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DESERTIFICATION AND AGRICULTURAL PRODUCTIVITY: EVIDENCE FROM 5,636 GRIDS*

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Evidence from 5,636 grids*

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Abstract

The economic effects of global warming have gained considerable attention in recent economic literature. However, the interaction between desertification and agricultural productivity has not received substantial consideration. In this paper, we explore the relationship between soil aridification (a process that considers both precipitation and potential evapotranspiration of the soil) and agricultural productivity. Our most conservative estimates show that the process of aridification, having occurred from 1995 to 2005, was associated with a decline in agricultural output of between 0.4 and 1.1 tons per hectare of cultivated cropland in Africa and of between 0.1 and 0.5 tons per hectare of cultivated cropland in Asia.

Keywords: Aridification, Climate Change, Agricultural Productivity, Desertification
JEL Classification: O13, Q54, Q56

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1. Introduction

Climate change is one of the most severe threats currently faced by humankind. Consequently, the economic effects of global warming in different areas of the world have been a central question in the recent economic literature. In this framework, there is an extensive number of studies dealing with the economic and social impacts of reduced rainfalls and higher temperatures, from both the macroeconomic and microeconomic perspectives (Dell et al., 2008, 2012; Burke et al., 2015; Zhang et al., 2017).

However, the variation in the intensity of precipitation and temperature rise are only two facets of a more complex process of profound changes occurring in the environment in which humans live. In this paper, we consider a phenomenon that the economic literature has almost wholly neglected: desertification, defined as the combined effect of precipitation with soil transpiration (United Nations Convention to Combat Desertification, 2020).

We assess the impact of desertification on agricultural productivity for four different crops between 1995 and 2005 by assembling a novel dataset covering the globe with 5,636 grids. The empirical estimates show that the aridification process in that period contributed to a decline in agricultural output of between 0.4 and 1.1 tons per hectare of cultivated cropland in Africa and between 0.1 and 0.5 tons per hectare of cultivated cropland in Asia.

The empirical evidence presented in this paper helps in several ways. First, it helps to collect, comprehend and present the available evidence on the interplay between climate warming and land productivity more meaningfully and methodically. Second, it helps identify the gaps in evidence and thus point to necessary future research. Third, by considering the Aridity Index rather than the standard climate variables used in the environmental economics literature, it promotes the discussion of policies needed to alleviate the impacts of climate change on land productivity.

The rest of the paper is organized as follows: Section 2 presents the data used to estimate the relationship between aridification and agricultural productivity. We first describe the time-series data used to measure agricultural productivity, defined as the total agricultural production of a specific crop expressed in tons over the number of hectares devoted to it. We then describe the grid-level time series climate variables used to construct the Aridity

Index (Middleton and Thomas, 1997), i.e., average annual precipitation levels and potential evapotranspiration (PET). Section 3 presents the empirical framework that can estimate the relationship between climate warming and agricultural productivity. Section 4 reviews the evidence regarding aridification's effects on land productivity. Finally, Section 5 concludes.

2. Data

Agricultural Productivity Data

Our main dataset comprises climate-related variables and certain variables related to agricultural productivity, covering the globe.

We use Ramankutty et al. (2002) to construct our subnational crop yields[1] for maize, rice, wheat, and soybean from approximately 5,636 grids across 51 countries. The group of 51 countries accounted for approximately 79% of maize, 80% of rice, 70% of wheat, and 97% of soybean harvested worldwide in the period 2004-2008. More important, those 51 countries, in global terms over the same years, accounted for approximately 91% of maize, 83% of rice, 78% of wheat, and 99% of soybean production. The resulting land-use datasets depict five-year averages for 1995, 2000, and 2005 for the area (harvested) and yield of wheat, maize, rice, and soybeans.

Climate Data and the Aridity Index

The aridity index (AI) is constructed using both precipitation and potential evapotranspiration (PET) data. For this construction, we refer to the definition provided by Middleton and Thomas (1997). Annual AI for grid cell "i" at year "t" is defined as the ratio between average precipitation and PET of year "t" in cell "i", and is therefore expressed in millimeters of water effectively available on the ground, as follows:

$$AI_{i,t} = \frac{P_{i,t}}{PET_{i,t}}$$

Tables 1 and 2 report respectively, summary statistics for weather variables and agricultural productivity. Precipitation, potential evapotranspiration, and temperature data are provided by the gridded Climatic Research Unit (CRU) Time-series (TS) version

[1] The yield is the ratio of production and harvested area

4.00. The data are provided on high-resolution (0.5 degrees × 0.5 degrees) grids. Precipitation and PET are expressed in millimeters (mm./month), while the surface temperature is expressed in C°. A total of 16,908 observations were collected for the years 1995, 2000, and 2005.

