

Warming and Snow Loss Threaten the Economic Viability of Irrigated Agriculture

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Abstract

Climate change reduces the capacity of snowfed runoff to buffer irrigated agriculture against warming. Yet this hydrologic reality is largely overlooked in economic estimates of agricultural climate impacts. By integrating hydrologic processes into econometric models of climate impacts, we quantify how warming and snow loss affect economic outcomes in 950 watersheds in the western United States. We find a current shift away from water-intensive crops in response to hydroclimatic change since 1980, with projected declines accelerating by 2100 (1.9°C–4.5°C warming). Annual losses could reach \$8.6–\$13.5 billion, driven by 14–49% reductions in irrigated area and 46–75% declines in land rental rates. The largest absolute losses are projected in highly productive regions such as the Central Valley and Great Plains, while other regions, including the Northern Rocky Mountains and Navajo Nation (Diné Bikéyah), face severe proportional losses. Projected losses approach planned federal adaptation spending, and these results can inform investment priorities.

Keywords: snowmelt, surface water, irrigated agriculture, agricultural land, climate change, cash rental rates

1 Introduction

Global crop production has an estimated gross value of \$5T USD, a substantial share of which is sustained through irrigation from snowfed runoff [1–3]. In regions including Central Asia, Europe, and the contiguous western United States (WUS, west of longitude -100°), rising temperatures reduce snow water storage (SWE) and alter melt timing [4–6], reducing water availability for irrigation in the growing season [7–9]. As a result, up to 40% of irrigation demand in these regions could go unmet in the future [3]. How producers respond—through crop choice, land use, and rental markets—has global implications for the viability of irrigated agriculture in critical snowfed regions, but remains poorly quantified [3, 9, 10]. Consequently, there are gaps in our understanding of the potential economic impacts of reduced snowpack on agriculture [11].

Economists have developed statistical approaches to quantify the causal impact of interannual weather variation and long-term climate changes on agricultural outcomes, but these methods have been applied primarily to rainfed settings and focus on temperature and precipitation [12–15]. While studies highlight the benefits of irrigation [16–18], or explore the interactive effects between temperature and water availability on yields [19, 20], none quantify the historical impact of snowpack changes on agriculture, including recent global analyses that otherwise account for producer adaptation [21]. Though Malek et al. [22] simulate future crop adaptation in a snowfed basin, they do not estimate empirical relationships between snow loss and economic outcomes using observational data. As such, existing approaches largely overlook how hydrologic variables shape key economic decisions and outcomes such as crop selection [23–25] and agricultural profitability, which can be proxied by cash rental rates—the price paid by a producer to lease land—that provide a direct measure of economic returns specific to farming [26, 27].

A major reason why existing studies have not examined how economic and agricultural output respond to changes in snowfed water supply is the prior lack of accessible, high-resolution hydrological data [28]. While existing climate economics literature relates outcomes at the county or farm level to local growing season temperature and precipitation, water supply in snowfed systems is shaped by weather patterns across multiple seasons in upland watersheds, often far from agriculture’s point-of-use. Hydroclimatic models now enable better estimates of snow dynamics in the complex terrain typical of snowfed systems [29], and reanalysis products, including ERA5-Land [30, 31], are increasingly skilled at representing SWE [32].

Here, we develop two statistical models that integrate hydrologic variables—specifically SWE and runoff—with traditional climate and agricultural data to estimate impacts of short- and long-term hydroclimatic change on agricultural producers in the semi-arid WUS over 2008-2023. Our models address two key questions: (1) how do expected and realized growing season conditions and snowfed

water supply influence producers' annual planting decisions (see [Equation 3](#), henceforth termed "annual model"), and (2) how do long-term hydroclimatic changes impact more permanent shifts in land use and rental rates (see [Equation 4](#), henceforth termed "long-term model")? Understanding the first question is important for managing seasonal water demands, as it can inform reservoir release strategies and leasing market opportunities at the start of each growing season. The latter question helps us understand the potential impacts of climate change in snowfed agricultural systems after accounting for behavioral responses by producers, which has implications for efficient investment in long-term adaptation strategies.

We focus on the WUS, where high-resolution hydrologic data are available but economic impacts of snow loss remain understudied [8, 11]. Over 75% of irrigation water supply in the WUS comes from surface water sources [33] with 53–70% of the runoff feeding these sources originating as snow [34, 35]. Unlike rainfed agriculture in the eastern US where precipitation directly determines agricultural water supply, agricultural producers in the arid WUS depend on the storage and release of snowfed runoff from upland watersheds to grow crops [6, 7, 36, 37].

