# Yet it Rains. Aridification, Agriculture and Farmers' Adaptation in Sub-Saharan Africa

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**Abstract**

Although the relationship between climate and agriculture has been extensively studied, the present study explores how the often-overlooked phenomenon of soil aridity (proxied with a measure of soil evapotranspiration) impacts agricultural productivity in Sub-Saharan Africa. Climate conditions and crop yield measures are collected over a grid of 0.5° x 0.5° for 32 African countries. We find that areas with higher soil aridity suffer from lower agricultural productivity. We document that those results are partly due to farmers' adaptation to changing climate conditions. Finally, we project how future climate conditions will affect agriculture in the African continent under different scenarios. The paper emphasizes the importance of accounting for aridity alongside precipitations when assessing the economic impact of climate change.

**Keywords: Climate, potential evapo-transpiration, agricultural productivity**

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

# 1 Introduction

The effects of climate change and global warming have been central issues in the recent scientific and economic literature. Studies have found strong evidence of a relationship between climate variations and economic welfare 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 relationship mentioned above 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 (Peri & Robert-Nicoud 2021).

Among the numerous implications of climate change, the water availability of the soil remains a key concern. A stable and reliable water source is crucial for as well as agricultural and economic systems. Soil water availability is strongly influenced by precipitation and its intensity. But how is soil water availability defined? Rainfalls provide the first source of water for agricultural practices. Part of this water evaporates. As a result, the effective amount of water the soil retains may vary greatly depending on the degree of evaporation. The degree to which water evaporates from the soil is measured with the potential evapotranspiration index (henceforth PET). The PET considers the combination of two sources of soil water loss, namely the 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; (Rind et al. 1990, Allen et al. 1998, Cherlet et al. 2018)).

In this study, we assess the role of precipitations when matched with our measure of soil water retention. We combine data on temperature and rainfall defined on a 0.5° latitude x 0.5° longitude (ca. 56km X 56 km at the equator) to study the differential impact of our measures on crop yields in 32 African countries.

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%.

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 socio-economic development in Sub-Saharan African countries. Indeed, especially in low-income countries and rural areas, agriculture directly supplies food and nutrition and constitutes a significant source of income for individuals. Still, little is known about the relationship between crop productivity and PET.

Given the exacerbated soil water loss, one may expect a rising trend in PET to negatively impact agricultural output, 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.

Early studies suggest that rainfall has a positive impact on human development in rural areas, mainly through its positive effects on agriculture. 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.

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.

Drawing from previous research identifying agriculture as the primary mechanism through which rainfall impacts socio-economic development, this work aims to clarify whether a relationship exists between precipitations, PET, and agricultural output. We gather data on crop suitability, production, harvested land, and yield for 21 crops covering 3,896 cells in 32 African countries. We combine agricultural data from the Food and Agriculture Organization (FAO) with precipitations, PET, and temperatures. Climate variables are calculated using the entire solar year or the cell-specific growing season months. We first show a negative relationship between PET and crop yield, although the ultimate effect depends on the composition of agricultural output in the area. Moreover, we find that precipitation alone cannot explain variations in agricultural productivity and becomes an even second-order factor when PET is considered.

This paper contributes to the economic and environmental literature on the effects of weather conditions and climate change in several ways. First, by using the most comprehensive 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 the increase in evapotranspiration negatively affects agricultural productivity. In this regard, the paper adds to the literature on rainfall's effect on agricultural productivity.

In addition, this paper relates 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).

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 present the data used to assess the relationship between Aridity and crop yields. In Section 4, we study the relationship between rainfall, PET, and agricultural productivity. In Section 5, we document the farmers' adaptation to aridification. In Section 6, we use projections of climate variables to compute the future impacts of soil aridification on agricultural outputs. Finally, Section 7 concludes.

## 2 Background

There is an ongoing debate about how global precipitation levels will change in the near future due to rising temperatures and changes in the earth's composition. Initially, climate change was thought to cause a wet-get-wetter and dry-get-drier pattern due to atmospheric moisture convergence and divergence (Held & Soden 2006). However, this idea has been challenged due to a lack of evidence. It is believed that precipitation will increase in high- and mid-latitudes but not decrease in subtropical regions (Kirtman et al. 2013, Donat et al. 2016). As a result, the global average rainfall is expected to increase in the coming years (Cherlet et al. 2018).

