Irrigation and Climate Change:
Long-run Adaptation and its Externalities

Charles A Taylor[*†]

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Abstract

As the largest user of global water, irrigated agriculture accounts for 20% of global cropland and 40% of food production. Irrigation is also a potential adaptive response to drought and extreme temperatures. This paper examines the extent to which the current global irrigation footprint reflects climate change over the last 50 years. Utilizing exogenous variation in geological structure, I find evidence that farmers adapt by increasing groundwater irrigation in places that became dryer and hotter. The results hold globally and in the US. Observed recent warming is responsible for 9% of global irrigation growth. GRACE satellite data shows that climate-driven irrigation contributes to aquifer stress, as well as increased soil salinity, thus representing large negative externalities of adaptation to climate change and a potential threat to future food security.

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[†]School of International and Public Affairs and The Earth Institute, Columbia University.
cat2180@columbia.edu

1 Introduction

Irrigation is critical for food security, economic livelihoods, and ecosystem health. It is also the largest user of the world's water: irrigation accounts for 70% of freshwater withdrawals and 90% of consumptive water use, and 43% of consumptive irrigation water use is from groundwater, which is growing fastest in absolute and relative terms (Siebert et al. 2010). This paper examines irrigation's role as an adaptive response to climate change in light of its ability to smooth crop production during drought (Hansen et al. 2011) and reduce the negative impact of extreme temperatures (Schauberger et al. 2017; Siebert et al. 2017; E. K. Carter et al. 2016).

This paper contributes to the climate adaptation literature, which generally has found little evidence of agricultural adaptation in the short or long run (Burke and Emerick 2016; Moore et al. 2017; Auffhammer 2018). This lack of adaptation is despite the well-documented negative impact of warming on agriculture (Mendelsohn et al. 1994; Deschênes and Greenstone 2007; Schlenker and Roberts 2009).

But while most studies have focused on yield responses, there are several other ways to adapt to climate change, including crop choice (Kurukulasuriya and Mendelsohn 2008; Hornbeck 2012), input use and management (Kala 2017), ecological practices (Schulte et al. 2017), and crop insurance (Annan and Schlenker 2015)—in addition to irrigation. Recent work, for example, has shown that heat-related damage to cereal crops has been mitigated by changes in crop choice and irrigation expansion (Sloat et al. 2020). In India, the country with the most irrigated land, farmers respond to monsoon pattern changes with irrigation investments (Taraz 2017).

Accounting for irrigation is important when studying the impact of climate change on agriculture, especially in hedonic analyses (Schlenker et al. 2005; Kurukulasuriya et al. 2011). Since irrigation is often highly subsidized, many US-focused studies limit their analysis to east of the 100$^{\text{th}}$ meridian to avoid irrigation-related complications. Irrigation investment may also reflect farmer perceptions of climate change rather than actual past climate change (Niles and Mueller 2016).

This paper also investigates the relationship between precipitation and adaptation. While extreme temperatures clearly reduce yields, the literature is mixed on the impact of precipitation. Inclusion of precipitation has not, for example, substantially improved statistical yield predictions for corn in the US relative to using temperature alone (Lobell et al. 2013; Schlenker and Roberts 2009). Since water is essential for crop growth, the often-negligible impact of precipitation may be due to several reasons: first, unlike temperature, farmers can manage water availability through investments in irrigation. Second, precipitation is spatially heterogeneous, less precisely measured than temperature, and subject to bias when spatially aggregated (Fezzi and Bateman 2015). Third, precipitation may be a poor proxy of water availability to crops given within season variation (Fishman 2016) and potential losses from runoff, drainage and evaporation. Incorporating soil moisture into models, for example, improves the accuracy of yield predictions (Ortiz-Bobea et al. 2019; Rigden et al. 2020; Proctor et al. 2021). This paper seeks to address these issues by exploring the relationship between irrigation patterns and alternative long-term measures of water availability like soil moisture and the PDSI drought index.

While irrigation increases agricultural land values and mitigates the impact of drought and extreme heat, over time it may facilitate an adjustment toward water-intensive crops and increased climate sensitivity (Hornbeck and Keskin 2014). Given that groundwater is a common pool resource, this increase in irrigation may stress aquifers and reduce water availability in already water-insecure places (Fishman 2018), and there is limited evidence of adaptation to water scarcity (Hagerty 2020). However, these costs can be mitigated by efficient water pricing: an emerging empirical literature demonstrates the substantial welfare gains from water markets (2019; Bruno and Sexton 2020; Rafey 2020; Bruno and Jessoe 2021; Ayres et al. 2021).

Other environmental costs of irrigation include water quality impairment from increased runoff (Brauman et al. 2013). Relatedly, irrigation contributes to soil salination, a major challenge across 7% of the world's land surface (Li et al. 2014; Singh 2015). Salt accumulates in irrigated soils, especially when the water is sourced from groundwater aquifers. Between 25% to 30% of irrigated lands are salt-affected, significantly reducing productivity. Losses from salinity are estimated at $27 billion annually (Shahid et al. 2018). However, in part due to the difficulty in measuring salinity at scale, little economic research has been done assessing the irrigation-salination linkage and its societal costs. This paper seeks to test the potential linkage between irrigation and both groundwater levels and salination using remotely-sensed measures of aquifer withdrawals and salinity levels.

In summary, I find that much of the variation in irrigation expansion, both globally and in the US, can be explained by climate change. Using panel and long-difference approaches over nearly 50 years, I show that irrigation increases more in places that got dryer and hotter. Interacting these climate change variables with geological features, I find the impacts strongest in places with groundwater potential, which is the primary water source for new irrigation. The relationship is similar when utilizing measures of water availability like soil moisture and the PDSI drought index. Further, I provide evidence that relationship cannot be explained by national agricultural policy and subsidies. In total, I estimate that observed recent warming is responsible for 9% of the growth of global irrigated lands from 1960 to 2005 (13.5 million hectares).

Overall these findings suggest farmers partially adapt to climate change [1] through increased groundwater irrigation in the short to medium term. This is consistent with a model of adaptation involving the substitution of natural capital (i.e., climate-driven water availability) for physical capital (i.e., groundwater irrigation infrastructure).

It is worth noting that this paper focuses on farmer decisions regarding groundwater, which is the primary source of marginal irrigation expansion over the last half century. But in many countries (and US states like California), surface water from reservoirs provides the majority of water for irrigation, and these systems can involve inter-basin transfers over long distances. Any such large-scale, often government-driven investments in surface water irrigation infrastructure that are made in response to climate change are not captured in this paper.

In terms of the externalities, this paper shows that groundwater-driven adaptive responses to climate change can have follow-on effects at a global scale. Global aquifer withdrawals driven by irrigation can lead to an unsustainable stress on aquifer commons, as well as higher soil salinity levels, thus representing potential negative externalities of adaptation to climate change.

2 General trends

Global trends and heterogeneity

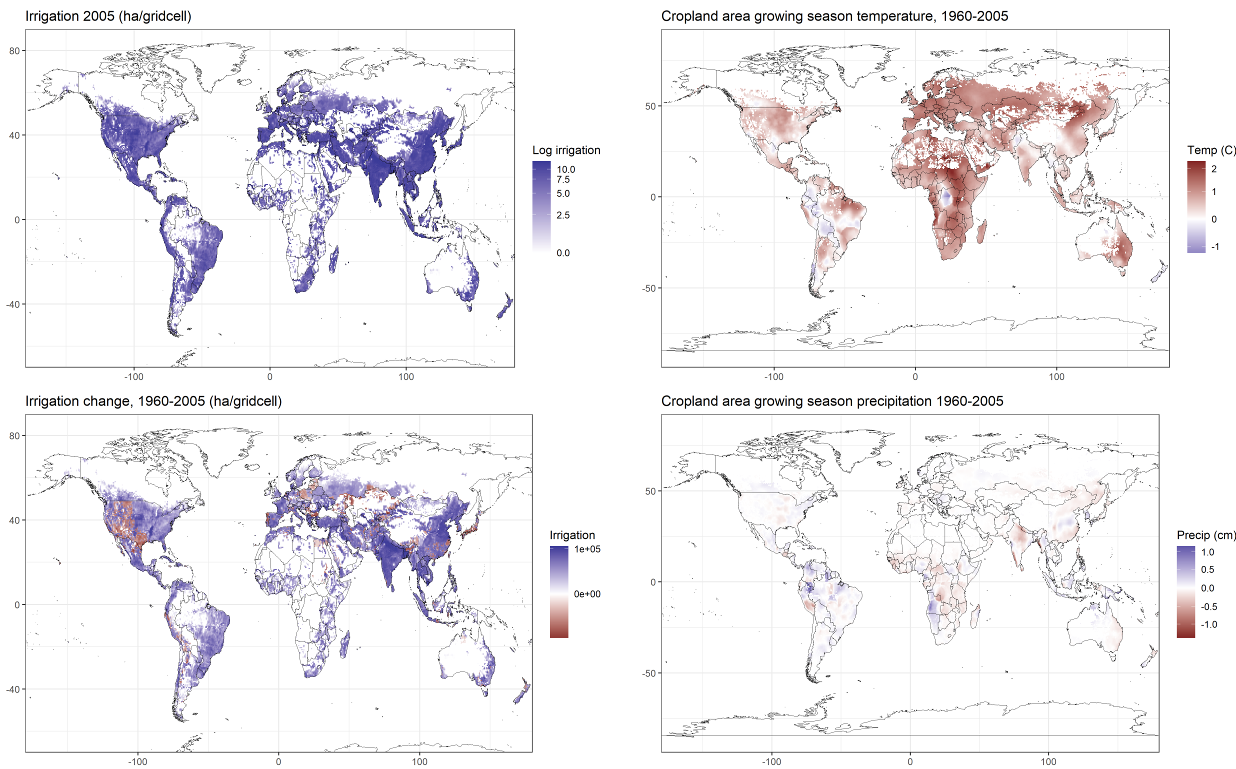
Since 1960, global irrigated lands have more than doubled to 300 million hectares, and now account for 20% of all cultivated lands and 40% of global food production. Figure 1 shows the distribution of irrigated lands globally, as well as the change in irrigated area from 1960 to 2005. India and China have the most irrigated land, while other important regions include Europe, the Middle East, the US, Mexico, and the Southern Cone of Latin America.

There has been widespread growth in irrigated area, particularly in India. But irrigation remained unchanged in many parts of the world. Some areas lost irrigated land, including the Western US, Eastern Europe, Iberia, North Africa, the former USSR, the Andes,

[1] This paper analyzes climate variation since 1960 and cannot differentiate between anthropogenic drivers of climate change and natural ones occurring at the decadal scale (e.g., Pacific Decadal Oscillation).

and parts of China. There is significant variation in irrigation trends within countries and continents.

