Groundwater in a changing climate

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Abstract

As climate change worsens, adaptation is increasingly necessary. To what extent is climate adaptation possible, and how might today's adaptation impact our ability to adapt tomorrow? We study these questions in agriculture, highly vulnerable sector where irrigation is a key method of adaptation. Using rich data on groundwater pumping from California, we find that farmers respond to hot temperatures by extracting more groundwater. By revealed preference, the average farm would pay at least $775 per year to avoid an additional day above 40°C. Simultaneously, as declining aquifer levels increase the cost of pumping, farmers extract less, and are willing to pay $1313 annually to avoid an aquifer level decline of 10%. We embed these features in a dynamic simulation model in which groundwater pumping responds to both temperature realizations and aquifer depth, and aggregate extraction feeds back into aquifer depth. We find that under climate scenario RCP 4.5 (8.5), aquifer depth will increase by an additional 90% (172%) by 2100. The aquifer's "natural scarcity" effect is important, mitigating 50% (47%) of the aquifer depletion that would occur under climate change alone. We quantify the associated welfare costs (work in progress).

Keywords: groundwater, agriculture, climate adaptation
JEL Codes: Q15, Q25, Q41

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1 Introduction

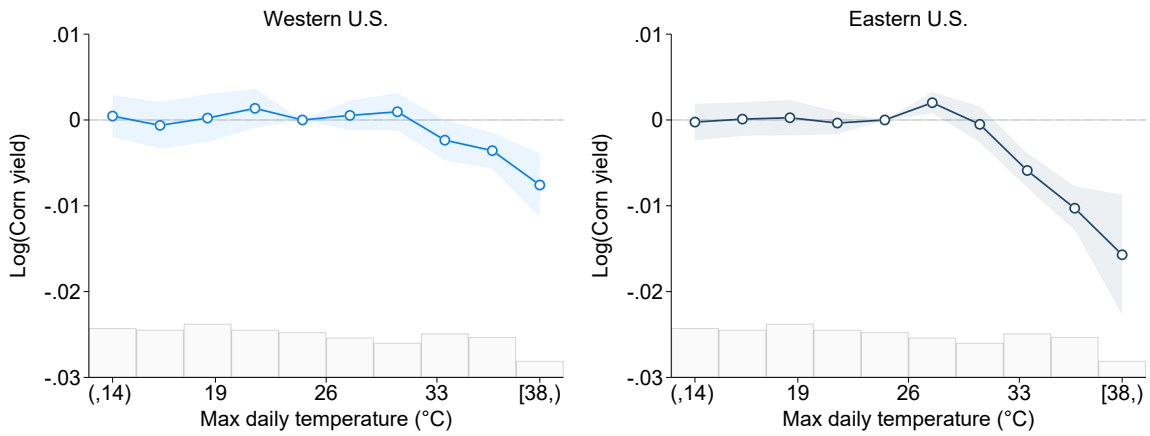
Projections suggest that anthropogenic climate change will exact significant costs on economic activity (Hsiang et al. 2017b; Nordhaus 2019). Current trajectories of greenhouse gas (GHG) emissions indicate that mitigation alone will not be sufficient to avoid these costs (Lee et al. 2023). As such, adaptation to an evolving climate will be vital in averting future costs and ensuring continued human well being (Carleton et al. 2024). Despite its growing importance, there exists relatively little empirical research focused on climate change adaptation (Carleton et al. 2022).

Though it may provide important protective benefits, adaptation is costly and may also generate feedback loops relevant to future climate (e.g., air conditioning adoption and future emissions Auffhammer (2022) and Abajian et al. (2025). Adaptation may also create feedback loops which impact the future costs of adaptation through natural resource dynamics. Marginal extraction costs for many non-renewable resources (e.g., groundwater) increase as stocks become depleted. When adaptation relies on natural resources subject to these dynamics, adaptation today can increase the costs of future adaptation, moderating the long-run effects of adaptation on resource stocks.

The sector is among the most vulnerable to the negative effects of climate change (Lobell, Schlenker, and Costa-Roberts 2011; Fuglie 2021; Ortiz-Bobea et al. 2021; Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005; Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Hultgren et al. 2022). The agricultural sector also has access to a potentially powerful adaptation technology: irrigation, which protects plants against hot temperatures by keeping soil moist (Tack, Barkley, and Hendricks 2017; Li et al. 2019; Li et al. 2020; Luan et al. 2021). Figure 1 demonstrates, using standard climate change econometric techniques, how the prevalence of irrigation can mitigate yield losses caused by hot temperatures. In the western U.S., where the majority of cropland is irrigated, the impacts of hot temperatures on yields is meaningfully attenuated relative to the eastern U.S., where agriculture is generally rainfed. At the same time, groundwater is a key source of irrigation water, but aquifers are rapidly being depleted (Jasechko

et al. 2024), potentially threatening both high-value crop production and climate change adaptation (Schlenker, Hanemann, and Fisher 2007; Hultgren et al. 2025).

Figure 1: Effect of temperature on yields, Eastern vs. Western U.S.



Notes: This figure plots the results of a regression of log corn yield against a flexible function of temperature. The left panel uses data from counties west of the 100th Meridian, where cropland is largely irrigated, while the right panel uses data from east of the 100th Meridian, where cropland is largely rain-fed. Data come from the USDA's National Agricultural Statistics Service county-level yield estimates from 1980-2020. Regressions include a growing season precipitation control, county fixed effects, and year fixed effects. Standard errors are clustered by county.

In this paper, we take the global importance of irrigation, its capacity as an adaptation tool, and the dynamics defining groundwater extraction costs as a starting point and empirically model how farmers adapt to high temperatures through irrigation. Specifically, we leverage a rich panel of well-level groundwater extraction in California's Central Valley, first described in Burlig, Preonas, and Woerman (2025), to produce reduced form estimates of farmer responses to both temperature shocks and variation in groundwater depth, leveraging year-over-year variation in temperature and depth within location. We use basic theory to bound farmers' willingness to pay to avoid hot days and further aquifer drawdown. We then use our econometric model to parameterize a simple dynamic model of agricultural groundwater pumping as a function of future temperature and aquifer depth. This dynamic model accounts for long-run groundwater pumping with respect to costs to reflect how increasing aquifer depths interact with the changing distribution of temperatures due to climate change.

Our reduced form empirical approach to estimate farmer pumping behavior reveals several insights. First, we find evidence of that farmers do adapt to climate change by pumping more groundwater: farmers increase annual pumping by 15.5 acre-feet (AF), or 2.8%, in re-

sponse to a day above 38°C. We find no evidence that farmers respond to hot temperatures by changing the use of other variable inputs (fertilizers or pesticides), implying that the amount farmers spend on this additional pumping is a lower bound on their willingness to pay to avoid high heat: $775 per year. Second, farmers reduce their groundwater pumping as the aquifer becomes deeper. As the water level falls, pumping becomes more costly; farmers thus have downward-sloping demand for groundwater (in keeping with Bruno, Jessoe, and Hanemann (2024) and Burlig, Preonas, and Woerman (2025)). Farmers reduce their pumping by 67 AF per year (12%) for every 10% increase in aquifer depth, and are willing to pay $1313 annually to avoid such a drop in the water level.

Our simple dynamic model of agricultural groundwater pumping as a function of future temperatures and depths produces three key insights. First, using our preferred model in which farmers respond both to temperature and groundwater depth, the aquifer depth increases from 153 feet in 2020 to 332 feet in 2100 under RCP 4.5 and 409 feet under RCP 8.5. We find that the aquifer depth is 90% (RCP 4.5) to 172% (RCP 8.5) deeper at end-of-century than what would have occurred absent climate change, and 47% (63%) of the increase in depth from 2020 to 2100 can be explained by farmers' pumping more in response to higher temperatures.

Our model also reveals a "natural scarcity" effect, wherein as the aquifer becomes deeper, farmers pump less. In a counterfactual where we shut down this effect, aquifer depth increases to 668 feet (775) in 2011 under RCP 4.5 (8.5). This natural scarcity mechanism mitigates 50% (47%) of the aquifer depletion that would have otherwise occurred due to climate change. In preliminary work, we compute welfare consequences of these changes in aquifer depth. Early results suggest that pumping costs rise by 148% (167%) by end of century under RCP 4.5 (8.5); absent climate change, expenditures increase by less than half of this amount (77%). These cost increases are a lower bound on farmers' willingness to pay to avoid climate change's impacts on the aquifer.

This paper contributes to several literatures. First, we build on the nascent literature empirically measuring the extent of climate adaptation. Much of the climate change economics literature has focused on mitigation e.g., Nordhaus (1993) and Pindyck (2013), or the costs of climate change e.g., Deschênes and Greenstone (2007) and Hsiang et al. (2017a).

However, current climate science indicates that mitigation alone is likely not sufficient to avoid the costs of climate change (Lee et al. 2023). More recent research highlights the potentially important role of adaptation in determining the future costs of climate change (Carleton et al. 2022; Hultgren et al. 2025), but do not measure specific adaptation strategies. We build on this literature by studying an important and generally overlooked margin of adaptation; irrigation (Burke and Emerick 2016). We find evidence of farmer adaptation to climate change along the margin of groundwater pumping for irrigation. Importantly, we observe the costs of this adaptation through expenditures on pumping, which we use to back out a lower bound on farmer willingness-to-pay to avoid high temperature exposure; we find that willingness to pay is substantial.

Second, we build on a rich literature on the dynamics of non-renewable (Hotelling 1931) and renewable (Gordon 1954) natural resources. We build on Provencher and Burt (1993) and Timmins (2002), who consider the dynamics of the groundwater resource, by adding the costs of climate change. In doing so, we contribute to a literature of hydro-economic models of the interaction between water resource dynamics and water use (Gisser and Sanchez 1980; Allen and Gisser 1984; Hrozencik et al. 2017; Rad et al. 2020). This literature has primarily focused on modeling feedback loops between aquifer levels and pumping costs, where groundwater depletion increases aquifer depths and the marginal cost of groundwater pumping. We build on this literature by incorporating both temperature and depth responsiveness into a hydro-economic modeling framework and demonstrating how these margins counteract each other in future projections of groundwater use and depletion. Our work is also related to that of Carleton, Crews, and Nath (2023), who focus on the impacts of trade on global water use in a similar modeling framework.

Finally, we build on the long strand of literature evaluating the impacts of climate change on the agricultural sector. Our results contribute to long-standing debates on the effect of climate change on agricultural production (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005; Schlenker and Roberts 2009; Deschênes and Greenstone 2007; Burke and Emerick 2016; Hultgren et al. 2025; Burke et al. 2024). Specifically, we demonstrate how irrigation acts as a form of climate change adaptation, potentially mitigating some of the damages associated with high temperature exposure in the short-run.

However, our dynamic model suggests that the irrigation margin of adaptation may be less effective in the long-run as depth responsiveness begins to constrain temperature induced increases in pumping. This feedback between temperature and depth responsiveness highlights an important tension between natural resource dynamics and adaptation previously unexplored in the literature.

2 Background

California is the most economically important agricultural state in the U.S. in terms of farm-level sales of agricultural goods (Johnson and Cody 2015). The unique climate of the state facilitates the production of many high value crops (e.g., perennial fruit and tree nuts). About half of the fruits and nuts consumed in the U.S. are grown in California. Agricultural production in the state is concentrated in the relatively arid Central Valley. Given the arid climate of the region, irrigation is necessary for the production of most crops. Large-scale state and federal investments in surface water irrigation infrastructure facilitated the state's agricultural development during the first half of the 20^{th} century. The Central Valley also overlies several aquifers with historically abundant stocks of groundwater. Advancements in groundwater pumping technology in the 1940s and 1950s opened these groundwater stocks to widespread use by the agricultural sector. Since then, groundwater has become an increasingly important source of water for the state's agricultural sector. As of 2023, about 50% of irrigated land in the state relied on groundwater as a primary or secondary water source (United States Department of Agriculture 2023).

The agricultural sector's increasing reliance on groundwater has severely taxed the state's aquifers. Pumping rates in excess of recharge have caused significant depletion of the aquifers supplying groundwater to farms, households, and municipalities of the Central Valley (Famiglietti et al. 2011; Liu et al. 2022). To address groundwater depletion concerns, the state passed the landmark Sustainable Groundwater Management Act in 2014, intended to bring aquifers into "sustainability" (i.e., ensure that recharge is greater than or equal to

extraction). Our sample period occurs prior to the enforcement of SGMA, and therefore our estimates currently do not consider this policy.[1]

3 Data

We present summary statistics of our key variables in Appendix Table A1, and a map of our sample in Appendix Figure A1.