The existing literature suggests that higher precipitation levels could help prevent drought and boost agricultural productivity, and rural communities may benefit from weather variations. Climate change could 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.

# 3 Data

## 3.1 Climate Variables

We access publicly available data from 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 climate variations over 1901–2019, provided on high-resolution (0.5 degrees by 0.5 degrees) grids.[2] To harmonize the different data sources on climatic factors and crops. We focus on an area covering almost 40% of the entire African continent. Moreover, this paper 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, briefly summarized in Section A.1.1 in the Appendix.

We report the evolution of our environmental measures over the sample period in Table 1. The 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

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

[2]As 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.

sample period; however, the study's series points in that direction. Indeed, the average precipitations appear 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, aridification and rising temperatures seem to accelerate from the 80s.

Table 1 reports summary statistics and correlations between the climate variables used in this research. The average yearly precipitations and PET level throughout the sample period are plotted in Figure 2 to visually represent the cross-sectional variability across grids. 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 exceeds the average precipitations.[3]

### 3.2 Crop Yields and Harvested Areas

To verify the relationship between PET, precipitations, and agriculture, we also collect crop and agricultural productivity data 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 is available for 22 crops, representing a consistent share of agricultural output in the area. 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) on the 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 the historical

[3]When PET exceeds actual precipitation, it indicates that the soil may eventually dry out unless irrigation is used to outset the loss. However, the effective amount of water dispersed depends also on the type of plants cultivated on the land.

climate between 1981 and 2010. This measure is a weighted sum of the component soil or terrain suitability rating factors.[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 in the African content relies highly 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. Cereals such as maize and millet, tubers such as cassava and yam, and olives account, on average, for a high share of the cultivated area in each cell. Moreover, while the cultivable area devoted to each crop remained constant, the average yield grew for almost all crops. This is explained by a progressive improvement in crop management techniques, for example, mechanization, 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 quantifies 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.

# 4 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

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

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

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 above-mentioned 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:

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

where $\log(Y)_{c,k,t}$ represents the natural logarithm of the yield of crop $k$ at time $t$ in cell $c$. The time dimension comprises only two years, 2000 and 2010. $PRE_{c,t}$ and $PET_{c,t}$ are 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 a set of crop- and cell-specific controls. To ensure 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 years 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 neighboring cells in the same year.[6] 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 of 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 precipitation. Indeed, if one considers precipitations and soil evapotranspiration as two independent processes, 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 help reconsider the role of rainfall in the literature.

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

# 5 Empirical findings

## 5.1 Baseline Results

The estimates of Equation 1 are reported in Table 3. To ease the interpretation of the estimates, 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 has a two-fold implication. First, evapotranspiration affects agricultural yield significantly: when PET increases by one standard deviation, yield is expected to decrease by 32.67% (Column 2). Second, the effect attributed to precipitations is almost three times lower than that in the previous regression and is still 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 coefficients of interest, while the significance is partially lost only for precipitations.[7]

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.[8] The 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 between 0.37% and 5.6%, with scattered significance.

Weather conditions, even outside growing season months, affect agricultural produc-

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

[8] Data on the growing season in each cell are available through the GAEZ v4 database, starting from 1960. The growing season is calculated using the beginning date of the earliest growing period and the total number of growing period days. Further details are provided in Section A.1 in the Appendix

tivity. This can be easily explained by the fact that farmers may not comply with model-derived harvesting periods since the latter considers the average crop composition in the cell. Similar considerations could be made for the effects of precipitation in the growing season. However, it is still evident that accounting for PET captures part of the effect previously attributed to rainfall.

### 5.2 Heterogeneous Effects by Crop

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 4. The graph shows that some crops benefit from increased 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 3 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 the impact of aridity and rainfall, we thus newly estimate Equation 1, this time using our data on the dry-mass caloric intake to express crop yield in kcal/m$^2$.

The results are reported in Appendix Table A.1. The results are very similar to those presented in Table 3, and the coefficients are relatively unchanged. Focusing on yearly values of precipitations and PET (Panel A), when precipitations are the primary 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 strong negative impact on caloric yield: one standard deviation increase in PET implies between a 32% and 45% kcal/m$^2$ 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.

From those results, we conclude 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 is e affected differently depending on the production mix adopted in the agricultural sector.

Section Farmers' adaptation to aridification

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. Based on 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 less water throughout the growing period. As a result, 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.