Our models evaluate the impacts of precipitation, temperature, runoff, and SWE on agricultural land use [38] and rental rates [39] across 950 WUS watersheds. We analyze land use changes in aggregate and by cropland allocation to high, moderate, and low water-use crops (HWU, MWU, LWU, respectively), as well as non-irrigated grass pasture and perennial crops (see [Table 1](#) and [subsection A.4](#)).

We estimate our models using ERA5-Land data from 2008-2023 and conduct additional validation and robustness checks across multiple hydroclimatic products to ensure that inference is not sensitive to input data (see Methods). Then, using the parameterized models, we estimate the historical impacts of hydroclimatic change since 1980-2007, prior to available land use and rental rate data, and project end-of-century impacts using hydrologic simulations driven by seven CMIP6 [40] Global Circulation Models (GCMs) across four emission scenarios (1.9–4.5°C warming; see [subsection 4.4](#)).

Our study makes three contributions. First, we incorporate estimates of snowfed water supply into methods from the climate economics literature. Second, we explore the extent to which temperature impacts are potentially mediated by water supply availability on land use and rental rates, moving beyond the prior focus on yields. Third, we distinguish long-term adaptation from responses to interannual variability. Our findings provide new insights that can help guide resource allocation and policy development for adaptation in the WUS and other vulnerable snowfed regions.

2 Results and Discussion

2.1 Hydroclimatic Drivers of Annual Cropping in the WUS

Results from the annual model (Equation 3) indicate that temperature and snowpack are key drivers of annual agricultural land use outcomes in the WUS (Table 2). Consistent with findings in rainfed systems [12], we show that growing season temperature significantly and non-linearly affects total irrigated, HWU, and MWU cropland area. An increase in temperature positively affects irrigated cropland up to a growing season mean of $\approx 15^\circ\text{C}$, beyond which further increases have a negative impact (Table 2). Additionally, the amount of snow on April 1 (April 1 SWE) significantly influences interannual planting decisions for irrigated crops, while runoff is not significant. For example, a 48% increase in SWE relative to the observed average across watersheds (10^8 m^3) drives a 3.8% increase in land planted in HWU.

April 1 SWE is observable prior to the growing season and is widely used by water managers and producers to guide planting decisions [41, 42]. While runoff is arguably a more accurate measure of irrigation potential during the growing season than SWE [43–45], two mechanisms could explain the estimated difference in significance. First, lower April 1 SWE signals increased probability of water curtailments [41], shifting producers (particularly junior water rights holders) toward less water-intensive crops or reduced acreage. Second, less April 1 SWE reduces surface water allocations at an irrigation district level, increasing reliance on self-pumped groundwater [46]. Producers pay a higher marginal cost for the latter, which could impact operating costs and profitability [47].

2.2 Impacts of Long-term Hydroclimatic Change on Agricultural Land Use and Rental Rates

In contrast to producer responses to interannual variability, the long-term model (Equation 4) captures adaptation over time. Temperature and runoff emerge as strong predictors of both agricultural land use and rental rates, while SWE is statistically insignificant (Table 2, Table B3). While April 1 SWE influences annual planting decisions, longer-term trends in runoff drive more permanent shifts in agricultural land use. Irrigated rental rates show little to no significant response to interannual variation in the annual model (Table B4), but the long-term model reveals significant temperature and runoff effects, suggesting persistent changes in climate affect expected profitability and changes in agricultural land markets.

Temperature remains strongly correlated with most outcomes, but its effect on total irrigated cropland, HWU cropland, and rental rates (Table 2) is interdependent with hydrologic conditions. Figure 1 illustrates that higher runoff can mitigate the adverse effects of rising temperatures on

irrigated land use (Figure 1A-B) and rental rates (Figure 1C). Conversely, low water availability amplifies these negative effects.

Water availability buffers irrigation-dependent agricultural systems against the adverse effects of rising temperatures [48, 49] and preserves rental rates—a relationship that, while intuitive, remains largely unquantified in the WUS. However, hydrologic buffering alone may be insufficient under continued warming, particularly in snow-fed systems. Holding temperature constant, a 10^8 m^3 (81,000 acre-feet) increase in runoff (17.1% increase relative to the mean) raises average irrigated rental rates by \$35.85 per hectare (7.2%). If runoff remains constant, a 1°C increase in temperature reduces irrigated rental rates by \$165.54 per hectare (33% decline). Put simply, offsetting the damage of 1°C warming to rental rates would require an increase in runoff on the order of $4.5 \times 10^8 \text{ m}^3$ (365,000 acre-feet), which approaches the storage capacity of many WUS reservoirs [50]. While prior work has revealed that the presence of irrigation and groundwater storage increases land values [51], our results suggest that hydrologic conditions, such as snowpack and runoff, are also capitalized into land rental values in snowfed systems.

