET): total, mm/year. See Section A.1.2 for computational details

Temperature: °C, average monthly value at $2m$ altitude.

Growing Season: growing season months are calculated using beginning date of earliest growing period (day-of-year) for the time period 1981-2010, and the total number of growing period days.

[17] For the original contribution on this computation, see Allen et al. (1994).

Both measures are accessed through the GAEZ v4 dataset, which employs climate data source HadGEM2-ES. More information can be found in Fischer et al. (2021).

Yield: tons/hectare of dry matter product. The corresponding yield expressed in kcal/m^2 is calculated according to the following formula: $Y_{kcal/m^2} = \frac{1}{100} Y_{ton/ha} \cdot Energy_{kcal/ton}$.

Suitability index (SI): Crop suitability index (range 0 – 10000); weighted sum of the component soil/terrain suitability rating factors. Extensive details on the methodology employed to compute the indicators reported can be found in Fischer et al. (2021).

Infant Mortality (1-5 years): binary indicator computed using mother-reported time of death after birth (in months).

BMI (SD): Body Mass Index, defined as her weight in kilograms divided by the square of her height in meters (W/H^2), and then expressed in standard deviations.

Weight/Height: Weight for Height standard deviations from the reference median based on the DHS reference standard.

Anemic: binary indicator telling whether a child is anemic. Anemia is measured as follows: levels below 7.0 g/dl hemoglobin are considered as severe anemia, levels between 7.1g/dl and 9.9g/dl are considered as moderate anemia and cases between 10.0 g/dl and 10.9 g/dl are considered as mild anemia. The indicator defines the presence of any form of anemia (mild to severe) against no anemia.

Education: Highest year of education gives the years of education completed.

Wealth index: a composite measure of a household's cumulative living standard, calculated using easy-to-collect data on a household's ownership of selected assets, such as televisions and bicycles; materials used for housing construction etc. Generated by principal components analysis, the index ranks individual households into five wealth quintiles.

Source of drinking water: Main source of drinking water for members of the household (major categories).

A.1.3 CRU TS.04 choice and comfront with alternative datasets

When it comes to environmental studies, more than one alternative to researchers in need of high-frequency data on weather and climate conditions. Researchers have been comparing and highlighting the peculiarities of these different sources . However, there exist no rule of thumb guiding through the adoption of one particular dataset

In their paper on weather shocks, malaria and child mortality, Kudamatsu et al. (2012) access observations on monthly rainfall through the 45-Year European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) data archive, provided by the European Centre for Medium-Term Weather Forecasting (ECMWF). The authors justify their choice by claiming the superiority over the more well-known CRU dataset. Their main argument relies on the fact that rainfall gauge data in Africa lack the necessary quality, and show bias in arid and semi-arid areas, where departures from standard seasonal fluctuations are more pronounced. A similar argument is provided by Harari & Ferrara (2018) to justify the adoption of the ERA-40. Other authors instead have deemed gauge data suitable for the purpose of their studies, and have thus turned at the

CRU dataset, usually in its previous versions (Vicente-Serrano et al. 2010, Couttenier & Soubeyran 2014).

While the concerns with gauge data are surely legitimate, significant drawback are implied also by the choice of reanalysis data. Firstly, the ERA-40 dataset is provided at more than twice the resolution of the CRU TS.04, 1.25 $\times$ 1.25 degress (roughly 139 km $\times$ 139 km), which is a significant loss in terms of spatial variation. Being our sample an unbalanced panel, variation across grid cells is of great importance and, as such, this could impinge the detection of an effect of precipitations and PET on agricultural productivity and infant health. As such, another alternative available to researchers is the ERA-5 dataset, in which near-surface meteorological variables have been re-gridded to a half-degree resolution. Yet, in addition to using monthly-scale bias corrections still based CRU data, this dataset is available only form 1980.

Secondly, re-analysis relies on a variety of sources, including weather stations, ships, aircrafts and satellites. To provide the corresponding weather measures, recorded data is analysed through an atmospheric circulation model (IFS CY23r4). Compared to gauge data, this augments the risk of measurement error.