Electricity and groundwater data We use confidential customer-level data from Pacific Gas and Electric (PG&E) to measure electricity and groundwater usage. We describe these data in detail in Burlig, Preonas, and Woerman (2025), and provide a parsimonious overview here.

We observe the universe of 108,172 agricultural electricity consumers in PG&E's service territory, and include monthly electricity billing data from 2008 to 2019 and hourly interval metering data from 2011 to 2017. In addition to electricity consumption, we observe the universe of agricultural pump tests—21,851 tests at 17,107 locations—from PG&E's Advanced Pumping Efficiency Program (APEP). These tests provide us with detailed measurements of pump characteristics. After matching our electricity consumption and APEP data, we are left with a sample of 10,277 confirmed groundwater pumpers. To compute the amount of groundwater extracted by each pump, we use basic physics; kWh per acre-foot (AF) is simply:

$$\frac{\text{kWh}}{\text{AF}} = \frac{[\text{Lift (feet)}] \times [\text{Constant}]}{\text{Operating pump efficiency (\%)}} \tag{1}$$

For each APEP pump test, we observe operating pump efficiency, flow, and lift, which we use to translate electricity in kWh into AF. We identify farms using California county assessor tax parcels, following Bruno, Jessoe, and Hanemann (2024), and collapse the pump data to the farm level by aggregating across all pumps in a parcel. We observe data on 7,817 unique parcels. The average parcel contains 1.91 pumps, 122.8 croppable acres, and uses 1,0004 acre-feet of groundwater per year.

1. In future work, we plan to compare our findings to SGMA targets, in order to inform how stringent SGMA will be required to be with and without climate change.

Weather data Our weather data come from PRISM, and consist of 4 kilometer gridded daily minimum and maximum temperatures and precipitation totals. This is a standard dataset in the climate impacts literature (see e.g., Schlenker and Roberts (2009) and Burke and Emerick (2016)). We geospatially locate each farm in our data in a PRISM grid cell. Temperatures are high in our area of study; the average parcel in our sample experiences 88 days above 32°C each year.

Groundwater depth data Our data on groundwater depths come from the California Department of Water Resources' California Statewide Groundwater Elevation Monitoring (CASGEM) Program, and consist of thousands of depth measurements across locations for each sample month. We rasterize these depth measurements, interpolating across space and time to construct a consistent panel of groundwater depths for all of our pump locations. Over our sample period, the average sub-basin groundwater depth is 120 feet. See Burlig, Preonas, and Woerman (2025) for more details.

Census of Agriculture Our data on other farm inputs come from the USDA's Census of Agriculture, which is conducted every five years. We use data spanning 1982 through 2017. This data contains per-cropland-acre spending on fertilizer and chemical inputs at the county level.

Climate projection data In constructing counterfactual aquifer depletion under climate change, we use annual county-level temperature and precipitation projections from Hsiang et al. (2017a) and Rasmussen, Meinshausen, and Kopp (2016), spanning the years 1981–2100. These projections are derived using an ensemble approach. This probability-weighted combination of climate models yields generate projections of daily temperature and precipitation data under RCP 4.5 and RCP 8.5. The ensemble of models contains 43 models for RCP 4.5 and 44 models for RCP 8.5. Appendix Figure A2 plots how temperature and precipitation evolve across climate models under both climate scenarios.

4 Reduced form estimation and results

Identification strategy and estimation We employ a standard panel fixed effects approach to identify the causal impact of temperature and groundwater depth on agricultural outcomes. The identifying variation for the temperature effects comes from comparing relatively warmer and relatively cooler years at the same location.

For the depth effects, the identifying variation comes from comparing years where the sub-basin-wide groundwater level is deeper or shallower. We use sub-basin-wide depth rather than depth at an individual location to ensure that farmers do not endogenously impact depth. Moreover, we measure depth in January to avoid as to avoid simultaneity bias.

Identification requires that there are no time-varying unobserved factors that are correlated with year-to-year fluctuations in temperature or sub-basin groundwater depth that also impact the outcome variable. As weather realizations are as-good-as-random after removing cross-sectional and temporal averages, this is likely to be satisfied (Deschênes and Greenstone (2007), Schlenker and Roberts (2009), and Hsiang et al. (2017a)).

To estimate the relationship between annual groundwater consumption and temperature and depth, our preferred model is:

$$Y_{it} \;=\; f(\mathbf{T}_{it}) \;+\; \beta\, \log(D)_{st} \;+\; g(P_{imt}) \;+\; \gamma_i \;+\; \delta_t \;+\; \varepsilon_{it} \tag{2}$$

where the dependent variable Y_{it} is an outcome for parcel (i.e., farm) i in year t. Our primary outcome variables are (i) annual groundwater pumping and (ii) annual groundwater pumping expenditures, which we use to estimate the cost of adaptation.

Our key independent variables are $f(\mathbf{T}_{it})$, which is a flexible function of temperature, and $\log(D)_{st}$, which is the log of groundwater depth. In our preferred specification, we represent $f(\mathbf{T}_{it})$ as a set of 10 bins of maximum daily temperature (Deschênes and Greenstone 2007; Hsiang et al. 2017a).[2] In this annual model, the bin variables are defined as the number of days in year t with a maximum daily temperature in each bin, and the temperature bin coefficients represent the marginal effect of having one additional day in a particular bin

2. We define 8 bins of 3°C increments spanning 14–38°C, as well as one bin for all temperatures below 14°C and one bin for all temperatures greater than 38°C. A day that falls exactly at the cutoff between bins is included in the higher bin.

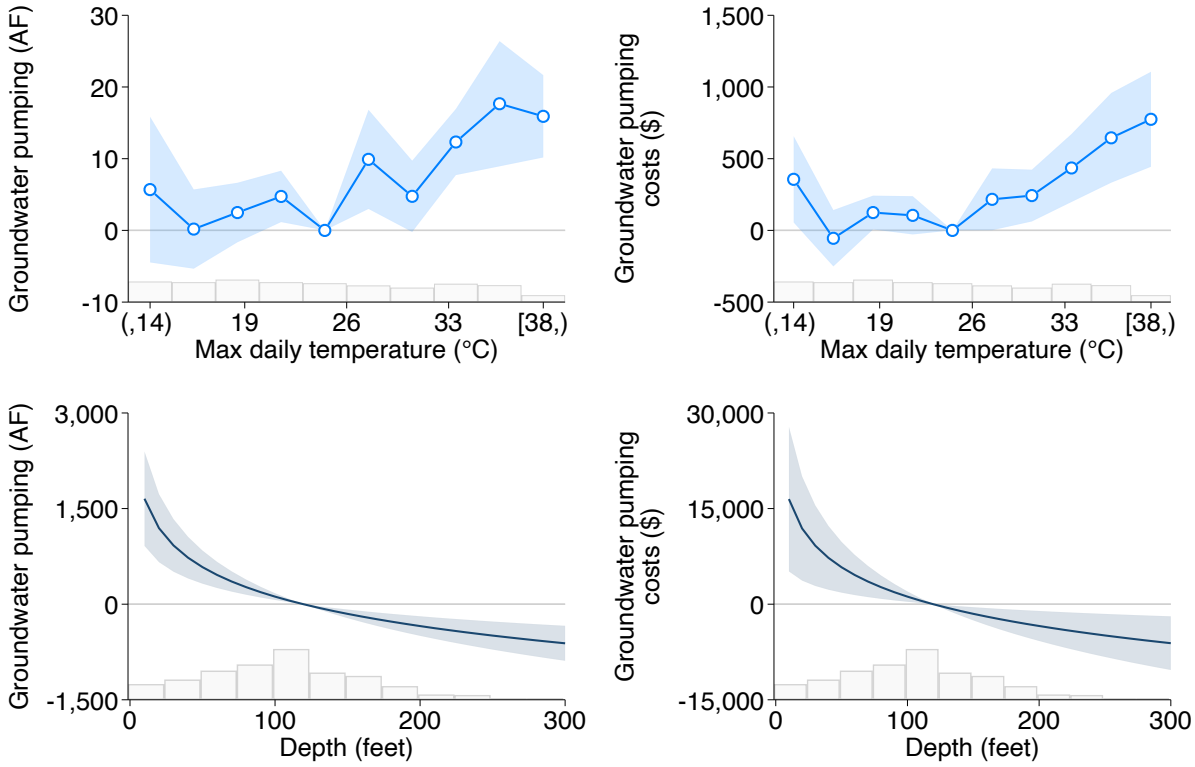
relative to the omitted bin of 23–26°C. Our main temperature coefficients of interest are those for each bin, which flexibly trace out the adaptive response of farmers to temperatures. $\log(D)_{st}$ is the log of average groundwater depth measured in January of year t across the full sub-basin s that contains parcel i; this variable measures how groundwater pumping responds to changes in costs induced by the additional energy required to lift water to the surface from greater depths (Burlig, Preonas, and Woerman (2025)).

Our regression controls for precipitation, $g(P_{imt})$. Our preferred specification is linear in the total precipitation for each calendar month m of year t, to account for the timing of precipitation (more common in winter months) not necessarily aligning with the growing season. γ_i are parcel fixed effects and δ_t are year fixed effects, which flexibly control for unobservable cross-sectional factors and common time-varying shocks, respectively. Finally, ε_{it} is an idiosyncratic error term that we cluster by water district to account for arbitrary correlation within water district over time.

Results Figure 2 presents the results of estimating Equation (2). The left panel of the top row characterizes the relationship between adaptive pumping behavior and temperature, plotting the marginal effect of an additional day in each temperature bin on annual groundwater consumption. The right panel depicts the effects of temperature on annual groundwater pumping expenditures, providing an estimate of the *cost* of this form of adaptation to extreme heat. The bottom row plots how pumping responds to increasing groundwater depths, with water consumption as the outcome variable in the left panel and the cost of pumping in the right panel.

We find that temperatures below 20°C have at most a modest impact on groundwater pumping or spending on groundwater extraction. However, at warmer temperatures, farmers meaningfully increase groundwater pumping. At the extreme, each day with a maximum daily temperature above 38°C increases annual groundwater consumption at the farm level (i.e., aggregated across all groundwater pumps in a parcel) by approximately 15.5 AF (2.8% of the mean) and annual spending by $775 (2.9% of the mean), compared to a day with a maximum temperature in the reference temperature bin of 23-26°C. This is consistent with

Figure 2: Effect of temperature and depth on groundwater pumping



Notes: This figure presents the results of estimating Equation (2), with annual water consumption as the outcome variable in the left panels, and total water cost as the outcome variable in the right panels. The top panels display the coefficients on our ten temperature bins (with the 23–26°C bin omitted). The bottom panels display the effects of depth, estimated using a log functional form, relative to the median depth of 100 feet. 95% confidence intervals are shaded. The bars show the distribution of the relevant right-hand side variable. All regressions include precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. Standard errors are clustered by water district.

farmers applying groundwater to cope with the high temperatures that have been shown to be detrimental to crop growth (e.g., Schlenker and Roberts (2009)).

Conversely, as the aquifer depth increases, farmers pump less, as doing so becomes more expensive. For every 10 percent increase in aquifer depth, we find that farmers reduce their pumping by 67 AF per year (12 % of the mean). This translates into a reduction in water costs of $665 per year (2.5% of the mean).[3] These results imply that farmers pump less when the costs of pumping rise (as in Burlig, Preonas, and Woerman (2025)), and that as water

3. Note that the relative temperature responses of pumping cost versus groundwater pumped implies a per-AF pumping cost of roughly $50 per AF, which generally aligns with the mean in our sample. The relative depth responses, however, imply a smaller value. This is because, as depth changes, the relationship between electricity consumption and groundwater extraction also changes: per Equation (1), at deeper aquifer depths, the same amount (and thus cost) of electricity yields less groundwater extraction. The temperature-response functions in the top panels hold this relationship fixed, while the depth-response functions show evidence of this negative feedback.

becomes more scarce under aquifer depletion, there is a natural mechanism to stem over-extraction. Taken together, these results suggest that while climate change may accelerate aquifer depletion because farmers pump more in response to warmer temperatures, these impacts will be attenuated by the impacts of increasing groundwater costs, and a dynamic model that incorporates both of these features is thus required to estimate the overall impact of climate change on aquifer depths.

