

Droughts and Deficits

The Global Impact of Droughts on Economic Growth

Esha D. Zaveri
Richard Damania
Nathan Engle



WORLD BANK GROUP

Water Global Practice

May 2023

Abstract

As climate change intensifies, dry rainfall shocks and droughts are a growing concern. At the same time, scientific evidence suggests that the world has surpassed the safe planetary boundary for green water, which is water stored in biomass and soil that is crucial for maintaining climate resilience. Yet, evidence at the global scale of these combined forces on economic growth is poorly understood. This paper attempts to fill this gap by using data on annual subnational gross domestic product for 82 countries from 1990–2014. Using rainfall shocks as plausibly exogenous variations in a spatially specific panel at the grid level, the analysis finds that the global effects of droughts on economic activity are substantial. Moderate to extreme droughts reduce gross domestic product per capita growth between 0.39 and 0.85 percentage point, on average, depending on the level of development and baseline climatic conditions, with

low- and middle-income countries in arid areas sustaining the highest relative losses. In high-income countries, moderate droughts have no impact, and only extreme droughts have adverse effects, reducing growth by about 0.3 percentage point, a little less than half the impact felt in the low- and middle-income country sample for the same intensity of drought. Crucially, the impact of a dry shock of a given magnitude also depends on antecedent green water availability. The results show that increases in soil moisture in previous years can neutralize the harmful impacts from a dry shock, with suggestive evidence that local and upstream forest cover are key channels through which these impacts manifest. These findings have important implications for measuring the economic impact of droughts and can inform adaptation investments.

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 ezaveri@worldbank.org; rdamania@worldbank.org; and nengle@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Droughts and Deficits: The Global Impact of Droughts on Economic Growth

Esha D. Zaveri¹, Richard Damania², Nathan Engle¹

Keywords: rainfall, droughts, GDP growth, soil moisture, land use

JEL Codes: O13, O44, Q5, Q25, Q24

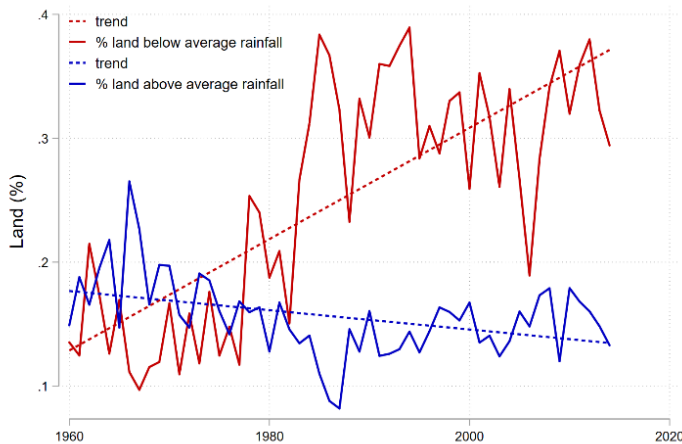
¹ Water Global Practice, The World Bank, Washington, D.C., ²Office of the Chief Economist for Sustainable Development, The World Bank, Washington, D.C.

1. Introduction

Drought, T.S. Eliot famously wrote, “is the death of the earth”, reflecting on a natural force that has long shaped our planet. Over the last twelve centuries of human civilization, megadroughts have played a significant role in the collapse of some of the most complex societies of the pre-industrial era, such as the Khmer and Mayan Empires, the Puebloan cliff-dwellers of the southwestern US, and the Yuan Dynasty of China (Ault, 2020; Cook et al., 2016). Rainfall variability remains a challenge even today. Over the past three decades, 1.8 billion people, or approximately 25 percent of humanity, have endured abnormal rainfall episodes each year, whether it was a particularly wet year or an unusually dry one (Damania et al. 2017). This variability has disproportionately impacted developing nations, with upward of 85 percent of affected people living in low- or middle-income countries (Damania et al. 2017). Adapting to rainfall variability is often much more challenging than accommodating long-term trends because of the unpredictable duration of a deviation, its uncertain magnitude, and its unknown frequency (Adams et al. 2013).

Climate change compounds these challenges by making rainfall even more variable. Though future rainfall projections are highly uncertain, there is unanimity across climate change models that rainfall will become more erratic and extreme with rising temperatures. There are already signs that the spatial distribution of rainfall has changed. Figure 1 shows a distinct drying trend over the past half-century. The proportion of land encountering below average rainfall has increased, while areas with above average rainfall are in decline. At the same time, drought frequency and duration have increased by nearly a third globally since 2000.² The frequency of *extreme* dry shocks³ has substantively increased by about 233 percent as shown in Figure 2.

Figure 1: Global Trends in Land Area with Above- and Below-Average Rainfall, 1960–2020

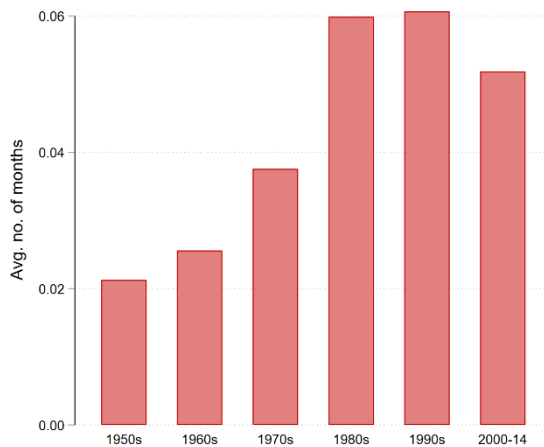


Source: Calculations using data from Willmott and Matsuura (2001)

² UNCCD Report “Drought in Numbers 2022.”

³ Defined here as shocks that are at least 2 standard deviations (SDs) below the long-term mean. Note that a 2 SD dry shock is a very rare event and includes the driest 2.5 years in a century.

Figure 2: Rainfall Trends in Low- and Lower-Middle-Income Countries, 1950s–2014



Source: Calculations using data from Willmott and Matsuura (2001)

These empirical findings are consistent with projections from some climate models that the global land area and population facing extreme droughts could more than double from 3 percent in 1976–2005 to around 7 to 8 percent by the late 21st century (Pokhrel et al. 2021). Even low levels of warming could amplify drought hazards across much of the world. These estimates mean that nearly 700 million people, or 8 percent of the projected future population, could be affected by extreme drought compared with 200 million over recent decades (Pokhrel et al. 2021).

This paper is related to the recent empirical literature on the effects of dry shocks and droughts on economic performance. Much of this work exploits granular data on local water availability, to estimate the direct and indirect impacts of rainfall variability or water availability on economic productivity. For instance, several studies utilizing high-resolution geospatial data on gross domestic product (GDP) with rainfall and runoff measures have shown that water availability matters for economic growth (Damania, Desbureaux, and Zaveri 2020; Russ 2020; Kotz et al., 2022). Other studies that exploit survey data on workers and firms show that unreliable water supplies and water shortages adversely affect productivity by reducing workers' incomes, inducing lower sales for firms, and worsening health outcomes (Desbureaux and Rodella 2017; Islam and Hyland 2019). An important lesson from this work is that it is critical to account for the localized nature of water availability when studying the impacts of water. It is quite common that one part of a country can be undergoing a drought while another part has abundant water. Using disaggregated data is thus critical since rainfall tends to exhibit significant spatial variability that is considerably higher than that of temperature. Globally, the within-country coefficient of variation is 1.9 times larger for precipitation than it is for temperature (in the year 2000, the CV was 0.055 for precipitation versus 0.029 for temperature (Damania, Desbureaux, Zaveri, 2020)). Aggregated levels of precipitation would therefore mask the considerable spatial heterogeneity causing important statistical distortions that can have direct impacts on the results.

This paper also provides some of the economic underpinnings to the new scientific literature on planetary boundaries. The planetary boundaries literature describes critical Earth system processes that determine

the stability and resilience of the Earth's biosphere (Rockstrom et al 2009). Recently, a new boundary – termed green water - has been introduced (Wang-Erlandson et al 2022). Green water represents the moisture that is stored in the root zone of soil and used by plants. It is essential for maintaining the productivity and health of terrestrial ecosystems, and it also plays a crucial role in regulating the Earth's climate. Climate change, deforestation, and water management practices can all impact the availability of green water. This paper contributes to the literature by empirically demonstrating the role of green water in promoting resilience to droughts and quantifying the resulting net economic benefits. The results are relevant to the large literature on adaptation to rainfall shocks and climate change. Most of the literature highlights the need for climate resilient infrastructure to reduce the adverse effects of floods and droughts (Adger et al., 2005, Kirschke et al, 2021). Others emphasize the importance of economic diversification, drought resistant crop management techniques, early warning systems and insurance schemes to address negative impacts on affected communities (Dasgupta et al., 2014, Lobell et al., 2015). We add further insights to this literature by empirically demonstrating how resilience to dry shocks is impacted by natural conditions such as green water which is affected by upstream forest cover and antecedent conditions.

Confirming previous work, this paper demonstrates that rainfall deficits have material impacts on GDP per capita growth rates. However, it provides new results to show that there is considerable heterogeneity across countries and over time. The paper also demonstrates that green water – a term used to describe the portion of precipitation that infiltrates into the root-zone of soil – plays a crucial role in determining the economic impact of a dry shock of a given magnitude. It is known that green water – soil moisture levels – can be influenced by the amount of precipitation that has occurred over an extended period, rather than just the most recent rainfall event (Niu et al., 2011, Pen Arabica et al., 2016). Accordingly, the results show that recent and past climate history are key factors in determining the magnitude of impacts (all else equal). When recent years are drier than normal, the impacts of dry shocks on economic growth are found to be considerably stronger. Conversely, if the recent past has been exceptionally wet, a one-off dry rainfall shock has a more muted impact on economic growth.

Forests also play an important role in regulating the water cycle and when managed appropriately can preserve green water and maintain soil moisture levels in watersheds (Piao et al. 2015, Sivaplan et al 2003, Grosset, Papp and Taylor 2023). Impacts of dry shocks are also found to be systematically more severe in regions where there has been local and upstream deforestation, highlighting the importance of halting forest loss to support green water functioning and climate resilience. These findings, perhaps the first empirical estimates, highlight the importance of “green water” (soil moisture) in shielding economic growth from adverse rainfall shocks. Negative growth effects are also found to be heavily concentrated in developing countries in arid and semi-arid regions. The disproportionate impact on poorer countries is a consequence of the often harsher climatic conditions and the limited resources to manage the consequences of dry shocks and droughts.

The rest of the paper is organized as follows. Section 2 describes the datasets used in this analysis. Section 3 presents the empirical strategy. Section 4 presents the main results, an analysis of heterogeneity of impacts and potential mechanisms, and robustness checks. Finally, Section 5 concludes with a discussion of the results and policy implications.

2. 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) that has widely been used in the economics literature (Dell Jones and Olken 2012, Burke Hsiang and Miguel 2015, among others). This data set provides monthly total precipitation and temperature at a 0.5-degree spatial resolution. Data are available for each month between 1901 and 2014. Annual precipitation at the cell level between 1990 and 2014 ranged between 3mL in Sudan to 10,187mL in India.