It is indeed true that CRU stations are partially dispersed in Sub-Saharan Africa and, since they cannot provide full direct coverage, the resulting data relies on interpolation. However, the data on station location and resulting cover contained in Harris et al. (2020), in which stations appear if they contribute at least 75% of observations in the decade, show that the problem of loss of variability due to interpolation may be more of a concern in the areas of scarce coverage (in this case, historical data would have a greater role in filling in for missing observations). In Figure A.1, we plot the spatial distribution of the clusters available from the DHS with the resulting coverage of the CRU stations in decades 1970-79 and 2000-09. Coverage in the CRU dataset is defined as an area having direct measurement of at least 75% of all potential observations in the decade. We notice that most of the clusters in the sample are actually within the declared coverage, which reassures at least on the probability of errors generated by the stations. As we use the area identified by DHS cluster to run the analysis on crop productivity, a similar reasoning applies for crop yield observations.

This evidence ultimately helps reduce the concern that our data may not capture properly the variability in precipitations and PET, which is essential to our research strategy, and contributes to justify the choice of the CRU TS.04 dataset.

A. Tables

Table A.1: Precipitations, PET and crop productivity in Africa - Caloric yield

Yield (kcal/m^2)	(1) OLS	(2) OLS	(3) OLS	(4) IV
		[A] Yearly values		
Prec $_t$	0.06***	0.02***	0.01*	0.0126*
	(0.01)	(0.01)	(0.01)	(0.0066)
PET $_t$		-0.33***	-0.45***	-0.3209***
		(0.02)	(0.02)	(0.0215)
Observations	36,971	36,971	36,971	36,971
R^2	0.90	0.90	0.90	
		[B] Growing season		
Prec GS $_t$	0.0187***	0.0169**	0.0100	-0.0062
	(0.0053)	(0.0075)	(0.0076)	(0.0081)
PET GS $_t$		-0.0066	-0.0547***	-0.0227
		(0.0151)	(0.0173)	(0.0193)
Observations	32,949	32,949	32,949	32,949
R^2	0.8978	0.8978	0.8979	
Controls	Y	Y	Y	Y
Lags	N	N	Y	N
Crop FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster FE	Y	Y	Y	Y
Crops				5 Major
F-stat. (excl.)				145

Notes: Panel [A] shows the estimates using yearly values of precipitations and PET. In Panel [B], precipitations and PET are calculated using only growing season months. Restricting the analysis to four major crops accounts on average for roughly 80% of the total harvested area in the cell. Robust standard errors are clustered at cell level, with significance levels at 10, 5, and 1 percent.

Table A.2: Impact of Precipitations and PET on infant health - Additional outcomes

	Mort (5y)			**W/H (SD)**		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
			[A] Yearly values			
Prec_t	-0.0048***	-0.0026***	-0.0008	7.9419***	5.4943***	4.6207***
	(0.0009)	(0.0010)	(0.0012)	(1.1803)	(1.2505)	(1.5327)
$\text{Prec}_{(t-1)}$	-0.0033***	-0.0013	0.0005	3.1379***	0.8670	-0.5593
	(0.0009)	(0.0010)	(0.0012)	(1.1443)	(1.2045)	(1.4665)
PET_t		0.0053	0.0045		-6.9669	-11.4910*
		(0.0045)	(0.0053)		(5.0209)	(5.8866)
$\text{PET}_{(t-1)}$		0.0033	0.0086		-5.1389	-15.5620***
		(0.0044)	(0.0052)		(4.9873)	(5.7643)
Observations	2,059,690	2,059,690	2,059,690	267,083	267,083	267,083
R^2	0.0601	0.0601		0.1964	0.1966	
			[B] Growing season			
Prec GS $_t$	-0.0027***	-0.0017*	-0.0001	3.0697***	1.9820*	2.0379
	(0.0009)	(0.0009)	(0.0011)	(1.0663)	(1.1028)	(1.2971)
Prec GS $_{(t-1)}$	-0.0034***	-0.0027***	-0.0017	2.9896***	1.7785	0.9190
	(0.0008)	(0.0009)	(0.0011)	(1.0694)	(1.1072)	(1.3014)
PET GS $_t$		0.0053**	0.0053		-4.1160	-3.0178
		(0.0025)	(0.0035)		(2.7023)	(3.6697)
PET GS $_{(t-1)}$		0.0006	0.0041		-5.8206**	-14.9041***
		(0.0024)	(0.0035)		(2.6913)	(3.6638)
Observations	1,721,384	1,721,384	1,721,384	228,387	228,387	228,387
R^2	0.0600	0.0600		0.1811	0.1812	
Controls	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y
Cluster FE	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y
F-stat. (excl.)			1833			675.3

