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The long-term economic effects of aridification

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ABSTRACT

We conduct a disaggregated empirical analysis of the economic effects of desertification, exploiting a novel grid-cell global dataset from 1990 to 2015. Our measure of desertification combines annual variation in precipitation and potential evapotranspiration of the soil. To ensure accuracy, we employed advanced spatial econometric techniques to account for the interdependence between economic development and both time and location. Our results indicate that a one standard deviation increase in desertification is associated with a 0.6% to 0.9% decrease in GDP per capita. Based on these estimates, we have predicted the potential impact of future desertification on economic development, with a particular focus on Africa and Southeast Asia.

1. Introduction

Approximately 52 million square kilometres 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 natural plant transpiration (Sidahmed, 2018). This "right" balance between rainfall and water evaporation is pivotal in maintaining biological productivity. However, climate change is steadily modifying this equilibrium, dramatically affecting liveability and food availability in many areas worldwide.

According to the Intergovernmental Panel on Climate Change (2019),[1] in 2015, about 500 million people lived in areas that had experienced desertification between the 1980s and 2000s. Desertification refers to the "deterioration of land in arid, semi-arid, and dry sub-humid areas due to various factors such as changes in climate and human actions". It is predicted that the problem of desertification, will escalate in the next few decades (IPCC, 2019).

This is because the population that is susceptible to this problem is expected to increase by 178–277 million people by the year 2050, depending on the global climate scenario. This increase is mainly expected to affect Asia and Africa, where the largest population of vulnerable individuals is predicted to be located. Despite these projections, there is little evidence to support the economic effects of desertification in both the short and long term, according to Dell et al. (2008, 2012) and Carleton and Hsiang (2016).

In recent economic literature, there has been extensive discussion surrounding the effects of global warming on the economies of various regions. This is an issue of significant importance, and it is crucial that we gain a detailed understanding of the economic ramifications of climate change. Researchers have primarily examined the economic consequences of changes in precipitation and temperature averages while overlooking other critical factors, such as variations in precipitation intensity and temperature increase.[2] However, it is essential to acknowledge that these factors are just two of the many complex alterations happening in our environment.

The present study aims to assess the economic effects of the often-overlooked phenomenon of climate-induced desertification. This process considers both precipitation and potential evapotranspiration of the soil. To this end, we first assembled a panel dataset of >66,000 cells with almost global coverage of the 26 years between 1990 and 2015. We combined annual grid-level data on GDP per capita (Kummu et al., 2018) with climate variables such as precipitation, average temperature, and potential evapotranspiration. The combination of rainfall and potential evapotranspiration allows us to use the Aridity Index (AI) to measure desertification (Middleton and Thomas, 1997).

To assess the differences between standard climate variables and the aridity index, we start with a preliminary exploration of the relationship between precipitation only and economic development by using high-

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[1] Intergovernmental Panel on Climate Change (IPCC), Sixth Assessment Report (2019). AR6 Climate Change 2021: Impacts, Adaptation and Vulnerability.
[2] Burke et al., 2015; Zhang et al., 2017 for a review of the economic impact of climate.

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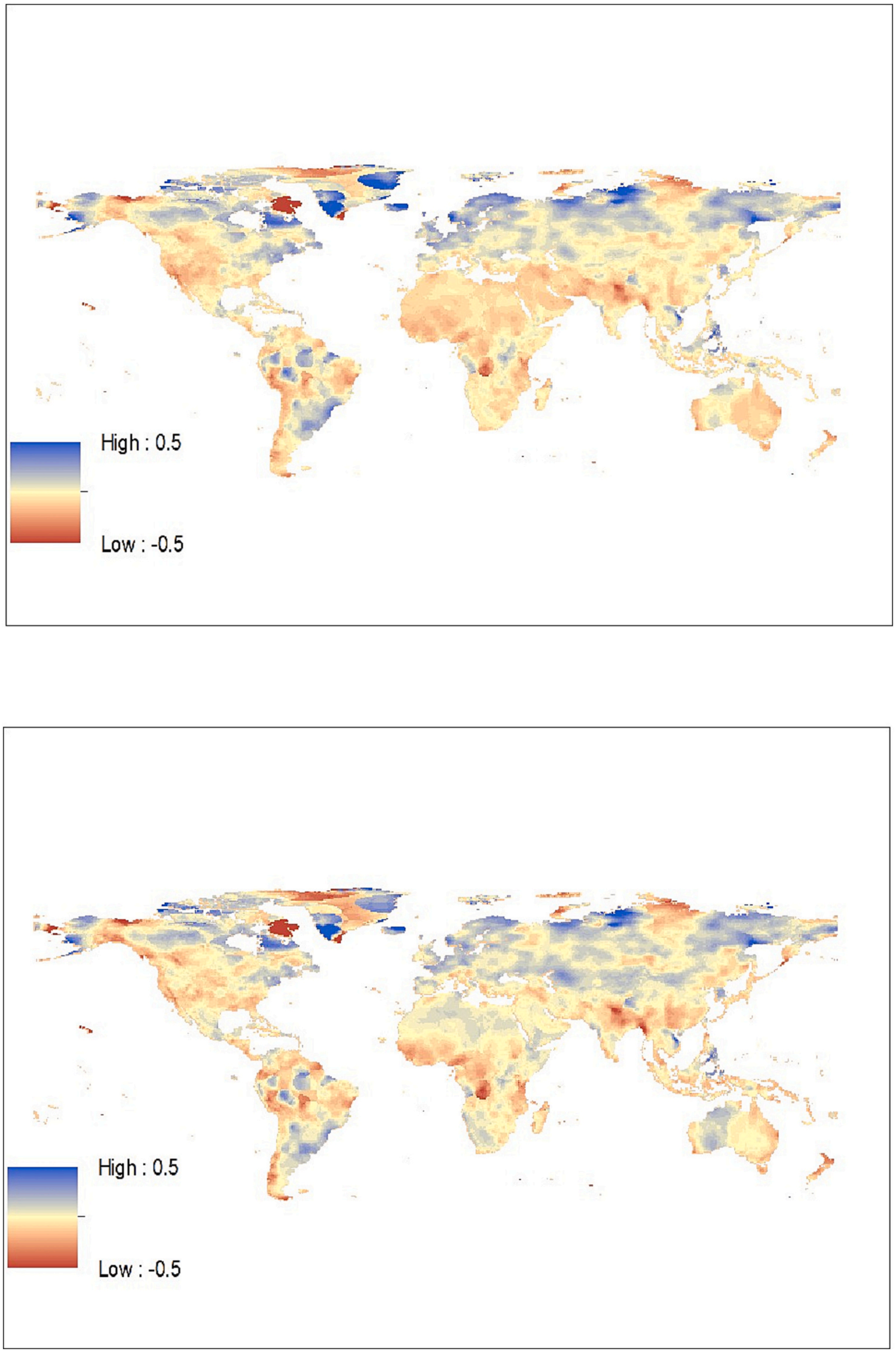


Fig. 1. Global distributions of percentage changes (%) in (a) precipitation and (b) PET between the present day (2000–2015) and the historical average (1900–1980).
Panel A: Precipitation changes.
Panel B PET changes.
Secular data on precipitation and PET were retrieved from Fu et al. (2016),

resolution spatial data through ordinary least squares (OLS) regressions controlling for cell-specific and geographic and climatic characteristics that might have direct effects on economic growth. The analysis controls for cell fixed effects and country-specific linear trends. We also include higher-order climatic variables. To account for the potential spatial autocorrelation of climate variables, we use Conley (1999) spatial autocorrection method. Furthermore, consistent with previous literature on the social effects of desertification, the inclusion of temporal and spatial lags in the baseline model confirms the negative relationship between desertification and GDP per capita (Harari and Ferrara, 2018).

This mitigates concerns about the exclusion restriction in the empirical estimation. We find a weakly positive relationship between the average annual amount of precipitation and GDP per capita. This result confirms the conclusions achieved in the economic literature that

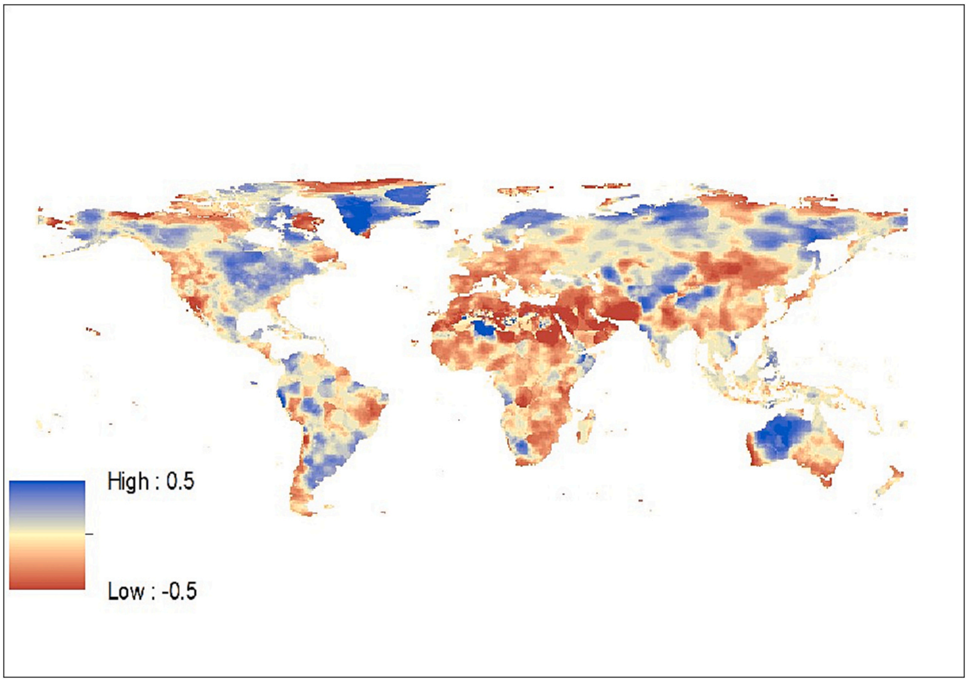


Fig. 2. Global distributions of percentage changes (%) in the AI between the present day (2000–2015) and the historical average (1900–1980). Secular data on precipitation and PET used to construct the AI were retrieved from the National Centre for Atmospheric Science (2020).

demonstrate that higher precipitation is associated with higher economic growth, in particular in more agricultural areas of the world. However, if the increase in precipitation were accompanied by higher evapotranspiration levels, the result would be an increase in aridification. Fig. 1 shows that most areas of the world have experienced an increase in annual precipitation during the period 1990–2015 compared to their historical average (1900–1980). Nevertheless, this was accompanied by higher evaporation of the soil. For this reason, we aim to estimate the combined effect of precipitations and evapotranspiration, that is, the so-called Aridity Index, on grid-level GDP.