To define when a grid cell experienced a shock, the z-score of rainfall is calculated in each grid cell, and in each time period as per $z_{it} = \frac{rain_{it} - \overline{rain}_i}{\sigma_i}$, where z_{it} is the z-score of rainfall in grid cell i at time t , $rain_{it}$ is rainfall in grid cell i at time t , \overline{rain}_i is mean rainfall in grid cell i over the full time period of the climate dataset, and σ_i is the standard deviation of rainfall in grid cell i over the same time period. The z-score for rainfall is interpreted as the number of SDs away from the long-run mean in time t . Once z-scores are calculated, binary variables are generated to indicate whether the z-score passes certain thresholds. A grid cell is considered to have a *dry shock* if rainfall in a given year is lower than the long-run annual mean for the grid cell by at least X SD ($z \leq -X$), where X can be any range of integer values. Similarly, a grid cell is considered to have a *wet shock* if rainfall in a given year is higher than the long-run annual mean for the grid cell by at least X SD ($z \geq X$). Doing this allows for a semiparametric test of the impacts of deviations from the long-run mean. It also allows for impacts to be both nonlinear and nonsymmetric around zero. These properties are important for distinguishing the possible heterogeneous impacts of deluges versus droughts.

Annual grid-level GDP data between 1990 and 2014 at a 0.5-degree resolution come from Kummu, Taka and Guillaume (2018). The data are primarily based on sub-national GDP per capita data constructed by Gennaioli, *et al.* (2013) and covers 82 countries, representing 85% of the global population and 92% of global total GDP (PPP) in 2015. Population data is taken from HYDE 3.2 (Klein, Beusen and Janssen 2010).

To give an indication of how wealth and economic composition impact the relationship between droughts and economic growth, we use World Bank income group classifications to divide the world into developing countries (that includes low-income, lower-middle and upper-middle income countries), and high-income countries. Classifications are based on mean per-capita GNI in 2015 where low-income countries have GNI per capita below \$1,025, middle-income countries are between \$4,036 and \$12,475, and high-income countries are above \$12,475. We also use the Global Aridity Index and Potential Evapotranspiration Climate Database (Trabucco and Zomer 2019) to differentiate grid cells based on their aridity. Additionally, local and upstream shares of forest cover are measured using satellite data from the European Space Agency.

3. Empirical Strategy

Our econometric specification uses a panel fixed-effects model to link data on droughts to data on economic growth at the level of 0.5-degree grid cells (approximately 56 kilometers x 56 kilometers at the equator) between 1991 and 2014, the period for which economic data is available at a granular scale.

In order to estimate the impact of droughts on economic growth, we follow much of the empirical climate change literature and estimate a reduced-form production function-style equation (Dell Jones and Olken 2012, Burke Hsiang and Miguel 2015; Deryugina and Hsiang, 2017; Newell *et al.*, 2018; Kahn *et al.*, 2019;

Tol, 2019; Diffenbaugh and Burke, 2019; Henseler and Schumacher, 2019; Burke and Tanutama, 2019; Damania, Desbureaux and Zaveri, 2020; Kotz, Levermann, and Wenz, 2022; Callahan and Mankin, 2022; Felbermayr et al., 2022). For each 0.5-degree grid cell and year, we calculate the annual growth rate of the cell's GDP per capita adjusted for inflation (g) and estimate equation (1) to determine if g is impacted by different levels of drought severity.

$$g_{i,t} = f(D_{it}) + \beta X_{it} + \gamma_i + \phi_t + \mu_{c \times t} + \epsilon_{i,t} \quad (1)$$

Cells are indexed by i and years by t . Thus, the unit of observation is the grid cell-year. The relationship between growth and droughts, $f(D_{it})$, could take many forms.

Following best practices, the analysis models the effect of shocks on growth in GDP per capita, instead of levels of GDP per capita, because GDP levels exhibit high serial correlation that are indistinguishable from a random walk and have a unit root (Burke, Hsiang and Miguel, 2015). Unit root processes are non-stationary and as a result regressions using unit root outcomes often generate spurious results and traditional test statistics fail. Accounting for country-specific trends in levels does not alleviate this concern. To avoid the statistical pitfalls, the exercise is performed in terms of first differences, i.e., using growth as an outcome. This also has important dynamic implications for the persistence of impacts. If rainfall shocks were to affect the level of GDP, it suggests a temporary impact that disappears the following year. For example, this may occur if agricultural yields collapse one year and recover the next year. But if there were an impact on the growth of GDP, this implies persistence because growth effects compound over time. Regressions in appendix B show that growth impacts persist for three years after a dry shock, after which there is a reversion to the previous growth rate.

To measure droughts, we use rainfall variability measured in terms of local deviations from the long-run mean, which is plausibly exogenous since it reflects random draws from a climate distribution (Dell, Jones, and Olken 2014). Much like the standard precipitation index, we define rainfall variability by using z-scores, and classify observations into bins based on the value of the z-score. In robustness checks we also make use of the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano, et al., 2010) that integrates evapotranspiration into the standard precipitation index. It should be noted that this index is very sensitive to the chosen definition of evapotranspiration (Vicente-Serrano and National Center for Atmospheric Research Staff 2015), hence we do not rely exclusively on this index. The main conclusions are found to be robust to the use of this alternative measure. We estimate the following model:

$$g_{it} = \alpha_1 + \sum_{bk} \alpha_b bin_{it} + \beta X_{it} + \gamma_i + \phi_t + \mu_{c \times t} + \epsilon_{i,t} \quad (2)$$

where bin_{it} indicates the distribution of drought severity where k denotes the threshold of the z-score and b denotes the number of bins. In the first specification we use $k=1$ and $b=3$. In this instance, a grid cell is considered to have a *dry shock*, if rainfall in a given year is lower than the long-run annual mean for the grid cell by at least 1 standard deviation ($z \leq 1$). Similarly, a grid cell is considered to have a *wet shock* if rainfall in a given year is higher than the long-run annual mean for the grid cell by at least 1 standard deviation ($z \geq 1$). Accounting for such shocks allows for a semiparametric test of the impacts of deviations from the long-run mean. It also allows for impacts to be both nonlinear, and nonsymmetric around zero. These properties are important for distinguishing the possible heterogeneous impacts of deluges versus droughts.

With 3 bins, coefficients α_2 and α_3 measure the impact of these dry and wet conditions relative to the near normal condition (the excluded category is $-1 < z < 1$).

$$g_{it} = \alpha_1 + \alpha_2 Z_{it}^{-1} + \alpha_3 Z_{it}^{+1} + \beta \mathbf{X}_{it} + \gamma_i + \phi_t + \mu_{c \times t} + \epsilon_{i,t} \quad (3)$$

We estimate several such 3-bin models, using different thresholds for $k= 1.6, 1.3, 0.8$ and 0.5 to check for sensitivity of the results to different thresholds. Next, we estimate models with different number of bins and corresponding thresholds together such that the estimated coefficients demonstrate how drought responses may change across the entire distribution of drought severity.

Following standard practices in the literature that use statistical analysis, we employ a fixed effects panel regression because of the wide variety of latent and non-latent factors that can impact economic growth. A very large and long-standing economics literature exists on the determinants of economic growth and development (see, for instance, Ciccone and Jarocinsky 2010; Acemoglu, Johnson, and Robinson 2005; Barro 2003). In this paper, we are not attempting to explore these factors. Rather, we wish to isolate the impact of one such potential impediment to growth—drought. In order to do so, we control for factors that may simultaneously impact both economic growth and droughts.

This is done through controlling for a strong set of fixed effects and time trends, including: grid cell fixed effects (γ_i), which control for time invariant, local characteristics that may impact economic growth; year fixed effects (ϕ_t), which controls for changes in global patterns of economic growth; country-specific time trends ($\mu_{c \times t}$) which accounts for country specific trends in both droughts and economic growth. Since weather variables tend to be correlated over time in the same location, we also include a vector \mathbf{X}_{it} that accounts for a quadratic in temperature to account for the well-established response of the overall economy to temperature increases. The rich set of fixed effects and controls in this specification isolates localized and unexpected fluctuations in shocks, facilitating causal inference, and is necessary to isolate the impact of exogenous changes in droughts on economic growth. Similar approaches have been used in previous climate and weather impact studies (Burke and Tanutama, 2019; Callahan and Mankin, 2022; Damania, Desbureaux, and Zaveri, 2020).

Standard errors are clustered at the Administrative 1 level (the largest subnational level in a country, e.g., a state in the US) in order to account for spatial and serial correlation. We test the robustness of the results through additional tests for spatial autocorrelation to account for spatial and temporal dependence. Following other literature, we weight observations based on grid cell population. Because observations corresponding to grids with higher population have smaller variance, population weighting in the grid cell regressions accounts for heteroscedasticity and yields more efficient estimates (Damania, Desbureaux, and Zaveri 2020; Solon et al. 2015).

Unlike studies which estimate economy-wide costs for specific drought events ex-post, our econometric approach yields estimates of economic impact for marginal increases in the occurrence and intensity of droughts. This information can be particularly useful for policy makers who need to allocate scarce financial resources for drought assistance and emergency programs.

Droughts covary with other variables that may drive heterogeneity in the effect of drought such as recent and past climate history, as well as income. Therefore, we also consider models that allow heterogeneity in the response to droughts, by soil moisture conditions, aridity and income characteristics of the grid cell. Equation (1) is modified to allow interaction between the drought variables and different measures of

heterogeneity (H_{it}). This will allow us to ascertain the sensitivity of drought impacts across recent wet and dry periods, arid versus humid climatic zones and income classes.

$$g_{i,t} = f(D_{it}) \times H_{it} + \beta X_{it} + \gamma_i + \phi_t + \mu_{c \times t} + \epsilon_{i,t} \quad (4)$$

To estimate how antecedent wet or dry conditions affect the relationship, the analysis calculates how much rainfall has deviated from long-run averages in the three years prior to the shock by summing z-scores over the three-year period. If there were significant rainfall deficits, these deficits would stack, and the cumulative z-score calculation would record a very deep three-year water deficit. This cumulative z-score is interacted with the main dry shock variables in the regression to assess whether wetter or drier conditions prior to a dry shock determines its impact on growth. For example, a higher and positive cumulative z-score captures rainfall increases in previous years that can raise green water or soil moisture in the root zone of crops.

To investigate the role of forests and landscapes in influencing conditions through which green water is maintained, past local and upstream share of forest cover is measured using satellite data from the European Space Agency. High forested areas denote places where the forest area is more than the 50th percentile of the forest distribution among all grid cells in each country. The interaction of high forested areas with the main dry shock variables in the regression allows us to assess whether higher local and upstream forest cover can help buffer the growth impacts of dry shocks.

Geography can also matter and different regions with different climatological baseline climates may respond differently to droughts. This also allows us to test for heterogeneous responses to droughts. On the one hand, if regions where dry shocks are common are able to adapt to drier conditions, droughts should be less harmful to economic growth. In other words, economic growth would be less sensitive to dry shocks in arid areas. Conversely, recurring dry shocks may have cumulative impacts that weaken adaptive capacity. We test for such effects using a binary indicator for arid and semi-arid areas as the interaction term. Likewise, poorer countries may also face higher marginal damages due to the limited ability of exposed populations to manage the consequences of droughts. We test this hypothesis by splitting the sample by country income level to give an indication of how wealth and economic composition impact this relationship. Our analytical strategy therefore incorporates both an absolute metric of baseline climate, as well as the relative ability of different populations in different regions to manage the risks of droughts.