Notes: the table presents the estimates of β_1 and β_2 for comparable outcome variables. Long controls include woman's education in single years, wealth index of the household, kid's month of birth, main source of water, cell temperature in the corresponding time period. Columns (1) to (3) are based on a sample of 33 countries and 22,757 clusters. Columns (4) to (9) are based on a sample of 34 countries and 22,909 clusters. In Panel [A], precipitations and PET are computer over the entire year; in Panel [B], only growing season months are considered. Robust standard errors are clustered at DHS cluster level, with significance levels at 10, 5, and 1 percent.

Table A.3: First stage coefficients - multiple equations

	Table 4 Col (6) Yield	Table 5 Col (3) Mort (1y/5y)	Table 5 Col (6) BMI (SD)	Table 5 Col (9) Size at birth	Table A.2 Col (6) W/H (SD)
			[A] Yearly values		
PRE_t	0.98	0.82	1.03	1.08	1.03
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$\text{PRE}_{(t-1)}$		0.82	1.03	1.07	1.03
		(0.00)	(0.00)	(0.00)	(0.00)
PET_t	0.91	0.79	0.72	0.76	0.72
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
$\text{PET}_{(t-1)}$		0.79	0.74	0.77	0.74
		(0.00)	(0.01)	(0.01)	(0.01)
			[B] Growing season		
PRE GS $_t$	0.98	0.79	1.04	1.06	1.04
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
PRE GS $_{(t-1)}$		0.79	1.04	1.05	1.04
		(0.00)	(0.00)	(0.00)	(0.00)
PET GS $_t$	0.65	0.71	0.84	0.77	0.84
	(0.05)	(0.01)	(0.02)	(0.01)	(0.02)
PET GS $_{(t-1)}$		0.69	0.76	0.72	0.76
		(0.01)	(0.01)	(0.02)	(0.01)

Notes: the table reports first-stage coefficients from the IV regressions in the paper. Standard errors are reported in parentheses. All models are just-identified and comprise of at least two instruments. As such, columns identify the model regression to which coefficients refer to. Rows capture instead the first stage dependent variable. The reported value is then the coefficient of the corresponding regressor in the first-stage equation (e.g. instrumented: PRE_t; reported coefficient: PRE_t (neighbours)).

Table A.4: Impact of Precipitations and PET on infant health - long-settled sample

	Mort (1y)		**BMI (SD)**		**Size at birth**	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
			[A] Yearly values			
Prec_t	-0.0017*	0.0029***	5.3897***	4.6965**	0.0169**	0.0228**
	(0.0009)	(0.0010)	(1.5072)	(1.8276)	(0.0083)	(0.0098)
$\text{Prec}_{(t-1)}$	-0.0009	0.0037***	2.2763	2.0342	0.0166**	0.0220**
	(0.0009)	(0.0010)	(1.4348)	(1.7275)	(0.0076)	(0.0089)
PET_t	0.0007	-0.0007	-7.4546	-12.2176*	0.0280	-0.0258
	(0.0044)	(0.0051)	(6.0538)	(7.2021)	(0.0315)	(0.0373)
$\text{PET}_{(t-1)}$	0.0015	0.0057	-2.4066	-10.5591	-0.0998***	-0.0475
	(0.0043)	(0.0051)	(6.0461)	(7.0854)	(0.0315)	(0.0370)
Observations	1,673,718	1,673,765	199,674	199,674	378,859	378,859
R^2	0.0436		0.2292		0.1529	
			[B] Growing season			
Prec GS $_t$	0.0005	-0.0003	2.8326**	2.7997*	0.0061	-0.0055
	(0.0007)	(0.0010)	(1.3546)	(1.5808)	(0.0077)	(0.0093)
Prec GS $_{(t-1)}$	0.0000	-0.0014	2.7837**	2.8029*	-0.0020	-0.0124
	(0.0008)	(0.0010)	(1.3257)	(1.5409)	(0.0072)	(0.0087)
PET GS $_t$	-0.0007	0.0004	-5.3823*	-0.1575	-0.0393**	-0.0656***
	(0.0023)	(0.0034)	(3.1412)	(4.4414)	(0.0172)	(0.0232)
PET GS $_{(t-1)}$	0.0007	0.0027	-3.1989	-16.1685***	-0.0229	-0.0316
	(0.0023)	(0.0033)	(3.1077)	(4.4204)	(0.0172)	(0.0231)
Observations	1,384,393	1,384,359	166,138	166,138	311,944	311,944
R^2	0.0207		0.2101		0.1467	
Controls	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y
Cluster FE	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y
F-stat. (excl.)		3126		424.7		517.5

