The global water footprint of distortionary agricultural policy

Tamma Carleton

[Preliminary, please do not cite or circulate]

Bren School of Environmental Science & Management
University of California, Santa Barbara
& NBER

July 22, 2021

Abstract

Global demands on freshwater resources are rising. While policy responses have focused on the design of local water institutions, distortions in the global market for agricultural goods can lead to overproduction of water-intensive goods in regions where water is relatively scarce. In this paper, I combine satellite-derived measures of water availability with a collection of spatial and administrative datasets to provide globally-comprehensive, empirical estimates of the influence of policy distortions in agricultural markets on local water supplies. I find that interventions raising domestic agricultural output prices significantly lower local water availability, particularly for water-intensive crops and in locations most suitable for those crops. I then quantify the impact that recent liberalization of agricultural markets has had on water resources. I find that in locations with declining water resources, water supplies would be 16% lower had liberalization not taken place. These water savings are largest in locations with higher baseline levels of water stress. In contrast, liberalization slightly reduces water supplies in locations with low water stress. These findings suggest that reducing agricultural market distortions may alleviate global water stress by slowing extraction where water is most scarce.

1 Introduction

The challenge of securing a stable and safe water supply is rapidly changing. Diets are becoming more water-intensive, economic growth has continued to raise water demand per capita, and the environmental damages of large-scale hydrologic interventions, such as wetland losses, are becoming more severe. Climate change looms as a driver of increased demand and a threat to both coastal aquifers and alpine storage of freshwater in ice and snow. Superimposed upon these challenges is the fact that throughout the globe, most ground and surface water resources are accessed through some form of common property regime, leading to extraction rates that far exceed socially optimal levels (Culp, Glennon, and Libecap, 2014; Gleick, 1993).

A large and influential literature in resource economics studies how to design local-level institutions to mitigate over-extraction of freshwater by formalizing property rights and creating markets in which water can be efficiently allocated across both space and time (e.g., Gisser, 1983; Leonard and Libecap, 2016; Olmstead, 2010; Schoengold and Zilberman, 2007). This literature has been largely local or regional in nature, focusing on optimal allocation across users within a freshwater basin or extracting from a shared groundwater aquifer. However, trade in water-intensive agricultural goods is expanding, linking production and consumption decisions across the globe and creating "virtual" water trades (Allan, 1998). Importantly, this virtual marketplace is notoriously distorted by domestic farm, food, and nutrition policies (Anderson, Rausser, and Swinnen, 2013). For example, agricultural subsidies make up 40% of the EU budget and farm subsidies form the largest per-capita transfer payment in the US. These large political interventions imply that even if property rights were well defined and local water markets functioned seamlessly, allocation of water use across the world's diverse regions could continue to cause over-extraction, as agricultural trade and production patterns are severely suboptimal (Chichilnisky, 1994; Tombe, 2015). While extensive research has focused on the role of poor property rights in depletion of freshwater resources, little is known about government intervention in agricultural markets as a second source of inefficiency.

In this paper, I utilize a novel satellite data source measuring changes in total water mass at all points on Earth's surface to empirically quantify the impact of agricultural market distortions on the spatial distribution of global water use. In particular, I ask: How do changes in agricultural policies impact freshwater resources? I demonstrate that political interventions which increase incentives to domestically produce staple crops

have substantial consequences for water availability, and I show that recent trends towards liberalization of these interventions have led to water savings in the regions of the globe that need it most.

Until recently, it has been impossible to study water empirically at global scale. Even in the U.S., basic water withdrawal, storage, and use data are not collected or distributed, despite public outcries over groundwater overdraft in places like California's Central Valley or the High Plains' Ogallala Aquifer (Gleick, 2016). To overcome this challenge, I employ a globally comprehensive satellite-based dataset from the Gravity Recovery and Climate Experiment (GRACE), a mission that uses the time-varying distance between two satellites to uncover changes in Earth's gravitational field, which in turn allow for derivation of estimates of changes in water mass at all points on Earth (Tapley et al., 2004). These water mass anomalies have been used extensively in hydrology, geology, and earth systems science to document water loss over time in particular regions (e.g., Famiglietti et al. (2011); Rodell et al. (2006); Rodell, Velicogna, and Famiglietti (2009)). While many studies uncover trends in agricultural regions that are consistent with irrigation-driven water depletion (Famiglietti et al., 2011; Richey et al., 2015; Rodell et al., 2006; Rodell, Velicogna, and Famiglietti, 2009), to my knowledge, no prior analyses use GRACE to statistically recover the influence of agricultural production or policy on water losses and gains.

I address this research question in three steps. First, noting that political interventions in agricultural markets manifest as wedges between domestic and global commodity prices, I set up a simple conceptual framework to generate an intuitive set of testable hypotheses regarding the influence of these wedges on water use. Second, I combine measures of "total water storage" – defined as any form of water mass below, upon or above the Earth's surface in a given location – with a variety of climate and socioeconomic data to estimate a differences-in-differences empirical model that tests for the influence of these policy levers on water availability at the grid cell level across the globe. I find, consistent with my conceptual framework, that policies which subsidize domestic production of agricultural output lead to losses in domestic total water resources. These effects are largest when water-intensive crops are subsidized, and are particularly severe in locations suitable to these crops. These findings are consistent with Sekhri (2019), who investigates the impact of Agricultural Export Promotion Zones (AEZs) on groundwater in India. Sekhri (2019) documents that higher prices resulting from government interventions within AEZs led to substantial declines in groundwater within these zones. To my knowledge, this is the only existing study

quantifying the impacts of agricultural market interventions on water resources.

Finally, I use these empirical estimates to quantify the impact that the recent liberalization of global agricultural markets has had on total water availability. To do so, I conduct a counterfactual simulation in which I estimate what total water losses and gains would have been had countries not gradually reduced agricultural interventions over the satellite record period. I find that observed policy changes since 2003 have compressed the global distribution of water losses and gains, relative to a counterfactual of fixed policy. This compression leads to large water savings in locations with otherwise declining water resources, and modest losses due to liberalization in locations experiencing overall gains in water resources. While a full welfare analysis of agricultural market liberalization accounting for imperfect property rights over water is beyond the scope of this paper, I show that the spatial pattern of policy impacts across the globe is suggestive of welfare gains from recent liberalization.

This paper proceeds as follows. Section 2 outlines a conceptual framework formalizing the link between policy interventions in international agricultural markets and domestic use of freshwater resources. In Section 3, I describe the water, climate, socioeconomic, and agricultural policy datasets I use, as well as the processing required to combine them. I detail the empirical methodology I employ in Section 4. In Section 5 I show estimation results and in Section 6 I describe and implement the simulation exercise I use to quantify the recent impacts of observed policy liberalization. I conclude in Section 7.

2 Conceptual framework

Explicit water markets are rare within countries, and virtually nonexistent internationally (Schoengold and Zilberman, 2007). Lack of water trade can theoretically lead to misallocation in water use across diverse users, with important welfare consequences (Culp, Glennon, and Libecap, 2014), and much research in water economics focuses on understanding how to build well-functioning local-level water markets (Chong and Sunding, 2006). However, lessons from trade theory suggest we need not necessarily be concerned about water as an immobile factor of production: early trade theory demonstrated (Samuelson, 1953) and very recent theory reaffirmed (Adao, Costinot, and Donaldson, 2017) that there is an equivalence between competitive equilibria in which factors are directly traded and where outputs are traded, while factors are not.

Thus, free trade in water-intensive goods could lead to welfare-maximizing allocations of this non-traded resource. As agricultural production accounts for 70-90% of total consumptive freshwater use (Chapagain and Hoekstra, 2008; O'Bannon et al., 2014), freely trading agricultural outputs could enable such an optimal allocation.

Two key impediments limit the possibility that efficient allocation of water resources arises through trade in water-intensive outputs. First, water is generally extracted in contexts with imperfect or nonexistent property rights, in which private costs of extraction fall far below their social costs (Gleick, 2016). This source of inefficiency has been studied for decades in environmental economics. Second, agricultural markets are notoriously distorted by political interventions such as subsidies, import tariffs, and export bans (Anderson, Rausser, and Swinnen, 2013). This implies that even if local property rights were restored and markets for water operated without friction at the scale of a basin or aquifer, inefficiency in the allocation of water across diverse global regions would remain. The presence of both distortions together generates a classic example of the theory of second-best, in which output market liberalization may not necessarily generate welfare gains, nor increase water use efficiency (Chichilnisky, 1994). Despite this ambiguity, previous work on global-scale water use has often implied that liberalization of agricultural trade poses an increased risk of water scarcity, particularly for low-income regions (e.g. Dalin et al. (2017); Seekell, D'Odorico, and Pace (2011)).

In this section, I adapt a simple, industry-level small open economy model from the trade and environment literature to formalize the relationship between distorted trade in agricultural goods and the use of water resources, in which imperfections in both water and agricultural markets are captured. I use this model to generate intuitive testable hypotheses regarding the influence of changes in policy distortions in the explicit market for agricultural goods on domestic usage of water resources. In Appendix A, I add slightly more detail to the production technology to account for within-country and across-crop heterogeneity, highlighting interaction effects between crop-specific policies and exogenous location-specific characteristics.

2.1 Setup

Until recently, most of the literature studying the role of trade costs and trade liberalization on the environment employed models and empirical tests derived at the industry level, implicitly abstracting from any relevant heterogeneity within industries (e.g. Ang and Zhang (2000); Levinson (2009)). The canonical model in this literature, discussed

in detail in Copeland and Taylor (2005), is an extension of the classic Heckscher-Ohlin trade model to include an environmental externality. In this section, I slightly modify this model to provide basic intuition and testable hypotheses that relate changes in agricultural trade policies to changes in the quantity of water extracted.[1]

Consider a small open economy with two industries, a non-agricultural sector producing a good Y, and the agricultural sector, producing agricultural output X. Both goods are produced with constant returns to scale technology using two primary factors of production, labor L and land K. Let the price of X be p, while Y serves as the numeraire. Production of agriculture is land-intensive, such that

$$\frac{K_x}{L_x} > \frac{K_y}{L_y}$$

where K_x indicates land used in sector X, K_y indicates land used in sector Y, and likewise for labor subscripts. The production function for good Y takes the following general form:

$$Y = H(K_y, L_y) \tag{1}$$

While production in both sectors requires land and labor, production in agriculture is generated as a joint output with irrigation water.[2] In particular, suppose that irrigation water is extracted from a common pool resource, at some cost, which includes physical costs as well as any government-regulated pricing mechanism. Call these extraction costs δ. We should think of the policy-induced penalties as a government's attempt to match private and social costs of water use; in reality, water in agriculture is almost ubiquitously underpriced, often with a price of zero. Thus, while not all water use is socially suboptimal from a welfare standpoint, private costs nearly always fall below social costs, at least in agriculture, due to externalities such as overuse from imperfect property rights, water pollution, land subsidence, and salinization, among others. For now, I put the nuances of these externalities in the background, assuming that δ includes the government's (possibly suboptimal) regulatory means of managing these externalities.

To avoid paying higher water extraction costs, the firm can invest in lowering water

[1]This section follows Copeland and Taylor (2005) closely.

[2]The model can easily be generalized to allow non-agricultural production to also require water. However, as approximately 70-90% of freshwater used by humans globally is estimated to be allocated to agriculture (O'Bannon et al., 2014), the simplification used here closely follows actual production patterns.

requirements per unit of agricultural output by reallocating some share $0 \leq \theta \leq 1$ of its inputs. For example, land and labor could be spent on increasing irrigation efficiency, changing varieties of crops grown, or shifting planting times within the year. Thus, while "potential output" is denoted X (agricultural output that could be realized were all irrigation water available used), I write the joint production of "net output" x and irrigation water z as:

$$x = (1 - \theta)F(K_x, L_x) \tag{2}$$

$$z = \phi(\theta)F(K_x, L_x) \tag{3}$$

Where, like $H(\cdot)$, $F(\cdot)$ is constant returns to scale, and increasing and concave in its arguments, and where $\phi(0) = 1$, $\phi(1) = 0$ and $\frac{\partial \phi}{\partial \theta} < 0$.[3] The scalar θ represents the share of factor resources expended in an effort to lower water use intensity – a lower θ implies that fewer factors of production are sacrificed to minimize irrigation water, and can instead be allocated to direct production of X. Higher levels of θ generate low water-intensity of output, but come at the cost of reallocating a substantial share of inputs K_x and L_x into water-saving technologies instead of direct generation of agricultural output. Note that "potential output" is realized when $\theta = 0$, and by choice of units, we have in this case that one unit of water is used in the production of one unit of agricultural output:

$$x = F(K_x, L_x) \tag{4}$$

$$z = x \tag{5}$$

Substitution of Equation 3 into Equation 2 shows that this joint production function can be rewritten to show irrigation water as a third input into production of net output x:

$$x = \left(1 - \phi^{-1}\left(\frac{z}{F(K_x, L_x)}\right)\right) F(K_x, L_x) \tag{6}$$

Let there be standard iceberg trade frictions in this economy such that the domes-

[3]Note that this structure implies that the technologies which lower irrigation water per unit of output use the same factor intensity as the production of the final agricultural good X.

tic relative price p^d may exceed or fall below the world price p; that is, an exporter faces prices $p^d = \frac{p}{1+\tau}$ while an importer faces prices $p^d = p(1+\tau)$, and τ represents the magnitude of the wedge between domestic and global prices. Government policy can influence these relative prices: domestic policy distortions can magnify the wedge between the domestic price under iceberg trade costs and the realized price. These distortions include, for example, the output subsidies and export and import tariffs that make agricultural policy so controversial globally (Anderson, Rausser, and Swinnen, 2013). Non-agricultural output is freely traded without frictions.

Given this setup, we can draw a three-dimensional production possibilities frontier, as in Copeland and Taylor (2005). In the top of Figure 1A, we have a standard 2-good production possibilities frontier between non-agriculture Y and net agricultural output x. Note that this frontier in $x - Y$ space depends on the level of θ – for higher levels of θ, more factors are allocated to water use efficiency, therefore shrinking the possibilities set. The use of water resources is shown in the third dimension in the bottom panel of Figure 1A: as net agricultural production increases, water use rises; the slope of this increase is governed by θ, with lower θs generating steeper slopes.

In Figure 1A, production occurs where the frontier is tangent to the relative domestic producer price p^d.[4] This point is indicated by A.

2.2 Changes in technology

Suppose a technology shock lowers the cost of extracting water resources. That is, consider a fall in δ. This decrease will lower firm's optimal allocation of factors K_x and L_x dedicated to water-saving technologies in agriculture, as liberal use of irrigation is now less costly. This is intuitive, as firms will face lower extraction costs per unit of water used, and will therefore reallocate factors of production away from water-saving technologies and toward production of agricultural goods, lowering θ. This lower θ shifts out the production possibilities frontier, as shown in Figure 1B, and for a given price, both agricultural output and total water use rise. Thus, all else equal, a decrease in the cost of extracting irrigation water will increase total water use. While my evidence is only correlational, I show results consistent with this hypothesis in Section 5.

[4]See Copeland and Taylor (2005) for derivation of this tangency. Note that the producer price for net output falls below the consumer price for agricultural output because some share of potential output is lost to water efficiency investments. This distinction does not affect the production-side comparative statics generated in this section, and is therefore omitted for simplicity.

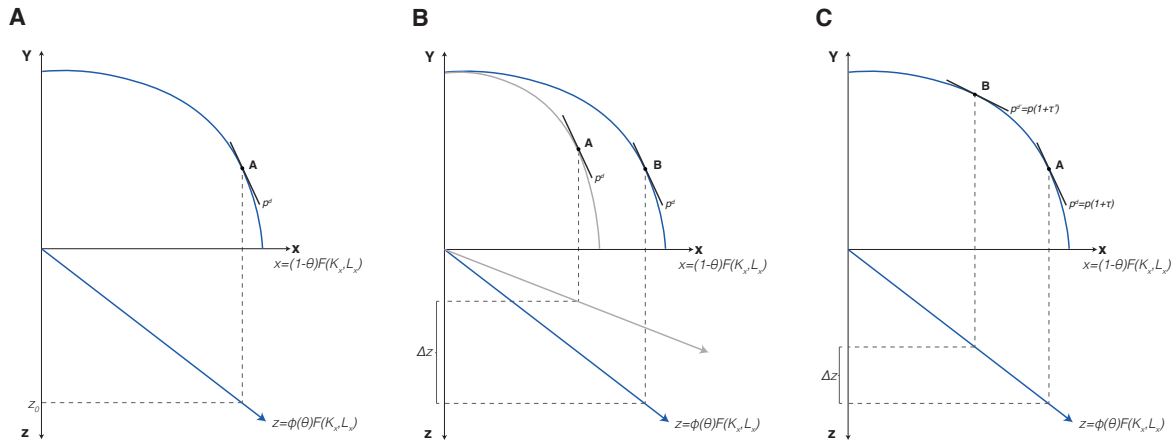


Figure 1: Production possibilities frontier with a water-intensive agricultural sector In all figures, the top panel illustrates a classic production possibilities frontier (PPF) in $x-Y$ space, representing possible output bundles across non-agriculture Y and net agricultural output x. Agricultural output x is "net" of factors allocated to the reduction of water needs: an endogenous fraction θ of factors used in agriculture are invested in water-saving technologies that lower total water needs in agriculture. Higher government penalties of water use, or increased cost of extraction, will increase θ. In the bottom panel, the use of water z is shown as a function of net output x, where the slope is governed both by θ and the exogenous water intensity function $\phi(\cdot)$. Panel **A** shows the production possibilities frontier with a water-intensive agricultural sector: production occurs at point A, the tangency between the PPF and the domestic producer price. Panel **B** shows the impact on water use of a decrease in cost of using irrigation water: a decrease in costs of extracting and applying irrigation water lowers θ from the grey to the blue line, and more water is used for every unit of agricultural production. The PPF shifts asymmetrically out in $x-Y$ space, as more resources are available for agricultural production. The total increase in water use is indicated by Δz, and production moves from point A to point B. Panel **C** shows the effect of trade liberalization on water use when the initial policy wedge is positive (i.e. $\tau > 0$): trade liberalization in agriculture implies a reduction in τ such that relative producer prices fall from $p^d = p(1+\tau)$ to $p^{d'} = p(1+\tau')$, where $\tau' < \tau$, and production moves from point A to point B. Figure adapted from Copeland and Taylor (2005).