Our findings can be summarised as follows. First, we find 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%, depending on the geographical area. The African continent experienced the highest decrease, with a total cost of 14% in GDP per capita, caused by desertification from 1990 to 2015.[3] Malpede and Percoco (2023) investigate the reduced crop yield as a result of aridification. This provides a possible channel explaining the negative association between desertification and GDP per capita.

Second, 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 experienced an increase in rainfall from 1990 to 2015, they showed a decline in AI, which partly explains the lower GDP per capita. In this regard, we show that desertification has a more significant effect compared with precipitation and temperature alone. Indeed, our baseline estimates indicate 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 was associated with a reduction in the GDP per capita by 0.5–2.9%, depending on the world's geographical area.

[3] Our results 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.

One potential relevant concern is the potential impact of the aridity index being endogenous to the treatment. In other words, regions that have transformed into deserts since 1990 may also be home to some of the world's most impoverished populations. This should be considered when making estimations and projections, as failing to do so may result in biased outcomes. To address this concern, we took several different approaches.

First and foremost, the AI uses the Potential Evapotranspiration (PET) rather than the Actual Evapotranspiration (AET) of the soil. PET is a measure of the ability of the atmosphere to remove water from the surface through the processes of evaporation and transpiration. As opposed, the AET is the quantity of water that is actually removed from a surface due to the processes of evaporation and transpiration. As such, AET is affected by human activity, and its use would make a causal investigation problematic. PET is void of any anthropogenic activity and, therefore, is reassuring in terms of exogeneity.

Our results indicate that the relationship between the Aridity Index and the GDP per capita is more significant in arid and semi-arid areas. In contrast, no significant effect is found in more humid regions. This confirms our predictions since we expect a variation in soil aridity to have little to no impact on the already desert or highly humid areas which are not highly populated. Second, we evaluate the impact of aridity on different income classes using the World Bank classification. This allows us to estimate the relationship between aridity and GDP within specific income classes and address concerns about the endogeneity of regressors. Our findings show that desertification significantly affects lower-middle and upper-middle-income areas but not high-income regions. These results are consistent with our baseline procedure.

Finally, based on a recent dataset on future projections of precipitation and potential evapotranspiration by Noce et al. (2020), we predict that by 2079, desertification will cost Sub-Saharan Africa as much as 10% in terms of GDP per capita. We obtained those results using a baseline scenario, which assumes that the release of greenhouse gases into the atmosphere would reach its maximum level by the year 2040, with a gradual decrease anticipated to occur over the course of the 21st century.

Table 1
Summary statistics, panel data sample.

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Precipitation	mm/month	1,601,730	5.209	5.675847	0	90.960
PET	mm/month	1,601,730	8.300	5.05923	0	24.500
Aridity Index	mm/month	1,601,730	0.959	0.942291	0	18.760
Temperature	°C	1,601,730	13.819	12.35726	−20.1	37.7
GDP per capita	USD 2011	1,601,730	22,828.79	24,064.07	0	199,439.6
Log (Population)	count	1,601,730	6.802	1.012	−30.35	15.02

Each observation is a cell.

Table 2
Effects of precipitations and temperature on GDP per capita. Year, cell fixed effects and Country trends.

	(1)	(2)	(3)	(4)	(5)
Variables	Whole sample	Whole sample	World (Arid and sub-humid)	Africa	Asia
Precipitation	0.00704***	0.00786***	0.0125***	0.0398***	0.0270***
	(0.000730)	(0.000717)	(0.00168)	(0.00277)	(0.00342)
Precipitation 2	−0.00172***	−0.00167***	0.00128**	−0.00905***	−0.00617***
	(0.000123)	(0.000119)	(0.000592)	(0.000985)	(0.00118)
PET	−0.00581***	−0.0430***	−0.0437***	−0.0376***	−0.0956***
	(0.00198)	(0.00212)	(0.00256)	(0.0106)	(0.00563)
PET2	−0.00314***	0.00182***	0.00461***	−0.00537***	−0.0193***
	(0.000254)	(0.000287)	(0.000363)	(0.00124)	(0.00102)
Temperature	−0.000294***	0.000730***	0.000597***	0.00934***	−0.000580***
	(1.75e-05)	(2.54e-05)	(3.08e-05)	(0.000999)	(8.23e-05)
Temperature 2	1.18e-05***	1.22e-05***	6.98e-06***	−0.000199***	2.86e-07
	(5.08e-07)	(4.38e-07)	(4.69e-07)	(1.83e-05)	(9.37e-07)
Log GDP t-1	0.909***	0.906***	0.907***	0.932***	0.908***
	(0.000440)	(0.000418)	(0.000510)	(0.00162)	(0.000955)
Constant	0.942***	1.006***	0.967***	0.370***	0.809***
	(0.00602)	(0.00573)	(0.00714)	(0.0302)	(0.0123)
Observations	1,623,531	1,623,531	1,048,167	137,182	396,074
R-squared	0.913	0.919	0.922	0.953	0.931
Number of id	65,247	65,247	53,664	6654	20,282
Cell FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES		
Country X Year FE		YES	YES	YES	YES
Asia					YES
Africa				YES	
Arid and Sub-Humid			YES		

This table presents the effects of variation in the average annual amount of precipitation and temperature on the GDP per capita at the cell level.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our findings add to the existing literature in several ways: First, they contribute to the growing body of knowledge on the effects of climatic conditions on the economy, offering novel insights into how the interaction between precipitation and soil evapotranspiration might impact economic development. Second, identifying the areas of the world that have historically been more affected by the process of desertification would help policymakers better address the necessary policies to alleviate the impacts of climate change on the most vulnerable areas. Third, we use a measure of aridity that only considers climate variables void of human interaction. This ensures the exogeneity of our measure. Fourth, using a recent grid-level dataset on GDP per capita, this is the first study addressing the impact of desertification on the local economy at a granular level. Finally, we use cell-level projections of future temperature and precipitation in 2016 through 2079 to estimate the future economic impacts of desertification in more agriculture-reliant regions of the world.

One clear limitation of the present study is that the Arity Index formula used in our study only allows for the use of potential evapotranspiration and not actual evapotranspiration. As such, we cannot evaluate the impact of human activities on the environment. This includes activities such as urbanization, farming, and the use of fertilizers, which can significantly affect the surrounding environment.

The remainder of the paper is organized as follows. Section 2 provides background information about human-induced climate change and desertification. Section 3 describes the data and provides descriptive statistics. Section 4 describes the empirical strategy examining the effects of the aridity index on the GDP per capita. Section 5 shows the baseline results from the empirical analysis. Section 6 contains robustness checks. Section 7 describes the future AI trajectories and investigates the projected economic cost of desertification. Finally, section 8 concludes.

2. The geography of desertification

Desertification was first defined as “land degradation in arid, semi-arid, and dry sub-humid areas resulting from various factors, including climatic variations and human activities” (Ma and Zhao, 1994). 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 (Ogallo and Gbeckor-Kove, 1989).

Global warming and the rapidly growing human population will exacerbate the risk of land degradation and desertification in the

Table 3
Effects of AI on GDP per capita. Year, cell fixed effects and Country trends.

	(1)	(2)	(3)	(4)	(5)
Variables	Whole sample	Whole sample	World (Arid and sub-humid)	Africa	Asia
AI	0.0225***	0.0199***	0.0790***	0.159***	0.243***
	(0.00146)	(0.00146)	(0.00592)	(0.00826)	(0.0107)
AI 2	−0.00658***	−0.00590***	−0.0726***	−0.137***	−0.314***
	(0.000513)	(0.000545)	(0.00723)	(0.0110)	(0.0126)
Temperature		0.000633***	0.000534***	0.00949***	−0.000475***
		(2.57e-05)	(3.19e-05)	(0.00100)	(8.58e-05)
Temperature 2		1.04e-05***	5.67e-06***	−0.000203***	3.18e-06***
		(4.36e-07)	(4.74e-07)	(1.83e-05)	(9.85e-07)
Log GDP t-1	0.909***	0.906***	0.907***	0.931***	0.906***
	(0.000433)	(0.000415)	(0.000508)	(0.00162)	(0.000958)
Constant	0.880***	0.902***	0.887***	0.429***	0.887***
	(0.00427)	(0.00408)	(0.00519)	(0.0185)	(0.00970)
Observations	1,623,531	1,623,531	1,048,167	137,182	396,074
R-squared	0.913	0.918	0.922	0.953	0.931
Number of id	65,247	65,247	53,664	6654	20,282
Cell FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES		
Country X Year FE		YES	YES	YES	YES
Africa				YES	
Asia					YES
Arid and Sub-Humid			YES	YES	YES

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

drylands of developing countries. 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 compared to the 1961–1990 baseline (Huang et al., 2016; Park et al., 2018; Hsiang, 2010). This expansion of drylands would reduce carbon sequestration and enhance regional warming, resulting in warming trends over present drylands double those over humid regions. Recently it was shown that aridity is projected to decrease (i.e., areas would become drier) because of anthropogenic climate change (Moore and Diaz, 2015). However, accomplishing the 1.5 °C temperature goal would substantially reduce the likelihood that large regions would face substantial desertification and its effects (Huang et al., 2016).

Figure 1 highlights that while overall precipitation levels (as shown in Panel A) have been decreasing in many parts of the world, specifically in Africa and the Middle East, certain regions in Latin America and Southeast Asia have actually seen an increase in precipitation compared to their historical average. However, it is important to note that these areas that have received more rainfall may also be experiencing increasing aridity. As demonstrated in Panel B of Fig. 1, the elevated precipitation levels in Latin America and Southeast Asia have been coupled with higher levels of evaporation.

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[4] (Kirkham, 2014). A detailed description of the calculation of the PET is in the Appendix. Higher evapotranspiration levels lead to more arid land at a given level of precipitation. In particular, PET is calculated by the Penman's (1948) method, which considers variables such as atmospheric humidity, solar radiation, and wind that can be affected by climate change (Salem et al., 1989).

It is important to note that the PET distinguishes from the Actual Evapotranspiration (AET). While PET is a measure of the ability of the atmosphere to remove water from the surface through the processes of evaporation and transpiration, the AET is the quantity of water that is actually removed from a surface due to the processes of evaporation and transpiration. As such, AET is limited by the amount of water that is available. Given that AET is endogenous, its use would make a causal investigation problematic, at most. For this reason, we use PET, which is void of any anthropogenic activity and, therefore, is reassuring in terms of exogeneity.

