Does drought reduce economic activity?

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Abstract: This paper examines the global effects of droughts on economic activity, proxied by remote-sensed nighttime lights data. We use two different, comprehensive indices of drought severity, one remote-sensed and one constructed from ground-sensed meteorological data, contributing to a literature on climate extremes that has previously focused on precipitation, rather than drought. Results suggest that moderate-or-worse droughts in the current year reduce luminosity by about 1 percent, with smaller but statistically significant impacts under even mild and incipient drought conditions. We estimate some lagged effects as well; moderate-or-worse droughts may reduce lights up to four years after they occur. We also test for mediating effects of access to groundwater resources of varying quality and access to reservoirs impounded by dams. We find evidence consistent with both groundwater and dams mitigating droughts' economic impacts, though some of these results are not fully robust to the choice of drought index.

Keywords: surface water, rivers, groundwater, large dams, spatial analysis, climate adaptation

JEL codes: Q25, Q28, Q20, Q54, O44

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1. Introduction and Literature Review

Drought regularly affects more people than any other natural hazard. The intensity and duration of droughts are increasing in many regions as the climate changes (Xu *et al.* 2019, Caretta *et al.* 2022). The frequency of drought events may also increase in some regions, though this potential impact is more uncertain (Trenberth *et al.* 2013, Caretta *et al.* 2022). Developing estimates of the global impact of these natural hazards on economic activity is thus a critical research goal.

Drought's impacts on agricultural productivity, migration, wages, employment and health are well-documented in rural areas in many individual countries (Dercon 2004, Mueller and Osgood 2009, Bastos *et al.* 2013, Hornbeck 2012, Lohmann and Lechtenfeld 2015). In contrast, the urban and broader regional economic impacts of drought are less well-understood, as are the impacts of this climate extreme on a global scale. The literature demonstrates that dry shocks from 2005-2014 in 78 Latin American cities negatively affected employment, wages and other labor market outcomes (Desbureaux and Rodella 2019). Water outages in Luska, Zambia increased disease incidence, reduced banking transactions, and increased the time spent on chores by girls (Ashraf *et al.* 2021). Drought may also increase local violence and social conflict, an effect that appears to be stronger in highly-populated areas (Almer *et al.* 2017). These are several ways in which drought might be expected to reduce economic activity in cities, but drought could also conceivably have either positive or negative urban impacts via migration of affected populations away from agricultural communities; for example, droughts have been shown to increase rural-to-urban migration in Africa (Henderson *et al.* 2017, Gray and Mueller 2012) and in Syria (Kelley *et al.* 2015).

In comparison to this rich and growing literature on the economic impacts of rural and, to a smaller extent, urban drought, and to the physical science literature establishing clear connections between drought and climate change, drought represents a substantial gap in the climate-economy literature. The impact of climate-related temperature extremes is well-explored: higher temperatures have been shown to reduce agricultural productivity (Schlenker and Lobell 2010, Schlenker and Roberts 2009, Deschênes and Greenstone 2007) and labor productivity (Heal and Park 2014), increase conflict (Hsiang *et al.* 2011, Burke *et al.* 2009), and reduce overall economic output (Dell *et al.* 2012). Some of these same studies also test for similar impacts of *precipitation* extremes, and find little notable impact at the global scale, concluding that temperature increases are the main economic concern with respect to climate change in these contexts. However, it is important not to conflate the singular parameter of precipitation, or even the departure of contemporaneous precipitation from historical averages, with drought. Drought is a complex phenomenon that tends to unfold slowly over time. Meteorological drought – a condition reflected in the types of anomalous precipitation deficits modeled in the prior climate-economy literature – can in some cases affect terrestrial systems over time, so that hydrologic drought develops and soil moisture is depleted, though not all meteorological droughts propagate in this manner (Zhu *et al.* 2021). Hydrologic drought can be exacerbated by additional evapotranspiration (ET), the transfer of water from land to the atmosphere by evaporation from soil and other surfaces and transpiration from plants. Depending on its season and duration, drought may lead to below-normal discharge of water in rivers and streams, lakes, and groundwater aquifers, to which urban economies may be more sensitive than to variations in contemporaneous rainfall. Thus, rather than asking whether negative *precipitation* shocks affect global economic activity, a more relevant question is whether *drought* shocks have such effects.

This paper examines the global effects of drought on economic activity and the influence access to groundwater and large dams on this relationship. We use spatially-specific data on drought severity and on economic activity (using the nighttime lights index as a proxy) to identify local effects that have not been previously studied.[1] Our econometric approach is similar to the approach in the climate-economy literature focused on temperature, in that we classify drought measures into bins and control flexibly and comprehensively for unobservable confounders using grid-cell fixed effects and continent-year effects. We also control for temperature itself, to be sure that our drought measures are not proxying for the temperature impacts that are already well-demonstrated in the literature. We use global data, allowing us to

[1] Two previous studies use the nighttime lights data to estimate the effect of *rainfall*. Henderson *et al*. (2017) examine the link between nighttime lights and rainfall in Africa in modeling the influence of aridity on rural-to-urban migration. Fisker (2014) conducts a global analysis of the effects of lagged monthly rainfall and temperature on the lights index.

study not just high- but also low- and middle-income countries, where vulnerability to droughts may be more severe.[2]

One of our primary contributions is the use of two drought indices, the MODIS Global Terrestrial Drought Severity Index (DSI) and the self-calibrating Palmer Drought Severity Index (sc-PDSI), to examine the relationship between hydrologic extremes and economic activity. These drought indices are both available globally at a fine spatial scale, and they both incorporate rich information on hydrologic drought, a function of not only rainfall, but also temperature and soil moisture. Preliminary results suggest that droughts reduce local economic activity as measured by nighttime lights; a moderate-or-worse drought reduces the lights index by about 1 percent, with some variation around that estimate depending on the drought index used to characterize drought conditions and the severity of the drought. Statistically significant, though, smaller, negative effects are detected even for mild and incipient drought conditions. Models including lagged values of the drought indices suggest that moderate-or-worse drought may reduce economic activity up to four years after its occurrence.

Just as human economic activity can adapt to temperature extremes (via irrigation (Siebert *et al.* 2017) or crop migration (Sloat *et al.* 2020) in agriculture, or air conditioning in residential and commercial settings (Barreca *et al.* 2016)), people have adapted to variability in rainfall since ancient times by managing water resources.[3] Natural surface water storage (e.g., in ponds and lakes), augmented surface water storage and transport (via dams and impoundments, aqueducts, storage tanks, etc.), and exploitation of groundwater that can be pumped to the surface all help to reduce the vulnerability of economic activity to variability in the contemporaneous supply of precipitation. Even in places where temperature-related adaptation

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[2] Kahn (2005) demonstrates that developing countries experience more severe death tolls from natural disasters (though drought is not included in the analysis) and concludes that "economic development provides implicit insurance against nature's shocks," via income and higher-quality institutions to mitigate impacts.

[3] The oldest continuously-operating dam is the Lake Homs dam in Syria, first constructed under Egyptian rule in 1319-1304 BCE and updated under the Roman Empire, which supplies the City of Homs via a canal system (https://www.water-technology.net/features/feature-the-worlds-oldest-dams-still-in-use/). Ancient hydraulic infrastructure in modern Japan, southern Europe, India and the Middle East provides evidence of ubiquitous human adaptation to variability in rainfall (Koutsoyiannis *et al.* 2008, Vetter and Rieger 2019). Ancient societies in arid regions, while adapted to low and variable rainfall, could nonetheless be severely impacted by drought (Manning *et al.* 2023, Gill *et al.* 2007).

may be minimal due to income or other constraints, when facing drought, economic activity benefits from the mediating influence of natural and constructed water storage. Thus, a global analysis of the impact of drought extremes on economic activity should both examine *drought* extremes rather than *precipitation* extremes, and also account for these potentially mediating water storage factors.

In principle, the impact of water development projects (focused on groundwater or surface water) on drought impacts at any point in time could be positive or negative: in the short run, such projects might reduce vulnerability to drought shocks, but in the long run, as irrigators plant more water-intensive crops, and firms and households install more water-intensive technologies, vulnerability may increase. For example, in the U.S. Great Plains, the historical accessibility of groundwater from the Ogallala Aquifer initially decreased agricultural drought sensitivity but resulted in no long-run impact because farmers switched to more water-intensive crops (Hornbeck and Keskin, 2014).

Other literature suggests that groundwater may play an important role in drought mitigation in the agricultural sector. For example, Taylor (2023) shows that global groundwater use for irrigation has accelerated as climate change has made some regions hotter and drier over the past 50 years, contributing to accelerating groundwater depletion. At a smaller scale, recent work demonstrates that groundwater provides more than two-thirds of California's irrigation water during drought (Liu *et al.* 2022), and Smith and Edwards (2021) show that stored irrigation water, generally, mitigates the impacts of drought on agriculture in the United States. We know of no prior work that attempts to quantify the importance of groundwater in mitigating the broader (non-agricultural) economic impacts of drought or that considers this question on a global scale.

Dams are an important component of climate change adaptation plans in many arid regions (Narain *et al*. 2011). One estimate suggests that global reservoir storage capacity will increase between 2010 and 2050 by 2800-3000 cubic kilometers, at an annual average net cost of about $12 billion (Ward *et al*. 2010). The literature is mixed, however, on whether dams' welfare effects are positive. Hansen *et al*. (2011) demonstrate significant increases in welfare among local downstream beneficiaries of federal irrigation dams in the United States. Duflo and Pande (2007) quantify the local and upstream impacts of irrigation dams in India; they find that dams' welfare costs appear to outweigh their downstream benefits, suggesting that dams may reduce welfare at the national level. By contrast, Strobl and Strobl (2011) find large downstream benefits of African dams, but no beneficial local effects. In a departure from the typical focus on irrigation dams, Lipscomb *et al.* (2013) consider the economy-wide benefits from hydroelectric dams in Brazil, identifying large positive impacts on development.

The literature often focuses on the effects of dams in typical years, but two studies have examined whether dams mitigate the economic effect of *drought*, specifically. Hansen *et al*. (2011) estimate the impacts of drought and excessive precipitation on agricultural productivity in five north-central U.S. states between 1900 and 2002, testing for a mitigating impact of federal irrigation dams, and accounting for potential endogeneity in dam placement. They find that, in the arid portions of these five states, irrigation dams increased agricultural productivity for some crops during both drought years and flood years. A study that assumes exogenous dam placement finds positive impacts of dams on agricultural productivity in Idaho, which appear to increase during droughts (Hansen *et al*. 2014). We know of no prior work that examines the mediating influence of dams on drought's economic impacts outside of the agricultural sector or that uses data from all regions of the world.

Thus, in addition to exploring the overall effects of drought, the second major contribution of our work is to test for mediating influences of both access to groundwater supplies and the presence of dams (and the reservoirs they impound) on drought's economic impacts. We use a novel dataset obtained from the World Bank on the global extent and character of groundwater resources at fine spatial scale (World Bank 2022) for our groundwater analyses. These data are constructed from several prior datasets, using only exogenous geophysical characteristics at the grid-cell level, removing any potential endogeneity concern that might have arisen using data that reflect current and historical human use of groundwater resources. Building on our prior work on dams (Olmstead and Sigman 2015), our examination of the local influence of drought and dams allows estimation of the effects of dams in either mitigating or exacerbating the link between drought and economic activity, recognizing that dams may help some local areas and hurt others sharing the same water resource. We separate the effects of local dams from those in upstream areas and address the potential endogeneity in dam location. We also consider whether hydroelectric dams, which tie electricity supply to water availability, as a special class of water infrastructure that may heighten drought sensitivity. Because we use the nighttime lights data as our independent variable, the impacts we measure go beyond agricultural productivity (the focus of much of the prior literature). We use hydrologic information to identify effects for regions downstream of dams that might counterbalance local effects. The question of whether dams may redistribute drought vulnerability (and its economic impacts) over geographic space, rather than reducing it altogether, has not yet been addressed in the literature.

Preliminary results from our groundwater analysis suggest that drought impacts in areas overlying the two most economically accessible types of groundwater resources – major alluvial or local/shallow aquifers – may be significantly mitigated, with further relief from each additional increment of long-term average water storage in underlying aquifers. In the dams analyses, local dams overall appear to just about completely mitigate the effect of most droughts, except for the most extreme. In contrast, local hydroelectric dams cause additional local reductions in economic activity during moderate or worse droughts. We find no additional marginal impact of the size of reservoirs impounded by hydroelectric or non-hydro dams. We also find no evidence that dams create spatial shifts in drought impacts at the global scale. Dams in river sub-basins upstream of a local area neither reduce the positive influence of local dams on drought mitigation, nor do they have any negative impact of their own. Our dams results are similar whether or not we use instrumental variables (IV) to account for potential endogeneity in dam placement. Neither the groundwater nor the dams results are fully robust to the choice of drought index as a measure of drought severity, a caveat to keep in mind in interpreting results.