2.3 Changes in policy

Consider now a change in agricultural policies, which govern τ, the wedge between the domestic and global relative price of agriculture. In particular, consider a liberalization which shrinks τ toward zero. Suppose for simplicity that water intensity of agricultural production stays fixed under this change (i.e. θ is unchanged). Under these assumptions, Figure 1C demonstrates how such a trade liberalization will affect water use differentially, depending on the initial conditions of the given country under study.

Figure 1C shows liberalization for a country using policy to increase the domestic producer price of agricultural goods above the global market clearing price. In this case, the relative price of X domestically, $p^d = p(1+\tau)$, exceeds the world relative price p,

as $\tau > 0$. Trade liberalization lowers the relative price of agricultural output, shifting production along the frontier up and to the left. Total water use falls by Δz, as the economy's mix of goods shifts toward Y and away from X. Thus, liberalization is water-saving in this case. In contrast, a country pursuing import substitution industrialization or other policies that relatively dis-incentivize agricultural production would have a domestic price below world prices, $p^d < p$, with $\tau < 0$. Liberalization brings p^d closer to the world price, shifting the economy toward agricultural production and raising water use z. Therefore, the sign of the water use effect of liberalization depends critically on the magnitude and sign of the initial wedge τ; in Section 6 I show empirically how recent trends toward liberalization have led to differential changes in water use across the globe. However, if we consider any policy which increases domestic agricultural prices relative to other sectors, factors will reallocate toward agricultural production and water use will increase, regardless of initial conditions. I use a panel regression model with a differences-in-differences identification strategy to quantify the magnitude of this effect across the globe in Section 5.2.

This aggregate industry-level model abstracts away from heterogeneity in production technologies across locations within a country, as well as heterogeneous production techniques used to produce different crops. In reality, there is wide dispersion in crop-specific productivity within countries (Fischer et al., 2002) and crops have heterogeneous water use requirements (Mekonnen and Hoekstra, 2011). Because the agricultural policies that influence production and trade patterns are often crop-specific (Anderson, Rausser, and Swinnen, 2013), such aggregation may mask quantitatively meaningful relationships between policy variation and water use. Moreover, my empirical setting allows me to observe crop-specific policy shocks and location-by-crop specific agricultural productivities. In Appendix A I add detail to the industry-level model described above to show that, intuitively, an increase in the domestic price of a particular crop due to policy intervention will increase water use if the crop is relatively water-intensive. I also show that the effect of policy on water use differs based on agricultural suitability; both of these additional comparative statics are taken to the data in Section 5.2.

3 Data

Basic data tracking groundwater withdrawals, surface water usage, aquifer recharge rates and other fundamental indicators of both human and natural influences on water

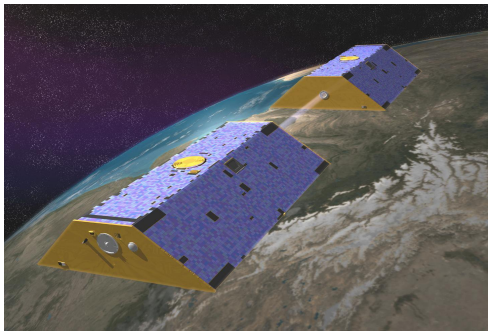
availability have been largely unavailable, at least for significant regions of the world, prior to the GRACE satellite mission. This paper represents, to my knowledge, the first effort to combine this novel source of comprehensive water storage measurements with additional social and biophysical datasets to statistically uncover human-induced changes in water availability. In this section I describe the GRACE mission in more detail, the additional sources of data I use, as well as the processing required to combine these datasets.

3.1 GRACE

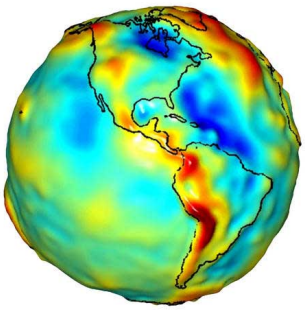
The Gravity Recovery and Climate Experiment (GRACE) satellite mission, launched in 2002, is a joint partnership between the National Aeronautics and Space Administration (NASA) in the United States and Deutsche Forschungsanstalt für Luft und Raumfahrt (DLR) in Germany. GRACE is composed of two identical spacecraft, flying 220 km apart in the same orbital plane about 500 km above the Earth. As the pair orbits the Earth, regions with greater mass concentration will exhibit stronger gravitational pull, affecting the lead satellite first and pulling it away from the trailing satellite. As the two continue circling, the trailing satellite is pulled back toward the lead as it passes over the same gravitational anomaly. Two instruments on board are used to generate extremely precise measurements of this changing distance between the satellites while in orbit: an accelerometer accounts for all non-gravitational accelerations, like those due to atmospheric drag, while a K-band ranging instrument measures distance due to remaining gravitational pull. In this way, only changes in acceleration due to gravity are captured and recorded. These distances are accurate up to one micrometer (μm) per second.

GRACE was designed to improve accuracy of models of the geoid – the hypothetical shape of the Earth under the influence of Earth's gravity and rotation alone, without wind and tidal effects – as well as to provide the first ever high-frequency (monthly) measures of variations in Earth's gravity field. Figure 2 depicts the two satellites in orbit and an example of gravitational anomalies from GRACE, where anomalies are shown relative to a mathematically perfect sphere.

Because water moves in sufficiently large quantities through the hydrologic cycle at a rate far faster than other processes that move mass across the Earth's surface, the month-to-month mass variations uncovered by GRACE are mostly due to changes in water content as it cycles between ocean, atmosphere, continents, glaciers, and



A



B

Figure 2: Gravity Recovery and Climate Experiment Panel **A** is an artistic representation of the pair of satellites that compose GRACE. Panel **B** is an example gravity anomaly field for the globe from GRACE. Both images were sourced from the Center for Space Research, University of Texas at Austin.

polar ice caps (Tapley et al., 2004). This monthly output has been used to study ocean currents (Wahr, Jayne, and Bryan, 2002), measure ground water storage on land (Rodell, Velicogna, and Famiglietti, 2009), and document exchanges between ice sheets or glaciers and the oceans (Jacob et al., 2012), among many other applications. GRACE "solutions" of these monthly data – a solution converts distances between satellites into estimates of mass – are available in gridded form across the entire globe. There are a range of different products available; I use the Goddard Space Flight Center (GSFC) mass concentration solution v02.4, which converts time-variable gravity into centimeters of equivalent water height for 41,168 equal-area blocks, called mascons, which measure $1^\circ \times 1^\circ$ ($\sim$ 111.11km$\times$111.11km) at the equator (Luthcke et al., 2013).

I follow the previous literature (e.g., Long et al. (2013); Richey et al. (2015); Rodell, Velicogna, and Famiglietti (2009)) in assuming that month to month changes in mass can be treated as changes in total water storage (TWS), and that the measure of aggregate change in TWS provided by GRACE can be theoretically decomposed into the following elements:

$$\begin{aligned} \Delta TWS = \Delta groundwater + \Delta surface_water + \Delta soil_moisture \\ + \Delta snow_water_equivalent \end{aligned} \tag{7}$$

Nearly all previous literature seeking to relate variations in ΔTWS from GRACE to human activity have focused on isolating the $\Delta groundwater$ component, using administrative data on reservoir levels to partial out changes in surface water, and relying on

land use models such as the Global Land Data Assimilation System (GLDAS) or the North American Land Data Assimilation System (NLDAS) to account for soil moisture, snow, and ice (e.g. Famiglietti et al. (2011); Richey et al. (2015)). However, the uncertainty across land surface models is large, making isolation of ground water from aggregate ΔTWS measures error-prone (Long et al., 2013). Moreover, in many parts of the globe, such as the central valley of California, surface water withdrawals are a major source of water use. Therefore, I abstract from decomposition of ΔTWS and directly use this aggregate measure of water storage throughout my empirical estimation.

Gridded ΔTWS data from the GSFC mascon solutions provide monthly observations of total water storage, measured as anomalies from the mean gravity field over the period 2004-2014. Covering the years 2003 to 2016, there are 165 observations per grid cell in the GSFC data.[5] Some missing data in 2003 are due to outages while the mission became fully operational, and later holes in the data were caused by solar panels failing to get enough sunlight – these holes occur more often in later years as the batteries aged. Each grid cell in these data is assigned to a hydrologically-determined water basin, of which there are 187 in my estimation sample. Estimates of grid-specific trends in ΔTWS over the entire satellite record are shown in Figure 3. Note that, importantly, I never observe the actual *level* of total water mass at any given point in time and space – because of the nature of the GRACE mission, the data are represented as *anomalies* in the average gravitational field, implying that in all my empirical estimations, I am focusing on changes in the size of anomalies, rather than changes in levels.

3.2 Spatial covariates

I merge gridded monthly ΔTWS data with a wide range of covariates described in this section, including climate data to capture natural variation in water availability, cropped area to proxy for agricultural suitability, and nighttime lights to proxy for the availability of electricity to power irrigation technologies. These covariates are used as controls in the main analysis, as well as in robustness checks and tests of heterogeneity.

Climate data For climate variables, I use observations of monthly average temperature and cumulative precipitation from the Global Meteorological Forcing Dataset (GMFD) version 3 (Sheffield, Goteti, and Wood, 2006), available at a global daily $0.25^\circ \times 0.25^\circ$ grid from 1900 to 2014. These are reanalysis data, meaning they are

[5] A follow-on GRACE mission was launched in 2018. Because available data on agricultural policy distortions do not extend past 2011, I do not utilize data from the follow-on mission.

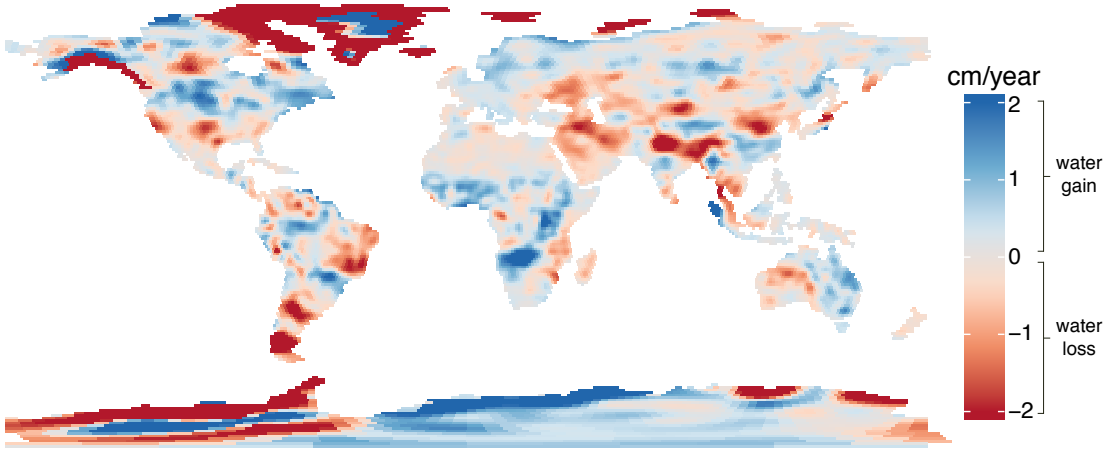


Figure 3: Annual changes in total water storage over land during the Gravity Recovery and Climate Experiment (GRACE) satellite record. Colors indicate the trend in total water storage (measured as changes in centimeters of water equivalent height per year per grid cell), where red indicates net water loss and blue indicates net water gain on average across the 2003-2016 GRACE satellite period. Raw total water storage values come from the Goddard Space Flight Center and are provided monthly from 2003 to 2016 on an equal-area grid with resolution $1^\circ \times 1^\circ$ ($\sim$ 111.11km$\times$111.11km) at the equator. Estimated trends come from a regression of monthly total water storage values on a running time variable, including month-of-year fixed effects to account for seasonality. The estimated coefficients were translated into annual values for display. Changes in total water storage as measured by GRACE include changes in soil moisture, groundwater, surface water, and snow and ice.

derived from a physical weather model calibrated to observational data from weather stations. I aggregate these higher-resolution pixels to the lower-resolution ΔTWS grid (see Figure 2) by crop-weighted averaging, where climate data pixel values are weighted by their cropped area, as measured by Monfreda, Ramankutty, and Foley (2008) in the year 2000. I make any nonlinear transformations used in my empirical specifications (e.g. quadratic monthly cumulative precipitation) at the grid cell level before averaging across space in order to preserve any pixel-level nonlinearities (Hsiang, 2016).

Agricultural suitability To measure cropped area globally, I use the global land cover data set created by Monfreda, Ramankutty, and Foley (2008). This high-resolution (approximately 10km $\times$ 10km) product provides cropped area fraction for every grid cell for 175 crops by combining national, state, and country census data with remotely sensed maps of land cover. I use data from 2000 for five crops: rice, wheat, maize, soybean, and cotton. I use an area-weighted average to aggregate pixels up to the equal-area GSFC grid based on the area of each cropped area pixel overlapping a GSFC grid cell. Note that these data provide proxies for location- and crop-specific productivities, described in Appendix A as A_x^{fk}. In Table C3 I show results using the U.N.

Food and Agriculture Organization's (FAO) Global Agro-Ecological Zones (GAEZ) Crop Suitability Index as an alternative measure of agricultural suitability. These data are crop-specific potential productivity estimates provided at 5 arc-minute resolution, developed using state-of-the-art agronomic modeling calibrated with a wide array of climatological datasets and observational yield data. Because these productivity estimates vary substantially based on assumed agricultural inputs, including fertilizer and irrigation, and because no across-crop metrics of aggregate suitability are provided, I rely on the Monfreda, Ramankutty, and Foley (2008) data in the main analysis. Moreover, these data incorporate information on water availability, recharge rates, and soil moisture, potentially confounding my estimation strategy.

Access to irrigation I use the National Oceanic and Atmospheric Administration's (NOAA) Global DMSP-OLS Nighttime Lights Time Series (Version 4) as a proxy for access to irrigation. These data are derived from satellites that have been circling the Earth multiple times daily since 1970, recording the intensity of lights as seen at night using sensors designed to detect low-light imaging data. NOAA processes raw light intensity data to remove intense sources of natural light, such that the remaining signal is largely human-caused. These data are available annually at 30 arc-second pixels, excluding very high latitude zones. The value recorded in the data is an integer between 0 (no light) and 63 (full light). This scale implies that a very small fraction of pixels (around 0.1%) are top-coded at 63 – these tend to be wealthy and densely populated areas. These data have been increasingly used to measure economic activity and access to electricity, providing a metric of human prosperity that can be particularly valuable in locations where administrative records are poor (Henderson, Storeygard, and Weil, 2012). I use variation in night lights to capture changes over time in δ, the cost of accessing water resources, as described in Section 2 and Appendix A. The limitations of this proxy should be appropriately noted – while access to electricity enables the adoption of irrigation, it also very likely changes the productivity of the outside option (denoted A_y in Appendix A), as well as other socioeconomic conditions. These results, therefore, should be interpreted with caution and are not intended to be interpreted causally. Appendix C7 shows that the main results do not depend on the inclusion of nighttime lights as a control.

Figure 4 displays some of these covariates, after aggregation to the GSFC total water storage equal area grid.

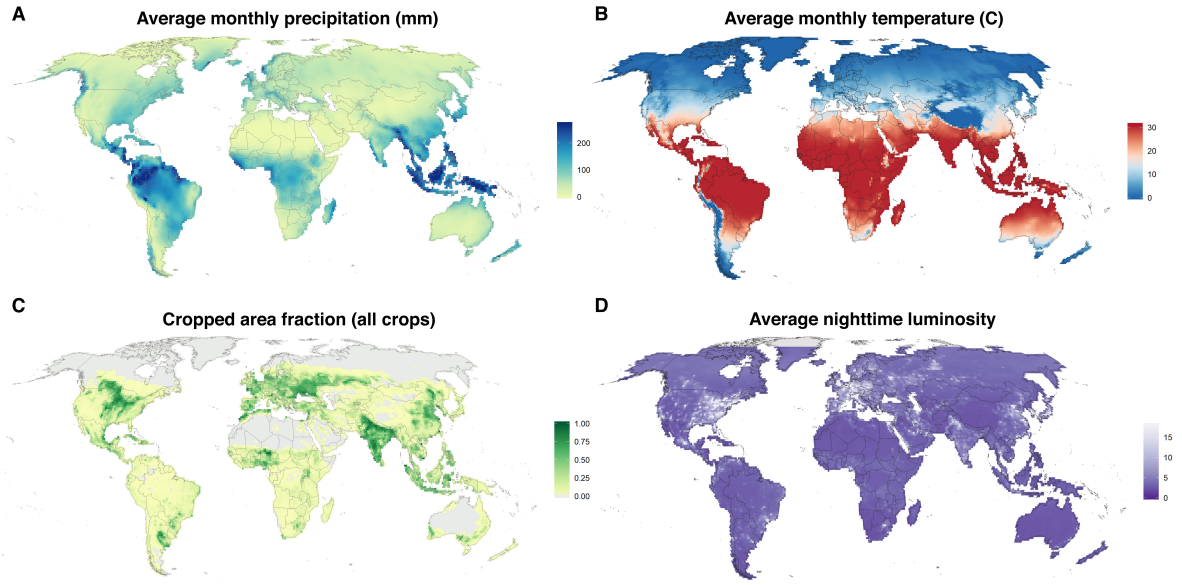


Figure 4: Maps of covariates used in regression analysis Panels **A** and **B** show average monthly precipitation in millimeters and temperature in degrees Celsius, respectively, both derived from the GMFD version 3 dataset and averaged over the sample used in analysis (2003-2011). Panel **C** shows cropped area fraction (ranging from 0 to 1) from Monfreda, Ramankutty, and Foley (2008), aggregated across all 175 modeled crops. Panel **D** shows average annual nighttime light intensity over the sample period, measured in a unitless indicator of luminosity which ranges from 0 to 63. All variables are aggregated from native resolution to correspond to the GSFC mascon grid cells from Luthcke et al. (2013).