Figure 1 shows the spatial variation in soil aridity during the period 1995-2005 and figures 2 to 4 show the global variation in crop yields during the same period. Taken together, these figures show clear evidence that the African continent is the most affected by aridification and suffered the most in terms of agricultural output loss.

3. Empirical Framework

To show the effect of desertification on agricultural productivity, we have estimated a set of baseline regressions in the form of:

$$y_{it} = \alpha + \beta_1 \overline{AI}_{it} + \beta_2 \overline{AI}_{it}^2 + \beta_3 \bar{P}_{it} + \beta_4 \overline{PET}_{it} + \beta_5 \bar{T}_{it} + \sigma_t + \rho_i + \varepsilon_{it}$$

We denote with y_{it} the natural logarithm of crop yield of grid *i* in year *t*. $\overline{AI}_{it}$ indicates the average aridity index in grid *i* in the two years previous to that reported (i.e., *t*-2 and *t*-1). $\bar{P}_{it}$ indicates the annual average amount of precipitation of grid *i* in years *t*-2 and *t*-1, while the variable $\overline{PET}_{it}$ reveals the average potential evapotranspiration of grid *i* in years *t*-2 and *t*-1. In addition, we also control for average mean surface temperature $\bar{T}_{it}$ of grid *i* in year *t*. Finally, the model considers year-fixed effects, denoted with σ_t, and grid-fixed effects, denoted with ρ_i. We estimate equation (2) via a panel-fixed effects estimator.

How we construct our desertification variable, namely by focusing on actual water availability of soil rather than on precipitation levels and temperature only, allows us to isolate effects specific to agricultural yields. As for other potential channels like the intra-country price of principal crops or a country's or region's suitability for crop cultivation, our benchmark specification includes the interaction of country and year dummies, which capture aggregate country-specific shocks.

4. Results

First, we show both linear and quadratic relationships between standard climate variables, such as precipitation and temperature, and the output of four major crops for which time series of actual yields at the sub-regional level is available. These results are shown in Table 3.

After showing the linear and non-linear relationships between precipitation and temperature and agricultural output, we then include PET and consider the effects on crop yield of variations in the Aridity Index. Table 4 contains our main results on the grid-level relationship between annual variations in the Aridity Index and crop production. Results in Table 3 show a positive relationship between precipitation and GDP. This is in line with previous economic literature (Dell et al., 2012, 2014; Burke et al., 2015).

However, Table 4 shows a stronger relationship between soil aridity and GDP per capita. This suggests that precipitation alone does not explain as much as GDP variability as the Aridity Index. In particular, columns (1-4) of Table 4 show that a decrease of one unit in the Aridity Index is associated with a reduction of 1.75 ton/ha in maize yield; 0.05 ton/ha of soybean yield; 0.6 ton/ha of rice yield, and 0.19 ton/ha of wheat yield.

We further restrict the sample of interest to African and Asian countries and for two reasons: first, African and Asian economies rely greatly upon their agricultural sector. Therefore we expect the impact of aridification to be more significant there than in the more advanced economies. Second, the local people may lack the finances and know-how needed to adapt to soil aridification. Estimates of the relationship between agricultural productivity and soil aridification on the African and Asian continents are stated in Tables 5 and 6, respectively. Columns (1-4) of Tables 5 and 6 show the linear and non-linear relationship between the Aridity Index and crop yields for Africa and Asia, respectively. These results reinforce our expectations that the impact of soil aridification on crop yield is more pronounced in economies predominantly relying on agriculture than in advanced economies.

5. Conclusion

Climate warming affects the social and economic growth of our societies in a multitude of dimensions. Whereas the relationship between temperature and per capita GDP has been extensively demonstrated, less is known about the channels through which climate affects the economy. This study empirically investigates the link between two often overlooked variables in recent economic literature: aridification of the soil and agricultural productivity. We assemble the most comprehensive panel dataset of climate and agricultural variables at a very disaggregated spatial level, covering the globe between 1995 and 2005. Our results show that first, there has been an increase of 3.9% in soil aridification during this period. Second, this implied a global loss of about 1.7 million tons of maize, 81,000 tons of rice, 786,000 tons of soybeans, and 430,000 tons of wheat, with Africa and Asia the world's most affected areas.