4. Results

This section is split into 4 subsections. Section 4.1 presents the main results of 1 SD dry shocks from estimating equation (3) and the various heterogeneities from estimating equation (4). Section 4.2 presents the impacts of dry shocks along the distribution of drought severity. To provide a sense of magnitudes of loss over the entire time-period, Section 4.3 uses the estimates to calculate the cumulative mean annual losses in GDP per capita growth in each grid cell. Section 4.4. presents robustness checks.

4.1 Impact of 1 SD rainfall shocks

Table 1 shows the main results. Columns (1) and (2) provide estimates of equation (1) for different specifications for rainfall. Column 1 includes a quadratic in precipitation and column 2 models rainfall as a z-score. In both models the coefficient is positive and significant showing that generally higher precipitation is associated with increases in growth.

Column (3) estimates equation (3) and uses three categories of bins comparing 1 SD dry and wet shocks relative to the excluded category ($-1 < z < 1$). Results in column (3) show that a 1 SD dry shock reduces GDP growth by 0.47 percentage points, with effects concentrated in the developing world where the impacts are slightly larger than in the full sample at 0.54 percentage points. In the high-income country sample, the impact of a 1 SD dry shock is small and statistically insignificant, indicating a precisely estimated null impact.

Positive 1 SD shocks show a less consistent pattern across income classes. They improve growth in the developing country sample but can be harmful in high-income countries. This may be because above-average rainfall could both be a blessing, in the form of increased water resources, or a curse, in the form of flooding. Because most developing countries are in drier parts of the world and are more dependent on agriculture, above-average rainfall is typically associated with increases in crop yields and may act as a buffer for future dry shocks by storing soil moisture in the root zone. These results are consistent with the hydrological literature which emphasizes the importance of green water for supporting biomass growth (Li et al, 2019). In high-income countries, the negative effects of wet shocks reflect the effects of floods on infrastructure and urban assets. Recent research has found that in high-income countries extreme wet events, such as extreme daily rainfall or the number of wet days, are particularly adverse for economic growth via the manufacturing and services sectors (Kotz, Levermann, and Wenz, 2022). Improvements in disaster risk management and relief also mean that recovery from floods is rapid in developed economies, with limited observable effect on economic activity (Kocornik-Mina et al. 2020).

Table 1 Impact of rainfall on GDP per capita growth

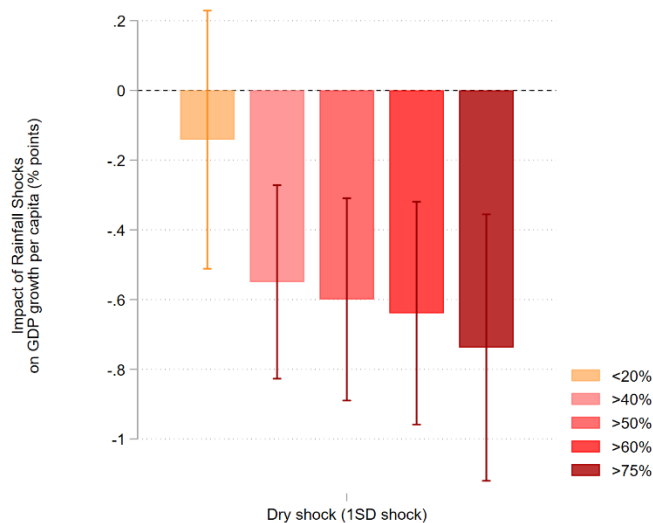
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Global	High Income	Developing	Global	High Income	Developing
$\Delta \log(\text{GDP p.c.})$						
Precip	1.5734*** (0.334)	-0.2635 (0.494)	1.9399*** (0.381)			
Precip sq	-0.2506*** (0.069)	-0.0869 (0.118)	-0.3000*** (0.081)			
Dry shock ($z < -1$)				-0.4761*** (0.107)	-0.1103 (0.100)	-0.5429*** (0.125)
Wet shock ($z > 1$)				0.0981 (0.121)	-0.4115+ (0.226)	0.2721* (0.137)
Avg Temp(C)	0.6928** (0.225)	0.2420* (0.107)	0.7683* (0.338)	0.6992** (0.225)	0.2458* (0.108)	0.7802* (0.340)
Avg Temp Sq.	-0.0211** (0.006)	-0.0129*** (0.004)	-0.0238** (0.008)	-0.0220*** (0.006)	-0.0130*** (0.004)	-0.0250** (0.008)
N	869447	201466	667981	869447	201466	667981
Cell FE	y	y	y	y	Y	Y
Year FE	y	y	y	y	Y	Y
Country Trends	y	y	y	y	Y	Y
R-sq	0.319	0.392	0.305	0.319	0.393	0.305

Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors in parentheses are clustered at the Administrative 1 level. Statistical significance is given by + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Is the relationship between dry shocks and GDP in the developing world explained by agriculture, the sector that is more directly affected by rainfall variability? 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 based on different shares of cropland ranging from less than 20 percent to more than 75 percent. Having

established that impacts of 1 SD dry shocks are robustly significant in the developing sample in Table 1, we restrict this analysis to the developing world. The baseline model in column (9) of Table 1 is then performed across the different samples of grid cells by share of cropland. Figure 3 shows that per capita GDP growth in cells with more than 75% of croplands is more sensitive to dry shocks suggesting that the adverse effects on economic growth are sharper in agriculture-dominated areas of the developing world. An implication is that much, but not all, of the variation in GDP per capita growth because of dry shocks in this sample is a consequence of the effects on agriculture. It also implies that socio-economic contexts strongly interact with climatic conditions. An economy that is heavily reliant on the agriculture sector is more exposed to adverse rainfall effects that may have wider development implications in less diversified economies and circumstances without adequate insurance schemes or safety nets.

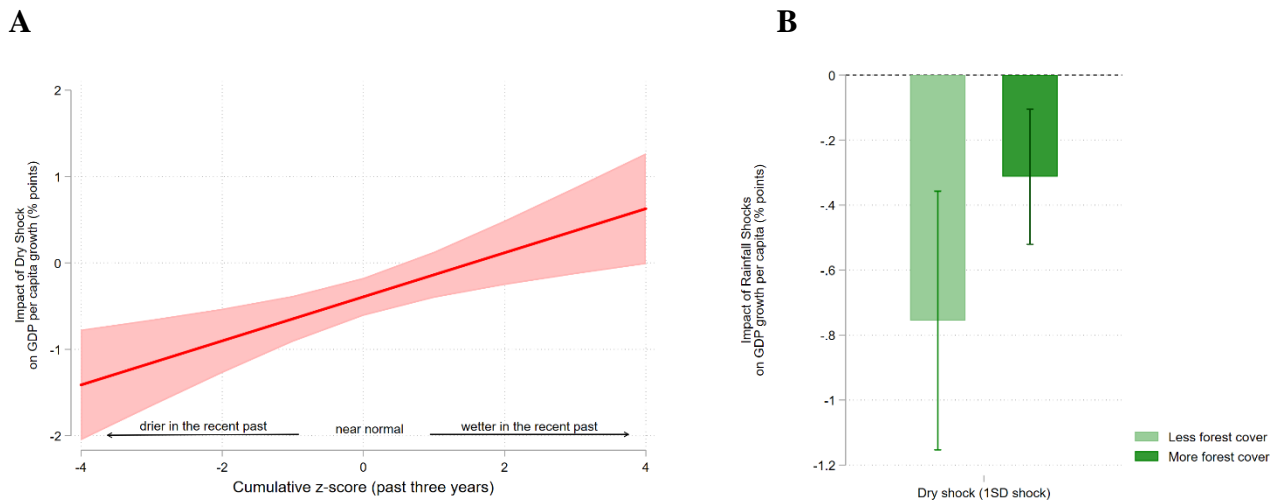
Figure 3 Impact of Dry Rainfall Shocks on GDP per Capita Growth, by Cropland Distribution, Low- and Middle-Income Countries



Note: Dependent variable is change in gridcell log(GDP p.c.). Similar regression as in Column (9) in Table 1 is employed across different samples of grid cells based on the share of cropland in each grid cell. Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown.

Next, the analysis tests whether the overall impacts in the developing world are determined by the availability of soil moisture when a dry shock occurs. Figure 4A and Appendix Table 1 show the results of estimating equation (4). The results illustrate that green water (soil moisture) matters for aggregate impacts. If a cell experiences high rainfall in the previous three years, i.e., a higher cumulative z-score, the GDP growth impacts of a dry shock are considerably diminished because of higher initial soil moisture conditions. As the degree of wetness in previous years rises, adequate soil moisture can neutralize and possibly even overturn the harmful impacts from a dry shock in some grid cells. Conversely, consecutive dry years have the opposite effect and substantially amplify the adverse growth impacts of a dry shock. Green water that is held in biomass and soils is critical for the functioning of the water cycle, and the Earth’s operating systems, and for climate resilience. Recent scientific assessments suggest that the Earth has crossed the safe planetary boundary for fresh water primarily due to the disruption to green water and rising modifications in soil moisture (Wang-Erlandsson et al. 2022). These results indicate that the consequences are immediate and economically significant.

Figure 4 Marginal Impact of Dry Rainfall Shocks on GDP per Capita Growth, by Antecedent Conditions, Low- and Middle-Income Countries



Note: Dependent variable is change in gridcell log(GDP p.c.). Cumulative z-score reflects antecedent conditions of past three years. High upstream forested areas denote places upstream from the gridcell where the forest area is more than the 50th percentile of the forest distribution among all grid cells in each country. Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown.

Healthy forests and landscapes are one of the key channels through which green water is maintained. Forests and trees add moisture to the air through transpiration and evaporation of water. The atmospheric water vapor passing over forests, in turn, can influence local and regional rainfall (Grosset, Papp, and Taylor 2023; Smith, Baker, and Spracklen 2023; Rockstrom et al., 2023). At the same time forests influence moisture in the soil. Across local watersheds and even thousands of miles away, forests can alter the movement and availability of water by regulating flow, absorbing water when it is plentiful, and releasing it when it is scarce (Miller, Mansourian, and Wildburger 2020). The dense canopy of trees provides a natural umbrella that traps rainwater, slowing the pace of rain and allowing it to enter the soil and thence to the ground below. Forest roots act as natural sponges, absorbing water and increasing the amount of water that can enter the earth, adding to soil moisture and recharging groundwater. Over time, forests slowly release that water, thus moderating downstream flows by lowering flooding, while improving dry season flow. Forests—especially fast-growing young plantations—may use more water than older, mixed, or natural forests and therefore reduce downstream freshwater availability. However, with proper management, forests, especially native forests, can help enhance the resilience of water supplies (Miller, Mansourian, and Wildburger 2020).