Therefore, farmers' expectations regarding future weather conditions must be considered. 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 $\rho$, according to the following equation:

$$\mathbb{E}[V]_t = \sum_{i=1}^{N} \frac{\rho^{i-1} V_{t-i}}{\rho^{i-1}} \tag{3}$$

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

$$\log(Y)_{c,k,t} = \sum_{r=0}^{1} \alpha_{1,r} \widehat{PRE}^{g}_{c,t-r} + \sum_{r=0}^{1} \alpha_{2,r} \widehat{PET}^{g}_{c,t-r} + \gamma X_{k,c,t} + \delta_{k(c)(t)} + \varepsilon_{k,c,t} \tag{4}$$

where $\widehat{V}_t = V_t - \mathbb{E}[V_t]$, 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 $\rho$ ($\rho \in \{0, 0.5, 0.7, 1\}$). These values 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 4. While the effect of unexpected variation in precipitations is fuzzy, with coefficient switching signs and generally high standard errors, the PET appears more stable: the coefficients are systematically negative and always significant. The magnitude of the coefficients is considerably lower than those estimated in Table 3, in order of magnitude of roughly 0.1 to 0.2. This, in turn, implies that the effect of PET cannot be attributed uniquely to its unexpected component, reinforcing even further the belief that limited adaptation, if at all, is not enough to obfuscate our findings significantly.

# 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. 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.

In this section, we use projections of future levels of PET and rainfall to compute future aridification impacts on agricultural outputs over two-time horizons (2040-2079 and 2060-2099) for the sample grid from five different Earth System Models (ESMs) over two representative concentration pathways (RCP) scenarios.[9]

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 focuses 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 $21^{st}$ 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 5, 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 precipitation is expected to boost crop yield by 0.77 to 1.72 percentage 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. 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

[9] The time series at $0.5° \times 0.5°$ grid resolutions are produced by five ESMs: GFDL-ESM2M, HadGEM2-ES, IPSL-CM54-LR, MIROC-ESM-CHEM, NorESM1-M. These are 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).

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%) turn into considerable losses (-5.8 to -45.89% for crop yield). While this is a less likely scenario, it provides a negative benchmark on how aridity could dramatically impact African households in the following decades.

## 7 Conclusion

In this study, we have reconsidered the role of climate variations on crop yields from 32 African countries. In particular, we have combined the effects of precipitation and soil evapotranspiration on agricultural productivity using grid-level data of more than 4,000 cells of 0.5° latitude x 0.5° longitude in Sub-Saharan Africa.

We show that when considered alone, higher rainfall positively affects crop yields. One standard deviation increase in precipitations leads to higher crop yields. However, when PET is included, the effect of precipitation fades. We show that soil evapotranspiration negatively affects crop yield. This effect counteracts the benefits of higher precipitation. As a result, areas that have experienced increased precipitation might have desertified if the soil evapotranspiration effect was greater than that of precipitation.

In the second part of the paper, we document that, to a certain degree, local farmers showed signs of adaptations to the process of aridification by changing the cultivation to less water "thirsty" crops. However, it is not enough to counteract the negative effects caused by the higher soil aridity.

In the last part of the paper, we used future projections of precipitations and PET to assess the future agricultural losses under different climate scenarios.

Our 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.

Future research should focus on understanding farmers' ability to adapt to the challenges of global warming and how 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.

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# 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:* The table reports mean values over a grid of 3,896 cells.
*Harvested area for each crop is expressed as the 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 millimeters per hectare of area cultivated.

Table 3: Precipitations, PET and crop productivity in Africa

| *Yield (ton/ha)* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | OLS | OLS | OLS | 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 the five major crops in each cell by harvested area, which account for an average of 80% of the total harvested area in the cell. Environmental variables are standardized. Controls include temperature and SI. Robust standard errors are clustered at the cell level, with 10, 5, and 1 percent significance levels.

Table 4: 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 4. 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.