Figure 1: Global irrigation (left) and climate change (right)



The right panel of Figure 1 displays the change in mean growing season temperature and precipitation across cropland regions from 1960 to 2005 (using five-year averages around the endpoint). Globally, the mean increase was 0.75°C while many regions warmed by over 2°C, as shown in the summary statistics in Table A1. There were small pockets of mild long-term term cooling in each continent. Mean global summer precipitation decreased by 0.29 cm, a smaller amount than temperature relative to the mean. But there is more variation in precipitation change globally and within countries. Central Africa, India, and part of China, for example, experienced strong drying.[2]

US trends and heterogeneity

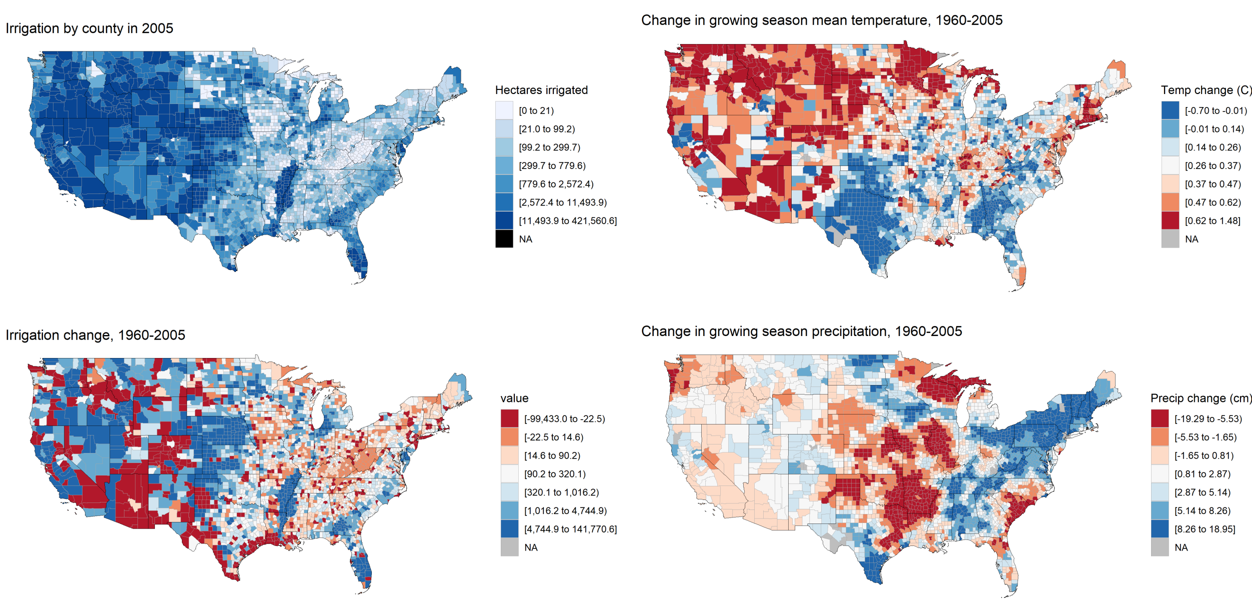
About 24 million hectares (59 million acres) are currently irrigated in the US, with 50% of this water coming from groundwater. Figure 2 shows a significant amount of irrigation occurring in the Great Plains and throughout the West. Other major irrigated regions include the Lower Mississippi and parts of the Cotton Belt. Nebraska has the largest share

[2] While there is a consistent global warming trend, global mean precipitation change can be slightly negative or positive depending on the endpoint (i.e., 2000 or 2010), but never far from zero.

of US irrigated area (15%), utilizing groundwater from the Ogallala aquifer, followed by California, Arkansas, Texas, Idaho, Kansas, Colorado, Montana, and Mississippi. Corn accounts for 25% of irrigated acreage, followed by hay and forage production, soybeans, vegetables, orchard crops, cotton, wheat, and rice (USDA, Irrigation and Water Use).

Irrigation in the US plateaued and began to decline in recent decades, much of this occurring in the Southwest and parts of the West. Exceptions with increased irrigation are parts of the Ogallala aquifer, the Lower Mississippi, and Florida. There is much geographic variation in where irrigation was gained and where it was lost, including within states. In terms of climate, Figure 2 shows the county-level change from 1960 to 2005 (using five-year averages around the endpoint) in mean temperature and precipitation averaged across the growing season on cropland areas. Note that blank or NA values have no cropland area. There has been a clear overall warming trend across the US except in parts of the lower Great Plains and the Southeast. Growing season precipitation, on average, increased in the US, with much of it occurring in the Northeast. Much of the Corn Belt got drier, whereas some northern pockets got wetter. Summary statistics for the US are included in Table A2.

Figure 2: US irrigation (left) and climate change (right)



3 Empirical approach

This paper employs two main specifications: a panel model to estimate medium-term responses at the decadal level, and a long difference model to estimate the overall response over half a century. Both approaches are used in light of the robust discussion in the literature on how to best approximate short- versus long-term impacts of climate change, and by extension, adaptive responses (Mérel and Gammans 2018; C. Carter et al. 2018; Kolstad and Moore 2020).

Panel model

$$\begin{aligned} area_{it} = &\beta_1 temp_{it} + \beta_2 precip_{it} + \\ &\beta_3 temp_{it} * gw_i + \beta_4 precip_{it} * gw_i + \\ &\beta_5 controls_{it} + \alpha_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{1}$$

Long difference model

$$\begin{aligned} \Delta area_i = &\beta_1 \Delta temp_i + \beta_2 \Delta precip_i + \\ &\beta_3 \Delta temp_i * gw_i + \beta_4 \Delta precip_i * gw_i + \\ &\beta_5 \Delta controls_i + \alpha_i + \epsilon_i \end{aligned} \tag{2}$$

The outcome variable, *area*, is irrigated land as a proportion of total land area (or alternatively area in hectares), with i = grid cell for global analysis, and i = county for US analysis. The analysis is limited to grid cells and counties where cropland area is greater than zero. For the panel, time t is the year of interest, which includes decadal values from 1960 to 2000 plus 2005. For the long difference, Δ represents the difference between the end year and the base year (i.e., 2005 and 1960) using a five year average (i.e., period 2000 is the average of 1998-2002) to reduce the likelihood of anomalous years influencing outcomes (Burke and Emerick 2016).

The climate variables, *precip* and *temp*, are averaged over cropland area and the six month growing season. Alternative climate measures of water availability like soil moisture and PDSI drought are also tested in the global analysis in place of precipitation and temperature. *gw* is a time-invariant physical measure of potential groundwater availability, further described later. Both the global and US analysis use 1960 to 2005 as the study period when both climate and irrigation data is available at both scales.

The main source of identifying variation comes from an exogenous measure of groundwater potential, *gw*, which is derived from a gridded global dataset of soil, intact regolith, and sedimentary deposit thicknesses (Pelletier et al. 2016). The main specification uses a binary indicator for whether the location's thickness is greater than 30 meters, which corresponds to the top quartile of observations (25% of locations have thickness levels greater than 30 meters). A map of the distribution is shown in Figure A1 (global) and Figure A2 (US), which correlates closely with the distribution of groundwater aquifers in Figure A3.

Like most econometric studies of the impacts of climate change, this approach assumes that changes in temperature and precipitation over time are random across space. Otherwise, estimates may be biased if variation in climate change is correlated with some other variable affecting the irrigation-related outcome of interest. Figure A6 plots each global grid cell by mean temperature change and precipitation change from 1960 to 2005. The bottom panel shows results for US counties. Significant regional differences exist, and while most places warmed, there is a less obvious pattern in precipitation. Overall there is little correlation between changes in temperature and precipitation, both at the global and US level, which is reassuring from an identification standpoint. A robustness check rules out the possibility that a spurious relationship between climate and agricultural policy is driving irrigation results.

One may also be concerned that the causal arrow flows the other way: that irrigation affects climate. There is evidence that irrigation expansion reduces temperatures and increases precipitation at a local level due to irrigation's impact on evapotranspiration and the water cycle (Lobell et al. 2008; DeAngelis et al. 2010; Mueller et al. 2016). However, this dynamic in which irrigation is positively associated with water availability is the opposite of what is seen in the data, and would bias coefficients downward, thus acting as a lower bound.

Temperature and precipitation serve as proxies for crop water availability, which ultimately drives crop yield and thus adaptive irrigation decisions. Figure A7 shows the correlations between long-term changes in climate variables including temperature, precipitation, PDSI drought index, soil moisture, and evapotranspiration (ET).[3] In line with the climatological literature, precipitation change is positively correlated with these measures of water availability, and temperature change is negatively correlated, albeit less strongly. The relationship is empirically tested in the next section: if irrigation increases in places that got

[3] PDSI measures the departure from the local average of atmospheric moisture. ET is the transfer of water from land to the atmosphere from evaporation and transpiration, which is related to potential evapotranspiration (PET) which measures the atmospheric demand for moisture assuming no water limitation. Both ET and PET are affected by soil depth and ground cover.

hotter and drier, one would also expect to see irrigation expansion where soil moisture declined or drought increased.

4 Data

Historical irrigation data come from a global gridded dataset of area equipped for irrigation from 1900 to 2005 (Siebert et al. 2015). The dataset was compiled from sub-national irrigation statistics and combined in a rule-based manner with different datasets on the historical extent of cropland and pasture. Information on historical climate trends is not an input in the irrigation mapping methodology, which mitigates concerns that the irrigation dataset is endogenous to recent climate change patterns. I rescale the data from 5 arcmin resolution (0.08 degrees) to 0.5° resolution.

Land use and cropland extent data are available at a 0.5° resolution from the HYDE historical gridded dataset as compiled by NOAA's National Climatic Data Center (Klein Goldewijk et al. 2011; Meiyappan and Jain 2012).

Global climate data come from University of Idaho's TerraClimate gridded 0.5 degree monthly dataset from 1958 to the present (Abatzoglou et al. 2018). Google Earth Engine was used to compute six-month summer growing season averages over cropland areas at different annual time periods. Variables available include temperature, precipitation, evapotranspiration, PDSI drought index, and soil moisture. Temperature is thus the mean summer in degrees Celsius, and precipitation is the average of each month's cumulative precipitation in centimeters over the summer months.

Groundwater potential is derived from a gridded global dataset of soil, intact regolith, and sedimentary deposit thicknesses (Pelletier et al. 2016), rescaled to 0.5° resolution. This product estimates the thickness of the layers above unweathered bedrock that control hydrologic and biogeochemical responses of landscapes. Places with shallow bedrock are less likely to contain aquifers. The measure ranges from 0 to 50 meters, which is the maximum value for depths greater than 50 meters. Areas with greater thickness (i.e., over 30 meter) are more likely to have extractable groundwater. To confirm this, Figure A4 plots a LOESS (i.e., local regression) line over a scatter plot of all grid cells by FAO's estimate of area equipped for groundwater irrigation and soil/sedimentary thickness. There is an increasing relationship, with a kink around 30 meter, implying that the potential for groundwater irrigation increases around this point. In a robustness check, the climate measures are interacted with soil thickness quartiles rather than an indicator.

Global groundwater aquifer locations were from UNESCO's Worldwide Hydrogeological Mapping and Assessment Programme (Richts et al. 2011).

Groundwater withdrawal estimates are derived from GRACE Tellus Monthly Mass Grids (Swenson 2012), which provide monthly gravitational anomalies in terms of Equivalent Water Thickness representing deviations of mass in terms of vertical extent of water. Using Google Earth Engine, estimates of the first two years and last two years of the dataset spanning 2002 to 2016 were calculated from the average monthly estimates of CSR (U. Texas/Center for Space Research), GFZ (GeoForschungsZentrum Potsdam), and JPL (NASA Jet Propulsion Laboratory), and then rescaled to 0.5° resolution.

Soil salinity is derived from a remote sensing product (Ivushkin et al. 2019) that utilizes a random forest algorithm to estimate soil salinity based on silt content, clay content, pH in H2O, cation exchange capacity, bulk density, organic carbon content, as well as the annual Landsat thermal band anomaly. Global maps are produced for 1986, 2000, 2002, 2005, 2009, and 2016 with an out-of-sample validation accuracy of 67–70% based on ground truth samples.

Country-level estimates of agricultural subsidies are utilized from the World Bank's 'Distortions to Agricultural Incentives' database, specifically the Relative Rate of Assistance to farmers in 75 countries (Anderson et al. 2013).

For the US, county-level land use, agriculture, and irrigation data come from USDA's historical census and National Agricultural Statistics Service (NASS). Decadal averages were computed using the census values immediately prior and following the year of interest. Groundwater aquifer maps and depletion rates come from the U.S. Geological Survey (Konikow 2013). County-level socioeconomic data come from the US Bureau of Economic Analysis. The earliest year available is 1969. Climate data come from PRISM's gridded daily dataset and values are averaged across the six-month summer growing season and over county cropland area (Schlenker and Roberts 2009).

A comparison of the global gridded irrigation data with USDA administrative data on irrigation at the county level helps validate the global dataset and ensure the comparability of the US and global results. Figure A5 shows scatter plots for the two different measures of county-level irrigation as a proportion of land area. There is a strong correlation: 0.87 in 1960, 0.98 in 2005, and 0.88 for the change in irrigated area between 1960 and 2005. Note that there is comprehensive and consistent agricultural reporting in the US, so the correlations may not be as high in other countries.

The resulting US dataset includes over 3,000 counties. The global dataset is gridded at

0.5° resolution, with an average grid cell of 50 x 50km, or 2,500km^2 which equates to about 250,000 hectares of land. For comparison, this scale is close to that of US counties which have a median area of 1,700 km^2 and a mean of 3,000km^2 (the distribution is right-skewed due to the presence of several large counties in the US West). Globally, there are 35,600 observations representing grid cells with at least some cropland. Summary statistics for the gridded global dataset are in Table A1 and for US counties in Table A2.