Our approach has some important limitations. For example, the analysis we conduct does not capture longer-run effects of drought; human health effects, for example, tend to occur *in utero* or in infancy or young childhood, with potential long-run educational and income impacts (Almond and Currie 2011, Maccini and Yang 2009, Dinkelman 2013, Shah and Steinberg 2013, Alderman *et al.* 2006). In addition, our focus on economic activity does not fully capture households' welfare losses, including those from reduced direct consumption of water (Mansur and Olmstead 2012). Nighttime lights may deviate even further than a more traditional measure of economic activity from true social welfare (Chen and Nordhaus 2011). Nonetheless, ours is the first paper to demonstrate that drought reduces economic activity using global data and at a subnational scale, and that groundwater and dams may have important economic value as insurance against drought. Given that groundwater is often an open-access resource (Edwards and Guilfoos 2020), our results highlight groundwater management as an important potential adaptation approach for arid regions expecting to encounter longer, more intense droughts as the climate changes. And while individual water development projects must undergo rigorous benefit-cost analysis to determine their individual net economic impacts, our analysis suggests that dams typically reduce local vulnerability to the economic impacts of drought. The value of this role should be reflected in economic analysis of water infrastructure projects.

The rest of our paper proceeds as follows. In Section 2, we present our basic econometric models. Section 3 describes the data sources and procedures used to integrate data on drought, lights, dams, and groundwater. Section 4 reports results, and we offer some conclusions in Section 5.

2. Econometric Models

A general model for the effect of drought on nighttime lights is equation (1):

$$Lights_{it} = f(D_{it}) + \sum_{m=1}^{M} \beta_m x_{it}^m T_{it} + \alpha_i + \nu_{ct} + \varepsilon_{it} \qquad (1)$$

where $Lights_{it}$ is the inverse hyperbolic sine (IHS) of the nighttime lights index for area i in year t, D_{it} is a drought severity index, $x_{it}^m T_{it}$ is a set of temperature controls (we use a cubic function of the deviation of annual average grid-cell temperature from the grid-cell mean), α_i are grid-cell fixed effects and ν_{ct} are year effects that vary across continents, c. The error term, ε_{it}, is clustered over time and within river sub-basins. The relationship between lights and droughts, *f(.)*, could take many forms. One flexible approach classifies observations into bins defined by the value of a drought severity index:

$$Lights_{it} = \sum_{k=1}^{K} \gamma_k drought_{it} + \sum_{m=1}^{M} \beta_m x_{it}^m T_{it} + \alpha_i + \nu_{ct} + \varepsilon_{it} \ , \qquad (2)$$

with the estimated coefficients γ_k reflecting the impact of varying drought conditions on lights, allowing the response to differ by drought severity**.** Equation (2) describes our basic models of the impact of drought on economic activity.

In Section 4, we also estimate models that allow two different types of water storage, groundwater and large dams, to mediate drought's impact on lights. These models interact the characteristics of groundwater aquifers or the presence of local and upstream dams with the drought condition as in Equation (3).

$$Lights_{it} = \sum_{k}^{K} \gamma_k drought_{it} + \sum_{k=1}^{K} \pi_k bin_{it} * aq\_dam_i + \sum_{m=1}^{M} \beta_m x_{it}^m T_{it} + \alpha_i + \nu_{ct} + \varepsilon_{it} \quad (3)$$

The variable aq_dam_i in Equation (3) stands in for several different ways in which we interact an area's aquifer characteristics and the presence of dams in an area with drought severity. Some models also treat the drought-dam interaction as endogenous. We describe each of these extensions in greater detail in Section 4.

3. Data

We integrate several global datasets on economic activity, drought, and the location of dams to estimate our econometric models.

3.1. Dependent variable: economic activity

The main measure of economic activity, our dependent variable, is a satellite-based measure of the brightness of nighttime lights, which the literature suggests is a helpful proxy for economic activity (Chen and Nordhaus 2011, Henderson *et al.* 2012). We use the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) Nighttime Lights Time Series, which is available annually from 1992-2013 at a very fine spatial scale (NOAA 2014).[4] The variable is an index ranging from 0 to 63; the densest cities are effectively top-coded with values of 63. We drop grid cells containing natural gas flares because these flares result in very bright lights that do not necessarily correspond to high levels of economic activity.[5]

Each half-degree grid cell in our data covers approximately 50 square kilometers, although the precise area varies with latitude. The spatial precision of the nighttime lights index is much finer than any measure of economic activity available through traditional national

[4] An alternative source of gridded economic data is downscaled national accounts data (e.g., Nordhaus *et al*., 2006, Wang and Sun, 2022). However, these downscaled data risk missing the short-term local effects of drought because they are downscaled from larger regions and may be measured much less frequent than annually in many countries, especially lower income ones. Measurement error is also much more likely to vary with levels of economic development in national accounts data.

[5] The data of Elvidge *et al* (2016) are used to identify grid cells containing flares; any .5 degree grid cell containing a flare at any time is dropped from entirely from the panel.

accounts or other survey-based data. However, the index is only a proxy and can deviate from underlying economic activity in systematic ways. Given that the models we estimate contain grid-cell fixed effects (α_i), we identify effects of drought only from variation in lights over time within a grid cell. Though the prior literature using the lights data uses the natural log of lights as the dependent variable (Henderson *et al.* 2012, Kocornik-Mina *et al.* 2020), we transform the lights data using the IHS to avoid dropping grid cells with zero lights before aggregating (by taking an average) from the 30-arc-second degree scale in the original DMSP-OLS data to the 0.5-degree scale we use in our analysis. This approach requires that we compute marginal effects post-estimation (Bellemare and Wichman 2020).

Newer remotely-sensed nighttime lights data are available from 2012 onward using the Visible Infrared Imaging Radiometer Suite (VIIRS), measured from a newer satellite designed for research (rather than for military aircraft navigation), and the literature discusses some advantages of using these newer data (Gibson *et al.* 2020). However, our remotely-sensed drought index is available only from 2000-2011, a period which pre-dates the availability of the VIIRS luminosity data. Thus, we follow the approach of current papers in the economics literature that use the DMSP-OLS data to address some of their shortcomings. In particular, we use year effects (which we allow to vary by continent) in all our specifications to deal with any measurement error from the use of different satellites in different years (Kocornik-Mina *et al.* 2020), we average the IHS of lights at the 0.5-degree grid cell rather than using it at the 30-arc-second grid in which these data are collected, which reduces the potential influence of measurement error from spatial "blurring" in the assignment of light to pixels in the DMSP data (Gibson *et al.* 2020), and we remove gas-flaring grid cells from the data (Elvidge *et al.* 2016).

One critique of the DMSP-OLS data in the development literature is that, while these data are often used to describe economic activity in less-populated regions (where more traditional economic growth measures are less likely to be available), the DMSP-OLS data will tend to underestimate economic activity in precisely those areas, given that rural and agricultural activity emits little or no light detected by the DMSP satellites (Keola *et al.* 2015). In our case, this aspect of the DMSP-OLS data actually provides an advantage, because we are more interested in the impacts of drought on urban and ex-urban activity than we are on agricultural impacts. As Gibson *et al.* (2020) note, "The lights that can be detected with satellites are mainly for urban economic activity...[and] are not usually found in rural areas" (p. 966).

3.2 Data on drought occurrence and severity

We use two different indices as measures of the severity of hydrologic drought, which results from a period of abnormally low rainfall and is sometimes exacerbated by additional evapotranspiration (ET), the transfer of water from land to the atmosphere by evaporation from soil and other surfaces and transpiration from plants. For the analysis, we average both drought indices to 0.5-decimal-degree grid cells (about 50 km wide at mid-latitudes) for tractability and to merge them with our aggregated lights data and the other dependent variables. [6]

The first drought measure, the MODIS Global Terrestrial Drought Severity Index (DSI), is a remote-sensed drought index based on satellite observations of ET and vegetation greenness (Mu *et al*., 2013). [7] In the raw data, annual averages for the index are provided at the .05-decimal degree grid from 2000 through 2011. The DSI is continuous, ranges from unlimited negative to unlimited positive values, and is normalized with mean zero and standard deviation 1. We work principally with categorical descriptions of the level of drought specified in Mu *et al.* (2013) to create the drought severity bins we employ in our econometric approach. The fact that the DSI is remotely-sensed is appealing, as it broadens the global coverage of our drought measure (it is available in areas where our second index, the self-calibrating Palmer Drought Severity Index (sc-PDSI) cannot be calculated due to lack of meteorological data) and is also measured consistently across all grid cells. We prefer the DSI for these reasons. However, one concern about using the DSI to measure the effect of relative water stress on economic activity is possible endogeneity of the greenness index that is one component of the DSI. For example, a positive economic shock that allows farmers to plant more crops (Szerman *et al.* 2022) might increase greenness and appear as a reduction in drought, while also brightening lights. This is not a large concern from our perspective, given two facts. First, as noted earlier, the DMSP luminosity data tend not to capture agricultural activity (Gibson *et al.* 2020, Keola *et al.* 2015), making this kind of endogenous brightness very unlikely. Second, the normal scale of agricultural expansions and

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[6] Earlier versions of the analysis at finer spatial levels yielded similar results but presented computational challenges.

[7] The MODIS Global Terrestrial Drought Severity Index is provided by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana at http://www.ntsg.umt.edu/project/modis/dsi.

contractions may not influence the satellite measurements of vegetation greenness enough to alter the DSI; the remote-sensing experts who constructed the index do not mention changes in land use as an issue with their measure. However, given the potential threat to identification from this aspect of the DSI, we also use a second drought measure and assess the robustness of our results using both indices throughout the paper.

That second drought measure, the sc-PDSI, is calculated using global meteorological data on temperature, precipitation, and soil moisture collected at the Earth's surface (Osborn *et al.* 2017, van der Schrier *et al.* 2013, Wells *et al.* 2004). The sc-PDSI is a continuous index ranging from -4 (extremely dry) to +4 (extremely wet), occasionally taking on values outside of these bounds during extreme events. It is "self-calibrating" in the sense that the wetness categories of the sc-PDSI are constructed so that the "extremely dry" and "extremely wet "categories in each cell capture events that occur in 2 percent or less of months in that cell over the period of calibration (in our case, 1901-2016) (Osborn *et al.* 2017). The index is available monthly in a 0.05-decimal degree grid in raw form; we average the monthly data to form an annual average at the 0.5-degree scale from 2000 through 2011 to be comparable to our DSI data.[8] We work primarily with a set of eleven categories for the sc-PDSI defined in van der Schrier *et al.* (2013). Like the DSI, the sc-PDSI has some drawbacks. The use of global meteorological data collected by many different institutions introduces measurement error, especially where ground observations are sparse, and the sc-PDSI may also underestimate the occurrence of anomalously dry and wet spells (having a bias toward "normal" conditions from both directions) for regions and times with poor data coverage (van der Schrier *et al.* 2013).[9] In contrast to the DSI, however,

[8] The global sc-PDSI is available starting in 1901 from the Climatic Research Unit at the University of East Anglia: https://crudata.uea.ac.uk/cru/data/drought/. We use the data from 2000-2011, with the index calibrated to the period 1901-2016.

[9] The earlier Palmer Drought Severity Index (PDSI) had additional problems. For example, it tended to lag emerging drought and was developed for semi-arid regions, making it less applicable elsewhere and inaccurate for mountainous areas with frequent climatic extremes (Keyantash and Dracup 2002, Mu *et al.* 2013). However, the sc-PDSI overcomes many of these problems and is more suitable than the PDSI for comparing relative moisture conditions between different climate regions (van der Schrier *et al.* 2013).

the sc-PDSI does not use contemporaneous surface vegetation measures and does not raise endogeneity concerns.[10]

By construction, both drought indices capture cumulative drought conditions, because they measure cumulative departures in the surface water balance. The sc-PDSI, for example, incorporates both water inputs (precipitation), water outputs (ET and runoff), and "antecedent soil moisture conditions" (Mu *et al.* 2013, p. 84). In addition, we average these indices at an annual time-step, so an area experiencing an annual average condition in the moderate-to-severe drought range of either index is experiencing more than a contemporaneous precipitation anomaly – it is experiencing hydrologic drought conditions that would have developed over time, as a function of precipitation and many other factors. However, we also estimate some models with lagged values of both drought variables on the right-hand side, to see whether drought conditions in preceding years affect contemporaneous economic activity. Our ability to run these tests is somewhat limited by the short time frame of our analysis (2000-2011), and by the fact that including each lagged value entails dropping some observations.

Although both drought indices have eleven categories with similar names, ranging from extremely wet to extremely dry (or extreme drought), the categories for each index capture different portions of the distribution of observed drought conditions in our data. Table 1 demonstrates that the differences in the two indices are particularly pronounced at the extremes, with many more annual average conditions categorized using the DSI as "extreme drought" and "extremely wet" than is the case using the sc-PDSI. This is consistent with a common critique that the sc-PDSI may underestimate the occurrence of anomalously dry and wet spells (van der Schrier *et al.* 2013). Given that each drought index has both appealing characteristics and drawbacks, we use both in the analysis.

3.3 Local hydrology data used to link drought, groundwater, dams and economic activity

[10] The sc-PDSI uses surface vegetation data in its ET calculation. However, the surface vegetation data used in calculating the sc-PDSI is from a reference period (April 1992-March 1993) that captures the "typical" vegetation types within each grid cell and is thus exogenous to economic activity underlying the nighttime lights index in a grid cell during our study period (2000-2011) (van der Schrier *et al.* 2013, p. 4030). The sc-PDSI "does not consider human impacts on the water balance, such as irrigation" (Fuchs 2012, p. 4).

