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BY 2079, ARIDIFICATION WILL HAVE REDUCED THE GDPS OF AFRICA AND ASIA BY 16% AND 6.3%, RESPECTIVELY.

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By 2079, Aridification Will Have Reduced the GDPs of Africa and Asia by 16% and 6.3%, respectively.

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Abstract

We examine the effects of human-induced desertification on economic growth by exploiting a 56 km-by-56 km grid-cell global dataset on the annual frequency from 1990–2015. We find that areas that experienced large soil aridification are associated with a reduction in GDP per capita. Our results indicate that from 1990–2015, aridification reduced the GDPs of African and Asian countries by 12% and 2.7%, respectively. Our estimates are robust to adding higher-order terms of geo-climatic variables and controlling for country-specific linear trends, which allows us to project future costs of desertification. Our findings show that desertification will generate losses in GDP growth by 16% and 6.7% in Africa and Asia, respectively.

(*) Financial support from Fondazione Invernizzi is gratefully acknowledged.

1. Introduction

Approximately 52 million square kilometers of the Earth's surface are dryland areas, defined as zones where the total amount of precipitation is balanced by the evaporation of water from land and the natural transpiration from plants [1]. This "right" balance between rainfall and water evaporation is pivotal in maintaining biological productivity. However, climate change is steadily modifying this equilibrium, with dramatic consequences for liveability and food availability in many areas worldwide.

According to the Intergovernmental Panel on Climate Change 2019 [2], in 2015, about 500 million people lived within areas that had experienced desertification between the 1980s and 2000s. Desertification is defined as land degradation in arid, semi-arid, and dry sub-humid regions caused by many factors, including climatic variations and human activities [2]. This situation is expected to worsen in future decades because the population vulnerable to habitat degradation, including desertification, is estimated to increase in intervals (178–277) of a million people by 2050, depending on the global climate scenario. Moreover, Asia and Africa are expected to have the highest number of vulnerable people [2]. Despite these projections, there is little knowledge about the economic effects of desertification in the short and long-term[1] [3,4,5].

The goal of this study is to assess the economic effects of climate-induced soil aridification. We assembled a panel dataset of more than 66,000 grid cells with almost global coverage of the 26 years between 1990 and 2015. We combined annual grid-level data on GDP per capita [7] with climate variables such as precipitation, average temperature, and potential

[1] A recent paper assessed the impact of climate variations on the onset of conflicts in Africa using the Spatial Potential Evapotranspiration Index (SPEI) [6]. However, no previous studies have examined relationships among aridification, development, and crop production. Nevertheless, the effects of soil aridification caused by human-induced climate change on economic growth is a novel issue for economists and social scientists.

evo-transpiration. The combination of rainfall and potential evo-transpiration enabled us to use the Aridity Index (AI) to measure desertification [8].

We assess the relationship between annual variations in the AI and GDP per capita using econometric panel models.[2] Our findings are summarised as follows:

i) There is a significant grid-level relationship between AI and GDP per capita. According to our benchmark specification, a one standard deviation shock to the AI is associated with a decline in the GDP per capita between 1.9% and 4.1%. The African continent exhibits the highest decrease, with a total cost of 14% in GDP per capita, caused by soil aridification during 1990–2015.

ii) Aridification has a more significant effect compared with precipitation and temperature alone. Our baseline estimates showed that a one standard deviation shock in annual precipitation levels affected GDP per capita by between 1.6% and 2.5%. In contrast, a standard deviation shock in temperature levels caused decreases in GDP per capita by 0.5–2.9%.

iii) The effects are higher in humid areas of the world (i.e., characterised by higher precipitation and lower evapotranspiration) than in arid areas. Furthermore, we find that lower-income countries are more affected by desertification compared with higher-income countries.

iv) The effects of precipitation alone do not entirely explain the economic impact of climate shocks. We find that although most areas in the southern hemisphere

[2] These estimates are robust to adding higher-order terms of geo-climatic variables and to controlling for country-specific linear trends. Moreover, our estimates are confirmed in a model that included spatially and temporally autoregressive terms to account for the fact that income trends may persist over time and that both the covariates and the GDP per capita may be correlated across space.

experienced an increase in rainfall from 1990–2015, they showed a decline in AI, which partly explains lower GDPs per capita.

v) Finally, based on a recent dataset on future projections of precipitation and potential evapotranspiration [9], we predict that desertification would cost as much as 10% in terms of GDP per capita in Sub-Saharan Africa by 2079. These results are obtained using a baseline scenario that assumed a peak in greenhouse gas emissions by 2040, followed by a decline throughout the 21st century.

2. The geography of desertification

“Desertification” was first defined as “land degradation in arid, semi-arid and dry sub-humid areas resulting from a range of factors, including climatic variations and human activities” [10]. Major climatic factors leading to desertification include climatic variables such as spatial and temporal distributions of precipitation, increases in land surface albedo, drought events, sudden and high-intensity rainfall, high temperatures, and high wind speeds [11].

Based on future carbon emissions scenarios, scientific literature showed that dryland areas would increase between 11% and 23% by the end of the present century in relation to the 1961–1990 baseline [12,13,14]. This expansion of drylands would reduce carbon sequestration and enhance regional warming, resulting in warming trends over present drylands double those over humid regions. Global warming and the rapidly growing human population will exacerbate the risk of land degradation and desertification in the drylands of developing countries. Recently it was shown that that aridity is projected to decrease (i.e., areas would become drier) because of anthropogenic climate change [15]. However, accomplishing the 1.5 °C temperature goal would substantially reduce the likelihood that large regions would face substantial aridification and its effects [12].

Figure 1 shows that despite the declining trend in total precipitation (Panel A) in most areas of the world, particularly in Africa and the Middle East, large parts of Latin America and South-East Asia have experienced increased precipitation compared with their historical mean. Nevertheless, zones that have experienced increases in precipitation might also have become increasingly arid. Panel B in Figure 1 shows that the increases in precipitation levels experienced in Latin America and Southeast Asia have been accompanied by higher evaporation levels.

To better measure dryness, the total amount of precipitation must be divided by the soil's potential evapotranspiration (PET), which is a measure of the "drying power" of the atmosphere in removing water from land surfaces by evaporation[3] [16]. Higher levels of evapotranspiration lead to more arid land at a given level of precipitation. In particular, PET is calculated by the method proposed by Penman in 1948 [17], and different variables are considered, such as atmospheric humidity, solar radiation, and wind. These variables are affected by climate change [18]. This ratio is defined as the Aridity Index (AI). The AI is a simple but convenient measure of the actual water availability of the land. Recently, the effects of rainfall and potential evapotranspiration soil moisture on distinct regions of the world were examined [19]. Their findings showed a significant difference between precipitation and aridity: if PET is larger than P, then the climate is arid[4].

To operationalise the concept of desertification, five types of arid lands or drylands were classified [20]:

- Hyper-arid ($AI < 0.05$)
- Arid ($0.05 < AI < 0.2$)

[3] This is achieved from the soil and plant canopy and via plant transpiration.
[4] Water deficits may also occur over shorter periods, such as seasonally or monthly, depending on their intensity and duration.

- Semi-arid (0.2 < AI < 0.5)
- Dry sub-humid (0.5 < AI < 0.65)
- Humid (AI > 0.65)

The process in which the biological activity of drylands decreases is called “desertification”, which corresponds to lower AI levels. During the last 40 years, the process of desertification has accelerated by more than 30 times its historical rate [21]. The principal factors of soil aridification are farming and human activities, such as clearing away trees and other vegetation. Hence, an increasing amount of literature focuses on the differences between rainfall and aridity. In this regard, a recent study has distinguished between droughts, which are transient regional extreme phenomena typically defined as departures from a local climatological norm that is presumed known, and so-called “background” dryness [22]. In addition to being a function of precipitation, the latter depends on how fast water evaporates. Indeed, a primary consequence of climate change is that average rainfall is predicted to increase in some areas of the world. However, evaporation is also expected to increase because of warmer temperatures. As a result, the net effects of the two forces on aridity are uncertain.

Figure 2 shows the global distributions of percentage changes in the AI measured by the difference between the present-day (1990–2015) and the historical average (1900–1980). As shown in Figure 2, the areas that are the most affected by desertification are primarily located in continental Europe, Africa, and South-East Asia. The AI in Africa decreased from an average of 0.25 for the period 1990-2015 to 0.23 compared with the period from 1900–1980. The overall change was equal to approximately 8%. However, areas on the west side of the continent showed aridification that had exceeded 50%. Similarly, the average AI in Southeast Asia had decreased by 3% compared with the period from 1980–1990, and areas in the west of China and Mongolia showed that aridification had increased by 25%.

3. Results

Our benchmark estimates indicated that higher AI values are positively associated with GDP per capita. Moreover, the effects are more significant in less developed areas of the world. To confirm our estimates, we explored the sensitivity of our estimates to several models, aridity classes, and income groups.