To investigate the role of forests in preserving soil moisture (green water), equation (4) is estimated with an interaction between dry shocks and the presence of high forest cover. Figures 4B and Appendix Figure 1 show the results of estimating equation (4). These illustrate that higher upstream and local forest cover can help buffer the growth impacts of dry shocks and on average reduce the growth impacts by almost 50 percent, suggestive of the provision of significant levels of natural resilience to dry episodes that have been largely overlooked.

Finally, to assess the sensitivity of the 3-bin results to different thresholds, we re-estimate equation (3) with thresholds ranging from 0.5 to 1.6. Table 2 shows that the results remain qualitatively unchanged, and the

coefficients of dry shocks monotonically increase in magnitude as the value of the threshold rises. Depending on the threshold used, GDP growth decreases between 0.38 to 0.72 percentage points, on average, indicating that more severe dry shocks have more damaging consequences. Wet shocks remain beneficial to growth, but the impacts are more muted, and are not always significant.

Table 2 Impact of drought severity on GDP per capita growth, 2 bins with various thresholds, Low- and Middle-Income Countries Sample

Dep. Var.	(1)	(2)	(3)	(7)	(8)
$\Delta \log(\text{GDP p.c.})$					
Threshold X:	1.6	1.3	1	0.8	0.5
Impacts are relative to category $(-X < z < X)$					
Extreme($z < -1.6$)	-0.7204*** (0.188)				
Extreme($z > 1.6$)	0.1554 (0.197)				
Dry ($z < -1.3$)		-0.6196*** (0.151)			
Wet($z > 1.3$)		0.2194 (0.159)			
Dry($z < -1$)			-0.5429*** (0.125)		
Wet($z > 1$)			0.2721* (0.137)		
Dry($z < -0.8$)				-0.5060*** (0.109)	
Wet($z > 0.8$)				0.2531* (0.128)	
Dry($z < -0.5$)					-0.3864*** (0.099)
Wet($z > 0.5$)					0.1295 (0.115)
Avg Temp(C)	0.7697* (0.340)	0.7742* (0.339)	0.7802* (0.340)	0.7818* (0.340)	0.7770* (0.340)
Avg Temp Sq.	-0.0263** (0.009)	-0.0257** (0.008)	-0.0250** (0.008)	-0.0247** (0.008)	-0.0250** (0.008)
N	667981	667981	667981	667981	667981
Cell FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y
R-sq	0.304	0.304	0.305	0.305	0.304

Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors in parentheses are clustered at the Administrative 1 level. Statistical significance is given by + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Impacts along the distribution of drought severity

What is clear from the previous section is that rainfall deficits that are 1 standard deviation below normal levels have adverse impacts on GDP per capita growth rates, especially in the developing country sample. To investigate how the impacts can vary based on different sizes of shocks, this section unpacks the baseline results to assess impacts across the full distribution of shocks that range from mild to extreme. To assess how the impacts differ across the entire distribution of drought severity, Table 3 assesses equation

(2) with different number of bins for both the developing and high-income sample. Columns (1) and (2) estimate models with $b=11$, using all of the bins defined in Mu et al. (2013).

Table 3 Impact of drought severity on GDP growth, various bins

Dep. Var. $\Delta \log(\text{GDP p.c.})$	(1)	(2)	(3)	(4)
# bins	10 bins		5bins	
	impacts relative to $(-0.5 < z < 0.5)$		impacts relative to $(-0.5 < z < 0.5)$ and all wet categories	
	High-income	Developing	High-income	Developing
<u>Dry shocks</u>				
Extreme($z < -1.6$)	-0.3946* (0.194)	-0.8595*** (0.207)	-0.3576* (0.169)	-0.9069*** (0.202)
Severe($-1.6 < z < -1.3$)	0.1911 (0.159)	-0.5760** (0.176)	0.2279 (0.139)	-0.6253*** (0.170)
High($-1.3 < z < -1$)	0.0037 (0.141)	-0.4691** (0.153)	0.0419 (0.128)	-0.5187*** (0.147)
Moderate($-1 < z < -0.8$)	-0.0161 (0.107)	-0.3920** (0.137)	0.0240 (0.127)	-0.4413*** (0.130)
Mild($-0.8 < z < -0.5$)	0.0465 (0.140)	-0.1106 (0.128)	0.0811 (0.096)	-0.1600 (0.140)
<u>Wet shocks</u>				
Mild($0.5 < z < 0.8$)	0.4168+ (0.215)	-0.0731 (0.175)		
Moderate($0.8 < z < 1$)	0.0399 (0.178)	0.1972 (0.127)		
High($1 < z < 1.3$)	-0.1549 (0.147)	0.3282* (0.158)		
Severe($1.3 < z < 1.6$)	-0.4733 (0.391)	0.2870 (0.194)		
Extreme($z > 1.6$)	-0.4320 (0.276)	0.1184 (0.215)		
Avg Temp(C)	0.2476* (0.111)	0.7826* (0.339)	0.2419* (0.106)	0.7729* (0.339)
Avg Temp Sq.	-0.0130*** (0.004)	-0.0245** (0.008)	-0.0124*** (0.004)	-0.0246** (0.008)
N	201466	667981	201466	667981
Cell FE	y	y	y	Y
Year FE	y	y	y	Y
Country Trends	y	y	y	Y
R-sq	0.395	0.305	0.392	0.305

Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors in parentheses are clustered at the Administrative 1 level. Statistical significance is given by + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 5 demonstrates the coefficients in columns (1) and (2) of Table 3 graphically. In the developing sample, the estimated coefficients on the dry side of z-score are negative and statistically significant for conditions of moderate ($-1 < z < -0.8$) to extreme drought ($z < -1.6$) compared to normal conditions. They are negative, but insignificant, for all of the other “non-normal” dry categories.

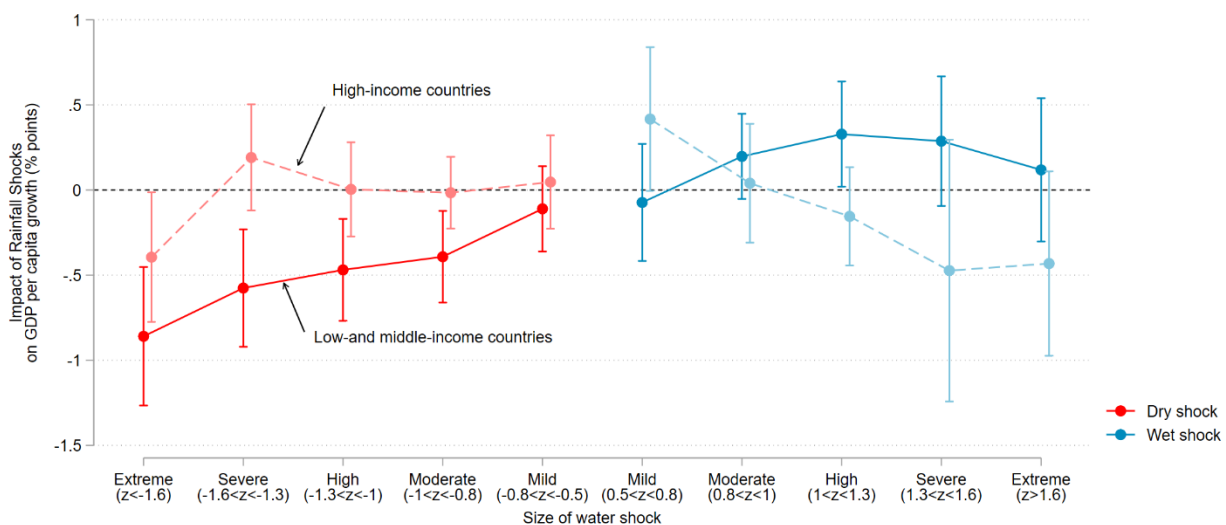
The magnitude of impacts appears to grow with drought severity. This is true for all of the coefficients moving away from normal on the dry side of z-score, though only the moderate, high, severe and extreme

categories have significant coefficients. Compared to normal conditions, moderate drought reduces growth in the developing sample by about 0.39 percentage points, and extreme drought reduces growth by about 0.85 percentage points. Compared with an average growth rate of 2.19 percent over the time period of the sample, this implies that even more moderate shocks can send impacted areas into a growth slump.

In high-income countries, the estimated coefficients on the dry side of z-score are negative and statistically significant *only* for conditions of extreme drought. Compared to normal conditions, extreme drought reduces growth in the high-income sample by about 0.39 percentage points, a little less than half the impact felt in the developing sample for the same intensity of drought. In contrast to section 1, this implies that for the high-income sample, the impacts on economic growth become visible only when they experience extreme events, which occur far less frequently, the sort of event that might be expected once in fifty years in a given location.

Finally, columns (3) and (4) demonstrate that these results are insensitive to condensing the “wet” categories and normal category into a single bin and comparing only the categories on the dry side of z-score with this condensed bin.

Figure 5: Impact of drought severity on GDP growth, various bins



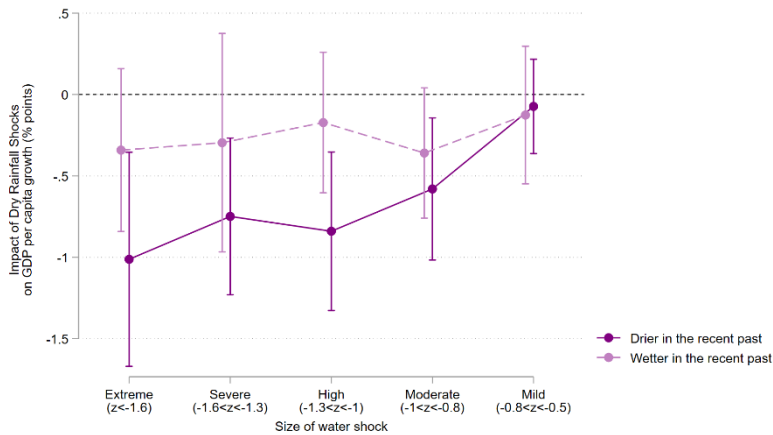
Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown. Graphical representation of Columns (1) and (2) in Table 3

These results are expanded upon by testing for the impact of green water across the distribution of drought severity. To facilitate interpretation, the continuous variable indicating the past 3-year cumulative z-score used in Figure 6, Section 4.1 is modified into an indicator variable to split grid cells that have experienced wetter or drier conditions in the past. Grid cells where the 3-year cumulative z-score is greater than 0.5 are denoted as grid cells that have experienced wetter recent conditions. Grid cells where the 3-year cumulative z-score is less than 0.5 are denoted as those that have experienced drier recent conditions. Following the model in column (2) in Table 3, a similar regression is then performed for the two samples. Figure 4A highlights the significance of green water (soil moisture) in mitigating GDP growth losses for different levels of dry shock severity levels. Adequate soil moisture’s powerful buffering impact can halve

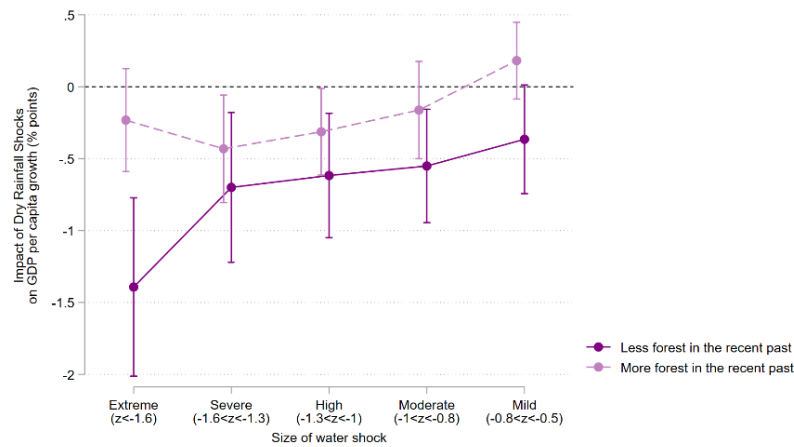
the adverse growth effects of an extreme dry shock, rendering these statistically insignificant. The buffering benefits of wet prior conditions increase with the magnitude of the dry shock. Figure 4B splits the sample into cells with high and low forest cover. It shows that more forest cover emerges as one of the key channels through which these impacts manifest. The presence of tree cover significantly mitigates the adverse impacts of droughts on per capita GDP growth.