Hydrologically-defined river sub-basins play two roles in our analysis. First, our estimates cluster standard errors at the sub-basin level to allow correlation within sub-basins in the impacts of drought on lights. We do this because the impacts of droughts and the mediating influence of groundwater and dams may depend on local hydrology. Second, the sub-basin defines the likely area of influence for local and upstream dams.

In our analysis, river sub-basins are defined by the HYDRO1k dataset from the US Geological Survey (USGS), which uses global elevation data to divide land area into river basins and sub-basins (USGS, 2012).[11] The HYDRO1k sub-basins are coded using the Pfafstetter system (Verdin and Verdin, 1999), which provides a hierarchical coding of river basins and their subdivisions into several possible levels of sub-basins. The finest sub-basin classification has 6 digits. We rely on the 4-digit sub-basin level, both for clustering standard errors and to create the dam variables and other sub-basin characteristics used in the analysis. Globally, there are about 13,100 4-digit Pfafstetter sub-basins. To focus on permanently populated places, our equations drop sub-basins that are completely dark during any year of the data as well as sub-basins outside of the latitude-longitude range for the nighttime lights and drought data. As a result, a total of up to 6,241 sub-basins are included in our analyses.

3.4 Groundwater data

Our work benefits from a novel groundwater dataset developed by the World Bank for its ongoing assessment on the economics of groundwater in a changing climate (World Bank 2022). This effort has assembled a global dataset of aquifer types and groundwater resource availability, building on four existing datasets: the World-wide Hydrogeological Mapping and Assessment Programme's (WHYMAP's) Groundwater Resources of the World and World Karst Aquifer maps (Richts *et al.* 2011), the Global Lithological Map (GLiM) dataset (Hartmann and Moosdorf 2012) and related Global Hydrogeology Maps (GLHYMPS) dataset (Gleeson *et al.* 2014), global soil thickness data from Pelletier *et al.* (2016), and global water-table depth data from Fan *et al.* (2013). Using these data, the Bank's new dataset characterizes the underlying aquifer characteristics for each 0.5-degree grid cell around the globe.

[11] HYDRO1k provides global coding except in polar areas and for the Australian mainland.

These new groundwater data describe the share of each cell represented by one of four different aquifer types: major alluvial, local/shallow, complex, and karstic. Major alluvial aquifers behave like "bathtubs" storing water underground, and tend not to respond much to local precipitation, making them more vulnerable to depletion from irrigation and other human uses (World Bank 2022). Alluvial aquifer systems, in addition to having high quantities of the water resource *in-situ*, can typically be accessed economically by individuals. Local/shallow aquifers store water more like an "egg carton" underground. They do tend to recharge with rainfall, and are typically the most economically accessible aquifer type for individuals, though availability of the water resource is less homogeneous than for alluvial aquifers within a given region. Importantly for our purposes, both of these two aquifer types have the potential to buffer local economic activity from inter-annual meteorological variability and can be cost-effectively accessed by individuals (World Bank 2022).

The other two types of aquifers identified in the World Bank data are complex and karstic. Complex aquifers share the "bathtub" characteristic with alluvial aquifers, in that they do not respond to local rainfall, but there is a high risk that individual wells will not tap a productive area of the resource. Karstic aquifers have both significant spatial heterogeneity in access to the resource (like complex aquifers), but have the additional challenge of typically requiring deep wells. Given these characteristics, the World Bank describes both complex and karstic systems as (on average) less economically accessible than alluvial and local/shallow systems (World Bank 2022). In our groundwater models in Section 4, we assign the aquifer type that underlies the maximum area of each grid cell and create a set of four indicator variables, one for each type (alluvial, local/shallow, complex, and karstic), which we interact with drought in order to capture the capacity of groundwater access to mediate drought's impact on economic activity.

A final groundwater variable that we adopt from these new data reflect the long-term average groundwater recharge in km^3/yr, also at the 0.5-degree grid cell scale, a measure of water resource availability, conditional on aquifer type. To develop these data, the Bank downscaled country-level variation in annual rainfall from the Food and Agriculture Organization (FAO 2022) using local lithology, permeability and porosity and other inputs (World Bank 2022). We use the resulting continuous groundwater resource availability variable in our models, interacting it with drought conditions as we do for the four aquifer type indicators described above.

These new data have some unique advantages. First, they are exogenous by design. Both the discrete aquifer type indicators and continuous groundwater resource variable are estimated globally using only geophysical and hydrological characteristics that do not reflect depletion due to extraction by local populations for irrigation or other purposes. While this means that we are unable to capture the influence of variation in groundwater quality due to potential contamination from surface activities, or the impact of depletion over time from pumping in excess of recharge – both, admittedly, important phenomena in many parts of the world – it also eliminates an important threat to identification in our study, because the economic activities that create these groundwater quality and quantity challenges would be correlated with luminosity.[12] Second, these new groundwater data were developed largely in response to perceived gaps and insufficiencies on the part of all four of the underlying data sources, which had resulted in mis-classification of aquifer types in some high-profile cases.[13] Third, while prior work in economics uses one of the four datasets that the Bank combined in these new groundwater data (e.g., Taylor 2023), using any of these inputs individually provides a less-complete picture of groundwater availability than what we are able to achieve with this new dataset.

Our expectations with respect to the impact of these groundwater access variables in mediating the influence of drought on lights are mixed. On the one hand, the water storage capacity of aquifers acts as a counterweight to variable surface water supply, so the presence of the more economically accessible aquifer types (alluvial and local/shallow aquifers) may reduce any impacts of drought on lights. On the other hand, prior work shows that in agricultural settings, farmers react maladaptively to accessibility of groundwater resources, planting less drought-tolerant crops and over time and reducing groundwater's drought-mitigating potential (Hornbeck and Keskin 2014). The same could be true in the urban areas captured by the lights data, where commercial and industrial activity and residential landscaping could become more water-intensive in response to groundwater access. Our results will indicate whether, at the

[12] For example, this threat to identification would be a concern in our context if we were using the well-known GRACE satellite data on water mass anomalies that has been used as a proxy for groundwater depletion (Unfried *et al.* 2022).

[13] For example, the WHYMAP data (Richts *et al.* 2011) had long classified parts of India within the "complex" aquifer type, which are more accurately classified as "local/shallow" (World Bank 2022).

global scale, aquifer access is on average a help, a hindrance or a neutral factor in determining drought sensitivity.

3.5 Data on dam location and dam characteristics

For data on the location of large dams, we use the Global Reservoir and Dams (GRanD) data set (Lehner *et al.*, 2011). GRanD provides latitude and longitude for 6,862 of the world's largest dams and reservoirs. GRanD includes all dams with reservoirs that have storage capacity greater than 0.1 km^3 and some dams with smaller reservoirs. The GRanD dataset also includes some information on the characteristics of the dams that we can consider in our analysis. For example, GRanD classifies dams by primary use and provides total reservoir capacity and dam height. Table 1 reports the main use category for all the dams in GRanD. Irrigation is the most frequent use, followed by hydroelectricity; unfortunately, the data lack information on primary use for 23 percent of dams. The dam location data are purely cross-sectional, but not much change occurred during the relatively short time scale of our panel (2000-2011).

GRanD provides geo-coded dam locations that make it straightforward to estimate the impacts of local dams (those within a grid cell's sub-basin) on economic activity. However, counting dams upstream of a grid-cell's sub-basin is considerably more involved. The Pfafstetter system (Verdin and Verdin 1999) provides a hierarchical coding of river basins and their subdivisions into several possible levels of sub-basins, coding them in a way that makes it possible to traverse a network of drainage basins and identify whether an area is downstream of another area in which dams are present. We use these codes to determine sub-basins that are immediately and more distantly downstream of large dams.

Similar to groundwater, the availability of dams and the reservoirs they impound may alleviate drought's impacts, but maladaptive responses are also possible. In the context of dams, maladaptive responses may have two different dimensions – they may induce behavioral changes that increase drought sensitivity locally, and they may have heterogeneous spatial impacts, so that drought is alleviated locally but exacerbated downstream. While we cannot model the first phenomenon directly at the global scale, our local dam estimates will reveal whether, on average, local impacts are on net positive or negative. The second maladaptive phenomenon (different impacts locally vs. downstream) we model directly.

3.6 Additional data on grid-cell characteristics

We include several additional variables in some equations to look for heterogeneity in effects. First, the literature concludes that temperature has a significant impact on economic growth (Dell *et al.* 2012). To address concerns that estimated effects of droughts may confound temperature effects on output, we also include a cubic function of the deviation of annual average grid-cell temperature from the grid-cell mean. The temperature data are based on the monthly gridded temperature series from the Climate Research Unit (specifically CRU TS 4.00, see Harris *et al.* (2014)). Second, we consider heterogeneity in the effects of drought according to the initial cropland share in the grid cell. Cropland share is a remote sensed measure from Ramankutty *et al.* (2010). These data are from 2000, the initial year of our data, to reduce the risk that they are affected by droughts during our study period. Finally, since dams are more common in more settled regions, one equation controls for population density in estimating the effects of dams on drought sensitivity. We use population data from the Gridded Population of the World version 3 (GPWv3), which provides estimates of population density in 2000 (CIESIN 2005); the units are thousand people per square kilometer.

3.7 Instruments for dams

To address the possible endogeneity of dam location, we use instrumental variables that reflect the physical suitability of the area for a dam and the political circumstances for dam placement. First, slope has been used in the prior literature as an instrument for dams because it measures the feasibility of dam placement (Duflo and Pande, 2007). As slope instruments, we use average and maximum slope in the sub-basin, constructed from the HYDRO1k data. Use of these slope instruments is somewhat controversial: some authors express concern that slope variables may be related to the suitability of the land for agriculture or urban development and thus not satisfy the exclusion restriction. Second, prior research suggests that dams are more likely to be located on shared rivers (Olmstead and Sigman, 2015). Thus, we use as instruments the number of different countries downstream from a given sub-basin. The downstream country count has the advantage of relating to conditions downstream of the location, not to local geographic heterogeneity. In addition, we include the number of countries that share the sub-basin where the dam is located as another measure of the water-resource commons problem.

3.8 Summary statistics

Table 3 reports summary statistics for the data in our analysis for the full sample, for sub-samples split by the presence or absence of a dam in the sub-basin, and for sub-samples split by whether or not the two most economically accessible aquifer types (major alluvial, and local/shallow) comprise a majority of the grid cell area. About 15-18 percent of grid-cell-years in our data experience moderate, severe or extreme drought, depending on whether we use the DSI or the sc-PDSI to estimate this share. The DSI is centered for each cell by construction and thus has the same mean across observations in total, and when we split the sample by groundwater aquifer or dam characteristics. There is a statistically significant difference in the mean sc-PDSI and the share of cell-years experiencing moderate-or-worse drought between both the groups divided by aquifer type and by the presence or absence of dams. Intuitively, sub-basins with dams are drier, on average, than those without dams. Areas with dams and those with local/shallow or major alluvial aquifers comprising the majority of underlying groundwater typology (the two most economically accessible types) also have higher average annual temperatures. As would be expected, the average nighttime lights index and population density are much greater in sub-basins with dams. Population density is also higher in areas with access to better groundwater aquifer types, though lights are less, not more bright in these areas. For these reasons and others, all equations include grid-cell fixed effects to control comprehensively for unobservable, non-time-varying characteristics.

Major alluvial aquifers underlie about 10 percent of grid cells as the majority groundwater typology, and local/shallow aquifers about 43 percent, with the less economically accessible types (complex and karstic) underlying the remaining 37 percent and 10 percent of cells. About 36 percent of observations are in a sub-basin with at least one local dam.

Four variables in Table 3 are used as instruments for the placement of dams in Section 4. Both average and maximum slope are higher in sub-basins with dams, as expected for these measures of the physical suitability of the sub-basin for a dam. The political instruments, which indicate resource sharing, are in the next rows. Although most sub-basins are in only one country, a few are in several, so the average number of countries per sub-basin is 1.2. The differences between the observations with and without dams counter expectations: basins without dams have more downstream countries though they are about equally likely to be in a shared basin.

Table 3 also includes variables that allow us to explore the effects of upstream dams. As noted earlier, we use the Pfafstetter system to establish which dams are upstream of which sub-basins. The upstream dam counts variables are based on far fewer observations because most grid cells have no upstream sub-basins; only 21% of observations are in sub-basins with at least one upstream basin. The upstream dam variables in Table 3 are summarized for just this subset of the data.

4. Results: overall impact of drought on economic activity

Our first two sets of results (sections 4.1 and 4.2) consider the overall drought sensitivity of economic activity and drought's lagged effects. Results in sections 4.3 and 4.4 describe the mediating influences of groundwater and dams on this relationship.