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Figures and Tables

Figure 1: Change in Aridity Index from 1995 to 2005

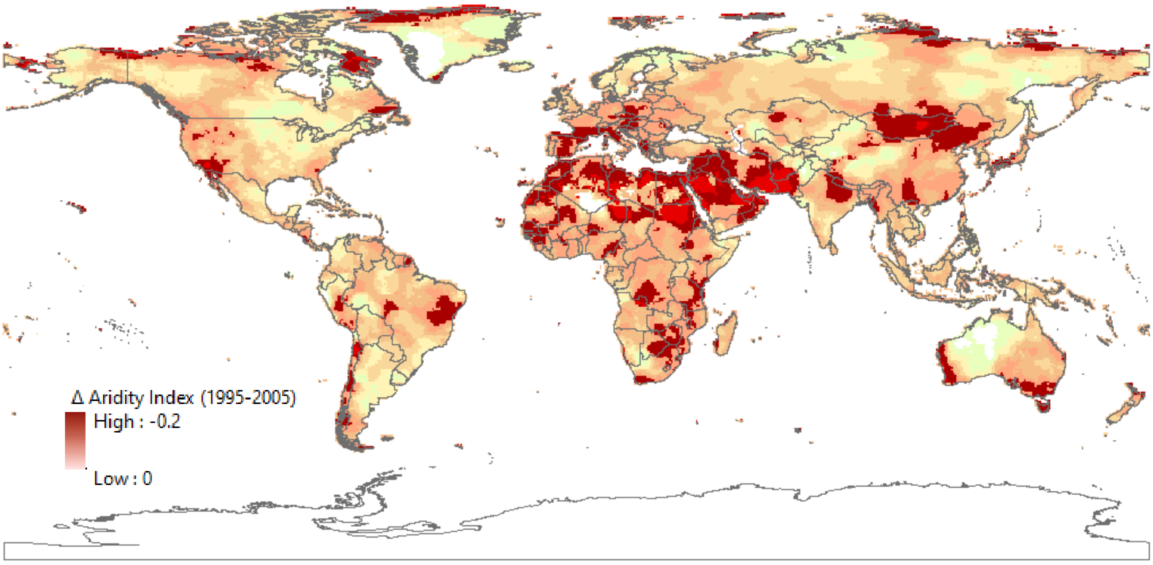

Figure 2: Percentage change in maize production per hectare from 1995 to 2005

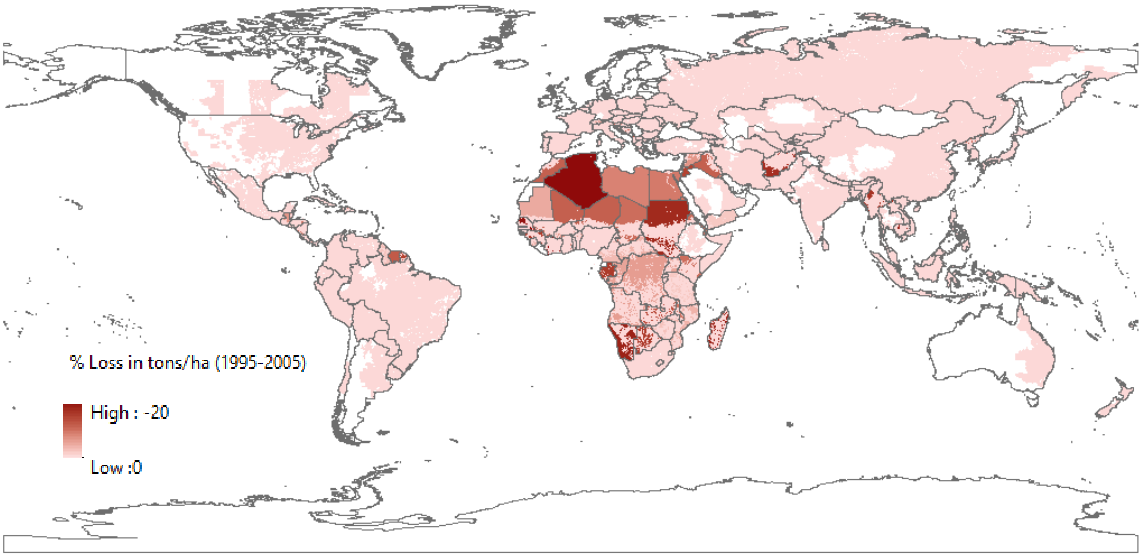

Figure 3: Percentage change in rice production per hectare from 1995 to 2005

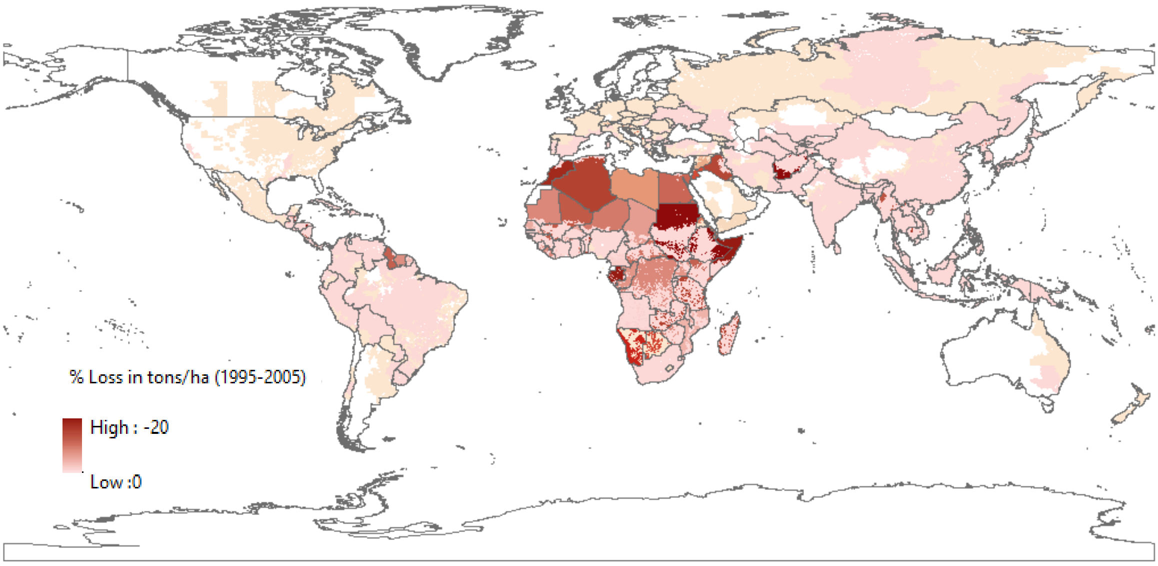

Figure 4: Percentage change in soybean production per hectare from 1995 to 2005

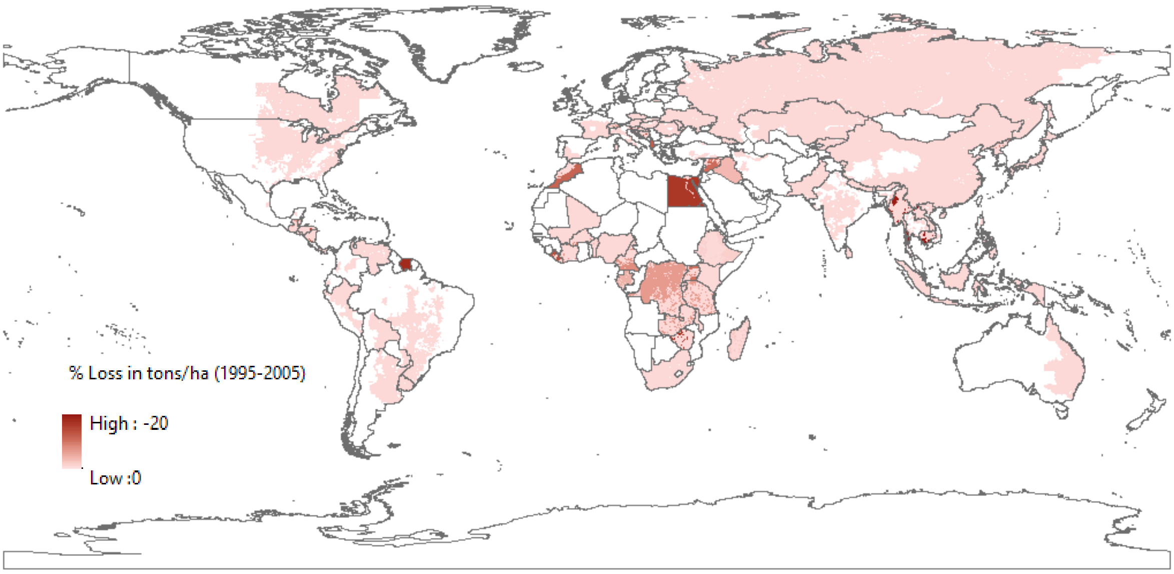

Figure 5: Percentage change in wheat production per hectare from 1995 to 2005

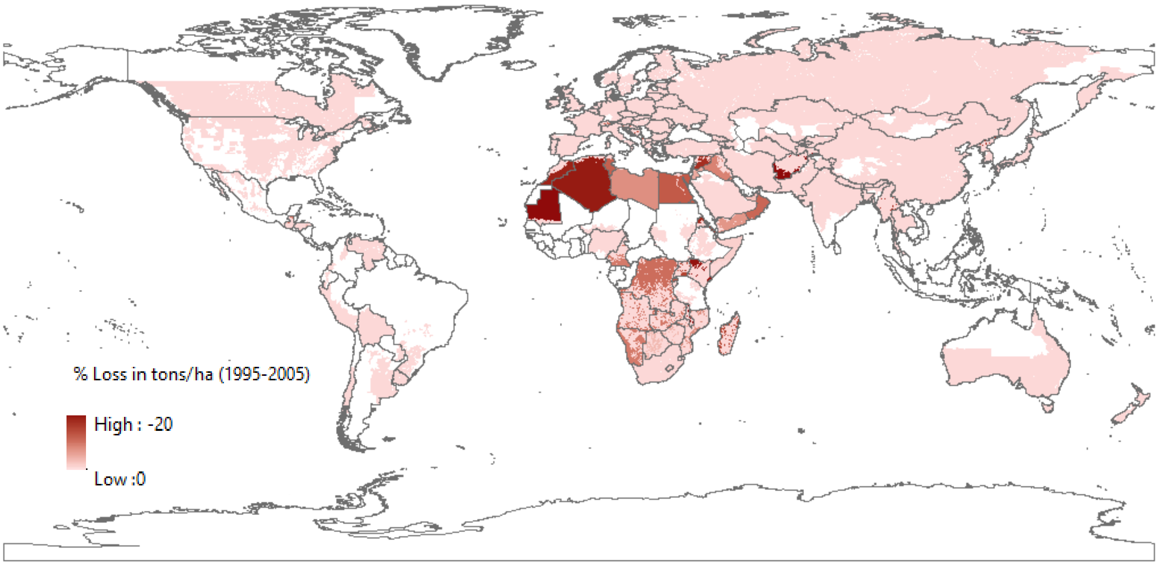

Table 1: Summary Statistics, Panel Data Sample

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Precipitation	mm./month	1,601,730	5.209725	5.675847	0	90.96001