Notes: the table presents the estimates of β_1 and β_2 on the sample of women who have been living in the same place of residence for at least 15 years. Long controls include woman's education in single years, wealth index of the household, kid's month of birth, main source of water, cell temperature in the corresponding time period. Columns (1) and (2) are based on a sample of **TBC**countries and **TBC**clusters. Columns (3) to (6) are based on a sample of **TBC**countries and **TBC**clusters. In Panel [A], precipitations and PET are computer over the entire year; in Panel [B], only growing season months are considered. Robust standard errors are clustered at DHS cluster level, with significance levels at 10, 5, and 1 percent.

Table A.5: Precipitations, PET and crop productivity - Unstandardized coefficients

Yield (ton/ha)	(1) OLS	(2) OLS	(3) OLS	(4) IV
		[A] Yearly values		
Prec_t	0.0001***	0.0000***	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PET_t		-0.0011***	-0.0015***	-0.0010***
		(0.0001)	(0.0001)	(0.0001)
Observations	38,520	38,520	38,520	38,520
R^2	0.8968	0.8971	0.8973	
		[B] Growing season		
Prec GS $_t$	0.0003***	0.0003**	0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PET GS $_t$		-0.0002	-0.0029***	-0.0013
		(0.0007)	(0.0009)	(0.0008)
Observations	34,208	34,208	34,208	34,208
R^2	0.8952	0.8952	0.8954	
Controls	Y	Y	Y	Y
Lags	N	N	Y	N
Crop FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cell FE	Y	Y	Y	Y
F-stat. (excl.)				83.42

Notes: Panel [A] shows the estimates using yearly values of precipitations and PET. In Panel [B], precipitations and PET are calculated using only growing season months. The sample comprises on the five major crops in each cell by harvested area. These account on average for roughly 80% of the total harvested area in the cell. Environmental variables are standardized. Robust standard errors are clustered at cell level, with significance levels at 10, 5, and 1 percent.

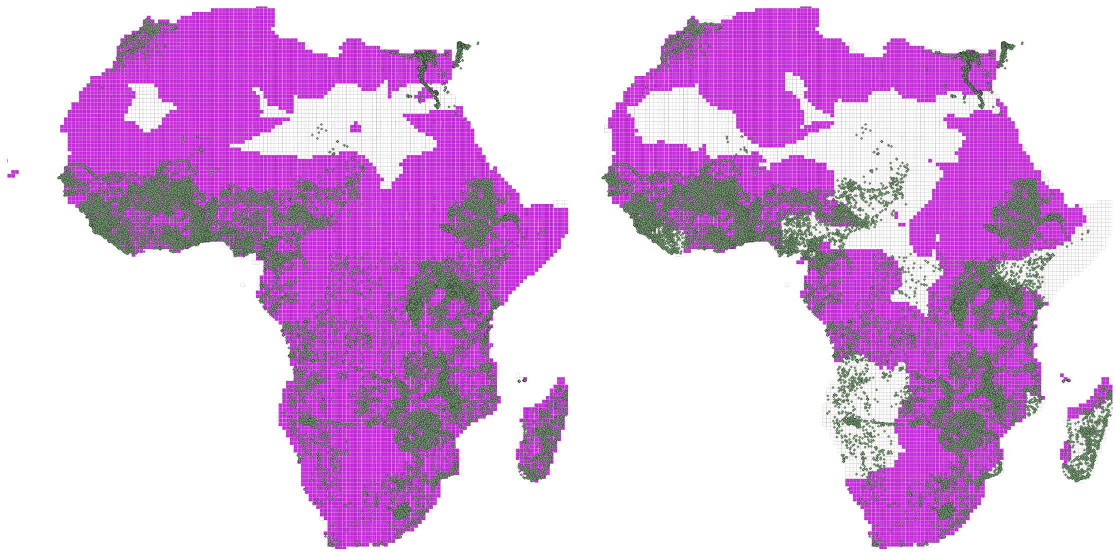
Table A.6: Precipitations, PET and child health - Unstandardized coefficients