4.1 Impact of drought on lights for full spectrum of hydrologic conditions using both indices

Tables 4 and 5 contain coefficient estimates from Equation (2) using the two alternative drought indices (DSI in Table 4, and sc-PDSI in Table 5), while Figure 1 presents a summary of the coefficients from these two tables. Each column also includes fixed effects for the grid cells and dummies that interact the year and the continent of the observation for each of 12 years (2000-2011). We cluster standard errors by sub-basin to allow for serial correlation in a cell over time and spatial autocorrelation in hydrologically-linked regions. The bins for each drought index are bounded by convention in the physical science literature[14] and are based on the annual average of monthly index values for a grid cell. For example, if the average sc-PDSI in a grid-cell-year is less than or equal to -4, that cell-year will be in the "extremely dry" category.[15] The omitted category is "near normal" hydrologic conditions (sc-PDSI = 0 +/- 0.5, and DSI = 0 +/- 0.3).

Looking at column (1) in both tables, we find that the impacts of drought on lights increases monotonically with drought severity, with statistically significant reductions in

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[14] We use the ranges listed in Table 2 of Mu *et al.* (2013).

[15] Results were similar if we instead used the summer values for the index (June in the Northern hemisphere and December in the Southern hemisphere) or the minimum annual value. This similarity is not surprising because these indices have built-in persistence to capture the effects of drought rather than simply short-run precipitation.

luminosity for all four levels of abnormally dry conditions (from incipient to extreme). This is true for both indices, and the coefficient estimates for each drought category in column (1) of Tables 4 and 5 are quite similar. While the confidence intervals overlap in some adjacent drought categories, for both indices, the impact of moderate, severe and extreme drought is of larger magnitude than the impact of mild and incipient drought. The fact that the coefficient estimate more than doubles between the "moderate" drought category and the next-less-severe category for both indices leads us to report estimates from a regression for each index in which we compress three drought categories of moderate or greater severity into a single binary drought variable. Those coefficient estimates are reported in column (3) of each table – results are quite similar using the two different indices, and both estimates are statistically significant. In several of the extensions in Section 4.2, we substitute this binary specification for the full set of drought bins in the interest of tractability and ease of interpretation.

In column 2 of Tables 4 and 5, we add the temperature controls, losing a small number of observations for grid-cell-years in which temperature data are not available. Using both indices and across the full spectrum of drought conditions, in almost all cases, adding temperature controls tends to reduce the magnitude of the drought bin coefficients. This demonstrates the importance of including temperature in the models, given its established links with economic growth, but it also establishes that conditional on temperature, drought has an independent, negative effect on the economic activity that is correlated with luminosity. The temperature variables are jointly statistically significant and are retained for the remaining models in the paper.

Note, also, that the estimate for the "extremely dry" category for the sc-PDSI is only weakly significant when temperature controls are included (Table 4, column 2), and that this coefficient estimate in both columns 1 and 2 of Table 4 is the only one to break the trend of monotonically increasing impacts with drought severity. Looking at Figure 1, we can see that at both ends of the hydrological spectrum, consistent with the physical science literature (and a comparison of counts within the most extreme bins between the sc-PDSI and the DSI in Table 1), that the sc-PDSI may underestimate the occurrence of anomalously dry and wet spells (van der Schrier *et al.* 2013). These smaller numbers produce noisier estimates of the impact of extreme drought using the sc-PDSI (the same is true at the wettest end of the spectrum). Given that our coefficient estimates for the two indices are otherwise very similar, and our argument from Section 3 that endogeneity in the DSI measure is not likely to be a significant concern given that the impacts we measure are in areas with luminosity bright enough to detect in the DSMP-OLS data, we proceed with the rest of the analysis using primarily the DSI drought measure, in some cases relegating the equivalent sc-PDSI results to Appendix A.

In terms of magnitude, areas in our data facing average annual hydrologic conditions in the "moderate drought" or worse (severe, extreme) categories experience about a 1 percent dimming of nighttime lights, compared to those experiencing anomalously wet, near-normal, or mildly dry conditions. These effects are somewhat stronger extreme droughts, and somewhat weaker for moderate droughts, and they are consistent across both drought indices (in Tables 4 and 5). Using the standard lights-GDP elasticity of about -0.3 (Henderson *et al.* 2012), this would translate to about a 0.3 percent reduction in GDP. It is difficult to directly compare the magnitude of drought's impact in our models with the prior literature, given that few papers address this question. Korcornik-Mina *et al.* (2020) find that large urban floods reduce luminosity by 2-8 percent in the year of the flood, and that lights typically rebound within one year. Floods can happen suddenly, thus we might expect a greater economic shock from these events than from drought, which develops slowly. Henderson *et al.* (2017) find that annual *rainfall* has no effect, on average, on luminosity from African cities. However, rainfall reduces lights (elasticity of -0.17) for the most industrialized countries on the continent, but has positive and insignificant effects on lights for the least industrialized countries. This pattern is consistent with other evidence in their paper that aridity drives urbanization.

Finally, the statistically significant, positive impacts on lights of moderately- to extremely-wet conditions in some specifications in Tables 4 and 5 are notable, as is the absence of negative effects on lights from even the most extreme wet conditions. This may appear to conflict with the prior literature, which suggests that economic activity migrates away from large urban floods (Kocornik-Mina *et al.* 2020). This is not necessarily the case, however. Both the DSI and sc-PDSI are *drought* indices, optimized to identify areas experiencing anomalously dry, rather than anomalously wet conditions. Even extremely wet conditions do not necessarily result in flooding, and the prior literature focuses on identifiable flooding events (for example, using inundation maps and spatial data on the known extent of identifiable, large floods). Given our focus on drought and the water storage approaches that may mediate its economic effects, we leave further exploration of impacts on the wet end of the hydrological spectrum to future work.

4.2 Extension: effects of moderate or worse drought in prior years

In Figure 2, we report results from estimating the effect of the binary moderate-or-worse drought indicator variable on lights, as we did in column 3 of Tables 4 and 5, but the Figure 2 models also include a set of lagged values of the binary drought indicator. For models including each of the two drought indices, we use a set of six lagged values, so that the equations capture the effect of an average annual index value reflecting moderate or worse drought conditions in each of the prior six years, in addition to the current year. With each lagged variable, we lose observations for the "marginal" year, where we cannot observed the earlier drought index value. At the top of Figure 2, where we include only the current year's value (equivalent to column 3 in Tables 4 and 5), we have about 448,000 observations in the DSI sample, and about 421,000 in the sc-PDSI sample. By the time we include six lagged values of the binary drought indicator, we have cut the number of observations in half using both indices (224,000 for the DSI sample, and 210,000 for the sc-PDSI sample). Thus, results from models with many lags may not be representative of the full sample, because they are based on a much shorter time series. However, the model results reported in Figure 2 suggest that moderate-or-worse drought conditions may reduce luminosity (and by proxy, economic activity) for at least four years. While the confidence intervals for the sc-PDSI lagged drought indicator mostly overlap, looking at the DSI results, it appears that a moderate-or-worse drought two to three years prior could have a stronger effect on economic activity than a drought in the current year. We cannot explain the counterintuitive positive and significant coefficient associated with a moderate-or-worse drought six years prior using the sc-PDSI data.

4.3 Extension: influence of access to groundwater on drought effects

In this extension, we test for a mediating influence of groundwater access on drought's impacts on economic activity. To do so, we estimate equation (4):

$$Lights_{it} = \gamma Drought_{it} + \sum_{j=1}^{4} \theta_j Drought_{it} * Aquifer_{ij} + \mu Drought_{it} * Resource_i + \sum_{m=1}^{M} \beta_m x_{it}^m T_{it} + \alpha_i + \nu_{ct} + \varepsilon_{it} \; , \tag{4}$$

in which the variable $Drought_{it}$ is equal to 1 if cell i experienced average annual conditions of moderate, severe or extreme drought in year t. The $Aquifer_{ij}$ variables are indicators for the four underlying aquifer types that represent the maximum share for each grid cell. $Resource_i$ is the long-term average recharge to groundwater aquifers of any type in cell i. The remaining variables and parameters are identical to those described in equations (1)-(3).

Table 6 reports estimates from three models, using the DSI as our drought measure. In column 1, we estimate our baseline model of the effect of moderate-or-worse drought on lights, using only the sample for which we observe our groundwater variables, obtaining an estimate very similar to those in Tables 4 and 5 – drought reduces lights by about 1 percent. In column 2, we include the interactions between drought and the majority groundwater aquifer types, excluding the "karstic" category, the least economically accessible resource, on average (World Bank 2022). Results suggest that in areas where alluvial aquifers represent the majority share of the local groundwater typology, the impact of moderate-or-worse drought is basically alleviated. The effects of the interactions with other aquifer types (local/shallow and complex) are positive, but not statistically different from zero. In column 3, we add the long-term groundwater recharge variable, finding similar results for alluvial aquifers, and also an additional marginal effect of long-term recharge. For every 1% increase in long-term average recharge, lights during drought are increased by 1.6%. Note that controlling comprehensively for groundwater access as we do in column 3 also increases our estimates of drought's impact on lights (in the first row) appreciably.

As a robustness check, we re-estimate the models in Table 6 using the sc-PDSI to characterize drought. Results (reported in Table A1 in Appendix A) are similar, with one difference: access to local/shallow aquifers as a majority share reduces drought's impact on lights in these models, but the coefficient for the alluvial aquifer interaction is positive and statistically insignificant. Thus, our aquifer type results are not fully robust to the choice of drought index (though the long-term recharge results are). Given that both the alluvial and local/shallow aquifer types are more economically accessible than complex and karstic aquifers, as described in Section 2, this difference in results is interesting, but qualitatively consistent with access to "better" aquifers alleviating drought, on average. Taken together, the results of these tests suggest that, while maladaptive responses could occur in some areas, on net, access to groundwater at the global scale is an important buffer against drought shocks.

4.4. *Extension: influence of dams on effect of droughts*

This section explores the effects of dams on drought sensitivity. To estimate the effects of dams and reservoirs on resilience to drought, we use interaction terms between presence of local and upstream dams and drought. We start by estimating equation (3), in which the water storage variable (aq_dam_i) is replaced with an indicator variable for the presence of any dam in the area's local sub-basin. Results using the DSI to characterize drought conditions are reported in Table 7, with sc-PDSI results reported in the Appendix, Table A2. Coefficient estimates for the drought bins (γ_k from eq. 3) are presented in column 1, and coefficients on the interactions between drought bins and the presence of a dam (π_k from eq. 3) in column 2.

For all but the most extreme droughts, local dams appear to mitigate their economic harm. The point estimates suggest that local dams reduce the net effect of droughts by over half for the "severe" drought category (though this effect is only weakly significant) and just about eliminate negative effects of moderate, mild and incipient drought. For extreme droughts, the interaction coefficient is small and not statistically significant. The lack of an effect in extreme droughts could be valid: dams might be able to smooth water access during ordinary events but be insufficient for extraordinary events. However, it might also be another manifestation of the difficulty estimating effects for the small observed numbers of such events. In the F-tests presented at the bottom of the Table 7, we can reject that dams have no effect in all the dryer-than-normal conditions at the 1 percent level (F=3.65). The sc-PDSI results in Table A2 are qualitatively similar, except that the mitigating effect of local dams is no longer significant for severe or incipient drought conditions, but it is for both moderate and mild drought.

Table 8 explores a broader set of dam variables, focusing on the simpler comparison of the droughts characterized as moderate or worse with all other conditions. Column 1 of Table 8 suggests that one or more dams in the area's local sub-basin mitigates more than half the effect of moderate-or-worse drought, on net. Column 2 adds a variable for the presence of at least one hydroelectric dam in the sub-basin. Areas that depend on electricity from their dams should suffer more dramatic drought-induced declines in lights than areas that use the dams for irrigation, urban water supply, recreation, or other uses in which the dams and the reservoirs they impound may provide a substitute for precipitation. The point estimate on hydroelectric dams is statistically significant and negative as expected, suggesting that this heterogeneity is important.

Having one or more hydroelectric dams in the local sub-basin approximately doubles the negative impact of drought on lights. Once we differentiate among dam types in this way, the point estimate on the generic dam interaction more than doubles compared to column 1.[16]

Table 8 also addresses a few other dimensions of heterogeneity in the potential mediating effect of dams on the impacts of drought. First, dams tend to be in more populous places, so one might worry that the dam interaction picks up differential effects in more- or less-settled places, rather than effects of dams, *per se*. To address this concern column 3 controls for the population density in the sub-basin at the beginning of the period. The interaction term between population density and moderate-or-worse drought is not statistically significant, and including this variable does not appreciably affect the coefficient on the dam-drought interaction, supporting our interpretation of the dam effect above.

Finally, column 4 of Table 8 explores another dimension of heterogeneity, the quantity of water impounded by dams. The new variable is the estimated reservoir capacity of dams in the sub-basin (summed over all dams present when there are multiple dams), in km^3. The GRanD Project calculated reservoir capacity for almost all dams, making this variable our preferred measure of dam size. Reservoir capacity has a very pronounced upper tail, so a few observations may be very influential. The variable as entered in the equation is the maximum reservoir storage capacity in trillions of cubic meters. Because the effect of hydro dams is expected to differ from that of other dams, we include the total reservoir capacity and the hydro dam reservoir capacity separately. Neither of these variables has a statistically significant effect on drought's impacts, so the presence of dam appears more important than its size.

[16] The comparison between hydro vs nonhydro dams in the analysis is likely biased toward zero because of lack of use classification for about a quarter of the GRanD dams. Some dams classified as non-hydro are presumably in fact hydro dams. Henderson *et al.* find no differential effect of hydropower dependence on the effects of *rainfall* on nighttime lights in Africa. This difference with our work is likely due to our focus on hydrologic *drought*, which is much more likely to affect hydroelectric dam operation than would contemporaneous rainfall.