This result contrasts a recent study that found that the relationship among temperature, precipitation, and economic growth was globally generalisable to agricultural and non-agricultural activity in rich and developing countries [23].

Our results showed that grid-level income per capita was non-linear and concave according to the AI. This finding indicates that income increases with higher water availability of the soil, whereas it decreases with excessive precipitation or too little soil transpiration caused by extreme heat and humidity. This non-linear effect of aridity on income per capita is in line with the estimates shown for temperature shocks (Figure 3) [23]. In particular, we find that above a threshold of approximately 0.65, a marginal variation in AI did not have economic effects.

However, our estimates show that the areas most affected by soil aridification are located on the African and Asian continents. As a result, these continents will pay the highest price in terms of GDP loss.

This finding is consistent with the "opportunity cost" mechanism related to local agricultural production. We argue that the adverse economic effects of soil aridification are partly due to less efficient crops. For example, if a particular area experiences substantially less precipitation in a given year (or a higher PET), the crop yield could be negatively affected, which would lead to economic losses. Several theoretical and empirical studies have offered insights relevant to our proposed interpretation [23, 24, 25, 26].

Based on the results in Appendix B and shown in Figure 3, it is possible to evaluate the average annual economic impact of desertification from 1990 to 2015. Figure 4 shows the average annual GDP per capita loss in Africa (Panel A) and Asia (Panel B). We estimate that during the last 25 years, in some areas on the African continent, climate-induced soil aridification had decreased the GDP per capita by more than 12%.

Our results show a slight but significant positive relationship between AI and GDP per capita worldwide. However, the economic effects of the decreased AI were more pronounced in Asia and Africa. We estimate that the cumulative reduction in AI between 1990 and 2015 has negatively affected the Asian GDP per capita by between one and six percentage points, and the African GDP per capita between 9 and 16%.

The results of the association between AI and GDP were used to project the costs of future desertification patterns. We first computed the future grid-cell projections of the AI by using annual precipitation and potential evapotranspiration data drawn from the most recent CMCC-BioClimInd[5] [5]. These projections are obtained from a variety of earth system models and two representative concentration pathways (i.e., RCP 4.5 and RCP 8.5), which are part of the World Climate Research Programme's Coupled Model Intercomparison Project phase 5 (CMIP5). In particular, we considered the RCP 4.5 emissions scenario. RCP 4.5 assumes a peak in greenhouse gas emissions between 2010 and 2030, followed by a decline throughout the 21st century. For the period 2021-2040, the WorldClim 2.1 database forecasts an increase in

[5] BioClim is a dataset of 35 bioclimatic indicators calculated from historical and future climate simulations. These indicators (e.g., annual mean temperature, temperature annual range, evapotranspiration, thermicity, annual and seasonal precipitation, and many others) are valuable for ecological modelling purposes. In addition to the historical period (1960–1999) in WATCH re-analyses, the 35 indicators for the future periods are based on time series of climate variables simulated under a combination of six earth system models (ESMs), two representative concentration pathways (RCP 4.5 and 8.5), and two-time horizons (2040–2079 and 2060–2099), amounting to 23 ensemble members for each indicator, all of which were provided as NetCDF files.

temperature between 0.93 and 1.27 °C, with precipitation predicted to increase between 10 and 30 percentage points in the northern hemisphere while decreasing between 10 to 40% in the southern hemisphere, depending on the Shared Socioeconomic Pathway (SSP) considered [27]. Conversely, the evapotranspiration is estimated to increase between 0.4 and 3.8% for 2021-2040 compared to the present-day mean (2011-2020) [28].

In our historical sample (1900–1980), the average AI was 0.489, which declined to 0.479 during the present day (1990-2015). It is predicted to be 0.438 in the projected period from 2040–2079. This result indicates that the average cell would experience rainfall shortages comparable to the present-day mean. Specifically, 17,926 grid cells were arid or hyper-arid (i.e., AI<0.2) during the historical period. However, this number was projected to increase to 20,998 in the period from 2040–2079. Based on this projection, more than 2,000 grid cells will become arid in the future (i.e., approximately 5 million km^2 or 3% of the world's land surface). Figure 5 shows the grid-cell differences in percentages between the projected AI and the present-day mean for the world, Africa, and Asia.

In Figure 7 (right), panel B presents the estimation of the effects of future AI variations on GDP per capita growth between the present day and 2079 under the baseline RCP 4.5 scenario. The patterns are similar to those in recent decades. Future variations in the AI resulted in a total cost of 6.7% in GDP per capita growth in Asia and about 15% in Africa.

4. Conclusion

The results of our study showed that climate-induced aridification was associated with a reduction in GDP per capita. Although the decline was high in Asia (-2.7%), we find that the effects of desertification were more significant in poor African countries that relied on agriculture (-12.74% of GDP during the period 1990–2015). We also showed that by 2079, aridification would cost African and Asian countries 16% and 6.7%, respectively.

Overall, our study provides a first step in understanding the effects of human-induced climate aridification on the economic development of areas that rely predominantly on agriculture. Moreover, the findings indicate that instead of precipitation, the Aridity Index should be used to determine the economic effects of climate change.

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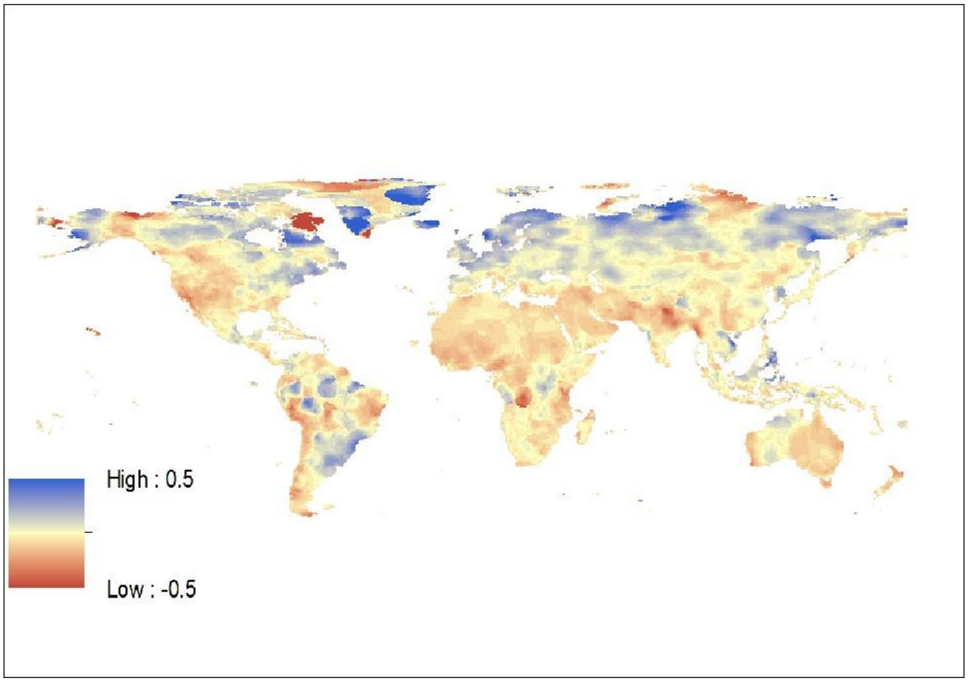
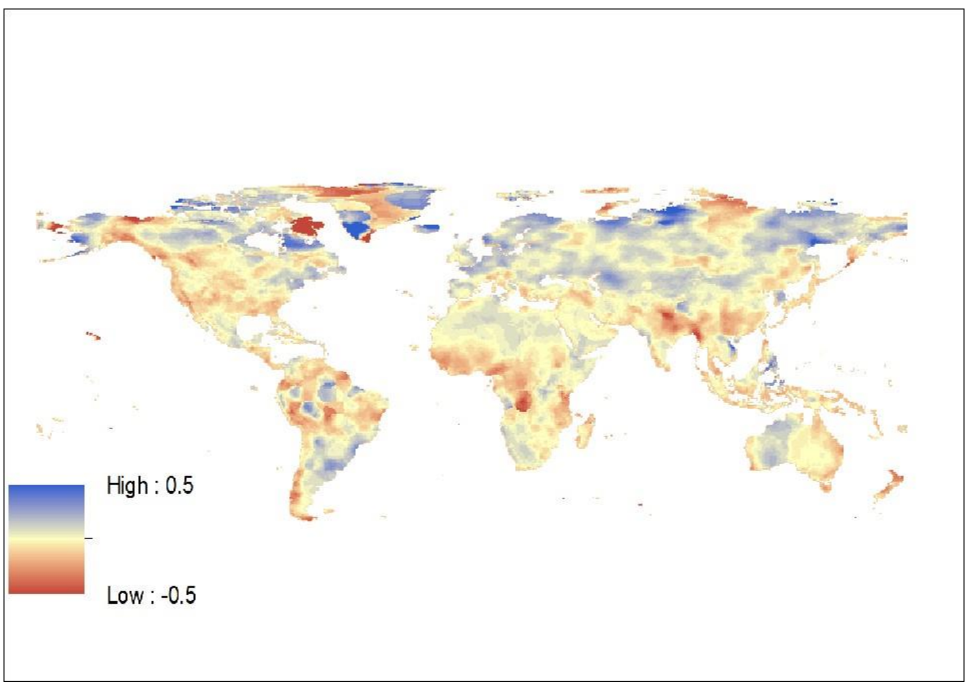
Figures and Tables