5 Results

Table 1: Decadal Panel (Global): Climate change impact on irrigation, 1960-2005

	Dependent variable:					
	Irrigated area (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	−0.006**	−0.008***	−0.009***	−0.026***	−0.031***	−0.032***
	(0.002)	(0.002)	(0.003)	(0.008)	(0.009)	(0.010)
Precipitation	−0.022**	−0.012**	−0.018**	−0.096**	−0.040**	−0.042**
	(0.010)	(0.005)	(0.007)	(0.040)	(0.018)	(0.019)
Temperature:Groundwater		0.007**	0.012**		0.017**	0.018**
		(0.003)	(0.005)		(0.008)	(0.009)
Precipitation:Groundwater		−0.040*	−0.078**		−0.182***	−0.195***
		(0.023)	(0.038)		(0.061)	(0.062)
Weights				Cropland	Cropland	Cropland
Sample			Irrigated			Irrigated
Grid FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	213,576	213,576	148,806	213,576	213,576	148,806
R^2	0.921	0.921	0.921	0.931	0.933	0.933

Notes: Linear regression. Dependent variable is irrigated area as a proportion of total land area in the grid cell. Temperature is average degrees Celsius over growing season. Precipitation is in meters summed over summer growing season. Regression weights based on cropland area in grid cell. Groundwater dummy if sediment thickness over 30m. Sample 'Irrigated' only includes grid cells with some irrigation at any point from 1960 to 2005. Standard errors clustered at the Koppen climate level.

Decadal panel

The regression output of the decadal panel analysis is shown in Table 1 for global grid cells and Table A3 for US counties. Columns (1) and (4) of both tables regress the pro-

Table 2: Long Difference (Global): Climate change impact on irrigation, 1960-2005

	Dependent variable:					
	Irrigation change (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	−0.015***	−0.005	−0.019***	−0.009***	−0.011***	−0.003
	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.002)
Precip change	−0.048**	−0.008	−0.019*	0.020*	−0.010	0.014
	(0.021)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)
Temp change:Groundwater			0.010**	0.012***	0.007**	0.009***
			(0.004)	(0.004)	(0.003)	(0.003)
Precip change:Groundwater			−0.110*	−0.095*	−0.093*	−0.085*
			(0.059)	(0.049)	(0.053)	(0.047)
Country FE		YES		YES		YES
Add'l Controls					YES	YES
Observations	35,616	35,616	35,616	35,616	35,616	35,616
R^2	0.027	0.301	0.043	0.315	0.244	0.396

Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Standard errors clustered at the Koppen climate level.

portion of the land that is irrigated on decadal mean temperature and precipitation levels. Columns (2) and (5) include climate interactions with the exogenous indicator of the groundwater potential, as measured by soil and sedimentary deposit thickness as shown in Figure A1 (global) and Figure A2 (US). Since most recent irrigation is sourced from groundwater (given that riparian systems have long been irrigated), the impacts of climate change should be greatest on places with groundwater potential. For robustness, columns (3) and (6) only include locations with some level of irrigation, and columns (4)-(6) weight the regression by cropland area.

A clear pattern emerges in both the global and US analysis. In areas with groundwater potential, irrigation increases in places that got hotter and drier.[4] It is worth noting that the signs flips for temperature with the inclusion of the interaction term. Overall temperature is negatively correlated with irrigation, which could reflect a reduction in overall cultivated area in response to extreme heat. But in places with groundwater, the relationship is positive. Further, the precipitation coefficient diminishes (and in the case of the US analysis becomes less significant) after including the groundwater interaction, implying that the relationship is limited mainly to places with the capacity to irrigate. Finally, the effect sizes are larger when weighting by cropland area or when limiting observations to those with some level of historical irrigation.

Long difference

The long difference analysis in Table 2 provides an alternate specification to test the longer-term response function between irrigation and climate (replicated for the US in Table A4). This is relevant because it may take over a decade for agents to become aware of local climate trends, in addition to the fact that medium-term changes in climate often reflect oceanic oscillations rather than human-driven climate change (Latif and Barnett 1994).

The same variables are used in the panel analysis, except with the computation of the cross-sectional change of each one. Columns (1) and (2) only include the climate change terms, and columns (3)-(6) include the interaction with groundwater potential. Fixed effects for geographic units are included in Columns (2), (4), and (6) to test for within-country (global) or within-state (US) variation. Finally, columns (5) and (6) control for possible confounders that may drive changes in the intensity and extent of agricultural cultivation. For the global analysis, these include population change and irrigation change in the neighboring grid cells, and for the US analysis, population change and income change

[4] For temperature change in the global analysis, Models (5) and (6) show that the loss in overall irrigated land attributable to warming is only partially offset by increased irrigation in areas with groundwater available. In the US, there is a net gain in irrigated lands in all models after accounting for groundwater.

at the county level. The results are consistently similar to the panel analysis. Among places with groundwater potential, irrigation increased (or decreased less) where it got hotter and drier.

For context, Table A5 replicates Table 2 except with cropland as the outcome variable. Cropland area does seem to respond to changes in climate, gaining in places that got less hot and more dry (the latter effect being in line with Zaveri et al. 2020). However, there is no differential effect in areas with groundwater potential. Likewise, controlling for cropland change in the irrigation regressions does not materially affect the results. But since change in cropland area is likely endogenous to irrigation decisions, it is omitted as a control in the main models.

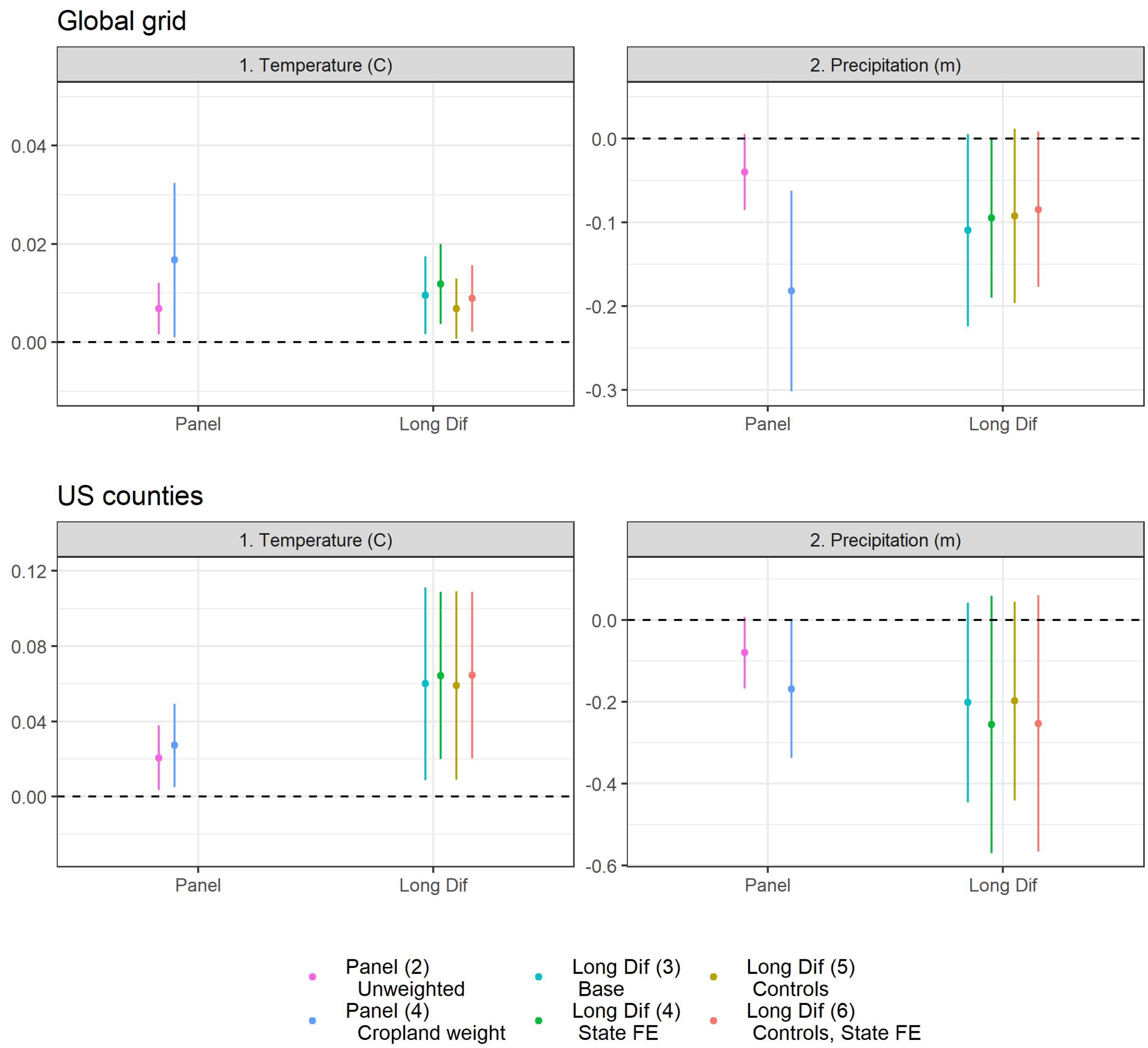
Figure 3 plots the climate-groundwater interacted coefficients from the global panel (Table 1) and long difference (Table 2). The bottom panel shows US results based on Table A3 and Table A4. In terms of marginal magnitudes, in places with groundwater potential, a 1°C increase in temperature reduces the proportion of irrigated land by [0.01 to 0.02] (global) and [0.02 to 0.06] (US). For precipitation, a decrease of one meter (100 cm) is associated with an increase in the proportion of irrigated land by [0.04 to 0.18] (global) and [0.08 to 0.2] (US).

The standard deviation of long-term temperature change is 0.49°C globally (Table A1) and 0.3°C in the US (Table A2). Thus a one standard deviation change equates to a percentage point change in the proportion of irrigated land of [0.3 to 0.9] (global) and [0.6 to 1.8] (US). Likewise, a one standard deviation change in long-term precipitation is 11.5 cm (global) and 6.5 cm (US). This equates to a percentage point change in the proportion of irrigated land of [0.5 to 2.1] (global) and [0.5 to 1.3] (US).

For context, the average grid cell has 250,000 hectares of land, and there are 36,000 grid cells containing cropland across the global sample, of which 25% are assigned groundwater potential, equating to about 2.3 billion hectares. Thus a 1% change in the proportion of irrigated land would equate to 23 million hectares, or about 8% of total irrigated land of 300 million hectares, and 16% of irrigation growth since 1960.

Table A6 shows another way to contextualize these results using the estimates of change in hectares of irrigation, as opposed to proportion of land, as the outcome variable. For the global analysis, in areas with groundwater potential (25% of the the 36,000 grid cells), a one standard deviation change in temperature (0.49°C) and precipitation (11.5 cm) is a associated with 1,000 and 2,900 additional hectares, respectively, of irrigated land on average. Multiplying these values by the 9,000 grid cells with cropland and groundwater

Figure 3: Climate-groundwater interaction coefficients



gives an estimate of 9 to 26 million additional hectares, or 3-9% of total global irrigation, which equates to 6-17% of 150 million hectares of new irrigation since 1960.

Historically, the climate dataset used in this paper shows, on average, 0.75°C in observed warming from 1960 to 2005. This implies that 13.5 million hectares of irrigation, or 9% of marginal irrigation, was a response to recent warming.

5.1 Extensions

Crop water availability

Given that temperature and precipitation both factor into water availability, the next analysis tests the relationship between irrigation and more direct measures water availability: soil moisture and the PDSI drought index. Table A7 shows the regression results. Since soil moisture and drought are highly correlated as shown in Figure A7 (note that a higher PDSI index means less drought conditions), it makes sense that declines in these water availability measures result in increased irrigation in places with groundwater potential. Figure 4 compares magnitudes of these coefficients after normalizing them to one standard deviation with those from the main model that uses temperature and precipitation. Change in soil moisture has the largest effect on irrigation extent, but one largely in line with precipitation change.

