Policy Research Working Paper 8888

Does Rainfall Matter for Economic Growth?

Evidence from Global Sub-National Data (1990-2014)

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WORLD BANK GROUP
Water Global Practice
June 2019

Policy Research Working Paper 8888

Abstract

Much micro-econometric evidence suggests that precipitation has wide ranging impacts on vital economic indicators such as agricultural yields, human capital, and even conflict. And yet paradoxically most macro-econometric evidence (especially in the climate economy literature) finds that precipitation has no robust and significant impact on various measures of aggregate economic output. This paper argues that spatial aggregation of weather at the country level explains this result. The paper uses annual subnational gross domestic product data to show a concave relationship between precipitation and local gross domestic product growth between 1990 and 2014. It then demonstrates that when the data are aggregated at larger spatial scales, the impact decreases and eventually vanishes. The impact of precipitation on aggregate economic activity is predominantly felt in developing countries; it is insignificant in developed countries. Agriculture is found to be the dominant pathway. The results have significant consequences for measuring the economic impacts of climate change.

This paper is a product of the Water Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at rdamania@worldbank.org, sdesbureaux@worldbank.org and ezaveri@worldbank.org.

Produced by the Research Support Team

Does Rainfall Matter for Economic Growth? Evidence from Global Sub-National Data (1990-2014)

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Keywords: rainfall, economic growth

***JEL* codes:** O13, Q25, Q54

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1- Introduction

Few would deny that water, as a necessity for life, is central to all forms of economic activities. And yet attempts to quantify its contribution to economic growth remain elusive and uncertain. The earliest efforts to establish such links relied upon simple correlations between rainfall and economic growth. Charts showing co-movements of rainfall and GDP growth are still presented as prima facia evidence of a link between the availability of water and economic growth by the World Bank and others (World Bank 2006). While perhaps a useful tool for policy discourse, such correlations provide little information about causal patterns.

More recently a number of papers have attempted to investigate the effects of either rainfall or water availability on economic growth. Two canonical papers in the growing climate economy literature empirically examine the joint effects of rainfall and temperature changes on aggregate economic outcomes (Dell Jones and Olken 2012, Burke Hsiang and Miguel 2015 – hereafter DJO and BHM). After many robustness checks, both papers conclude that there is little discernible, robust evidence that rainfall has a statistically significant and consistent impact on GDP growth. However, temperature is shown to have a consistent and non-linear effect on GDP growth, with productivity being maximized at 13 ^{1}C in BHM. Following this pioneering work, recent research in the economics literature has focused upon the consequences of rising temperatures (Deryugina and Hsiang, 2017; Diffenbaugh and Burke, 2019; Henseler and Schumacher, 2019; Burke and Tanatuma, 2019). A typical finding is that temperature has negative economic impacts, but precipitation has no consistent and statistically significant impact.

To our knowledge there are only four recent papers that seek to specifically explore whether rainfall has an impact on aggregate economic activity at a global scale (Barrios et al. 2010, Brown et al. 2013, El Khanji & Hudson 2016, Sadoff et al 2016 – See Table Sup 1).[2] All these studies use national data. Only Brown et al. (2013) find an impact of precipitation shocks on GDP growth, noting that both dry and wet episodes of rainfall lead to a decline in per capita GDP growth rates. Surprisingly they find no impact on agricultural GDP growth, though it is the sector that is most affected by rainfall. None of the other papers finds a robust relationship between the chosen measure of precipitation or water availability (which varies across papers) and indicators of economic growth. Further details are provided in Sup 1.

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[2] In this discussion we exclude a handful of country-specific studies and studies that use simple correlations between GDP and rainfall or runoff, or cross sectional regressions as the latter group can make no claim about causal impacts and the findings of the former are similar to those of the global studies – no consistent pattern is found between GDP or GDP growth and rainfall.

At the other end of the spectrum is evidence which finds causal impacts between precipitation and agriculture (Auffhammer *et al.* 2006; Rowhani *et al*. 2011; Fishman 2016; Lesk et al. 2016; Zaveri, Russ and Damania 2018); industry and firm performance (Islam and Hyland 2018); urban growth (Desbureaux and Rodella 2018), and health (Maccini and Yang, 2009; Hyland and Russ, 2018).