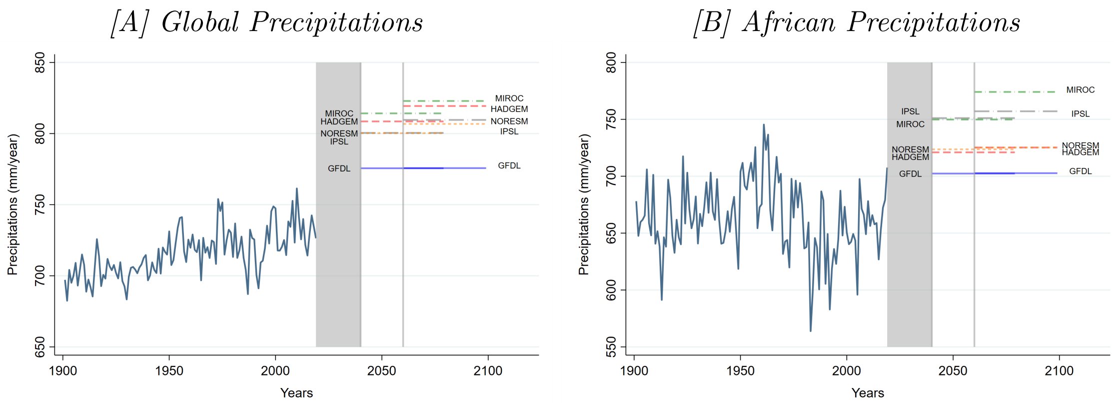
Table 5: Precipitations and PET projections - sample average

| | 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.