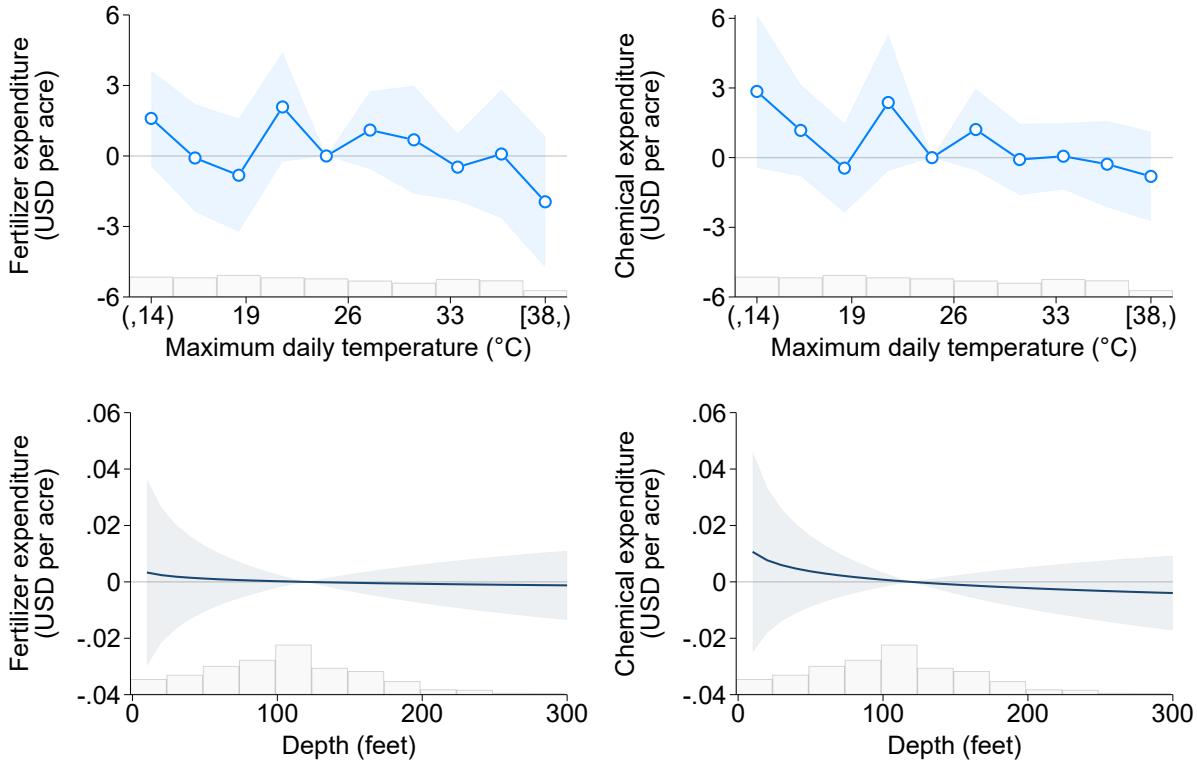
Robustness Because temperature is stochastic, and based on climatalogical processes, we expect that it is plausibly exogenous with respect to groundwater pumping. The main confounder in estimating the impacts of temperature on groundwater pumping is the time-varying availability of surface water, which is governed by a complicated mix of riparian and appropriative rights (see Hagerty (2023) for an excellent overview). Though annual access is typically determined in advance, it is possible that surface water availability is correlated with temperature; because farmers substitute surface for groundwater when available as it is generally less expensive, this could lead to omitted variables bias. To test for this, we estimate separate temperature coefficients for parcels with and without surface water access (as measured by being located within a surface water district). We cannot reject that the impacts are the same between the two groups (Appendix Figure B7).

The major threat to identification with respect to the effects of depth is that while farmers cannot impact their local temperature, they could impact their local depth by pumping. We construct our groundwater depth variable specifically to avoid this problem. Specifically, we use *sub-basin-wide* groundwater depths, *measured in January*, as our regressor of interest. Farmers are small relative to the sub-basin and thus we shut down the cross-sectional form of endogeneity. By measuring depth at the beginning of the year, we avoid the simultaneity concern.

Appendix B demonstrates that our results are also robust to alternative functional forms for both the left- and right-hand side variables (Appendix Figures B1 and B4); two-way clustering by water district and county-year (Appendix Figure B5); and alternative weighting and aggregation (Appendix Figure B6).

Additional outcomes We use a county-level version of Equation (2) to measure the effects of temperature and depth on non-water variable inputs to crop production, using the log of total county-level fertilizer expenditure and log of total county-level chemical expenditure (both as reported in the USDA's Census of Agriculture) as our primary outcomes of interest.[4] These indicators allow us to examine whether higher temperatures or deeper depths cause farmers to make other changes to their production processes beyond increasing irrigation.

Figure 3: Effect of temperature on other farm inputs



Notes: This figure presents the results of estimating a modified version of Equation (2), with fertilizer expenditure (in USD per acre) as the outcome variable in the left panels, and chemical expenditure (in USD per acre) as the outcome variable in the right panels. Outcome data are from the USDA Census of Agriculture five-yearly waves from 1982 through 2017, and are measured at the county level. We accordingly aggregate our temperature and drought data to the county level. The top panels display the coefficients on our ten temperature bins (with the 23–26°C bin omitted). The bottom panels display the effects of depth, estimated using a log functional form, relative to the median depth of 100 feet. 95% confidence intervals are shaded. The bars show the distribution of the relevant right-hand side variable. All regressions include precipitation controls, county fixed effects, and year fixed effects. Standard errors are clustered by county.

Figure 3 presents these results. The left panel presents results for fertilizer, and the right panel presents results for chemicals (i.e., pesticides, herbicides, fungicides, etc.). We

4. We choose these specific outcomes because they are plausibly impacted by growing conditions.

find no systematic evidence that higher temperatures or greater depths cause changes in the use either input. These results suggest that increased water use is the primary short-run temperature adaptation mechanism for California farmers.

Willingness to pay We use our regression estimates to derive (bounds on) farmers' marginal willingness to pay to avoid increases in temperature and increases in aquifer depth. Appendix C provides more details on this approach.

With respect to temperature, the effect of moving a day from 23–26°C to above 38°C on groundwater pumping expenditures provides a lower bound on the WTP to avoid high heat. To see this, note that this coefficient represents the additional amount farmers are willing to spend on pumping on a hot day. Because we find that farmers do not adjust other inputs in response to high heat, we treat this as a lower bound on WTP. This is not a point estimate of the WTP to avoid a hot day because it does not include direct yield losses due to temperatures, which may be greater still. Nonetheless, our results imply that farmers are willing to pay at least $775 annually to avoid an additional day above 38°C.

With respect to depth, we note that aquifer depth is a cost shifter for groundwater extraction. To measure willingness to pay to avoid increased aquifer depths, we therefore convert our regression of groundwater pumping on depth into an inverse demand curve, scaling depth by expenditure per acre foot at the mean depth, and integrate under this curve. Our estimates imply that WTP is $1313 annually to avoid a 10% increase in aquifer depth.

5 Effects of climate change on the California aquifer

In this section, we move beyond our reduced-form effects to measure the impacts of climate change on California's aquifer and on welfare. Doing so requires a dynamic model, because groundwater extraction in one period will raise aquifer depth (i.e., lower water levels) in the subsequent period.

5.1 A model of aquifer depth under climate change

We specify a stylized dynamic model of adaptive irrigation and groundwater depletion for a unified groundwater basin. The basin contains N heterogeneous farmers (indexed by i) who extract groundwater for irrigation. Farmer i's total AF of groundwater use in year t is:

$$W_{it} \;=\; F\Big(\mathbf{T}_{it}, R_{it}, D_{st}; \boldsymbol{\beta}\Big) \;+\; \gamma_i \;+\; \delta_t \;+\; \varepsilon_{it} \tag{3}$$

Hotter temperatures ($\mathbf{T}_{it}$) increase Q_{it}^{water} through adaptive irrigation, while rainfall (R_{it}) reduces farmers' water use (i.e., $\frac{\partial F}{\partial \mathbf{T}} > 0$, $\frac{\partial F}{\partial R} < 0$). Groundwater depth ($D_{st}$) for sub-basin s governs farmers' costs of irrigation, since deeper aquifer levels increase the energy costs of pulling groundwater up to the surface, leading to demand response (i.e., $\frac{\partial F}{\partial D} < 0$). Unit fixed effects ($\gamma_i$) control for farm-specific factors (e.g., crop choice, irrigation capital), while time fixed effects (δ_t) account for common shocks (e.g., market prices, drought severity). Finally, ε_{it} accounts for idiosyncratic time-varying determinants of groundwater use.

To model the dynamic link between groundwater extraction and groundwater depths, we specify the following aggregate equation of motion (following Carleton, Crews, and Nath (2023)):

$$\overline{D}_{t+1} \;=\; \overline{D}_t \;+\; \rho\Big[(1-\psi)\overline{W}_t \;-\; \overline{R}_t\Big] \tag{4}$$

$\overline{D}_t$ is defined as the average groundwater depth (in feet) in year t across the full aquifer. $\overline{R}_t$ is annual precipitation (in feet) averaged across the full area of the aquifer; rainfall adds water to the aquifer, decreasing $\overline{D}_{t+1}$. $\overline{W}_t$ is the average groundwater extraction (in feet) across the full basin, equivalent to $\sum_{i=1}^{N} W_{it}$ divided by the area of the basin (in acres). The scalar $\psi \in [0, 1]$ accounts for the return flow of irrigation: for every unit of groundwater extracted, the proportion ψ re-percolates back into the aquifer, while the proportion $1 - \psi$ leaves the aquifer via evapotranspiration. Finally, ρ is the inverse of specific yield, which accounts for soil porosity in translating groundwater displacement to changes in depth (Loheide, Butler, and Gorelick (2005)).[5]

5. Specific yield is the volume of water that can be drained from porous soil by gravity, relative to the total soil volume. Higher porosity is associated with higher specific yield (lower ρ). Extracting 1 AF from (porous) sandy soil increases depth by less than extracting 1 AF from (less porous) sandy clay soil, since the former yields more water per unit of volume.

To operationalize Equation (3), we slightly modify our preferred temperature response specification (Equation (2)) to reduce the number of parameters and avoid overfitting. First, we replace our preferred $f(T_{it})$ of 10 temperature bins with a piecewise quadratic in annual degree days. Second, we replace our preferred $g(R_{imt})$ of 12 monthly precipitation coefficients with a quadratic in annual temperature.[6]

To simulate forward, we populate temperature and precipitation using climate projections from Hsiang et al. (2017b). These projections combine a suite of 45 climate models, yielding projected counts of days in 1°C temperature bins and in 2mm precipitation bins at a county-year resolution. We aggregate bins to construct projected degree days (linear and squared terms, separately above an below 24.5°C) and projected annual precipitation (in mm) at the county-year level. We present results for two climate scenarios: RCP 4.5 and RCP 8.5.

Appendix D describes our model calibration and simulation procedure in detail. We present a few salient aspects here. First, we restrict our focus to the San Joaquin Valley groundwater basin, which contains 71% of our estimation sample and is the most economically important groundwater basin in California. The San Joaquin basin comprises 16 sub-basins with spatially heterogeneous climate realizations, irrigation practices, groundwater depths, and soil characteristics. We therefore calibrate ρ separately for each sub-basin, following Loheide, Butler, and Gorelick (2005). We set $\psi = 0.2$, following Dewandel et al. (2008). We then aggregate the rightmost term of Equation (4) up from the sub-basin to the basin, which allows for horizontal diffusion across sub-basins of the aquifer.

In each year, we predict W_{it} by plugging climate projections and depth into our fitted model of Equation (3). We initialize the model using observed baseline depth, and then endogenize depth in all subsequent years by implementing a calibrated parameterization of Equation (4). We consider three main models, which we simulate under both RCP 4.5 and RCP 8.5. In our preferred model, farmers' groundwater pumping depends both on temperature and on aquifer depth. We also consider alternative scenarios in which farmers respond only to depth, or only to temperature.

6. Appendix Figure B1 shows that this modified specification recovers parameter estimates that are nearly identical to Equation (2).