Although the results in Table 8 suggest an important role for non-hydro dams in mitigating the effects of drought, a caveat is that these results are not fully robust to using the alternative measure of drought. Results using the sc-PDSI are reported in Table A3 in Appendix A. Consistent with the results using the DSI measure, the overall dam interaction variable with the sc-PDSI is positive. However, it is not statistically significant. The lack of statistical significance may not be surprising because it may stem from the imprecision in the estimates of the effects of the worst droughts using this alternative drought measure. The positive point estimate on the interactions between hydro dam and drought with the sc-PDSI may be more surprising, but again, this coefficient is far from significant.

Upstream dams

Table 9 considers the role of upstream dams. Upstream dams may result in reduced water flow (or differently timed flow) that could reduce the resilience of downstream areas to droughts. To examine their effect, we separate upstream dams into two groups: those in the immediately adjacent upstream basin and those that are farther (two or more sub-basins) upstream. Immediately upstream dams may be quite close to the basin in question and thus any benefits of proximity to the dam may mix with any costs that dams impose downstream. We expect dams farther upstream to generate costs more exclusively but also to have more diluted effects because many different sub-basins may be upstream of a given grid cell.

To estimate the effects of upstream dams, we restrict the sample to cells in sub-basins that have other sub-basins upstream of them. If no sub-basins are upstream, the sub-basin will necessarily not have any upstream dams and this difference in position in the river system may confound any estimate of the effects of upstream dams. Column 1 of Table 9 addresses this concern by repeating the equation from Column 1 of Table 8 with the restriction to areas with at least one upstream sub-basin; as a result, the upstream dam models that follow in the remaining columns of Table 9 use a comparable subset of the data. Notice that these models must drop 84 percent of the cells and 75 percent of sub-basins used in the local dams analysis in Table 8. Nonetheless, the coefficient estimates for the baseline drought impact on lights and the mediating impact of local dams are quite similar to those in Table 8.

Column 2 adds a variable for the presence of a dam in the sub-basin immediately upstream of a grid cell's sub-basin. This variable has no statistically significant mediating effect on lights under moderate-or-worse drought. Column 3 adds a variable for the presence of a dam two or more sub-basins upstream, which has an unexpected (weakly) positive effect on lights during drought. The final column of Table 9 again considers the role of hydroelectric dams separately, adding variables for both local and near upstream hydroelectric dams. The local dam coefficients are not statistically significant, although the *hydro dam * drought* interaction has the same sign and is similar in magnitude to equivalent coefficients in Table 8. Near-upstream hydro dams are not significant, though the sign on this coefficient is negative. The results using the sc-PDSI (Table A4 in Appendix A) instead of the DSI to characterize drought are similar except that (as in Table A3) the local dam effects on drought sensitivity are not statistically significant.

Instrumental variable estimates of the effect of dams

The potential endogeneity of dam locations is a concern in estimating equation (3). For example, if dams strengthen resilience against drought, they might preferentially be built in places that expect strong effects of drought. The presence of dams may also simply be correlated with other factors that affect resilience, such as access to capital. To address these concerns, this subsection reports instrumental variable estimates of equation (3).

The potentially endogenous variable in our equations is the interaction between the local dam and the drought condition. All equations include grid cell fixed effects, so instruments cannot be based only on geographic variation. Therefore, we construct instruments based on the interactions of drought conditions and the instruments described in Section 2. This strategy makes it difficult to interpret the first-stage coefficients but should yield instruments that satisfy the relevance and exclusion conditions for IV estimators.

Table 10 presents the IV estimates focusing just on conditions of moderate-or-worse drought. To address concerns about the suitability of the instrument sets, Table 10 reports results using just the slope instruments, just the political instruments, and using all available instruments. With all instrumental variable sets, the point estimates of the coefficients remain similar to the estimates of the same equation without instruments in Table 8 column 1. However, the standard errors are much larger with the IV estimates and the interaction between the presence of a dam and drought is not statistically significant. The estimates provide some reassurance that our earlier results are not driven by endogenous dam placement: in addition to the similarity of the point estimates, Durbin-Wu-Hausman tests reported in Table 10 fail to reject exogeneity of the interaction variable, supporting a causal interpretation of our earlier dam results.[17] We report the same model results using the sc-PDSI as the drought index, instead of the DSI, in Table A5 in Appendix A. Results are similar but somewhat stronger; the interaction between drought and dams in two of the IV models using the sc-PDSI (those using only the slope instruments, and those using all instruments) are positive and significantly different from zero, consistent with the main results reported in Table 8.

4.5 Additional extensions and robustness

Figure 3 plots coefficient estimates from equations like those in Table 4 column 2, but allowing heterogeneity in the responses by the initial amount of cropland in the grid cell. This analysis provides a bit more information on the nature of the economic effects we observe with the nighttime lights as the dependent variable. Not surprisingly, we observe the most dramatic effects of drought in places that are most heavily farmed, but even the cells in the lowest tercile of cropland experience statistically significant negative effects from extreme and severe droughts. Figure 3 provides some reassurance that the greenness component of the remote-sensed drought index (the DSI) does reflect moisture availability rather than crop area because droughts cause damage even in places with little agriculture. Except for the most severe drought conditions, we have more confidence of the negative effects of drought in places with less cropland.

5. Conclusion

Our work suggests that droughts significantly reduce local economic activity. Use of the nighttime lights index as a proxy for economic activity means that the impacts we estimate are more likely to capture effects on urban economic activity than agricultural effects, which have been studied more frequently in the prior literature. The panel fixed effects models we estimate suggest that moderate-or-worse droughts reduce the lights index by about 1 percent, with slightly larger effects for more severe droughts and smaller but still statistically significant effects for

[17] However, this test does maintain the assumption that the instruments themselves are valid, which might be a concern because J-tests reject the overidentification restrictions for both sets of instruments and the combined instrument set.

even mild and incipient droughts. These effects are similar whether we use remotely-sensed or ground-sensed measures of drought severity (except for the most extreme drought, which our ground-sensed drought measure, the sc-PDSI, does not capture as well as the remote-sensed measure), and they may persist for up to four years. While the effects we measure are small (translating to a one-third of one percent reduction in local GDP), they provide a useful contrast to prior climate-economy papers that consider rainfall extremes and find no effect.

One reason that drought may have small effects on economic activity is that cities may locate where it is possible to smooth the variability in surface water supply via access to groundwater or by impounding surface water to create reservoir storage, a common practice even in ancient societies. Our analysis shows that both of these factors do, in fact, mitigate drought's impacts at a global scale. Access to more economically-accessible aquifers and aquifers with higher long-term average recharge mitigates drought's impacts on lights. Local dams appear to mitigate the impacts of incipient-to-severe droughts using the remote-sensed DSI drought measure, but only those of mild-to-moderate droughts using the sc-PDSI. While we obtain some intriguing and intuitive results with respect to the tendency of dependence on hydroelectric dams for electricity supply to worsen the impact of drought on lights, these results are not robust to the choice of drought index. Prior work demonstrates that countries may be strategic in the choice of dam locations in international river basins (Olmstead and Sigman 2015), but our current paper finds no detrimental effects of upstream dams on downstream drought impacts (though upstream dams do not appear to mitigate drought in the manner of local dams).

In the context of a literature finding mixed long-run impacts of access to groundwater and dams (Hornbeck and Keskin 2014, Duflo and Pande 2007), our work demonstrates that, on net, these water resources do reduce the impacts of drought shocks on economic activity at a global scale – one of many potential economic benefits. However, this does not speak to whether individual water development projects have net benefits, as our results could easily mask local heterogeneity in dams' and aquifers' impacts given behavioral reactions to their availability, differences in property rights structures, and other institutional and policy differences. Given increasing intensity, duration and possibly frequency of droughts in a changing climate (Caretta *et al.* 2022), more work is needed to understand the economic impacts of these climate hazards and the water management infrastructure investments that may alleviate them.

References

Alderman, Harold, John Hoddinott and Bill Kinsey. 2006. Long term consequences of early childhood malnutrition. *Oxford Economic Papers* 58(3): 450-474.

Almer, Christian, Jérémy Laurent-Lucchetti, and Manuel Oechslin. 2017. Water scarcity and rioting: disaggregated evidence from Sub-Saharan Africa. *Journal of Environmental Economics and Management* 86: 193-209.

Ashraf, Nava, Edward Glaeser, Abraham Holland and Bryce Millet Steinberg. 2021. Water, health and wealth: the impact of piped water outages on disease prevalence and financial transactions in Zambia. *Economica* 88: 755-781.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro. 2016. Adapting to climate change: the remarkable decline in the U.S. temperature-mortality relationship over the Twentieth Century. *Journal of Political Economy* 124(1): 105-159.

Bastos, Paulo, Mattías Busso, and Sebastián Miller. 2013. Adapting to climate change: long-term effects of drought on local labor markets. IDB Working Paper No. IDB-WP-466. Inter-American Development Bank, Washington, DC.

Bellemare, Marc F. and Casey J. Wichman. 2020. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics* 82(1): 0305-9049.

Burke, M., Miguel, E., Satyanath, S., Dykema, J. & Lobell, D. 2009. Warming increases risk of civil war in Africa. *Proceedings of the National Academy of Sciences* 106, 20670–20674.

Caretta, M.A., A. Mukherji, M. Arfanuzzaman, R.A. Betts, A. Gelfan, Y. Hirabayashi, T.K. Lissner, J. Liu, E. Lopez Gunn, R. Morgan, S. Mwanga, and S. Supratid. *Water*. In: *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, 551–712 (2022).

Chen, Xi and William D. Nordhaus. 2011. Using Luminosity Data as a Proxy for Economic Statistics. *Proceedings of the National Academy of Sciences* 108(21): 8589–94.

CIESIN (Center for International Earth Science Information Network), Centro Internacional de Agricultura Tropical (CIAT). 2005. Gridded population of the world, version 3 (GPW v3) data collection. Palisades, NY: Columbia University. http://sedac.ciesin.columbia.edu/gpw/index.jsp.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics* 4(3):66–95. http://dx.doi.org/10.1257/mac.4.3.66

Dercon, Stephan. 2004. Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics* 74: 309-329.

Desbureaux, Sébastien and Aude-Sophie Rodella. 2019. Drought in the city: the economic impact of water scarcity in Latin American metropolitan areas. *World Development* 114: 13-27.

Deschênes, Olivier and Michael Greenstone. 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review* 97(1): 354-385.

Duflo, Esther and Rohini Pande. 2007. Dams. *Quarterly Journal of Economics* 122(2): 601-646.

Edwards, Eric C., and Todd Guilfoos. 2020. The economics of groundwater governance institutions across the globe. *Applied Economic Perspectives and Policy* 43(4): 1571-1594.

Elvidge, Christopher D. *et al.* 2016. Methods for Global Survey of Natural Gas Flaring from Visible Infrared Imaging Radiometer Suite Data. *Energies*. 9, 14; doi:10.3390/en9010014.

Fan, Y., Li, H., and Miguel-Macho, G. 2013. Global Patterns of Groundwater Table Depth. *Science* 339: 940–943. DOI: 10.1126/science.1229881.

FAO. 2022. AQUASTAT Database. AQUASTAT. http://www.fao.org/nr/water/aquastat/data/query/index.html?lang=en.

Fisker, Peter. 2014. Green Lights: Quantifying the economic impacts of drought. University of Copenhagen IFRO Working Paper.

Fuchs, Brian. 2012. Palmer Drought Severity Index (PDSI and scPDSI). Presentation to the Caribbean Drought Workshop, May 2012. National Drought Mitigation Center, the University of Nebraska – Lincoln. https://drought.unl.edu/archive/Documents/NDMC/Workshops/136/Pres/Brian%20Fuchs--PDSI%20and%20scPDSI.pdf.

Furnans, Jordan Ernest. 2001. Topologic Navigation and the Pfafstetter System. Report. UT Austin Center for Research in Water Resources.

Gibson, John, Susan Olivia and Geua Boe-Gibson. 2020. Night lights in economics: sources and uses. *Journal of Economic Surveys* 34(5): 955-980.

Gill, Richardson B., Paul A. Mayewski, Johan Nyberg, Gerald H. Haug, and Larry C. Peterson. 2007. Drought and the Maya collapse. *Ancient Mesoamerica* 18(2): 283-302.

Gleeson, T., Moosdorf, N., Hartmann, J., and Van Beek, L. P. H. 2014. A Glimpse Beneath Earth's Surface: GLobal HYdrogeology MaPS (GLHYMPS) of Permeability and Porosity. *Geophysical Research Letters* 41(11): 3891–3898.

Gray, Clark L., and Valerie Mueller. 2012. Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences* 109(16): 6000-6005.

Harris, I., P.D. Jones, T.J. Osborn and D.H. Lister. 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology* 34: 623–642.

Hartmann, J., and Moosdorf, N. 2012. The New Global Lithological Map Database GLiM: A Representation of Rock Properties at the Earth Surface. *Geochemistry, Geophysics, Geosystems* 13, Q12004. DOI: 10.1029/2012GC004370.