3.3 Distortions to agricultural incentives

Domestic governments distort agricultural markets using a wide array of policy interventions, ranging from direct taxes and subsidies to import tariffs, input subsidies, and manipulation of foreign exchange markets (Anderson, Rausser, and Swinnen, 2013). These interventions have long been studied by agricultural economists interested in how such distortions bolster or constrain productivity growth in the agricultural sector (e.g., Adamopoulos and Restuccia, 2014; Block, 2014; Headey, 2011). However, enumerating and quantifying the many channels through which production incentives are influenced by policy is a major enterprise and multiple datasets have been assembled, updated, and expanded over time. I rely on the internationally comparable dataset provided by the World Bank's "Distortions to Agricultural Incentives" (DAI) project, which uses comprehensive crop and product-specific price and output data to measure government induced distortions to farmer production incentives for 80 farm products across 82 countries that together account for more than 90% of world's population, farmers, extreme poor, and agricultural GDP (Anderson et al., 2008). While both

GTAP (Aguiar et al., 2019) and the OECD are widely used alternative sources, I rely on the World Bank due to its extensive coverage of developing countries and its inclusion of non-tariff barriers to trade (e.g., quotas, sanctions), which have been shown to play a substantial role in overall trade restrictiveness (Anderson, Neary et al., 2005).

In particular, I leverage two measures from the DAI project. First, I use the Nominal Rate of Assistance (NRA), which quantifies the wedge between current domestic prices and the prices that would prevail without any governmental intervention in the agricultural sector. A positive NRA is a subsidy to farmers of that crop or product product, while a negative NRA is a tax, and the value is intended to account for direct taxes and subsidies, trade interventions such as import tariffs and export subsidies, non-tariff barriers to trade, and government manipulation of foreign exchange markets (Anderson et al., 2008).[6] These values are calculated as the percentage by which domestic farm-gate prices exceed or fall below the international price of the same product, after netting out estimates of transportation and distribution costs. Importantly, the NRA measure explicitly does *not* include any subsidies to water use or irrigation technology, nor changes in water policy (Anderson et al., 2008). In addition to crop-specific estimates, the DAI project also constructs an aggregate NRA across all agricultural products, calculated as the output-weighted average of all covered crop-specific NRA values, plus estimates for the rate of protection on uncovered farm products and other non-crop specific assistance (Anderson, Rausser, and Swinnen, 2013).

The second metric I use is the Relative Rate of Assistance (RRA), which measures the distortion of the *relative* price of agricultural to non-agricultural tradable goods:

$$RRA = \left[\frac{100 + NRA_ag_tradables}{100 + NRA_nonag_tradables} - 1\right] \times 100, \tag{8}$$

where $NRA_ag_tradables$ is the aggregate NRA for all tradable agricultural goods, and $NRA_nonag_tradables$ is an estimate of the same value for tradable goods outside the agricultural sector. A negative RRA value indicates an anti-agricultural bias in a government's assistance regime, while a positive RRA value indicates a pro-agricultural bias. Because relative and not nominal prices drive production incentives, I use these aggregate RRA values measured by country and year throughout the main analysis to capture variation in τ, the distortion to the relative price of agricultural to non-agricultural goods shown in Figure 1. However, in analyses where I investigate crop-

[6] If a product is not traded, its NRA value only includes domestic taxes or subsidies.

specific heterogeneity, I use crop-specific NRA values to quantify τ_k, the crop-specific price distortion described in Appendix Equation A.4. The DAI data are available from 1955 to 2011, although not all countries have data in all years or for all crops – on average a country is observed over 45 years for 12 different crops. The NRA and RRA variables from the DAI database have been used extensively in studies of agricultural political economy (e.g., Anderson, Rausser, and Swinnen, 2013), productivity implications of agricultural distortions (e.g., Headey, 2011), and the role of distortions in agricultural factor misallocation (Adamopoulos and Restuccia, 2014).

To merge these administrative records with the rest of my gridded data, I match the GSFC equal-area grid cells measuring ΔTWS to countries based on the location of their centroids.[7] Figure 5 displays the average RRA value for all GSFC grid cells falling within countries covered by the DAI project database (see Figure B3 for the analogous figure for NRA), as well as some policies used by a few example countries. As has been widely documented throughout the agricultural economics literature, higher income countries tend to subsidize agricultural production (green to blue regions in Figure 5), while lower income countries tend to tax it (orange to red regions in Figure 5). For example, in the United States, price loss coverage and tariff rate quotas raise relative prices for farmers, while export taxes lower them for Argentinian farmers.

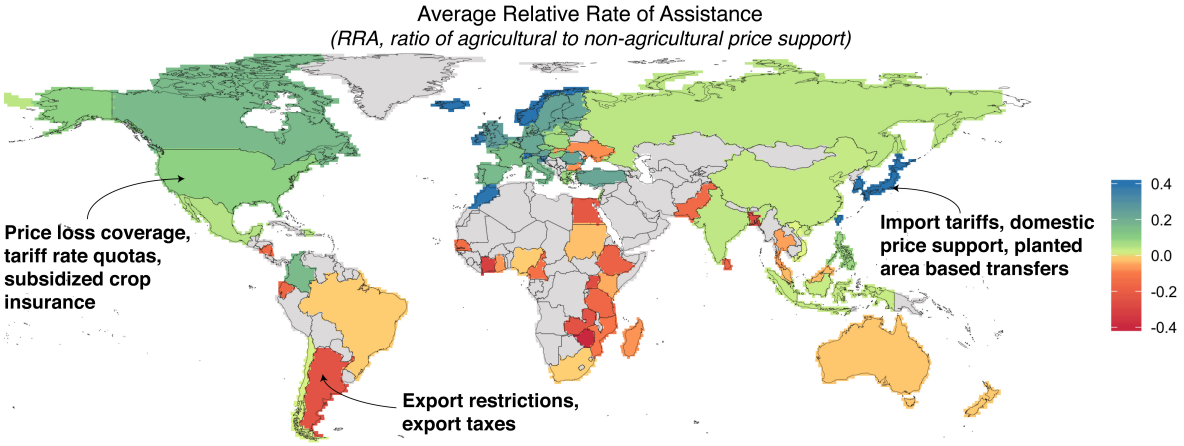


Figure 5: Average Relative Rates of Assistance (RRAs) to agricultural products (2003-2011) Relative Rate of Assistance values by country-year are from the World Bank Distortions to Agricultural Incentives (DAI) project and are averaged here over the years that overlap with the GRACE satellite record. Positive values (green to blue) indicate a pro-agricultural bias in domestic policy, while negative values (orange to red) indicate an anti-agricultural bias. See text for details.

[7]This approach leads to some lost data, as there are grid cells with some area over land, but with centroids over water bodies. To avoid including variation in ΔTWS based on changes in the density and volume of oceans and inland seas, these grid cells are dropped.

The bifurcated nature of agricultural intervention highlighted in Figure 5 makes clear that liberalization of agricultural markets may lead to strongly heterogenous changes in water use across the globe. For (largely high income) countries that have historically subsidized agriculture, removal of these interventions is likely to lower total agricultural production, reallocate land and labor to alternative uses, and ultimately save water resources, as long as agriculture is water intensive relative to non-agricultural goods production. In contrast, for (largely low income) countries that have historically taxed agriculture, the opposite is likely to unfold under liberalization. Quantifying the net effect on water resources, and its spatial distribution, is the focus of Section 6.

4 Methods

Variation in GRACE anomalies can, in theory, be driven by any movement of mass underneath or above Earth's surface. Because this measure does not directly correspond to variation in water resources, and in particular to human extraction and use of water, it has been difficult to attribute observed changes in anomalies to any particular human activity (Rodell et al., 2018). While many studies have compared time series of GRACE data to other measures of of water availability, such as well gauges (e.g. Long et al. (2013)) or general trends in rainfall (Rodell et al., 2018), to my knowledge there has been no statistical analysis of GRACE data beyond descriptive exercises. Therefore, before estimation of the relationship of interest – the effect of agricultural market distortions on total water storage – I first estimate a standard panel fixed effects model to verify that intuitive relationships between variations in the climate and changes in total water storage can be recovered using linear regression models with the GRACE data. Second, I outline the empirical approach I use to identify the effect of changes in agricultural policy interventions on water use.

4.1 Using GRACE in linear regression

To investigate whether intuitive relationships between climate, irrigation availability, and cropped area can be uncovered in a model exploiting monthly variation in total water storage, I estimate a standard panel fixed effects model at the grid cell level. I exploit month-to-month variation in temperature and rainfall to explain changes in monthly ΔTWS. I interact nonlinear temperature and precipitation response functions with cropped area fraction and estimates of area equipped for irrigation to capture the

differential effects that may occur in regions where agriculture dominates the landscape. My estimating equation is:

$$\begin{aligned}\Delta TWS_{imt} = f(\boldsymbol{T}_{imt}|CAF_i, AEI_i) + g(\boldsymbol{P}_{imt}|CAF_i, AEI_i) \\ + \psi_i + \alpha_{bm} + \mu_{bt} + \lambda_b^1(mt) + \lambda_b^2(mt)^2 + \varepsilon_{imt},\end{aligned} \tag{9}$$

where i indicates the GRACE GSFC grid cells, m indicates month-of-year, and t indicate years. The functions $f(\cdot)$ and $g(\cdot)$ are linear combinations of the vectors $\boldsymbol{T}$ and $\boldsymbol{P}$, which themselves contain nonlinear functions of daily pixel temperatures and precipitation, respectively.[8] In some specifications, and as indicated in Equation 9, both functions are conditional on cropped area fraction (CAF) and area equipped for irrigation (AEI), which are time-invariant measures of cropping intensity and accessibility of irrigation, respectively.[9] In the main specification, $\boldsymbol{T}_{imt}$ contains binned daily average temperature (5°C bins) and $\boldsymbol{P}_{imt}$ contains polynomials of daily precipitation (up to fourth order).

Following the large climate impacts literature (Carleton and Hsiang, 2016), this regression leverages a suite of spatial and temporal fixed effects to isolate plausibly random variation in climatological conditions. Grid cell fixed effects (ψ_i) account for all time-invariant unobservables at the level of each grid cell, basin-by-month fixed effects (α_{bm}) capture differential seasonality at the level of each of ∼200 global water

[8]To see how temperature and precipitation vectors are created, consider the aggregation of gridded daily average temperatures T_{zd} across pixels z and days d to create the monthly GSFC grid cell-level vector $\boldsymbol{T}_{imt}$. This calculation is computed as:

$$\boldsymbol{T}_{imt} = \left[\sum_{z\in i} w_{zi} \sum_{d\in m} h_1(T_{zd}), ..., \sum_{z\in i} w_{zi} \sum_{d\in t} h_P(T_{zd})\right]$$

where transformations $h_p(\cdot)$ indicate one of P nonlinear functions of gridded daily average temperature. Aggregation across pixels within a GSFC grid cell is performed using time-invariant cropped area weights w_{zi}, which represent the share of i's cropped area that falls into pixel z. An analogous procedure is performed for precipitation.

[9]The exact implementation of Equation 9 is:

$$\begin{aligned}\Delta TWS_{imt} = \boldsymbol{\beta^T}\boldsymbol{T}_{imt} + \boldsymbol{\gamma_1^T}\boldsymbol{T}_{imt} \times CAF_i + \boldsymbol{\gamma_2^T}\boldsymbol{T}_{imt} \times AEI_i + \boldsymbol{\gamma_3^T}\boldsymbol{T}_{imt} \times CAF_i \times AEI_i \\ + \boldsymbol{\beta^P}\boldsymbol{P}_{imt} + \boldsymbol{\gamma_1^P}\boldsymbol{P}_{imt} \times CAF_i + \boldsymbol{\gamma_2^P}\boldsymbol{P}_{imt} \times AEI_i + \boldsymbol{\gamma_3^P}\boldsymbol{P}_{imt} \times CAF_i \times AEI_i \\ + \psi_i + \alpha_{bm} + \mu_{bt} + \lambda_b^1(mt) + \lambda_b^2(mt)^2 + \varepsilon_{imt},\end{aligned}$$

where all variables are defined as in the text. Note that bold font indicates vectors – because $\boldsymbol{T}$ and $\boldsymbol{P}$ are vectors of nonlinear transformations of temperature and precipitation, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of estimated coefficients on each nonlinear term.

basins, basin-by-year fixed effects (μ_{bt}) capture annual shocks at the water basin level, and basin-specific quadratic time trends ($\lambda_b^1(mt)$ and $\lambda_b^2(mt)^2$) account for possibly nonlinear within-year basin-specific trending behavior. These controls imply that the effects of climate are identified using month-to-month variation within a single grid cell, after controlling for basin-level trends, annual shocks, and seasonal effects. Standard errors clustered within basins (to account for correlation over time within a grid cell as well as correlation across grid cells within the same water basin) and results are shown under various alternative sets of temporal fixed effects.

4.2 Estimating the effects of agricultural market distortions on changes in total water storage

The central focus of this paper is to estimate the impact of changes in agricultural policy on water availability. Recall from Section 2 that the treatment variable of interest is the wedge between domestic and global agricultural output prices, either in aggregate (τ), or at a crop-specific level (τ_k). Changes in these wedges are affected by political forces governing incentives to domestically produce, import, or export agricultural goods. To measure these policy treatments, I use the crop-specific Nominal Rate of Assistance (NRA) and all-crop aggregate Relative Rate of Assistance (RRA) measures described in Section 3, which are defined at the country-by-year level.

The ideal experiment to identify the causal effect of policy intervention on total water storage would be to randomly allocate arable land to different agricultural policies, allowing some to face undistorted market prices ($\tau = 0$), others to benefit from positive incentives ($\tau > 0$), and others to face disincentives ($\tau < 0$). Because such an experiment is infeasible in this context, as it is in the study of of trade liberalization more broadly (Cherniwchan, Copeland, and Taylor, 2017), I follow recent papers in the trade and environment literature in estimating a panel model that exploits variation in protection of agricultural markets across both time and space (Cherniwchan, 2017; Martin, 2012). While agricultural policy is clearly not randomly assigned, I isolate variation that is plausibly uncorrelated with unobservable determinants of changes in total water storage using a design similar in spirit to differences-in-differences, and conduct a set of tests to rule out the most likely sources of endogeneity.

My first source of variation is temporal. As shown in Figure B2, there are substantial changes over time in the degree to which governments manipulate agricultural markets. As described in Anderson, Rausser, and Swinnen (2013), these changes come

from diverse sources, ranging from increased desire for food self-sufficiency in light of shocks to trading partners' supplies, changes in the politics of import substitution industrialization in developing countries and of farm protection in high-income countries, and local and foreign lobbying from particular interest groups, such as farmers, land conservation groups, input suppliers, or industry groups. In small countries, much of the variation in the wedge between domestic and global prices comes from a fixed policy landscape combined with large fluctuations in global prices (Anderson, Rausser, and Swinnen, 2013). Some of this temporal variation, perhaps much of it, is plausibly exogenous to changes in total water storage. To the extent that changes in domestic policy are driven by concerns in manufacturing import competition, broad concern for nationwide food insecurity, or lobbying from an interest group facing changes in their global competition, it is unlikely that other unobservables correlate both with these policy drivers and with month-to-month variations in total water storage. Similarly, if variation in τ derives from global price shocks, it will be unrelated to local water storage for small price-taking countries. However, it is possible that changes in water storage could generate reverse causality in some contexts; for example, if falling aquifer levels cause farmers to lobby for increased support, negative anomalies in ΔTWS would correlate with increases in NRA. I therefore do not rely on this temporal variation alone.

My second source of variation is spatial. While all grid cells within a country are assigned the same temporal pattern of national policy changes, I combine this country-level temporal variation with spatial heterogeneity in grid cell level agricultural productivity to conduct a repeated differences-in-differences analysis. In particular, I estimate an interaction model in which τ, as measured by NRA/RRA, is interacted with a grid cell level indicator of agricultural suitability. In the main specification, I use cropped area fraction in 2000 (prior to my sample by two years) as a proxy for suitability, which has the benefit of being strongly correlated with existing cropped area, but not endogenous to year-to-year variation exploited in my estimation.[10] The identifying assumption for causal interpretation of the interaction effect between rates of assistance and suitability is that there are no unobserved factors that correlate with agricultural policies and with water loss or gain *differentially* across locations of high versus low suitability. In regressions exploiting crop-specific policy variation, this interaction exploits

[10]Using the Food and Agriculture Organization's (FAO) Global Agro-Ecological Zones (GAEZ) Crop Suitability Index in place of cropped area fraction when possible (i.e., in crop-specific regressions) does not change results substantially, as shown in Tables C2 and C3. However, these data present a number of challenges described in Section 3 and therefore are not used in the main set of results.

crop-specific suitability, and therefore a violation of identification requires differential correlation between unobservables, agricultural policies, and total water storage on the basis of crop-specific suitability. I discuss below a test to provide evidence that such an identifying assumption is reasonable in this context.

The main estimating equation is:

$$\begin{aligned}\Delta TWS_{icmt} = \beta RRA_{ct} + \gamma RRA_{ct} \times CAF_i + \rho lights_{ict} + \phi lights_{ict} \times CAF_i \\ + \boldsymbol{\eta} \boldsymbol{X}_{icmt} + \psi_i + \alpha_{bm} + \mu_{bt} + \lambda_b^1(mt) + \lambda_b^2(mt)^2 + \varepsilon_{icmt},\end{aligned} \tag{10}$$

where c subscripts indicate countries, $\boldsymbol{X}_{icmt}$ is a vector of nonlinear climate controls (as described above), *lights* indicate time-varying grid-cell level nighttime lights values, and where all other variables are defined as in Equation 9. When investigating crop-specific policies, I estimate Equation 10 with a set of crop-specific nominal rates of assistance.[11] Standard errors are clustered at the water basin level and results are shown using various sets of temporal fixed effects and controls (including dropping nighttime lights).

The parameter of interest is γ, which measures the differential impact of agricultural price distortions on local water storage in locations of high versus low agricultural suitability. A salient possible violation of the identifying assumption is that agricultural protection may be achieved through lobbying from growers producing in high-suitability regions *because* they are facing water shortages. While this story is plausible, such a reverse causality violation would have to occur *conditional on basin-specific time trends*, basin-year shocks, and grid cell time-invariant characteristics. To directly test this possibility, I estimate a distributed lag model in which Relative Rates of Assistance are regressed on 24 months of lagged ΔTWS values interacted with cropped are fraction, controlling for the same set of fixed effects shown in Equation 10. As shown in Figure B4, current changes in RRA are not driven by previous changes in ΔTWS, either in high or low suitability regions. While proof of strict exogeneity is of course impossible, these findings support a causal interpretation of both β, and γ in Equation 10.