To capture both econometric uncertainty (from our estimate model) and climate uncertainty (from the projections), we simulate 10,000 iterations for each scenario. Each iteration makes joint draws from (i) the sampling distribution of regression model coefficients (including year fixed effects for 2008–2019); (ii) a vector of simulated years drawing from $\{2008, \ldots, 2019\}$ with replacement (to populate year fixed effects out of sample); and (iii) one of the 45 climate models (weighting models following the procedure outlined in Hsiang et al. (2017b); Carleton et al. (2022)).

5.2 Simulation results

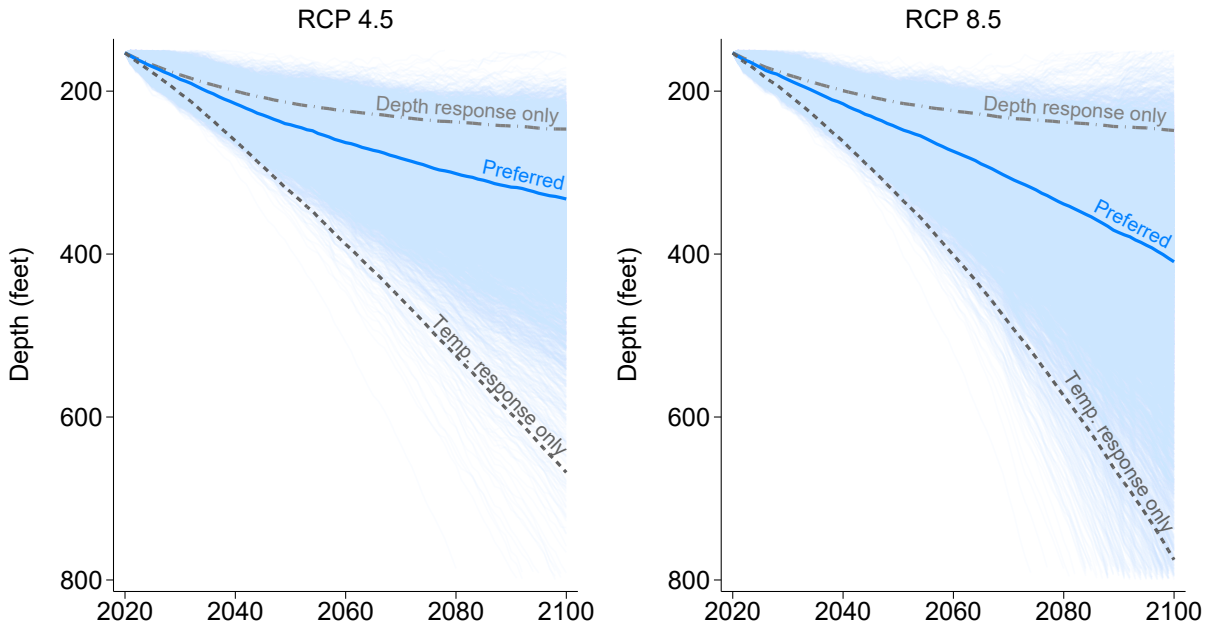
Groundwater depth Figure 4 presents the results of this simulation exercise. Under our preferred model (blue line), we find that groundwater depth increases from 153 feet in 2020 to 332 feet in 2100 under RCP 4.5, and to 409 feet in 2100 under RCP 8.5. We report the uncertainty in this mean outcome by plotting all 10,000 iterations of our simulations in light blue. This suggests that even accounting for uncertainty, climate change will lead to a significant fall in aquifer levels in the San Joaquin basin, already among the most stressed aquifers on the planet.

How much of this increase in depth is driven by climate change-induced adaptive irrigation? We can compare our preferred model to the "depth response only" model (dash-dotted gray line in Figure 4), where farmers do not change their pumping in response to temperature, but still reduce pumping in response to greater depths. Under "depth response only", depth increases from 153 feet in 2020 to 247 feet in 2100. This comparison implies that RCP 4.5 (RCP 8.5) leads to 90% (172%) greater end-of-century depth than what end-of-century would be absent increased temperature response. It also suggests that 47% (63%) of the increase in depth from 2020 to 2100 is explained by temperature response.

Our results also highlight the importance of the "natural scarcity" effect, whereby farmers' depth response moderates the rate of aquifer depletion. Our "temperature response only" model (dashed gray line in Figure 4) removes this moderating effect, such that farmers pump more in response to increasing temperatures, but do not pump less in response to increase depth. This results to a staggering increase in aquifer depth from 153 feet in 2020 to 668 feet (775 feet) in 2100 under RCP 4.5 (RCP 8.5). This suggests that the "natural scarcity" effect

mitigates 50% (47%) of the aquifer depletion likely to occur as a result of climate change. Taken together, these results demonstrate that climate change will meaningfully alter the trajectory of California's aquifers.

Figure 4: Impact of climate change on aquifer levels, welfare



Notes: This figure presents the results of our simulation exercise. In the top panels, we model groundwater depth from 2020 through 2100. The left panel shows results under RCP4.5 (moderate climate change) and the right panel shows results under RCP8.5 (severe climate change). In both panels, the blue line denotes our preferred model, where farmers' groundwater extraction responds to both temperature and depth. We run 10,000 draws of the model. The thick blue line plots the mean over these simulation runs. The individual light blue lines show individual simulations. These draws incorporate both econometric and climate model uncertainty. The two gray lines plot the means over simulation runs where we only have farmers responding to depth (dash-dot) and only have farmers responding to temperature (dashed). The bottom panel (in progress) will plot the welfare consequences of climate change, as measured by revealed preference.

Welfare consequences (in progress!) Next, we use our preferred estimates to generate a lower bound on the welfare costs of climate change from aquifer drawdown. This exercise is highly preliminary. The general idea is: suppose electricity prices remain the same. Then, we can compute changes in total pumping expenditures under climate change as:

$$\Delta Expenditure = P_{2100} \times Q_{2100} - P_{2020} \times Q_{2020} = P_{2020} \times (Depth_{2100} - Depth_{2020}) \times (Q_{2100} - Q_{2020})$$

That is, the difference in pumping expenditures between 2020 and 2100 is the change in the cost of pumping multiplied by the change in the amount of pumping. Because pumping costs are proportional to depth, we can simply scale costs by the change in depth to compute the first component. The model directly simulates the amount of pumping (see Appendix Figure E1).

In our preferred model, between 2020 and 2100, depth increases by 117% and pumping declines by 32% under RCP 4.5, for a total expenditure increase of 148%. Under RCP 8.5, depth increases by 167%, and pumping declines by 1%, for a total expenditure increase of 264%. In contrast, without climate change, depth increases by 61%, and pumping falls by 52%, for a total expenditure increase of 77%.

This is a lower-bound estimate on the costs of climate change. Pumping less presumably has consequences on crop yields, and in turn, farm profits. However, by revealed preference, if the value of this pumping in profit terms was greater than the cost of this pumping, farmers would pump rather than suffer yield consequences.

Note that unlike in Timmins (2002), we do not need to estimate farmers' value function in order to quantify the welfare consequences of aquifer depletion. This is because farmers – unlike the utilities and regulators studied in Timmins (2002) – are small, and thus do not internalize their (dynamic) impact on the aquifer. As a result, adding up static WTP is sufficient to measure welfare.

6 Conclusion

Climate change is already impacting economic activity and human health (Tol 2018; Fishman, Carrillo, and Russ 2019). Climate science now recognizes that mitigation alone will not fully moderate future climate change costs (Lee et al. 2023). A growing body of literature demonstrates the necessity of climate change adaptation in moderating current and futures costs of an evolving climate (Carleton et al. 2024). However, very little empirical research evaluates the extent to which individuals and firms engage in adaptation, or measures the costs of that adaptation (Carleton et al. 2022). In this paper, we use rich data to empirically characterize adaptation behavior and its costs in the context of agricultural water use. We

evaluate how farmers in California's Central Valley respond to high temperature exposure through the margin of groundwater irrigation as adaptation. We find evidence that farmers are actively adapting. This adaptation comes at a cost, however: farmers are willing to pay at least $775 per year to avoid an additional day above 38°C. We further document that farmers pump less as aquifer depth increases, because pumping costs rise. This creates a feedback loop: if farmers respond to hot temperatures this year by pumping additional groundwater, the costs of groundwater pumping rise in the future.

We incorporate these features into a dynamic model of the aquifer. We find that climate change will increase pumping and significantly exacerbate groundwater depletion by end of century. However, we also document that the aquifer's "natural scarcity" effect moderates the overall impact of climate change on groundwater extraction. Failing to take this into account would lead to a substantial *over*estimate of the costs of climate change. In ongoing work, we use our model to calculate the welfare consequences of climate change, accounting both for farmers' responses to temperature and to depth.

These results have implications for groundwater management policy. We find that absent climate change, the "natural scarcity" effect leads aquifer depletion to slow substantially by end of century, suggesting that major policy intervention may not in fact be needed to reach aquifer sustainability. With climate change, however, policy such as California's landmark Sustainable Groundwater Management Act (SGMA), which aims to curb pumping, appears to be necessary to stem aquifer level decline.

While we model the dynamics of climate change adaptation in one specific context, agricultural groundwater in California, the lessons from this paper are likely broader. There is also a clear feedback loop in adapting to extreme heat with air conditioning: while operating an air conditioner can keep you cooler today, the electricity this same air conditioner consumers – and thus the greenhouse gases it produces – lead to worsening climate change tomorrow. Even more broadly, whenever there is an upward-sloping supply curve of adaptation actions, taking some adaptation action in the present makes future adaptation more costly. Future research about the dynamic consequences of climate change is thus required to understand adaptation.

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Groundwater in a changing climate

Supplementary Appendix: For online publication

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Appendix contents

A Data **A1**

B Additional reduced form results **A3**

C Bounding willingness to pay **A11**

D Model calibration **A12**

E Additional model results **A14**

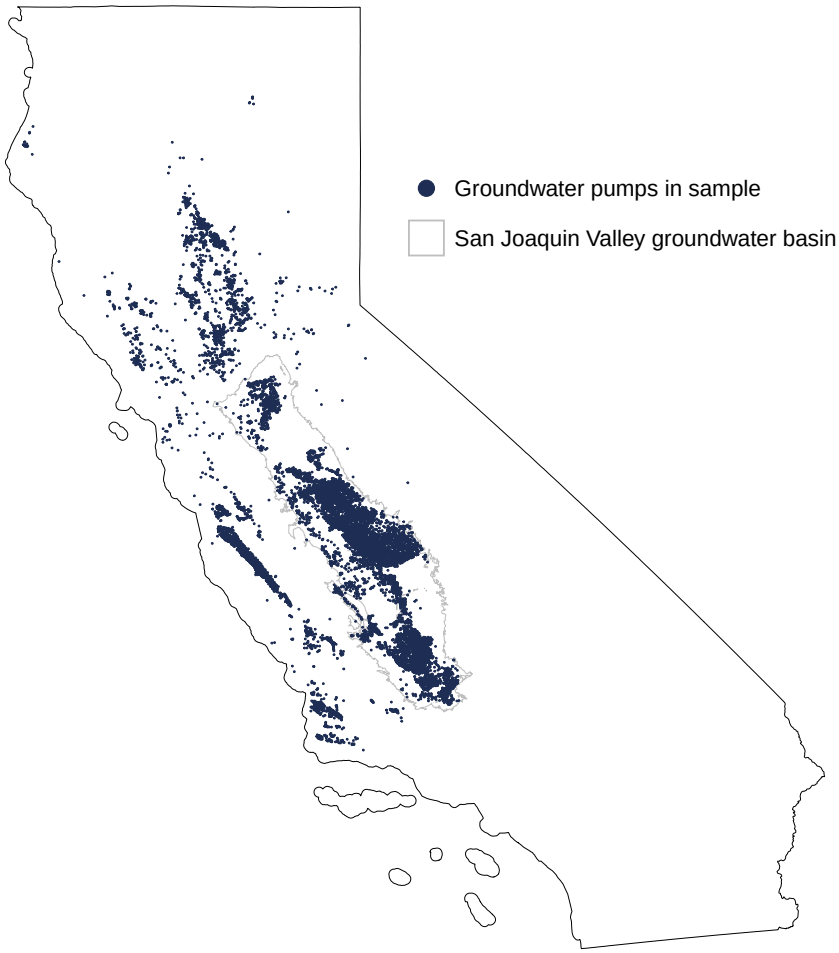
Appendix references **18**

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A Data

Details on our estimation sample Appendix Figure A1 shows the geographic distribution of groundwater pumps in our sample. Appendix Table A1 presents summary statistics for key variables.