Figure 6: Impact of drought severity on GDP growth, various bins (Antecedent conditions and forest cover)

A



B

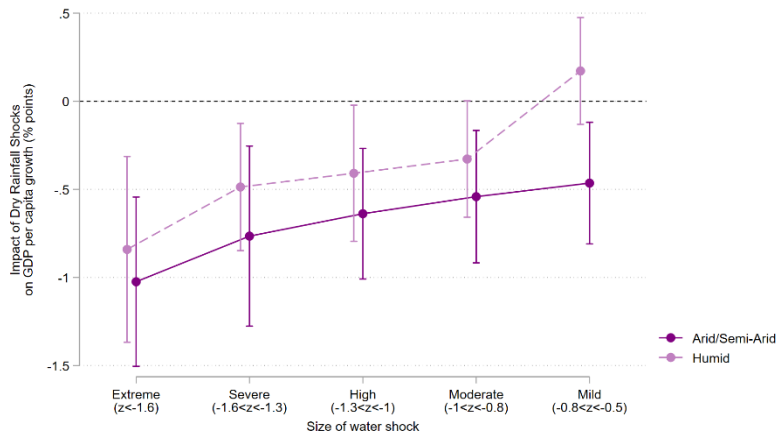


Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown. Similar regression model as column (2) in Table 3 is employed for the “wetter in recent past” versus “drier in the recent past” sample, as well as for the high versus low upstream cover sample. Graphical representation shows only the coefficients on dry shocks.

Next, these results are expanded upon by looking at how climatic endowments might influence these impacts in the developing sample. To do so, grid cells in the database are split based on whether they lie in the arid/semi-arid or humid climatic zone. The regression model used in Column (2), Table 3 is then employed for grid cells in the arid/semi-arid and humid climate zone. One might conjecture that grids that are in more arid areas are more accustomed to dry conditions and hence better adapted to dry periods. Surprisingly, however, results in Figure 7 show the opposite. Although we see similar adverse impacts on

GDP growth p.c. based on the size of the dry shock with the severity rising from mild to extreme, arid areas are more impacted by dry shocks. This may reflect the greater vulnerability of crops to heat stress in these areas coupled with lower levels of development that limit investments in water infrastructure. In humid areas, the impacts are more muted, and it is only when the shocks fall in the severe to extreme category that negative impacts are statistically significant.

Figure 7: Impact of drought severity on GDP growth, various bins (Arid versus Humid)



Note: Dependent variable is change in gridcell log(GDP p.c.). Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown. Similar regression model as column (2) in Table 3 is employed for the arid/semi-arid versus humid sample of gridcells. Graphical representation shows only the coefficients on dry shocks.

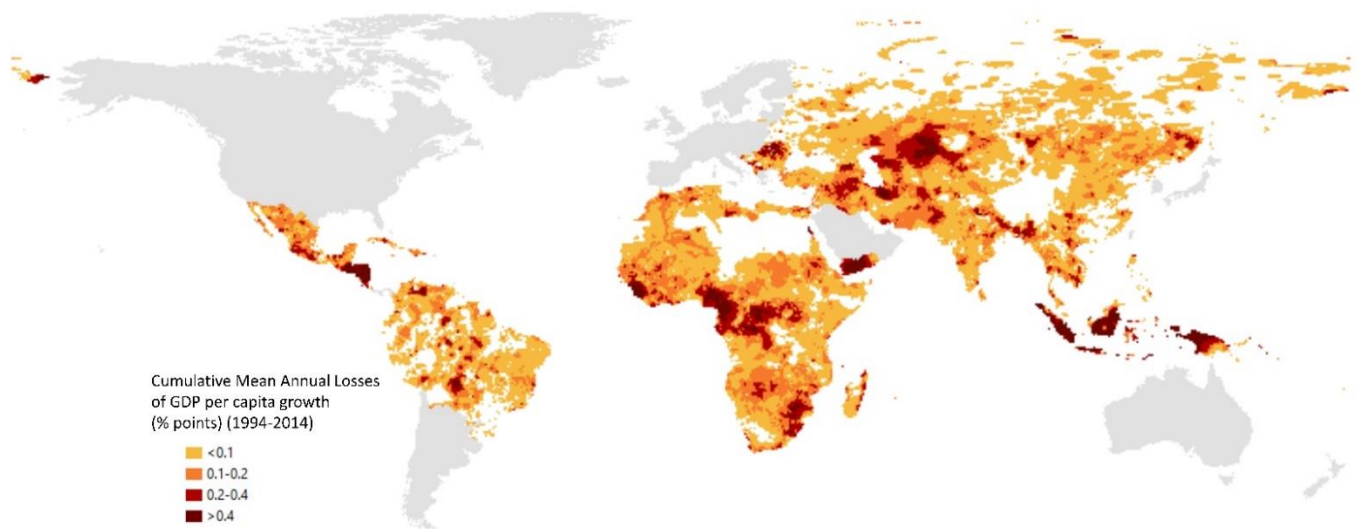
These results demonstrate that droughts can translate into a widened poor-rich gap. The magnitudes of the effects are also consistent with the recent 2022 Global Assessment Report on Disaster Risk Reduction which looks at all types of disasters from rapid onset events like typhoons, floods, earthquakes to other events like droughts, saltwater intrusion, air pollution. The report finds that poorer countries lose on average 0.8%–1% of their GDP growth per capita to disasters per year, compared to 0.1%–0.3% in higher income countries. That we find similar magnitude of impacts on GDP growth suggests that the silent crises of droughts can have much greater economic impact globally than other disasters. This complements a growing body of empirical evidence that shows the adverse effect of droughts and rainfall shocks on welfare outcomes within countries. These country-specific studies find that droughts make households vulnerable to poverty and can severely impact food consumption, nutritional intake and labor market outcomes (Christiaensen and Subbarao, 2004; Skoufias, Essama-Nssah, Katayama, 2011; Hill and Porter, 2017; Pape and Wollburg, 2019; Carpena, 2019; Baquie and Fuje, 2020; Skoufias et al., 2021; Kochar and Knippenberg, 2023; Alfani et al., 2023). Other studies show that the impacts of early-life droughts can leave permanent marks throughout life. Female infants in Sub-Saharan Africa who are born during severe droughts grow up physically shorter, receive less education, and ultimately, become less wealthy (Hyland and Russ 2019).

4.3 An Atlas of Impacts

To provide a sense of magnitudes, this section uses the estimates from the main results presented in Section 1 to calculate the cumulative mean annual losses in GDP per capita growth in each grid cell. We employ the estimated coefficients on the 1 SD dry shock and the cumulative -z-score from Figure 4A and

Appendix Table 1 to calculate the impact of each additional dry shock for the grid. These impacts are then averaged over the entire time period of the study. Figure 8 shows that these impacts are unevenly distributed around the globe and vary significantly across and within countries. The patterns highlight the disproportionate losses in developing countries and suggest the need for urgency in increasing adaptive capacity in the poorest parts of the world. The estimates can help policy makers prioritize and spatially target interventions to areas of greatest growth impacts. With limited fiscal space, such information is particularly valuable in enabling more efficient responses to the increasing threats from climate change.

Figure 8 Atlas of the Economic Costs of Droughts, 1994–2014



Note: Map shows the cumulative mean annual loss of GDP per capita growth over two decades from 1994 to 2014 calculated using the estimated coefficients on 1 SD dry shock and the cumulative -z-score obtained from Figure 2A and Appendix Table 1

4.4 Robustness checks

We test for a broad range of alternative specifications that are common in the environmental econometrics literature. 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 US; third, we include a 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 account for one lag and three lags of GDP growth account for one lag of GDP growth to model convergence as in a Solow growth model. Table 4 shows that results are robust across the alternate specifications. Table 5 replicates the main results but replaces the GDP pc growth rate with the GDP growth rate. And Table 6 replicates the main results but uses SPEI in place of rainfall shocks. The results are qualitatively similar.

Table 4 Robustness checks, alternative specifications

Dep. Var. $\Delta\log(\text{GDP p.c})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	base	No oil countries	No US/China	Continent Yr FE	Continent Yr FE + no Trend	Country Trend - No Yr FE	LDV 1 Lag	LDV 3 Lags
Dry($z < -1$)	-0.5429*** (0.125)	-0.5092*** (0.128)	-0.5258*** (0.146)	-0.5293*** (0.114)	-0.5643*** (0.120)	-0.7250*** (0.130)	-0.4943*** (0.129)	-0.3112* (0.138)
Wet($z > 1$)	0.2721* (0.137)	0.2420+ (0.139)	0.4093* (0.169)	0.2492+ (0.134)	0.1873 (0.132)	0.2446+ (0.148)	0.3214* (0.137)	0.2903* (0.136)
N	667981	532121	589933	667981	667981	667981	640152	584494
R-sq	0.305	0.319	0.207	0.368	0.342	0.269	0.306	0.274

Notes: This table presents robustness checks for our main result presented in Table 1, column 6. 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. Columns 7 and 8: as in (1) but including one lag and three lags of growth as in a Arellano Bond approach. Clustered standard errors at the Administrative 1 level in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 5 Robustness checks, alternative specifications using GDP growth rate

Dep. Var. $\Delta\log(\text{GDP})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	base	No oil countries	No US/China	Continent Yr FE	Continent Yr FE + no Trend	Country Trend - No Yr FE	LDV 1 Lag	LDV 3 Lags
Dry($z < -1$)	-0.5895*** (0.127)	-0.5590*** (0.131)	-0.5717*** (0.150)	-0.5759*** (0.118)	-0.6043*** (0.125)	-0.7692*** (0.131)	-0.5500*** (0.132)	-0.3512* (0.137)
Wet($z > 1$)	0.2876* (0.137)	0.2512+ (0.138)	0.4312* (0.168)	0.2660* (0.133)	0.2051 (0.132)	0.2548+ (0.147)	0.3395* (0.138)	0.3045* (0.135)
N	667879	532039	589831	667879	667879	667879	640052	584394
R-sq	0.290	0.296	0.224	0.355	0.327	0.254	0.291	0.256