Figure 4

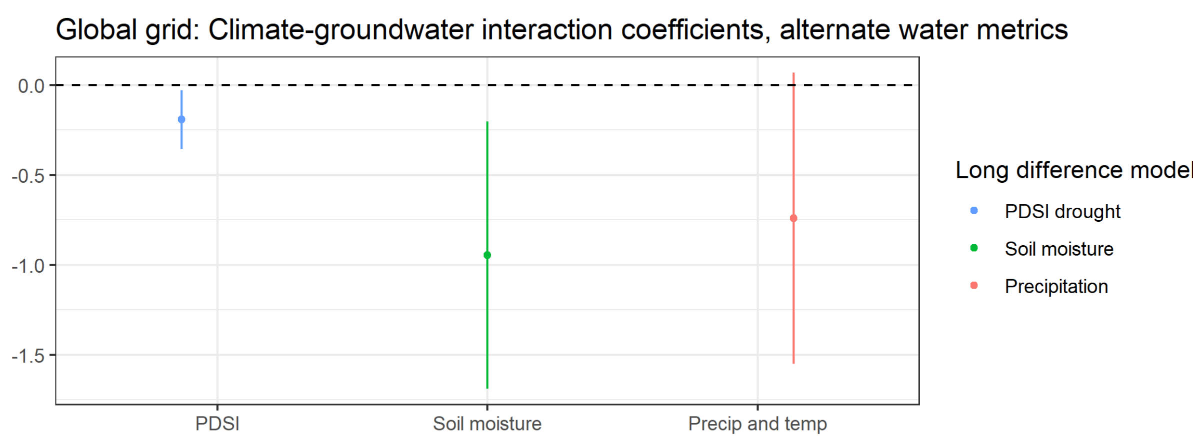


Figure 5: Coefficients are normalized to a one standard deviation change over time.

Subsidies and technological change

Irrigation investment is often driven by agricultural policy via subsidized inputs to farmers (e.g., water, electricity) or prices of farm products that require irrigation. The link between irrigation growth and climate may be spurious if agricultural subsidies tended to increase more in places experiencing climate change. To test this, I draw on an approach to estimating the impact of agricultural market distortions on water resources (Carleton 2021) that uses the World Bank's Relative Rate of Assistance (RRA) to farmers as a proxy for country-level irrigation subsidies (Anderson et al. 2013). RRA is computed as:

$$RRA = (1 + NRA_{agtrad})/(1 + NRA_{nonagtrad}) - 1,$$

where NRA_{agtrad} is the country-level subsidy rate of primary agricultural products (production-weighted by value) and $NRA_{nonagtrad}$ is similarly the subsidy rate of the country's non-agricultural, tradable products. Therefore, a higher RRA implies that a country is subsidizing the agricultural sector relatively more and its non-agricultural sector.

RRA change is calculated over time using the average RRA from 1960-1970 as the starting point and 2005 as the end point. I use a broad window from 1960-1970 for the starting point to increase the number of countries included (many countries do not enter the World Bank database until the mid-1960s, and early-on many countries do not have annual entries). However, the dataset starts in 1955 and using a pre-period range of 1955-1965 yields similar results.

Regression results are in Table 3, which is similar in setup to the long difference specification in Table 2 plus the inclusion of RRA change as a control. The number of observations drops in half reflecting the subset of countries with RRA data. Column (1) shows the positive relationship between the change in RRA and change in irrigation. For reference, a one-standard deviation in RRA change across countries, 0.32, equates to a 1.4 percentage point increase in the proportion of irrigated land. Columns (2)-(7) include the climate change variables. The estimates of the irrigation response to warming and drying in places with groundwater potential remain largely unchanged after controlling for change in agricultural subsidies. Note that country-level fixed effects are excluded from this analysis because the agricultural subsidy measure varies at the country level.

Conley standard errors

A major concern in spatial econometrics is spatial correlation, especially when dealing with gridded data. Adjacent locations are likely to have similar agricultural practices and to experience similar climate shocks. Table A8 adjusts the standard errors for correlation across space using an autocorrelation consistent (HAC) estimator (Conley 1999). For comparison, columns (1) and (4) are identical to columns (5) and (6) in Table 2, which is the global long difference model that controls for neighboring changes in irrigation. Columns (2) and (5) allow standard errors to be correlated up to 500km in space, and columns (3)

Table 3: Long Difference (Global): Climate change impact on irrigation, 1960-2010, controlling for agricultural subsidies

	Dependent variable:						
	Irrigation change (proportion of land area)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RRA Subsidy Change	0.044***		0.039***		0.040***		0.021***
	(0.013)		(0.012)		(0.012)		(0.008)
Temp change		−0.015*	−0.010	−0.020**	−0.015*	−0.011**	−0.008*
		(0.009)	(0.009)	(0.008)	(0.008)	(0.005)	(0.005)
Precip change		−0.104***	−0.089***	−0.053**	−0.036**	−0.030	−0.022
		(0.037)	(0.031)	(0.021)	(0.019)	(0.019)	(0.018)
Temp change:Groundwater				0.016**	0.017**	0.010	0.011*
				(0.008)	(0.008)	(0.006)	(0.006)
Precip change:Groundwater				−0.195**	−0.200**	−0.177**	−0.180**
				(0.091)	(0.089)	(0.086)	(0.085)
Add'l Controls						YES	YES
Observations	18,814	18,814	18,814	18,814	18,814	18,814	18,814
R^2	0.049	0.037	0.073	0.068	0.106	0.275	0.285

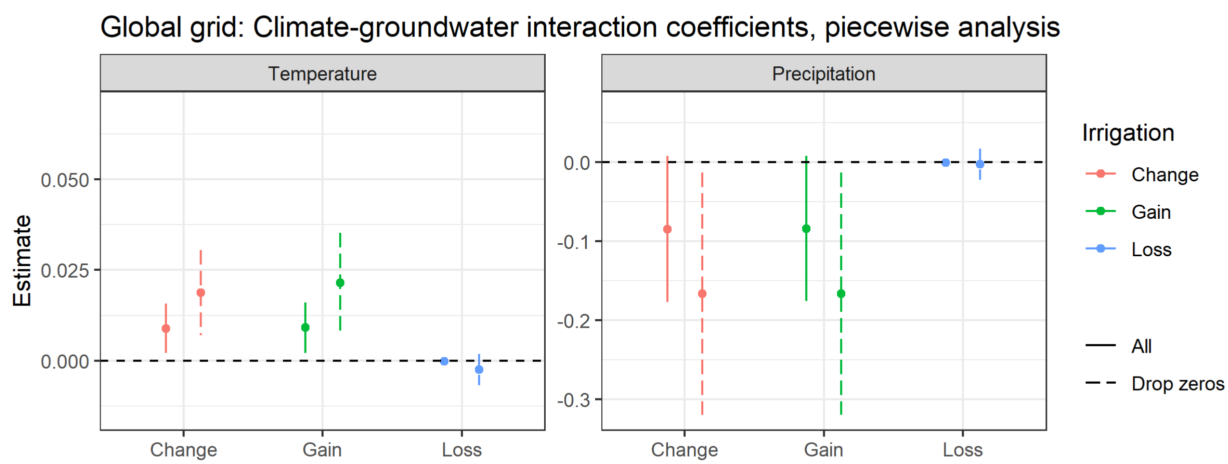
Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. RRA Subsidy Change is the change in the World Bank's Relative Rate of Assistance at the country-level to farmers between the 1960s mean and 2005 level. Additional controls include population change and irrigation change in neighboring grid cells. Observations restricted to grid cells in countries wth available RRA data. Standard errors clustered at the Koppen climate level.

and (6) set the cut off at 1,000 km. This Conley treatment increases the magnitude of the standard errors in most cases, but it does not materially change the significance of the coefficients.

Piecewise analysis

Another question is whether the observed effect is driven by investments in irrigation (increases) as opposed to abandonment of irrigation infrastructure (decreases). To test this, Table A9 shows results from a piecewise analysis separating out irrigation gain from loss. The climate-driven effect is only relevant for irrigation gain. These coefficients are plotted in Figure 6. These results make sense in light of the high fixed costs of installing irrigation, making it unlikely that farmers would abandon or disassemble irrigation infrastructure in response to marginal changes in climate.

Figure 6



Groundwater measure

Another concern is that this paper's results are driven by the particular cut off of soil/sedimentary thickness (30 meter) used to construct the indicator of groundwater potential. Table A10 is based on the main model but includes an interaction with quartile of soil thickness. Across specifications, the effect of temperature and precipitation change on irrigation increases with soil thickness level.[5]

I also run the US analysis just for counties east of the 100th in Table A11 and see similar, albeit less precise, results.

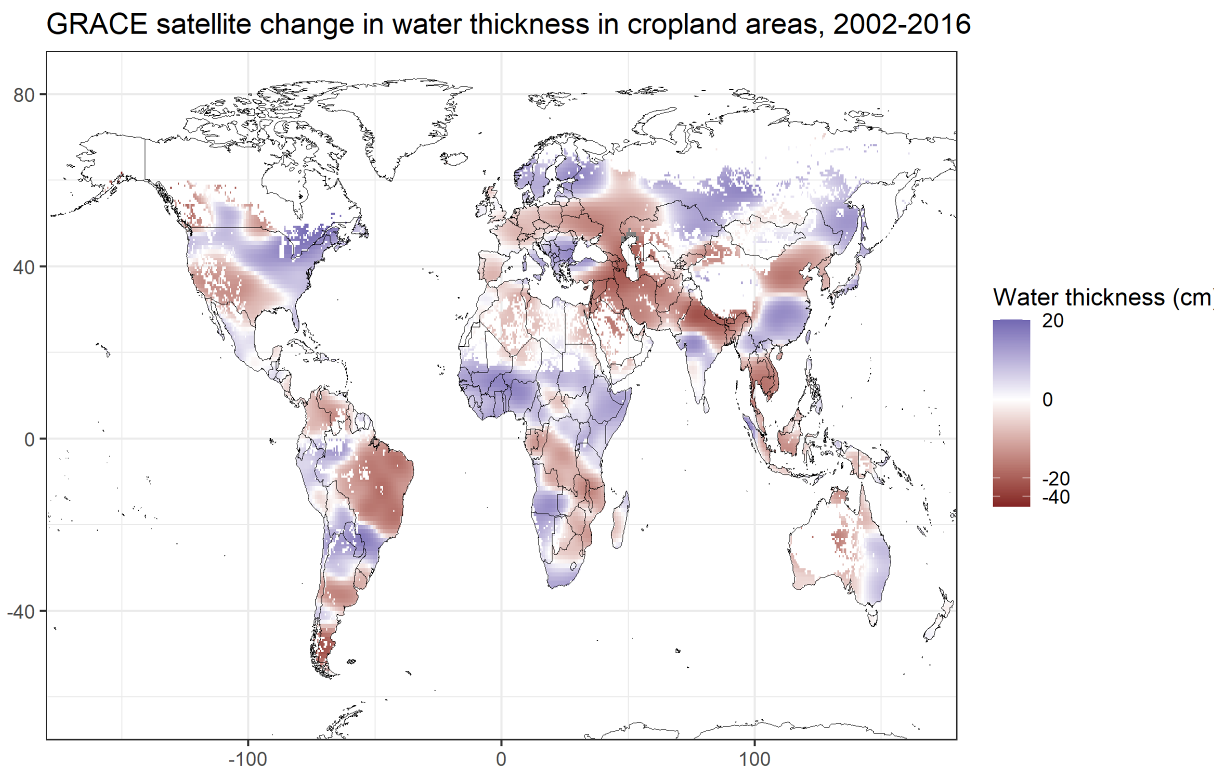
[5] Note an interaction with a continuous geological measure is not used because the gridded product is capped at 50 meters.

6 Externalities

6.1 Aquifer depletion

Next I analyze whether these changes in irrigated area affect global aquifer levels. I regress change in aquifer depth derived from the GRACE satellite on change in irrigation as well as precipitation and temperature. The measure of aquifer withdrawal is the change in equivalent water thickness from GRACE between 2002/2003 and 2015/2016, which are the endpoints of when the satellite was operational). Figure 7 is a map of the change in aquifer thickness during this time.