Figure A1: Sample of groundwater pumpers



Notes: This figure plots the groundwater pumpers in our sample. As described in Section 3, our sample is made up of groundwater pumpers in the Pacific Gas and Electric service territory. In light gray, we plot the outline of the San Joaquin Valley groundwater basin, home to 71% of our pumps.

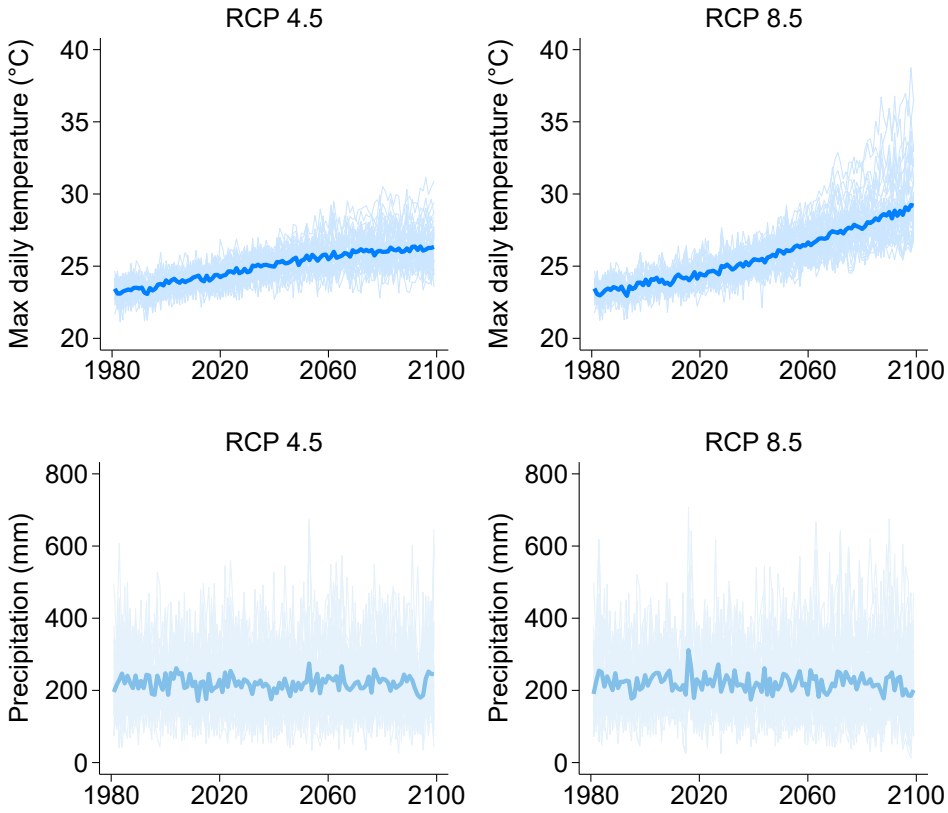
Table A1: Summary statistics

Unique parcels	7,817
Count of observed pumps per parcel	1.91
	(1.70)
"Croppable" area of parcel (acres)	121.77
	(187.23)
Average electricity use (kWh/year)	286,161
	(462,100)
Average electricity bill ($/year)	43,706
	(58,386)
Average groundwater use (AF/year)	1,004
	(1,648)
Average groundwater use (AF/acre per year)	4.83
	(24.66)
Average count of days/year above 32°C	87.94
	(34.05)
Average annual precipitation (mm)	289.70
	(173.93)
Average groundwater depth in sub-basin (feet)	119.51
	(55.38)
Parcel within surface water district (1/0)	0.61
	(0.49)
Parcel within San Joaquin Valley groundwater basin (1/0)	0.72
	(0.45)

Notes: We report means and standard deviations (in parentheses) across parcel-specific averages, weighted by (time-invariant) croppable acreage. The number of pumps, electricity use, and electricity bill are derived from PG&E electricity data. The groundwater use statistics use PG&E data in conjunction with groundwater depth data from CASGEM, following Equation (**??**). Temperature and precipitation data come from PRISM. Surface water data come from Hagerty (2022).

Climate projections Appendix Figure A2 shows how temperature and precipitation in the San Joaquin basin are projected to change by end of century, using data from Hsiang et al. (2017) and Rasmussen, Meinshausen, and Kopp (2016). We plot individual projections from each climate model in the ensemble, as well as a weighted mean.

Figure A2: Projected temperature and precipitation



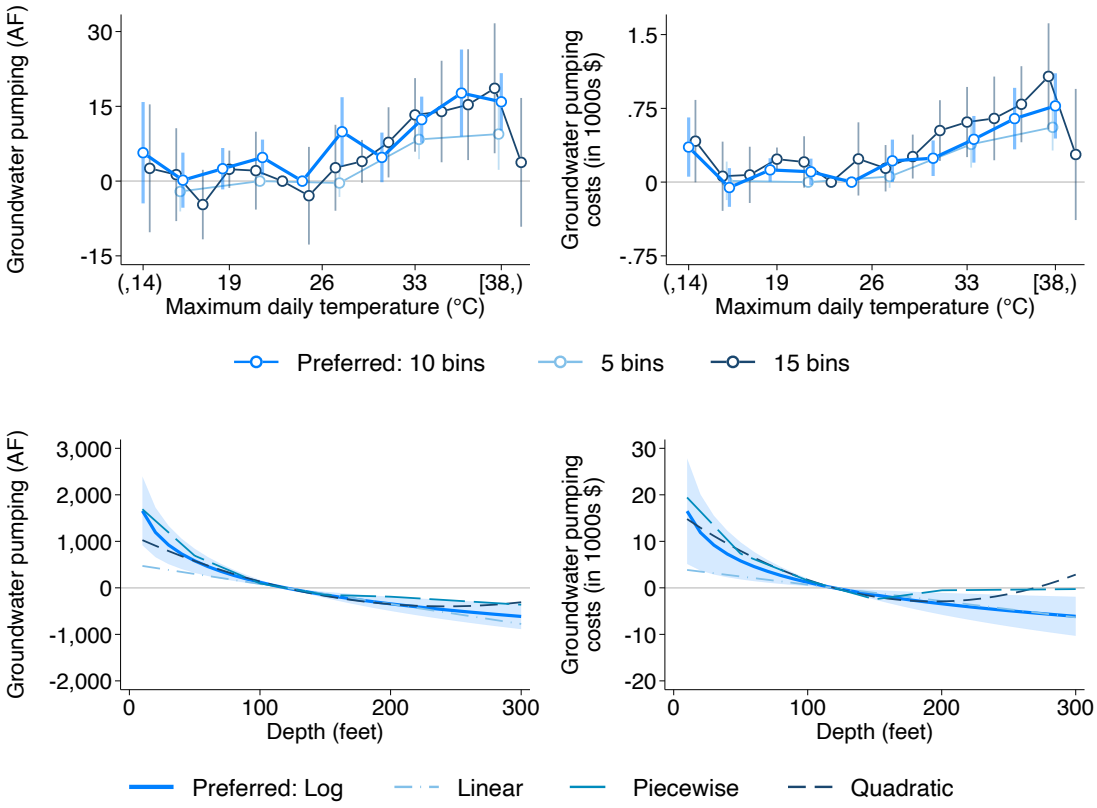
Notes: This figure plots projected temperature (top row) and precipitation (bottom row) in the San Joaquin basin from 1980 to 2100. We plot RCP 4.5 (moderate climate change) on the left, and RCP 8.5 (severe climate change) on the right. Projection data come from Hsiang et al. (2017) and Rasmussen, Meinshausen, and Kopp (2016), and are derived from an ensemble of 43 climate models for RCP 4.5 and 45 models for RCP 8.5. The thick line displays the probability-weighted mean, according to weights laid out in Rasmussen, Meinshausen, and Kopp (2016). The light lines present the projection from each individual model.

B Additional reduced form results

Functional forms Our results shown in Figure 2 are robust to alternative functional forms. Appendix Figure B1 demonstrates that the number of temperature bins does not meaningfully impact our results, and nor does the functional form of our depth regressor. Appendix Figure B2 shows our results are robust to a more parsimonious functional form for

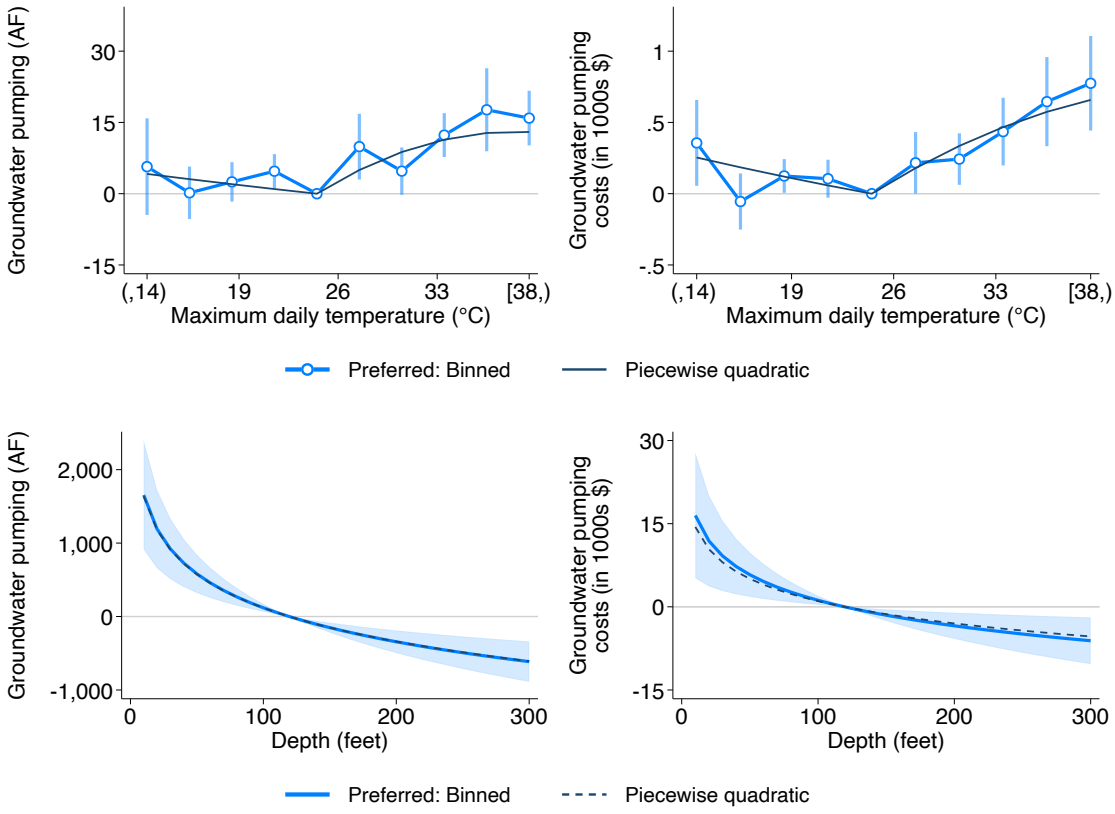
temperature (as we employ for the simulation model). Appendix Figure B3 shows our results are robust to a more parsimonious precipitation control (as we employ for the simulation model). Appendix Figure B4 shows that our estimated treatment effects are similar when we log-transform the outcome variables. Finally, Appendix Figure B5 demonstrates that our results are quantitatively and qualitatively similar when we two-way cluster by water district and county-year rather than one-way cluster by water district alone.