Here, we argue that spatial aggregation of weather data at the country level explains why impacts of precipitation on GDP are found to be fragile and inconsistent at the macroeconomic level and yet are found to have powerful economic effects at the level of individual sectors. We demonstrate that highly aggregated statistical models may underestimate the impact of rainfall due to measurement error, since rainfall is spatially heterogenous, and much more so than temperature (Lobell and Asseng, 2017). Aggregation masks heterogeneity of impacts across regions (Barrios *et al.* 2010) -- a problem termed Modifiable Areal Unit Problem, or MAUP in the economic geography literature (Briant et al. 2010). Our results cast light on this issue by suggesting the need for spatial disaggregation to capture local heterogeneity. This remains an area that warrants further research.

Rainfall and water availability exhibit spatial variability – that is considerably higher than that of temperature. Indeed, the wettest areas in Alaska (4,880mL year^{-1}) received 4,830mL more precipitation on average per year between 1990 and 2014 than the Mojave Desert (52mL year^{-1}). Such differences are also observed in the major urban centers of the United States, with a difference of 1,800mL year^{-1} near Miami, Florida and 72mL year^{-1} in the Coachella Valley, California. And even higher spatial variability between the driest and wettest areas is found in India (10,083mL year^{-1}), Colombia (7,138mL year^{-1}), Peru (6,518mL year^{-1}) or Papua New-Guinea (6,476mL year^{-1}). Temperature also varies within countries (e.g., a 40 ºC difference between the coldest parts of Alaska and Miami, Florida) but globally, the within-country coefficient of variation is twice as large for precipitation than it is for temperature. Therefore, more heterogeneity is lost for precipitation than for temperature in studies at the country level, causing important statistical distortions that have direct impacts on the results.

We use recent global sub-national aggregated output data (Kummu, Taka and Guillaume 2018a) derived from Gennaioli et al. (2013) and show a robust impact of rainfall on local GDP growth between 1990 and 2014. Following the literature, we use fixed effects panel regressions to isolate the impact of weather variables from time invariant factors or common time-varying factors that could be correlated with both weather and aggregate economic outputs.

At the smallest spatial resolution available (0.5 degree), we find a concave relationship between precipitation and GDP growth. Rainfall increases total economic productivity at a decreasing rate, until it reaches a peak beyond which the marginal economic return declines with additional rainfall. The impact of temperature is in line with previous findings at a small spatial scale (e.g., BHM 2015). We then demonstrate that as the data are aggregated to larger spatial scales, the impact of precipitation becomes smaller until it ultimately disappears when the spatial unit is the country level.

Our results further indicate that the relationship between rainfall and GDP growth is sharper in low-income countries. However, in contrast, economic activity remains affected by temperatures in the developed economies. As a likely mechanism, we show that the relationship between precipitation and GDP growth is stronger in cells with large areas of croplands.

2- Methods

2.A Data

We use weather data taken from the *Terrestrial Air Temperature and Precipitation Version 4.01* compiled by the University of Delaware (Willmott and Matsuura 2001). This data set provides monthly mean precipitation and temperature at a 0.5-degree spatial resolution. Data are available for each month between 1901 and 2014. These data are widely use in the economics literature, including in DJO and BHM. Annual precipitation at the cell level between 1990 and 2014 ranged between 3mL in Sudan to 10,187mL in India (659mL average, Figure 1-A). Annual temperature at the cell level between 1990 and 2014 ranged between -32.4ºC in Greenland and 37.2 ºC in Peru (14.8 ºC average, Figure 1-B).

Annual grid-level GDP data between 1990 and 2014 at a 0.5-degree resolution come from Kummu, Taka and Guillaume (2018a). The data are primarily based on sub-national GDP per capita data constructed by Gennaioli, *et al.* (2013) and cover 82 countries, representing 85% of the global population and 92% of global total GDP (PPP) in 2015.

In figure 1, we plot the average cell-level precipitation between 1990 and 2014 against the level of GDP per capita observed in 2014 (y-axis), and cell-level temperature against GDP per capita in 2014. A local weighted scatterplot smoothing (LOWESS) represents the non-parametric correlation between weather variables and GDP across cells. Precipitation and GDP per capita follows an inverted U-shape. Up to a level of 500mL to 700mL of precipitation, an additional drop of rainfall is correlated with a higher level of GDP per capita. The relationship then turns negative (Fig 1-A). Above -20ºC, temperature and GDP are negatively correlated (Fig 1-B).

In Figure 1 C-D, we collapse weather data to the country level. Following DJO and BHM, we weight each cell by its total population. Observe that the inverted U-shape correlation between population-weighted precipitation and GDP per capita at the cell level is lost at the country level in Figure 1-C. After an initial decrease in GDP per capita in the most arid countries, the relationship between rainfall and GDP is flat. This initial decrease is in fact driven by a specific set of countries – rich oil and gas exporting countries from the gulf. The downward relationship between GDP per capita and temperature is preserved with country level data, with the notable exception again of the Gulf countries (Figure 1-D). In the following section we provide more robust evidence of these patterns.