This repeated difference-in-differences identification strategy is a similar to Martin (2012), who compares changes in emissions in industries affected by a change in trade

[11] In crop-specific analyses, the regression becomes:

$$\begin{aligned}\Delta TWS_{icmt} = \sum_k \beta^k NRA_{ct}^k + \sum_k \gamma_k NRA_{ct}^k \times CAF_i^k + \rho lights_{ict} + \phi lights_{ict} \times CAF_i \\ + \boldsymbol{\eta} \boldsymbol{X}_{icmt} + \psi_i + \alpha_{bm} + \mu_{bt} + \lambda_b^1(mt) + \lambda_b^2(mt)^2 + \varepsilon_{icmt},\end{aligned}$$

where k indicates each of the following crops: maize, wheat, rice, soybean, and cotton.

policy to changes in emissions in industries left unaffected. My estimation approach also closely follows Cherniwchan (2017), who compares plant-level emissions before and after NAFTA in industries affected and unaffected by the liberalization, in states with higher and lower trade costs (a triple difference).

Recall from Section 2 that a decrease in the cost of accessing irrigation water – i.e. a decrease in δ – should increase total water use through expanding agricultural production and through increasing water used per unit of output. Just like the policy shocks, Figure B1 shows how the effect of irrigation costs is likely to differ across agriculturally productive and unproductive regions. While I cannot directly test this hypothesis empirically in a causal manner, as I do not have data on exogenous changes in irrigation technology, Equation 10 includes luminosity as measured in the night lights dataset as a means of capturing availability of electricity to power irrigation. Because access to electricity dramatically lowers the cost of accessing groundwater, and can aid the diversion of surface water, it serves as a proxy for costs of obtaining and using irrigation water. Interpretation of the ϕ coefficients can provide suggestive evidence either for or against this basic prediction of the effects of irrigation costs on total water use.

5 Results

5.1 Climatological impacts on GRACE in panel regression

To my knowledge, no previous studies use GRACE to statistically uncover the socioeconomic and climatic drivers of changes in total water storage. Thus, here I verify that these data can be used to recover intuitive relationships between water availability, key climatic variables, and measures of agricultural activity using a panel fixed effects framework that is standard in the climate impacts literature.

The effects of temperature on ΔTWS are shown in Figure 6 (the effects of precipitation and nighttime lights are discussed below in Section 5.2). Panel **A** shows that increases in temperature cause decreases in total water storage, with a largely linear relationship estimated on average across all grid cells in the sample. This is intuitive, as higher temperatures increase evapotranspiration, causing plants and crops to use more available water resources from the soil or from ground and surface water reservoirs accessed through irrigation technologies. The magnitude of this effect is large –

on average, one day at 35°C causes 12 acre-feet[12] of water loss over the course of a month across one grid cell (∼111×111km).

Panel **B** shows, through estimation of the model in Equation 9, that these losses due to temperature are larger in cropped areas (gold line) and most severe in areas that are both cropped and equipped for irrigation (green line). Additionally, both cropped areas and cropped and irrigated areas exhibit nonlinear temperature relationships with larger water losses at temperatures above 29°C, the value at which cereal yields fall precipitously with rising temperature (Schlenker and Roberts, 2009). In grid cells with no cropped area as of 2000, there is no statistically significant effect of temperature on water storage (blue line). Again, these effects are substantial – on 35°C days, cropped and irrigated grid cells lose ∼70 acre-feet more water than do grid cells with no cropped area. Increased sensitivity of total water storage to high temperatures in locations with irrigated crops aligns well with agronomic research documenting increased crop water demands on hot days, which can be fully met when farmers have access to irrigation.

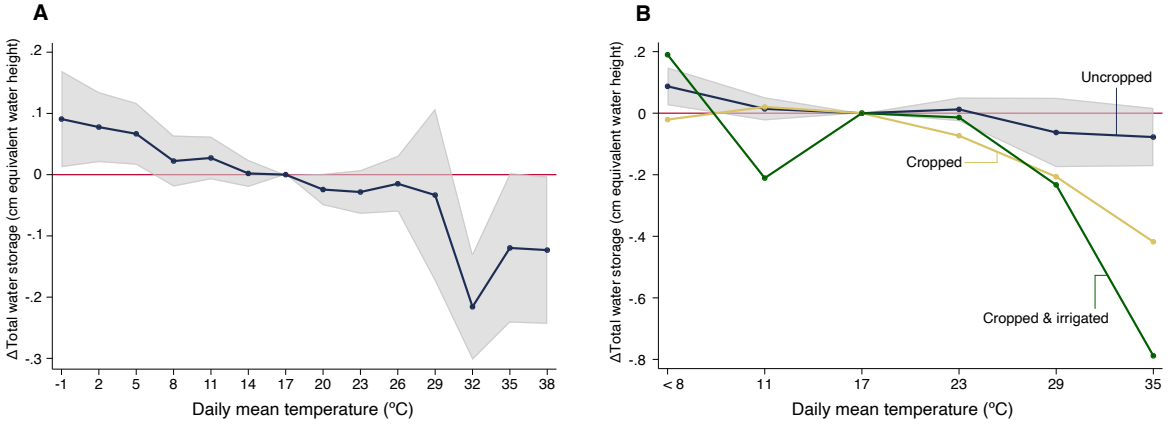


Figure 6: Nonlinear impact of temperature on total water storage Both panels show the effect of a single day's temperature on the monthly total water storage anomaly ΔTWS, as measured by GRACE. Both figures show the effect of binned temperatures relative to a moderate temperature bin centered at 17°C. Results shown are from regression models with grid cell fixed effects, basin-by-month fixed effects, basin-year fixed effects, and basin-specific quadratic trends. Panel **A** shows the average treatment effect across all global grid cells between latitudes 50°S and 60°N. Panel **B** shows results from the estimation of Equation 9, where temperature is interacted with cropped area fraction and with area equipped for irrigation. "Uncropped" indicates a grid cell with a cropped area fraction (CAF) value of zero in 2000, "cropped" indicates a CAF of 1, and "cropped and irrigated" indicates a fully cropped and fully irrigation equipped grid cell. Because this model includes a triple interaction, the bin width is increased from 3°C in panel **A** to 6°C in panel **B**. Standard errors are clustered at the water basin level in both panels.

[12]An acre-foot of water is roughly the quantity of water needed to cover an acre of land with one foot of water. There are 325,851 gallons of water in an acre-foot.

5.2 The effects of agricultural market distortions on total water storage

In this section, I demonstrate that policy distortions which increase the relative domestic producer price of agricultural output – that is, increases in τ – decrease anomalies in total water storage. This is consistent with the hypothesis that these distortions shift the composition of the economy toward agriculture, causing an increase in the use of water, the factor which agriculture uses relatively intensively. Panel **A** of Figure 7 shows this result: the bars represent the point estimate of the effect of a one unit increase in RRA on ΔTWS, in un-cropped (gold) and fully cropped (green) grid cells, and confidence intervals are shown with whiskers. The negative and statistically significant coefficient on RRA in cropped areas implies that an increase in distortions favoring agriculture is associated with lower total water storage in regions that are agriculturally suitable; this coefficient is negative and statistically significant in specifications using less stringent fixed effects (Table C1 and Figure 9). Robustness to specification of control variables is shown in Table C7. As shown in Table C1, analogous results for the *nominal* metric of agricultural assistance (NRA) are similar in sign and magnitude, although are statistically insignificant when considering the aggregate NRA metric across all agricultural products (crop-specific analyses are discussed below).

These effects are quantitatively meaningful. For example, in a grid cell fully planted to crops, a policy change which raises the relative producer price (e.g. a subsidy or import tariff) by 100 percentage points causes a water loss of 5.3cm of equivalent water height across the grid cell over the course of one month. This amounts to ∼6,300 acre-feet of water lost over the course of a year, or 60% of the total water needed to fully plant a grid cell with almonds, a highly water-intensive crop.

Panel **B** of Figure 7 shows the effect of control variables on total water storage. As expected, and as shown in the previous section, hot temperatures lower water storage. In contrast, higher cumulative precipitation (light blue bar) substantially increases water storage. Additionally, decreasing costs of irrigation, as proxied by increasing luminosity in nighttime lights, are negatively correlated with total water storage anomalies in cropped areas, although this effect is statistically insignificant on average across the sample.

Figure 7 likely masks important heterogeneity in treatment effects across different crops and different regions of the globe. As shown in Section 2, all else equal, policy-induced increases in the domestic producer price for crops that are relatively

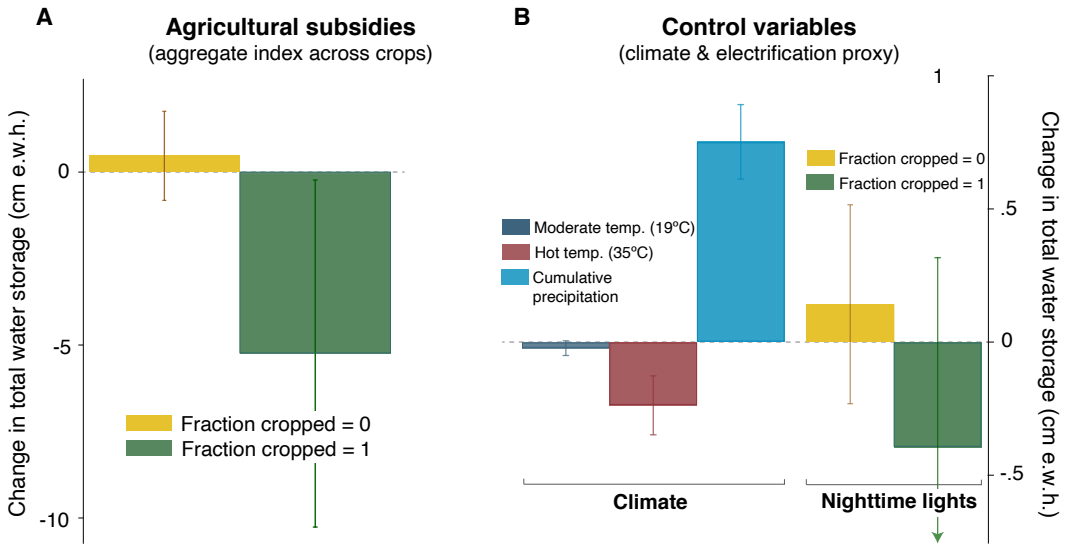


Figure 7: Domestic policies with pro-agricultural bias lead to declines in total water storage All results shown are jointly estimated via Equation 10, a panel model with grid cell fixed effects, basin-by-month fixed effects, basin-by-year fixed effects, and basin-specific quadratic time trends. Magnitudes in yellow show coefficients corresponding to locations where cropped area fraction was zero in 2000; magnitudes in dark green show coefficients corresponding to locations where the cropped area fraction was 1 in 2000. Standard errors are clustered at the water basin level in both panels.

water-intensive should cause relatively larger increases in water use. Similarly, regions of the world with lower private costs of accessing and using irrigation water (δ) – either because of poor property rights or for geographical reasons – should see larger losses in total water storage for a given increase in pro-agricultural policies. To investigate such heterogeneity, I estimate multiple versions of Equation 10 that either subset based on region of the globe, estimate the effect of crop-specific Nominal Rates of Assistance (NRA^k for crop k) in place of aggregate, sector-wide Relative Rates of Assistance (RRA), or do both simultaneously. As above for the aggregate-level policy shocks, in these regressions I identify a differential effect of NRA on total water storage across locations based on agricultural suitability.

Figure 8 shows a selected set of results from a version of Equation 10 that subsets by region of the globe[13] *and* estimates heterogeneity by crop for maize, wheat, rice,

[13]I follow the World Bank DAI database region definitions, estimating heterogeneous responses for Asia (excluding Japan), Eastern Europe, "High Income Countries" (Western Europe, Australia, US, Canada, and Japan), Latin America, and Africa. I additionally investigate the US, India, and China individually, given their outsized importance in global agricultural production. Note that there are insufficient data in Africa to estimate crop-specific policy effects.

soybean, and cotton.[14] In these crop-specific regressions, Nominal Rates of Assistance are crop-specific, indicating policy interventions applying only to individual crops, and are interacted with crop-specific suitability, as proxied by year 2000 grid cell level cropped area fraction. Coefficients for rice and wheat show the effect of a one unit increase in crop-specific NRA on total water storage in a grid cell planted fully with the corresponding crop for China, India and all of Asia (excluding Japan), while nighttime lights coefficients show the effect of a one unit increase in luminosity in a grid cell planted fully with any crop. I focus on Asia, and India and China in particular, as agricultural production in this region is rapidly rising, massive water infrastructure projects have recently been completed or are underway (e.g. the Three Gorges Dam, the world's largest power station), and because total irrigation water use is enormous – Mekonnen and Hoekstra (2011) estimate that the Indus and Ganges river basins in China, India and Pakistan together account for 25% of global surface and ground water use in agriculture. Similarly, I focus here on wheat and rice as they are estimated to consume more surface and ground water than any other crop: Mekonnen and Hoekstra (2011) estimate that these two crops together account for 45% of global consumptive use of surface and groundwater resources. In Table C8, results for all regions are provided.

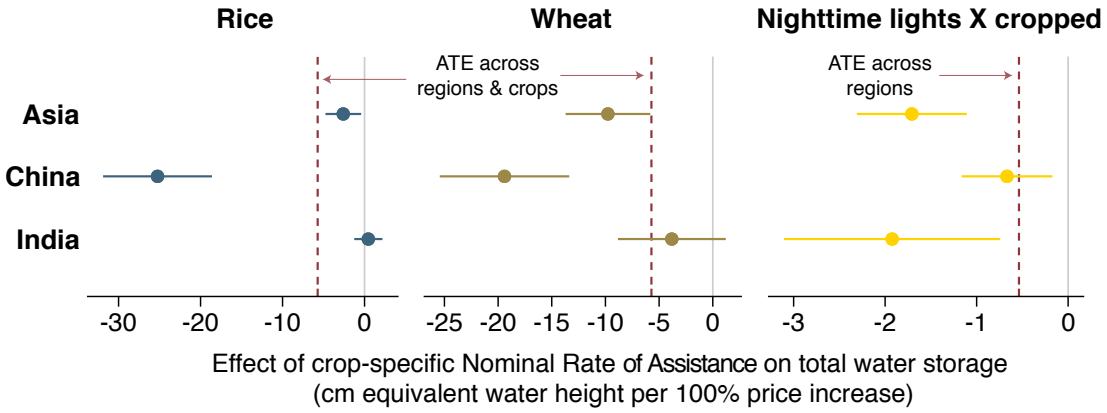


Figure 8: Impact of crop-specific agricultural subsidies on total water storage: Heterogeneity in select regions Results shown are from three independent panel models (one for each region shown) including grid cell fixed effects, basin-by-month fixed effects, basin-by-year fixed effects, and basin-specific quadratic trends. All point estimates shown indicate the coefficient on the interaction effect between Nominal Rates of Assistance (left and middle panels) or nighttime luminosity (right panel) and cropped area fraction. Average treatment effects indicated by the dotted red line are from a model that pools regions and estimates an all-crop aggregate NRA or nighttime lights effect. Standard errors are clustered at the grid cell level.

[14]Note that because there are insufficient numbers of basins within many of these regional subsets, I cluster my standard errors at the grid cell level.

Figure 8 shows that across Asia, increases in production incentives for wheat lead to substantially larger water storage losses than do policies for other crops and other regions. This is particularly true in China, where the effect of the wheat-specific Nominal Rate of Assistance is nearly four times larger than the average treatment effect across regions and crops. Water storage in China is also particularly sensitive to policy changes affecting rice production incentives. China is the world's largest producer of both rice and wheat, and over 90% of its rice production is estimated to be irrigated (Food and Agriculture Organization of the United Nations, 2020). In contrast, while India is second to China in production of both crops, I do not detect statistically significant effects of policy distortions on water loss for these crops in India. In contrast, increased nighttime luminosity is correlated with large declines in water storage in cropped regions of India, perhaps reflecting large increases in irrigation due to expansion of electricity to rural areas in recent years (e.g., Burlig and Preonas (2016)). Table C2 shows that across the sample, increases in producer incentives for wheat production appear most damaging to water resources, a result that is consistent across alternative measures of agricultural suitability (Table C3) and the use of a distinct measure of production distortions (Table C4).

Unfortunately, because few countries have data for all five of these staple crops, the regressions shown in Tables C2-C4 are limited to grid cells in Australia, Brazil, China, Columbia, India, and the US. Moreover, because the subsidy data end in 2011, the sample is restricted to 2003-2011 for all regressions. I show results in Appendix Table C5 in which I estimate each crop independently, so as to include far more countries in each regression. These results are qualitatively similar, with large and statistically significant effects for wheat in cropped areas.

5.3 Robustness: Exploiting long-run variation

To isolate plausibly random variation in agricultural policy distortions, the main specification above exploits spatially-differentiated year-to-year variation in rates of agricultural assistance. However, reallocation of domestic production toward or away from water-intensive agricultural production may occur slowly, or may only occur when producers observe a consistent trend toward higher or lower intervention. To examine whether the short-run effects recovered above generalize to longer-run changes in agricultural policy, here I estimate a long differences model in which trends in total water storage anomalies over the sample period (2003-2011) are regressed on trends in agri-

cultural policy (RRA) interacted with cropped area fraction.

This long differences regression approach exploits cross-sectional variation in the magnitude of trends in RRA to identify the marginal effect of agricultural assistance on ΔTWS, making it vulnerable to confounding influences of unobservable variables that may correlate both with trends in policy and trends in water storage. To mitigate these concerns, I show results that include 1° latitudinal band fixed effects, water basin fixed effects, or country fixed effects. However, these spatial controls cannot fully address omitted variables bias concerns; thus, I treat this analysis as secondary to the primary specification shown in the previous subsection.

A comparison of the long differences model with the annual panel regression results is shown in Figure 9, where the coefficients on the interaction between RRA and cropped area fraction are plotted for a host of alternative fixed effects. My preferred specification for each regression approach is shown in dark green (annual model) or dark purple (long differences). Across all specifications, the long differences model recovers a negative effect of increasing Relative Rates of Assistance to agricultural production in cropped areas, although the magnitude of this effect is substantially smaller when exploiting longer-run variation. When comparing my preferred specifications for each approach, the long differences model recovers an effect approximately 34% smaller than the annual panel model. However, the consistency in the effect of RRA on total water storage in a model exploiting distinct variation in agricultural policies is reassuring, and aligns with a large agricultural economics literature on the productivity implications of NRA and RRA, which finds minimal differences in responses to short- versus long-run variation (e.g., Fuglie and Rada, 2013; Hendricks, Smith, and Villoria, 2018). As shown in Table C6, all controls, including the interaction between nighttime lights and cropped area, have correlations with total water storage in this long differences model that are consistent with the annual model discussed above.