As a result, the Aridity Index (AI) is a convenient measure used to determine water availability for a particular land area. This measure is obtained by comparing the total amount of precipitation received (P) against the potential evapotranspiration (PET) within a specific time frame. The AI is an essential tool that helps to determine whether an area is experiencing drought or has sufficient water for its needs. For a 30-year period, the formula used to calculate the AI is as follows:

$$AI_t = \frac{\sum_{t}^{t+30} \frac{P_t}{PET_t}}{30}$$

where t denotes the t^{th} year. We chose the Aridity Index, which considers both over other common drought indices since the latter considers the effects of precipitation, which may underestimate the risk of future droughts, especially in Africa. Moreover, the Aridity Index uses surface temperature, water evaporation, relative humidity, wind speed, and UV radiation intensity in addition to precipitation.

A similar metric that can be used to assess drought conditions is the Standardized Precipitation Evapotranspiration Index (SPEI). Both the SPEI and the AI use potential evapotranspiration (PET) as a variable to account for the effects of temperature and other factors on water demand. However, there are some differences between them.

One difference is that SPEI is calculated based on the difference between precipitation and PET, while IAI is calculated based on the ratio of PET to precipitation. This means that SPEI is more sensitive to changes in precipitation, while AI is more sensitive to changes in PET (Pathak and Dodamani, 2020). For example, a decrease in precipitation would result in a lower SPEI (more drought) and a higher AI (more aridity), but a decrease in PET would result in a higher SPEI (less drought) and a lower AI (less aridity).

[4] This is achieved from the soil and plant canopy and via plant transpiration.

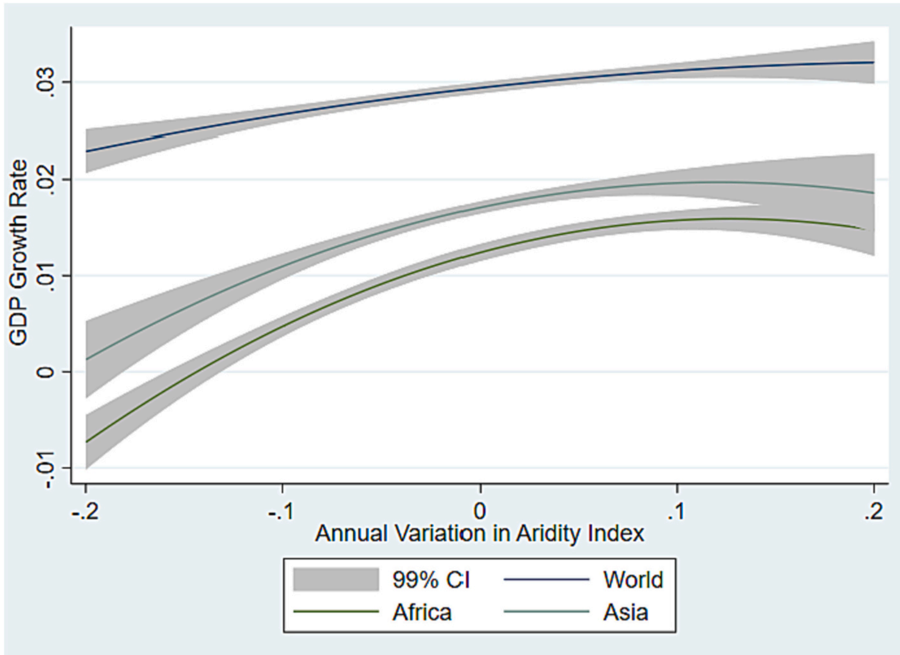


Fig. 3. Relationship between grid-cell annual variations in Aridity Index and GDP per capita from 1990 to 2015 in World, Africa, and Asia.
Note. Grid-level data used to construct the Aridity Index were retrieved from the National Centre for Atmospheric Science (2020), and grid-level GDPs per capita were adopted from Kummu et al. (2018). The parameters used to draw the functions are shown as estimates in Table 2 in Appendix B.

This is an important difference since climate change has not a univocal impact on rainfalls. Indeed, rainfall might increase in one region of the world and decrease in another. Or rainfalls might decrease overall but increase the chance of floods. In comparison, potential evapotranspiration increases relatively smoothly due to climate change (Zargar et al., 2011). This allows us to better understand the future impacts of desertification.

Another difference is that SPEI and AI can vary on different time scales, depending on the accumulation period of precipitation and PET. For instance, SPEI and AI can be calculated on monthly, seasonal, annual or longer timescales. The choice of timescale affects the magnitude and frequency of droughts and aridity events. Generally, SPEI and AI show more agreement on longer timescales (>10 years), as they both reflect the long-term average state of the water balance. On shorter timescales (1–12 months), SPEI and AI can show significant differences as they capture the stochastic variability of precipitation and PET.

As we are considering annual aridity events, the AI might lead to different results for the SPEI.

Recently, the effects of rainfall and potential evapotranspiration of soil moisture on distinct regions of the world were examined (Cowley et al., 2017). Their findings showed a significant difference between precipitation and aridity: if PET is larger than P, the climate is arid[5].

Arid lands are classified into five types by Cherlet et al. (2018), taking into account the aridity index (AI). The hyper-arid type is characterized by an AI of <0.05. The arid type has an AI >0.05 but <0.2. The semi-arid type has an AI >0.2 but <0.5. The dry sub-humid type has an AI >0.5 but <0.65. Finally, the humid type has an 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, desertification has accelerated by >30 times its historical rate (Burrell et al., 2020). The principal factors of desertification 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.

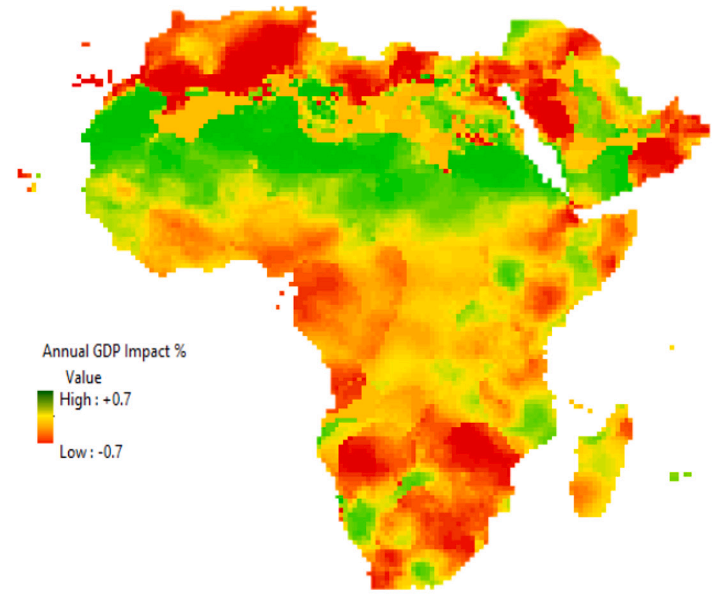
In this regard, a recent study has distinguished between droughts, which are transient regional extreme phenomena typically defined as departures from a local climatological norm that is presumed known, and so-called "background" dryness (Sherwood and Fu, 2014). In addition to being a function of precipitation, 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 Aridity Index (AI) measured by the difference between the present-day (1990–2015) and the historical average (1900–1980). As shown in Fig. 2, the areas most affected by desertification are primarily located in continental Europe, Africa, and Southeast 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 to 1980.

The overall change was equal to approximately 8%. However, areas on the west side of the continent showed desertification that had exceeded 50%. Similarly, the average AI in Southeast Asia had decreased by 3% compared with the period from 1980 to 1990, and areas in the west of China and Mongolia showed that desertification had increased by 25%.

[5] Water deficits may also occur over shorter periods, such as seasonally or monthly, depending on their intensity and duration.

A: Africa



B: Asia

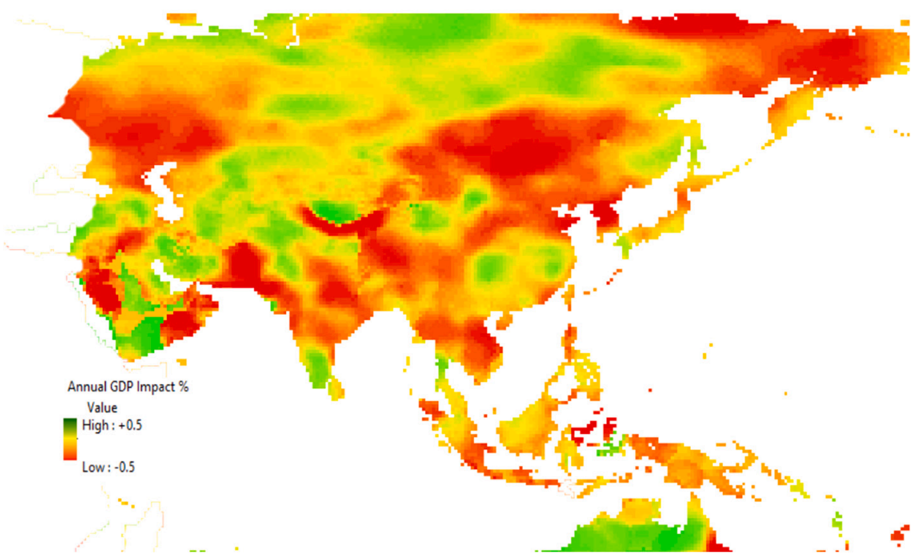


Fig. 4. Average annual effects of Aridity Index on GDP per capita from 1990 to 2015.
Panel A: Africa.
Panel B: Asia.
The areas in red indicate the highest impact of the Aridity Index on GDP per capita from 1990 to 2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Data and descriptive statistics

We combine high-frequency, geo-referenced data from various sources and construct a dataset covering 189 countries worldwide. Estimating the impact of desertification on economic development considers annual data for a total of 26 time periods, from 1990 through 2015. We have assembled a dataset containing socioeconomic, weather, and agricultural information. The data is organized based on a raster cell structure, with each observation unit representing a subnational "cell" measuring 0.5 degrees of latitude by 0.5 degrees of longitude (approximately 56 km by 56 km at the equator). Details on countries and sources can be found in the Appendix.