Figure 1: Global distributions of percentage changes (%) in (a) precipitation and (b) PET between the present day (2000–2015) and the historical average (1900–1980)

Panel A: Precipitation changes

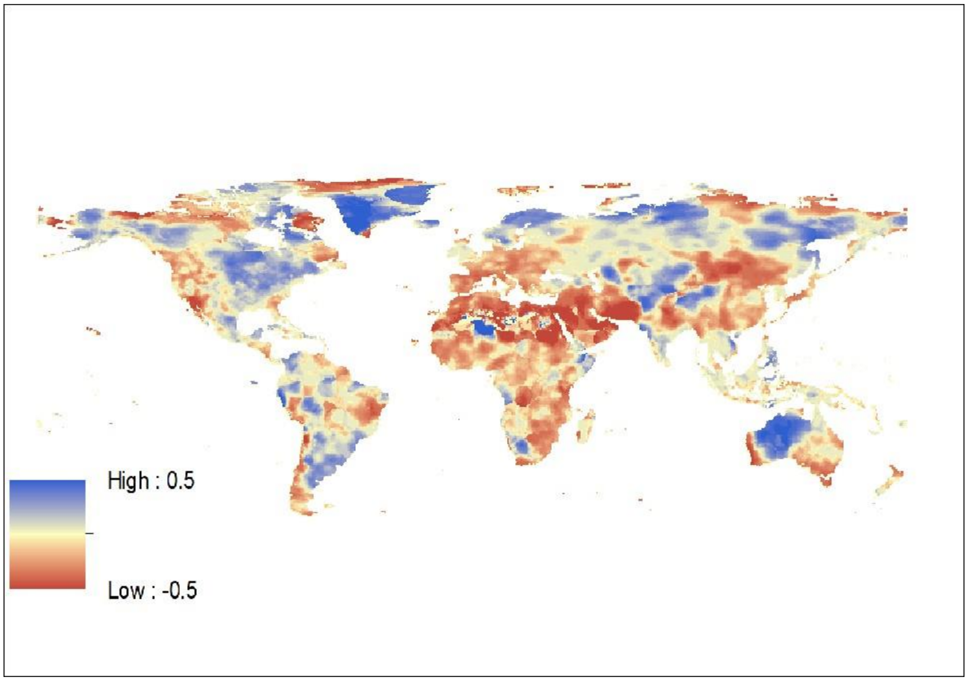


Panel B PET changes



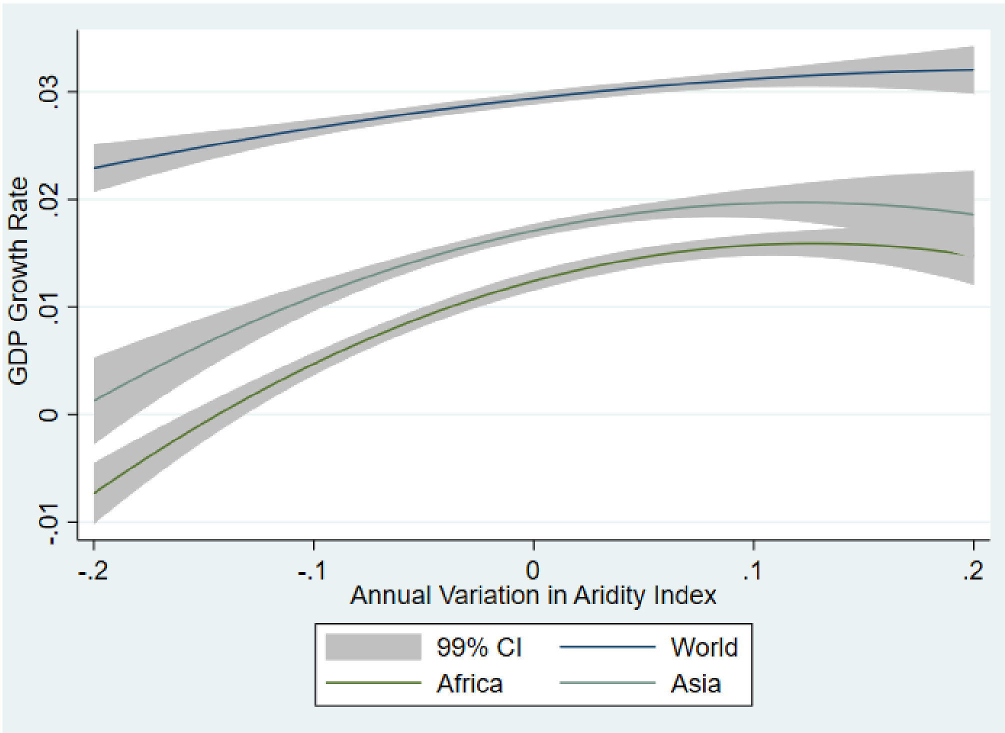
Note. Secular data on precipitation and PET were retrieved from Fu et al. (2016), [26]

Figure 2: Global distributions of percentage changes (%) in the AI between the present day (2000–2015) and the historical average (1900–1980)



Note. Secular data on precipitation and PET used to construct the AI were retrieved from the National Centre for Atmospheric Science (2020) [30].

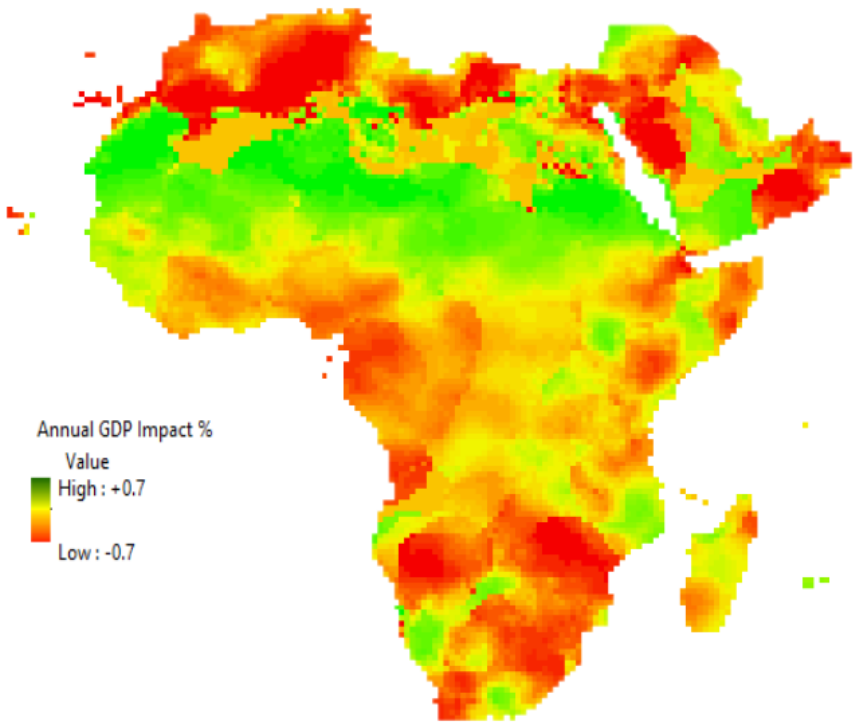
Figure 3: Relationship between grid-cell annual variations in Aridity Index and GDP per capita from 1990–2015 in World, Africa, and Asia.



Note. Grid-level data used to construct the Aridity Index were retrieved from the National Centre for Atmospheric Science (2020), and grid-level GDPs per capita were adopted from Kummu et al. (2018) [7]. The parameters used to draw the functions are shown as estimates in Table 2 in Appendix B.