6 The effect of recent agricultural market liberalization on the spatial distribution of water use

6.1 Recent liberalization of global agricultural markets

National governments have substantially intervened in agricultural markets throughout much of modern history. Anderson, Rausser, and Swinnen (2013) estimate that in 2004,

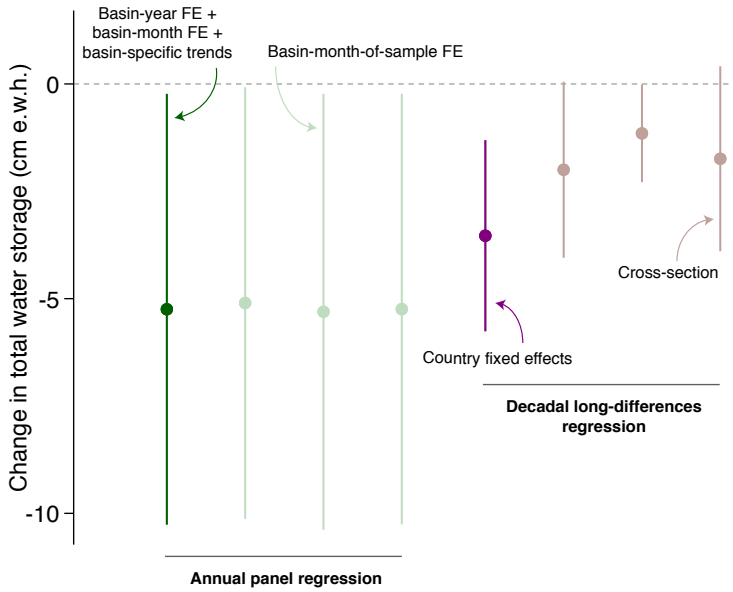


Figure 9: Marginal effects of Relative Rates of Assistance (RRA) on total water storage using short- versus long-run variation. All coefficients shown indicate an interaction effect between RRA and cropped area fraction. Coefficients in green are estimated from a version of Equation 10, which exploits spatially differentiated annual variation in agricultural policy. The main specification (dark green) includes basin-year and basin-month fixed effects as well as basin-specific quadratic time trends. Alternative specifications shown in light green include alternative fixed effects shown in Table C1. Coefficients in purple are estimated using a long differences specification over the period 2003 to 2011. The dark purple coefficient includes country fixed effects, while light purple indicates alternative fixed effects shown in Table C6. All regressions include climate controls and nighttime lights. Standard errors are clustered at the basin level.

agricultural policies accounted for 70% of the global welfare cost of all merchandise trade distortions, despite the fact that agricultural goods composed just 6% of global trade and 3% of global GDP. In general, high-income nations such as the USA, EU, and Japan have invested heavily in subsidies and other forms of protection to incentivize domestic production of main crops. In contrast, developing countries' policies have generally depressed prices for domestic famers, largely through the pursuit of import-substituting industrialization strategies (Anderson, Rausser, and Swinnen, 2013). The result has been an overproduction of agricultural products in wealthy nations, the underproduction in poor nations, and a reduction in the volume of agricultural trade (Tombe, 2015).

However, in recent decades there has been a dramatic decline in intervention, both from countries subsidizing agriculture and from those dis-incentivizing crop and live-

stock production. Figure 10A shows country-level time series of agricultural Relative Rates of Assistance (RRAs) for all countries in the World Bank's Distortions to Agricultural Incentives database, and for all years available in both the GRACE satellite record and the World Bank data. Country time series are colored by the sign of their temporal trend in RRA; declining trends in RRA are shown in green, and increasing trends in RRA are shown in brown.[15] The general convergence of countries' time series toward zero indicates that agricultural policies have led to liberalized markets in both countries that incentivize agriculture (RRA>0) and those that dis-incentivize it (RRA<0), although the trends have been strongest for countries that initially were heavily subsidizing agricultural production. Figure 10B shows that in general, wealthier countries have reduced RRA values over the 2003-2011 period, while poor countries, particularly those in Africa, have undertaken policies that have raised the RRA. These same temporal and spatial patterns hold if we consider nominal price interventions (NRA), as shown in Figure B5, and this transition toward increasing liberalization has been even more pronounced prior to the satellite record (Anderson, Rausser, and Swinnen, 2013).

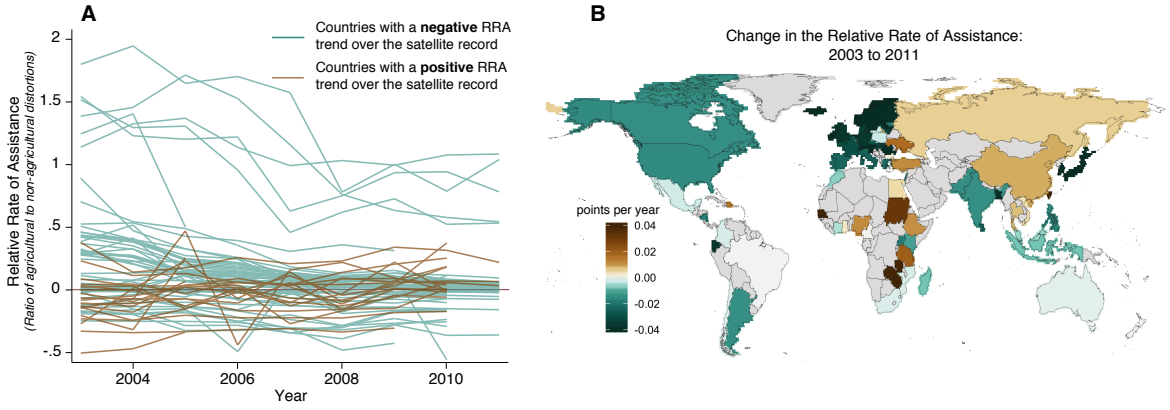


Figure 10: Relative Rates of Assistance (RRAs) to agriculture converge toward zero over the GRACE satellite record Both panels show trends in the agricultural Relative Rate of Assistance (RRA), governmental intervention in the relative price of agricultural production. In panel **A**, each line shown is a country-specific time series of the agricultural RRA, where a positive value indicates a pro-agricultural policy bias and a negative value an anti-agricultural policy bias. Lines are shown for all countries present in the World Bank's Distortions to Agricultural Incentives (DAI) database. Green lines indicate countries for which the RRA has declined over the 2003-2011 period, while brown lines indicate countries for which the RRA has increased. In panel **B**, the magnitude of these RRA trends are shown for each grid cell in the GRACE satellite data residing within a country contained in the DAI database. Green again indicates falling RRA over the 2003-2011 period, while brown indicates an increase in RRA. The sign and magnitude of each country's trend was determined based on a linear regression of RRA on year.

[15]Trends used to distinguish color for each country time series are estimated linearly.

This global trend toward liberalized agricultural markets will have an ambiguous effect on total water use in agriculture, and on the spatial distribution of water use. As shown in Section 2, liberalization will shift productive resources away from agricultural production, lowering water use due to agriculture's relative water intensity, only if the initial distorted domestic price is above the global market price (i.e. when initial values of RRA exceed zero). In countries where distortions have kept agricultural prices artificially low (i.e. where RRA is negative), liberalization will reallocate productive activity toward agriculture and increase the use of water.

In the following section, I use the empirical estimates from Section 5.2 to conduct a simulation exercise in which I compute, at grid cell, country, and global levels, the effect that the observed liberalization of agricultural markets shown in Figure 10 has had on total water storage gains and losses over the period 2003-2011.

6.2 Simulating changes in total water storage under a "fixed-policy" counterfactual

To quantify the effect of recent liberalization of agricultural policy on total water storage, I compare observed changes in total water storage at each grid cell globally to a counterfactual simulated estimate of total water storage under a fixed policy scenario. The construction of this counterfactual proceeds in two steps.

First, for each country for which RRA data are available, I compute a linear time trend in RRA from 2003 to the most recent year available (often 2010 or 2011). I use this result to create a counterfactual RRA time series that de-trends the annual RRA values for each country. This counterfactual time series preserves the observed year-to-year variability in RRA, as that would likely persist even in the absence of a general trend toward liberalization, but removes the trend toward zero in RRA. I treat this counterfactual time series as a "fixed-policy" scenario in which liberalization is not pursued.

Second, I use the coefficients from Table C1 to compute predicted total water storage in each grid cell and each year using *(a)* the observed RRA values, and *(b)* the de-trended RRA values (agricultural suitability, as proxied by cropped area fraction in the year 2000, is held fixed across scenarios). The difference between predictions from *(a)* and those from *(b)* represents the impact of policy liberalization on total water storage (measured in units of centimeters of equivalent water height) for each grid cell and each year. While the difference in observed and simulated RRA values will be the

same for all grid cells within a country, the magnitude of the difference in total water storage will vary based on the level of each grid cell's cropped area fraction. In turn, total gains and losses due to policy liberalization will vary across countries based on the extent of cropped area in each country. Summing these differences in predicted total water storage between observed policy and the "fixed-policy" scenario across years, I compute the total change in water storage for each grid cell between 2003 and 2011 that is attributable to liberalized policy.[16] To put the quantities of water lost or gained due to policy liberalization in perspective, I also compute the observed total water storage lost or gained over the satellite record for each grid cell globally using the linear time trend by grid cell shown in Figure 2.

6.3 Results: The effect of liberalization on total water storage

Figure 11A shows the grid cell distribution of changes in total water storage over the satellite record under two scenarios.[17] In red, the distribution is shown under observed policy conditions; the relative symmetry around zero reflects both the large declines and large increases in water availability detected by GRACE and shown in Figure 2. In grey, the distributions is shown under the simulated counterfactual distribution in which observed changes in total water storage are shifted by the estimated grid cell-specific impact of liberalization over the satellite record. The differences between these distributions 11 shows that recent liberalization of agricultural markets has *compressed* the global distribution of water gains and losses. That is, for locations losing water over the course of the satellite record (values <0 on the x-axis), reductions in distortionary policy have saved a significant volume of water, as seen by the long left tail of the grey distribution relative to the red. In contrast, for locations gaining water over the satellite record (values >0 on the x-axis), liberalization has slightly lowered water resources, pulling the red distribution to the left, relative to the grey. This compression of the global water gains and losses distribution is even more pronounced when only considering grid cells for which the effect of policy liberalization is statistically significant at the 10% level (Figure B6).

The impact of liberalization shown in Figure 11 is quantitatively important, but

[16]Note that for some countries, RRA data are not available for all years; in this case, I report changes only for the years in which there is perfect overlap between RRA data and GRACE observations.

[17]Note that the distributions shown in Figures 11 include only grid cells that are located within countries for which RRA data are available. This is a total of 82 countries, which together account for more than 90% of the world's agricultural GDP.

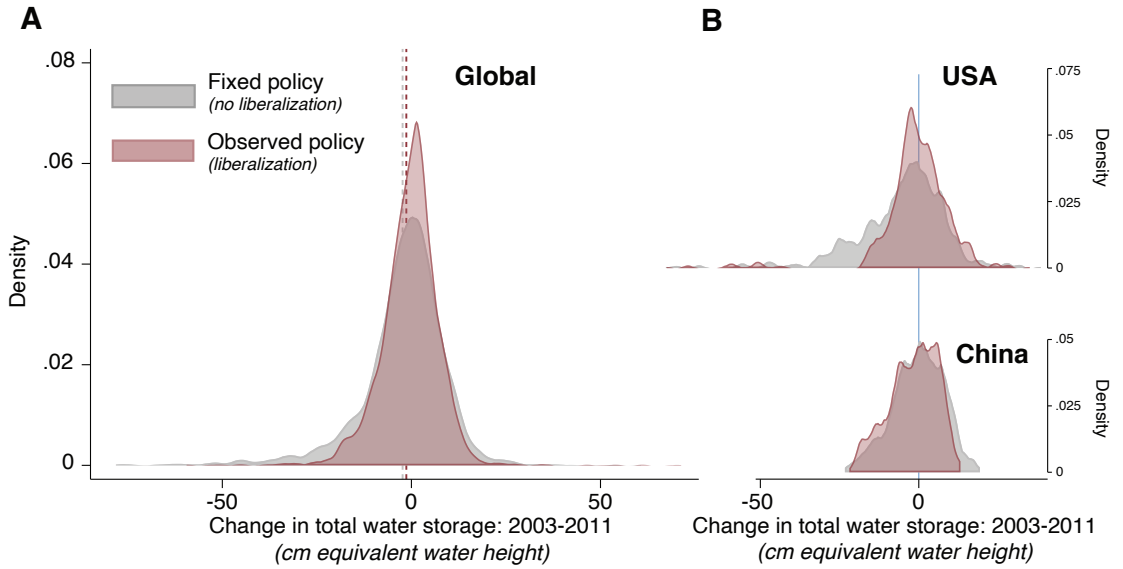


Figure 11: The impact of agricultural liberalization on the distribution of grid cell-level total water losses and gains In all panels, red and grey distributions represent the distribution across grid cells in changes in total water storage experienced over the 2003-2011 period. Values below zero indicate water loss, values above zero indicate water gain. Red distributions show changes in water storage under observed policy conditions, while grey distributions are the result of a simulated counterfactual in which the liberalization of policy distortions is removed and policy is held fixed at initial conditions. Distributions include only grid cells that fall within countries present in the World Bank's "Distortions to Agricultural Incentives" (DAI) database. Panel **A** shows all grid cells in the DAI database, while **B** isolates grid cells in the US (top) and China (bottom).

it does not dominate the overall trends in total water storage gains and losses. For example, I find that across all locations with declining water availability during the satellite record, about 300 billion cubic meters of freshwater was saved by liberalization. This amount is equivalent to 16% of the total water lost over the observed record, or ∼30% of the total volume of water estimated to have been lost in the Aral Sea from 1960 to today (Gaybullaev, Chen, and Gaybullaev, 2012). In contrast, among locations with increasing water availability over the satellite record, about 60 billion cubic meters were lost due to liberalization of policies that were keeping productive assets out of agriculture. While these losses in water-rich regions are relatively small compared to the gains in water-poor regions, 60 billion cubic meters is more than 4 times the total volume of surface water delivery cuts imposed throughout the state of California during its devastating 2014-2015 drought (Cooley et al., 2015).

The compression of the global distribution of changes in total water storage due to the gradual removal of agricultural policy distortions over the 2003-2011 period

is the result of considerable heterogeneity across countries. The strong declines in RRA over time have been driven by relatively high-income countries, while smaller but significant increases in RRA have come from relatively low-income countries. In Figure 11B, an analogous set of distributions to those in Panel A are shown in which grid cells within the US (top) and China (bottom) are isolated in order to show how these differences in the direction of policy change lead to compression in the global distribution. In the US, large reductions in pro-agricultural policies (such as output subsidies and tariff rate quotas) have shifted the total water storage distribution to the right, saving substantial water resources relative to the fixed policy scenario. I find that over the 2003-2011 period, changes in US agricultural policy saved a volume of water equivalent to ∼30% of Lake Erie. In contrast, China has seen a reduction in anti-agricultural policy distortions, which has shifted the total water storage distribution to the left, causing increased water loss. However, much of this water loss has taken place in grid cells that were overall gaining water storage over the satellite record, as can be seen by the separation of the two distributions at positive values of total change in water storage. While there are large differences across countries due to heterogeneous policy regimes, water losses and gains are concentrated *within* countries based on the distribution of agricultural suitability, because of the strong interaction effects between RRA and suitability. Figure 12 shows that the largest effects of liberalization are in locations of high suitability, such as northeastern China and the Great Plains.

It is beyond the scope of this paper to assess the economic welfare implications of agricultural liberalization, inclusive of changes in the spatial distribution of water resource use. However, as water resources globally are rarely managed under clear private property regimes in which functioning markets enable optimal allocation across users, over-extraction abounds (Gleick and Ajami, 2014). The results in Figure 11 suggest that in regions where total water storage is declining most rapidly, the effect of agricultural liberalization has been to slow the rate of loss. In contrast, liberalization has increased water extraction largely in places where water availability is rising. This is suggestive evidence of welfare gains from recent policy trends.

To further investigate possible welfare implications, Figure 13 shows correlations between the impact of recent agricultural policy liberalization and three spatially-explicit covariates: baseline water stress, income, and population share employed in agriculture. Panel A shows that policy liberalization has led to the largest gains in water storage in locations facing the highest baseline water stress, as measured by the estimated ratio of total water consumption to available surface and groundwater supplies

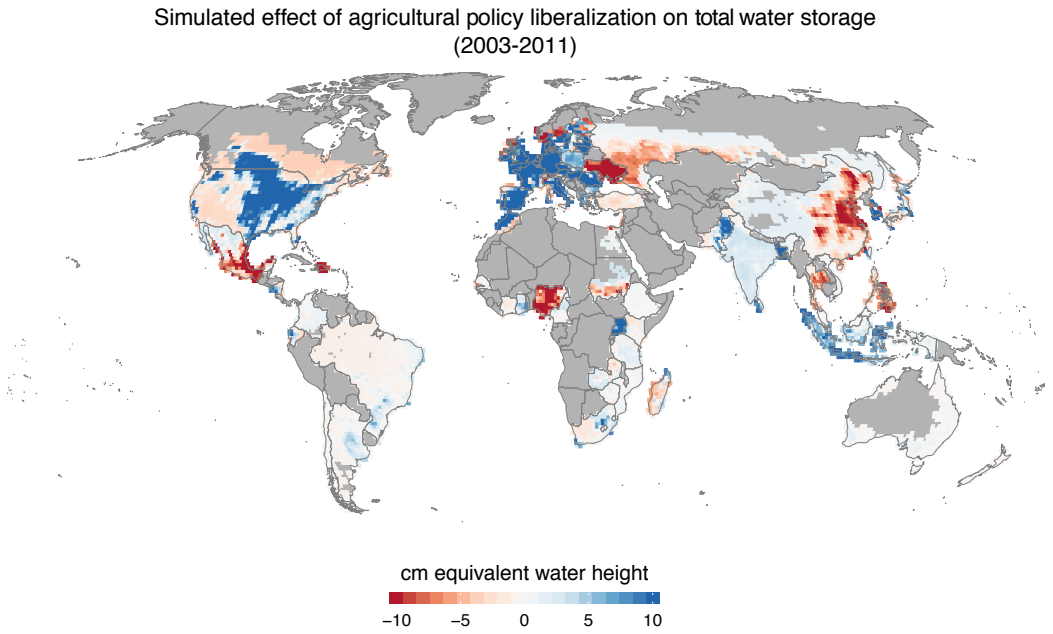


Figure 12: Spatial distribution of total changes in water storage due to the liberalization of agricultural policy Colors by grid cell indicate simulated changes in total water storage caused by trends in agricultural policy over the 2003-2011 period. Values below zero indicate water loss, values above zero indicate water gain, relative to a counterfactual in which observed liberalization of policy distortions is removed and national-level policies are held fixed at initial conditions. All grey areas are countries not present in the World Bank's "Distortions to Agricultural Incentives" database, or are regions with no cropped area.