2.3 Historical Responses to Hydroclimatic Change Since 1980

Due to the lack of consistent agricultural land-use and rental-rate data over this period, we use our parameterized long-term models to “backcast” changes in agricultural outcomes from 1980 to the present based on observed changes in hydroclimatic conditions (Table B5). Our results suggest that land dedicated to HWU crops in the WUS is approximately 25% lower than it would have been under a stationary climate, while estimated changes in MWU crops are not statistically distinguishable from zero. Similarly, irrigated and dryland rental rates are estimated to be \$111.51 (25.4%) and \$18.42 (23.9%) per hectare lower, respectively.

While these counterfactual estimates appear large, they coincide with a mean growing-season temperature increase of $\approx 0.75^\circ\text{C}$ and mean runoff decline by $\approx 0.55 \times 10^8 \text{ m}^3$. As shown in Figure 1, simultaneous changes to temperature and runoff can compound adverse effects on agricultural land use and profitability. To assess validity, we benchmark our estimates using Agricultural Census [52, 53] data as an external check. The model-implied 25% reduction in HWU cropland corresponds to ≈ 1.97 million hectares, or 6.1% of the mean total irrigated agricultural land in our study area over 2008–2023. Census data indicate a 6.2% decline in irrigated land across states fully west of the 100^{th} meridian between 1987 and 2022 [52, 53]. Census documentation attributes irrigation declines primarily to drought and reduced water supplies [54].

2.4 Projected Impacts to Agriculture by 2100

Changes in [Figure 2](#) are consistent with recent assessments of both warming and snow loss. Warming increases incrementally across SSPs ([Figure 2A-D](#)), is concentrated in higher-latitude interior regions consistent with others [\[55\]](#), and is within $\pm 0.3^{\circ}\text{C}$ of contemporary estimates [\[56\]](#). April 1 SWE declines by 25-42% ([Figure 2E-I](#)) with strong convergence among GCMs under higher emissions. Higher emissions estimates align with estimated $50\% \pm 10\%$ reductions reported in literature [\[57\]](#). Despite declines in April 1 SWE, runoff is more variable ([Figure 2I-L](#)). This may partly reflect nonlinear responses between streamflow and snow arising from factors like compensatory spring precipitation [\[58–60\]](#), but also that changes in seasonality and earlier peak runoff [\[4\]](#) are not captured by our metric. As such, the impact of snow loss on water availability during the irrigation season may be more severe than annual runoff volumes suggest.

Projected hydroclimatic changes ([Figure 2](#)) consistently lead to unfavorable conditions for irrigated agriculture in the WUS by the end-of-century ([Figure 3](#)). Estimated reductions in total irrigated land area relative to a baseline with no hydrologic or climatic changes range from 14% to 49% ([Figure 3A](#)), which modestly overlap with existing estimates of 4% to 17% using older data and excluding hydrologic variables [\[61\]](#). LWU cropland expands across all GCMs ([Figure 3B](#)), potentially reflecting a reallocation toward less water-intensive production, while grass-based pasture contracts by 31%–35% across all simulated futures ([Figure 3C](#)), which aligns with recent evidence of widespread rangeland degradation across the WUS from 1995-2022 [\[62\]](#).

Rental rates are similarly responsive to hydroclimatic change and decline significantly across futures relative to a stationary climate. Reductions for irrigated rental rates range from \$226.05 to \$368.42 per hectare ([Figure 3D](#)) relative to an observed average of \$458.32 ([Table B6](#)), and dryland rental rates fall by \$22.42 to \$58.85 per hectare ([Figure 3E](#)) relative to an observed average of \$91.18. Grass pasture rental rates show only slight, insignificant changes across GCMs ([Figure 3F](#)). Our estimates extend prior work, which did not account for irrigation effects and projected per-hectare rental losses of \$77.19 under 2°C warming and \$217.03 under 4°C warming for portions of the interior Western and Central US [\[63\]](#).