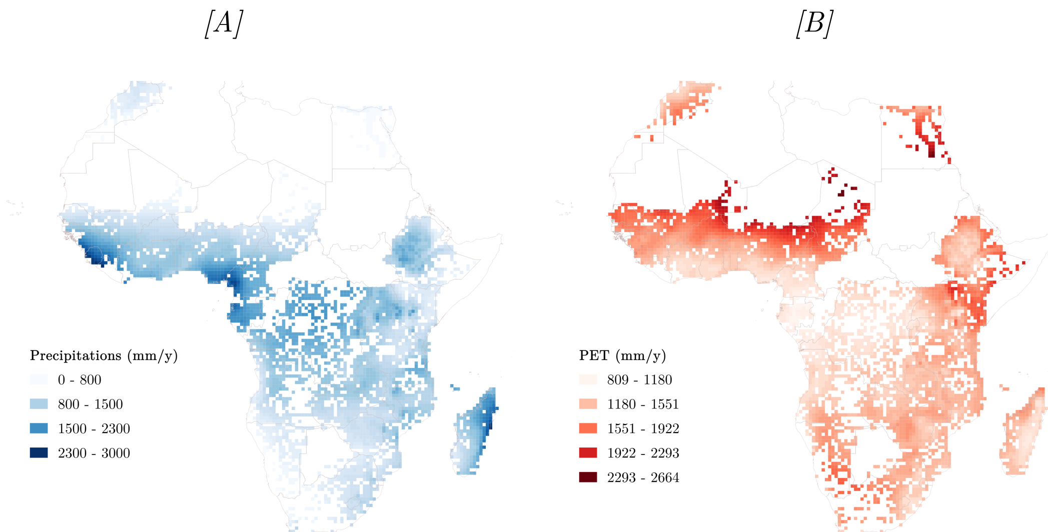
# Figures

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



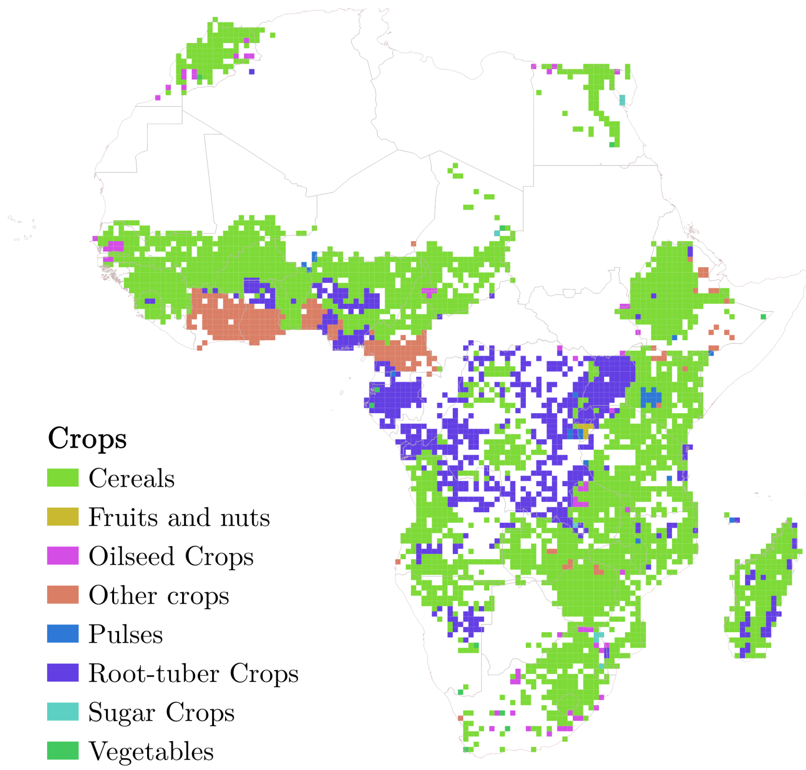

*Notes:* the figure depicts the trend in yearly precipitations (mm/year) starting form 1901. The series between 1901 and 2019 is computed from the CRU TS4.04 dataset. Projections for two time horizons (2040-2079 and 2060-2099) are accessed from five commonly employed Earth System Models (ESMs): GFDL-ESM2M, 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.

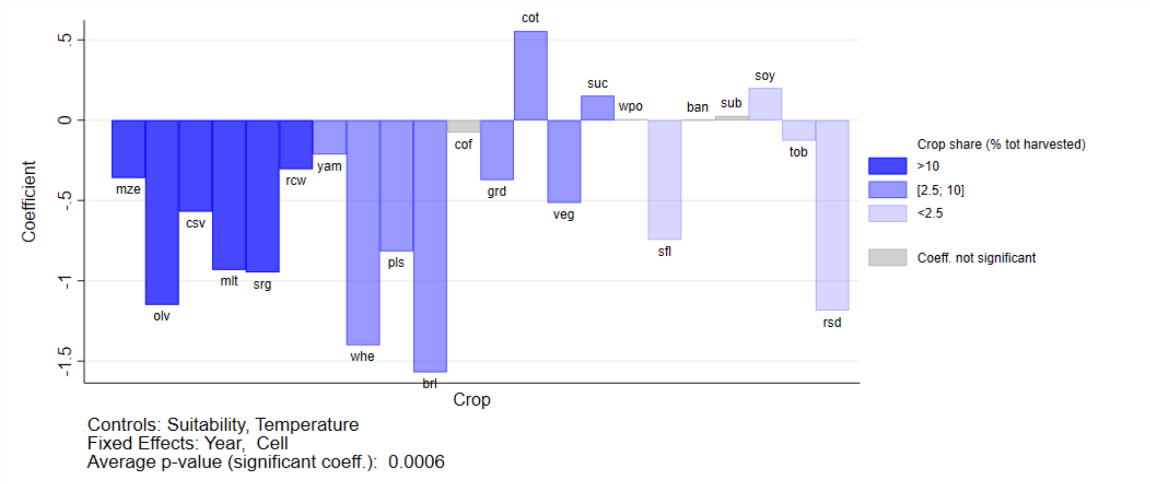
Figure 3: Most frequently harvested crop family per cell - average (2000; 2010)