(World Resources Institute, 2019). This is consistent with the pattern in Figure 11 and suggests welfare gains from reallocation of agricultural production away from water-scarce regions of the globe. However, panels B and C show that water savings due to policy liberalization have been largest in the world's richest countries, and those with the smallest share of their workforce employed in agriculture. Thus, if water has high marginal social returns in relatively poor and agriculturally-dependent economies, panels B and C are not necessarily consistent with welfare gains. To quantitatively conclude whether agricultural policy liberalization raises or lowers welfare globally would require an assessment of the heterogeneous marginal values of water in economies across the globe. While I do not pursue this analysis here, it is a fruitful area for future research.

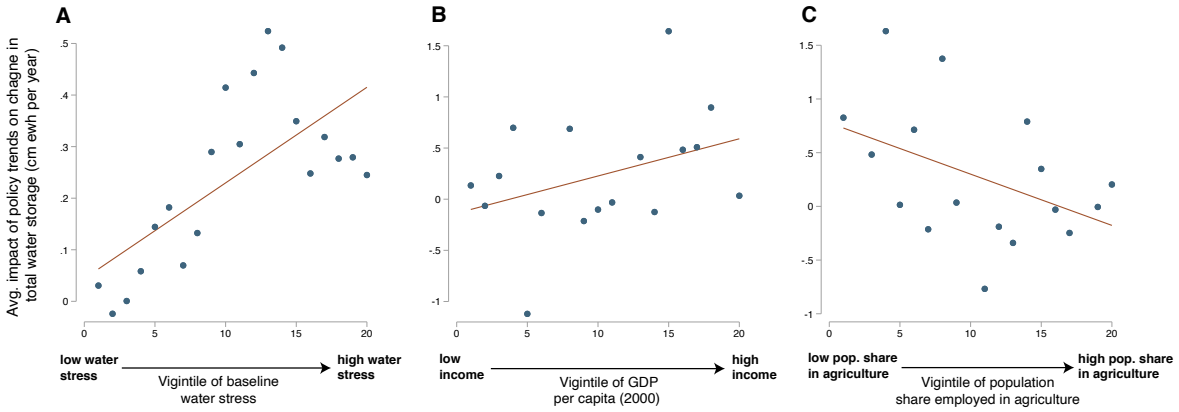


Figure 13: Impacts of agricultural policy liberalization are correlated with water stress, income, and economic agricultural dependence Each panel shows the relationship between grid cell-specific estimates of the impact of agricultural policy trends on total water storage per year (y-axis) and location-specific characteristics (x-axis). In each panel, policy impacts on the y-axis are plotted as averages across grid cells within each vigintile of a covariate, shown on the x-axis. Panel **A** plots the average policy impact against vigintiles of baseline water stress, as measured by the "baseline water stress index" in the Aqueduct Global Maps Data 3.0 (World Resources Institute, 2019). Higher values on the x-axis indicate locations with higher baseline water stress, measured as the ratio of total water consumption to available renewable surface water and groundwater supplies. Panel **B** plots the average policy impact against vigintiles of GDP per capita, as measured in 2000 by the World Bank's World Development Indicators. Panel **C** plots the average policy impact against vigintiles of the share of the population employed in agriculture in year 2000, as measured by FAOSTAT.

7 Discussion

Global scale dynamics increasingly govern local water management challenges and solutions. However, for decades, data limitations have constrained researchers' ability to empirically ground hypotheses linking large-scale processes, such as climate change and international trade, to depletion of freshwater resources. In this paper, I use a satellite-based dataset to provide what are, to my knowledge, the first plausibly causal empirical estimates of the relationships between the policies which shape international trade in water intensive goods and rates of domestic water depletion. In particular, I develop a conceptual framework that ties international trade and production patterns of water-intensive agricultural goods to local depletion of water resources. This framework adapts a classic trade and environment model to the context of water use under distortionary agricultural policy, and demonstrates how policy-induced changes to agricultural producer prices influence depletion of water resources. I take this model to grid-level data on changes in total water storage made available by the GRACE satellites, a unique mission that uses measures of changes in Earth's gravitational field to

derive estimates of water storage across the globe. My empirical analysis demonstrates that changes in the global market for agricultural goods have substantial implications for local water resources.

In a differences-in-differences framework in which crop-by-location policy shocks are plausibly random conditional on a suite of fixed effects, I find, consistent with my conceptual framework, that policies which increase the domestic price of agricultural output lead to substantial depletion of domestic water resources stored in aquifers, soil, surface water, snow and ice. This effect is particularly severe for wheat, a highly water-intensive crop, as well as for the locations within country borders that are most suitable for agricultural production. I additionally show that commonly discussed drivers of water depletion, such as climate changes and proxies for access to irrigation are also statistically recoverable in GRACE.

In a partial equilibrium simulation, I use these empirical estimates to quantify the impact that the recent liberalization of agricultural markets has had on total water availability. I find that observed policy changes over the satellite record have compressed the global distribution of water losses and gains, relative to a counterfactual of fixed policy. For example, across all locations with declining water availability during the satellite record, about 300 billion cubic meters of freshwater was saved by liberalization, an amount equivalent to 16% of the total water lost. In contrast, among locations with rising water availability, about 60 billion cubic meters was lost due to policy liberalization. Together, these findings demonstrate the importance of accounting for and quantifying the role of global agricultural market distortions in determining local freshwater resource outcomes.

References

Adamopoulos, Tasso and Diego Restuccia. 2014. "The size distribution of farms and international productivity differences." *The American Economic Review* 104 (6):1667–1697.

Adao, Rodrigo, Arnaud Costinot, and Dave Donaldson. 2017. "Nonparametric counterfactual predictions in neoclassical models of international trade." *The American Economic Review* 107 (3):633–689.

Aguiar, Angel, Maksym Chepeliev, Erwin L Corong, Robert McDougall, and Dominique van der Mensbrugghe. 2019. "The GTAP data base: version 10." *Journal of Global Economic Analysis* 4 (1):1–27.

Allan, J.a. 1998. "Virtual Water: A Strategic Resource Global Solutions to Regional Deficits." *Ground Water* 36 (4):545–546.

Anderson, James E, J Peter Neary et al. 2005. "Measuring the restrictiveness of international trade policy." *MIT Press Books* 1.

Anderson, Kym, Marianne Kurzweil, Will Martin, Damiano Sandri, and Ernesto Valenzuela. 2008. "Methodology for measuring distortions to agricultural incentives."

Anderson, Kym, Gordon Rausser, and Johan Swinnen. 2013. "Political economy of public policies: Insights from distortions to agricultural and food markets." *Journal of Economic Literature* 51 (2):423–477.

Ang, Beng Wah and FQ Zhang. 2000. "A survey of index decomposition analysis in energy and environmental studies." *Energy* 25 (12):1149–1176.

Block, Steven A. 2014. "The post-independence decline and rise of crop productivity in sub-Saharan Africa: measurement and explanations." *Oxford Economic Papers* 66 (2):373–396.

Burlig, Fiona and Louis Preonas. 2016. "Out of the darkness and into the light? development effects of rural electrification." *Energy Institute at Haas WP* 268:26.

Carleton, Tamma A and Solomon M Hsiang. 2016. "Social and economic impacts of climate." *Science* 353 (6304):aad9837.

Chapagain, A and A Hoekstra. 2008. *Globalization of Water: Sharing the Planet's Freshwater Resources*. Oxford, UK: Blackwell Publishing.

Cherniwchan, Jevan. 2017. "Trade liberalization and the environment: Evidence from NAFTA and US manufacturing." *Journal of International Economics* 105:130–149.

Cherniwchan, Jevan, Brian R Copeland, and M Scott Taylor. 2017. "Trade and the environment: New methods, measurements, and results." *Annual Review of Economics* 9:59–85.

Chichilnisky, Graciela. 1994. "North-south trade and the global environment." *The American Economic Review* :851–874.

Chong, Howard and David Sunding. 2006. "Water markets and trading." *Annual Review of Environment and Resources* 31 (1):239–264.

Cooley, Heather, Kristina Donnelly, Rapichan Phurisamban, and Madhyama Subramanian. 2015. "Impacts of California's ongoing drought: agriculture." *Pacific Institute: Oakland, CA, USA* :24.

Copeland, Brian R. and M. Scott Taylor. 2005. "Free trade and global warming: a trade theory view of the Kyoto protocol." *Journal of Environmental Economics and Management* 49 (2):205–234.

Costinot, Arnaud, Dave Donaldson, and Cory Smith. 2016. "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world." *Journal of Political Economy* 124 (1):205–248.

Culp, Peter W, Robert J Glennon, and Gary Libecap. 2014. *Shopping for water: How the market can mitigate water shortages in the American West*. Springer.

Dalin, Carole, Yoshihide Wada, Thomas Kastner, and Michael J Puma. 2017. "Groundwater depletion embedded in international food trade." *Nature* 543 (7647):700–704.

Diamond, Jared. 2005. *Collapse: How societies choose to fail or succeed*. Penguin.

Famiglietti, JS, M Lo, SL Ho, J Bethune, KJ Anderson, TH Syed, SC Swenson, CR De Linage, and M Rodell. 2011. "Satellites measure recent rates of groundwater depletion in California's Central Valley." *Geophysical Research Letters* 38 (3).

Fischer, Günther, HT Van Velthuizen, MM Shah, and Freddy O Nachtergaele. 2002. "Global agro-ecological assessment for agriculture in the 21st century: Methodology and results." *IIASA* .

Food and Agriculture Organization of the United Nations. 2020. "FAOSTAT database." URL `http://www.fao.org/faostat/en/#data/QC`.

Fuglie, Keith and Nicholas Rada. 2013. "Resources, policies, and agricultural productivity in sub-Saharan Africa." *USDA-ERS Economic Research Report* (145).

Gaybullaev, Behzod, Su-Chin Chen, and Dilmurod Gaybullaev. 2012. "Changes in water volume of the Aral Sea after 1960." *Applied Water Science* 2 (4):285–291.

Gisser, Micha. 1983. "Groundwater: focusing on the real issue." *Journal of Political Economy* 91 (6):1001–1027.

Gleick, Peter H. 1993. *Water in crisis: a guide to the worlds fresh water resources.* New York New York Oxford University Press 1993.

———. 2016. "Water strategies for the next administration." *Science* 354 (6312):555–556.

Gleick, Peter H and Newsha Ajami. 2014. "The world's water volume 8: The biennial report on freshwater resources."

Hardin, Garrett. 1968. "The tragedy of the commons." *Science* 13 (162):1243–1248.

Headey, Derek. 2011. "Rethinking the global food crisis: The role of trade shocks." *Food Policy* 36 (2):136–146.

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

Hendricks, Nathan P, Aaron D Smith, and Nelson B Villoria. 2018. "Global Agricultural Supply Response to Persistent Price Shocks." .

Hsiang, Solomon. 2016. "Climate econometrics." *Annual Review of Resource Economics* 8:43–75.

Hsiang, Solomon M, Marshall Burke, and Edward Miguel. 2013. "Quantifying the influence of climate on human conflict." *Science* 341 (6151):1235367.

Jacob, Thomas, John Wahr, W Tad Pfeffer, and Sean Swenson. 2012. "Recent contributions of glaciers and ice caps to sea level rise." *Nature* 482 (7386):514–518.

Leonard, Bryan and Gary D Libecap. 2016. "Economic analysis of property rights: First possession of water in the American West." *Working paper* .

Levinson, Arik. 2009. "Technology, international trade, and pollution from US manufacturing." *The American Economic Review* 99 (5):2177–92. URL `http://www.aeaweb.org/articles?id=10.1257/aer.99.5.2177`.

Long, Di, Bridget R. Scanlon, Laurent Longuevergne, Alexander Y. Sun, D. Nelun Fernando, and Himanshu Save. 2013. "GRACE satellite monitoring of large depletion in water storage in response to the 2011 drought in Texas." *Geophysical Research Letters* 40 (13):3395–3401.

Luthcke, Scott B, TJ Sabaka, BD Loomis, AA Arendt, JJ McCarthy, and J Camp. 2013. "Antarctica, Greenland and Gulf of Alaska land-ice evolution from an iterated GRACE global mascon solution." *Journal of Glaciology* 59 (216):613–631.

Martin, Leslie A. 2012. "Energy efficiency gains from trade: Greenhouse gas emissions and India's manufacturing firms." *Department of Agricultural and Resource Economics, University of California Berkley* .

Mekonnen, M. M. and A. Y. Hoekstra. 2011. "The green, blue and grey water footprint of crops and derived crop products." *Hydrology and Earth System Sciences* 15 (5):1577–1600.

Monfreda, Chad, Navin Ramankutty, and Jonathan A Foley. 2008. "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000." *Global Biogeochemical Cycles* 22 (1).

O'Bannon, C., J. Carr, D. A. Seekell, and P. D'Odorico. 2014. "Globalization of agricultural pollution due to international trade." *Hydrology and Earth System Sciences* 18 (2):503–510.

Olmstead, Sheila M. 2010. "The economics of managing scarce water resources." *Review of Environmental Economics and Policy* 4 (2):179–198.

Richey, Alexandra S., Brian F. Thomas, Min-Hui Lo, John T. Reager, James S. Famiglietti, Katalyn Voss, Sean Swenson, and Matthew Rodell. 2015. "Quantifying renewable groundwater stress with GRACE." *Water Resources Research* 51 (7):5217–5238.

Rodell, Matthew, Jianli Chen, Hiroko Kato, James S. Famiglietti, Joe Nigro, and Clark R. Wilson. 2006. "Estimating groundwater storage changes in the Mississippi River basin (USA) using GRACE." *Hydrogeology Journal* 15 (1):159–166.

Rodell, Matthew, JS Famiglietti, DN Wiese, JT Reager, HK Beaudoing, Felix W Landerer, and M-H Lo. 2018. "Emerging trends in global freshwater availability." *Nature* 557 (7707):651.

Rodell, Matthew, Isabella Velicogna, and James S. Famiglietti. 2009. "Satellite-based estimates of groundwater depletion in India." *Nature* 460 (7258):999–1002.

Samuelson, Paul A. 1953. "Prices of factors and good in general equilibrium." *The Review of Economic Studies* :1–20.

Schlenker, Wolfram and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of Sciences* 106 (37):15594–15598.

Schoengold, Karina and David Zilberman. 2007. "The economics of water, irrigation, and development." *Handbook of Agricultural Economics* 3:2933–2977.

Seekell, D. A., P. D'Odorico, and M. L. Pace. 2011. "Virtual water transfers unlikely to redress inequality in global water use." *Environmental Research Letters* 6 (2):024017.

Sekhri, Sheetal. 2019. "Agricultural Trade and Depletion of Groundwater." *Working paper* .

Sheffield, Justin, Gopi Goteti, and Eric F Wood. 2006. "Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling." *Journal of Climate* 19 (13):3088–3111.

Tapley, Byron D., Srinivas Bettadpur, John C. Ries, Paul F. Thompson, and Michael M. Watkins. 2004. "GRACE Measurements of Mass Variability in the Earth System." *Science* 305 (5683):503–505.

Tombe, Trevor. 2015. "The Missing Food Problem: Trade, Agriculture, and International Productivity Differences." *American Economic Journal: Macroeconomics* 7 (3):226–258.

Wahr, John M, Steven R Jayne, and Frank O Bryan. 2002. "A method of inferring changes in deep ocean currents from satellite measurements of time-variable gravity." *Journal of Geophysical Research: Oceans* 107 (C12).

World Resources Institute. 2019. "Aqueduct Global Maps 3.0 Data." URL `https://www.wri.org/data/aqueduct-global-maps-30-data`.

A Adding sub-industry, sub-country heterogeneity to the conceptual framework

The aggregate industry-level model in Section 2 abstracts away from possibly important heterogeneity in production technologies across locations within a country, as well as any heterogeneous production techniques used to produce different crops. Because my empirical setting allows me to observe crop- and location-specific policy shocks and productivities, here I add detail to the model, following closely the production side of the model developed by Costinot, Donaldson, and Smith (2016). This model was designed to estimate the general equilibrium effects of climate change on agricultural output; it is helpful to frame the study of policy shocks on water use due to its parsimonious means of capturing rich heterogeneity across space and crops. I make small changes to the underlying structure of this model, and then explore basic comparative statics with respect to changes in parameters that affect agricultural production.

As above, our small open economy is endowed exogenously with labor (L) and land (K), and we continue to have just two sectors in the economy, non-agriculture Y and agriculture X. In agriculture, we now allow for multiple crops $k \in \mathcal{K} \equiv \{1, ..., K\}$ to be grown. While labor is freely mobile within a country, land is composed of many fields $f \in \mathcal{F} \equiv \{1, ..., F\}$. Each field f is made up of a continuum of parcels $\omega \in [0, 1]$. In my empirical setting, each field f corresponds to a grid cell derived from the GSFC equal-area grid. Let the area of each grid cell be indicated by a; we can thus express total land endowment as $L = aF$. Because the consumption side of this model is not necessary for me to generate the partial equilibrium comparative statics I take to the data, I omit its exposition here. However, one should keep in mind that there is a representative agent with utility defined over consumption of non-agriculture and an aggregate of all crops, with a constant elasticity of substitution across crops, as well as a constant elasticity of substitution across varieties of the same crop originating in different countries. Details can be found in Costinot, Donaldson, and Smith (2016).