Figure B1: Alternative estimates: Functional form sensitivity



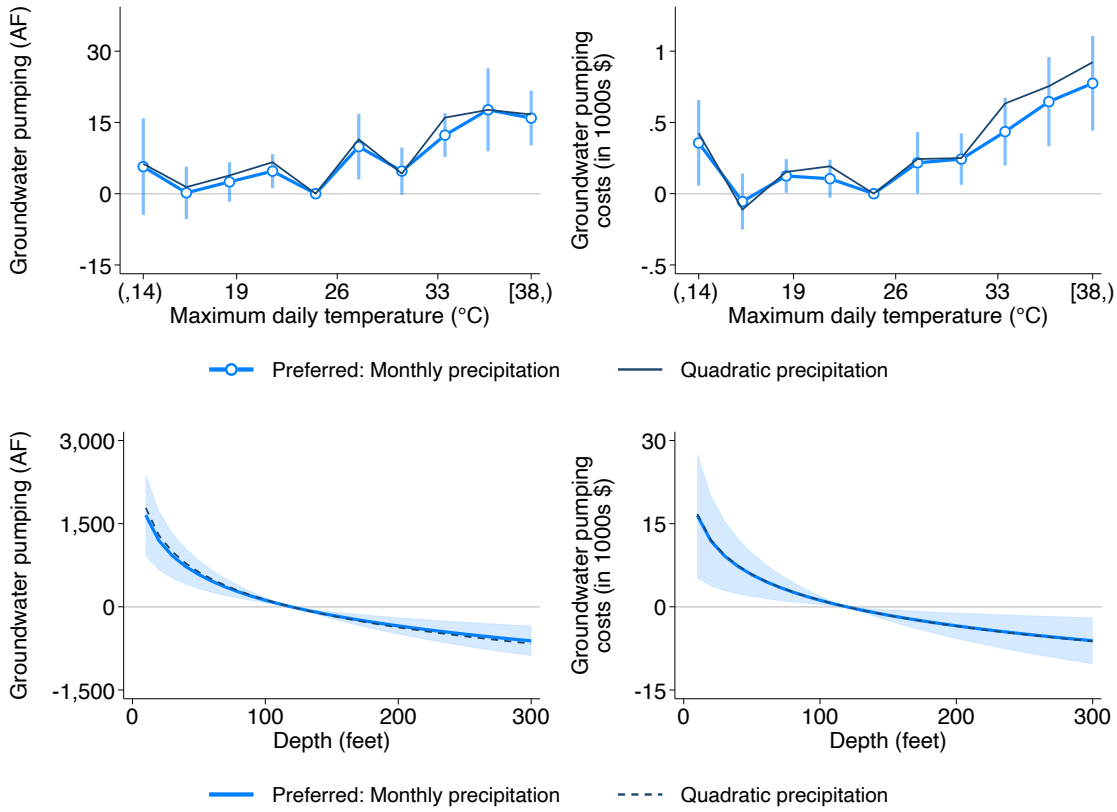
Notes: This figure presents sensitivity of our temperature and effects to the functional form of these variables. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. The top row shows effects of temperature. We reproduce our main specification in the middle blue color. In lighter blue, we use only 5 bins. In navy, we use 15 bins. All three sets of estimates are similar. The bottom row shows effects of depth. In middle blue, we show our preferred specification, which uses log(Depth). We present three alternatives: linear in depth (dash-dot), piecewise linear (long dash), and quadratic (short dash). Results are similar across the four. All regressions are estimated using Equation (2, and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

Figure B2: Alternative estimates: Piecewise quadratic temperature sensitivity



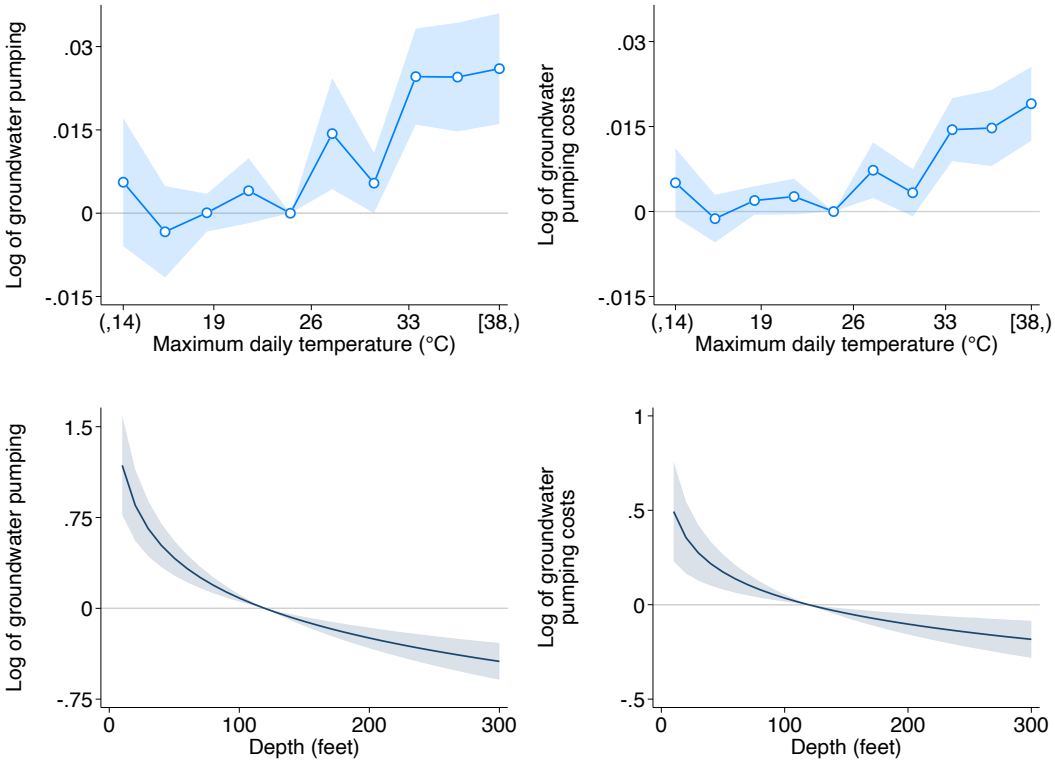
Notes: This figure presents sensitivity of our temperature and depth effects to using a piecewise quadratic in annual degree days for temperature instead of bins. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. The top row shows effects of temperature; the bottom row shows effects of depth. We reproduce our main specification in the middle blue color. In the darker blue, we use a quadratic in precipitation as the control. The results are extremely similar. All regressions are estimated using Equation (2, and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

Figure B3: Alternative estimates: Precipitation control sensitivity



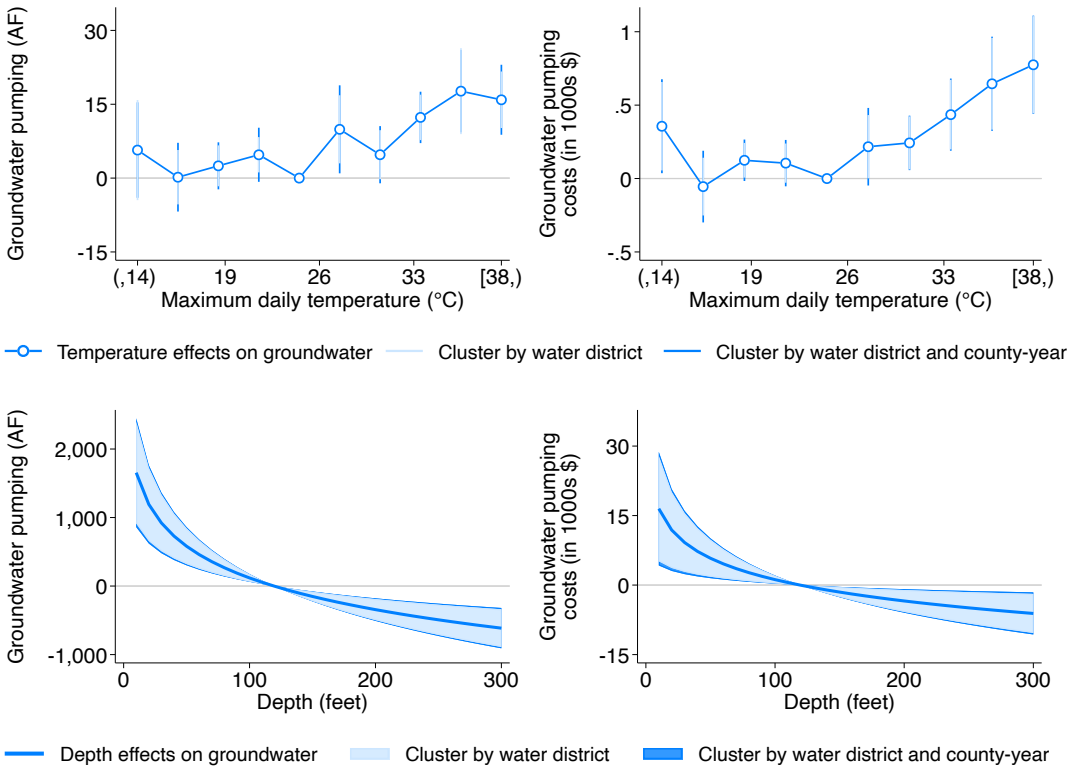
Notes: This figure presents sensitivity of our temperature and depth effects to functional form of the precipitation control we use for estimation. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. The top row shows effects of temperature; the bottom row shows effects of depth. We reproduce our main specification in the middle blue color, which controls linearly for monthly precipitation. In the darker blue, we use a quadratic in precipitation as the control. The results are extremely similar. All regressions are estimated using Equation (2, and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

Figure B4: Alternative estimates: Log transformation



Notes: This figure presents an alternative version of our main estimates where we log-transform our outcome variables. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. We estimate effects using Equation (2, with 10 temperature bins (omitting the 23–26°C bin) and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. Standard errors are clustered at the water district level; we shade 95% confidence intervals.

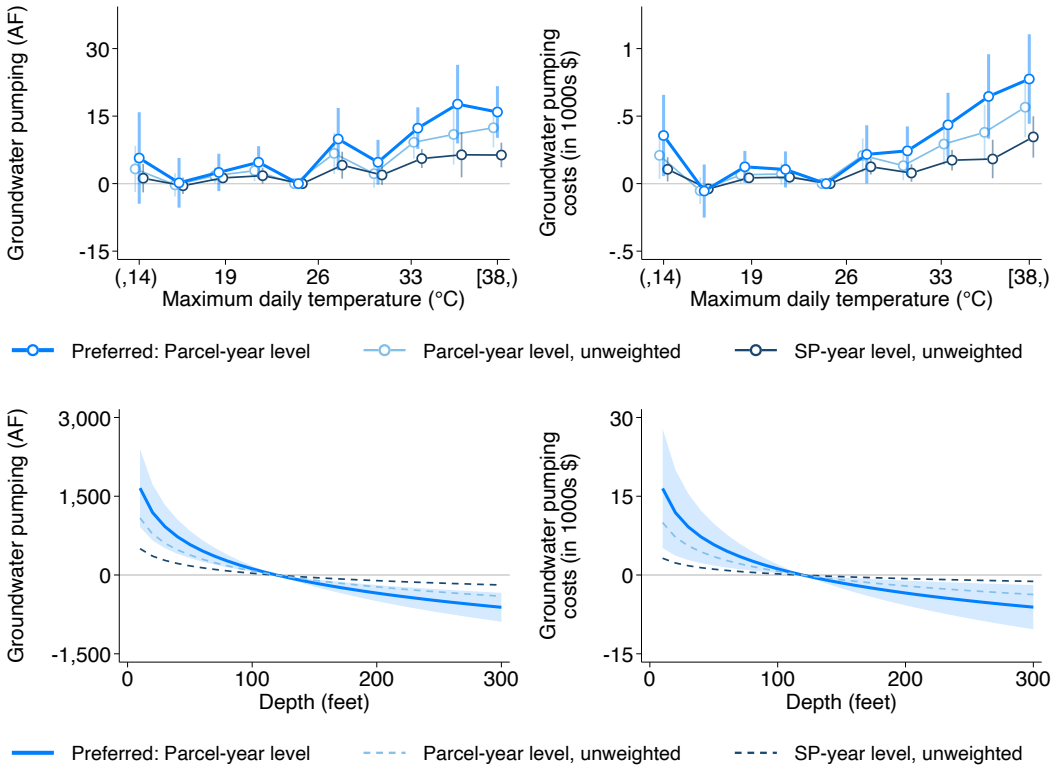
Figure B5: Alternative standard errors



Notes: This figure presents sensitivity of our standard error estimates to our choice of clustering. We reproduce our main specification, clustered by water district, in the middle blue color. In navy, we two-way cluster by water district and county-year. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. Both standard error estimates are quantitatively identical. All regressions are estimated using Equation (2, and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. We weight parcels by croppable acres. We plot 95% confidence intervals with vertical lines.