2.B Empirical Strategy

We start the analysis at the grid level using data from Kummu, Taka and Guillaume (2018). For each 0.5-degree grid cell and year between 1991 and 2014, we calculate the annual growth rate of the cell's GDP per capita adjusted for inflation (g). We use a panel regression to determine if g is impacted by rainfall and temperature. We estimate the following model:

$$g_{i,t} = \beta_1 Rainfall_{i,t} + \beta_2\, Rainfall_{i,t}{}^2 + \beta_3 Temperature_{i,t} + \beta_4 Temperature_{i,t}{}^2 + \gamma_i + \phi_t + \mu_{c\times t} + \mu_{c\times t}{}^2 + \epsilon_{i,t} \quad (1)$$

Where cells are indexed by i and year by t. We allow a quadratic relationship between the two weather variables, total annual rainfall in liters and average annual temperature in Celsius degrees, and GDP per capita. Time invariant factors that affect cells' growth rates are controlled by grid cell fixed effects (γ_i). Global events are captured by year fixed effects (ϕ_t). Unobserved country changes are accounted for by quadratic country specific time trends $\mu_{c\times t} + \mu_{c\times t}{}^2$. Deviations in rainfall and temperature are likely to be randomly distributed and unexpected and therefore orthogonal to any possible confounders. The rich set of fixed effects in this specification isolates these localized and unexpected fluctuations in rainfall and temperature, facilitating causal inference. Standard errors are clustered at the Administrative 1 level (one level below country, i.e., a state in the United States) in order to account for spatial and serial correlation. Following Dell et al. *op* cit among others, we weight observations based on grid cell population, to ensure that results are representative of the global economy. This implies that quasi empty cells in Siberia and say densely populated San Francisco receive different weights. Population is taken from HYDE 3.2 (Klein, Beusen and Janssen 2010).

Grid-cells data are then aggregated at the Administrative 1 level and at the country level to investigate how aggregation of weather data affects the results. Our identification strategy relies on the assumption that annual variations in precipitation and temperature are exogeneous with respect to cells' economic activity.

3- Results

3.A Causal Results

Our main results are presented in Table 1. Column 1 displays the results of the baseline model (equation 1). Columns 2 and 3 aggregate data at the administrative 1 and country levels. Our results suggest a consistent increasing and concave relationship between rainfall and GDP growth -- a result that departs from findings in the literature. At the grid-cell level, the marginal economic return of an additional drop of rainfall is highest in arid areas and slowly decreases as the weather becomes wetter. The first 500mL of precipitation each year increases GDP per capita growth by 1 percent; precipitation between 500mL and 1,000mL a year raises growth by about an extra 0.8 percent. Eventually, extra precipitation brings no additional GDP per capita growth (Fig Sup 1). The temperature curve in the baseline regression is similar to that found in a variety of studies and peaks at 20 degrees Celsius as observed in micro studies (BHM 2015).

Next, we explore the consequences of aggregating weather and economic outputs data at a coarser spatial resolution. In column 2, we show the consequences of aggregating data at the Administrative 1 level (one level below a country; i.e., a state in the United States). We determine population-weighted levels of total annual precipitation, average temperature and average GDP per capita. Results at the administrative 1 level (state) are similar in magnitude and significance to those at the cell level. They suggest that the first 500mL of precipitation brings an additional 0.8 percent of GDP per capita growth, and that passing from 500mL to 1,000mL increases against growth by 0.6 percent. The concave relationship between temperature and GDP per capita growth is also retained.

In column 3, we aggregate data at the country level, following the same weighting procedure. This time the results vanish for rainfall, consistent with findings from DJO, BHM and other studies. However, temperature remains significant and is consistent with previous findings. At the country level, the optimal level of temperature is also found to be 13.9 °C, as in BHM.

Robustness checks are presented in the Supplementary Material. In Tables Sup 2, 3 and 4, we test different specification models at the cell, administrative 1 and country levels: first, we exclude the 10 major oil producing countries for which economic production is expected to be significantly less affected by weather; second, we exclude China and the United States; third, we include region by year fixed effects instead of year fixed effects; fourth, we control for region fixed effects but exclude country-year trends; fifth, we eliminate year fixed effects; sixth, we include linear instead of quadratic country time trends; and seventh, we account for one lag and three lags of GDP growth. Results are robust to a large number of alternate specifications. In Table Sup 5, we estimate our main equation 1 on trimmed outliers. We consecutively exclude the top/bottom 1% and the top/bottom 5% of the observations with the highest levels of precipitation. Results are unchanged, with an increasing concave relationship between rainfall and GDP growth, implying that the results are not driven by extremes.