PET	mm./month	1,601,730	8.300419	5.05923	0	24.5
Aridity Index	mm./month	1,601,730	.9595675	.942291	0	18.76085
Temperature	C°	1,601,730	13.81946	12.35726	-20.1	37.7

Note: Each observation is a cell.

Table 2: Summary Statistics, Panel Data Sample, Crop Yields

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Maize	ha./tons	8,541	1.05004	2.217958	0	37
Rice	ha./tons	12,798	1.041983	1.937873	0	58
Soybeans	ha./tons	10,800	.3715471	.7404208	0	8
Wheat	ha./tons	16,347	.7417051	1.380763	0	10

Note: Each observation is a cell. Gridded crop yields for maize, rice, soybean and wheat are available for the years 1995, 2000 and 2005.

Table 3: Effects of Precipitation and Temperature on Total Yield of four major crops. Year, Grid-Fixed Effects and Country Trends

VARIABLES	(1) Maize Yield	(2) Soybean Yield	(3) Rice Yield	(4) Wheat Yield
Precipitation	0.0825	0.0557**	0.213***	0.0116**
	(0.0609)	(0.0220)	(0.0322)	(0.00558)
$Precipitation^2$	-0.0403***	-0.0116***	-0.0438***	-0.0475*
	(0.00908)	(0.00410)	(0.00594)	(0.0265)
Temperature	0.0669***	0.00613	0.0188***	0.00529
	(0.0160)	(0.00406)	(0.00643)	(0.00371)
$Temperature^2$	-0.00282***	0.000715***	0.00267***	-0.000350*
	(0.000513)	(0.000135)	(0.000387)	(0.000200)
Constant	1.363***	0.139	-0.824**	0.942***
	(0.366)	(0.0919)	(0.328)	(0.103)
Observations	9,090	11,259	13,367	16,903
R-squared	0.037	0.018	0.048	0.007
Number of id	3,031	3,754	4,456	5,636
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