Hansen, Zeynep, Scott Lowe, and Gary Libecap. 2011. Climate Variability and Water Infrastructure: Historical Experience in the Western United States, In: *Climate Change Past and Present: Uncertainty and Adaptation*, ed. Gary Libecap and Richard Steckel. Chicago: NBER and University of Chicago Press.

Hansen, Zeynep K., Scott E. Lowe, and Wenchao Xu. 2014. Long-term impacts of major water storage facilities on agriculture and the natural environment: evidence from Idaho (U.S.). *Ecological Economics* 100: 106-118.

Heal, Geoffrey, and Jisung Park. 2014. Feeling the heat: temperature, physiology and the wealth of nations. NBER Working Paper No. 19725. Cambridge, MA: National Bureau of Economic Research, Inc.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. Measuring economic growth from outer space. *American Economic Review* 102(2): 994–1028.

Henderson, J. Vernon, Adam Storeygard, and Uwe Deichmann. 2017. Has climate change driven urbanization in Africa? *Journal of Development Economics* 124: 60-82.

Hsiang, Solomon M, Kyle C. Meng, and Mark A. Cane. 2011. Civil conflicts are associated with the global climate. *Nature* 476: 438- 441 http://dx.doi.org/10.1038/nature10311

Hornbeck, Richard. 2012. The enduring impact of the American Dust Bowl: short- and long-run adjustments to environmental catastrophe. *American Economic Review* 102(4): 1477-1507.

Hornbeck, Richard, and Pinar Keskin. 2014. The historically evolving impact of the Ogallala Aquifer: agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics* 6(1): 190-219.

Kahn, Matthew E. 2005. The death toll from natural disasters: the role of income, geography and institutions. *Review of Economics and Statistics* 87(2): 271-284.

Kelley, Colin P., Shahrzad Mohtadi, Mark A. Cane, and Yochanan Kushnir. 2015. Climate change in the Fertile Crescent and implications of the recent Syrian drought. *Proceedings of the National Academy of Sciences* 112(11): 3241-3246.

Keola, Souknilanh, Magnus Andersson, and Ola Hall. 2015. Monitoring economic development from space: using nighttime light and land cover data to measure economic growth. World Development 66: 322-334.

Keyantash, John, and John A. Dracup. 2002. The quantification of drought: an evaluation of drought indices. *Bulletin of the American Meteorological Society* 83: 1167-1180.

Kocornik-Mina, Adriana, Thomas K. J. McDermott, Guy Michaels, and Ferdinand Rauch. 2020. Flooded cities. *American Economic Journal: Applied Economics* 12(2): 35-66.

Koutsoyiannis, D., N. Zarkadoulas, A. N. Angelakis, and G. Tchobanoglous. 2008. Urban water management in ancient Greece: legacies and lessons. *Journal of Water Resources Planning and Management* 134(1): 45-54.

Lehner, B., C. Reidy Liermann, C. Revenga, C. Vörösmarty, B. Fekete, P. Crouzet, P. Doll, M. Endejan, K. Frenken, J. Magome, C. Nilsson, J.C. Robertson, R. Rodel, N. Sindorf, and D. Wisser. 2011. *Global Reservoir and Dam Database, Version 1 (GRanDv1): Dams, Revision 01*. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://sedac.ciesin.columbia.edu/data/set/grand-v1-dams-rev01.

Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham. 2013. Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil. *American Economic Journal: Applied Economics*, 5(2): 200-231.

Liu, Pang-Wei, James S. Famiglietti, Adam J. Purdy, Kyra H. Adams, Avery L. McEvoy, John t. Reager, Rajat Bindlish, David N. Wiese, Cédric H. David, and Matthew Rodell. 2022. Groundwater depletion in California's Central Valley accelerates during megadrought. *Nature Communications* 13: 7825.

Lohmann, Steffen, and Tobias Lechtenfeld. 2015. The effect of drought on health outcomes and health expenditures in rural Vietnam. *World Development* 72: 432-448.

Manning, Sturt W., Cindy Kocik, Brita Lorentzen, and Jed P. Sparks. 2023. Severe multi-year drought coincident with Hittite collapse around 1198-1196 BC. *Nature* 614: 719-724.

Mansur, Erin T., and Sheila M. Olmstead. 2012. The value of scarce water: measuring the inefficiency of municipal regulations. *Journal of Urban Economics* 71: 332-346.

Mu, Q., M. Zhao, J. S. Kimball, N. G. McDowell, S. W. Running. 2013. A Remotely Sensed Global Terrestrial Drought Severity Index. *Bulletin of the American Meteorological Society*, 94 (1): 83-98. DOI:10.1175/BAMS-D-11-00213.1

Mueller, Valerie A., and Daniel E. Osgood. 2009. Long-term impacts of droughts on labour markets in developing countries: evidence from Brazil. *Journal of Development Studies* 45(10): 1651–1662.

Narain, Urvashi, Sergio Margulis, and Timothy Essam. 2011. Estimating costs of adapting to climate change. *Climate Policy* 11: 1001–1019.

National Oceanographic and Atmospheric Administration (NOAA). 2014. DMSP-OLS Nighttime Lights Time Series. http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

Nordhaus, William, Qazi Azam, David Corderi, Kyle Hood, Nadejda Makarova, Victor, Mukhtar Mohammed, Alexandra Miltner, and Jyldyz Weiss. 2006. The G-Econ Database on Gridded Output: Methods and Data. Yale University Working Paper. http://gecon.yale.edu

Olmstead, Sheila M., and Hilary Sigman. 2015. Damming the commons: an analysis of international cooperation and conflict in dam location. *Journal of the Association of Environmental and Resource Economists* 2(4): 497-526.

Osborn, T. J., J. Barichivich, I. Harris, G. van der Schrier, and P. D. Jones. 2017. Monitoring global drought using the self-calibrating Palmer Drought Severity Index. In: *State of the Climate in 2016*. Special supplement to the *Bulletin of the American Meteorological Society* 98(8): S32-S33.

Pelletier, J. D., Broxton, P. D., Hazenberg, P., Zeng, X., Troch, P. A., Niu, G., Williams, Z. C., Brunke, M.A., and Gochis, D. 2016. Global 1-km Gridded Thickness of Soil, Regolith, and Sedimentary Deposit Layers. Oak Ridge National Laboratory Distributed Active Archive Center: Tennessee, USA. DOI: 10.3334/ORNLDAAC/1304

Ramankutty, N., A.T. Evan, C. Monfreda, and J.A. Foley. 2010. Global Agricultural Lands: Croplands, 2000. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4C8276G.

Richts, A., Struckmeier, W. F., and Zaepke, M. (2011). WHYMAP and the Groundwater Resources Map of the World 1:25,000,000. In Jones, J. A. A., editor, *Sustaining Groundwater Resources*, pp. 159–173. Springer Netherlands, Dordrecht.

Schlenker, W. and D. B. Lobell. 2010. Robust Negative Impacts of Climate Change on African Agriculture. *Environmental Research Letters* 5(1): 1-8.

Schlenker, W. and M. J. Roberts. 2009. Non-linear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences* 106(37): 15594-15598.

Siebert, Stefan, Heidi Webber, Gang Zhao, and Frank Ewert. 2017. Heat stress is overestimated in climate impact studies for irrigated agriculture. *Environmental Research Letters* 12 (5): 054023.

Sloat, Lindsey L., Steven J. Davis, James S. Gerber, Frances C. Moore, Deepak K. Ray, Paul C. west, and Nathaniel D. Mueller. 2020. Climate adaptation by crop migration. *Nature Communications* 11: 1243.

Smith, Steven M., and Eric C. Edwards. 2021. Water storage and agricultural resilience to drought: historical evidence of the capacity and institutional limits in the United States. *Environmental Research Letters* 16: 124020.

Strobl, Eric and Robert O. Strobl. 2011. The distributional impact of large dams: evidence from cropland productivity in Africa. *Journal of Development Economics* 96: 432-450.

Szerman, Dimitri, Juliano Assunção, Molly Lipscomb, and Ahmed Mushfiq Mobarak. 2022. Agricultural productivity and deforestation in Brazil. Working Paper, Yale University. https://elischolar.library.yale.edu/cgi/viewcontent.cgi?article=2090&context=egcenter-discussion-paper-series

Taylor, Charles. 2023. Irrigation and climate change: long-run adaptation and its externalities. Working Paper, https://drive.google.com/file/d/1aaVxsJMUQCwLy1HtDq5rb4oU2Ixw3srB/view.

Trenberth, Kevin E., Aiguo Dai, Gerard van der Schrier, Philip D. Jones, Jonathan Barichivich, Keith R. Briffa, and Justin Sheffield. 2013. Global warming and changes in drought. *Nature Climate Change* 4: 17-22.

Unfried, Kerstin, Krisztina Kis-Katos, and Tilman Poser. 2022. Water scarcity and social conflict. *Journal of Environmental Economics and Management* 113: 102633

U.S. Geological Survey (USGS). 2012. HYDRO1k Elevation Derivative Database. http://eros.usgs.gov/.

van der Schrier, G., J. Barichivich, K. R. Briffa, and P. D. Jones. 2013. A scPDSI-based global data set of dry and wet spells for 1901-2009. *Journal of Geophysical Research: Atmospheres* 118: 4025-4048.

Verdin, K.L, and J. P. Verdin. 1999. A topological system for delineation and codification of the Earth's river basins. *Journal of Hydrology* 218: 1–12.

Vetter, Thomas, and Anna-Katharina Rieger. 2019. Ancient water harvesting in the Old World Dry Belt – synopsis and outlook. *Journal of Arid Environments* 169: 42-53.

Ward, Philip J., Pauw, Pieter, Brander, Luke M., Jeroen, C.J.H. Aerts, Strzepek, Kenneth M., 2010. Costs of adaptation related to industrial and municipal water supply and riverine flood protection. World Bank Development and Climate Change Discussion Paper Number 6. International Bank for Reconstruction and Development, Washington, DC.

Wells, Nathan, Steve Goddard, and Michael J. Hayes. 2004. A self-calibrating Palmer Drought Severity Index. *Journal of Climate* 17(12): 2335-2351.

World Bank. 2022. The hidden wealth of nations: the economics of groundwater in times of climate change. Technical note describing data on aquifer typologies and groundwater resources. Washington, DC.

Xu, Lei, Nengcheng Chen, and Xiang Zhang. 2019. Global drought trends under 1.5 and 2 C warming. *International Journal of Climatology* 39: 2375-2385.

Zhu, Ye, Yi Liu, Wen Wang, Vijay P. Singh, and Liliang Ren. 2021. A global perspective on the probability of propagation of drought: from meteorological to soil moisture. *Journal of Hydrology* 603, Part A: 126907.

Table 1. Distribution of observations across sc-PDSI and DSI categories

sc-PDSI category	Frequency	Percent	DSI category	Frequency	Percent
Extremely dry	5,954	1.41	Extreme drought	17,122	3.76
Severely dry	24,964	5.91	Severe drought	20,195	4.44
Moderately dry	50,072	11.85	Moderate drought	31,610	6.95
Slightly dry	64,338	15.23	Mild drought	42,423	9.33
Incipient dry spell	39,344	9.31	Incipient drought	54,110	11.89
Near normal	107,962	25.56	Near normal	121,521	26.71
Incipient wet spell	33,085	7.83	Incipient wet spell	55,222	12.14
Slightly wet	45,374	10.74	Slightly wet	45,341	9.97
Moderately wet	32,237	7.63	Moderately wet	32,094	7.05
Severely wet	15,332	3.63	Very wet	19,315	4.25
Extremely wet	3,774	0.89	Extremely wet	15,967	3.51
Total	422,436	100.00		454,920	100.00

Notes: sc-PDSI is the self-calibrating Palmer Drought Severity Index constructed from meteorological data, and DSI is the remotely sensed Drought Severity Index.

Table 2. Main uses of dams in GRanD

Main use	Number	Share
Irrigation	1,781	25.95
Missing	1,577	22.98
Hydroelectricity	1,541	22.46
Water supply	847	12.34
Flood control	547	7.97
Recreation	293	4.27
Other	206	3.00
Navigation	56	0.82
Fisheries	14	0.20
Total	6,862	100.00

Source: Authors' calculations based on data from GRanD (Lehner *et al*., 2011).
Notes: A few dams also have major or secondary uses indicated, but most do not. "Other" includes dams with primary uses of livestock watering and water pollution control, in addition to those labeled in GRanD as "other".