Estimates are supported by recent USDA survey-based evidence on producer behavior, which reports that since 2018, more than 600,000 hectares of previously irrigated land within our study domain are currently idle or no longer irrigated [\[54\]](#). Frequently cited reasons for discontinuation include irrigation becoming uneconomical, loss of water rights, regulatory restrictions on water use, and shortages of surface water supply ([Figure C3](#)).

2.5 Total Economic Costs and Regional Impacts

Figure 4 shows how hydroclimatic changes influence agricultural land exchange value—area by crop type times average rental rate—across the WUS using our long-term model. Agricultural land value declines by 53.7% to 86.0% (Figure 4A), equating to \$8.6 to \$13.5 billion (2020 USD), driven by highly significant estimates of reduction in irrigated cropland (Figure 3A) alongside decreases in both irrigated and dryland rental rates (Figure 3D-E). The impact on land asset values, which reflect the present value of all future rental income, could be substantially larger, unless current prices already capitalize expected climate changes [64].

Absolute dollar losses are largest in highly productive WUS regions: Yakima Valley, the Snake River Plain, the Central Valley, and Great Plains (Figure 4B). However, absolute values obscure proportional impacts in smaller agricultural economies [65]. Areas with consistent and substantial losses across all 28 futures, including the Northern Great Plains, Northern Rocky Mountains, and Four Corners, specifically the Navajo Nation (Diné Bikéyah), are also high-priority targets for adaptation investment (Figure 4C, Figure C4).

Our results provide a targeted estimate of agricultural economic losses attributable specifically to hydroclimatic change, helping to clarify how projected changes from the most recent climate models translate into agricultural outcomes. Previous work has focused more narrowly on physical climate vulnerability [66, 67] with the largest impacts to irrigated regions like the San Joaquin and Colorado River Basins [3]. To quantify potential damages, other analyses have combined agricultural losses with indirect sectoral costs, yielding economy-wide damage estimates of up to \$1 trillion USD annually [11, 68]. Figure 2 shows that assuming a direct, linear relationship between climate risks and economic losses obscures how complex dynamics between temperature and water supply influence agricultural outcomes.

3 Conclusion

Historically, producers in the WUS have used snowfed irrigation supply to offset aridity, heat, and hydrological variability [34, 36, 37]. We show how long-term hydroclimatic trends influence economic outcomes for irrigated agriculture, with limitations outlined in subsection 4.8. Results imply that changes in snowfed runoff may amplify the negative effects of warming, posing significant challenges to sustaining irrigated agriculture in the WUS at historical scales.

We find that hydroclimatic changes have resulted in a movement away from water-intensive crops. Relative to a stationary climate since 1980, current land allocated to water-intensive crops is approximately 25% lower, and irrigated rental rates are \$111.51 per hectare lower. Future warming could amplify these shifts, with total irrigated land area declining by 14% to 49% and irrigated rental

rates declining by \$226.05–\$368.42 per hectare. Declines are steepest for land allocated to water-intensive crops, which decreases by 44% to 85% compared to 2008-2023 averages. The resulting costs to producers range from \$8.6 to \$13.5 billion USD per year, with sharp declines expected across high-output regions such as the Great Plains, Pacific Northwest, and Central Valley and severe proportional impacts in places such as the Northern Rockies, Great Plains, and Four Corners regions.

To our knowledge, this is the first demonstration of how warming and snow loss affect agricultural land use and profitability in snowfed systems. By separately examining annual and long-term responses, we reveal how producers and markets adapt at different timescales. Conceptually, we consider two categories of producer responses. First, producers respond to immediate signals of water availability. In our case, annual model results suggest that water supply expectations based on SWE influence annual land use decisions, as opposed to realized runoff. This is intuitive because snowpack is observable when planting decisions are made, whereas runoff arrives later in the year and can be difficult to predict. In the long-term, however, the amount of surface water actually delivered (i.e., runoff) shapes how much land is in production, the types of crops planted, and the value of that land.

As warming and snow loss continue, these shifts have significant economic consequences. To reduce damages from climate change, the US government has invested approximately \$120 billion over the past decade ($\approx$ \$12 billion per year) in adaptation [69]. However, multiple and sometimes conflicting strategies have been proposed. Some research advocates for increasing irrigation to offset the adverse effects of higher temperatures [70] while other work suggests optimizing food production by reducing certain water-intensive crops [9]. With federal spending on adaptation projected to rise by 3.5-22% [69], projected losses could approach the scale of adaptation spending. Our highest projected annual losses in the WUS (\$13.5 billion 2020 USD) closely align with the estimated annual cost of planned adaptation across CONUS under similar future warming (\$14.6 billion USD) [69]. Against this backdrop, targeted investments in adaptation strategies that perform under diverse futures are critical [71–73].