For non-agriculture Y, let us put some simple structure on the production function in Equation 1 and assume this numeraire good is produced using only labor with constant returns to scale technology characterized by an exogenous productivity parameter, A_y:

$$Y = H(L_y) = A_y L_y$$

Recall from Equation 6 that the joint production function specified above can be

rewritten treating water as an input into agricultural production. Here, we put structure on Equation 6 and assume that parcels of land, units of labor, and units of water are perfect complements, such that a firm in location (f, ω) can produce:

$$x^k(\omega) = A_x^{fk}(\omega)\min\{K_x^{fk}(\omega), L_x^{fk}(\omega), z^{fk}(\omega)/v^{fk}(\omega)\} \tag{A.1}$$

In this expression, $A_x^{fk}(\omega) \geq 0$ is location-by-crop specific productivity, which is exogenously determined, and $v^{fk}(\omega) > 0$ is location-by-crop specific water intensity of production, supplanting the industry-wide $\phi(\theta)$ term used in the previous section. The higher is $v^{fk}(\omega)$, the more water is required per unit of labor and land to produce a given level of output.[18] $A_x^{fk}(\omega)$ is randomly assigned, and I denote the average field level productivity for crop k as $A_x^{fk} = \mathbb{E}_\omega[A_x^{fk}(\omega)]$. For simplicity, let us assume that characteristics of each crop fix water intensity such that $v^{fk}(\omega) = v^k \ \forall(i, f, \omega)$. While this is unlikely to be true in reality, in my empirical setting I am only able to exploit heterogeneity in water intensity across crops, but not across space.

As above, let the outside good be freely traded, while crops k have standard iceberg trade costs. In this new setting with preferences defined over varieties of crops originating in different countries, we no longer need to classify countries into exporters or importers of agricultural production. Instead, we let there be iceberg trade costs that are specific both to crops and to trading partners: ν_{ij}^k is the cost associated with shipping a unit of crop k from country i to country j (trade costs within countries are assumed to be zero). Thus, the domestic consumer price in country j for purchasing crop k from country k is $p_{ij}^k = \nu_{ij}^k p_i^k$, where p_i^k is the local price in origin country i.

Profit maximization in the outside good ensures that the wage $w = A_y$, as long as there is sufficient labor to produce the outside good (I assume so). Profit maximization in the agriculture sector requires that each parcel ω is: *(i)* allocated to the crop which maximizes the value of the marginal product, less the costs of water, if this value is less than the wage bill to farm that parcel, and *(ii)* left uncropped if the maximum value of the marginal product less the cost of water falls below the wage bill. Note that the wage bill for any parcel, given the Leontief production technology in Equation A.1, is simply $w = A_y$.

With δ^f the exogenous marginal cost of accessing water resources for field f, this cost includes, as above, the energy costs of groundwater extraction or the maintenance

[18] In the aggregate industry model, more water intensity corresponds to a larger $\phi(\theta)$ value, conditional on θ.

costs of a canal, in addition to any government penalties for water extraction. Given the conditions *(i)* and *(ii)* above, the probability that a parcel ω in field f is allocated to crop k can be written as:

$$\pi^{fk} = Pr\left\{ p^k A_x^{fk}(\omega) - \delta^f v^k = max\{A_y, p^1 A_x^{f1}(\omega) - \delta^f v^1, ..., p^K A_x^{fK}(\omega) - \delta^f v^K\} \right\} \quad \text{(A.2)}$$

That is, the probability of allocating ω to k is the probability that the returns to growing k on parcel ω exceed the returns to growing all other crops, as well as exceed the wage bill. Note that because each f is composed of a continuum of parcels, π^{fk} is also the share of f planted to k. If, for simplicity, we let the area of each field be $a = 1$, we can then write total water use at field f as:

$$z^f = \sum_k \pi^{fk} v^k \quad \text{(A.3)}$$

A.1 Changes in crop-specific policies

Governments can influence domestic producer prices for locally produced varieties of individual crops, by direct subsidies or taxes or indirectly by influencing ν_{ij}^k, which changes demand abroad and ultimately changes domestic producer returns (see Section VI of Costinot, Donaldson, and Smith (2016)). This intervention analogous to the policy-driven changes in producer prices for aggregate agricultural output in the industry-level model above. Let the effects of these policies on domestic prices be denoted by τ_k. The probability that a parcel ω in field f is allocated to crop k becomes:

$$\begin{aligned} \pi^{fk} &= Pr\Big\{ p^k(1+\tau_k) A_x^{fk}(\omega) - \delta^f v^k \\ &\quad = max\{A_y, p^1(1+\nu_1) A_x^{f1}(\omega) - \delta^f v^1, ..., p^K(1+\tau_K) A_i^{fK}(\omega) - \delta^f v^K\} \Big\} \end{aligned} \quad \text{(A.4)}$$

All else equal, an increase in τ_k makes production of k more attractive relative to all other crops and the outside option of leaving ω uncropped. This implies that π^{fk} rises, while π^{fm} weakly falls for all $m \neq k$.

$$\frac{\partial \pi^{fk}}{\partial \tau_k} > 0$$

And the effect on water use is:

$$\frac{\partial z^f}{\partial \tau_k} = \sum_{m \in \mathcal{K}} \frac{\partial \pi^{fm}}{\partial \tau_k} v^m = \underbrace{\frac{\partial \pi^{fk}}{\partial \tau_k}}_{>0} v^k + \sum_{m \neq k} \underbrace{\frac{\partial \pi^{fm}}{\partial \tau_k}}_{\leq 0} v^m$$

Note that the first term of this expression is positive, as increasing the returns to k raises the share of f allocated to crop k. The second term is weakly negative, as the share allocated to other crops m may fall. Therefore, the total effect on water use will depend on the relative magnitudes of $\frac{\partial \pi^{fk}}{\partial \tau_k}$ and $\frac{\partial \pi^{fm}}{\partial \tau_k}$, as well as on the relative water intensity of k. The higher is v^k – the more water-intensive is the crop for which the price exogenously rises – the more likely is z^f to rise.

A.2 Heterogeneous agricultural productivity interacts with policy and technological change

The higher resolution decomposition shown in Equation A.4 highlights that the influence of crop-specific policies τ_k on water use in a given field f will depend on agricultural productivity A_x^{fk}. Before a price shock, the share of land in field f that is planted to crop k is increasing in exogenous productivity A_x^{fk}. When a policy change of $\Delta\tau_k > 0$ further increases the return to planting crop k, the effect on land allocation and hence water use will depend on initial productivity A_k^{fk}. It is possible that higher productivity locations will generate larger changes in area planted, and thus in water use. Imagine two fields above a shared aquifer resource, where one field is highly productive and the other has poor soil. Initially, wages are sufficiently high that no crops are grown on either field. An increase in τ_k raises the returns to planting crop k for both fields. For the highly productive field, this cost shock pushes returns for crop k above the wage bill, increasing the share of that field that is cropped. For the low productivity field, this shock is still not sufficient to ensure returns to cropping exceed the wage bill, and no change in proportion cropped occurs.

While this is intuitive, the direction of this second derivative is theoretically ambiguous, without adding further structure on the distribution of productivities across space and crops. For example, if all high-productivity locations are already fully planted to crop k, an increase in domestic price for crop k will only influence cropping patterns and water use in locations of relatively lower k-specific productivity. Therefore, the second derivative is ambiguous:

$$\frac{\partial^2 z^f}{\partial \nu^k \partial A_x^{fk}} = \frac{\partial^2 \pi^{fk}}{\partial \nu^k \partial A_x^{fk}} v^k + \sum_{m \neq k} \frac{\partial^2 \pi^{fm}}{\partial \nu^k \partial A_x^{fm}} v^m \lesseqgtr 0$$

In my empirical setting, I can directly test for this interaction effect using proxies for location-specific productivity A_x^{fk}. Moreover, this interaction between location-specific productivity and a policy shock applies to the irrigation technology shock as well, as shown in Appendix B. However, in this case, a negative irrigation cost shock unambiguously leads to larger water losses in agriculturally productive regions, as shown in Figure B1. In contrast, for both the sector-wide policy shock and the crop-specific policy shock, the effect on total water storage is theoretically ambiguous without imposition of further structure. In my empirical estimation, I treat grid cells as heterogeneous fields f, and directly measure the effect of changes in τ (policy shocks to aggregate agricultural output), τ_k (crop-specific policy shocks), and δ (costs of extracting water) on water use in a given location. I allow these treatment effects to vary based on heterogeneous proxies of grid cell productivity, A_x^{fk}, to identify the direction and magnitude of this possibly important interaction effect.

B Supplementary figures

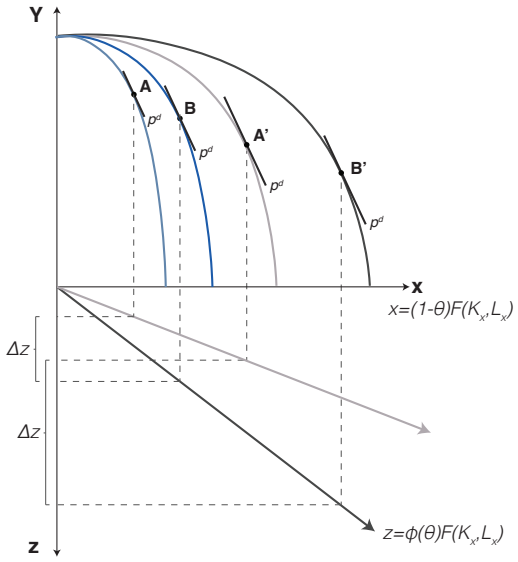
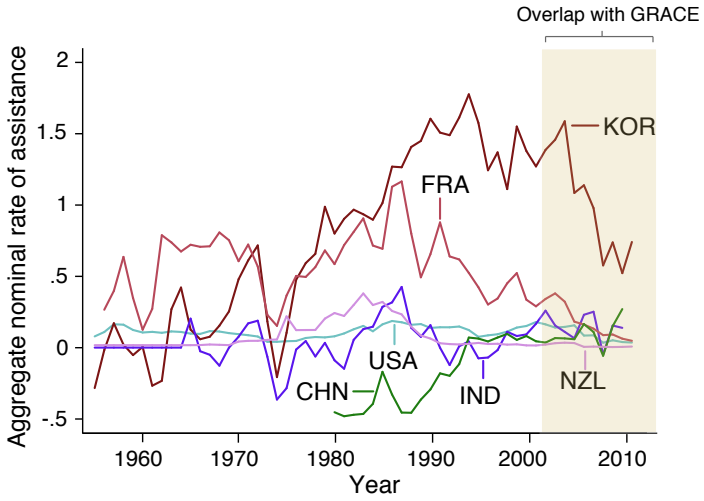
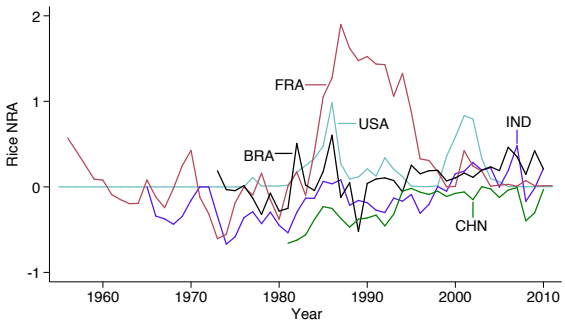


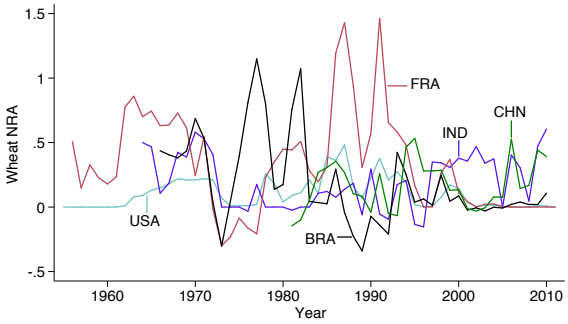
Figure B1: Interaction between a decrease in cost of irrigation and exogenous agricultural productivity This figure illustrates heterogeneity in the treatment effect of an irrigation cost shock on total water storage. The blue curves apply to a location with relatively low agricultural productivity (i.e. $F(\cdot)$ is low conditional on inputs K_x and L_x), while the gray curves apply to a location with relatively high agricultural productivity. A decrease in irrigation costs leads to a decrease in factors allocated within agriculture toward mitigating water use, and therefore to a shift outward in the production possibilities frontier, as well as an increase in slope in the $z - x$ dimension. For the location with lower productivity, this decrease in irrigation cost leads to a smaller increase in water use (Δz) than for the location with higher agricultural productivity ($\Delta z'$). Figure adapted from Copeland and Taylor (2005).



(a) Aggregate



(b) Rice



(c) Wheat

Figure B2: Nominal rates of assistance (NRAs) in aggregate, and for rice and wheat in selected countries An NRA of 0.5 indicates that after accounting for all distortions imposed by governments, domestic producer gross returns are 50% above counterfactual undistorted gross returns. Data from Anderson, Rausser, and Swinnen (2013).

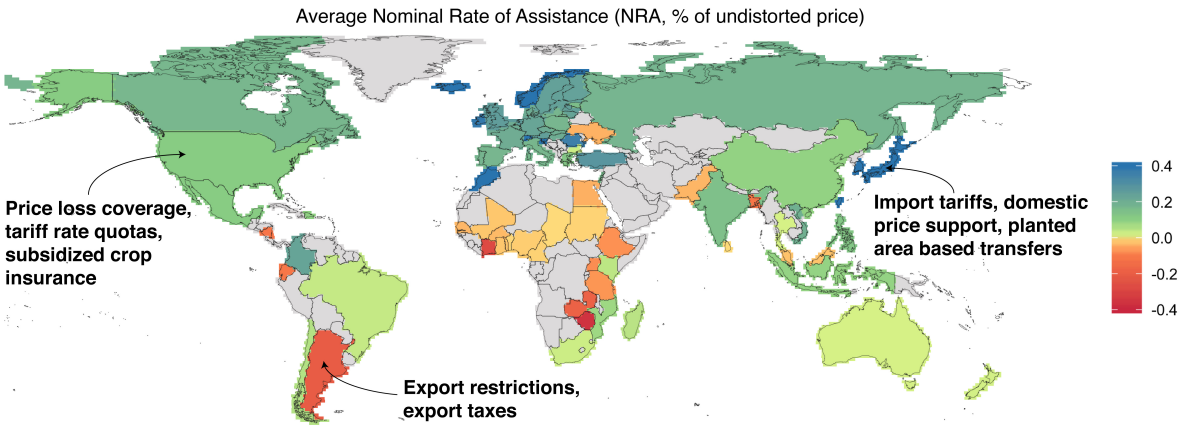
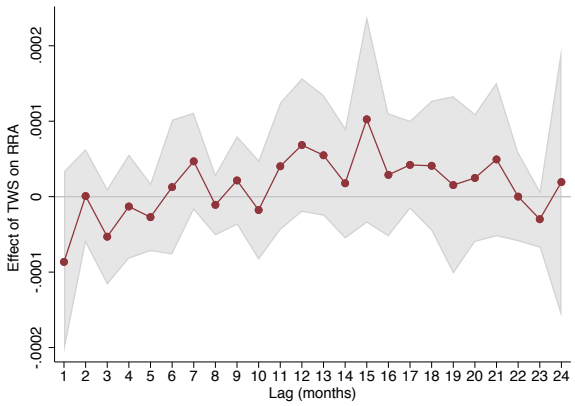
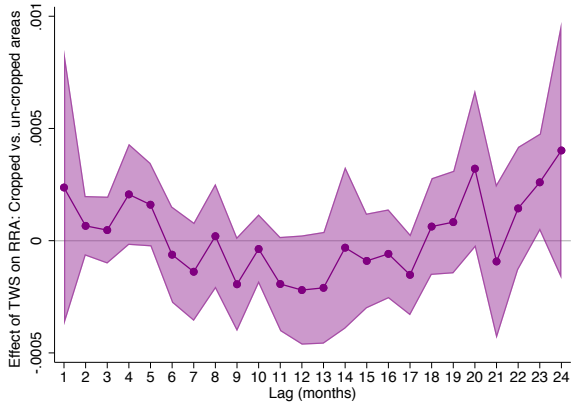


Figure B3: Average Nominal Rates of Assistance (NRAs) to agricultural products (2003-2011) Nominal Rate of Assistance values by country-year are from the World Bank Distortions to Agricultural Incentives (DAI) project and are averaged here over the years that overlap with the GRACE satellite record. Positive values (green to blue) indicate the percentage by which government policies have increased producer prices above a no-intervention counterfactual price; negative values (orange to red) indicate the percentage by which policies have lowered producer prices. See text for details.



(a) Estimates of lagged ΔTWS on current Relative Rate of Assistance (RRA)



(b) Estimates of lagged ΔTWS interacted with cropped area fraction on current Relative Rate of Assistance (RRA)

Figure B4: Placebo test for reverse causality between total water storage and policy intervention. These figures show estimated coefficients from a distributed lag model regressing aggregate agricultural Relative Rate of Assistance (RRA) on grid cell total water storage anomalies (a) and an interaction between total water storage anomalies and cropped area (b). Panel (a) shows coefficients measuring the effect of lagged total water storage on RRA. Panel (b) shows coefficients measuring the differential effect of cropped area fraction on the response of NRA to lagged total water storage. All effects are statistically insignificant and economically very small (the mean RRA in the sample is 0.2).

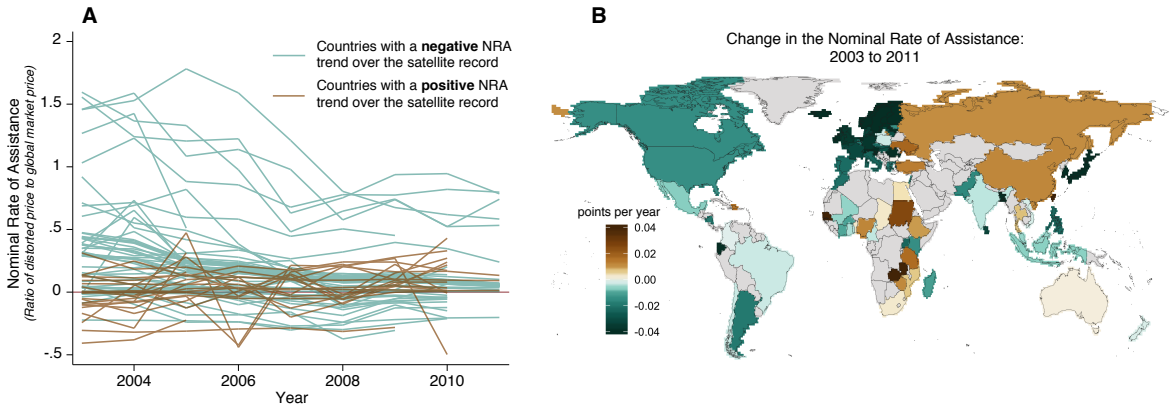


Figure B5: Nominal Rates of Assistance (NRAs) to agriculture converge toward zero over the GRACE satellite record Both panels show trends in the agricultural Nominal Rate of Assistance (NRA), a measure of the wedge between current domestic relative agricultural prices and the prices that would prevail without any governmental intervention. In panel **A**, each line shown is a country-specific time series of the agricultural NRA, where a positive value indicates subsidies to agriculture and a negative value indicates taxes. Lines are shown for all countries present in the World Bank's Distortions to Agricultural Incentives (DAI) database. Green lines indicate countries for which the NRA has declined over the 2003-2011 period, while brown lines indicate countries for which the NRA has increased. In panel **B**, the magnitude of these NRA trends are shown for each grid cell in the GRACE satellite data residing within a country contained in the DAI database. Green again indicates falling NRA over the 2003-2011 period, while brown indicates an increase in NRA. The sign and magnitude of each country's trend was determined based on a linear regression of NRA on year.