3.1. Precipitations, PET, and the construction of the AI

The annual aridity index (AI) is created by taking into account the yearly average precipitation and potential evapotranspiration data. We follow the definition given by the World Atlas of Desertification of the Joint Research Centre (JRC) to construct the AI. The AI for a particular cell in a given year is calculated as the ratio of the average precipitation and PET of that year in that cell. This ratio is expressed in millimetres of water that is effectively available on the ground.

$$A_{it} = \frac{P_{it}}{PET_{it}}$$

AI is the yearly average of total precipitation over Potential

Table 4
Effects of AI, precipitation, and temperature on GDP per capita. Arellano bond estimates.

Variables	(1) Whole sample	(2) Whole sample	(3) Whole sample	(4) Africa	(5) Asia	(6) World (Arid and sub-humid)	(7) Africa (Arid and sub-humid)
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)
AI 2		−0.0896***	0.00400***	0.00285*	−0.00243	0.00261***	−0.00135**
		(0.00223)	(0.00153)	(0.00173)	(0.00232)	(0.000298)	(0.000536)
Precipitation			0.0665***	0.385***	0.0370	0.0614***	0.102***
			(0.0175)	(0.0360)	(0.0363)	(0.00281)	(0.00699)
Temperature			−0.00827***	0.00269	−0.00863***	0.00485***	0.00499***
			(0.00138)	(0.00417)	(0.00175)	(0.000321)	(0.000587)
PET			−0.0108	−0.128***	−0.124***	−0.0779***	−0.189***
			(0.00690)	(0.0285)	(0.0148)	(0.00333)	(0.00901)
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)
Cell 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	6654

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

Table 5
Effects of AI on GDP on different aridity classes. Year, Cell fixed effects and Country trends.

Variables	(1) Hyper Arid	(2) Arid	(3) Semi-Arid	(4) Sub-Humid	(5) Humid
AI	0.203**	0.143***	0.0771***	0.0753	0.00335
	(0.0829)	(0.0321)	(0.0193)	(0.157)	(0.00254)
AI 2	−5.329***	−0.109	−0.0945***	−0.0365	0.00109
	(1.623)	(0.127)	(0.0265)	(0.137)	(0.000795)
Temperature	−0.000767***	−0.000208***	0.000433***	0.00110***	0.000265***
	(0.000164)	(7.66e-05)	(4.61e-05)	(7.51e-05)	(4.66e-05)
Temperature 2	3.59e-05***	2.46e-05***	−5.69e-07	1.83e-06	−1.60e-05***
	(3.43e-06)	(1.34e-06)	(6.72e-07)	(1.32e-06)	(1.20e-06)
Log GDP t-1	0.917***	0.890***	0.911***	0.891***	0.900***
	(0.00239)	(0.00191)	(0.000606)	(0.00147)	(0.00103)
Constant	0.767***	1.052***	0.855***	1.041***	0.989***
	(0.0216)	(0.0185)	(0.00712)	(0.0470)	(0.0105)
Observations	173,816	278,056	540,059	218,343	413,084
R-squared	0.894	0.928	0.923	0.917	0.927
Number of id	11,009	21,490	38,653	29,371	28,032
Cell 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

This table presents 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 6
Effects of AI on GDP on different income classes. Year, Cell fixed effects, and Country trends.

	(1)	(2)	(3)	(4)
Variables	Low	Lower Middle	Upper Middle	High
AI	0.0593***	0.268***	0.0327***	−0.00803
	(0.00389)	(0.0101)	(0.00941)	(0.00789)
AI 2	−0.0155***	−0.259***	−0.0106	−0.00674
	(0.00188)	(0.0119)	(0.0109)	(0.00949)
Temperature	−0.00362***	−0.00154***	0.000873***	0.00194***
	(0.000455)	(7.46e-05)	(0.000122)	(4.78e-05)
Temperature 2	7.50e-05***	1.04e-05***	4.23e-05***	−3.34e-05***
	(9.20e-06)	(1.63e-06)	(2.16e-06)	(1.08e-06)
Log GDP t-1	0.831***	0.731***	0.608***	0.619***
	(0.00361)	(0.00382)	(0.00722)	(0.00352)
Constant	1.371***	2.432***	3.743***	4.079***
	(0.0309)	(0.0354)	(0.0698)	(0.0377)
Observations	320,256	158,923	178,564	498,483
R-squared	0.902	0.885	0.749	0.812
Number of id	17,520	17,088	21,552	31,322
Cell FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

This table presents 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.

evapotranspiration (PET). We use the month-by-month variations in Precipitation and Potential evapotranspiration data from the gridded Climatic Research Unit (CRU) Time-series (TS)[6] over the period 1901–2015 (Harris et al., 2020). The CRU time-series data are validated and extensively used in the literature (Le and Nguyen, 2021; Watts et al., 2021; Burrell et al., 2020).[7]

The University of East Anglia's CRU has produced high-resolution (0.5 degrees × 0.5°) data on precipitation, which is funded by the UK National Centre for Atmospheric Science (NCAS), a NERC collaborative centre. This data covers monthly rainfall in millimetres (mm/month) from 1901 to 2015. We analyzed the average monthly precipitation (mm/month) for each year, as well as the daily potential evapotranspiration (expressed in mm/day) for the same time range. To evaluate the effects of precipitation and PET for each year, we computed the average monthly PET (mm/month). The Appendix has more details on the construction of climate data use. We also used average annual temperature as a climate grid-specific control variable, which was retrieved from CRU Time-Series Dataset.

The total precipitation ranges from 0 to 91 mm/month, with an average of 5.2 mm/month and a standard deviation of 5.7 mm/month. Throughout the analysis period, potential evapotranspiration exhibited a range of 0 to 24.5 mm per month, with an average of 8.3 mm per month and a standard deviation of 5.1 mm per month. The mean annual surface temperature demonstrated variability between −20.1 and 37.7 °C, with an average of 13.8 °C and a standard deviation of 12.3 °C.

[6] The version of the CRU dataset used in this analysis is 4.00

[7] However, climate data at higher resolution exists. This is the case of the ERA5 reanalysis (Hersbach et al., 2020). We chose to use the CRU data since spatial data on the GDP per capita from 1990 to 2015 are available at 0.5° latitude x 0.5° longitude (Kummu et al., 2018). The use of more disaggregated climate data would imply a further rescale of the GDP data, thus likely inducing bias in our estimates. We want to avoid this.

3.2. GDP per capita

To assess the economic impact of desertification due to climate change, we use the GDP per capita (PPP) dataset from Kummu et al. (2018) and represent the average gross domestic product per capita in each administrative area unit. GDP is given in 2011 international US dollars.[8] Although only recently available, this dataset has been widely used in the recent economic literature (Damania et al., 2020; Cruz and Rossi-Hansberg, 2021; Chen et al., 2022). This dataset contains information on sub-national GDP per capita that was collected and analyzed by Gennaioli et al. (2013). The data includes 82 countries, which make up 85% of the world's population and 92% of the global GDP (PPP) as of 2015. Summary statistics for weather variables along with GDP per capita, are reported in Table 1.

The sample of data on GDP per capita is more limited both in spatial and temporal terms than climate variables. Kummu et al. (2018) provide annual data on GDP per capita at high-resolution (0.5 degrees × 0.5° grids) for the period 1990–2015. A total of 1,601,730 observations ranging from a minimum of zero USD 2011 to a maximum of 199,439 USD 2011 were collected, with an average of 22,828 USD 2011 (standard deviation of 24,064 USD 2011).

4. Methodology

Our empirical methodology consists of two consecutive steps. First, we verify the impact of precipitation on local GDP in order to cast our analysis in the track of existing literature. In the second step, we assess the impact of desertification as an interaction between rainfalls and potential evapotranspiration.

We estimate a model that includes linear and quadratic regressors for the total annual precipitation specific to the cell to assess the non-linear impacts of the desertification process. A rationale behind this hypothesis is that we expect precipitation to positively impact economic development (at least in agriculture-cantered economies through an increase in agricultural output). However, when precipitation increases too much (e.g., in the form of floods), the economic impact might turn negative (Burke et al., 2015).

Our baseline regression is:

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \beta_2 P_{ict} + \beta_3 P_{ict}^2 + \delta_1 T_{ict} + \delta_2 T_{ict}^2 + \sigma_t + \omega_i + \rho_c + \varepsilon_{ict} \quad (1)$$

We denote with y_{ict} the natural logarithm of GDP per capita of cell 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 cell i, in country c, in year t − 1). P_{ict} indicates the average annual precipitation of cell i in country c, at year t. To account for the non-linear relationship between rainfalls and GDP per capita, we follow Burke et al. (2015) and include the quadratic term P^2 in our baseline model.

In addition, we control for the average yearly mean surface temperature T_{ict}. Finally, the model considers year-fixed effects, denoted with σt, grid-fixed effects represented with ω_i, and country linear trends to account for country-specific trends over time; this is indicated with $\rho_c\tau$. The inclusion of grid-fixed effects and country-specific time trends effectively allows us to consider any other factor affecting the GDP, such as different levels of industrialization, institutional quality, urbanization, and health.

[8] Gap-filled sub-national data were used, supplemented by national data where necessary. Data gaps were filled by using national temporal pattern. Dataset has global extent at 5 arc-min resolution for the 26-year period of 1990–2015. The complete dataset provides annual gridded datasets for GDP per capita (PPP), total GDP (PPP), and the Human Developed Index, for the whole world at 5 arc min resolution for the 26-year period ranging from 1990 to 2015. Additionally, total GDP (PPP) is provided with 30 arc *sec* resolution for three-time steps (1990, 2000, 2015). More detail in the data used are found in the Appendix.

Table 7
Effects of AI on GDP with the inclusion of temporal dependence. Year, cell fixed effects and Country trends.

	(1)	(2)	(3)	(4)	(5)
Variables	Whole sample	Whole sample	Whole sample	World (Arid and sub-humid)	Africa
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)
Precipitation		−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
Cell 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	

This table presents results of the effects of the aridity index on GDP per capita considering both spatial and temporal dependence.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We estimate eq. (1) via the panel fixed effects estimator. After estimating the relationship between standard climatic variables and GDP, we replicate the empirical analysis to compute the relationship between the Aridity Index and our economic variable. To do this, we estimate the following regression:

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \beta_2 AI_{ict} + \beta_3 AI^2_{ict} + \delta_1 T_{ict} + \delta_2 T^2_{ict} + \sigma_t + \omega_i + \rho_c \tau + \varepsilon_{ict} \quad (2)$$

Where AI_{ict} indicates the aridity index of cell i in country c, at year t. As in eq. (1), we account for the non-linear relationship between aridity and GDP per capita and include the quadratic term AI^2 eq. (2). Finally, we consider the same grid-specific controls and fixed effects, and country-specific linear trends as in eq. (1).