Notes: This table presents robustness checks for our main result presented in Table 1, column 6 but replaces the GDP pc growth rate with the GDP growth rate. 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. Columns 7 and 8: as in (1) but including one lag and three lags of growth as in a Arellano Bond approach. Clustered standard errors at the Administrative 1 level in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 6 Robustness checks, alternative specifications using SPEI

Dep. Var. $\Delta\log(\text{GDP p.c})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	base	No oil countries	No US/China	Continent Yr FE	Continent Yr FE + no Trend	Country Trend - No Yr FE	LDV 1 Lag	LDV 3 Lags
Dry(spei < -1)	-0.3279* (0.150)	-0.3251* (0.157)	-0.3848* (0.179)	-0.3253* (0.136)	-0.3751** (0.124)	-0.4268* (0.171)	-0.3480* (0.152)	-0.3818** (0.135)
Wet(spei > 1)	0.0888 (0.125)	-0.0575 (0.125)	0.2805+ (0.147)	0.1174 (0.127)	0.1315 (0.125)	0.1182 (0.144)	0.1268 (0.122)	0.2078 (0.134)
N	666383	530645	588383	666383	666383	666383	638619	583091
R-sq	0.302	0.316	0.203	0.365	0.341	0.266	0.302	0.271

Notes: This table presents robustness checks for our main result presented in Table 1, column 6 but replaces rainfall shocks with SPEI shocks. 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. Columns 7 and 8: as in (1) but including one lag and three lags of growth as in a Arellano Bond approach. Clustered standard errors at the Administrative 1 level in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

The main specification allows for arbitrary serial correlation of errors across observations from the same Level 1 administrative level or the same country. This approach assumes no correlation in the error structure for grid cells in different areas, even though they may be proximate in space. In Appendix Table 2, we relax this assumption and account for spatial autocorrelation by using spatially corrected Conley standard errors (Conley, 1999). Due to computation limits, we focus attention on the grid cells in the South Asia region (~1,700 cells) among the ~60,000 available for cell-level regression. We implement the procedure using the `acreg` package developed by Colella et al. (2019). The results continue to remain significant at the 5 percent level.

5. Policy Implications and Way Forward

While the evidence points to water scarcity as a growing problem, it is floods that have captured the attention of policy makers and researchers. This may be a consequence of the greater visibility of floods, which are rapid, high-impact events that destroy infrastructure, damage homes, and disrupt livelihoods. They are difficult to ignore. Consequently, a flood typically triggers a rapid policy response through the array of relief systems available within countries, with the backstop support of international relief agencies (Botzen et al., 2019). Perhaps as a result, recent research suggests that even when the short-term impacts of a flood are severe and alarming, economic recovery can come rapidly too (Kocornik-Mina et al., 2020; Felbermayr et al., 2022). Droughts, on the other hand, are spatially diffuse, slow onset natural disasters that are harder to identify. Their impacts can emerge gradually and less visibly and perhaps as a consequence the trigger for a policy response is less evident (Damania et al., 2017). At the same time, these long, silent crises can have much greater economic impact globally than other disasters.

The findings of this paper have several implications for development practitioners. First, they are a starting point for understanding and appreciating the vulnerability to drought within and between countries. The spatial differences in economic impacts need unpacking to gain a more nuanced understanding toward the drivers of these vulnerabilities and how droughts manifest in a particular economy.

Second, they send a clear message that the developing world has been ill-prepared for managing the risks and impacts of droughts over the past few decades. Climate change is expected to lead to greater drought severity in many regions. Without significant improvements to how policy makers manage droughts, the world is on a path to even greater losses in economic growth and development gains due to these prolonged dry shocks.

And third, the results highlight the significance of green water (soil moisture and forests) in mitigating drought impacts, which has been overlooked in economic deliberations. It highlights the need for stewardship of forests and other natural capital that affect the hydrological cycle but are seldom associated with the growth impacts of droughts. As the climate heats up, many regions will face less predictable local rain. There is already evidence that there is a drying trend across much of the developing world. This makes the dependable waters of soils, groundwater and rivers, and the well-managed forests that nurture them frontline climate warriors.

Countries need to proactively invest to address the vulnerabilities through upgrades in information systems, institutions, and infrastructure that build drought resilience. There are several specific ways in which the World Bank and other development partners can support countries in addressing these challenges and needs.

Foremost is to support the development, implementation, and integration of early warning systems in countries and regions where they are lacking or insufficient. Governments often monitor drought by a single indicator, such as the SPI or soil moisture levels, and the indicator often changes depending on the sector or ministry. This creates competing definitions and understanding of the country's drought situation. Thus, the lack of triangulation across indicators for monitoring droughts and inconsistent definitions in a given country context result in inaccuracies and, ultimately, inaction. Integrated and consistent monitoring programs that more comprehensively and objectively define drought can help countries get ahead of a drought. These programs can also link drought severity designations with predetermined actions that are triggered as a drought unfolds. The World Bank can develop similar internal protocols for monitoring drought situations worldwide, so the institution is better positioned to offer timelier and less reactive support to clients as drought situations worsen in a given location.

There is a need for more regular and proactive evaluation of the vulnerabilities and impacts, as well as determining countries' drought preparedness capabilities. With floods, tropical cyclones, earthquakes, and other types of natural disasters, the vulnerabilities, impacts, capabilities, and needs are often evaluated in the immediate wake of the event through the application of a post-disaster needs assessment (PDNA). Unfortunately, such exercises inadequately capture drought events. This is because of the slow onset nature of the event and the highly diffuse and cascading impacts that cross multiple sectors across space and time, among other reasons. Therefore, policy makers need to develop new diagnostic approaches that not only accommodate the unique nature of the hazard, but also address the historical shortcomings of how countries have previously prepared or not for the impacts. The approaches need to encompass evaluation and inclusion of immediate response and recovery activities and build a pipeline of longer-term investments to minimize risks in future drought events. Unlike a traditional PDNA, drought needs assessments (DNAs) would be done iteratively, not only during a drought crisis, and consider potential impacts from shifting drought hazard profiles due to climate change.

Conducting DNAs would help countries prioritize amid potential investments for bolstering drought resilience. Investment packages might include (a) upgrades to information systems, such as early warning systems; (b) infrastructure, such as storage, nature-based solutions, groundwater and managed aquifer recharge, desalination, water reuse and recycling, nonrevenue water reduction, irrigation schemes, or rainwater harvesting; (c) institutions, such as drought policy and legislation to codify roles and responsibilities and standing drought committees; and (d) risk financing mechanisms tailored to vulnerable groups in each country.

Managing through a drought efficiently, effectively, and equitably requires considerable investments in coordinated planning before a drought hits. These include short-term emergency planning and drought contingency planning at scales that define who does what and when as a drought is unfolding. These actions would be triggered with the early warning system and associated drought protocols. Similarly, countries need strategic long-term planning efforts, including scenario planning, to identify the most robust set of measures for improving long-run drought resilience. The scales for these two sets of planning activities are manifold, and include utility, city or town, river basin, province, and national levels.

Appendix C provides two examples of recent or ongoing World Bank engagements that illustrate how Brazil and Eswatini have addressed these challenges and needs. However, there is considerably more work to do on this agenda. The World Bank is well-placed to help structure a more effective program around drought

resilience-building that can be offered to clients in all regions around the world. This assistance can help countries avoid drought-induced poverty traps in the future.

References

- Acemoglu, D., Johnson, S., & Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. *Handbook of economic growth*, 1, 385-472.
- Adger, W. N., Arnell, N. W., & Tompkins, E. L. (2005). Successful adaptation to climate change across scales. *Global Environmental Change*, 15(2), 77-86. doi:10.1016/j.gloenvcha.2004.12.005
- Alfani, F., Molini, V., Pallante, G., & Palma, A. (2023). Job Displacement and Reallocation Failure: Evidence from Climate Shocks in Morocco. World Bank, Washington, DC. © World Bank. WORLD BANK POLICY RESEARCH WORKING PAPER, 2023.
- Ault, T. R. (2020). On the essentials of drought in a changing climate. *Science*, 368(6488), 256-260.
- Barro, R. J. (2003). Determinants of economic growth in a panel of countries. *Annals of economics and finance*, 4, 231-274.
- Baqueie, Sandra and Habtamu Fuje (2020) "Vulnerability to Poverty Following Extreme Weather Events in Malawi."
- Botzen, W. W., Deschenes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*.
- Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. "Global non-linear effect of temperature on economic production." *Nature* 527.7577 (2015): 235.
- Burke, M., and V. Tanutama. 2019. "Climatic Constraints on Aggregate Economic Output." Working Paper 25779. National Bureau of Economic Research, Cambridge, MA.
- Callahan, C. W., and J. S. Mankin. 2022. "Globally Unequal Effect of Extreme Heat on Economic Growth." *Science Advances* 8 (43). DOI: 10.1126/sciadv.add3726.
- Carpena, F. (2019). How do droughts impact household food consumption and nutritional intake? A study of rural India. *World Development*, 122, 349-369.
- Christiaensen, L. and K. Subbarao (2004) "Towards an Understanding of Household Vulnerability in Rural Kenya," World Bank Policy Research Working Paper (3326).
- Ciccone, A., & Jarociński, M. (2010). Determinants of economic growth: will data tell?. *American Economic Journal: Macroeconomics*, 2(4), 222-46.
- Colella, F., Lalive, R., Sakalli, S. O., & Thoenig, M. (2019). Inference with arbitrary clustering.
- Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of econometrics*, 92(1), 1-45.
- Cook, B.I., Cook, E.R., Smerdon, J.E., Seager, R., Williams, A.P., Coats, S., Stahle, D.W. and Díaz, J.V., 2016. North American megadroughts in the Common Era: Reconstructions and simulations. *Wiley Interdisciplinary Reviews: Climate Change*, 7(3), pp.411-432.
- Damania, R., S. Desbureaux, M. Hyland, A. Islam, A. S. Rodella, J. Russ, and E. Zaveri. 2017. *Uncharted Waters: The New Economics of Water Scarcity and Variability*. Washington, DC: World Bank.