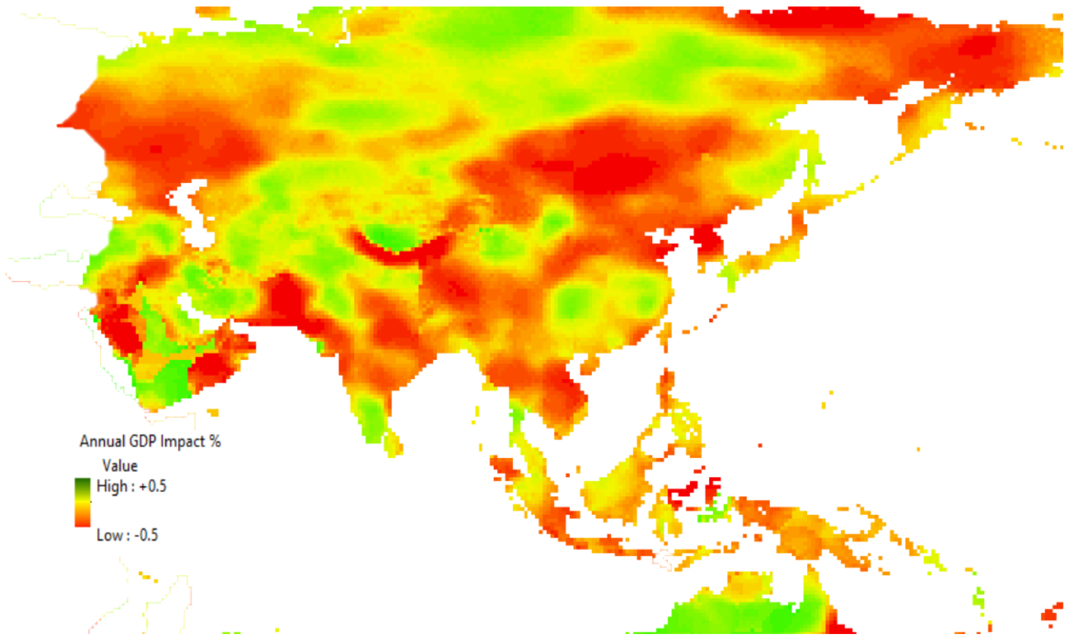
Figure 4: Average annual effects of Aridity Index on GDP per capita from 1990–2015

Panel A: Africa



Note. The areas in red indicate show the highest impact of the Aridity Index on GDP per capita from 1990–2015.

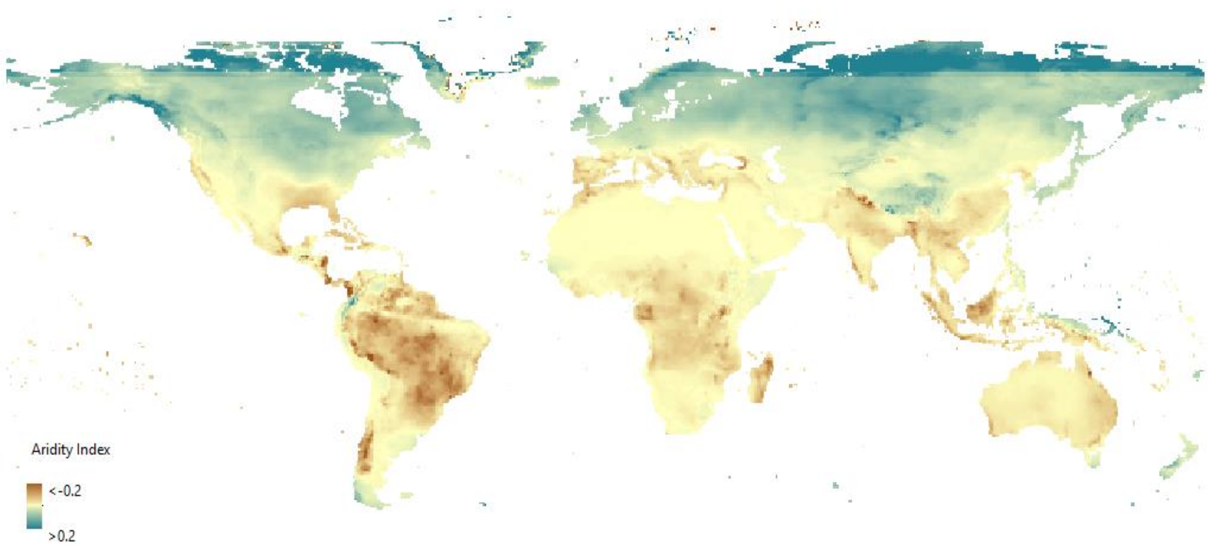
Panel B: Asia



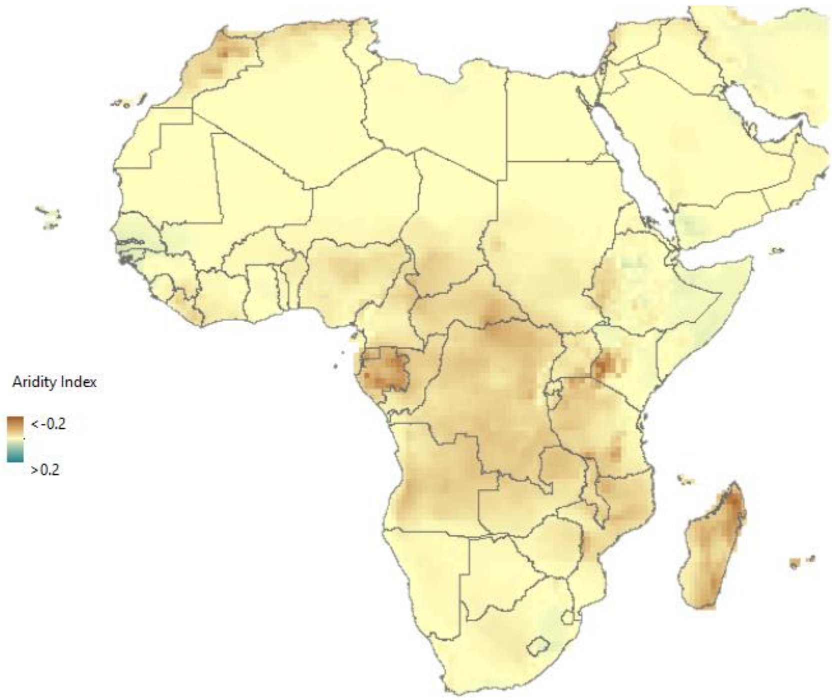
Note. The areas in red indicate the highest impact of the Aridity Index on GDP per capita from 1990–2015.

Figure 5: Distributions of percentage changes (%) in the Aridity Index, shown as the difference between the period 2040–2079 and the present day (1990–2015). Future data on precipitation and PET used to construct the AI were retrieved from the CMCC-BioClimInd [9]. The dark brown colour indicates areas that are projected to be most affected by desertification.

Panel A: World



Panel B: Africa



Panel C: Asia

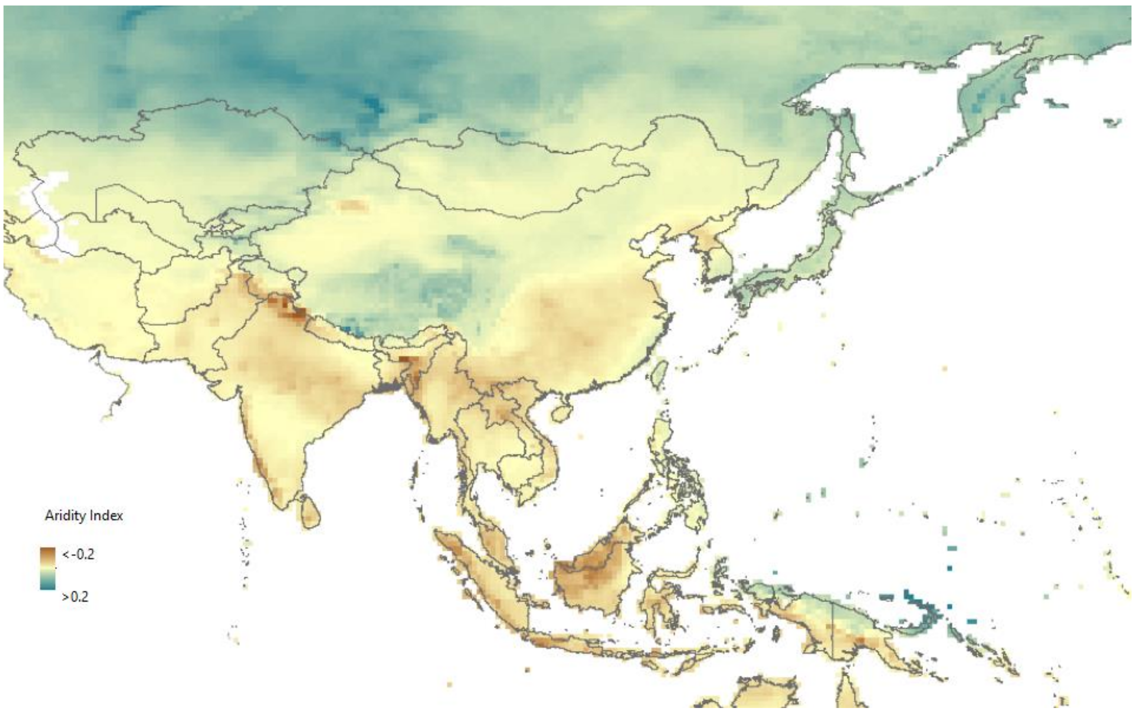
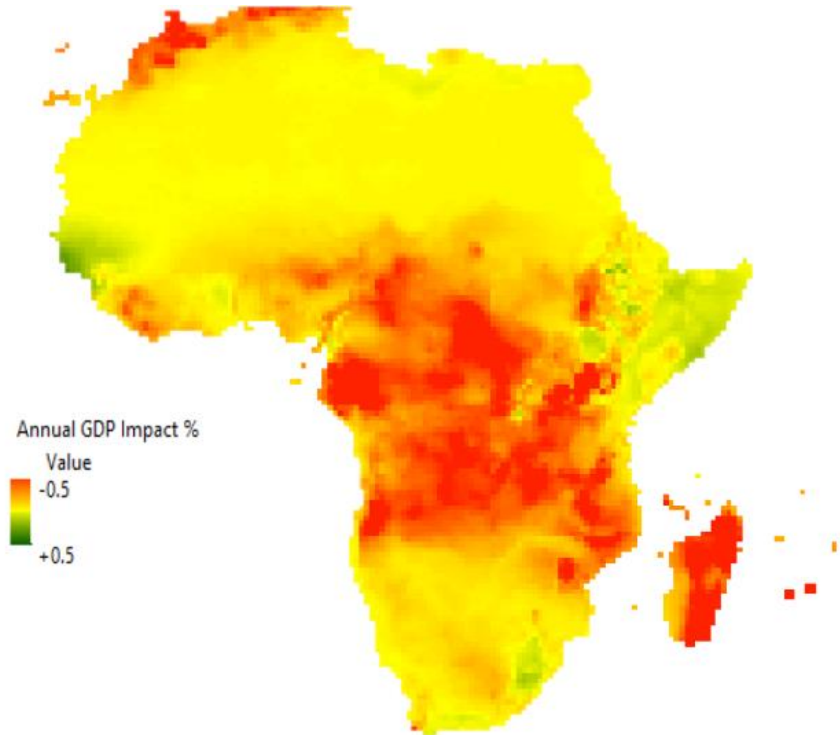