In Table Sup 6, we check that our findings are not driven by the use of interpolated GDP values. We estimate equation 1 with the sub-national GDP per capita data used as inputs by Kummu, Guillaume and Taka (2018b) and derived from Genaioili et al. (2013), in place of the modeled grid-level disaggregated data. In column 1, we estimate equation 1 on the sub-sample of observed sub-national GDP per capita data. In column 2, we estimate equation 1 using the completed version of the sub-national GDP data that use national data for those countries missing in the Genaioili et al. (2013) data set. In column 3, we estimate equation 1 using the interpolated and extrapolated sub-national GDP data. Finally, in column 4, we estimate equation 1 using sub-national and national filled-in data. Results for rainfall are consistent with previous findings and indicate an increasing concave relationship between GDP per capita growth and precipitation for more than 99% of the sample.

3.B Heterogeneity

For completeness, we explore the relationship between cell-level precipitation, temperature and growth patterns across grid cells with different levels of development (3.C.1) and shares of cropland (3.C.2).

3.B.1 Income category

Table 2 shows that rainfall impacts growth in developing countries, but not in high-income countries. However, temperature remains significant in both high- and low-income countries. One reason could be a greater dependence on agriculture and rainfall sensitive economic activities in developing countries. One way to test for this is to explore if impacts differ across cells by levels of agricultural activity.

3.B.2 Agriculture

Is the relationship between rainfall and GDP explained by agriculture? We use data from the ESA CCI project to determine the share of cropland within each cell at the beginning of the period (ESA starts in 1992) and split the sample into quartiles based on the shares of cropland. Table 3 shows that growth in cells with more than 75% of cropland is found to be more sensitive to rainfall variations than the global average. A clear implication of this finding is that much, but not all, of the variation in GDP growth is a consequence of the effects of rainfall on agriculture.

4- Discussion and Concluding Remarks

This paper has provided an explanation for an empirical paradox: The micro-econometric literature relating to agriculture, health, industry performance and conflict consistently finds that variations in rainfall causally impact economic outcomes. And yet the macro-econometric literature has failed to find a robust and statistically significant impact. In this paper we demonstrate that the consequence is that aggregation to large spatial scales masks the heterogeneity of impacts of rainfall on aggregated economic growth. Not implausibly the relationship is found to be concave, implying that in dry areas the marginal economic returns are greater than in wetter areas and that these effects are particularly pronounced in areas dependent on agriculture.

Why should we care about a relationship between aggregate economic outputs and growth? Climate change is expected to have profound effects on the hydrological cycle, leading to more variable rainfall patterns (Menon et al., 2013; Donat et al., 2016). So far, the climate-econometric literature has highlighted the cost of rising temperature on GDP growth (Hsiang and Kopp 2018). Accounting for changes in rainfall is likely to be equally critical when estimating the economic costs of climate change. However, climate models diverge significantly on the effect of climate change on precipitation across regions. This has two implications for predictions on future economic growth. First, it implies that the joint temperature and rainfall impacts may be significantly different from the predictions that rely only upon temperature. Second, these findings add further uncertainty to the future cost of climate change.