- Damania, R., S. Desbureaux, and E. Zaveri. 2020. "Does Rainfall Matter for Economic Growth? Evidence from Global Sub-national Data (1990–2014)." *Journal of Environmental Economics and Management* 102: 102335.
- Dasgupta, S., Laplante, B., Murray, S., & Wheeler, D. (2014). Exposure to flood risks and changes in vulnerability over time: Evidence from large-scale floods in India. Policy Research Working Paper 6936. The World Bank. doi:10.1596/1813-9450-6936
- De Nys, E., N. Engle, and A. R. Magalhães, editors. 2016. *Drought in Brazil: Proactive Management and Policy*. Boca Raton, FL: CRC Press.
- Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics* 4.3 (2012): 66-95.
- Deryugina, Tatyana, and Solomon Hsiang. The marginal product of climate. No. w24072. National Bureau of Economic Research, 2017.
- Desbureaux, S., and A. S. Rodella. 2019. "Drought in the City: The Economic Impact of Water Scarcity in Latin American Metropolitan Areas." *World Development* 114: 13–27.
- Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences*, 116(20), 9808-9813.
- Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V., & Steinwachs, T. (2022). The economic impact of weather anomalies. *World Development*, 151, 105745.
- Gennaioli, N., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. 2013. "Human Capital and Regional Development." *Quarterly Journal of Economics* 128 (1): 105–64.
- Grosset, F., A. Papp, and C. Taylor. 2023. "Rain Follows the Forest: Land Use Policy, Climate Change, and Adaptation." *Social Science Research Network Working Paper*.
- Hall, J. W., D. Grey, D. Garrick, F. Fung, C. Brown, S. J. Dadson, and C. W. Sadoff. 2014. "Coping with the Curse of Freshwater Variability." *Science* 346 (6208): 429–30.
- Hallegatte, S., Fay, M., & Barbier, E. B. (2018). Poverty and climate change: Introduction. *Environment and Development Economics*, 23(3), 217-233.
- Henseler, Martin, and Ingmar Schumacher. "The impact of weather on economic growth and its production factors." *Climatic Change* (2019): 1-17.
- Hill, Ruth Vargas and Catherine Porter (2017) "Vulnerability to drought and food price shocks: Evidence from Ethiopia," *World Development*, 96, 65–77.
- Hyland, M., and J. Russ. 2019. "Water as Destiny: The Long-term Impacts of Drought in Sub-Saharan Africa." *World Development* 115: 30–45.
- Islam, A., and M. Hyland. 2019. "The Drivers and Impacts of Water Infrastructure Reliability: A Global Analysis of Manufacturing Firms. *Ecological Economics* 163: 143–57.

Kahn, M. E., Mohaddes, K., Ng, C., Ryan, N., Pesaran, M. H., Raissi, M., & Yang, J. C. (2019). Long-term macroeconomic effects of climate change: A cross-country analysis.

Kirschke, S., Staszak, A., & Vliet, M. V. (2021). Climate change adaptation pathways for water infrastructure: A review of global case studies. *Journal of Environmental Management*, 291, 112650. doi:10.1016/j.jenvman.2021.112650

Kochhar, Nishtha; Knippenberg, Erwin. 2023. Droughts and Welfare in Afghanistan. Policy Research Working Papers;10272.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., & Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, 12(2), 35-66.

Kotz, M., A. Levermann, and L. Wenz. 2022. "The Effect of Rainfall Changes on Economic Production." *Nature* 601 (7892): 223–27.

Kummu, M., M. Taka, and J. H. Guillaume. 2018. "Gridded Global Datasets for Gross Domestic Product and Human Development Index over 1990–2015." *Scientific Data* 5 (1): 1–15.

Liang, X.-Z. 2022. "Extreme Rainfall Slows the Global Economy. *Nature* 601: 193–94.

Li, Y., Li, C., Ding, Y., Nie, Q., & Wang, X. (2019). Changes in water availability regulate the growth, biomass, and water use efficiency of shrubs in an alpine desert. *Science of The Total Environment*, 647, 1249-1258.

Lobell, D. B., Hammer, G. L., Chenu, K., Zheng, B., McLean, G., & Chapman, S. C. (2015). The shifting influence of drought and heat stress for crops in northeast Australia. *Global change biology*, 21(11), 4115-4127.

Matsuura, K., and C. J. Willmott. 2018. "Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1900–2017)." http://climate.geog.udel.edu/~climate/html_pages/download.html.

Miller, D., S. Mansourian, and C. Wildburger. 2020. *Forests, Trees and the Eradication of Poverty: Potential and Limitations. A Global Assessment Report. IUFRO World Series 39.* Vienna: International Union of Forest Research Organizations.

Mekonnen, M. M., and A. Y. Hoekstra. 2016. "Four Billion People Facing Severe Water Scarcity. *Science Advances* 2 (2). e1500323. <https://www.science.org/doi/10.1126/sciadv.1500323>

Mu, Q., Zhao, M., Kimball, J. S., McDowell, N. G., & Running, S. W. (2013). A remotely sensed global terrestrial drought severity index. *Bulletin of the American Meteorological Society*, 94(1), 83-98.

Newell, R. G., Prest, B. C., & Sexton, S. (2018). *The GDP-Temperature Relationship: Implications for Climate Change Damages.* RFF Working Paper. Available at: <http://www.rff.org/research/publications/gdp-temperature-relationship-implicationsclimate-change-damages>.

Niu, S., Yang, Z., Zhang, Z., Sun, S., Li, L., Li, Q., & Li, D. (2011). The role of pre-event soil moisture conditions in precipitation events over eastern China. *Journal of Geophysical Research*, 116(D4). doi:10.1029/2010JD014734

- Pape, Utz Johann and Philip Randolph Wollburg (2019) "Impact of Drought on Poverty in Somalia," World Bank Policy Research Working Paper (8698).
- Peña-Arancibia, J. L., van Dijk, A. I. J. M., Renzullo, L. J., Mueller, N. D., & Lehmann, W. (2016). Understanding the importance of antecedent moisture conditions to groundwater recharge in a large semi-arid basin: The Murray-Darling Basin, Australia. *Journal of Hydrology*, 536, 203-222. doi:10.1016/j.jhydrol.2016.02.025
- Piao, S., Yin, L., Liu, Q., Chen, A., Janssens, I. A., Ciais, P., . . . Yang, Y. (2015). Detection and attribution of vegetation greening trend in China over the last 30 years. *Global Change Biology*, 21(4), 1601-1609.
- Pokhrel, Y., F. Felfelani, Y. Satoh, J. Boulange, P. Burek, A. Gädeke, et al. 2021. "Global Terrestrial Water Storage and Drought Severity under Climate Change. *Nature Climate Change* 11 (3): 226–33.
- Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J. and Nykvist, B., 2009. A safe operating space for humanity. *nature*, 461(7263), pp.472-475.
- Rockström, J., Mazzucato, M., Andersen, L. S., Fahrländer, S. F., & Gerten, D. (2023). Why we need a new economics of water as a common good. *Nature*, 615(7954), 794-797.
- Russ, J. (2020). Water runoff and economic activity: The impact of water supply shocks on growth. *Journal of Environmental Economics and Management*, 101, 102322.
- Sivapalan, M., Blöschl, G., Zhang, L., Vertessy, R., & Gupta, H. V. (2003). Watershed processes and water resources management in a changing climate: A holistic approach. *Journal of Hydrology*, 274(1-4), 1-29.
- Essama-Nssah, R., Katayama, R. S., & Skoufias, E. (2011). Too little too late: welfare impacts of rainfall shocks in rural Indonesia. *Bulletin of Indonesian economic studies*, 48(78987), 1-24.
- Skoufias, Emmanuel, Katja Vinha, and Berhe Mekonnen Beyene (2021) "Quantifying Vulnerability to Poverty in the Drought-Prone Lowlands of Ethiopia.
- Smith, C., J. C. A. Baker, and D. V. Spracklen. 2023. "Tropical Deforestation Causes Large Reductions in Observed Precipitation. *Nature* 1–6. <https://doi.org/10.1038/s41586-022-05690-1>.
- Solon, G., Haider, S.J., Wooldridge, J.M., 2015. What are we weighting for? *J. Hum. Resour.* 50 (2), 301e316.
- Tol, R. S. (2019). A social cost of carbon for (almost) every country. *Energy Economics*.
- Trabucco, A., and R. Zomer. 2019. Global Aridity Index and Potential Evapotranspiration Climate (database v2), CGIAR Consortium for Spatial Information, Nairobi, Kenya. <https://cgiarcsi.community/2019/01/24/global-aridity-index-andpotential-evapotranspiration-climate-database-v2>.
- United Nations Office for Disaster Risk Reduction (2022). Global Assessment Report on Disaster Risk Reduction 2022: Our World at Risk: Transforming Governance for a Resilient Future. Geneva
- Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate*, 23(7):1696–1718.

Vicente-Serrano, S., and National Center for Atmospheric Research Staff, eds. 2015. "The Climate Data Guide: Standardized Precipitation Evapotranspiration Index (SPEI)."

Wang-Erlandsson, L., A. Tobian, R. J. van der Ent, et al. 2022. "A Planetary Boundary for Green Water." *Nature Reviews Earth and Environment* 3: 380–92. <https://doi.org/10.1038/s43017-022-00287-8>.

World Bank. 2022. *Disaster Risk Finance Diagnostic for Eswatini*. Washington, DC: World Bank.

Zaveri, E., J. Russ, and R. Damania. 2020. "Rainfall Anomalies Are a Significant Driver of Cropland Expansion." *Proceedings of the National Academy of Sciences*, 117 (19): 10225–33.

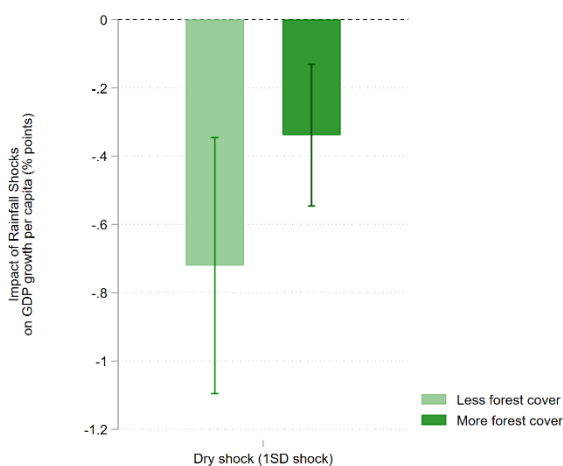
Appendix A Additional Tables and Figures

Appendix Table 1 Impact of 1SD Dry shock on GDP growth, antecedent conditions

Dep. Var. $\Delta \log(\text{GDP p.c.})$	(1)	(2)	(3)
	All	Arid&Semi-Arid	Humid
	Developing		
Dry shock($z < -1$)	-0.3919*** (0.112)	-0.5400** (0.169)	-0.2549* (0.127)
Wet shock($z > 1$)	0.3083* (0.138)	0.3096 (0.208)	0.2764+ (0.162)
Dry x cumulative z-score	0.2550*** (0.077)	0.0937 (0.084)	0.3602*** (0.101)
Wet x cumulative z-score	-0.0407 (0.088)	-0.1077 (0.078)	0.0334 (0.160)
Avg Temp(C)	0.7774* (0.338)	0.5699 (0.389)	1.1215* (0.498)
Avg Temp Sq.	-0.0246** (0.008)	-0.0234* (0.010)	-0.0270* (0.013)
N	667981	388799	279182
Cell FE	y	y	y
Year FE	y	y	y
Country Trends	y	y	y
R-sq	0.305	0.317	0.302

Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. Observations are weighted by population. Standard errors in parentheses are clustered at the Administrative 1 level. Statistical significance is given by + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Figure 1: Impact of Dry Rainfall Shocks on GDP per Capita Growth, by Local Forest Cover, Low- and Middle-Income Countries



Note: Dependent variable is change in gridcell $\log(\text{GDP p.c.})$. High forested areas denote gridcells where the forest area is more than the 50th percentile of the forest distribution among all grid cells in each country. Observations are weighted by population. Standard errors are clustered at the Administrative 1 level and 95 percent confidence intervals are shown.