Note: This table presents the linear and non-linear effects of precipitation and temperature on the total yield of four major crops in tons/ha.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effects of Aridity Index on Total Yield of four major crops. Year, Grid-Fixed Effects and Country Trends

VARIABLES	(1) Maize Yield	(2) Soybean Yield	(3) Rice Yield	(4) Wheat Yield
AI	1.753***	0.0514	0.603***	0.194**
	(0.247)	(0.0662)	(0.164)	(0.0795)
AI^2	-0.123**	0.0343	-0.276***	-0.000255
	(0.0614)	(0.0328)	(0.0474)	(0.0327)
PET	0.133	0.128***	0.342***	-0.139***
	(0.125)	(0.0404)	(0.0722)	(0.0391)
Temperature	-0.0126	0.000135	0.0392***	0.00141
	(0.0242)	(0.00384)	(0.0111)	(0.00430)
Constant	1.222***	0.178*	-0.979***	1.278***
	(0.386)	(0.105)	(0.289)	(0.134)
Observations	9,090	11,259	13,367	16,903
R-squared	0.040	0.021	0.073	0.018
Number of id	3,031	3,754	4,456	5,636
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

Note: This table presents the effects of desertification on the total yield of four major crops in tons/ha.

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects of Aridity Index on Total Yield of four major crops. African Continent. Year, Grid-Fixed Effects and Country Trends

VARIABLES	(1) Maize Yield	(2) Soybean Yield	(3) Rice Yield	(4) Wheat Yield
AI	4.290***	1.517***	0.452	-1.067*
	(0.730)	(0.525)	(0.413)	(0.642)
AI^2	-0.435***	-0.236***	-0.216***	0.158*
	(0.0940)	(0.0911)	(0.0566)	(0.0895)
Precipitation	-1.225***	-0.339**	-0.0170	0.187
	(0.211)	(0.135)	(0.102)	(0.162)
PET	0.656***	0.468***	0.218**	-0.379***
	(0.158)	(0.0663)	(0.0928)	(0.0720)
Temperature	0.121*	0.0450**	0.268***	0.0668**
	(0.0720)	(0.0188)	(0.0357)	(0.0262)
Constant	-3.985***	-2.193***	-6.559***	1.197**
	(1.473)	(0.443)	(0.884)	(0.515)
Observations	3,821	4,518	7,842	7,082
R-squared	0.078	0.132	0.130	0.026
Number of id	1,274	1,506	2,614	2,361
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

Note: This table presents the effects of desertification on the total yield of four major crops in tons/ha.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of Aridity Index on Total Yield of four major crops. Asian Continent. Year, Grid-Fixed Effects and Country Trends

VARIABLES	(1) Maize Yield	(2) Soybean Yield	(3) Rice Yield	(4) Wheat Yield
AI	0.875*	0.0832	1.458***	0.578***
	(0.508)	(0.0544)	(0.216)	(0.107)
AI^2	-0.153	-0.0504	-0.429***	0.0175
	(0.105)	(0.0400)	(0.0955)	(0.0731)
Precipitation	-0.355**	0.0340	-0.163***	-0.195***
	(0.179)	(0.0370)	(0.0630)	(0.0504)
PET	-0.600**	0.173***	0.755***	0.0698
	(0.293)	(0.0483)	(0.181)	(0.0795)
Temperature	0.0314	0.0159***	-0.0204*	0.0463***
	(0.0415)	(0.00385)	(0.0112)	(0.00816)
Constant	3.068***	-0.0207	-0.872*	0.179
	(0.670)	(0.0960)	(0.497)	(0.194)
Observations	2,144	4,113	3,248	5,139
R-squared	0.077	0.032	0.136	0.078
Number of id	715	1,371	1,083	1,713
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

Note: This table presents the effects of desertification on the total yield of four major crops in tons/ha.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix

Additional Literature

Here, we have provided evidence on a global scale of the impact of soil aridification on agricultural productivity.