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Figures and Tables

Figure 1: Precipitation, temperature and GDP per capita

1-A

1-B

1-C

1-D

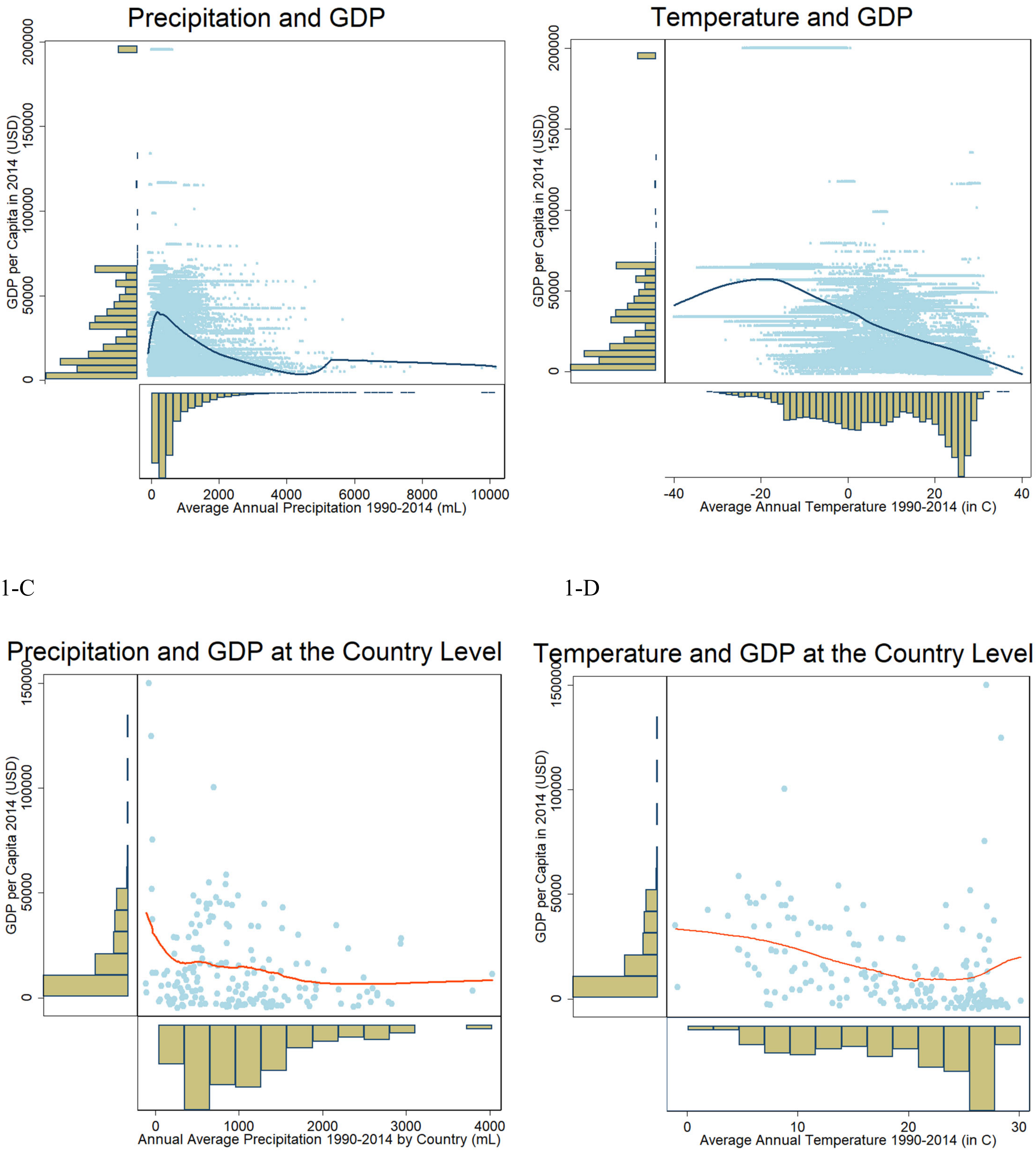


Table 1: The impact of precipitation on GDP growth

	(1)	(2)	(3)
Spatial Aggregation	Cell	Adm 1	Country
Rainfall	1.261***	1.075***	1.185
	(0.325)	(0.244)	(1.139)
Rainfall^2	-0.211***	-0.205***	-0.310
	(0.064)	(0.052)	(0.253)
Temperature	0.574**	0.424*	1.727**
	(0.213)	(0.216)	(0.580)
Temperature^2	-0.015*	-0.016**	-0.061**
	(0.006)	(0.006)	(0.020)
Observations	869,447	60,530	4,128
R-squared	0.359	0.251	0.355

Columns 1 and 2: Clustered standard errors at the administrative 1 level in parentheses. Column 3: Clustered standard errors at the country level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 2: The impact of precipitation on GDP growth by income level

	(1) High Income	(2) Developing	(3) Low Income	(4) Lower Middle Income	(5) Upper Middle Income
Rainfall	-0.204	1.595***	2.201**	1.792***	1.614*
	(0.546)	(0.356)	(0.827)	(0.440)	(0.686)
Rainfall^2	-0.113	-0.253***	-0.791**	-0.257**	-0.265+
	(0.125)	(0.072)	(0.281)	(0.085)	(0.150)
Temperature	0.246*	0.579+	-0.072	2.898+	0.428
	(0.115)	(0.318)	(0.538)	(1.502)	(0.349)
Temperature^2	-0.012**	-0.016*	-0.009	-0.068*	-0.012
	(0.004)	(0.008)	(0.011)	(0.030)	(0.010)
Observations	201,466	667,981	110,324	165,151	392,506
R-squared	0.443	0.344	0.392	0.403	0.303