Figure 7



Regression results are shown in Table 4. Irrigation change is measured as the change in the irrigated proportion of total land area per grid cell from 1960 to 2005 (same as the main specification). The sample is restricted to grid cells with at least some level of irrigation from 1960 to 2005. Columns (1)-(2) show just the relationship between irrigation and aquifer levels. The remaining columns account for concurrent temperature and precipitation change as controls. Columns (3)-(4) show that temperature increase is negatively associated with aquifer levels while precipitation increase is positively associated, as

Table 4: Long Difference (Global): Irrigation impact on GRACE aquifer levels, 2002-2016

	Dependent variable:							
	Change in Equivalent Water Thickness (cm)							
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Irrigation change	−22.34***	−12.59***	−24.81***	−13.64***	−23.98	−41.73**	−19.41	−29.58**
	(5.05)	(4.01)	(4.93)	(3.73)	(20.41)	(17.86)	(13.46)	(12.44)
Temp change			−2.31***	−2.59***	−2.30***	−2.83***	−1.58*	−2.13**
			(0.76)	(0.87)	(0.73)	(0.84)	(0.94)	(0.99)
Precip change			0.04***	0.04***	0.04***	0.04***	0.06***	0.06***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Country FE		YES		YES		YES		YES
Only irrigated							YES	YES
F-stat (1st stage)								
**Cluster Lat-Lon					14.8	14.8	21.7	19.7
**Cluster Koppen					4.2	3.7	4.9	5.6
Observations	35,561	35,561	35,561	35,561	35,561	35,561	23,602	23,602
R^2	0.04	0.39	0.09	0.42	0.09	0.38	0.09	0.43

Notes: Linear regression. Dependent variable is change in GRACE's equivalent water thickness (cm) from 2002 to 2016. Irrigation change is change in irrigated proportion of grid cell from 1960 to 2005. Sample restricted to grid cells with non-zero irrigation at some point from 1960 to 2005. Temperature is change in average degrees Celsius over growing season from 2000 to 2015. Precipitation is change in meters summed over summer growing season from 2000 to 2015. Instruments are temperature and precipitation change from 1960 to 2000 and their interactions with the groundwater indicator. Standard errors clustered at the Koppen climate level.

expected: rainfall recharges aquifers and high temperatures increase evapotranspiration, which stress aquifers. Increased irrigation reduces aquifer levels across all specifications, both globally and within country. Columns (5)-(8) use the prior period's climate change from 1960 to 2000 and its interaction with the groundwater indicator as an instrument for irrigation change, with Columns (7)-(8) dropping grid cells without any irrigation.

The first-stage is akin to the main models that regress irrigation on climate. The IV coefficients are larger but less precise. The first stage F-statistics for the excluded instruments are included in the table. Standard error clustering by Koppen climate zone leads to potentially weak instruments, but clustering by latitude and longitude produces F-statistics well above 10. Note a one standard deviation in irrigation change from 1960 to 2005 among pixels with positive irrigation is 6.4% of land area per grid cell, or 16,100 hectares on average. This would equate to an reduction in aquifer levels by 0.8 to 2.7 cm in equivalent water thickness, which is relative to the average reduction in aquifer levels among grid cells with irrigation of 1.5 cm with a 6 cm standard deviation.

6.2 Soil salination

Next I test whether changes in irrigated area have an impact on soil salinity levels. Figure 8 shows current salinity levels (top) and change in salinity levels (bottom) from 1986 to 2016, which is the period encompassing the dataset. The maps are masked across grid cells containing cropland. High salinity levels are apparent across Ethiopia, an agriculturally-dependent country facing well-documented soil salination challenges (Qureshi et al. 2018). High salinity levels can also be observed in the highly-irrigated Indian subcontinent, in particular Northwest India (Datta and De Jong 2002). Other regions with well-known salination problems can be seen, including Mexico and the western US, the Middle East, the Mediterranean, and northeastern China (Shahid et al. 2018).

Similar in structure to the aquifer analysis, Table 5 regresses grid cell-level change salinity on change in irrigated area and change in climate. Columns (1)-(2) show just the relationship between irrigation and salinity levels. Columns (3)-(4) include climate controls which show no meaningful or consistent relationship. If anything, temperature is negatively correlated with salinity, which may alleviate concerns of a link between the salinity measure and thermal anomalies. While insignificant, the precipitation coefficients are negative which makes sense given that rain leaches salts in the soil. Columns (5)-(8) use prior-period climate change from 1960 to 2000 and its interaction with the groundwater indicator as an IV for irrigation change, with Columns (7)-(8) dropping grid cells without

Figure 8: Soil salinity

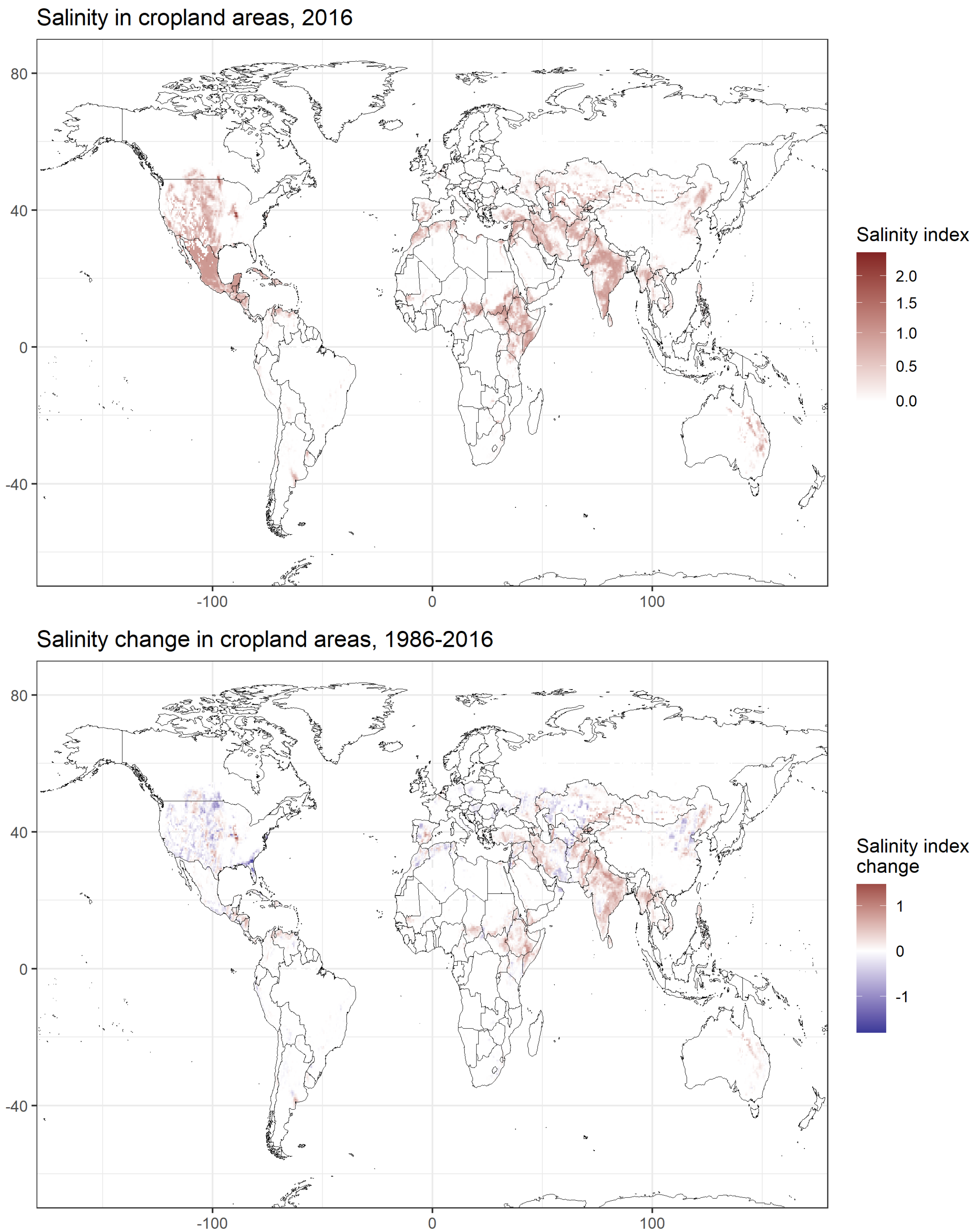


Table 5: Long Difference (Global): Irrigation impact on salinity change, 1986-2016

	Dependent variable:							
	Salinity change							
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Irrigation change	0.496***	0.211*	0.479***	0.204*	1.026**	0.415	0.873**	0.230
	(0.134)	(0.119)	(0.131)	(0.119)	(0.415)	(0.376)	(0.387)	(0.335)
Temp change			−0.024**	−0.020*	−0.015	−0.018*	−0.020	−0.018
			(0.010)	(0.010)	(0.011)	(0.011)	(0.015)	(0.016)
Precip change			−0.00003	0.0001	−0.0001	0.0001	−0.0002	−0.00004
			(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Country FE		YES		YES		YES		YES
Only irrigated							YES	YES
F-stat (1st stage)								
**Cluster Lat-Lon					14.7	14.8	21.6	19.7
**Cluster Koppen					4.2	3.7	4.9	5.6
Observations	35,616	35,616	35,616	35,616	35,616	35,616	23,629	23,629
R^2	0.035	0.194	0.039	0.195	−0.003	0.191	0.019	0.219

Notes: Linear regression. Dependent variable is change in remotely sensed soil salinity levels from 1986 to 2016. Irrigation change is change in irrigated proportion of grid cell from 1960 to 2005. Sample restricted to grid cells with non-zero irrigation at some point from 1960 to 2005. Temperature is change in average degrees Celsius over growing season from 2000 to 2015. Precipitation is change in meters summed over summer growing season from 2000 to 2015. Instruments are temperature and precipitation change from 1960 to 2000 and their interactions with the groundwater indicator. Standard errors clustered at the Koppen climate level.

and irrigation.

Overall irrigation increases salinity across all specifications with the exception of the IV with country-level fixed effects, for which the coefficients are positive but insignificant. The same first-stage approach is used as in the GRACE groundwater analyses, and again there is risk of weak instruments. Given that salt accumulation is generally a cumulative process (i.e., it is hard to reduce soil salination), I re-run the analysis using total salinity in 2016 rather than change from 1986 to 2016. The estimated effects are larger and more precisely estimated, as shown in Table A12.

It is worth noting that the IV models for both aquifer depletion and salination, while less precise and in some cases not significant, produce coefficients with higher magnitudes than the OLS estimates, implying that climate-driven changes in irrigation present greater stress on the commons than irrigation decisions driven by other factors.

7 Discussion and conclusion

The global and US analyses support a similar conclusion: farmers adapt to climate change through irrigation and land use decisions. Facing a warming and drying climate, agents invest in irrigation to mitigate water scarcity. The impact is greatest in areas suitable for groundwater irrigation. Observed recent warming is estimated to account for 9% of the growth of global irrigated lands from 1960 to 2005 (13.5 million hectares).

There is evidence that these climate-driven changes in irrigation stress the aquifer commons in terms of both quantity (i.e., groundwater levels) and quality (i.e., salination) as farmers substitute natural capital (rainfall) for physical capital (groundwater irrigation infrastructure). It is important to note that despite these negative externalities of irrigation, the adaptive benefits of irrigation may extend beyond the local agricultural and environmental context. Weather-driven crop failures have been linked to migration (Feng et al. 2010; Missirian and Schlenker 2017), and access to irrigation may mitigate this effect (Benonnier et al. 2019).

The good news is that policy can mitigate much of the costs of irrigation-driven water scarcity. Recent empirical work demonstrates the substantial welfare gains from water markets and trading (Hagerty 2019; Bruno and Sexton 2020; Rafey 2020; Bruno and Jessoe 2021; Ayres et al. 2021), which can help stabilize and even increase groundwater levels. While this paper is limited in what it can say about any such large-scale (and often government-driven) investments in surface water irrigation infrastructure made in response to climate change, many of these same lessons about market efficiency would likely apply.

This paper also showcases potential uses of new remotely-sensed products for economic and environmental analyses. Satellite-derived groundwater and salinity measures improve our understanding of the distribution and costs of factors which are difficult to consistently measure at scale.

This paper highlights the agricultural sector's potential to adapt to climate change, as well as the potential costs of one type of adaptation: irrigation from groundwater. In addition to the direct negative effects of extreme heat on yield, as groundwater becomes more scarce and soil more saline, it may become increasingly difficult to supply the food required for a growing global population from the intensive margin—especially in the absence of improved management of the water commons.