To the best of our knowledge, the effect of soil aridification on different economies due to human-induced climate change on a global scale is a novel question for economists and social scientists.[2] However, Maccini and Yang (2009) studied the long-term effects of variations in rainfalls in Indonesia and found a positive impact of precipitation on the health and economic wellbeing of individuals who had grown up during years characterized by higher levels of precipitation. Furthermore, a more recent study by Peri and Sasahara (2019) has found that rising temperatures reduce rural-urban migration in poor countries, while the opposite effect is shown for middle-income countries.

Although early papers such as those of Boellstorff and Benito (2005), Atis (2006), and Hein (2007) were the first to focus on an estimation of the relationship between agricultural productivity and land degradation, all did so at the farm level. Salvati (2010) is the first author to have attempted to estimate this novel relationship on a regional scale, considering the example of Italy. He uses the total agricultural value, expressed in euros per hectare, of utilized agricultural area in order to approximate total agricultural productivity. He finds mixed results for various regions of the country depending on economic development status. Increasing land degradation was associated with declining agricultural productivity. However, using the total agricultural value per hectare of cultivated area will incorporate confounding factors linked to the value of the land. Indeed, the value of land may depend not only on climatic conditions. Instead, variation in value may result from variations in regional agricultural policies or in national and international demand for a specific crop. Thus, for a better assessment of the relationship between climate and land productivity, we should first consider another measure of agricultural productivity, one which does not consider the actual value of land but uses the total output per different crop. In the second instance, the use of data available at a very disaggregated spatial level helps alleviate concerns of omitted variables – other than climatic variations – affecting agricultural productivity.

[2] One of the first papers is that of Harari and La Ferrara (2018), in which the authors assess the relationship between the potential evapotranspiration (or SPEI, which stands for Spatial Potential Evapotranspiration Index) and the onset of conflicts in Africa. However, no studies have made use of findings regarding the impact of aridification on development, or on crop production.

Data description

Our dataset consists of high-frequency, geo-referenced data from various sources, constituting a base covering the globe between 1990 and 2015. We construct a dataset of weather and agricultural variables with a raster grid structure: the observation units are subnational "cells" of 0.5 degree of latitude by 0.5 degree of longitude (approximately 56 km at the equator) for three time periods between 1995 and 2005 (i.e., the years 1995, 2000 and 2005).

Climate variables are retrieved from the CRU TS4.04 dataset, which provides monthly data on cloud cover, diurnal temperature range, frost day frequency, wet day frequency, potential Evapotranspiration (PET), precipitation, daily mean temperature, monthly average daily maximum and minimum temperatures, and vapor pressure for the period January 1901 to December 2019. Total precipitation amounts range from a minimum of zero to a maximum of 91 millimeters per month. Potential evapotranspiration ranges from a minimum of zero to a maximum of 24.5 millimeters per month.[3] Finally, the annual mean surface temperature ranges from a minimum of -20 C° to a maximum of 37.7 C°.

The CRU TS4.04 data were produced using angular-distance weighting (ADW) interpolation. The CRU TS4.04 data are monthly gridded fields based on monthly observational data calculated from daily or sub-daily data by national meteorological services and other external agents. Both the ASCII and NetCDF data files contain monthly mean values for the various parameters. The NetCDF versions include an additional integer variable, "stn", which provides, for each datum in the primary variable, a count (between 0 and 8) of the number of stations used in such interpolation. The missing value code for "stn" is -999. All CRU TS output files are actual values and do not consider anomalies.

As for precipitation, potential evapotranspiration data are retrieved from the gridded Climatic Research Unit (CRU) Time-series (TS) version 4.00. Data are month-by-month variations in climate variables over the period 1901-2015. The data are provided on high-resolution (0.5 degree × 0.5 degree) grids, produced by CRU at the University of East Anglia and funded by the UK National Centre for Atmospheric Science (NCAS), a NERC

[3] As for annual averages: precipitations range between zero and 1,092 millimiters, and PET ranges between zero and 294 millimeters.

collaborative center. Precipitation data are available for each month from 1901 to 2015 and are expressed as average monthly rainfalls in millimeters (mm./month). We compute the average monthly precipitation (mm./month) for each year. Unlike precipitation data, potential evapotranspiration is available daily from the same period range and is expressed in mm./day. To assess the empirical evaluation of precipitation and PET's effects, we compute the average monthly PET (mm./month) for each year. We also use average annual temperature as a climate grid-specific control variable. Gridded data on temperature are retrieved from CRU Time-Series Dataset.