Figure 6: Average annual effects of Aridity Index on GDP per capita 2040–2079 (CMCC-BioClimInd – RCP 4.5 Projections). Future data on precipitation and PET used to construct the AI were retrieved from the CMCC-BioClimInd [9].

Panel A: Africa



Panel B: Asia

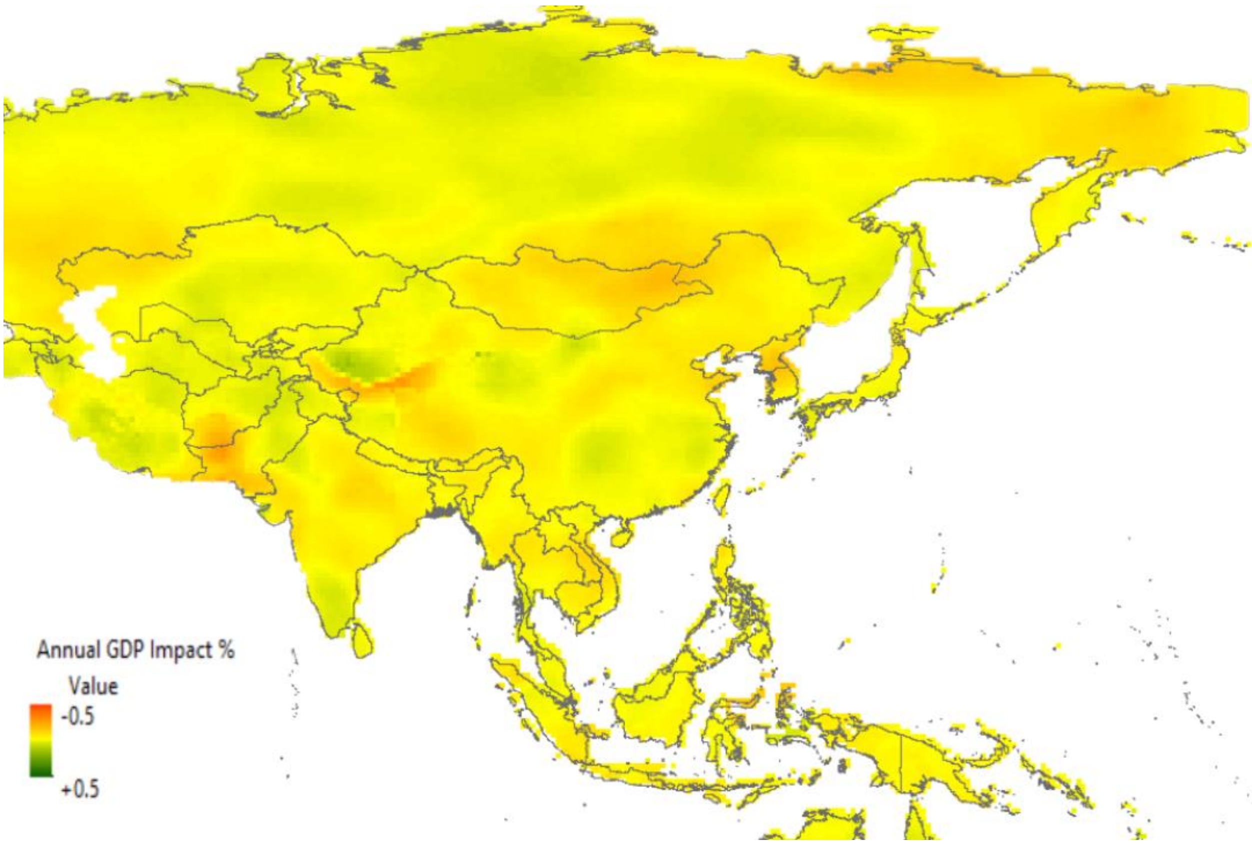
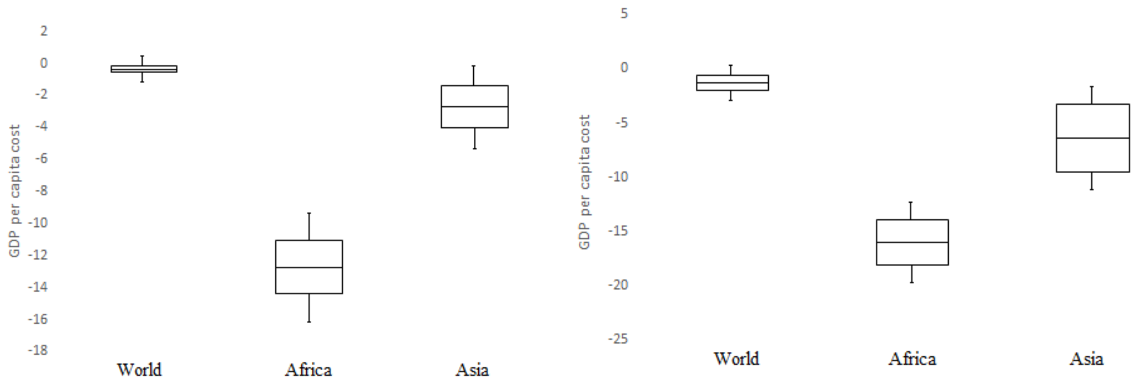


Figure 7: GDP per capita cost due to soil aridification between 1990 and 2015 (left) and between the present day and 2079 in the world, Africa, and Asia. Future data on precipitation and PET used to construct the AI were retrieved from the CMCC-BioClimInd [9].



Appendix

A. Data description

We collected high-frequency, geo-referenced data from various sources. We compiled a global dataset for the period 1990–2015. We constructed a dataset of socio-economic, weather, and agricultural variables with a raster grid structure: the units of observation were subnational "cells" of 0.5 degrees of latitude by 0.5 degrees of longitude (approximately 56 km at the equator) for a period of 26 years[6].

Climate time-series data

The Climatic Research Unit (CRU) TS4.04 variables are cloud cover, diurnal temperature range, frost day frequency, wet day frequency, potential evapotranspiration (PET), precipitation, daily mean temperature, monthly average daily maximum and minimum temperature, and vapour pressure for the period from January 1901–December 2019 [27].

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 using daily or sub-daily data at the National Meteorological Services and other external agents. The ASCII and NetCDF data files both 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 that interpolation. The missing value code for "stn" is -999. All CRU Time-series (TS) output files are actual values and do not consider anomalies.

Regarding precipitation, potential evapotranspiration data were retrieved from the gridded Climatic Research Unit (CRU) Time-series (TS) version 4.00. Data are month-by-month variations in climate variables from 1901–2015. The data are provided on high-resolution ($0.5^{\circ} \times 0.5^{\circ}$) grids, produced by CRU at the University of East Anglia and funded by the UK National Centre for Atmospheric Science (NCAS), a NERC collaborative centre.