	Mort (1y)			BMI (SD)			Size at birth		
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					[A] Yearly values				
Prec_t	-0.0000***	-0.0000**	0.0000	0.0125***	0.0087***	0.0070***	0.0001***	0.0000***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0020)	(0.0022)	(0.0027)	(0.0000)	(0.0000)	(0.0000)
Prec_{t-1}	-0.0000**	-0.0000	0.0000**	0.0056***	0.0022	-0.0001	0.0001***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0020)	(0.0021)	(0.0025)	(0.0000)	(0.0000)	(0.0000)
PET $_t$		0.0000	0.0000		-0.0309*	-0.0437**		0.0000	-0.0001
		(0.0000)	(0.0000)		(0.0166)	(0.0196)		(0.0001)	(0.0001)
PET $_{t-1}$		-0.0000	0.0000		-0.0044	-0.0401**		-0.0002***	-0.0001
		(0.0000)	(0.0000)		(0.0166)	(0.0192)		(0.0001)	(0.0001)
Observations	2,059,719	2,059,690	2,059,706	266,469	266,469	266,469	518,591	518,591	518,591
R^2	0.0352	0.0391		0.1999	0.2000		0.1331	0.1332	
					[B] Growing season				
Prec GS_t	-0.0000***	0.0000	-0.0000	0.0700***	0.0489**	0.0525**	0.0003***	0.0002	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0220)	(0.0228)	(0.0267)	(0.0001)	(0.0001)	(0.0002)
Prec GS_{t-1}	-0.0000	0.0000	-0.0000**	0.0658***	0.0445**	0.0315	0.0002**	0.0001	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0219)	(0.0227)	(0.0267)	(0.0001)	(0.0001)	(0.0001)
PET GS_t		0.0025	0.0040		-7.2105*	-3.2012		-0.0655***	-0.1025***
		(0.0032)	(0.0046)		(4.2934)	(5.8215)		(0.0231)	(0.0316)
PET GS_{t-1}		-0.0019	0.0001		-7.2090*	-23.6809***		-0.0216	-0.0388
		(0.0032)	(0.0046)		(4.2735)	(5.8300)		(0.0230)	(0.0314)
Observations	1,721,409	1,721,391	1,721,384	227,786	227,786	227,786	432,729	432,729	432,729
R^2	0.0349	0.0198		0.1833	0.1835		0.1287	0.1289	
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat. (excl.)			1639			674.4			457.9

Notes: the table presents the estimates of $\beta_{\mathbf{1}}$ and $\beta_{\mathbf{2}}$. Long controls include woman's education in single years, wealth index of the household, kid's month of birth, main source of water, cell temperature in the corresponding time period. Columns (1) to (3) are based on a sample of 33 countries and 22,757 clusters. Columns (4) to (9) are based on a sample of 34 countries and 22,909 clusters. In Panel [A], precipitations and PET are computer over the entire year; in Panel [B], only growing season months are considered. Robust standard errors are clustered at DHS cluster level, with significance levels at 10, 5, and 1 percent.

A. Figures

Figure A.1: Positive PET trend in 1951-2019 and crop WRI distribution



[1970-79] [2000-09]

Notes: green dots represent the spatial distribution of DHS clusters in our sample. The purple shaded area identifies grid cell station coverage of the CRU dataset in decades 1970-79 and 2000-09.
Source: Harris et al. (2020)

GREEN
Centre for Geography, Resources, Environment, Energy and Networks
via Röntgen, 1
20136 Milano - Italia

www.green.unibocconi.eu