Crop Yields Data

Most global land cover datasets obtained from satellite photography group croplands into just a few categories, thereby excluding information that is critical for answering key questions ranging from biodiversity conservation to food security to biogeochemical cycling. Information about agricultural land use practices like crop selection, yield and fertilizer use is even more limited.

Ramankutty et al. (2002) present land use datasets created by combining national, state, and county-level census statistics with a global dataset of croplands on a 5-arc minute by 5-arc minute scale (which corresponds to a grid of approximately 10 km by 10 km latitude/longitude). Approximately 600,000 census statistics per crop have been used to construct the crop yield data. Out of the 226 political units (nations) for which the Food and Agriculture Organization (FAO) provides national-level data, we collected data at the next administration level for 51 countries and at the third administration level for 17 countries.

We use Ramankutty et al. (2002) to retrieve data on crop yields. Data on crop yields are available for the years 1995, 2000, and 2005. However, for some regions, these data refer to the year previous to that reported. For example, crop yield for 2005 refers to data observed in the year 2004. For this reason, when evaluating the impact of precipitation on crop yields, we use the average precipitation levels of the two years previous to that reported.

The sample of data on crop production over hectares of crop cultivated is limited, compared with climate variables, both in spatial and temporal terms. We consider crop yields for maize, rice, soybean, and wheat available for 1995, 2000, and 2005.

Specifically, for maize cultivation, we have a total of 8,541 observations ranging from a minimum of zero to a maximum of 37 tons per hectare of land. For rice, we have 12,798 observations ranging from a minimum of zero to a maximum of 58 tons per hectare. For soybean, we have 10,800 observations ranging from a minimum of zero to a maximum of 8 tons per hectare. Finally, for wheat, we have 16,347 observations ranging from a minimum of zero to a maximum of 10 tons per hectare.

In this database, where sub-national data are available, the frequency of reporting varies among countries. Our most significant gap in subnational information concerns the former Soviet Republics.

Not all crops need the same amount of water. Schuyt and Brander (2004) sought to determine the exact water usage for major crops. Their study identified a range of well-known agricultural products commonly defined as the "thirstiest" water users. Overall, four of these commodities stand out as the "thirstiest", i.e., the most significant total water users in the river basins concerned, namely: rice, sugar, cotton, and soybeans, with vegetables being crucial locally in many cases. Rice is the thirstiest crop, using about 70 million m^3 of water annually, with cotton, soybeans, and sugar using about 50 million m^3 each. For example, it takes from 3,000 to 5,000 liters of water to produce 1 kilogram of rice; on the other hand, 2,000 liters of water are needed to produce 1 kg of soybeans, while only 500 liters of water are needed to produce 1 kg of potatoes. Furthermore, the study estimates that 50 million m^3 of water are also needed annually to grow wheat since more hectares of wheat are grown than all of the other three crops put together.

Finally, some numbers: maize, rice, soybean, and wheat are produced globally on 100 million hectares[4] (on 162 million hectares[5], 131 million hectares[6], and 215 million hectares[7] , respectively).

[4] Source: Global Demand and production of Maize. The CGIAR Research Program on Maize. https://maize.org/projects-cimmyt-and-iita-2/

[5] Source: World rice acreage 2010-2019 (Shahbandeh, 2021). https://www.statista.com/statistics/271969/world-rice-acreage-since-2008/

[6] Voora et al. (2020)

[7] Source: Global Demand and production of Wheat. The CGIAR Research Program on Wheat. https://wheat.org/wheat-in-the-world/

Relationships between AI and Crop Yields

Column (1) of Tables 5 and 6 shows that a decrease of one unit in the Aridity Index is associated with a reduction in maize yield of 4.3 tons/ha. and 0.9 ton/ha., respectively, for African and Asian countries. Column (2) of Tables 5 and 6 shows that a decrease of one unit in the Aridity Index is associated with a reduction in rice yield of 1.5 ton/ha. for African countries. At the same time, no effect on Asian countries is noted. Column (3) of Tables 5 and 6 shows that a decrease of one unit in the Aridity Index is associated with a reduction in soybean yield of 1.5 tons per hectare cultivated for Asian countries, while no effect is noted for Africa. Finally, column (4) of Tables 5 and 6 shows that a decrease of one unit in the Aridity Index is associated with a reduction in wheat yield of 0.6 ton/ha. for Asian countries. At the same time, no substantial effect on African wheat production is noted.

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