5. Results

Our dependent variable is y_{ict}, the natural logarithm of GDP per capita of cell i, in country c, in year t Log GDP. As discussed in section 4, we consider two baseline equations: the first equation estimates the empirical relationship between traditional climate variables (i.e., precipitations and temperature) and local economic development. The second equation considers the aridity index as the interaction between precipitation and potential evapotranspiration of the soil. Higher values of this variable correspond to higher "effective" water availability. On the other hand, smaller values of the AI correspond to lower effective water availability and, thus, more arid soil. All specifications include the quadratic term of AI, P, PET, and T to account for the non-linear relationship between climate and GDP per capita. Eqs. (1) and (2) also include cell and time-fixed effects and country-specific linear trends.

Tables 2 and 3 contain our baseline results. For Table 2, the regressors of interest are P, defined as the annual precipitation during year t, expressed in mm, and T, defined as the average annual surface temperature during year t, expressed in degrees Celsius. Column 1 considers the whole sample of grids for the entire world. Column 1 shows that

Table 8
Effects of AI on GDP with the inclusion of temporal and spatial dependence. Year, cell fixed effects and Country Trends.

	(1)	(2)	(3)	(4)
Variables	Whole sample	Whole sample	World (Arid and sub-humid)	Africa
Log GDP t-1	0.186***	0.178***	0.147***	0.284***
	(0.00395)	(0.00386)	(0.00409)	(0.0157)
W * Log GDP	0.832***	0.840***	0.869***	0.752***
	(0.00380)	(0.00371)	(0.00395)	(0.0152)
AI t-1	−0.00943**	−0.00591	−0.000208	0.0438**
	(0.00454)	(0.00454)	(0.00984)	(0.0197)
AI 2		−0.00153***	−0.000877	0.00102
		(0.000444)	(0.00344)	(0.00899)
AI	−0.00251	−0.000431	0.0178**	0.0690***
	(0.00361)	(0.00312)	(0.00783)	(0.0190)
W * AI	0.0122***	0.0118***	0.00387	−0.0412**
	(0.00469)	(0.00432)	(0.00937)	(0.0180)
W * AI t-1	0.00221	−0.000617	−0.0207***	−0.0701***
	(0.00374)	(0.00322)	(0.00792)	(0.0187)
T		−0.00378***	−0.00331***	0.00669*
		(0.000675)	(0.000916)	(0.00389)
Constant	−0.178***	−0.184***	−0.166***	−0.315***
	(0.00784)	(0.00834)	(0.0101)	(0.0313)
Observations	1,615,130	1,550,067	1,001,265	239,856
R-squared	0.999	0.999	0.999	0.999
Cell 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	

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

higher amounts of precipitation are positively associated with the GDP of a particular grid. Moreover, the relationship appears to be concave (i. e., considerably higher amounts of precipitation are negatively associated with GDP).[9]

Our results remain statistically unchanged when we include country-specific linear trends (column 2). In column 3, we exclude from the sample areas which are either already desert or very humid. We perform this restriction since we expect no significant relationship between climate warming and economic development in the inhabited desert or very humid areas (i.e., AI <0.05 or AI >0.65). Column 3 shows a more significant relationship between precipitation and GDP when restricting the sample to only semi-arid or sub-humid regions compared to Columns 1 and 2. Finally, in columns 4 and 5, we consider only the African and Asian continents, respectively.

We do these further restrictions for two reasons: first, these two continents have considerably been affected by climate warming during the last decades (IPCC, 2019); and second, African and Asian economies notably rely upon the agricultural sector. As a result, we expect to find a larger association between climate and economic growth in those two continents. Indeed, we find that a standard deviation variation in annual precipitation is associated with about 0.8 percentage points of African GDP per capita (column 4) and around 0.4 percentage points of Asian GDP per capita (column 5).

These estimates are in line with Carleton and Hsiang (2016). Moreover, the coefficient of PET confirms that the annual variations in the potential evapotranspiration of the soil counterbalance the positive effects of precipitation. These results are consistent across all specifications and sample restrictions (columns 1–5) and suggest including an index considering the interplay between precipitation and PET to better estimate the relationship between climate warming and economic development.

Table 3 presents the empirical relationship between annual variations in the Aridity Index and GDP per capita. The regressor of interest is AI, defined as the ratio between precipitation and PET during year t. Starting with column 1, which considers the whole sample of grids for the whole world, we find a positive relationship between AI and GDP. In particular, one standard deviation decrease in the Aridity Index (i.e., more arid soil) is associated with a reduction of 7 percentage points in the GDP per capita of the whole world. These results do not statistically change when we include country-specific linear trends (column 2).

As in Table 2, in column 3 of Table 3, we exclude areas that are either desert or very humid from the sample. Column 3 shows a more significant relationship between AI and GDP when restricting the sample to only semi-arid or sub-humid regions compared to Columns 1 and 2. Finally, in columns 4 and 5, we consider only the African and Asian continents, respectively. Here, we find the effects to be more significant in less developed areas of the world. A standard deviation decrease in the AI is associated with a 0.6 percentage points and 0.9 percentage points reduction in the African and Asian continents, respectively. This result contrasts with a recent study that found that the relationship between temperature, precipitation, and economic growth was globally generalizable to agricultural and non-agricultural activity in rich and developing countries (Burke et al., 2015).

To confirm our estimates, we explored the sensitivity of our estimates to several models, aridity classes, and income groups. Our results showed that grid-level income per capita was non-linear and concave with the AI. This finding indicates that income increases with higher soil water availability, 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 aligns with the estimates shown for temperature shocks (Fig. 3) (Burke et al., 2015). 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 desertification 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 desertification 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 (Burke et al., 2015; Parry, 2019; Dell et al., 2014; Tol, 2009).

Based on these results, it is possible to evaluate the average annual economic impact of desertification from 1990 to 2015. Fig. 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 desertification has decreased the GDP per capita by >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 percentage points.

We have explored the sensitivity of our estimates to different models, aridity classes, and income groups. To confirm the results obtained in Table 3, we first employ the Arellano-Bond estimation (Arellano and Bond, 1991). Here, we also consider the lagged values of the predetermined regressors as instruments. Results are shown in Table 4 and confirm the adverse effects of desertification on GDP per capita. We also test for serial correlation. We reject no autocorrelation of order one and cannot reject autocorrelation of order 2. There is evidence that the Arellano–Bond model assumptions are satisfied. Furthermore, we clustered the error terms at the country level. The results of this robustness check are in Table A.1 in the Appendix and reinforce the validity of the baseline estimates reported in Table 2.

Finally, a possible threat to the identification may arise from the process of deforestation. Indeed, Brazil and Indonesia are both deforestation hot spots (Burgess et al., 2012). In particular, deforestation may directly influence wind speed, affecting the estimates reported in Table 3.

To alleviate such a concern, we control for the percentage of forest loss between 2000 and 2016. We computed the percentage of forest loss from the data provided by Intact Forest Landscapes (IFL).[10] The IFL map is a spatial database (scale 1:1,000,000) that shows the extent of the intact forest landscapes (IFL) for the years 2000, 2013, 2016, and 2020.

The percentage of forest loss for each grid "i" was computed using the following simple formula:

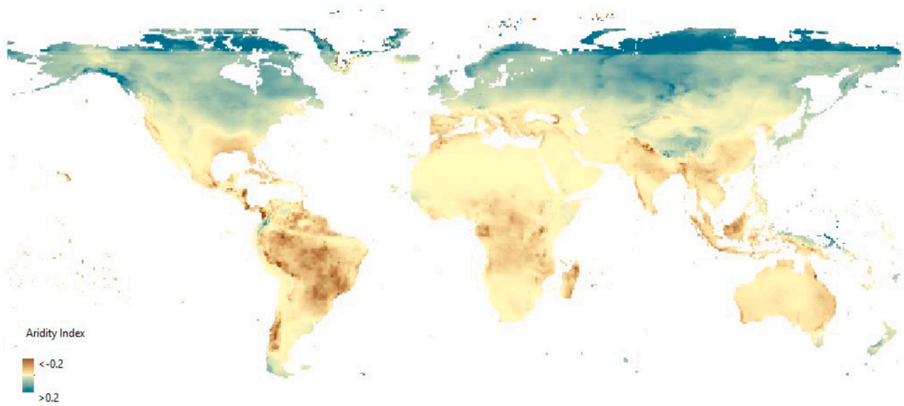
$$\frac{Forest\ Area(2016)_i - Forest\ Area(2000)_i}{Forest\ Area(2000)_i} * 100$$

Table A.2 in the Appendix presents the empirical relationship between annual variations in the Aridity Index and GDP per capita, controlling for the percentage of forest loss during the period 2000 and 2016. These results indicate that areas which with greater deforestation showed indeed higher desertification, confirming the prediction that deforestation can directly impact the potential evapotranspiration of the soil. Nevertheless, the coefficient estimates are consistent with our

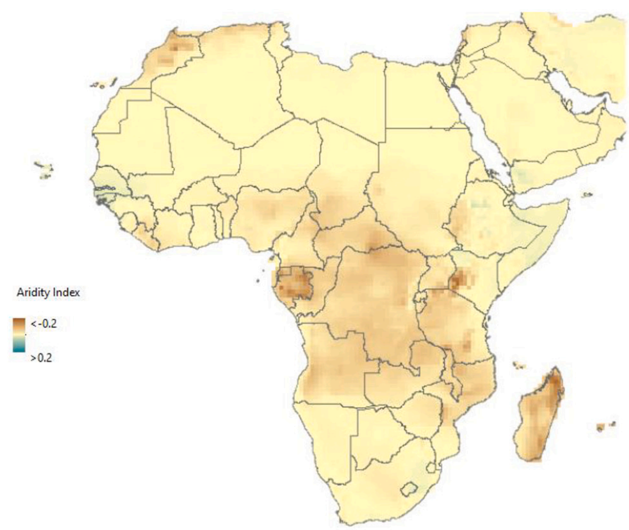
[9] Malpede and Percoco (2023) go beyond the Gross Domestic Product, investigating the relationship between desertification and other dimensions of human development, namely health standards and education, with a particular focus on developing countries.