Clustered standard errors at the administrative 1 level in parentheses

Table 3: The impact of precipitation on GDP growth by agricultural activity

Share of Cropland	(1) No Cropland	(2) >0 to 0.25	(3) 0.25 to 0.5	(4) 0.5 to 0.75	(5) >0.75
Rainfall	2.542	1.091*	1.003**	1.392**	2.151***
	(2.391)	(0.454)	(0.364)	(0.447)	(0.346)
Rainfall^2	-0.350	-0.139+	-0.135**	-0.325**	-0.453***
	(0.504)	(0.082)	(0.047)	(0.114)	(0.094)
Temperature	0.369	0.721**	1.500***	0.392	-0.092
	(0.537)	(0.239)	(0.386)	(0.268)	(0.205)
Temperature^2	0.008	-0.021**	-0.040**	-0.011	-0.005
	(0.007)	(0.006)	(0.013)	(0.010)	(0.006)
Observations	90,932	494,505	110,904	82,596	90,510
R-squared	0.140	0.301	0.344	0.336	0.456

Specification is the baseline model from Table 2. Clustered standard errors at the Administrative 1 level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

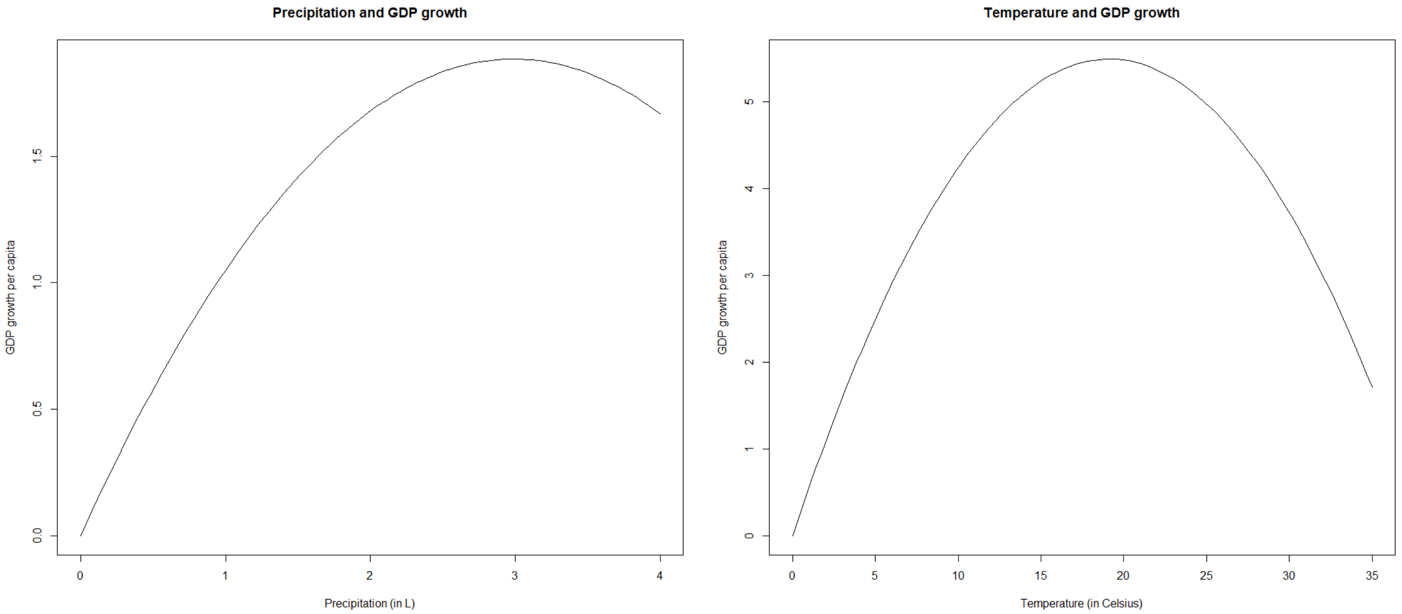
Supplementary Tables

Table Sup 1: Papers using panel regressions of water availability on measures of aggregate economic activity

	Water	**GDP Growth**	**GDP**	**Agricultural GDP Growth**
Barrios et al. 2010	Z-score Precipitation levels	Significant only in Africa		
Burke et al 2015	Precipitation level	No significant impact		
Dell et al 2012	Precipitation level	No significant impact		No significant impact
Brown et al 2013	Precipitation shocks	Significant impact		No significant impact
Sadoff et al 2016				Significant impact
Khanji & Hudson 2016	Water utilization	No significant impact	Significant impact	

Note: A blank cell implies that impact on that dependent variable has not been reported in the paper

Fig Sup 1: Precipitation, Temperature and local GDP growth



Note: This figure graphs the results from Table 1 column 1. It shows an increasing concave relationship between GDP growth and precipitation taken at the cell level. The relationship between GDP growth and temperature is an inverted U-shape as in BHM 2015.