Precipitation is available for each month from 1901 to 2015 and is expressed as the average monthly millimetres of rainfalls (mm/month). For each year, we computed the average monthly precipitation (mm/month). Different from precipitation data, potential

[6] Grid level data of precipitation, temperature, potential evapotranspiration, and agricultural suitability are available at a lower resolution scale than GDP per capita data (0.083 degrees of latitude by 0.083 degrees of longitude, which correspond to approximately 10 km at the equator). Annual GDP per capita data is available at 0.5 degrees of latitude by 0.5 degrees of longitude. Therefore, to conduct the empirical procedure, we first up-scaled the weather variables to the same grid resolution of GDP per capita.

evapotranspiration data are available daily in the same period and are expressed as mm/day. To assess the empirical evaluations of both precipitation and the effects of PET, we computed the average monthly PET (mm/month) for each year. Further details on the construction of climate data use are provided in Appendix A. We also used average annual temperature as a climate grid-specific control variable. Gridded data on temperature were retrieved from the CRU TS dataset.

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

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

Therefore, AI is defined as the yearly average of precipitation (P) over potential evapotranspiration (PET).

GDP per capita

An increasing amount of high-resolution global spatial data is available for use in various assessments. However, key economic and human development indicators are still mainly provided only at the national level, and they are downscaled by users for gridded spatial analyses. Instead, it would be beneficial to adopt data for subnational administrative units where available, supplemented by national data where necessary. To assess the economic effects of soil aridification due to climate change, we used the GDP per capita (PPP) dataset from Kummu et al. (2018) and represented the average gross domestic product per capita in a given administrative area unit. GDP is shown in 2011 international US dollars.[7] The complete dataset provides annual gridded datasets on GDP per capita (PPP), total GDP (PPP), and the Human Development Index for the entire five arc-min resolutions for the 26 years ranging from 1990–2015.

The statistics on weather variables and GDP per capita are summarised in Table 1.

[7]This dataset comprises gap-filled sub-national data, supplemented by national data where necessary. Data gaps were filled by using national temporal pattern. The dataset has a global extent at a 5 arc-min resolution for the 26 years from 1990–2015.

Table 1: Summary statistics and 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
GDP per capita	USD 2011	1,601,730	22828.79	24064.07	0	199439.6

Note. Each observation is a cell.

B. Methodology

This section describes the analytical method used to assess the effects of soil aridification on economic development. We estimated a model that includes linear and quadratic regressors for the Aridity Index (AI) specific to the cell to assess the non-linear effects of the desertification process. The rationale for this hypothesis is that we expected precipitation to positively affect economic development (at least in agriculture-centred economies through an increase in agricultural output). However, when precipitation increases too much (e.g., in the form of floods), the economic effects might be negative (Burke et al., 2015).

Our baseline regression was as follows:

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \beta_2 AI_{ict} + \beta_3 AI_{ict}^2 + \beta_4 P_{ict} + \beta_5 PET_{ict} + \delta T_{ict} + \sigma_t + \omega_i + \rho_c \tau + \varepsilon_{ict} \tag{1}$$

where y_{ict} denotes the natural logarithm of GDP per capita of grid i, in country c, in year t. The temporal dependence of GDP per capita is represented by y_{ict-1} (i.e., the natural logarithm of GDP per capita of grid i, in country c, in year t − 1). AI_{ict} denotes the natural logarithm of the average annual Aridity Index of grid *i* in country *c* at year *t*. To account for the non-linear relationship between aridity and GDP per capita, we followed Burke et al. (2015)[8] and included the quadratic term AI^2 in our baseline model. P_{ict} is the logarithm of the average monthly amount of precipitation, while the variable PET_{ict} indicates the logarithm of the annual potential evapotranspiration. We also controlled for the average yearly mean surface temperature T_{ict}. Finally, the model considers year-fixed effects, denoted as σ_t, grid fixed effects as ω_i, and country linear trends as $\rho_c\tau$ to account for country-specific trends over time. We estimated equation (1) via a panel fixed effects estimator.

[8] Burke et al. (2015) showed that economic productivity was non-linear in temperature in all countries, with productivity peaking at an annual average temperature of 13 °C and declining strongly at higher temperatures.

We first assess the effects of precipitation on GDP per capita, as obtained in previous economic studies. We find that annual variations in temperature and precipitation slowed economic growth, measured by GDP per capita by roughly 0.1 percentage points. These estimates are in line with Carleton and Hsiang (2016).

Table 1 shows our main results. The variables of interest are the annual Aridity Index, and the Aridity Index squared. Higher values of this variable corresponded to more humid and, therefore, less arid soil. We also controlled for the average near-surface temperature. The linear and quadratic terms for all climate indicators are included.

Columns (1)–(7) show the results of different specifications of the model described in equation 1. All specifications include year and grid fixed effects, as well as country linear trends. Specifically, in column (1), we consider only the contemporaneous linear effects of AI on GDP per capita. In this specification, a percentage point decrease in the AI in grid i is associated with a 0.5% decline in GDP per capita in the same grid. Column (2) shows both contemporaneous linear and quadratic effects of AI on the natural logarithm of GDP per capita. This specification confirms the positive relationship between the Aridity Index and GDP per capita. However, the inclusion of the quadratic term AI shows that significant increases in precipitation[9] and PET[10]are not positively associated with economic growth.

The inclusion of additional controls in the baseline equation (1) does not appear to change the impact of AI on GDP per capita change either in sign or in magnitude. In column (3), we added precipitation, PET, and temperature controls. In column (4), we restrict the analysis to only the African continent, whereas in column (5), we focus on Asian countries. These two continents are shown to be the most affected by human-induced soil aridification. Column (6) shows the effects of soil aridification, excluding areas that are already desert (i.e., AI < 0.05) or very humid (i.e., AI > 0.65). This further restriction is done because we expect the effects of desertification to be more pronounced in areas of the world that are not already desert. This specification shows that a one deviation decrease in the Aridity Index is associated with a 5.6% decrease in the GDP per capita of grid i in year t. Finally, column (7) replicates the results shown in column (6), focusing on Africa. Equation (1) also shows the positive relationship between additional climate variables (i.e., precipitation and temperature) and GDP per capita. Columns (3) to (7) show that a one standard deviation shock in annual precipitation levels affects GDP per capita between 1.6 and 2.5 percentage points. In contrast, a standard deviation shock in temperature levels contributes from 0.5 to 2.9 percentage points to the GDP per capita. However, the magnitude is lower compared to that of the Aridity Index. As shown in Table 2, the results revealed a robust positive relationship between GDP per capita and the Aridity Index.

We explored the sensitivity of our estimates to several models, aridity classes, and income groups. To confirm the results shown in Table 3, we first employed the Arellano-Bond estimation [22]. Here, we also considered that the lagged values of the predetermined

[9] Examples of large increases in precipitation are sudden floods which might hamper agriculture yields).

[10] A significant increase in potential evo-transpiration substantially reduces water in the soil.

regressors were instruments. The results are shown in Table 3, and they confirmed the adverse effects of soil aridification on GDP per capita. We also tested for serial correlations. We rejected no autocorrelation of order one but could not reject autocorrelation of order 2. There was evidence that the Arellano-Bond model assumptions were satisfied.

We explored robustness to several types of soil aridity class and income groups because we expected that aridification would primarily affect poor economies more than advanced ones. The results of these robustness checks are shown in Tables 4 and 5 in the Appendix. The estimates reported in Tables 4 and 5 showed no relationship between the Aridity Index and GDP per capita in arid and humid areas of the world, respectively. This finding is consistent with the assumption that the effects of soil aridification should not be significant in regions already arid or areas characterised by high precipitation levels throughout the entire year. However, semi-arid and sub-humid areas are the most heavily penalised by the process of desertification. Second, soil aridification significantly affects areas characterised by low- and middle-income levels because they rely on agriculture, compared with high-income areas, which depend on other sectors. Finally, we controlled for the temporal as well as spatial dependence of both the dependent variable and covariates.

First, to control for temporal correlation of the Aridity Index and GDP per capita, we included temporal lags of the regressor and dependent variable.

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \sum_{k=0}^{2} \beta_{2k}\, AI_{ict-k} + \sum_{k=0}^{2} \beta_{3k}\, \boldsymbol{X}_{ict-k} + \sigma_t + \omega_i + \rho_c + \varepsilon_{ict} \qquad (2)$$

where y_{ict} denotes the natural logarithm of GDP per capita of grid i in country c at time t. We considered the same fixed effects and linear trends used in the baseline equation (1) and estimate (2) via OLS.

Table 6 shows the results of equation (2). The regressor of interest is Log AI, which is defined as the natural logarithm of the Aridity Index in grid i at year t. Higher values of this variable correspond to higher "effective" water availability in the soil. In contrast, lower values correspond to the soil's lower water availability (i.e., aridification of the land). We also controlled for additional grid-specific climate control variables, such as precipitation, potential evapotranspiration, and temperature, as well as year and grid fixed effects and country linear trends.

Column (1) shows a contemporaneous positive relationship between the Aridity Index and GDP per capita worldwide, including year and grid fixed effects but without considering additional climate controls. The positive relationship between the Aridity Index and GDP per capita did not vary when we included grid-specific controls (column 2) and temporal dependence of 2 years (column 3).