Aggregation and weights In our preferred specification, our unit of analysis is the farm (i.e., parcel) level. We sum all groundwater extraction among pumps belonging to the same farm. We also weight our regression by croppable area, in order to make our estimates representative per acre of cropland, and to avoid giving small farms undue weight in estimation. Appendix Figure B6 reproduces our main result (middle blue) and then presents two alternatives: first, a version estimated at the farm level, but unweighted (light blue), and second, a version estimated at the SP (i.e., pump) level, also unweighted (dark blue). Our effects are somewhat smaller when we do not weight, suggesting that larger farms are more responsive than smaller farms. When we estimate effects at the pump level, they fall by approximately half, in line with the fact that the average farm in our sample contains 1.9 pumps.

Figure B6: Alternative estimates: Aggregation

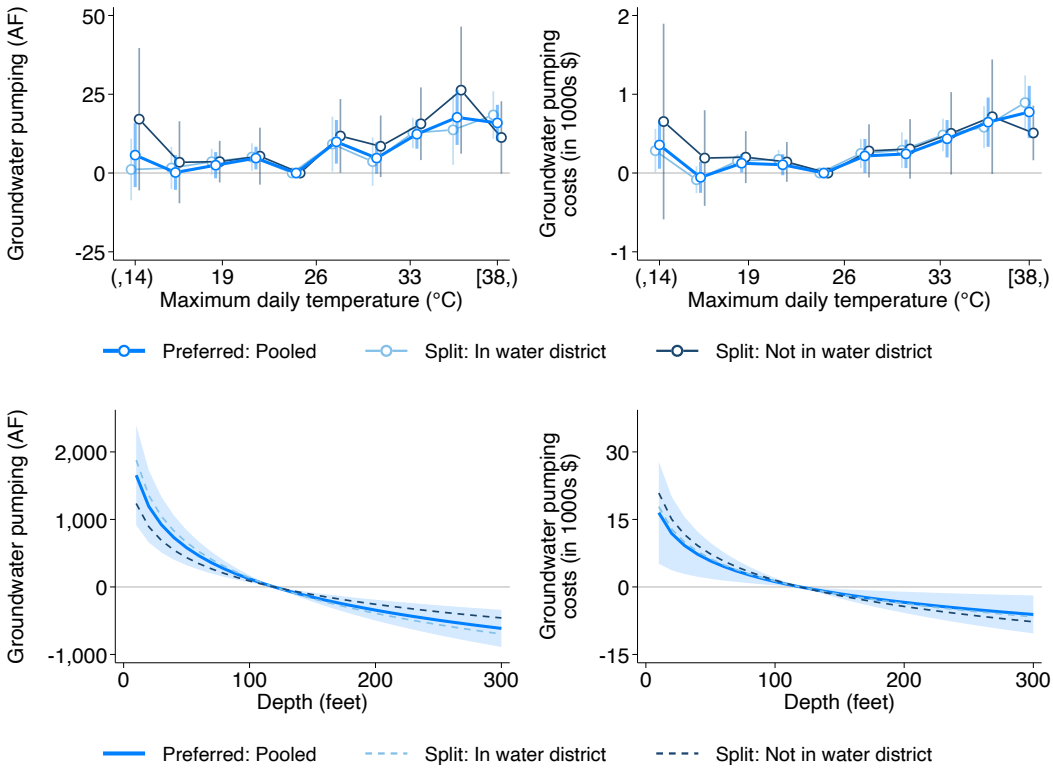


Notes: This figure demonstrates how our main results vary with weighting and aggregation. Our preferred estimates are in middle blue. In light blue, we continue to use the farm (i.e., parcel) as the unit of analysis, but instead of weighting by croppable area, we do not weight. In navy blue, we instead use the pump (i.e., SP or PG&E "service point") as the unit of analysis, and also do not weight. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. We estimate effects using Equation (2, with 10 temperature bins (omitting the 23–26°C bin) and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

Identification check The main threat to identification for our temperature effects is that surface water allocations, which we do not observe, may be co-varying with both temperature

and groundwater pumping. While we cannot control for surface water allocations directly, a test for whether this matter empirically is splitting the sample into farms that lie within water districts (and therefore have ready access to surface water) and farms that do not (and therefore are unlikely to have surface water access). Figure B7 demonstrates that our main estimates are remarkably similar for both sets of farms; we cannot reject equality in temperature effects for farms inside vs. outside of water districts.

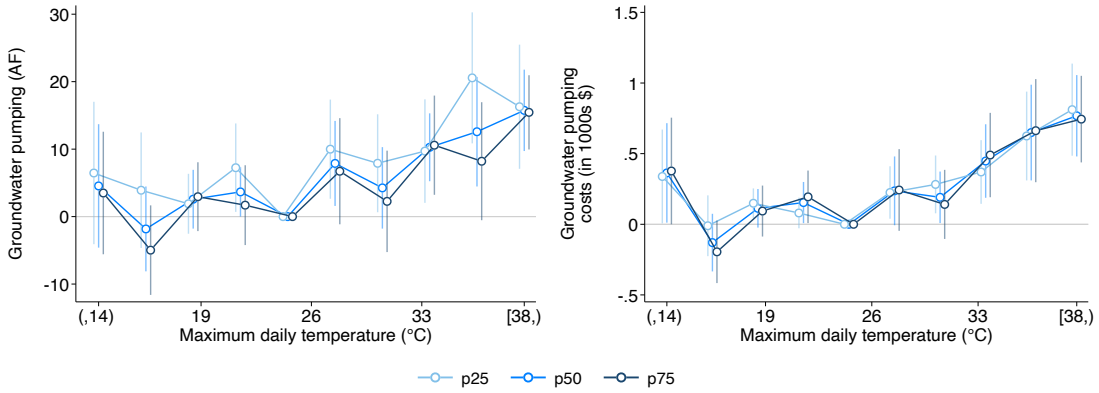
Figure B7: Access to surface water sensitivity



Notes: This figure demonstrates how our main results vary with surface water access in the form of belonging to an irrigation water district. Our pooled estimates are in middle blue. In light blue, we plot treatment effects for farms who do lie within a water district. In navy blue, we plot treatment effects for farms who do not lie within a water district. The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. We estimate effects using Equation (2, with 10 temperature bins (omitting the 23–26°C bin) and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

Extended models We extend our main model to incorporate additional heterogeneity. In Appendix Figure B8, we test whether our temperature effects vary at different groundwater depths. We find no evidence of strong interaction effects; the impact of temperature on groundwater pumping is similar at the 25th percentile of depth as at the 75th percentile of depth in our sample.

Figure B8: Temperature-x-depth interactions



Notes: This figure demonstrates how our main results vary with groundwater depth. In light, middle, and navy blue, respectively, we plot temperature effects at the 25th, 50th, and 75th percentiles of the depth distribution. We generate these estimates by adding a linear interaction between each temperature bin and sub-basin-wide groundwater depth to Equation (2). The left panel plots effects on annual groundwater extraction at the farm level; the right panel plots effects on groundwater costs. As in our main estimate, we use 10 temperature bins (omitting the 23–26°C bin) and include log depth, month-specific linear precipitation controls, parcel fixed effects, and year fixed effects. Standard errors are clustered at the water district level; we plot 95% confidence intervals with vertical lines.

C Bounding willingness to pay

We aim to quantify (bounds on) farmers' willingness to pay to avoid increasing heat and increasing aquifer depth. To do so, we begin with a simple model of farmer profits:

$$\pi(Q_w; T, D) = p_C Q_c(Q_w(D); T) - p_w(D) Q_w(T; D)$$

$Q_c(Q_w(D); T)$ is the quantity of crop produced, which depends on the amount of water used and temperature. $Q_w(D)$ is the quantity of water used, which depends on depth (as depth is a cost shifter). p_c is the price of the crop, which we assume is exogenous. $p_w(D)$ is the price of water, which depends on depth.

In this model, temperature and aquifer depth do not interact directly. Therefore, we separately solve for the change in profits as temperatures change and the change in profits as depth change (which in turn reveals WTP).

WTP for temperature

$$\pi^* = p_c Q_c(T, Q_w^*(T)) - p_w Q_w^*(T)$$
$$\frac{d\pi^*}{dT} = P_c \left[\frac{\partial Q_c}{\partial T} + \frac{\partial Q_c}{\partial Q_w} \cdot \frac{\partial Q_w^*}{\partial T} \right] - p_w \frac{\partial Q_w^*}{\partial T}$$

To sign this expression, note that $\frac{\partial Q_c}{\partial T} < 0$ (i.e., yields fall as temperatures rise, per a large literature including our own Figure 1); $\frac{\partial Q_c}{\partial Q_w} \cdot \frac{\partial Q_w^*}{\partial T} > 0$, as increases in water improve

crop yields, and we show in Figure 2 that farmers increase water use as temperatures rise. Though the overall sign of this term is ambiguous, Figure 1 suggests that the overall effect of temperature on crop yields, even accounting for irrigation, is negative. Then, note that $p_w \frac{\partial Q_w^*}{\partial T} > 0$, as prices are positive, and again, farmers apply more water as temperatures rise. Thus, both terms in this equation are negative, meaning we can use the change in expenditure on water in response to temperature (the second term) as a lower bound on farmers' WTP to avoid high temperatures.

WTP for depth

$$\begin{aligned}
\pi^* &= p_c Q_c(Q_w^*(D)) - p_w(D) Q_w^*(D) \\
\frac{d\pi^*}{dD} &= p_c \frac{\partial Q_c}{\partial Q_w} \frac{\partial Q_w}{\partial D} - \left[Q_w^*(D) \frac{\partial p_w}{\partial D} + p_w(D) \frac{\partial Q_w}{\partial D} \right] \\
&= \left[p_c \frac{\partial Q_c}{\partial Q_w} - p_w(D) \right] \frac{\partial Q_w}{\partial D} - Q_w^*(D) \frac{\partial p_w}{\partial D} \\
&= -Q_w^*(D) \frac{\partial p_w}{\partial D}
\end{aligned}$$

where the equality follows from the fact that, from the first-order condition for Q_w^*, $p_c \frac{\partial Q_c}{\partial Q_w} = p_w$, so the first term of the third line equals zero. Thus, we can use the relationship between water and depth (as in Figure 2) scaled by the effect of depth on price to measure WTP to avoid increases in depth.

D Model calibration

To operationalize Equation (3), we slightly modify our preferred temperature response specification (Equation (2)) to reduce the number of parameters and avoid overfitting. First, we replace our preferred $f(T_{it})$ of 10 temperature bins with a piecewise quadratic in annual degree days. Second, we replace our preferred $g(R_{imt})$ of 12 monthly precipitation coefficients with a quadratic in annual precipitation.[2] We also simulate an alternate model that interacts temperature with groundwater depth, analogous to Appendix Figure B8.

To simulate forward, we populate temperature and precipitation using climate projections from Hsiang et al. (2017). These projections combine a suite of 33 climate models, yielding projected counts of days in 1°C temperature bins and in 2mm precipitation bins at a county-year resolution. We aggregate bins to construct projected degree days (linear and squared terms, separately above an below 24.5°C) and projected annual precipitation (in mm) at the county-year level. Our preferred climate scenario is RCP4.5, and we consider alternate climate scenarios for robustness.

2. Appendix Figures B2 and B3 show that this modified specification recovers parameter estimates that are nearly identical to Equation (2).

To operationalize Equation (4), we restrict our focus to the San Joaquin Valley groundwater basin, which represents 71% of our estimation sample and is the most economically important groundwater basin in California. The San Joaquin basin contains 16 sub-basins with spatially heterogeneous climate realizations, irrigation practices, groundwater depths, and soil characteristics. To capture this inter-sub-basin heterogeneity close to the point of groundwater extraction and recharge, we populate the rightmost term of Equation (4) separately for each sub-basin s and average up to the basin level (weighting by sub-basin acreage A_s):

$$\overline{D}_{t+1} \;=\; \overline{D}_t \;+\; \frac{1}{\sum_s A_s} \sum_s A_s \rho_s \Big[(1-\psi)\alpha \widehat{\overline{W}}_{st} \;-\; \overline{R}^{\text{proj}}_{st} \Big] \tag{D1}$$

$$\text{where} \quad \widehat{\overline{W}}_{st} \;=\; \frac{\alpha_s}{A_s} \sum_{i \in s} \widehat{W} \left(T^{\text{proj}}_{it} \,,\, R^{\text{proj}}_{it} \,,\, \tilde{D}_{st} \,;\, \widehat{\boldsymbol{\beta}} \,,\, \widehat{\gamma}_i \,,\, \widehat{\delta}_{\tilde{t}} \right) \tag{D2}$$

$$\text{and} \quad \tilde{D}_{st} \;=\; \overline{D}_t \;+\; \gamma_s \tag{D3}$$

1. Start with basin-wide average depth $\overline{D}_t$.

2. Adjust $\overline{D}_t$ by γ_s to arrive at $\tilde{D}_{st}$, which accounts for persistent differences in depth across San Joaquin's 16 sub-basins. We calibrate γ_s using time-invariant average sub-basin depths during our 2008–2019 sample period.