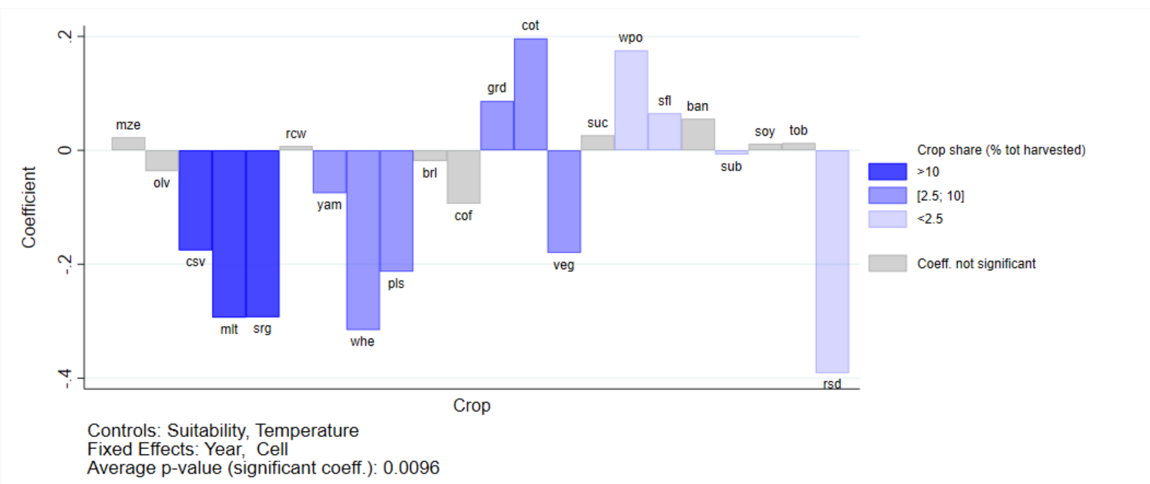

*Notes:* the figure reports the crop family with the widest relative harvested area in each cell. Families are defined by the following crops: cereals (barley, maize, millet, rice, sorghum, wheat); fruits and nuts (banana); oilseed crops (groundnut, olive, rapeseed, soy, sunflower); pulses; root-tuber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

Figure 4: PET and crop yield - single crop regressions coefficients

*[A] Yearly values*

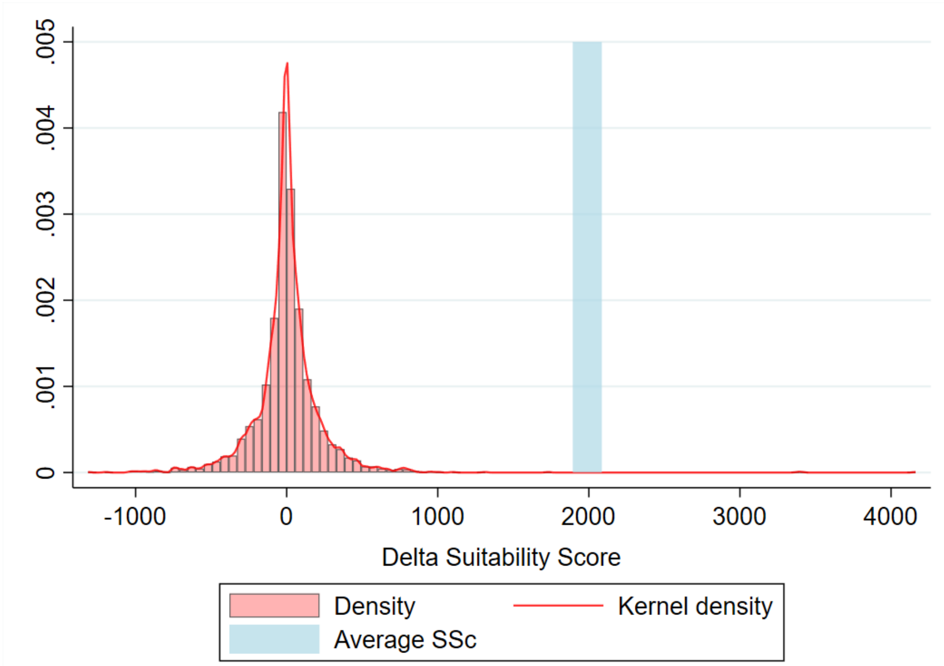



*[B] Growing Season*




*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 5: 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 modeling 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 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 [10] PET is computed according to the following equations:

$$PET = \frac{0.408\Delta\left(R_n - G\right) + \gamma + \frac{900}{T+273.16}U_2\left(e_a - e_d\right)}{\Delta + \gamma\left(1 + 0.34U_2\right)} \tag{5}$$

where $R_n$ represents 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 $\Delta$ are respectively vapor pressure deficit and the relative slope of the vapor pressure curve ($\frac{kPa}{\circ C}$), and $\gamma$ 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 5, while the temperature is indeed relevant in the computation of PET (which justifies 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 can isolate the effect of soil water availability without capturing potential noise 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,

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

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 the 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 the beginning date of the earliest growing period (day-of-year) for the period 1981-2010 and the total number of growing period days. 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); the 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).

### A.1.3 CRU TS.04 choice and confront 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 exists 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 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 normal 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 drawbacks are also implied by 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 degrees (roughly 139 km $\times$ 139 km), which is a significant loss in terms of spatial variation. Our sample consists of an unbalanced panel, so variation across grid cells is significant. As such, this could influence 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, besides using monthly-scale bias corrections based on CRU data, this dataset has been available only since 1980.

Secondly, re-analysis relies on various sources, including weather stations, ships, aircraft, and satellites. Recorded data is analyzed through an atmospheric circulation model (IFS CY23r4) to provide the corresponding weather measures. Compared to gauge data, this augments the risk of measurement error.

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 justifying 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 the cell level, with 10, 5, and 1 percent significance levels.