To account for spatial correlations in the covariates, we included spatial lags of the variables of interest. The spatial dependence structure is defined by a symmetric weighting matrix W, and the spatial lag of a variable is obtained by multiplying the matrix W by the vector of observations:

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \beta_2 W \cdot y_{ict} + \sum_{k=0}^{2} \beta_{3k} AI_{ict-k} + \sum_{k=0}^{2} \beta_{4k} W \cdot AI_{ict-k} + \sum_{k=0}^{2} \beta_{5k} \boldsymbol{X}_{ict-k} + \sum_{k=0}^{2} \beta_{6k} W \cdot \boldsymbol{X}_{ict-k} + \sigma_t + \omega_i + \varepsilon_{ict} \qquad (3)$$

where y_{ict} denotes the natural logarithm of GDP per capita of grid i in country c at time t. As in equation (2), **X** denotes the vector of all grid-specific climate controls.

Most previous empirical work on the effects of climate on economic development has assumed that observations are independent across space. Instead, we estimate this relationship following Hsiang (2010) to adjust standard errors for both spatial and serial correlation. The spatial matrix W included in the dynamic model described in equation (2) exploits variations in the Aridity Index occurring in grids whose centroids are located within 56 km (or within 0.5-degree latitude and 0.5-degree longitude) as “first-degree neighbours”. In comparison, grids whose centroids are situated between 56 and 112 km (or within 1-degree latitude and 1-degree longitude) are defined as “second-degree neighbours”. Thus, our implicit identifying assumption is that climate shocks occurring in cells beyond 1-degree latitude and 1-degree longitude do not affect GDP in their own cells, with the exception of GDP per capita, which then spills over in space.

We chose to estimate a model that includes spatially and temporally autoregressive terms because, as highlighted in Harari and Ferrara (2018), ignoring the term W · Y could lead to an omitted-variable bias. As a result, the GDP would be attributed to GDP determinants that are clustered spatially, and the contemporaneous impact of climate shocks would tend to be overestimated. The results are shown in Table 7.

Finally, Tables 8 and 9 show the results of equation (3). In these tables, we consider both spatial and temporal dependence of the Aridity Index’s effects on the GDP per capita per income class as defined by the World Bank. Specifically, in column (1) of Table 8, we limit the effects to low-income areas of the world (i.e., a GDP per capita of 4,000USD or below). Column (2) shows the impact of the annual variations in the Aridity Index on lower-middle-income areas (i.e., between 4,000 USD and 8,000 USD). Finally, column (4) shows the effects on high-income regions (i.e., 12,000 USD and above). As usual, the regressor of interest is Log AI, showing the contemporaneous impact of the Aridity Index on the GDP per capita for each grid i. As expected, the strongest relationship is shown in columns (1) and (2) in low-and lower-middle-income areas. This result confirms that soil aridification primarily affects underdeveloped areas of the world. Those areas rely extensively on agriculture.

Table 2: Effects of AI, precipitation, and temperature on GDP per capita by year, grid fixed effects, and country trends

VARIABLES	(1) Ln (GDP)	(2) Ln (GDP)	(3) Ln (GDP)	(4) Ln (GDP)	(5) Ln (GDP)	(6) Ln (GDP)	(7) Ln (GDP)
Log AI	0.00400***	0.00822***	0.00140	0.0692***	0.0131**	0.00180	0.0364***
	(0.000268)	(0.000471)	(0.00209)	(0.00903)	(0.00637)	(0.00282)	(0.0101)
Log AI2		0.000640***	0.00132***	0.00109***	0.000989***	0.00459***	0.00371***
		(5.74e-05)	(6.49e-05)	(0.000106)	(0.000207)	(0.000376)	(0.000640)
Log Prec			0.0144***	-0.0557***	0.00377	0.0319***	-0.00841
			(0.00235)	(0.00944)	(0.00709)	(0.00310)	(0.0102)
Log Temp			0.00426***	0.0889***	-0.00305***	0.00347***	0.0126***
			(0.000218)	(0.00323)	(0.000440)	(0.000281)	(0.00442)
Log GDP t-1	0.909***	0.909***	0.929***	0.885***	0.917***	0.928***	0.931***
	(0.000433)	(0.000433)	(0.000677)	(0.00170)	(0.00123)	(0.000874)	(0.00163)
Constant	0.894***	0.897***	0.659***	0.787***	0.819***	0.678***	0.571***
	(0.00420)	(0.00420)	(0.00691)	(0.0187)	(0.0146)	(0.00938)	(0.0245)
Grid FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE			YES	YES	YES	YES	YES
World	YES	YES	YES			YES	
Africa				YES			YES
Asia					YES		
Arid and Sub-Humid						YES	YES
Observations	1,623,531	1,623,531	1,101,680	250,125	293,405	680,713	137,182
R-squared	0.913	0.913	0.921	0.884	0.951	0.926	0.953
Number of id	65,247	65,247	55,026	10,005	18,320	43,299	6,654

Note. This table presents the effects of variation in the Aridity Index on GDP per capita at the grid level. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Effects of AI, precipitation, and temperature on GDP per capita by Arellano-Bond estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Ln (GDP)	Ln (GDP)	Ln (GDP)	Ln (GDP)	Ln (GDP)	Ln (GDP)	Ln (GDP)
Log AI	0.00259	-0.211***	0.0365**	0.386***	0.0770**	0.0796***	0.113***
	(0.00194)	(0.00536)	(0.0157)	(0.0364)	(0.0342)	(0.00251)	(0.00690)
Log AI2		-0.0896***	0.00400***	0.00285*	-0.00243	0.00261***	-0.00135**
		(0.00223)	(0.00153)	(0.00173)	(0.00232)	(0.000298)	(0.000536)
Log Prec			0.0665***	0.385***	0.0370	0.0614***	0.102***
			(0.0175)	(0.0360)	(0.0363)	(0.00281)	(0.00699)
Log Temp			-0.00827***	0.00269	-0.00863***	0.00485***	0.00499***
			(0.00138)	(0.00417)	(0.00175)	(0.000321)	(0.000587)
Log PET			-0.0108	-0.128***	-0.124***	-0.0779***	-0.189***
			(0.00690)	(0.0285)	(0.0148)	(0.00333)	(0.00901)
Log GDP t-1	0.566***	0.529***	0.724***	0.580***	0.591***	0.232***	0.308***
	(0.00431)	(0.00509)	(0.0118)	(0.0251)	(0.0216)	(0.00639)	(0.00915)
Constant						7.383***	6.362***
						(0.0596)	(0.084)
Grid FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country X Year FE			YES	YES	YES	YES	YES
World	YES	YES	YES			YES	
Africa				YES			YES
Asia					YES		
Arid and Sub-Humid						YES	YES
Observations	1,623,531	1,623,531	1,101,680	250,125	293,405	680,713	137,182
Number of id	65,247	65,247	55,026	10,005	18,320	43,299	6,654

Note. This table presents the effects of variation in the Aridity Index on GDP per capita at the grid level using the Arellano-Bond estimator. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effects of AI on GDP on different aridity classes by year, grid fixed effects, and country trends

VARIABLES	(1) Hyper_Arid	(3) Arid	(2) Semi-Arid	(4) Sub-Humid	(5) Humid
Log AI	-0.177***	-0.00311	0.0813***	0.126***	-0.00406
	(0.0176)	(0.00816)	(0.0105)	(0.0466)	(0.00397)
Log AI 2	0.000282**	-0.00943***	0.00507***	-0.0575	0.0112***
	(0.000134)	(0.00314)	(0.00153)	(0.0408)	(0.00188)
Log Prec	0.180***	0.00990*	-0.0490***	0.0614***	0.00671
	(0.0177)	(0.00521)	(0.00852)	(0.00612)	(0.00451)
Log Temp	0.00356***	-0.000952**	0.00627***	0.000364	0.00144***
	(0.00130)	(0.000435)	(0.000915)	(0.000490)	(0.000305)
Log GDP t-1	0.912***	0.910***	0.891***	0.917***	0.925***
	(0.00249)	(0.000960)	(0.00226)	(0.00154)	(0.000909)
Constant	0.509***	0.857***	1.154***	0.713***	0.698***
	(0.0386)	(0.0112)	(0.0288)	(0.0196)	(0.00849)
Observations	170,754	306,093	242,718	124,974	257,080
R-squared	0.883	0.933	0.921	0.951	0.945
Number of id	10,723	28,852	17,896	18,392	19,813
Grid FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES	YES	YES

Note. This table presents the results of the effects of the Aridity Index on GDP per capita per different classes of aridity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects of AI on GDP on different income classes by year, grid fixed effects, and country trends