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8 Appendix

8.1 Figures

Figure A1

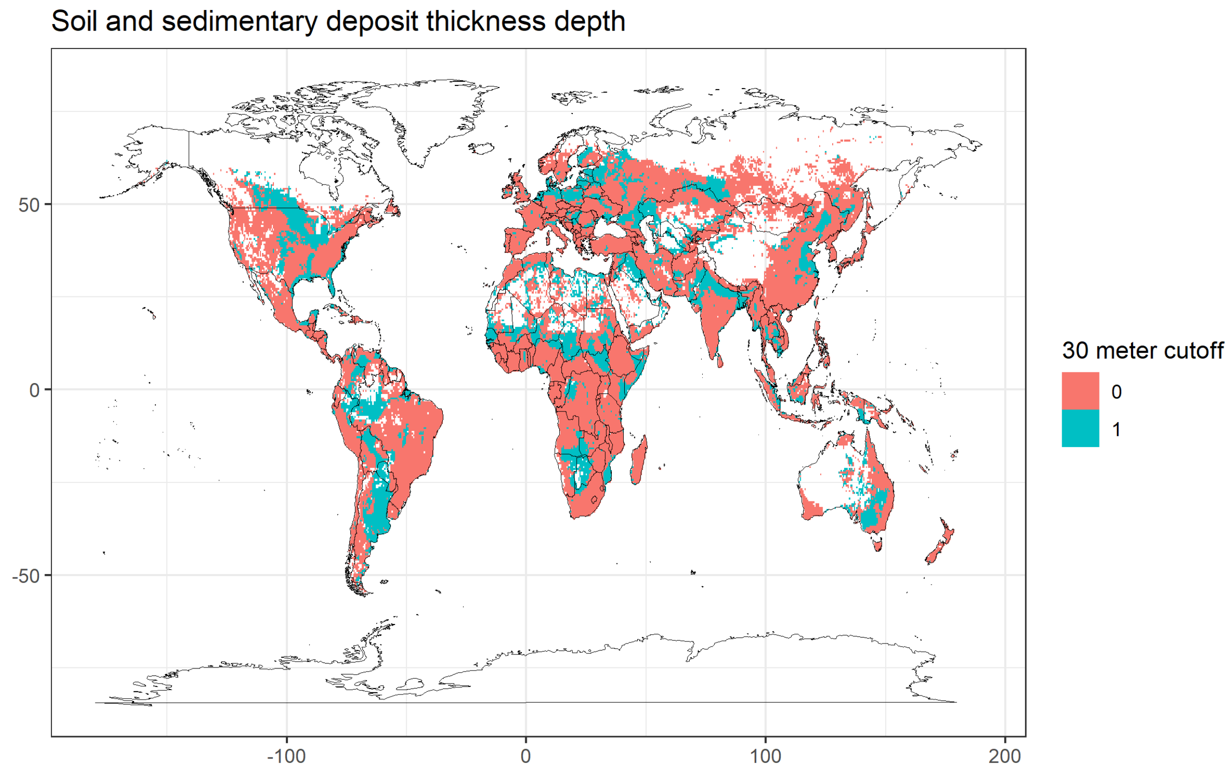


Figure A2

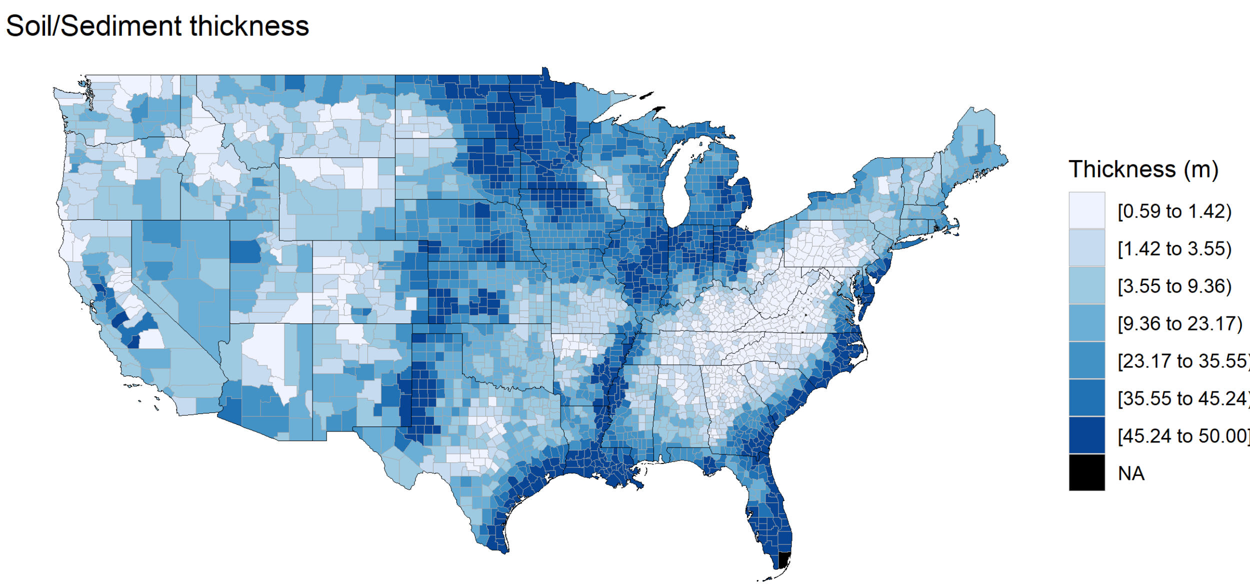
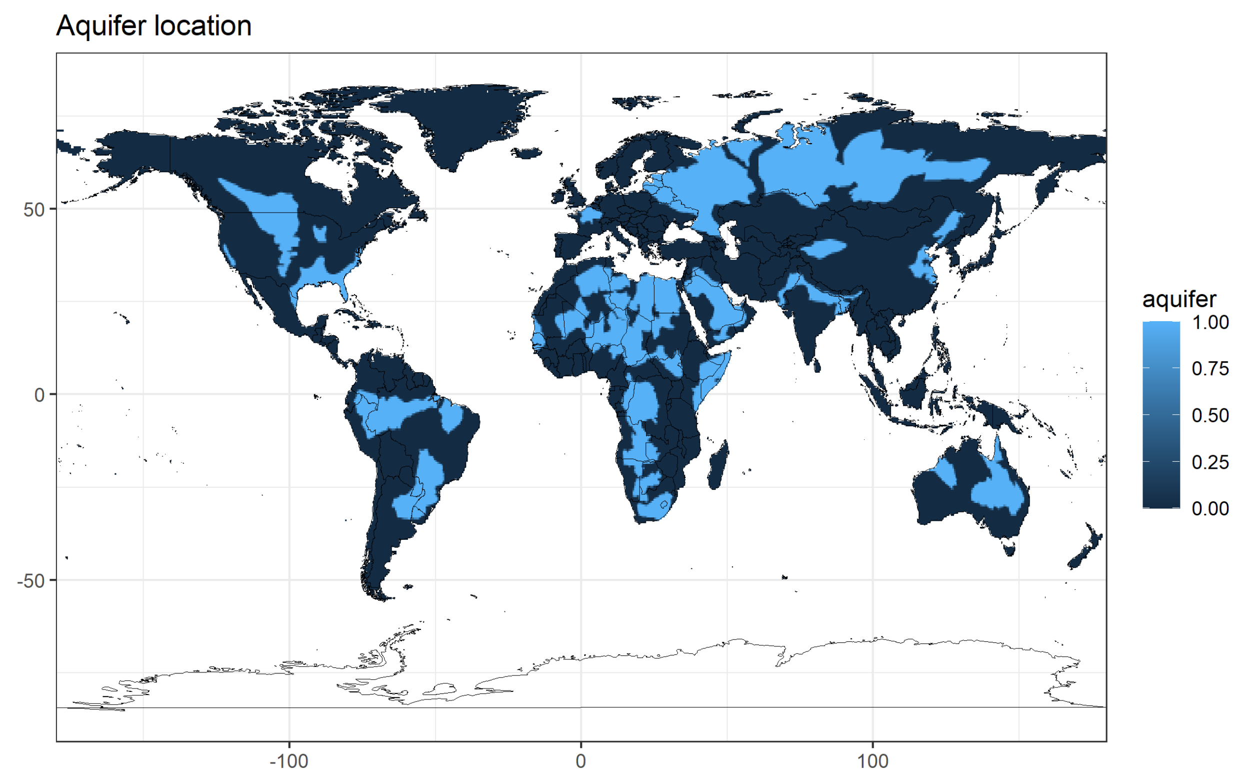

Soil/Sediment thickness
Thickness (m)
[0.59 to 1.42)
[1.42 to 3.55)
[3.55 to 9.36)
[9.36 to 23.17)
[23.17 to 35.55)
[35.55 to 45.24)
[45.24 to 50.00]
NA