Table 3. Summary Statistics

	Total		Alluv/LS		Other GW		With dam		No dam	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Nighttime lights index	1.984	4.257	1.747	4.141	2.252*	4.368	3.088	5.275	1.370*	3.415
Inverse hyperbolic sine (lights index)	0.524	0.836	0.462	0.809	0.594*	0.860	0.797	0.986	0.372*	0.694
Drought variables										
Drought Severity Index (DSI)	0.000	0.849	0.000	0.859	-0.000	0.839	0.000	0.847	-0.000	0.850
Moderate or worse drought (DSI)	0.153	0.360	0.152	0.359	0.154	0.361	0.153	0.360	0.153	0.360
Self-calibrating PDSI	-0.208	1.818	0.311	1.799	-0.091*	1.832	-0.208	1.818	-0.267*	1.816
Moderate or worse drought (sc-PDSI)	0.176	0.381	0.189	0.391	0.162*	0.369	0.188	0.391	0.170*	0.375
Groundwater variables										
Major alluvial aquifer is maximum share	0.102	0.303	0.192	0.394			0.095	0.294	0.106*	0.308
Local/shallow aquifer is maximum share	0.429	0.495	0.808	0.394			0.468	0.499	0.407*	0.491
Complex aquifer is maximum share	0.370	0.483			0.788	0.408	0.332	0.471	0.391*	0.488
Karstic aquifer is maximum share	0.099	0.299			0.212	0.408	0.105	0.306	0.096*	0.295
Long-term water resource availability (km^3/yr)	0.408	0.597	0.449	0.627	0.361*	0.558	0.518	0.623	0.347*	0.574
Dam variables (including instruments)										
Local dam	0.357	0.479	0.379	0.485	0.333*	0.471				
Local hydro dam	0.167	0.373	0.144	0.351	0.194*	0.395	0.468	0.499		
Reservoir capacity of local dams (km^3)	2726	11336	2499	10788	2984*	11921	7628	17948		
Reservoir capacity of local hydro dams (km^3)	2170	11061	1889	10462	2491*	11694	6074	17850		
Near upstream dam[a]	0.238	0.426	0.255	0.436	0.219*	0.413	0.475	0.499	0.106*	0.308
Near upstream hydro dam[a]	0.066	0.248	0.070	0.256	0.061*	0.238	0.138	0.345	0.026*	0.158
Further upstream dam[a]	0.581	0.493	0.577	0.494	0.584*	0.493	0.786	0.410	0.466*	0.499
Mean slope in sub-basin	1.384	1.832	1.695	2.152	1.030*	1.293	1.715	2.030	1.200*	1.684
Max slope in sub-basin	1.865	2.660	2.325	3.113	1.344*	1.898	2.575	3.345	1.470*	2.086
Number of downstream countries	0.562	1.081	0.677	1.124	0.431*	1.016	0.471	1.023	0.613*	1.109
Number of countries in sub-basin	1.224	0.478	1.273	0.506	1.169*	0.436	1.226	0.497	1.223*	0.466
At least one upstream sub-basin	0.208	0.406					0.163	0.369	0.255*	0.430
Other independent variables										
Population density in 2000 (000/km^2)	59.37	163.6	74.08	195.1	42.71*	115.9	88.75	180.7	43.04*	150.8
Average annual temp, deg C	12.09	11.59	13.63	12.03	10.35*	10.81	13.69	9.77	11.20*	12.40
Observations using sc-PDSI	423,456		249,480		173,460		191,136		232,320	
Observations using DSI	453,444		265,464		185,760		205,740		247,704	

Notes: An observation is a grid-cell-year. Asterisk indicates the t-test for difference in means (with dam vs. no dam, and major alluvial or local/shallow aquifer vs. others) is significant at 0.05. [a]Near upstream dam and further upstream dams summarized only for the subset with at least one upstream sub-basin.

Table 4. Impact of droughts on nighttime lights using remote-sensed DSI, 2000-2011

	(1) DSI	(2) DSI with temperature	(3) DSI binary variable
Moderate or worse drought			-0.009**
			(0.0016)
Extreme drought	-0.018**	-0.013**	
	(0.0029)	(0.0028)	
Severe drought	-0.0093**	-0.0067**	
	(0.0021)	(0.0021)	
Moderate drought	-0.0086**	- 0.0063**	
	(0.0017)	(0.0017)	
Mild drought	-0.0041**	-0.0028*	
	(0.0013)	(0.0013)	
Incipient drought	-0.0028**	-0.0021*	
	(0.0010)	(0.0010)	
Incipient wet spell	0.0016+	0.0012	
	(0.0009)	(0.0009)	
Slightly wet	0.0038**	0.0031*	
	(0.0012)	(0.0012)	
Moderately wet	0.0071**	0.0063**	
	(0.0015)	(0.0015)	
Very wet	0.0099**	0.0087**	
	(0.0019)	(0.0019)	
Extremely wet	0.0139**	0.0118**	
	(0.0031)	(0.0031)	
Grid cell FEs	yes	yes	yes
Continent-year	yes	yes	yes
Temp controls	no	yes	yes
R^2	0.213	0.220	0.219
N sub-basins	6141	6133	6133
N cells	37787	37277	37277
N observations	453444	447324	447324

Notes: Dependent variable is the inverse hyperbolic sine of the DMSP-OLS nighttime lights index. Excluded DSI category is near normal (DSI=0+/-0.29). Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. Temperature controls in all models are a cubic function of the deviation of annual average grid-cell temperature from the grid-cell mean, 2001-2011. All models include fixed effects for cells and continent-year interactions.
$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 5: Impact of drought on nighttime lights using sc-PDSI, 2000-2011

	(1) sc-PDSI	(2) sc-PDSI with temperature	(3) sc-PDSI binary variable
Moderately dry or worse			-0.0081**
			(0.0016)
Extremely dry	-0.0132**	-0.0076+	
	(0.0046)	(0.0046)	
Severely dry	-0.0147**	-0.0111**	
	(0.0025)	(0.0025)	
Moderately dry	-0.0097**	-0.0074**	
	(0.0018)	(0.0018)	
Slightly dry	-0.0044**	-0.0026*	
	(0.0013)	(0.0013)	
Incipient dry spell	-0.0020+	-0.0007	
	(0.0011)	(0.0011)	
Incipient wet spell	0.0029*	0.0020+	
	(0.0012)	(0.0012)	
Slightly wet	0.0042**	0.0029*	
	(0.0014)	(0.0014)	
Moderately wet	0.0040*	0.0029	
	(0.0019)	(0.0019)	
Severely wet	0.0073**	0.0060*	
	(0.0028)	(0.0028)	
Extremely wet	0.0061	0.0040	
	(0.0054)	(0.0054)	
Grid cell FEs	yes	yes	yes
Continent-year	yes	yes	yes
Temp controls	no	yes	yes
R^2	0.217	0.223	0.223
N sub-basins	6044	6040	6040
N cells	35288	35067	35067
N observations	423456	420804	420804

Notes: Dependent variable is inverse hyperbolic sine of nighttime lights index. Excluded sc-PDSI category is near normal (PDSI=0+/-0.49). Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. Temperature controls are a cubic function of the deviation of annual average grid-cell temperature from the grid-cell mean, 2001-2011. All models include fixed effects for cells and continent-year interactions.

$^{+}$ p < .10, * p < .05, ** p < .01

Table 6: Effects of groundwater access on impacts of moderate or worse drought

	(1) No groundwater	(2) Groundwater aquifer type	(3) Groundwater aquifer type & resource
Moderate or worse drought	-0.0095**	-0.0115**	-0.0179**
	(0.0016)	(0.0033)	(0.0034)
Major alluvial * drought		0.0100*	0.0112*
		(0.0049)	(0.0049)
Local/shallow*drought		0.0004	0.0014
		(0.0036)	(0.0036)
Complex*drought		0.0027	0.0038
		(0.0041)	(0.0041)
Groundwater resource* drought			0.0160**
			(0.0030)
R^2	0.220	0.220	0.220
N sub-basins	6132	6132	6102
N cells	37176	37176	36889
Observations	446112	446112	442668

Notes: Dependent variable is inverse hyperbolic sine of nighttime lights index. Drought variable is equal to 1 if annual average DSI drought category is moderate, severe or extreme. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent*year effects, and a constant. Relative to Tables 4 and 5, these models drop all grid cells for which the maximum groundwater aquifer type was missing or unidentified. The three aquifer type coefficients are all relative to the excluded category, which is "karstic."

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 7: Effects of local dams for full set of drought conditions

	(1) Base effects	(2) Interaction with dam
Extreme drought	-0.0140**	0.0017
	(0.0031)	(0.0057)
Severe drought	-0.0101**	0.0074^{+}
	(0.0026)	(0.0043)
Moderate drought	-0.0116**	0.0117**
	(0.0021)	(0.0035)
Mild drought	-0.0071**	0.0094**
	(0.0017)	(0.0027)
Incipient drought	-0.0055**	0.0075**
	(0.0013)	(0.0021)
Incipient wet spell	0.0032**	-0.0044*
	(0.0012)	(0.0019)
Slightly wet	0.0053**	-0.0050*
	(0.0015)	(0.0025)
Moderately wet	0.0061**	0.0004
	(0.0017)	(0.0031)
Very wet	0.0089**	-0.0007
	(0.0024)	(0.0038)
Extremely wet	0.0094*	0.0051
	(0.0037)	(0.0061)
F test all coefficients in column (2) jointly= 0	2.54 p=0.005	
F test coefficients 1-5 in column (2) jointly =0	3.65 p=0.003	
R^2	0.220	
Number of sub-basins	6133	
Number of cells	37277	
Observations	447324	

Notes: Dependent variable is inverse hyperbolic sine of nighttime lights index. Drought index is remote-sensed DSI , with "near-normal" category excluded. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent*year effects, and a constant. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 8: Effects of dams on impacts of moderate-or-worse drought

	(1)	(2)	(3)	(4)
Moderate, severe or extreme drought	-0.0127**	-0.0127**	-0.0135**	-0.0127**
	(0.0019)	(0.0019)	(0.0020)	(0.0019)
Dam* drought	0.0071*	0.0158**	0.0147**	0.0163**
	(0.0038)	(0.0042)	(0.0041)	(0.0041)
Dam reservoir capacity* drought				-0.0001
				(0.0003)
Hydro dam* drought		-0.0175**	-0.0172**	-0.0203**
		(0.0056)	(0.0055)	(0.0060)
Hydro reservoir capacity* drought				0.0003
				(0.0003)
Pop density* drought			0.0202	
			(0.0130)	
R^2	0.220	0.220	0.220	0.220
N sub-basins	6133	6133	6133	6133
N cells	37277	37277	37277	37277
Observations	447324	447324	447324	447324

Notes: Dependent variable is value of nighttime lights index. Drought variable is equal to 1 if annual average DSI drought category is moderate, severe or extreme. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent-year effects, and a constant. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 9: Effects of upstream dams on impacts of moderate-or-worse drought

	(1)	(2)	(3)	(4)
Moderate-or-worse drought	-0.0168**	-0.0172**	-0.0216**	-0.0172**
	(0.0028)	(0.0029)	(0.0037)	(0.0029)
Dam* drought	0.0145**	0.0131*	0.0112+	0.0201**
	(0.0055)	(0.0064)	(0.0063)	(0.0062)
Near upstream dam* drought		0.0038	0.0005	0.0044
		(0.0072)	(0.0074)	(0.0077)
Far upstream dam* drought			0.0101+	
			(0.0486)	
Hydro dam* drought				-0.0149
				(0.0104)
Near upstream hydro* drought				-0.0053
				(0.0132)
R2	0.218	0.218	0.218	0.218
N sub-basins	1980	1980	1980	1980
N cells	7837	7837	7837	7837
Observations	94044	94044	94044	94044

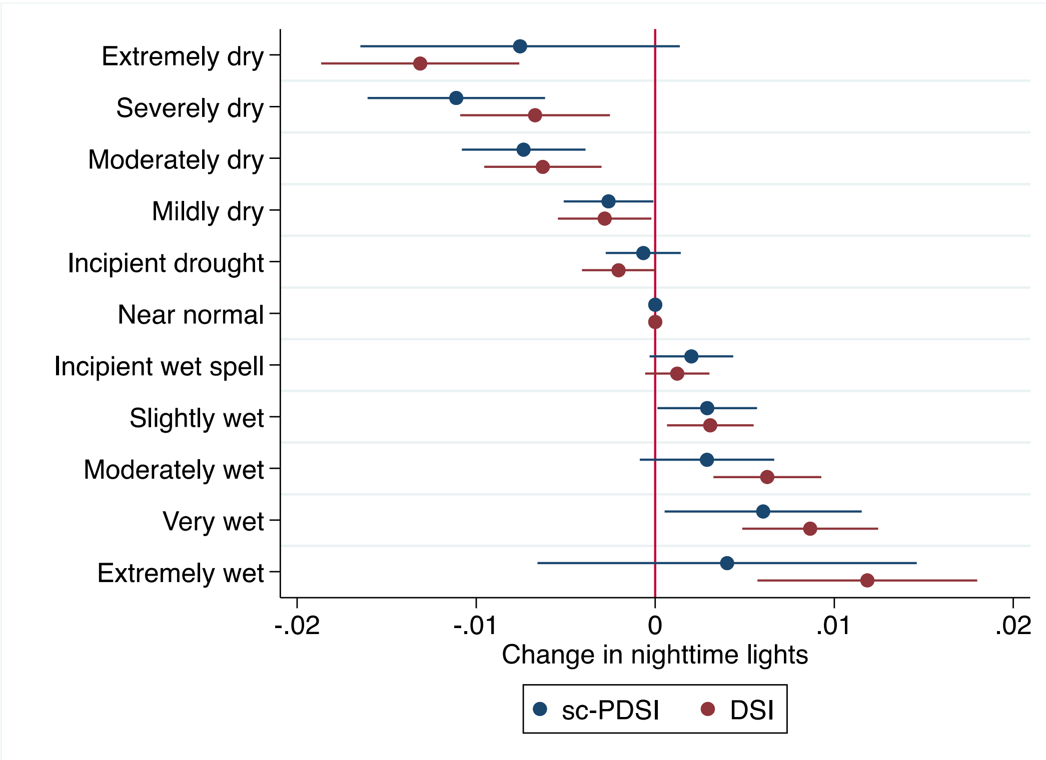
Notes: Dependent variable is value of nighttime lights index. Drought variable is equal to 1 if annual average DSI drought category is moderate, severe or extreme. Standard errors in parentheses are clustered by 4-digit sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent-year effects, and a constant. Restricted to areas with at least one upstream sub-basin. $^{+}$ p < .10, * p < .05, ** p < .01