Table Sup 2: Cell level robustness checks

This table presents robustness checks for our main result presented in Table 1, column 1. Robustness checks are: Column 2: as in (1) but excluding the 10 major oil producing countries for which economic production is expected to be significantly less affected by weather. Column (3): as in (1) but excluding China and USA. Column (4): as in (1) but including a WB region Year FE instead of Year FE. Column (5): as in (4) but without country year trends. Column (6): as in (1) but without Year FE. Column (7): as in (1) but with a linear instead of quadratic country time trend. Columns 8 and 9: as in (1) but including one lag and three lags of growth as in a Arellano Bond approach.

	(1) Base	(2) No Oil	(3) No US/China	(4) ContYr FE	(5) ContYr FE + no Trend	(6) No YrFE	(7) Linear Time	(8) LDV 1 Lag	(9) LDV 3 Lags
Rainfall	1.261***	1.322***	1.456***	1.430***	1.696***	1.403***	1.573***	1.157***	0.947**
	(0.325)	(0.339)	(0.391)	(0.361)	(0.378)	(0.390)	(0.334)	(0.308)	(0.343)
Rainfall^2	-0.211***	-0.220***	-0.225**	-0.256**	-0.250**	-0.237**	-0.251***	-0.189**	-0.165**
	(0.064)	(0.066)	(0.070)	(0.078)	(0.078)	(0.078)	(0.069)	(0.058)	(0.062)
Temperature	0.574**	0.650*	0.685**	0.600**	1.020***	0.493*	0.693**	0.363+	0.330
	(0.213)	(0.283)	(0.265)	(0.229)	(0.250)	(0.202)	(0.225)	(0.216)	(0.216)
Temperature^2	-0.015*	-0.019*	-0.017*	-0.027***	-0.036***	-0.017**	-0.021**	-0.012+	-0.010
	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	869,447	642,439	725,697	869,447	869,447	869,447	869,447	833,226	760,784
R-squared	0.359	0.366	0.261	0.379	0.314	0.336	0.319	0.364	0.329

Clustered standard errors at the Administrative 1 level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table Sup 3: Admin 1 level robustness checks

This table presents robustness checks for Table 1, column 2. Robustness checks are: Column 2: as in (1) but excluding the 10 major oil producing countries for which economic production is expected to be significantly less affected by weather. Column (3): as in (1) but excluding China and USA. Column (4): as in (1) but including a WB region Year FE instead of Year FE. Column (5): as in (4) but without country year trends. Column (6): as in (1) but without Year FE. Column (7): as in (1) but with a linear instead of quadratic country time trend. Columns 8 and 9: as in (1) but including one lag and three lags of growth using an Arellano Bond approach.

	(1) Base	(2) No Oil	(3) No US/China	(4) ContYr FE	(5) ContYr FE + no Trend	(6) No YrFE	(7) Linear Time	(8) LDV 1 Lag	(9) LDV 3 Lags
Rainfall	1.075***	1.200***	1.090***	1.253***	1.847***	1.366***	1.626***	0.998***	0.758**
	(0.244)	(0.243)	(0.250)	(0.249)	(0.284)	(0.244)	(0.255)	(0.245)	(0.251)
Rainfall^2	-0.205***	-0.221***	-0.206***	-0.262***	-0.363***	-0.264***	-0.324***	-0.194***	-0.163**
	(0.052)	(0.051)	(0.052)	(0.053)	(0.057)	(0.053)	(0.055)	(0.052)	(0.053)
Temperature	0.424*	0.491*	0.433+	0.296	0.838***	0.279	0.744***	0.180	-0.018
	(0.216)	(0.198)	(0.225)	(0.226)	(0.218)	(0.216)	(0.221)	(0.222)	(0.235)
Temperature^2	-0.016**	-0.018***	-0.016**	-0.012*	-0.028***	-0.015*	-0.025***	-0.013*	-0.004
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	60,530	54,530	58,586	60,530	60,530	60,530	60,530	58,007	52,962
R-squared	0.251	0.272	0.246	0.288	0.185	0.226	0.195	0.261	0.220

Clustered standard errors at the administrative 1 level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table Sup 4: Country level robustness checks

This table presents robustness checks for Table 1, column 3. Robustness checks are: Column 2: as in (1) but excluding the 10 major oil producing countries for which economic production is expected to be significantly less affected by weather. Column (3): as in (1) but excluding China and USA. Column (4): as in (1) but including a WB region Year FE instead of Year FE. Column (5): as in (4) but without country year trends. Column (6): as in (1) but without Year FE. Column (7): as in (1) but with a linear instead of quadratic country time trend. Columns 8 and 9: as in (1) but including one lag and three lags of growth following an Arellano Bond approach.