Figure A3


Aquifer location
50
0
-50
-100
0
100
aquifer
1.00
0.75
0.50
0.25
0.00

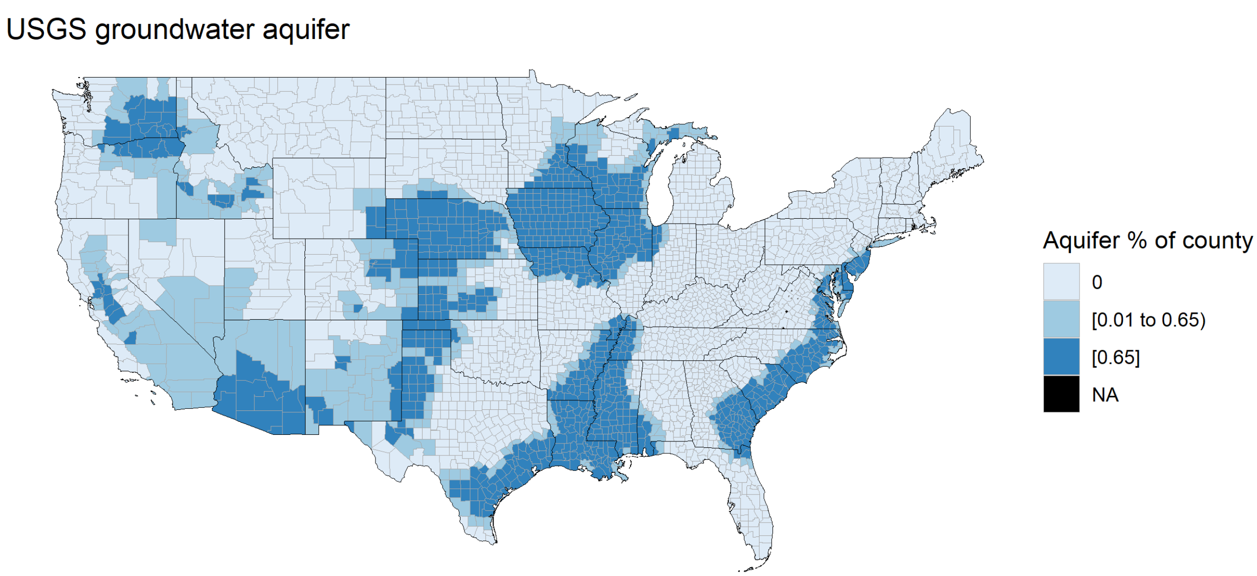

USGS groundwater aquifer
Aquifer % of county
0
[0.01 to 0.65)
[0.65]
NA

Figure A4

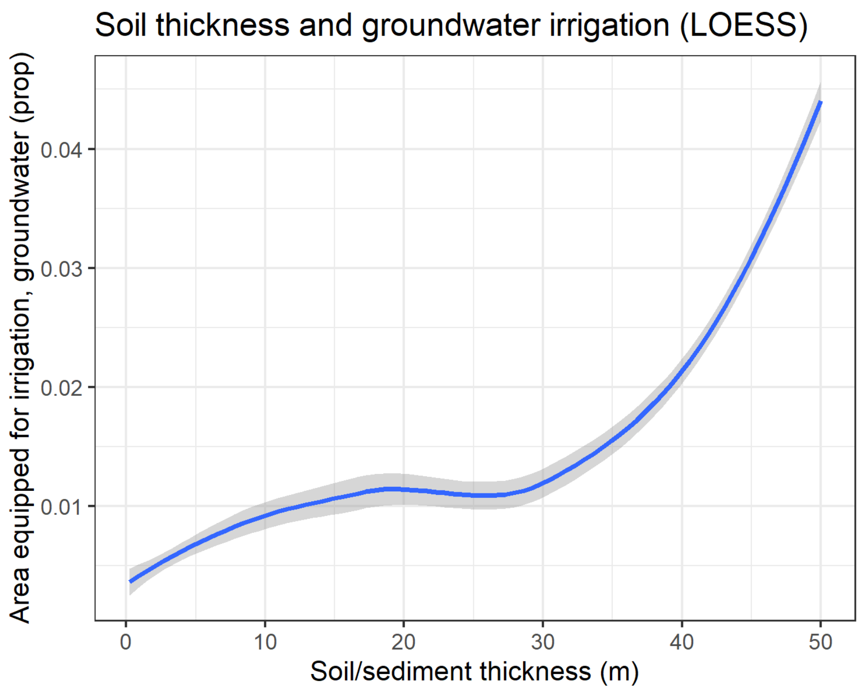


Figure A5

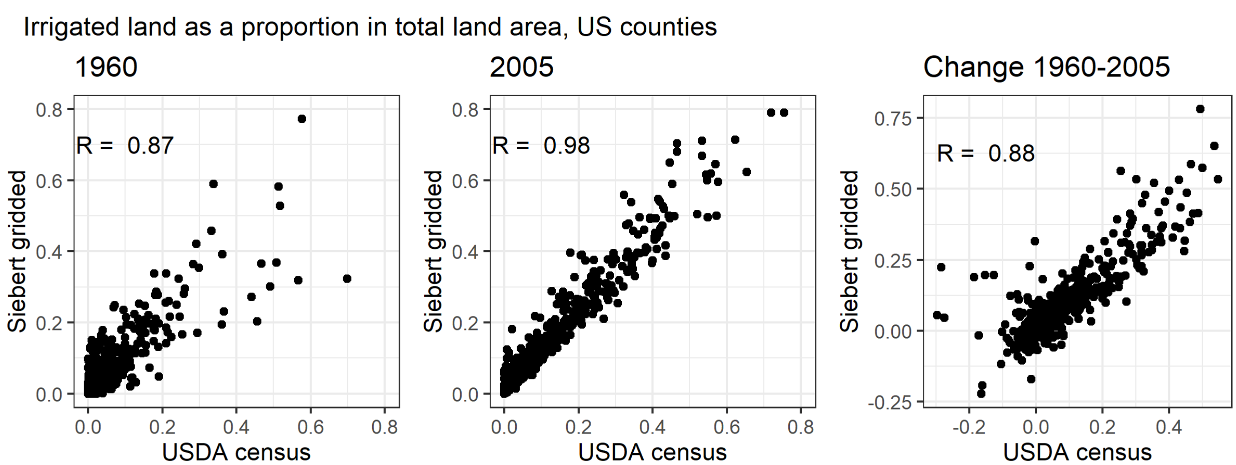
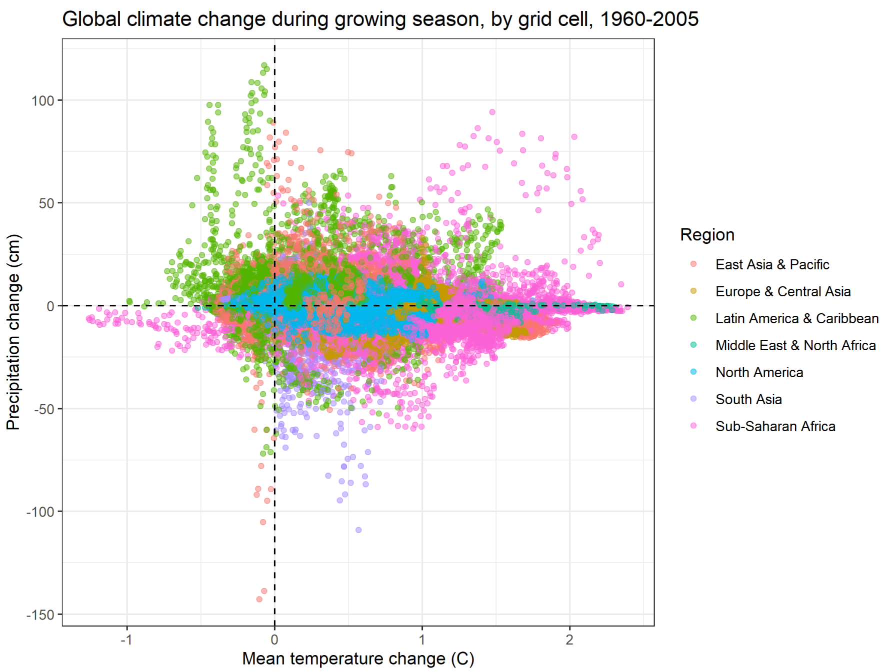
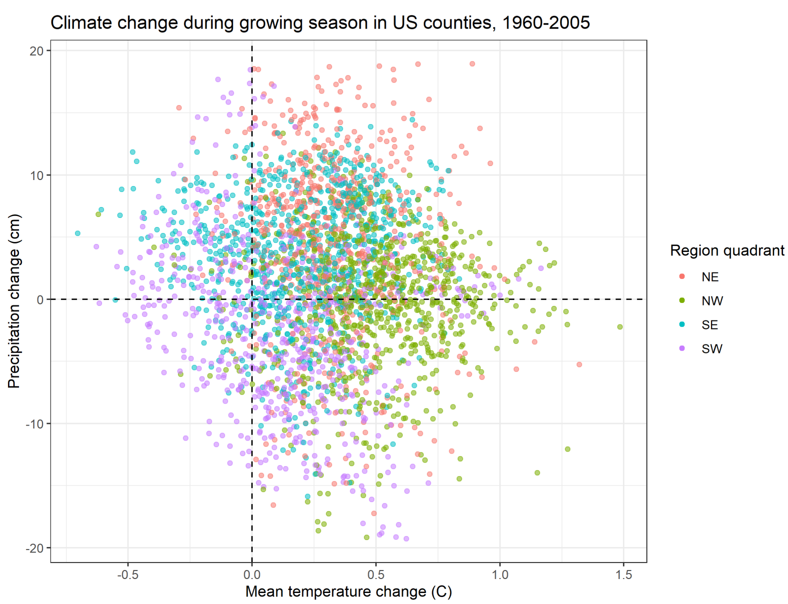


Figure A6

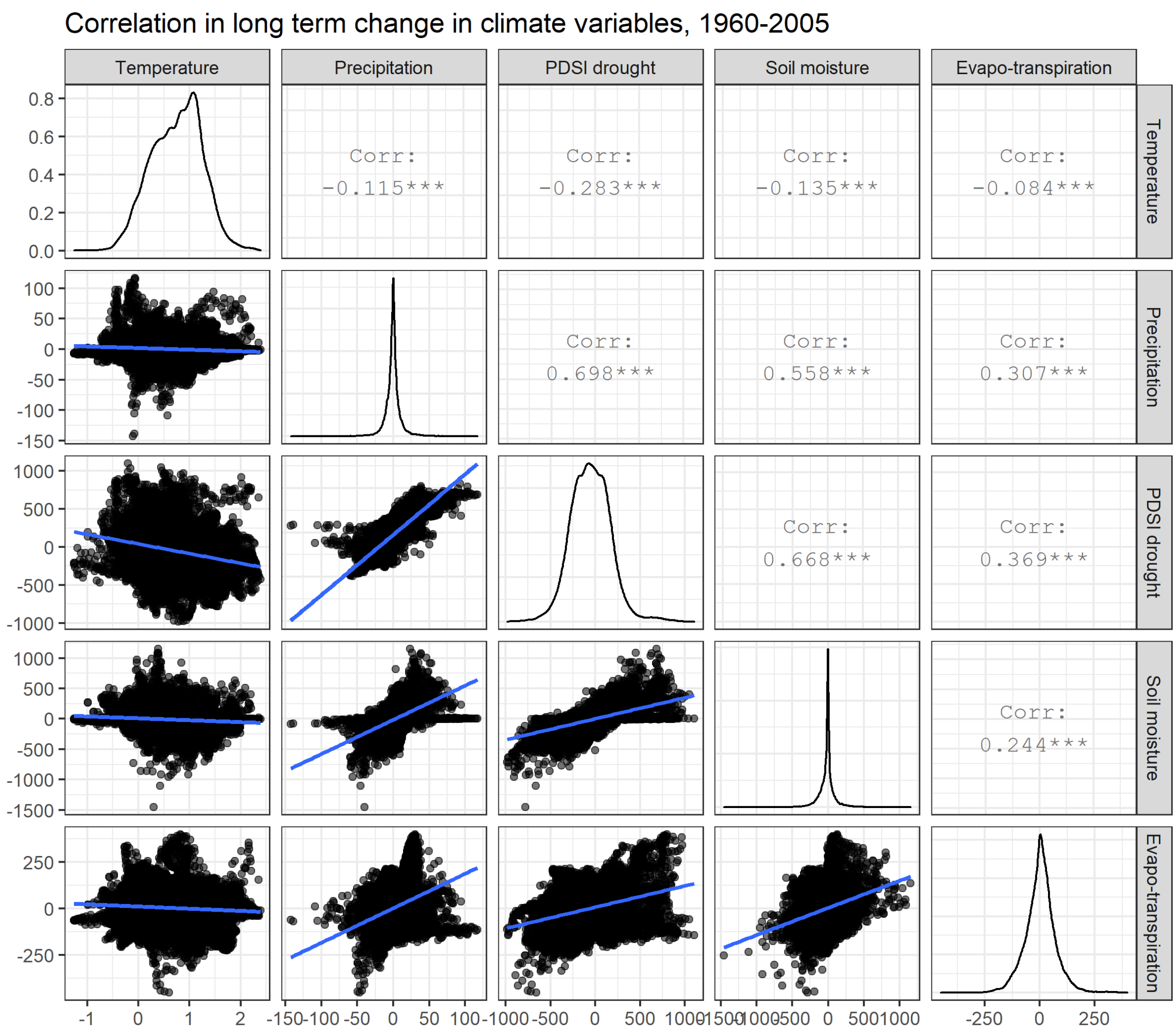


Global climate change during growing season, by grid cell, 1960-2005
Precipitation change (cm)
100
50
0
-50
-100
-150
-1
0
1
2
Mean temperature change (C)
Region
East Asia & Pacific
Europe & Central Asia
Latin America & Caribbean
Middle East & North Africa
North America
South Asia
Sub-Saharan Africa



Climate change during growing season in US counties, 1960-2005
Precipitation change (cm)
20
10
0
-10
-20
-0.5
0.0
0.5
1.0
1.5
Mean temperature change (C)
Region quadrant
NE
NW
SE
SW

Figure A7


Correlation in long term change in climate variables, 1960-2005
Temperature
Precipitation
PDSI drought
Soil moisture
Evapo-transpiration
Corr:
-0.115***
Corr:
-0.283***
Corr:
-0.135***
Corr:
-0.084***
Corr:
0.698***
Corr:
0.558***
Corr:
0.307***
Corr:
0.668***
Corr:
0.369***
Corr:
0.244***

8.2 Tables

Table A1: Global summary statistics of grid cells with cropland, 1960-2005

Statistic	Mean	St. Dev.	Min	Max
Latitude	20.01	28.32	−54.75	72.25
Land area (ha)	250,182.40	50,460.25	19,458.94	308,822.40
Cropland avg (ha)	38,632.88	53,590.81	4.94	297,608.30
Cropland change (ha)	6,104.61	21,149.41	−113,899.40	171,240.80
Cropland change (prop)	0.02	0.09	−0.64	0.58
Irrigation avg (ha)	6,067.07	18,108.99	0.00	231,122.70
Irrigation change (ha)	4,360.76	13,875.25	−73,685.35	192,514.70
Irrigation change (prop)	0.02	0.05	−0.32	0.69
Temp summer mean (C)	21.42	6.71	−0.72	36.30
Temp summer change (C)	0.75	0.49	−1.26	2.39
Precip summer mean (cm)	59.94	50.46	0.00	507.53
Precip summer change (cm)	−0.29	11.45	−142.83	116.97
Aquifer presence (dummy)	0.29	0.44	0	1
Soil thickness (m)	16.45	16.98	0.23	50.00
GRACE change 2002-2016 (cm)	−0.90	5.78	−58.71	20.33
Salt change 1986-2016 (index)	0.02	0.14	−1.97	1.54

Table A2: US summary statistics of counties with cropland, 1960-2005

Statistic	Mean	St. Dev.	Min	Max
Latitude	38.28	4.82	22.04	48.83
Land area (ha)	250,686.20	340,771.60	12,092.66	5,193,574.00
Cropland avg (ha)	25,305.30	34,223.85	0.02	245,667.60
Cropland change (ha)	9,619.72	20,791.69	−52,980.06	242,631.20
Cropland change (prop)	0.06	0.11	−0.22	0.57
Irrigation avg (ha)	6,546.48	19,660.61	0.00	420,659.90
Irrigation change (ha)	3,245.05	12,636.95	−99,432.97	141,770.60
Irrigation change (prop)	0.02	0.06	−0.30	0.55
Temp summer mean (C)	19.90	3.50	9.08	29.51
Temp summer change (C)	0.29	0.30	−0.70	1.27
Precip summer mean (cm)	54.49	17.51	2.55	113.10
Precip summer change (cm)	1.43	6.51	−19.29	18.95
Aquifer presence (dummy)	0.31	0.43	0	1
Soil thickness (m)	20.46	17.89	0.57	50.00
GRACE change 2002-2016 (cm)	1.80	4.07	−8.13	13.26
Salt change 1986-2016 (index)	−0.02	0.29	−4	4

Table A3: Decadal Panel (US counties): Climate change impact on irrigation, 1960-2005

	Dependent variable:					
	Irrigated area (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	−0.004	−0.009***	−0.011**	−0.008	−0.022**	−0.025**
	(0.002)	(0.003)	(0.004)	(0.006)	(0.010)	(0.011)
Precipitation	−0.051**	−0.021**	−0.020*	−0.143*	−0.031	−0.030
	(0.025)	(0.009)	(0.011)	(0.075)	(0.021)	(0.025)
Temperature:Groundwater		0.021**	0.023**		0.027**	0.031**
		(0.009)	(0.010)		(0.011)	(0.013)
Precipitation:Groundwater		−0.080*	−0.099*		−0.168*	−0.189**
		(0.045)	(0.052)		(0.086)	(0.093)
Weights				Cropland	Cropland	Cropland
Sample			Irrigated			Irrigated
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	17,712	17,712	14,142	17,712	17,712	14,142
R^2	0.869	0.872	0.871	0.841	0.844	0.844

Notes: Linear regression. Dependent variable is irrigated area as a proportion of total county land area. Temperature in average degree Celsius over growing season. Precipitation is in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Regression weights based on cropland area in grid cell. Sample 'Irrigated' only includes counties with at least 100 acres of irrigation at any point from 1960 to 2005. Standard errors clustered at the US state level.