VARIABLES	(1) Low	(2) Lower Middle	(3) Upper Middle	(4) High
Log AI	0.00168**	0.161***	0.123***	0.0230***
	(0.000839)	(0.00800)	(0.00878)	(0.00330)
Log AI 2	-0.102***	-0.00240***	-0.00349***	0.000781**
	(0.0101)	(0.000806)	(0.000926)	(0.000373)
Log Prec	0.130***	0.158***	0.146***	-0.0261***
	(0.0104)	(0.00869)	(0.0104)	(0.00359)
Log Temp	0.00999***	0.00591***	0.00520***	0.000458
	(0.00167)	(0.000814)	(0.000423)	(0.000311)
Log GDP t-1	0.837***	0.729***	0.599***	0.731***
	(0.00517)	(0.00376)	(0.00774)	(0.0101)
Constant	1.130***	2.658***	3.967***	2.887***
	(0.0438)	(0.0384)	(0.0803)	(0.110)
Observations	194,162	138,762	110,414	237,375
R-squared	0.878	0.860	0.741	0.897
Number of id	13,307	16,130	14,058	21,015
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

Note. This table presents the results of the effects of the Aridity Index on GDP per capita per different classes of income. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of AI on GDP with the inclusion of temporal dependence by year, grid fixed effects, and country trends

VARIABLES	(1) Ln (GDP)	(2) Ln (GDP)	(3) Ln (GDP)	(4) Ln (GDP)	(5) Ln (GDP)
AI	0.00861***	0.0633***	0.0525***	0.0535***	0.0137***
	(0.000481)	(0.00368)	(0.00204)	(0.00277)	(0.00112)
AI 2	0.000664***	-0.000144**	0.000186***	0.000744*	0.0141
	(5.87e-05)	(6.49e-05)	(6.49e-05)	(0.000420)	(0.0105)
AI t-1	-0.00401***	-0.0882***	-0.118***	-0.195***	0.262***
	(0.000284)	(0.00251)	(0.00265)	(0.00359)	(0.0131)
AI t-2			0.144***	0.158***	-0.0853***
			(0.00257)	(0.00344)	(0.0111)
Prec		-0.0650***	-0.0497***	-0.0458***	0.00368
		(0.00377)	(0.00230)	(0.00305)	(0.0109)
Log GDP t-1	0.909***	0.909***	0.902***	0.900***	0.883***
	(0.000442)	(0.000443)	(0.000491)	(0.000611)	(0.00162)
Prec t-1		0.0898***	0.121***	0.204***	-0.262***
		(0.00262)	(0.00276)	(0.00383)	(0.0130)
Prec t-2			-0.144***	-0.163***	0.0875***
			(0.00266)	(0.00365)	(0.0111)
Constant	0.892***	0.888***	1.021***	1.005***	1.274***
	(0.00432)	(0.00554)	(0.00603)	(0.00726)	(0.0266)
Observations	1,623,531	1,623,531	1,558,284	1,005,684	240,120
R-squared	0.993	0.993	0.993	0.993	0.996
Grid FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES	YES	
Africa					YES
Arid and Sub-Humid				YES	

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

Table 7: Effects of AI on GDP with the inclusion of temporal and spatial dependence by year, grid fixed effects, and country trends

VARIABLES	(1) Ln (GDP)	(2) Ln (GDP)	(3) Ln (GDP)	(4) Ln (GDP)
Log GDP t-1	0.176***	0.272***	0.913***	0.244***
	(0.00380)	(0.00607)	(0.00246)	(0.00762)
W * Log GDP	0.841***	0.746***	1.014***	0.772***
	(0.00366)	(0.00599)	(0.00289)	(0.00741)
Log AI	-0.000974	0.00549**	0.00244*	0.0145***
	(0.000963)	(0.00221)	(0.00131)	(0.00414)
Log AI t-1	0.00131	0.000957	0.00536***	0.00162**
	(0.000925)	(0.000851)	(0.000924)	(0.000669)
Log AI t-2		0.00208**	0.00538***	0.00244***
		(0.000929)	(0.00125)	(0.000749)
W * Log AI	0.00177*	0.00140	-0.000601	0.000701
	(0.000987)	(0.000928)	(0.00106)	(0.000716)
W * Log AI t-1	-0.00194**	-0.00106	-0.00538***	-0.00161**
	(0.000955)	(0.000885)	(0.000938)	(0.000680)
W * Log AI t-2		-0.00197**	-0.00536***	-0.00267***
		(0.000961)	(0.00127)	(0.000762)
Log Prec		-0.00562***	-0.00223***	0.0147***
		(0.00200)	(0.000833)	(0.00415)
Log Temp		5.04e-05	6.74e-06	-0.000261
		(0.000135)	(6.13e-05)	(0.000257)
Constant	-0.162***	-0.149***	-0.00216*	-0.143***
	(0.00730)	(0.00635)	(0.00112)	(0.00796)
Observations	1,615,180	1,052,744	651,187	520,667
R-squared	0.999	0.999	1.000	0.999
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	
Africa				YES
Arid and Sub-Humid			YES	

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

Table 8: Effects of AI on GDP per class of aridity by temporal and spatial dependence, year, grid fixed effects, and country trends

VARIABLES	(1) Hyper-Arid	(2) Arid	(3) Semi-Arid	(4) Sub-Humid	(5) Humid
Log GDP t-1	0.927***	0.890***	0.918***	0.932***	0.929***
	(0.00457)	(0.00610)	(0.00303)	(0.00418)	(0.00284)
W * Log GDP	1.006***	1.012***	1.012***	1.026***	1.008***
	(0.00275)	(0.00424)	(0.00442)	(0.0101)	(0.00473)
Log AI	0.000313*	0.00432***	0.00451***	0.0111***	0.00420***
	(0.000184)	(0.00132)	(0.00137)	(0.00319)	(0.00152)
Log AI t-1	-0.00320	0.00182	0.00116	0.00902*	-0.00380
	(0.00333)	(0.00247)	(0.00180)	(0.00515)	(0.00246)
Log AI t-2	0.000171	0.00869***	0.000826	0.00998*	1.73e-05
	(0.000206)	(0.00161)	(0.00146)	(0.00537)	(0.00138)
W * Log AI	-0.000283	-0.00437***	-0.00458***	-0.0104***	-0.00375**
	(0.000190)	(0.00134)	(0.00140)	(0.00319)	(0.00154)
W * Log AI t-1	1.88e-05	0.000621	0.00140	-0.0121***	0.00167
	(0.000195)	(0.00169)	(0.00145)	(0.00440)	(0.00185)
W * Log AI t-2	-0.000159	-0.00868***	-0.000895	-0.00980*	-0.000174
	(0.000210)	(0.00164)	(0.00148)	(0.00536)	(0.00141)
Log Prec	0.00321	-0.00260	-0.00291**	-0.00166	0.00177
	(0.00334)	(0.00201)	(0.00130)	(0.00222)	(0.00172)
Log Temp	-0.000248	7.40e-05	-6.96e-06	-6.77e-05	- 0.000151***
	(0.000188)	(0.000185)	(9.52e-05)	(8.97e-05)	(5.35e-05)
Constant	-0.00317	-0.00183	-0.00151	-0.00861***	-0.00108
	(0.00527)	(0.00267)	(0.00153)	(0.00235)	(0.00233)
Observations	163,157	232,551	292,638	119,395	244,943
R-squared	1.000	1.000	1.000	1.000	1.000
Grid FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES	YES	YES

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

Table 9: Effects of AI on GDP per income class by temporal and spatial dependence, year, grid fixed effects, and country trends

VARIABLES	(1) Low	(2) Lower Middle	(3) Upper Middle	(4) High
Log GDP t-1	0.868***	0.854***	0.820***	0.868***
	(0.00832)	(0.00511)	(0.0116)	(0.00884)
W * Log GDP	1.032***	0.955***	0.983***	1.007***
	(0.00425)	(0.00630)	(0.00406)	(0.00438)
Log AI	0.00520***	0.00628***	-0.00402	0.00193*
	(0.00144)	(0.00207)	(0.00292)	(0.00105)
Log AI t-1	0.00790**	0.00183	-0.000947	-0.00519***
	(0.00353)	(0.00322)	(0.00411)	(0.00137)
Log AI t-2	0.00328**	0.00721***	-0.00330	-0.000120
	(0.00156)	(0.00207)	(0.00331)	(0.00104)
W * Log AI	0.00555***	-0.00387*	0.000623	0.00256**
	(0.00192)	(0.00234)	(0.00367)	(0.00115)
W * Log AI t-1	-0.00553***	-0.00601***	0.00370	-0.00207*
	(0.00147)	(0.00211)	(0.00305)	(0.00106)
W * Log AI t-2	-0.00385**	-0.00733***	0.00442	2.34e-05
	(0.00157)	(0.00213)	(0.00343)	(0.00104)
Log Prec	-0.0137***	0.00136	0.000333	0.00257***
	(0.00292)	(0.00252)	(0.00224)	(0.000820)
Log Temp	9.25e-05	0.000421*	0.000343***	-3.58e-05
	(0.000621)	(0.000217)	(0.000119)	(4.69e-05)
Constant	0.00649	0.0898***	0.191***	0.0442***
	(0.00398)	(0.00694)	(0.0147)	(0.00644)
Observations	236,659	195,001	148,505	309,422
R-squared	0.999	0.993	0.988	0.998
Grid FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

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

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