Appendix Table 2 Impact of 1SD Dry shock on GDP growth, spatial Conley corrected standard errors

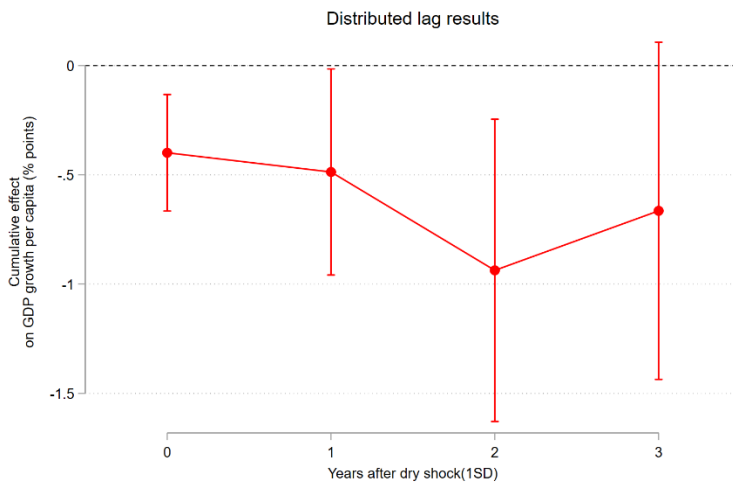
South Asia		
	(1)	(2)
	Conley Corrected S.E.	Clustered S.E. at ADMIN1
Dry(z<-1)	-0.8577** (0.266)	-0.8577*** (0.227)
Wet(z>1)	0.1920 (0.240)	0.1920 (0.215)
Avg Temp(C)	1.2481 (0.811)	1.2481 (0.783)
Avg Temp Sq.	-0.0430* (0.019)	-0.0430* (0.021)
N	42962	42962
Cell FE	Y	Y
Year FE	Y	Y
R-sq	0.361	0.361

*Note: Dependent variable is change in gridcell log(GDP p.c.). Observations are weighted by population. Standard errors in parentheses. Columns 1 and 2 show models using spatial Conley corrected standard errors where spatial correlation for a distance of up to 500kms is assumed and clustered standard errors at the administrative 1 level. Statistical significance is given by + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Appendix B Persistence of Impact

To determine whether the effects of dry shocks persist beyond the year in which they occur, a distributed lag model of the main regression specification is estimated. This model adds lags to the 1 SD dry shock to account for potential economic recovery. If shocks cause only a fall in the level of output, the year after an event would see increased growth as economies rebound to their pre-shock income trajectories. However, if shocks affect growth, then future years will not necessarily rebound. Therefore, if shocks affect the level of output but not its growth rate, then the contemporaneous and lagged effects should have opposite signs. The negative effect of a dry shock on output in a given year would be followed by a positive effect the following year as the economy rebounds. In this case, the cumulative effect converges to zero, a characteristic of level effects. However, if dry shocks affect the growth rate of output, then lagged effects would be zero or could have the same sign if the effects persist. Figure A.1 shows the cumulative impact of a 1 SD dry shock on GDP per capita growth and provides some evidence for persistent effects. The negative and statistically significant impact on GDP per capita growth appears to hold for two years after the dry shock.

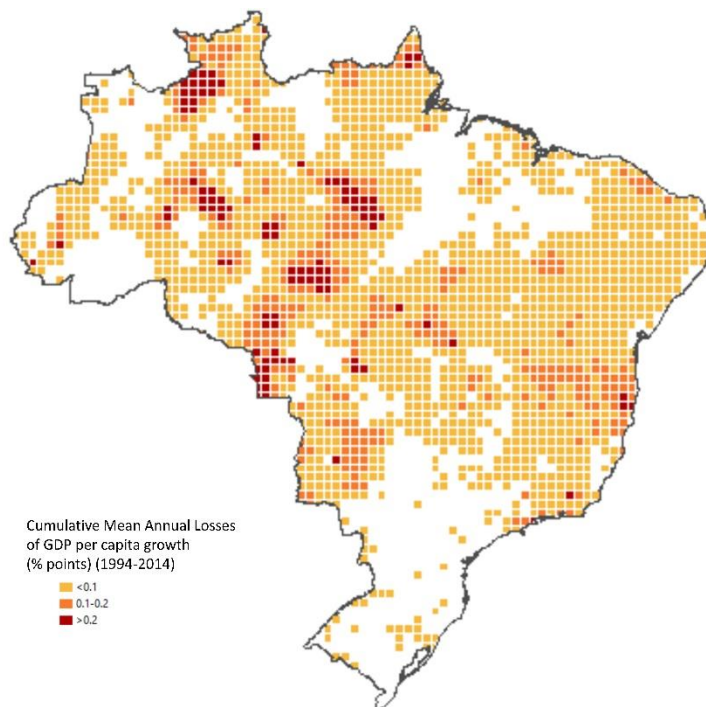
Figure A.1 Cumulative Impact of a 1 SD Dry Shock on GDP per Capita Growth



Appendix C Examples of Recent and Ongoing World Bank Engagements in Drought Responses

Brazil

Figure B.1 Map of Cumulative Mean Annual Losses of GDP per Capita Growth, Brazil, 1994–2014



Source: World Bank.

Figure B.1 shows how the GDP impacts of drought vary considerably across Brazil. Northeast Brazil is predominantly semi-arid and historically prone to wide swings in climate variability, including prolonged droughts. It is also one of the poorest regions in the country. With the onset of the recent multiyear drought of 2012–15, the World Bank mobilized support to shift the paradigm on drought management in the region. As with most cases, the typical approach in Brazil had been to apply poorly planned and uncoordinated measures as the crisis unfolded. This inefficient and costly ad hoc approach was slow to respond to the needs and often failed to address the underlying drought vulnerabilities of the communities most affected by the droughts.

The first step toward a proactive approach was to develop and implement a drought monitor to categorize stages of drought severity. Previously, the accepted definition had been a qualitative understanding of drought (*seca*) or no drought. Under the new drought monitor, Monitor de Secas, five stages were demarcated using an evidence-based approach that provided a more objective understanding of when areas in the region were entering or exiting drought status. The effort was inspired by the U.S. Drought Monitor (USDM) and involved USDM experts and experienced officials from Mexico, which had recently implemented a similar drought monitor process. They developed the

technical and institutional protocols for producing and sustaining a monthly drought map. The nine-state map was initially produced by three northeastern states with significant capacity in meteorology, climatology, and hydrology: Ceará, Pernambuco, and Bahia. Now 23 out of 26 states and the Federal District produce a monthly map. The joint ownership of the process is between the national water agency, Agência Nacional de Águas, and the states.

The growth and sustainability of the Brazil Drought Monitor prove its effectiveness in helping governments to better mobilize and target resources as a drought unfolds. Developing preidentified actions triggered at different stages of a drought, or drought preparedness planning, was supported by the World Bank program during the 2012–15 period. This support helped to pilot drought preparedness plans across vulnerable sectors and scales of decision-making with respect to droughts in the Northeast; two cities and their water utilities, one river basin, one reservoir system, and one rainfed agricultural municipality. These plans have been expanded in many of these contexts and address vulnerabilities before, during, and after droughts have hit the region.

A final component was a post-drought assessment of the costs and impacts to understand how expensive this reactive approach was for the region and country. The analysis quantified the budgetary costs of the policy responses, estimated to be close to US\$4.5 billion. It also looked at the longer-term impacts on key sectors of the economy. For example, relative to normal levels, the drought resulted in a 13 percent loss in gross real value of agriculture output (De Nys, Engle, Magalhães 2016). These findings further justified the World Bank programs that supported the government's shift to a more proactive approach for managing future droughts.

Eswatini

The severe 2015–16 drought in Eswatini in Southern Africa resulted in significant negative impacts on livelihoods, decimating agricultural production and wiping out traditional forms of savings, especially in rural households. Roughly 620,000 people were forced to rely on food support or cash transfers for survival. It also wreaked havoc on flora and fauna, increased poverty, and forced workers to migrate into neighboring countries or economies.

The World Bank performed a disaster risk financing diagnostic to gain a more nuanced understanding of the economic impacts of the drought throughout the Eswatini economy. The drought cost the government 19 percent of its annual expenditure, equivalent to 7 percent of its GDP (World Bank 2022). It also found that droughts are not only the most severe natural hazard facing Eswatini but also the most frequent, which can be a devastating combination. These findings are consistent with the analysis of this paper, which flags Eswatini as having suffered significant impacts on per capita GDP growth rate over the past several decades.

World Bank support for building drought resilience was mobilized after the 2015–16 drought through the Eswatini Water Supply and Sanitation Access Project (EWSSAP). It aims to improve long-term management of water resources, investment planning, sustainability of water supply service provision, and community resilience to climate and disaster risks, especially drought. Similar to Brazil's government, the Eswatini government has relied on reactive response and external assistance to finance its interventions during drought crises. Addressing core vulnerabilities requires a more proactive approach that includes upgrades to infrastructure, institutions, and information systems.

The main infrastructure component under the project is a 65-kilometer main pipeline that carries treated water from one portion of the country to another, both in regions that have the least access to water supply and sanitation services and are particularly prone to droughts. During a given drought event, however, one area may be affected and the other to a lesser extent, or not at all. Therefore, the pipeline's design will consider allowing for flow reversibility to make the infrastructure and the communities that depend on it more resilient during times of drought.

Also integral to the EWSSAP are information systems and institutional strengthening activities. These include the development of a drought risk profile to give a more granular perspective of the communities and sectors most vulnerable to drought risks throughout the country. The project incorporates the operationalization of a drought monitor and early warning system, drawing from U.S. experience and expertise and recent efforts in Brazil. The monitoring approach in Eswatini relies on advancements in Earth observation data synthesis techniques to build a more automated process to produce a combined drought index (CDI) for Eswatini. The CDI includes process-related improvements that incorporate feedback mechanisms to validate drought impacts on the ground with the communities, which requires increased institutional support and coordination by the Eswatini National Disaster Management Agency (NDMA).

The NDMA is leading the development of drought contingency plans for all 14 towns and cities in Eswatini. The plans will include detailed vulnerability assessments and linkages with the CDI drought characterization to develop protocols that trigger actions when a drought hits. The project includes the development of a disaster risk financing strategy to identify and implement risk layering instruments and delivery mechanisms to better prepare the country for dry shocks and other disasters.

The country will stitch these elements and related efforts to build drought resilience over the past years, such as a national drought preparedness plan funded under UN auspices, to develop a national drought policy and legislation. This will codify and formalize roles, responsibilities, and processes for an ongoing and iterative approach to drought resilience, ultimately ensuring sustainability and longevity beyond the lifetime of the project.

Countries can do more to address drought risks before a drought crisis ensues. Even in the cases of World Bank support highlighted here, the support has come only during or after a drought emergency. While droughts provide windows of opportunity to improve countries' resilience to the next drought, the World Bank should assist countries to get ahead of the next drought crisis before it emerges. Thus, the analysis and findings in this paper regarding the economic impacts on per capita GDP growth rates represent an opportunity. They can stimulate dialogue with development partner governments on the significant costs of drought for their respective economies and bolster the case for prioritizing drought resilience building investments in infrastructure, institutions, and information systems.