[10] IFL is freely accessible at the following link: https://intactforests.org/data.ifl.html

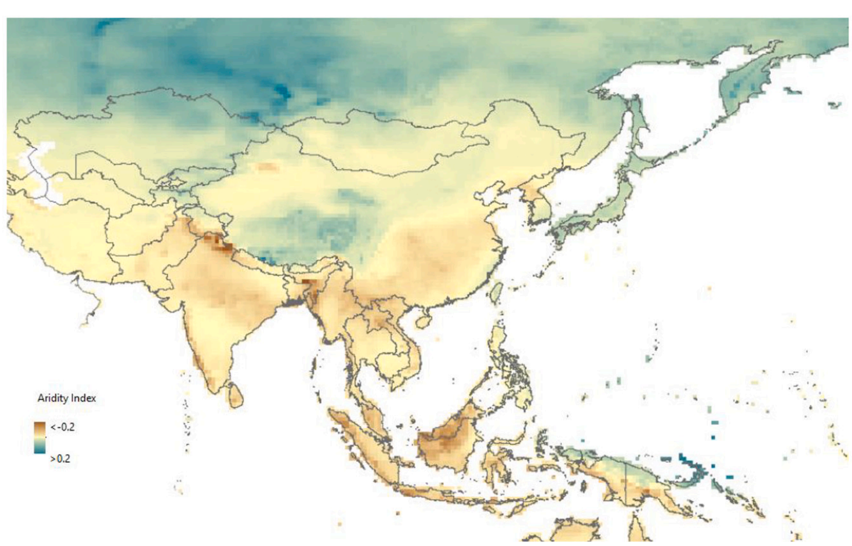
A: World



B: Africa



C: Asia



(caption on next page)

Fig. 5. Distribution of projected Aridity Index changes from 1990 to 2015 to 2040–2079.
Panel A: World.
Panel B: Africa.
Panel C: Asia.
Percentage change in the Aridity Index comparing the period of 2040–2079 with the present day of 1990–2015. To construct the AI, future data on precipitation and PET were obtained from CMCC-BioClimInd. The areas projected to be most affected by desertification are indicated by the dark brown colour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

baseline procedure and further corroborate the negative effects of desertification on the GDP per capita.

5.1. Heterogeneous effects by class of Aridity

Further, we explore the robustness of our estimates to different types of soil aridity classes. Results of this robustness check are shown in Table 5, which indicates no relationship between the Aridity Index and GDP per capita in hyper-arid and humid areas of the world. This is consistent with the assumption that desertification's impact should not be significant in the regions already arid or areas characterized by high precipitation levels throughout the whole year. On the other hand, semi-arid and sub-humid areas are the most penalized by desertification.

5.2. Heterogeneous effects by income class

Similarly, we evaluate the impact of aridity on different income classes using the World Bank classification. According to this income classification, areas with a GDP per capita of 4000 USD or below are considered low-income. Areas with a GDP per capita between 4000 and 8000 USD are lower-middle-income. Areas with a GDP per capita between 8000 and 12,000 USD are upper-middle-income. Areas with a GDP per capita of 12,000 USD or above are high-income.

This allows us to estimate the relationship between aridity and GDP within specific income classes and reduce concerns about the endogeneity of treatment. Our findings, shown in Table 6, indicate that desertification significantly affects lower-middle and upper-middle-income areas but not high-income regions. We find that desertification primarily affects areas where the local economies heavily rely on agriculture and livestock. In contrast, negligible effects are found for advanced economies. The reasons behind this differential impact are manifold.

However, agricultural productivity is regarded as one of the main channels (Malpede and Percoco, 2023). Desertification can reduce the economic productivity of the land, including its ability to support crops and livestock, which can have severe impacts on the livelihoods of local populations.

Advanced economies are often less dependent on agriculture and more diversified, and they have greater resources to invest in land management practices and technologies to prevent or mitigate the effects of desertification. Furthermore, advanced economies typically have better infrastructure and policies in place to manage water resources sustainably.

Finally, irrigation practices may play a crucial role in mitigating the impacts of aridification. While developing countries depend mostly depend on precipitations for their harvest, advances economies generally use more efficient irrigation methods that allow water to be injected directly to the plant roots or near the soil surface, reducing water loss (Caretta et al., 2022; FAO, 2021).

However, it is important to note that while advanced economies may not be directly impacted by desertification in the same way as developing nations, they can still feel indirect effects. For instance, desertification can lead to increased migration, potentially displacing around 135 million people by 2045 (IPCC, 2019). This could lead to increased pressure on resources in areas where these populations relocate to, including advanced economies.

In addition to the estimation of the effects of desertification on GDP, we also investigate how drought and aridification affect the local populations on a global scale using a validated panel dataset of historical population and urbanization data (HYDE) developed by Klein Goldewijk et al. (2011). This dataset collects population and urbanization data from existing historical archives at the most local level available. This allows us to compare the relative impact of desertification on population.

Table A.3 in the Appendix presents the empirical relationship between annual variations in the Aridity Index and Log Population. As for the baseline equation, the regressor of interest is AI. Starting with column 1, which considers the sample for the low-income areas, we find a positive relationship between AI and Population. In particular, one standard deviation decrease in the Aridity Index (i.e., more arid soil) is associated with a reduction of 8 percentage points in the Log of Population. As in Table 6, results in Table A.3 indicate that desertification significantly affects the population of lower-middle and upper-middle-income areas but not high-income regions.

6. Inclusion of spatial and temporal dependence

Finally, we control for temporal as well as spatial dependence of both the dependent variable and covariates. First, to address the temporal correlation between the aridity index and GDP per capita, we incorporate temporal lags of the regressor and dependent variables.

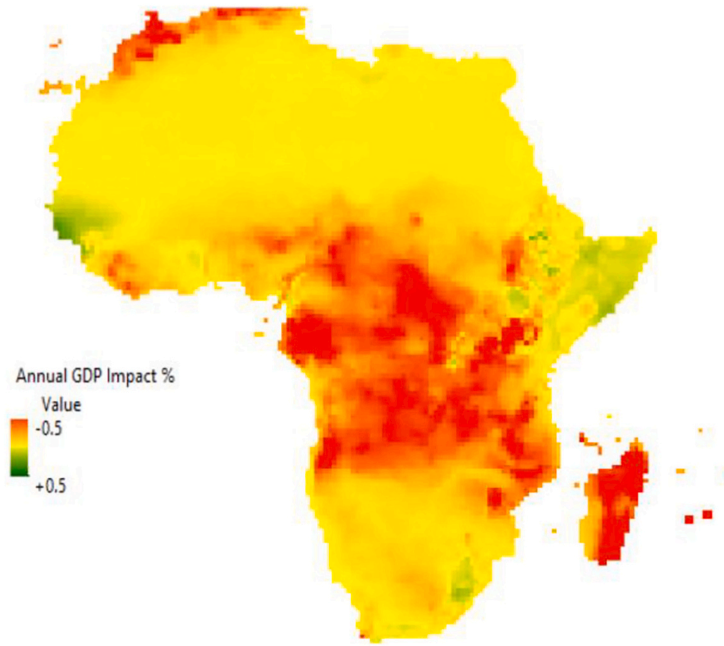
$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \sum\nolimits_{k=0}^{2} \beta_{2k} \mathrm{AI}_{ict-k} + \sum\nolimits_{k=0}^{2} \beta_{3k} X_{ict-k} + \sigma_t + \omega_i + \rho_c + \varepsilon_{ict} \tag{3}$$

Where y_{ict} denotes the natural logarithm of GDP per capita of cell i, in country c at time t. We consider the same fixed effects and linear trends used in the baseline eq. (1), and estimate (3) via OLS.

Table 7 illustrates the results of eq. (2). The regressor of interest is AI, defined as the natural logarithm of the Aridity Index in cell i, at year t. Higher values of this variable correspond to higher "effective" water availability of the soil. In contrast, lower values correspond to the soil's lower water availability (i.e., aridification of the land). We also control for additional grid-specific climate control variables such as Precipitation, Potential Evapotranspiration, and Temperature, along with year and cell fixed effects and country linear trends. Column (1) shows the contemporaneous positive relationship between the Aridity Index and the GDP per capita for the whole world, including year and cell fixed effects and without considering additional climate controls. The positive relationship between Aridity Index and GDP per capita does not vary when we include grid-specific controls (column 2) and temporal dependence of 2 years (column 3).

To better understand how variables are related to each other, we take

A: Africa



B: Asia

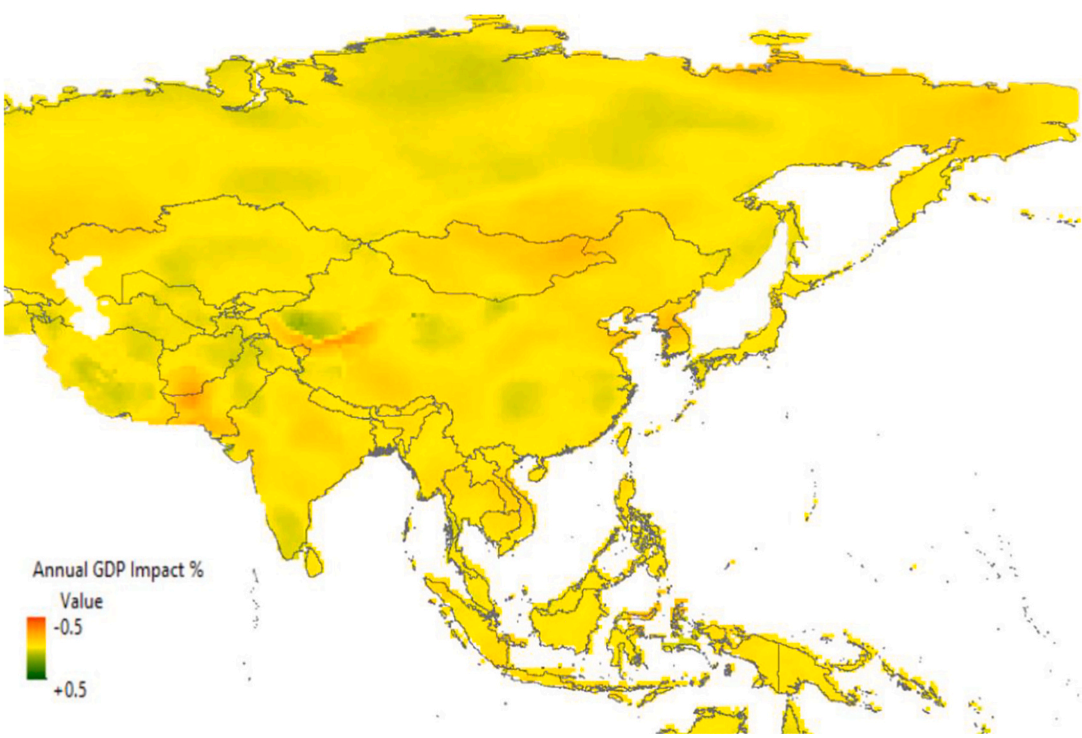


Fig. 6. Average annual effects of Aridity Index on GDP per capita 2040–2079.
Panel A: Africa.
Panel B: Asia.
Notes: Average annual effects of Aridity Index on GDP per capita 2040–2079 (CMCC-BioClimInd – RCP 4.5 Projections). Future data on precipitation and PET used to construct the AI were retrieved from the CMCC-BioClimInd.