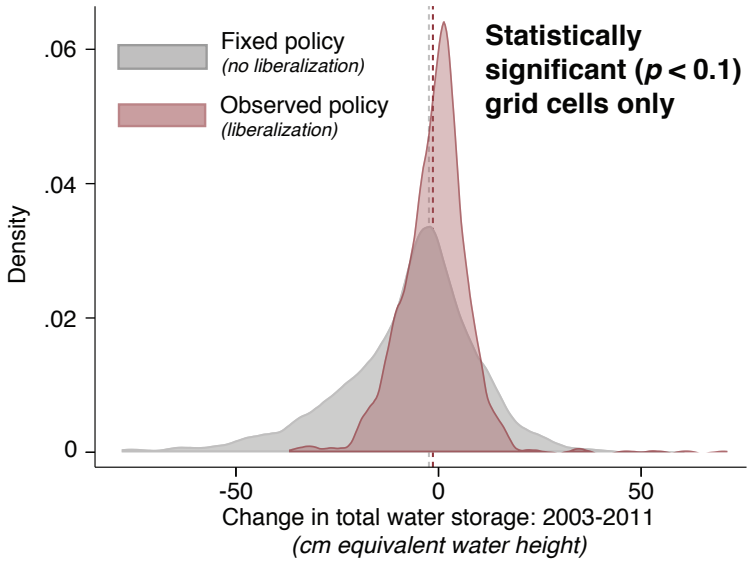


Figure B6: The impact of agricultural liberalization on the distribution of grid cell-level total water losses and gains: Statistically significant grid cells Red and grey distributions represent the distribution across all grid cells for which the effect of policy trends over the 2003-2011 period on total water storage is statistically significant at the 10% level. Values below zero indicate water loss, values above zero indicate water gain. Red distributions show changes in water storage under observed policy conditions, while grey distributions are the result of a simulated counterfactual in which the liberalization of policy distortions is removed and policy is held fixed at initial conditions. Distributions include only grid cells that fall within countries present in the World Bank's "Distortions to Agricultural Incentives" database.

C Supplementary tables

	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate NRA	0.510	0.508	0.520			
	(0.664)	(0.664)	(0.633)			
Aggregate NRA × CAF	-3.558	-3.561	-3.469			
	(2.439)	(2.441)	(2.432)			
Aggregate RRA				0.472	0.470	0.473
				(0.657)	(0.657)	(0.624)
Aggregate RRA × CAF				-5.715**	-5.717**	-5.575**
				(2.835)	(2.837)	(2.823)
Night lights intensity	0.112	0.112	0.114	0.142	0.142	0.144
	(0.192)	(0.192)	(0.194)	(0.190)	(0.191)	(0.193)
Night lights × CAF	-0.443	-0.443	-0.417	-0.537	-0.537	-0.510
	(0.520)	(0.520)	(0.520)	(0.518)	(0.519)	(0.519)
Observations	733,844	733,844	733,844	709,815	709,815	709,815
R-squared	0.649	0.650	0.856	0.649	0.651	0.857
Basin-month FE	YES	YES	NO	YES	YES	NO
Grid-month FE	NO	NO	YES	NO	NO	YES
Basin trends	NO	YES	YES	NO	YES	YES
Basin Year FE	YES	YES	YES	YES	YES	YES

Table C1: Impact of aggregate agricultural policy distortions on total water storage Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "NRA" indicates Nominal Rate of Assistance, the wedge between domestic prices inclusive of policy interventions and the counterfactual undistorted border price, and is aggregated here across all agricultural production. "RRA" indicates Relative Rate of Assistance, the magnitude of agricultural policy distortion *relative* to non-agricultural sectors. "CAF" indicates grid cell level cropped area fraction. All regressions include a suite of climate controls as described in the text. Standard errors in parentheses are clustered at the water basin level.

	(1)	(2)	(3)	(4)	(5)
NRA cotton × cotton CAF	13.844*	12.311*	12.300*	11.947*	11.934*
	(7.427)	(6.727)	(6.736)	(6.614)	(6.891)
NRA maize × maize CAF	7.829	-9.719	-9.782	-11.813	-11.445
	(10.613)	(11.219)	(11.214)	(10.743)	(10.984)
NRA rice × rice CAF	-10.780**	-2.255	-2.246	-1.666	-2.192
	(4.525)	(4.709)	(4.702)	(4.344)	(4.445)
NRA soybeans × soy CAF	-22.160*	-8.744	-8.690	-8.226	-7.850
	(11.330)	(10.073)	(10.067)	(8.663)	(10.217)
NRA wheat × wheat CAF	-18.283***	-16.141***	-16.168***	-16.960***	-16.075***
	(3.997)	(5.186)	(5.193)	(5.065)	(5.404)
Night lights × CAF	0.313	-0.192	-0.192	-0.170	-0.194
	(0.719)	(0.841)	(0.842)	(0.851)	(0.856)
Observations	292,290	292,290	292,290	291,597	292,091
R-squared	0.632	0.647	0.650	0.887	0.680
Basin-month FE	YES	YES	YES	NO	NO
Grid-month FE	NO	NO	NO	YES	NO
Basin trends	YES	NO	YES	YES	NO
Grid trends	NO	NO	NO	NO	NO
Basin Year FE	NO	YES	YES	YES	NO
Basin-MOS FE	NO	NO	NO	NO	YES

Table C2: Impact of crop-specific agricultural policy distortions on total water storage Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "NRA" indicates Nominal Rate of Assistance, the wedge between domestic prices inclusive of policy interventions and the counterfactual undistorted border price. An NRA increase of one amounts to 100 percentage point increase in the effective producer price. "CAF" indicates grid cell level cropped area fraction. All regressions include un-interacted NRA and nighttime lights variables as well as a suite of climate controls as described in the text. Standard errors in parentheses are clustered at the water basin level.

	(1)	(2)	(3)	(4)	(5)
NRA cotton × cotton potential yield	1.057	2.298	2.297	2.212	2.255
	(1.857)	(1.921)	(1.923)	(1.927)	(1.924)
NRA maize × maize potential yield	0.335	0.000	0.001	0.078	0.018
	(0.395)	(0.257)	(0.257)	(0.243)	(0.258)
NRA rice × rice potential yield	0.672**	0.661	0.660	0.574	0.667
	(0.335)	(0.407)	(0.407)	(0.380)	(0.407)
NRA soybeans × soy potential yield	-3.501**	-0.843	-0.842	-1.068	-0.867
	(1.712)	(0.880)	(0.880)	(0.861)	(0.902)
NRA wheat × wheat potential yield	0.092	-1.019***	-1.020***	-1.013***	-1.031***
	(0.421)	(0.357)	(0.357)	(0.364)	(0.355)
Night lights × max. potential yield	-0.134	-0.213***	-0.214***	-0.215***	-0.214***
	(0.096)	(0.051)	(0.051)	(0.051)	(0.051)
Observations	292,290	292,290	292,290	291,597	292,091
R-squared	0.638	0.654	0.657	0.888	0.686
Basin-month FE	YES	YES	YES	NO	NO
Grid-month FE	NO	NO	NO	YES	NO
Basin trends	YES	NO	YES	YES	NO
Grid trends	NO	NO	NO	NO	NO
Basin Year FE	NO	YES	YES	YES	NO
Basin-MOS FE	NO	NO	NO	NO	YES

Table C3: Impact of crop-specific agricultural policy distortions on total water storage using UN FAO's GAEZ suitability metric Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "NRA" indicates Nominal Rate of Assistance, the wedge between domestic prices inclusive of policy interventions and the counterfactual undistorted border price. An NRA increase of one amounts to 100 percentage point increase in the effective producer price. Crop-specific potential yields are from the UN FAO GAEZ database, are derived from GAEZ's "intermediate" input scenario, and are inclusive of irrigation. All regressions include un-interacted NRA and nighttime lights variables as well as a suite of climate controls as described in the text. Standard errors in parentheses are clustered at the water basin level.

	(1)	(2)	(3)	(4)	(5)	(6)
NRA cotton × cotton CAF	12.311*	12.300*	11.947*			
	(6.727)	(6.736)	(6.614)			
NRA maize × maize CAF	-9.719	-9.782	-11.813			
	(11.219)	(11.214)	(10.743)			
NRA rice × rice CAF	-2.255	-2.246	-1.666			
	(4.709)	(4.702)	(4.344)			
NRA soybeans × soy CAF	-8.744	-8.690	-8.226			
	(10.073)	(10.067)	(8.663)			
NRA wheat × wheat CAF	-16.141***	-16.168***	-16.960***			
	(5.186)	(5.193)	(5.065)			
PSE cotton × cotton CAF				0.211	0.212	0.228
				(0.285)	(0.285)	(0.288)
PSE maize × maize CAF				0.003	0.003	-0.043
				(0.093)	(0.093)	(0.091)
PSE rice × rice CAF				-0.070	-0.070	-0.059
				(0.064)	(0.065)	(0.059)
PSE soybeans × soy CAF				0.121	0.121	0.131
				(0.198)	(0.199)	(0.213)
PSE wheat × wheat CAF				-0.226***	-0.226***	-0.236***
				(0.042)	(0.042)	(0.043)
Observations	292,290	292,290	291,597	276,012	276,012	276,012
R-squared	0.647	0.650	0.887	0.617	0.617	0.875
Basin-month FE	YES	YES	NO	YES	YES	NO
Basin trends	NO	YES	YES	NO	YES	YES
Basin Year FE	YES	YES	YES	YES	YES	YES

Table C4: Impact of crop-specific agricultural policy distortions on total water storage using OECD Producer Support Estimates (PSE) Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "NRA" indicates Nominal Rate of Assistance, the wedge between domestic prices inclusive of policy interventions and the counterfactual undistorted border price. "PSE" indicates the OECD's Producer Support Estimates, which are similar to NRA but ignore non-tariff barriers and other forms of assistance (Anderson et al., 2008) and are available in a more limited geographic sample. Note that NRA values are two orders of magnitude larger than PSE values by construction. All regressions include un-interacted NRA/PSE and nighttime lights variables as well as a suite of climate controls as described in the text. Standard errors in parentheses are clustered at the water basin level.

	Cotton	Maize	Rice	Soy	Wheat	Cotton	Maize	Rice	Soy	Wheat
NRA cotton × cotton CAF	7.664					7.679				
	(6.684)					(6.675)				
NRA maize × maize CAF		-6.919					-6.913			
		(5.847)					(5.842)			
NRA rice × rice CAF			1.541					1.542		
			(1.531)					(1.532)		
NRA soybeans × soy CAF				0.196					0.169	
				(18.027)					(18.016)	
NRA wheat × wheat CAF					-13.648***					-13.642***
					(2.656)					(2.652)
Observations	431,013	651,508	506,086	501,710	656,569	431,013	651,508	506,086	501,710	656,569
R-squared	0.653	0.651	0.643	0.641	0.645	0.651	0.649	0.642	0.639	0.643
Basin-month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Basin trends	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO
Basin Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Basin-MOS FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Table C5: Impact of crop-specific agricultural policy distortions on total water storage: Crops estimated independently Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "NRA" indicates Nominal Rate of Assistance, the wedge between domestic prices inclusive of policy interventions and the counterfactual undistorted border price. An NRA increase of one amounts to 100 percentage point increase in the effective producer price. "CAF" indicates grid cell level cropped area fraction. All regressions include uninteracted NRA and nighttime lights variables as well as a suite of climate controls as described in the text. Standard errors in parentheses are clustered at the water basin level.

	(1)	(2)	(3)	(4)
Aggregate RRA	0.730***	0.827***		0.423
	(0.254)	(0.255)		(0.376)
Cropped area fraction (CAF)	0.049	0.019	0.045	0.046*
	(0.037)	(0.032)	(0.034)	(0.024)
Aggregate RRA × CAF	-2.473*	-2.826**	-3.535***	-1.574**
	(1.257)	(1.195)	(1.135)	(0.748)
Daily avg. temperature (°C) 0	-2.197	-1.722	-2.514	-2.464
	(1.340)	(1.157)	(1.561)	(1.693)
Daily precipitation (mm)	3.326*	3.636**	3.082*	2.890**
	(1.889)	(1.702)	(1.681)	(1.365)
Nighttime lights	0.047	0.044	0.054	0.054**
	(0.046)	(0.037)	(0.042)	(0.025)
Nighttime lights × CAF	-0.254**	-0.208**	-0.220**	-0.207***
	(0.111)	(0.087)	(0.096)	(0.067)
Observations	7,377	7,377	7,377	7,373
R-squared	0.050	0.171	0.173	0.518
Latitude FE	NO	YES	NO	NO
ISO FE	NO	NO	YES	NO
Basin FE	NO	NO	NO	YES

Table C6: Impact of crop-specific agricultural policy distortions on total water storage using long-run variation Regression of trends in total water storage on trends in agricultural policy, climate, and nighttime lights over the sample period (2003-2011). Observations are equal-area grid cells measuring $1° \times 1°$ at the equator, excluding latitudes above 60° and below -50°C. The outcome variable is measured in units of cm of equivalent water height lost or gained per day, and trends in all other variables are analogously computed as daily rates of change over the sample. "RRA" indicates Relative Rate of Assistance, the magnitude of agricultural policy distortion *relative* to non-agricultural sectors. "CAF" indicates grid cell level cropped area fraction. Standard errors in parentheses are clustered at the water basin level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate RRA	0.522	0.473	-0.028	0.409	0.520	0.471	-0.028	0.406
	(0.707)	(0.680)	(0.643)	(0.694)	(0.706)	(0.680)	(0.643)	(0.693)
Aggregate RRA × CAF	-6.039**	-5.569*	-5.930*	-5.072*	-6.038**	-5.571*	-5.930*	-5.071*
	(2.795)	(2.841)	(3.103)	(2.956)	(2.796)	(2.843)	(3.104)	(2.958)
Nighttime lights	0.139	0.142	0.152		0.139	0.142	0.152	
	(0.190)	(0.189)	(0.215)		(0.190)	(0.190)	(0.215)	
Nighttime lights × CAF	-0.528	-0.537	-0.528		-0.528	-0.537	-0.528	
	(0.517)	(0.518)	(0.574)		(0.517)	(0.518)	(0.574)	
Observations	709,815	709,815	709,815	709,815	709,815	709,815	709,815	709,815
R-squared	0.645	0.652	0.631	0.645	0.646	0.653	0.633	0.646
Basin-month FE	YES	YES	YES	YES	YES	YES	YES	YES
Basin trends	NO	NO	NO	NO	YES	YES	YES	YES
Basin Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table C7: Impact of aggregate agricultural policy distortions on total water storage: Robustness to specification of control variables Observations are equal-area grid cells measuring 1° × 1° at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "RRA" indicates Relative Rate of Assistance, the magnitude of agricultural policy distortion *relative* to non-agricultural sectors. "CAF" indicates grid cell level cropped area fraction. Column 1 is the main specification, which includes a linear daily average temperature term, as well as a quadratic in contemporaneous precipitation and a linear control for cumulative precipitation over the prior 12 months. Column 2 replaces climate controls with a set of 3°C bins of daily temperature, a fourth order polynomial of contemporaneous precipitation, and cumulative precipitation over the prior 12 months. Column 3 omits the lagged precipitation term, while column 4 omits nighttime lights. Columns 5-8 are identical to 1-4, but include basin-specific quadratic time trends in addition to basin-month and basin-year fixed effects. In all regressions, standard errors in parentheses are clustered at the water basin level.

	USA	IND	CHN	Africa	Lat. Amer.	Asia	E. EUR	HIC
Aggregate RRA				-1.112***	12.063***	-3.539	3.975	-1.860
				(0.343)	(3.500)	(5.316)	(2.765)	(4.306)
Aggregate RRA × CAF	-21.800**	-7.206***	4.880	3.251*	4.526	1.828	-7.598	-14.733***
	(8.837)	(1.916)	(4.229)	(1.866)	(12.691)	(2.834)	(5.270)	(5.401)
Nighttime lights	-0.479**	-0.177	0.415	-0.098	0.901**	0.352	0.210	0.019
	(0.183)	(0.661)	(0.537)	(0.217)	(0.339)	(0.425)	(0.356)	(0.235)
Nighttime lights × CAF	1.069***	-2.207*	-1.159	0.502	-1.313**	-1.835**	-1.113	0.448
	(0.332)	(1.161)	(0.733)	(0.339)	(0.505)	(0.713)	(0.738)	(0.416)
Observations	74,984	26,125	75,335	92,215	133,997	151,084	85,494	247,025
R-squared	0.738	0.825	0.590	0.717	0.591	0.705	0.756	0.692
Basin-month FE	YES	YES	YES	YES	YES	YES	YES	YES
Grid-month FE	NO	NO	NO	NO	NO	NO	NO	NO
Basin trends	YES	YES	YES	YES	YES	YES	YES	YES
Basin Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table C8: Impact of aggregate agricultural policy distortions on total water storage: Regional heterogeneity Observations are equal-area grid cells measuring 1° × 1° at the equator, excluding latitudes above 60° and below -50°C. The outcome variable ΔTWS is measured in units of cm of equivalent water height. "RRA" indicates Relative Rate of Assistance, the magnitude of agricultural policy distortion *relative* to non-agricultural sectors. "CAF" indicates grid cell level cropped area fraction. "HIC" indicates high-income countries, which includes Western Europe, Australia, US, Canada, and Japan. In all regressions, standard errors in parentheses are clustered at the water basin level.