3. Estimate $\widehat{W} \left(\mathbf{T}^{\text{proj}}_{it}, R^{\text{proj}}_{it}, \tilde{D}_{st} \right)$ for each unit i in year t, by plugging climate projections ($\mathbf{T}^{\text{proj}}_{it}$, R^{proj}_{it}) and sub-basin-specific depths ($\tilde{D}_{st}$) into our fitted regression model, using estimated coefficients $\widehat{\boldsymbol{\beta}}$, estimated unit fixed effects $\widehat{\gamma}_i$, and estimated year fixed effect $\widehat{\delta}_{\tilde{t}}$. Since we are forward-simulating beyond our 2008–2019 sample period, we draw $\tilde{t} \in \{2008, \ldots, 2019\}$ for out-of-sample year t.[3]

4. Aggregate $\widehat{W}_{ist}$ (in AF) up to the sub-basin-year level, and scale up by α_s to extrapolate our estimation sample to the full population of agricultural groundwater pumpers in sub-basin s. We calibrate α_s by dividing the total number of agricultural/irrigation pumps in the sub-basin (as reported by the DWR's Well Completion Reports) by the number of pumps in our sample.[4]

5. Divide by sub-basin acreage A_s to arrive at $\widehat{\overline{W}}_{st}$, the average projected feet of groundwater extracted in year t across sub-basin s.

3. By drawing year fixed effects from within our sample period, we are effectively assuming stationary. While this is a strong assumption, we prefer it to the alternative of extrapolating parametric time trends. Because we are using the model mainly to make comparisons across scenarios, this assumption is relatively innocuous.

4. This assumes that our estimation sample is representative of the full population of agricultural groundwater pumpers within each sub-basin. Scaling up from sample to population is essential for simulating the equation of motion, since observed groundwater depths are impacted by *total* groundwater extraction, not just groundwater extracted by pumps in our sample.

6. Calculate $\left[(1-\psi)\alpha\widehat{\overline{W}}_{st} - \overline{R}_{st}^{\text{proj}}\right]$, averaging projected precipitation across sub-basin s. We assume $\psi = 0.2$, which is consistent with relatively efficient drip irrigation (Dewandel et al. (2008)). We also scale up groundwater extraction by $\alpha = 1.38$, a calibration factor that ensures Equation (D1) holds as an accounting identity within our sample. This additional adjustment accounts for factors outside of our model that impact groundwater depths, including groundwater extracted for non-agricultural uses, errors in specifying α_s, and recharge due to precipitation outside of the basin (e.g. snowmelt). This step yields the projected feet of net groundwater extraction across the full area of sub-basin s.

7. Apply the multiplier ρ_s to translate groundwater extraction into changes in depth. We parameterize ρ_s for each sub-basin by combining data on soil characteristics from XXX with specific yield estimates from Loheide, Butler, and Gorelick (2005).

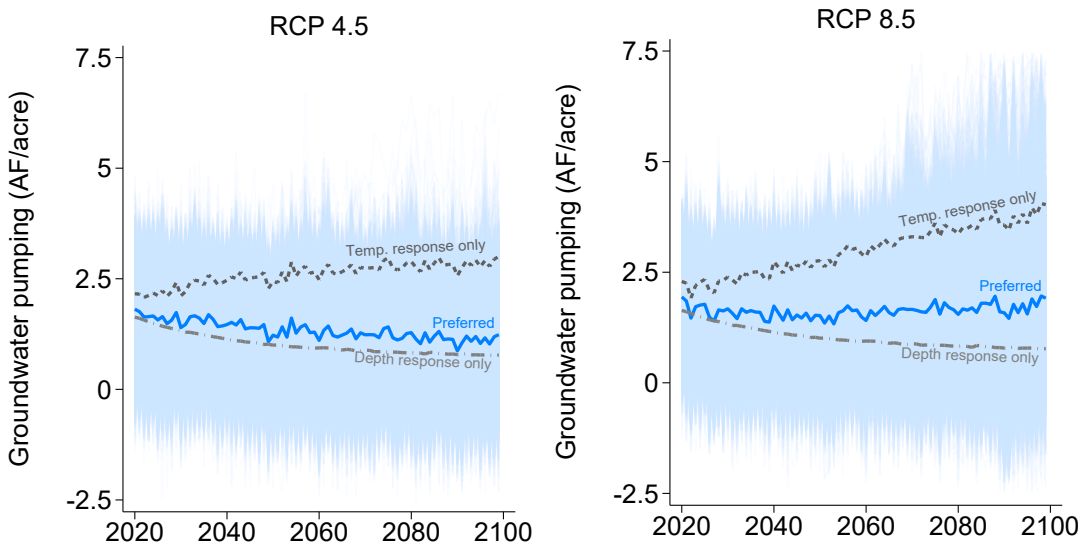
8. Average changes in depth up to the basin level, weighting by sub-basin acreage.

9. Calculate $\overline{D}_{t+1}$, step forward one year, and repeat.

E Additional model results

Impacts on groundwater pumping Appendix Figure E1 presents simulation results showing groundwater extraction from 2020 through 2100 under both RCP 4.5 (left panel) and RCP 8.5 (right panel). As with our main simulations, we present results for three scenarios: our preferred model, in which farmers respond both to temperature and to groundwater depth; an alternative model where farmers respond only to depth; and an alternative where farmers respond only to temperature. We find that when farmers respond only to depth, groundwater pumping falls over time, as the slowly deepening aquifer leads costs to rise. When farmers respond only to temperature, pumping increases substantially, increasing by approximately 50% under RCP 4.5 and nearly doubling by end of century under RCP 8.5. In our preferred model, groundwater extraction stays relatively stable under RCP 4.5 and increases somewhat under RCP 8.5.

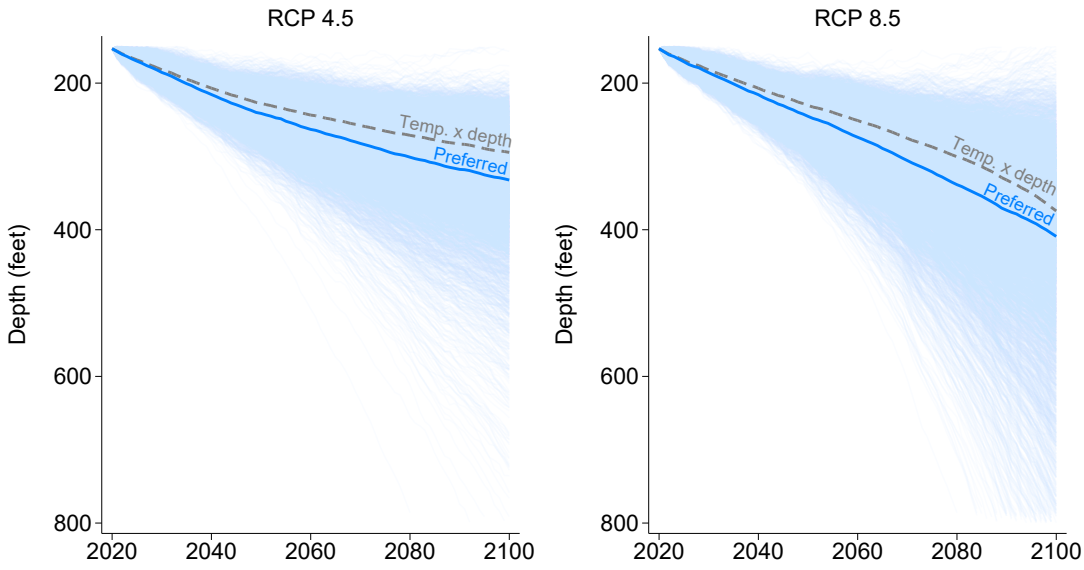
Figure E1: Impact of climate change on groundwater pumping



Notes: This figure presents the results of an extension of our simulation exercise. We model groundwater pumping from 2020 through 2100. The left panel shows results under RCP 4.5 (moderate climate change) and the right panel shows results under RCP 8.5 (severe climate change). In both panels, the blue line denotes our preferred model, where farmers' groundwater extraction responds to both temperature and depth. We run 10,000 draws of the model. The thick blue line plots the mean over these simulation runs. The individual light blue lines show individual simulations. These draws incorporate both econometric and climate model uncertainty. The two gray lines plot the means over simulation runs where we only have farmers responding to depth (dash-dot) and only have farmers responding to temperature (dashed).

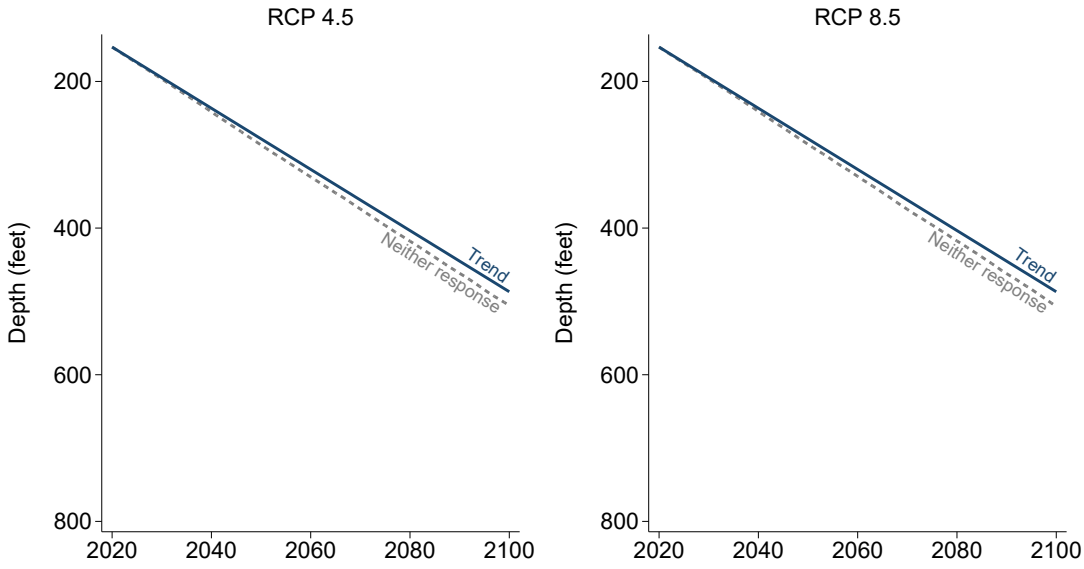
Extended model: temperature interacted with depth In Appendix Figure E3, we extend our model to allow for an interaction between temperature and groundwater depth. That is, as the aquifer gets deeper, we reduce farmers' groundwater pumping slightly, in accordance with Appendix Figure B8. We plot this alternative model (grey dashed line) against our preferred model (blue line), and find that it yields a somewhat smaller increase in aquifer depth under both climate scenarios than our preferred model does.

Figure E2: Impact of climate change on aquifer levels, extended model



Notes: This figure presents the results of an extension of our simulation exercise. We model groundwater depth from 2020 through 2100. The left panel shows results under RCP 4.5 (moderate climate change) and the right panel shows results under RCP 8.5 (severe climate change). In both panels, the blue line denotes our preferred model, where farmers' groundwater extraction responds to both temperature and depth. We run 10,000 draws of the model. The thick blue line plots the mean over these simulation runs. The individual light blue lines show individual simulations. These draws incorporate both econometric and climate model uncertainty. The dashed line shows our extended model, where in addition to having farmers respond to both temperature and depth independently, we also allow the impact of temperature on groundwater pumping to vary with aquifer depth.

Figure E3



Notes: .

Appendix references

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