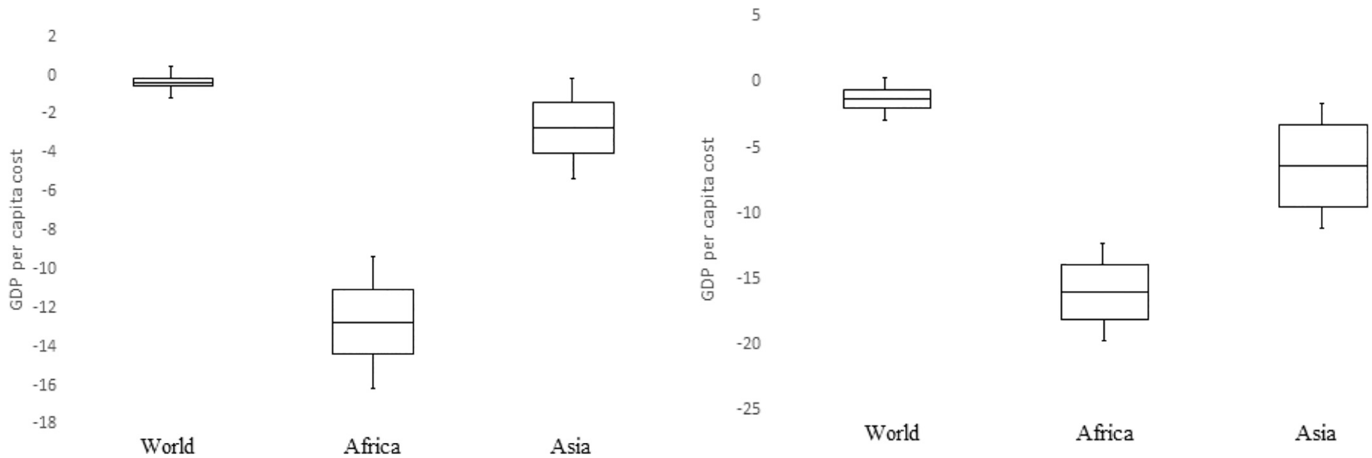


Fig. 7. GDP per capita cost due to desertification between 1990 and 2015 (left) and between the present day and 2079 (right).

into account their spatial relationship. This is done by including spatial lags of the relevant factors. To achieve this, we use the symmetric weighting matrix W to define the spatial dependence structure. By multiplying the observation vector with the matrix W, we can obtain the spatial lag of a variable.

$$y_{ict} = \alpha + \beta_1 y_{ict-1} + \beta_2 W \bullet y_{ict} + \sum_{k=0}^{2} \beta_{3k} AI_{ict-k} + \sum_{k=0}^{2} \beta_{4k} W \bullet AI_{ict-k} + \sum_{k=0}^{2} \beta_{5k} X_{ict-k} + \sum_{k=0}^{2} \beta_{6k} W \bullet X_{ict-k} + \sigma_t + \omega_i + \varepsilon_{ict} \tag{4}$$

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

When studying how climate affects economic development, most researchers assume that observations in different locations are independent. However, we take a different approach and use Hsiang's method to adjust for both spatial and serial correlation.

To do this, we use a spatial matrix called W in our dynamic model (eq. 2). This matrix considers grids with centroids located within 56 km (or within 0.5-degree latitude and 0.5-degree longitude) as "first-degree neighbours" and grids within 56–112 km (or within 1-degree latitude and 1-degree longitude) as "second-degree neighbours." Essentially, we assume that climate shocks in grids beyond 1-degree latitude and 1-degree longitude do not directly affect the GDP of their own cell, but rather indirectly affect the GDP per capita that then spills over in space.

We chose to incorporate spatially and temporally autoregressive terms in our model, as ignoring the W · Y term can lead to omitted variable bias, as highlighted in Harari and Ferrara (2018). This could result in attributing GDP to determinants that are spatially clustered and overestimating the impact of climate shocks. We report our results in Table 8.

Finally, Tables A.4 and A.5 in the Appendix illustrate the results of the heterogeneous effects of AI on different classes of aridity and income level in the spatial and temporal lag model in eq. (4). Specifically, in Column (1) of Table A.4, we limit the effects to low-income areas of the world only (i.e., with a GDP per capita of 4000 USD in 2011 or below). Column (2) considers the impact of the annual variations in the Aridity Index on lower-middle-income areas (i.e., between 4000 USD and 8000 USD). Finally, Column (4) considers the effects on high-income regions (i.e., 12,000 USD or above). As usual, the regressor of interest is AI, showing the contemporaneous impact of the Aridity Index on the GDP per capita for each cell i. As expected, the most robust relationship is shown in columns (1) and (2) in low and lower-middle-income areas. This result confirms that desertification affects primarily underdeveloped areas of the world. Those areas extensively rely upon agriculture.

7. Future economic cost of desertification

The results of the association between AI and GDP were used to project the costs of future desertification patterns. We projected future AI grid-cells using the latest version of the CMCC-BioClimInd[11] (Noce et al., 2020), which includes precipitation and potential evapotranspiration data. These forecasts were produced by different earth system models and two representative concentration pathways (RCP 4.5 and RCP 8.5) as part of the Coupled Model Intercomparison Project phase 5 (CMIP5) of the World Climate Research Programme. Our analysis focused on the RCP 4.5 emissions scenario, which predicts a significant increase in greenhouse gas emissions from 2010 to 2030, followed by a gradual decrease throughout the 21st century. According to the WorldClim 2.1 database, we can expect a temperature increase of 0.93–1.27 °C and a precipitation increase of 10–30% in the northern hemisphere. However, the southern hemisphere is expected to experience a decrease of 10–40%, depending on the Shared Socioeconomic Pathway (SSP) considered, from 2021 to 2040. During the same period, evapotranspiration is projected to increase by 0.4–3.8% compared to the present-day mean (2011−2020).

Our results indicate that the aridity index (AI) has experienced a decline from 0.489 during the period of 1900–1980 to 0.479 in the present time frame of 1990–2015. We anticipate that this trend will persist, resulting in a further decrease to 0.438 between 2040 and 2079. This indicates that the typical region will encounter comparable levels of drought as it presently does. Throughout the historical era, approximately 17,926 regions were classified as arid or hyper-arid (with an AI below 0.2).

However, this number is projected to increase to 20,998 in the period of 2040–2079. This means that over 2000 cells will become arid in the future, covering approximately 5 million km2 or 3% of the world's land surface. Fig. 5 displays the percentage differences between projected AI and current mean for the world. Fig. 6 shows the results for Africa, and Asia at the grid-cell level.

In Fig. 7 (right), panel B depicts the estimated effects of future AI

[11] 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.

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 observed in recent decades. Future AI variations are expected to result in a total cost of 6.7% in GDP per capita growth in Asia and around 15% in Africa.

8. Conclusion

In this paper, we conduct a spatially disaggregated analysis of desertification on a global scale from 1990 to 2015. The Aridity Index, which considers both precipitation and potential evapotranspiration of the soil, is used to measure desertification annually. The findings suggest that desertification is linked to a decline in GDP per capita, especially in Asia and Africa. The study also examines the connection between economic development and spatial and temporal dependence, both of which are highly significant.

In the second part of the paper, future desertification patterns are predicted based on the most conservative estimates. It is assumed that the responsiveness of the GDP to soil aridity will remain constant in the coming decades. The study predicts that by 2079, African and Asian countries will experience a decline in GDP per capita growth by 15% and 6.7%, respectively, due to desertification.

The study highlights the need to understand the impact of human-induced climate desertification on agricultural areas' economic development. It also emphasizes that precipitation and temperature alone are insufficient variables to determine climate warming's effects. The Aridity Index should also be considered to provide a more thorough understanding of the impact of desertification on the environment and the economy.

CRediT authorship contribution statement

Maurizio Malpede: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Marco Percoco:** Conceptualization, Funding acquisition, Writing – original draft.

Declaration of Competing Interest

Disclosure Statement regarding the research article "Long-term Economic Effects of Aridification on the GDPs of Africa and Asia" by Maurizio Malpede (Bocconi University) and Marco Percoco (Bocconi University).

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

The author declares that the research described in this paper has received no financial support.

The author also declares that neither he nor his close relatives are holding any position as a officer, director, or board member of a non-profit organization.

Data availability

Data will be made available on request.

Appendix A. Data description

Our dataset is comprised of high-frequency data that is geo-referenced and sourced from various locations. It covers the globe between 1990 and 2015. The dataset we have created includes socioeconomic, weather, and agricultural variables, and is structured with a raster cell system. Each observation is a subnational "cell" that measures 0.5 degrees of latitude by 0.5 degrees of longitude (which is approximately 56 km at the equator). This covers a time period of 26 years.[12]

A.1. Climate time series data

The CRU TS4.04 dataset is a comprehensive collection of climate variables that span from January 1901 to December 2019. Included in the data are cloud cover, diurnal temperature range, frost and wet day frequency, potential evapotranspiration, precipitation, daily and monthly mean temperature, and vapor pressure.

The information contained in this dataset is the result of angular-distance weighting (ADW) interpolation. National Meteorological Services, as well as external sources, provided observational data which was used to create monthly gridded fields. This dataset is available in both ASCII and NetCDF format and displays the monthly average values for various variables. The NetCDF version also provides information on the number of stations used in the interpolation process. Please be advised that this dataset reflects actual values and does not factor in anomalies.

In terms of precipitation data, potential evapotranspiration values are obtained from the CRU Time-series (TS) version 4.00 dataset. This dataset presents month-by-month variations in climate variables from 1901 to 2015 and is funded by the UK National Centre for Atmospheric Science (NCAS). The data is provided on high-resolution grids of $0.5 \times 0.5^\circ$ and contains precipitation values for each month from 1901 to 2015, expressed as average monthly millimetres of rainfall. Potential evapotranspiration values are also available daily over the same period range and expressed in millimetres per day. The CRU TS4.04 dataset is an invaluable resource for researchers and scientists who seek to understand climate patterns and their variations over the past century.