	(1) Base	(2) No Oil	(3) No US/China	(4) ContYr FE	(5) ContYr FE + no Trend	(6) No YrFE	(7) Linear Time	(8) LDV 1 Lag	(9) LDV 3 Lags
Rainfall	1.185	1.603	1.185	1.456	-0.131	1.607	0.530	1.021	1.007
	(1.139)	(1.109)	(1.141)	(1.155)	(1.200)	(1.142)	(1.116)	(1.131)	(1.156)
Rainfall^2	-0.310	-0.397	-0.309	-0.434+	-0.179	-0.367	-0.217	-0.256	-0.339
	(0.253)	(0.247)	(0.254)	(0.253)	(0.241)	(0.253)	(0.247)	(0.252)	(0.266)
Temperature	1.727**	1.747**	1.731**	1.907**	1.885**	1.239*	2.240***	1.417*	0.725
	(0.580)	(0.601)	(0.581)	(0.656)	(0.665)	(0.554)	(0.628)	(0.585)	(0.455)
Temperature^2	-0.061**	-0.062**	-0.061**	-0.068**	-0.074***	-0.051**	-0.079***	-0.060**	-0.037*
	(0.020)	(0.019)	(0.020)	(0.022)	(0.019)	(0.018)	(0.019)	(0.019)	(0.016)
Observations	4,128	3,936	4,080	4,128	4,128	4,128	4,128	3,956	3,612
R-squared	0.355	0.380	0.352	0.396	0.233	0.321	0.269	0.383	0.366

Clustered standard errors at the administrative 1 level in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$.

Table Sup 5: Trimming data

This table presents robustness checks for our main result presented in Table 1, column 1. We exclude extreme precipitation values. In column 2, we exclude the observations with the lowest and highest five percent annual level of rainfall. In column 3, we exclude the observations with the lowest and highest 1 percent annual level of rainfall. Results remain robust.

	(1) All data	(2) Trim top / bottom 5%	(3) Trim top / bottom 1%
Rainfall	1.261**	1.857*	2.275**
	(0.399)	(0.715)	(0.776)
Rainfall^2	-0.211***	-0.424*	-0.614*
	(0.052)	(0.183)	(0.276)
Temperature	0.574**	0.572**	0.555**
	(0.205)	(0.203)	(0.189)
Temperature^2	-0.015*	-0.015*	-0.014*
	(0.006)	(0.006)	(0.006)
Observations	869,447	854,141	787,508
R-squared	0.359	0.360	0.369

Clustered standard errors at the administrative 1 level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table Sup 6: Estimating equation 1 using original data used as inputs in Kummu, Taka and Guillaume (2018)

This table presents robustness checks for our main result presented in Table 1, column 2. Instead of using filled-in disaggregated data provided by Kummu, Taka and Guillaume (2018), we use the inputs data coming from Genaioli et al. (2013). Column 1 uses the sub-sample of observed data available at the sub-national level (no national data, no extrapolated or interpolated data). Column 2 uses sub-national and nationally observed GDP data (no extrapolated or interpolated data). Column 3 uses sub-national data with both observed, extrapolated and interpolated data (no national data). Column 4 uses sub-national and national data, including interpolated data. Results for precipitation remain robust.

	(1)	(2)	(3)	(4)
$Rainfall$	0.571**	0.555**	0.462***	0.430***
	(0.211)	(0.195)	(0.112)	(0.114)
$Rainfall^2$	-0.166*	-0.161*	-0.095**	-0.091**
	(0.073)	(0.065)	(0.030)	(0.030)
$Temperature$	0.017	0.046	0.051	0.076*
	(0.043)	(0.044)	(0.034)	(0.035)
$Temperature^2$	-0.000	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Include regional data	Yes	Yes	Yes	Yes
Include national data	No	Yes	No	Yes
Include filled-in data	No	No	Yes	Yes
Observations	18,458	20,434	31,665	33,745
R-squared	0.379	0.377	0.248	0.254

Clustered standard errors at the administrative 1 level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.