Table 10. IV estimates of effects of local dams on drought sensitivity

	(1) Geophys IV	(2) Political IV	(3) All IV
Moderate or worse drought	-0.0150**	-0.0116*	-0.0128**
	(0.00541)	(0.00536)	(0.00468)
Dam * drought	0.0121	0.00482	0.00740
	(0.0112)	(0.0113)	(0.00967)
Montiel-Pflueger robust F-test (weak instruments)	28.8	28.1	19.2
Critical value for F with 10% bias	12.0	17.7	19.2
Durbin-Wu-Hausman test	.22	.04	.00
(exogeneity)	(.64)	(.84)	(.97)
Hansen's J test (overidentification)	8.023	3.652	12.1
	(.005)	(.06)	(.007)
N sub-basins	6133	6119	6119
N cells	37277	37262	37262
Observations	447324	447144	447144

Notes: Dependent variable is the inverse hyperbolic sine of the nighttime lights index. Standard errors in parentheses are clustered by 4-digit sub-basin and all tests are cluster-robust. All models include a cubic in the deviation from mean temperature, fixed effects for cells and continent-year effects. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Figure 1. Effects of droughts on lights, two indices compared



Notes: DSI estimates are from Table 4, column 2, and sc-PDSI estimates are from Table 5, column 2. The excluded case for both indices reflects "near normal" conditions: -0.3 to 0.3 for the DSI, and -0.5 to 0.5 for the sc-PDSI.

Figure 2. Effects of moderate or worse drought in prior years

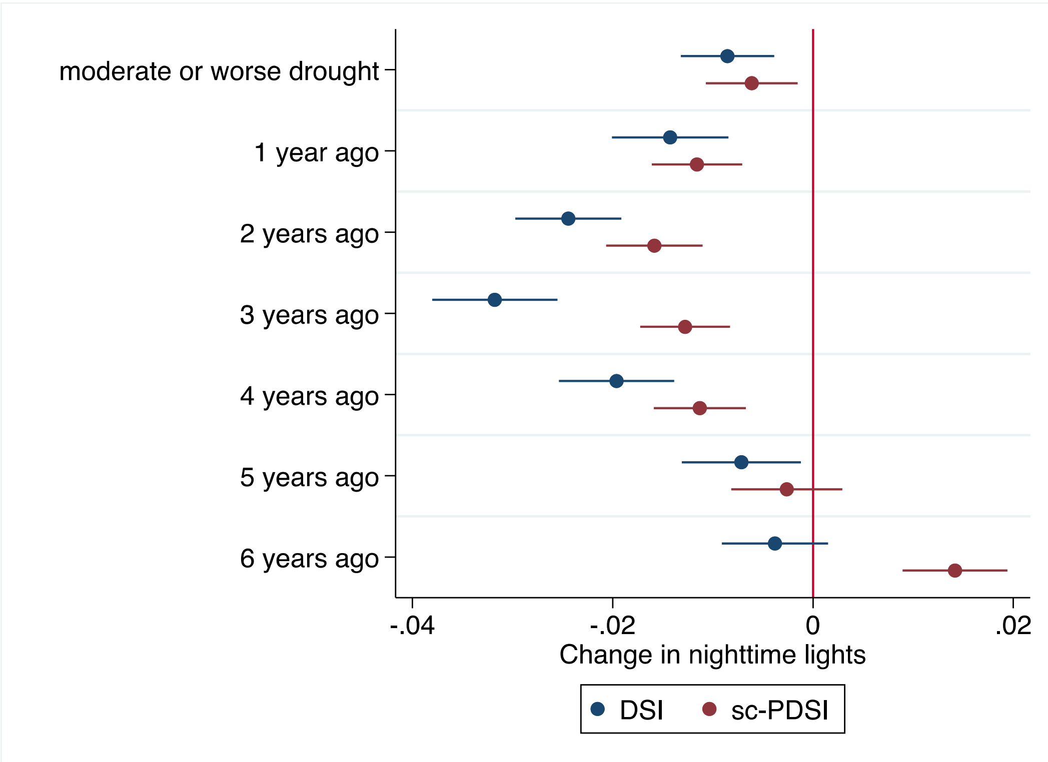
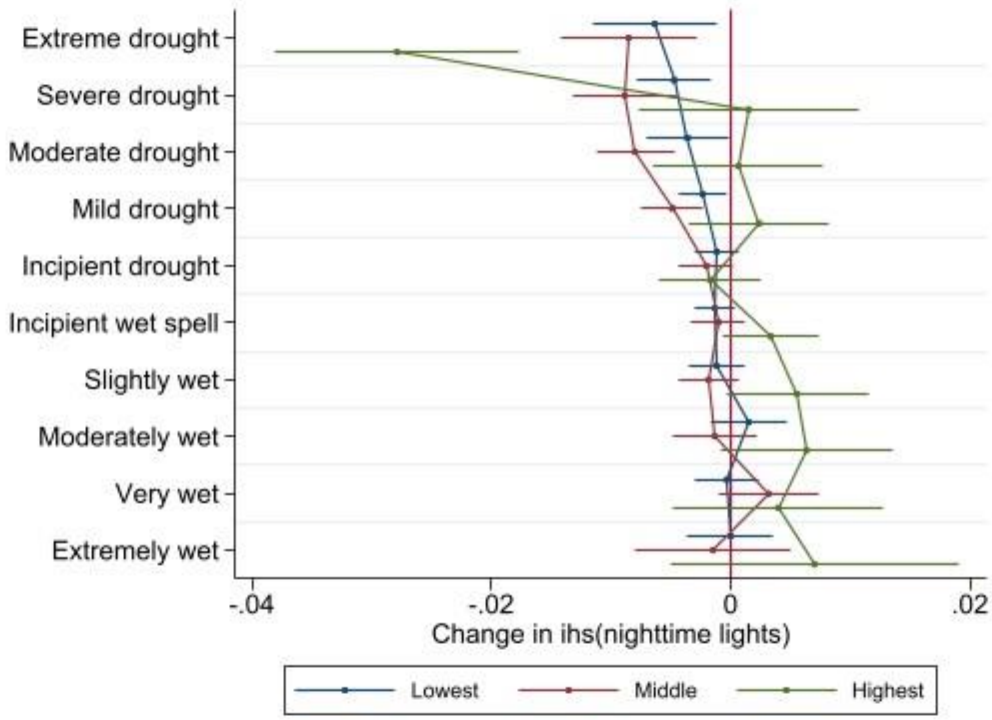


Figure 3. Effects of remote-sensed drought index by initial cropland acreage



Note: Based on estimates of the equation in Table 4 column 2 separately by initial cropland tercile.

Appendix A. Additional results and robustness

Table A1. Groundwater models using sc-PDSI instead of DSI

	(1) No groundwater	(2) Groundwater aquifer type	(3) Groundwater aquifer type & resource
Moderate or worse drought	-0.0081**	-0.0156**	-0.0217**
	(0.0016)	(0.0047)	(0.0049)
Major alluvial * drought		0.0039	0.0055
		(0.0067)	(0.0067)
Local/shallow*drought		0.0112*	0.0124*
		(0.0050)	(0.0049)
Complex*drought		0.0050	0.0062
		(0.0055)	(0.0056)
Groundwater resource* drought			0.0140**
			(0.0036)
R^2	0.223	0.223	0.223
N sub-basins	6040	6040	6010
N cells	35042	35042	34841
Observations	420504	420504	418092

Notes: Dependent variable is inverse hyperbolic sine of nighttime lights index. Drought index is the remote-sensed DSI. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent*year effects, and a constant. Relative to Tables 4 and 5, these models drop all grid cells for which the maximum groundwater aquifer type was missing or unidentified. The three aquifer type coefficients are all relative to the excluded category, which is "karstic." $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A2: Effects of local dams for full set of drought conditions using sc-PDSI

	(1) Base effects	(2) Interaction with dam
Extreme drought	-0.0061	-0.0031
	(0.0052)	(0.0091)
Severe drought	-0.0131^{**}	0.0042
	(0.0029)	(0.0050)
Moderate drought	-0.0125^{**}	0.0109^{**}
	(0.0021)	(0.0036)
Mild drought	-0.0060^{**}	0.0073^{**}
	(0.0016)	(0.0026)
Incipient drought	-0.0022^{+}	0.0033
	(0.0013)	(0.0023)
Incipient wet spell	0.0023	-0.0006
	(0.0015)	(0.0025)
Slightly wet	0.0016	0.0031
	(0.0018)	(0.0030)
Moderately wet	0.0009	0.0046
	(0.0022)	(0.0040)
Very wet	0.0041	0.0043
	(0.0035)	0.0059)
Extremely wet	0.0011	0.0063
	(0.0078)	(0.0107)
F test all coefficients in column (2) jointly= 0	1.62 p=0.094	
F test coefficients 1-5 in column (2) jointly =0	2.61 p=0.023	
R^2	0.223	
Number of sub-basins	6040	
Number of cells	35067	
Observations	420804	

Notes: Dependent variable is inverse hyperbolic sine of nighttime lights index. Drought index is sc-PDSI , with "near-normal" category excluded. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent*year effects, and a constant. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A3: Effects of dams on impacts of drought using sc-PDSI

	(1)	(2)	(3)	(4)
Moderate, severe or extreme drought	-0.0104**	-0.0104**	-0.0091**	-0.0104**
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Dam* drought	0.0047	0.0028	0.0044	0.0023
	(0.0033)	(0.0041)	(0.0041)	(0.0040)
Dam reservoir capacity* drought				0.0001
				(0.0004)
Hydro dam* drought		0.0040	0.0037	0.0031
		(0.0057)	(0.0058)	(0.0061)
Hydro reservoir capacity* drought				-0.0001
				(0.0004)
Pop density* drought			-0.0283^{+}	
			(0.0161)	
R^2	0.220	0.220	0.220	0.220
N sub-basins	6040	6040	6040	6040
N cells	35067	35067	35067	35067
Observations	420804	420804	420804	420804

Notes: Dependent variable is value of nighttime lights index. Drought variable is equal to 1 if annual average sc-PDSI drought category is moderate, severe or extreme. Standard errors in parentheses are clustered by 4-digit Pfafstetter sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent-year effects, and a constant. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A4: Effects of upstream dams on impacts of drought using sc-PDSI

	(1)	(2)	(3)	(4)
Moderate-or-worse drought	-0.0129**	-0.0120**	-0.0174**	-0.0121**
	(0.0033)	(0.0035)	(0.0046)	(0.0035)
Dam* drought	0.0046	0.0072	0.0048	0.0031
	(0.0068)	(0.0066)	(0.0066)	(0.0080)
Near upstream dam* drought		-0.0071	-0.0106	-0.0095
		(0.0080)	(0.0081)	(0.0089)
Far upstream dam* drought			0.0118*	
			(0.0058)	
Hydro dam* drought				0.0094
				(0.0116)
Near upstream hydro* drought				0.0126
				(0.0163)
R2	0.221	0.221	0.222	0.222
N sub-basins	1968	1968	1968	1968
N cells	7768	7768	7768	7768
Observations	93216	93216	93216	93216

Notes: Dependent variable is value of nighttime lights index. Drought variable is equal to 1 if annual average DSI drought category is moderate, severe or extreme. Standard errors in parentheses are clustered by 4-digit sub-basin. All models include a cubic in deviation from mean temperature, fixed effects for cells, continent-year effects, and a constant. Restricted to areas with at least one upstream sub-basin. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A5: IV estimates of effects of local dams using sc-PDSI

	(1) Geophys IV	(2) Political IV	(3) All IV
Moderate or worse drought	-0.0264**	-0.0110	-0.0194**
	(0.00628	(0.00884)	(0.00601)
Dam * drought	0.0376**	0.00590	0.0231+
	(0.0120)	(0.0182)	(0.0125)
Montiel-Pflueger robust F-test	34.6	20.5	16.1
Critical value for 10% bias	9.8	16.5	19.0
Durbin-Wu-Hausman test	9.73	.000	3.40
(for exogeneity)	(.002)	(.95)	(.07)
Hansen's J test	1.06	10.5	11.5
(overidentification)	(.30)	(.001)	(.009)
N sub-basins	6133	6119	6119
N cells	37277	37262	37262
Observations	447324	447144	447144

Notes: Notes: Dependent variable is the inverse hyperbolic sine of the nighttime lights index. Standard errors in parentheses are clustered by 4-digit sub-basin and all tests are cluster-robust. All models include a cubic in the deviation from mean temperature, fixed effects for cells and continent-year effects. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$