A.2. Potential evapotranspiraton (PET)

The PET used in the present analysis is constructed using the FAO Penman-Monteith equation (FPME). The (FPME) is a modification of the original Penman-Monteith Equation (Penman, 1948).

The PET for day t is therefore defined as follows:

$$ET_t = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{A1}$$

[12] As for the resolution of the grid, levels of precipitation, temperature, potential evapotranspiration and agricultural suitability are available at a lower scale (0.083 degrees of latitude by 0.083 degrees of longitude which correspond to approximately 10 km at the equator). However, annual data on GDP per capita are only available at a higher scale (0.5 degrees of latitude by 0.5 degrees of longitude) as a result, in order to run the empirical procedure, we have first, up-scaled weather variables to the same cell resolution of GDP per capita.

Where ET_t stands for the reference evapotranspiration at day t [mm day-1], Rn is the net radiation at the crop surface [MJ m-2 day-1], G is the soil heat flux density [MJ m-2 day-1], T mean daily air temperature at 2 m height [°C], u_2 is the wind speed at 2 m height [m s-1], e_s is the saturation vapor pressure [kPa], e_a actual vapor pressure [kPa], $e_s - e_a$ is the saturation vapor pressure deficit [kPa], Δ is the slope of the vapor pressure curve [kPa °C-1], whereas γ is the psychrometric constant [kPa °C-1].

The FAO Penman-Monteith equation requires air temperature, humidity, radiation, and wind speed data for daily, weekly, ten-day, or monthly calculations.[13] To accurately calculate weather parameters, it is important to provide the altitude above sea level (in meters) and latitude (in degrees north or south) of the location. This information is necessary to adjust for atmospheric pressure and to calculate extraterrestrial radiation (Ra) and daylight hours (N) using the latitude in radians. For the northern hemisphere, use a positive value, and for the southern hemisphere, use a negative value.

Additionally, please provide the daily maximum and minimum air temperatures in Celsius (°C). If only the mean daily temperature is available, the calculations can still be done, but there may be some underestimation due to the non-linear relationship between saturation vapor pressure and temperature. Using the mean air temperature instead of the maximum and minimum air temperatures will result in a lower reference evapotranspiration estimate.

The daily actual vapor pressure in kilopascals (kPa) is also required. If this information is not available, it can be derived from maximum and minimum relative humidity, psychrometric data, or dewpoint temperature.

The average daily net radiation in megajoules per square meter per day (MJ m-2 day-1) is not commonly available but can be calculated using the average shortwave radiation measured with a pyranometer or the average daily duration of bright sunshine (in hours per day).

Finally, please provide the average daily wind speed in meters per second (m s-1) measured at a height of 2 m above the ground level. It is important to verify the height at which the wind speed is measured, as measurements taken at different heights may differ.

A.3. GDP per capita

There is now more high-resolution global spatial data available that is being used for various assessments. However, important economic and human development indicators are still mainly provided only at the national level, and users must downscale them for gridded spatial analyses. It would be more beneficial to use data for subnational administrative units where possible, along with national data where needed. To evaluate the economic impact of desertification due to climate change, we used the GDP per capita (PPP) dataset from Kummu et al. (2018), which shows the average gross domestic product per capita in a given administrative area unit. The GDP is displayed in 2011 international US dollars.[14] The complete dataset provides annual gridded datasets for GDP per capita (PPP), total GDP (PPP), and the Human Development Index for the whole world at five arcmin resolution for the 26 years ranging from 1990 to 2015.

Table A.1: Effects of AI on GDP per capita. Standard errors clustered at the country level.

	(1)	(3)	(4)
Variables	Whole sample	Africa	Asia
AI	0.0199***	0.159***	0.243***
	(0.00151)	(0.00854)	(0.0121)
AI 2	−0.00590***	−0.137***	−0.314***
	(0.000499)	(0.0162)	(0.0171)
Temperature	0.000633***	0.00949***	−0.000475***
	(0.000102)	(0.00199)	(0.000201)
Temperature 2	0.000041***	−0.000203***	0.000032***
	(0.000001)	(0.00002)	(0.000009)
Log GDP t-1	0.906***	0.931***	0.906***
	(0.000399)	(0.00084)	(0.00165)
Observations	1,623,531	137,182	396,074
R-squared	0.918	0.953	0.931
Number of id	65,247	6654	20,282
Cell FE	YES	YES	YES
Year FE	YES	YES	YES
Country X Year FE	YES	YES	YES

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

Table A.2: Effects of AI on GDP per capita. Inclusion of deforestation area.

	(1)	(2)	(3)	(4)	(5)
Variables	Whole sample	Whole sample	World (Arid and sub-humid)	Africa	Asia
AI	0.0213***	0.0138***	0.0678***	0.131***	0.199***
	(0.00231)	(0.00201)	(0.00543)	(0.00898)	(0.0171)
AI 2	−0.00481***	−0.00376***	−0.0329***	−0.098 ***	−0.183***
	(0.000313)	(0.000201)	(0.00431)	(0.0109)	(0.0100)

(continued on next page)

[13] The FAO Penman-Monteith equation, retrieved at http://www.fao.org/3/x0490e/x0490e06.htm
[14] Sub-national data with national temporal pattern filled data gaps in global 5 arc-min dataset covering 1990–2015.

(*continued*)

	(1)	(2)	(3)	(4)	(5)
Variables	Whole sample	Whole sample	World (Arid and sub-humid)	Africa	Asia
Temperature		0.000633***	0.000534***	0.00949***	−0.000475***
		(2.57e-05)	(3.19e-05)	(0.00100)	(8.58e-05)
Deforestation	0.0004***	0.0004***	0.0002	0.0006***	0.0009***
	(0.00011)	(0.00014)	(0.00016)	(0.00009)	(0.0006)
Log GDP t-1	0.909***	0.906***	0.907***	0.931***	0.906***
	(0.000433)	(0.000415)	(0.000508)	(0.00162)	(0.000958)
Constant	0.799***	0.809***	0.787***	0.385***	0.407***
	(0.00657)	(0.00511)	(0.00601)	(0.0216)	(0.0176)
Observations	1,623,531	1,623,531	1,048,167	137,182	396,074
R-squared	0.930	0.928	0.921	0.950	0.929
Number of id	65,247	65,247	53,664	6654	20,282
Cell FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
World	YES	YES	YES		
Country X Year FE		YES	YES	YES	YES
Africa				YES	
Asia					YES
Arid and Sub-Humid			YES	YES	YES

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

Table A.3: Effects of AI on Log Population on different income classes. Year, Cell fixed Effects, and Country Trends.

	(1)	(2)	(3)	(4)
Variables	Low	Lower Middle	Upper Middle	High
AI	0.078***	0.095***	0.065***	0.048
	(0.027)	(0.031)	(0.021)	(0.039)
AI 2	−0.020	−0.259***	−0.086	−0.009
	(0.022)	(0.0119)	(0.071)	(0.010)
Temperature	−0.036***	−0.014***	−0.008***	0.001
	(0.001)	(0.000)	(0.001)	(0.003)
Temperature 2	−0.007***	−0.014***	−0.004***	−0.001***
	(0.002)	(0.000)	(0.001)	(0.000)
Log Pop t-1	0.443***	0.431***	0.389***	0.508***
	(0.003)	(0.004)	(0.001)	(0.003)
Observations	320,256	158,923	178,564	498,483
R-squared	0.679	0.758	0.612	0.701
Number of id	17,520	17,088	21,552	31,322
Cell FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

This table presents results of the effects of the aridity index on Log Population per different classes of income.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Effects of AI on GDP per class of aridity. Temporal and spatial dependence. Year, cell fixed effects and Country trends.

	(1)	(2)	(3)	(4)	(5)
Variables	Hyper-Arid	Arid	Semi-Arid	Sub-Humid	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)
AI	0.000313*	0.00432***	0.00451***	0.0111***	0.00420***
	(0.000184)	(0.00132)	(0.00137)	(0.00319)	(0.00152)
AI t-1	−0.00320	0.00182	0.00116	0.00902*	−0.00380
	(0.00333)	(0.00247)	(0.00180)	(0.00515)	(0.00246)
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 * AI	−0.000283	−0.00437***	−0.00458***	−0.0104***	−0.00375**
	(0.000190)	(0.00134)	(0.00140)	(0.00319)	(0.00154)
W *AI t-1	1.88e-05	0.000621	0.00140	−0.0121***	0.00167
	(0.000195)	(0.00169)	(0.00145)	(0.00440)	(0.00185)

(*continued on next page*)

(*continued*)

	(1)	(2)	(3)	(4)	(5)
Variables	Hyper-Arid	Arid	Semi-Arid	Sub-Humid	Humid
W * AI t-2	−0.000159	−0.00868***	−0.000895	−0.00980*	−0.000174
	(0.000210)	(0.00164)	(0.00148)	(0.00536)	(0.00141)
P	0.00321	−0.00260	−0.00291**	−0.00166	0.00177
	(0.00334)	(0.00201)	(0.00130)	(0.00222)	(0.00172)
T	−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
Cell 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

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

Table A.5: Effects of AI on GDP per income class. Temporal and spatial dependence. Year, cell fixed effects and Country trends.

	(1)	(2)	(3)	(4)
Variables	Low	Lower Middle	Upper Middle	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)
AI	0.00520***	0.00628***	−0.00402	0.00193*
	(0.00144)	(0.00207)	(0.00292)	(0.00105)
AI t-1	0.00790**	0.00183	−0.000947	−0.00519***
	(0.00353)	(0.00322)	(0.00411)	(0.00137)
AI t-2	0.00328**	0.00721***	−0.00330	−0.000120
	(0.00156)	(0.00207)	(0.00331)	(0.00104)
W * AI	0.00555***	−0.00387*	0.000623	0.00256**
	(0.00192)	(0.00234)	(0.00367)	(0.00115)
W * AI t-1	−0.00553***	−0.00601***	0.00370	−0.00207*
	(0.00147)	(0.00211)	(0.00305)	(0.00106)
W * AI t-2	−0.00385**	−0.00733***	0.00442	2.34e-05
	(0.00157)	(0.00213)	(0.00343)	(0.00104)
P	−0.0137***	0.00136	0.000333	0.00257***
	(0.00292)	(0.00252)	(0.00224)	(0.000820)
T	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
Cell FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country X Year FE	YES	YES	YES	YES
World	YES	YES	YES	YES

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

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2023.108079.

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