Table A4: Long Difference (US County): Climate change impact on irrigation, 1960-2005

	Dependent variable:					
	Irrigation change (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	−0.005	−0.012	−0.020**	−0.026**	−0.019**	−0.024**
	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.010)
Precip change	−0.136**	0.014	−0.045**	0.144	−0.046*	0.145
	(0.057)	(0.072)	(0.022)	(0.123)	(0.024)	(0.123)
Temp change:Groundwater			0.060**	0.064***	0.059**	0.064***
			(0.026)	(0.023)	(0.026)	(0.023)
Precip change:Groundwater			−0.202	−0.255	−0.198	−0.253
			(0.124)	(0.160)	(0.124)	(0.160)
State FE		YES		YES		YES
Add'l Controls					YES	YES
Observations	2,965	2,965	2,965	2,965	2,965	2,965
R^2	0.021	0.267	0.066	0.309	0.070	0.312

Notes: Linear regression. Dependent variable is change in irrigated area as proportion county land area. Temperature is change in average degree Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include change in county-level income and population. Standard errors clustered at the state level.

Table A5: Long Difference (Global): Climate change impact on cropland area, 1960-2005

	Dependent variable:					
	Cropland change (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	-0.020^{***}	0.001	-0.020^{***}	0.0001	-0.017^{***}	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Precip change	-0.040^{**}	-0.028^{**}	-0.047^{*}	-0.036^{*}	-0.044^{*}	-0.037^{**}
	(0.017)	(0.012)	(0.026)	(0.019)	(0.024)	(0.019)
Temp change:Groundwater			0.002	0.005	-0.0001	0.003
			(0.005)	(0.006)	(0.006)	(0.006)
Precip change:Groundwater			0.024	0.027	0.031	0.030
			(0.043)	(0.033)	(0.043)	(0.033)
Country FE		YES		YES		YES
Add'l Controls					YES	YES
Observations	35,616	35,616	35,616	35,616	35,616	35,616
R^2	0.013	0.224	0.013	0.224	0.027	0.231

Notes: Linear regression. Dependent variable is change in cropland area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Standard errors clustered at the Koppen climate level.

Table A6: Long Difference (Global): Climate change impact on irrigation, 1960-2005, by hectares

	Dependent variable:					
	Irrigation change (hectares)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	−4,240***	−1,460*	−5,125***	−2,279***	−3,149***	−759
	(1,366)	(850)	(1,407)	(828)	(712)	(479)
Precip change	−12,992**	−1,984	−5,136*	5,230*	−2,753	3,818
	(5,810)	(2,381)	(3,058)	(2,693)	(2,476)	(2,373)
Temp change:Groundwater			2,195**	2,733***	1,508**	1,981**
			(935)	(958)	(693)	(780)
Precip change:Groundwater			−29,098*	−24,963*	−24,588*	−22,352*
			(15,835)	(12,996)	(14,369)	(12,593)
Country FE		YES		YES		YES
Add'l Controls					YES	YES
Observations	35,616	35,616	35,616	35,616	35,616	35,616
R^2	0	0	0	0	0	0

Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 in hectares. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Standard errors clustered at the Koppen climate level.

Table A7: Long Difference (Global): Crop water availability and irrigation, 1960-2005

	Dependent variable:			
	Irrigation change (proportion of land area)			
	(1)	(2)	(3)	(4)
Soil moisture	0.003	0.001		
	(0.006)	(0.003)		
PDSI			0.002	0.0003
			(0.004)	(0.003)
Soil moisture:Groundwater	-0.104^{**}	-0.109^{**}		
	(0.045)	(0.044)		
PDSI:Groundwater			-0.036^{*}	-0.043^{**}
			(0.019)	(0.019)
Country FE		YES		YES
Add'l Controls	YES	YES	YES	YES
Observations	35,616	35,616	35,616	35,616
R^2	0.234	0.397	0.229	0.392

Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. The index of soil moisture and PDSI are scaled down by 1000. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Standard errors clustered at the Koppen climate level.

Table A8: Long Difference (Global): Climate change impact on irrigation, 1960-2005, Conley Standard Errors

	Dependent variable:					
	Irrigation change (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	−0.011***	−0.011***	−0.011**	−0.003	−0.003	−0.003
	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)	(0.005)
Precip change	−0.010	−0.010	−0.010	0.014	0.014*	0.014*
	(0.009)	(0.013)	(0.015)	(0.009)	(0.009)	(0.010)
Temp change:Groundwater	0.007**	0.007***	0.007***	0.009***	0.009***	0.009***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Precip change:Groundwater	−0.093*	−0.093*	−0.093*	−0.085*	−0.085*	−0.085*
	(0.053)	(0.063)	(0.066)	(0.047)	(0.059)	(0.065)
SE cluster	Koppen	Conley 500km	Conley 1000km	Koppen	Conley 500km	Conley 1000km
Controls	X	X	X	X	X	X
Country FE				X	X	X
Observations	35,616	35,616	35,616	35,616	35,616	35,616
R^2	0.244	0.244	0.244	0.396	0.396	0.396

Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Standard errors clustered at the level described in the table.

Table A9: Long Difference (Global): Climate change impact on irrigation, 1960-2005, piecewise

	Dependent variable:					
	Irrigation change		Irrigation gain		Irrigation loss	
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	−0.003	−0.004	−0.003	−0.007**	0.0001	−0.002
	(0.002)	(0.004)	(0.002)	(0.003)	(0.0002)	(0.004)
Precip change	0.014	0.028**	0.014	0.025*	0.00001	−0.006
	(0.009)	(0.014)	(0.009)	(0.015)	(0.001)	(0.006)
Temp change:Groundwater	0.009***	0.019***	0.009**	0.022***	−0.0002	−0.002
	(0.003)	(0.006)	(0.004)	(0.007)	(0.0002)	(0.002)
Precip change:Groundwater	−0.085*	−0.167**	−0.084*	−0.166**	−0.001	−0.003
	(0.047)	(0.078)	(0.047)	(0.078)	(0.001)	(0.010)
Drop zero-values		YES		YES		YES
Country FE	YES	YES	YES	YES	YES	YES
Add'l Controls	YES	YES	YES	YES	YES	YES
Observations	35,616	23,416	35,616	21,014	35,616	2,402
R^2	0.396	0.388	0.417	0.442	0.129	0.277

Notes: Linear regression. Dependent variable is gain and loss in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include population change and irrigation change in neighboring grid cells. Drop zero-values drops all observations where there was no change in the outcome variable. Standard errors clustered at the Koppen climate level.

Table A10: Long Difference (Global): Climate change impact on irrigation, 1960-2005, by soil thickness quartile

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change:Thickness (Binary)	0.007**		0.009***		0.019***	
	(0.003)		(0.003)		(0.006)	
Temp change:Thickness (q2)		0.002***		0.002***		0.006***
		(0.001)		(0.001)		(0.001)
Temp change:Thickness (q3)		0.007***		0.007***		0.014***
		(0.002)		(0.002)		(0.003)
Temp change:Thickness (q4)		0.010***		0.012***		0.027***
		(0.003)		(0.004)		(0.007)
Precip change:Thickness (Binary)	−0.093*		−0.085*		−0.167**	
	(0.053)		(0.047)		(0.078)	
Precip change:Thickness (q2)		−0.003		−0.004		−0.003
		(0.007)		(0.007)		(0.012)
Precip change:Thickness (q3)		−0.012		−0.013		−0.019
		(0.015)		(0.011)		(0.019)
Precip change:Thickness (q4)		−0.097*		−0.091*		−0.174**
		(0.055)		(0.048)		(0.079)
Drop zero-values					YES	YES
Country FE			YES	YES	YES	YES
Add'l Controls	YES	YES	YES	YES	YES	YES
Observations	35,616	35,616	35,616	35,616	23,416	23,416
R^2	0.244	0.246	0.396	0.398	0.388	0.392

Notes: Linear regression. Dependent variable is change in irrigated area from 1960-2005 as a proportion of total land area in the grid cell. Temperature is change in average degrees Celsius over growing season. Precipitation is change in meters summed over summer growing season. Thickness is the groundwater availablity proxy, including a binary for grid cells over 30m, and quartiles for thickness (coefficients relative to omitted firt quartile). Additional controls include population change and irrigation change in neighboring grid cells. Drop zero-values drops all observations where there was no change in irrigation. Standard errors clustered at the Koppen climate level.

Table A11: Long Difference (US County): Climate change impact on irrigation east of 100th Meridian, 1960-2005

	Dependent variable:					
	Irrigation change (proportion of land area)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temp change	0.006	0.004	-0.019^{**}	-0.015^{**}	-0.019^{***}	-0.014^{*}
	(0.011)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Precip change	-0.133^{**}	0.033	-0.040^{**}	0.165	-0.041^{*}	0.166
	(0.060)	(0.080)	(0.020)	(0.133)	(0.023)	(0.134)
Temp change:Groundwater			0.062^{**}	0.064^{**}	0.062^{**}	0.064^{**}
			(0.027)	(0.024)	(0.026)	(0.024)
Precip change:Groundwater			-0.195	-0.249	-0.192	-0.248
			(0.129)	(0.169)	(0.128)	(0.168)
State FE		YES		YES		YES
Add'l Controls					YES	YES
Observations	2,400	2,400	2,400	2,400	2,400	2,400
R^2	0.024	0.328	0.066	0.368	0.068	0.369

Notes: Linear regression. Counties east of the 100th Meridian. Dependent variable is change in irrigated area as proportion county land area. Temperature is change in average degree Celsius over growing season. Precipitation is change in meters summed over summer growing season. Groundwater dummy if sediment thickness over 30m. Additional controls include change in county-level income and population. Standard errors clustered at the state level.

Table A12: Long Difference (Global): Irrigation impact on salinity levels in 2016

	Dependent variable:							
	Salinity							
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Irrigation change	1.050***	0.559***	1.044***	0.563***	2.337***	1.778***	1.864***	1.147***
	(0.190)	(0.164)	(0.182)	(0.163)	(0.662)	(0.561)	(0.433)	(0.363)
Temp change			0.016	0.011	0.037**	0.021*	0.033	0.009
			(0.022)	(0.014)	(0.017)	(0.012)	(0.026)	(0.015)
Precip change			0.001***	0.0001	0.001***	0.0001	0.001***	0.00002
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
Country FE		YES		YES		YES		YES
Only irrigated							YES	YES
Observations	35,616	35,616	35,616	35,616	35,616	35,616	23,629	23,629
R^2	0.057	0.489	0.065	0.490	−0.020	0.436	0.011	0.489

Notes: Linear regression. Dependent variable is remotely sensed soil salinity levels in 2016. Irrigation change is change in irrigated proportion of grid cell from 1960 to 2005. Sample restricted to grid cells with non-zero irrigation at some point from 1960 to 2005. Temperature is change in average degrees Celsius over growing season from 2000 to 2015. Precipitation is change in meters summed over summer growing season from 2000 to 2015. Instruments are temperature and precipitation change from 1960 to 2000 and their interactions with the groundwater indicator. Standard errors clustered at the Koppen climate level.