In summary, our results indicate that rising temperatures and changing runoff compound to decrease the profitability of irrigated agriculture, encouraging a shift to more water-efficient alternatives. Policies and tools that align with these shifts can promote efficient, realistic, and timely adaptation in agricultural communities, but additional research is needed to inform adaptation approaches. Future studies can build on our findings by: (1) exploring the impact of changes in snowfed water supply and temperature on yields of different crops; (2) examining how changes in snowpack are mediated by existing infrastructure, institutions (e.g., water rights), and groundwater storage; and (3) testing whether the findings here generalize to other snowfed regions beyond the WUS, where crop selection, infrastructure, institutions, and groundwater availability may differ considerably.

4 Methods and Data

Methods and data products are described below and visualized in [Figure C7](#).

4.1 Study Domain and Spatial Scale

Our study domain is the WUS defined as all US counties and watersheds west of the 100th meridian. Although watersheds are not always the foundation for water governance in the WUS and may not fully capture all connections and interactions between systems, they are used for managing water resources in the region [74].

The study domain comprises 950 HUC8 watersheds ranging from 330 km² to 26,000 km² (median = 3,675 km², mean = 4,530 km²). This includes all watersheds that intersect the 100th meridian. HUC8s were chosen because watersheds are an appropriate (albeit imperfect) unit for water governance [74] and the spatial scale of HUC8s most closely matches county-level economic data and finer-scale watersheds provide limited additional insight given that key economic variables are only available at the county scale. Even at HUC8 scale, the coarsest climate product (ERA5-Land at 9 km resolution) provides 4–5 pixels for the smallest watersheds and approximately 45 for the median.

Based on these considerations, we established HUC8 watersheds as our primary analytical unit and harmonized all data to this scale. Gridded observed hydroclimate data were aggregated to HUC8 watersheds using area-weighted means. For county-scale products (irrigated land rent and population data described in [subsection 4.7](#)), we calculated the area of overlap between each county polygon and each watershed polygon, then obtained area-weighted means for each watershed following established methods [75].

4.2 Historical Hydroclimate Data

4.2.1 Observational Products

Data to estimate seasonal, annual, and 5-year estimates of precipitation, SWE, temperature, and runoff were obtained from multiple products with temporal coverage varying from 1980-2019 to 1980-2023 depending on product. A full list of the metrics compiled for use in our statistical models is provided in [Table B8](#). We use products with different resolutions to estimate each of these variables to ensure conclusions about land use change and profitability are robust to forcing data choices. These are:

- **Western Land Data Assimilation System (WLDAS):** Western US hydrology and climate data at a 1 km resolution (Erling et al., 2021). Data are estimated 1980-2023.

- **Daymet-VIC:** Continuous US daily meteorological data from Daymet (Daymet) at 1 km [76] forced through the Variable Infiltration Capacity (VIC) hydrological model to produce runoff estimates at 4 km resolution [77]. Data are estimated 1980-2019.
- **Daymet-PRMS:** Continuous US daily meteorological data at 1 km [76] forced through the Precipitation Runoff Modeling System (PRMS) hydrological model [78] to produce runoff estimates at 4 km resolution [77]. Data are estimated 1980-2019.
- **ERA5-Land:** Global hydrology and climate data at a 9 km resolution [30, 31]. Data are estimated from 1980-2023.

Each product and the two hydrologic models, VIC and PRMS, have distinct benefits and limitations discussed in subsection A.2. Like large-scale hydrologic models [79], neither VIC nor PRMS explicitly simulates reservoir operations, interbasin transfers, or deep groundwater dynamics that characterize much of the WUS. We discuss handling of water management in subsection 4.7.

4.2.2 Data Processing and Quality Control

Daily ERA5-Land data were extracted from Google Earth Engine (GEE) [80]. For spatial aggregation to HUC8 scale, we calculated the mean of all ≈ 9 km pixels ($0.1^\circ \times 0.1^\circ$ native resolution) whose centers fall within each watershed boundary, with reduction performed using Google Earth Engine with a mean reducer. Daily WLDAS data were accessed via a private Climate Engine asset [81]. Spatial aggregation to HUC8 scale was the same as for ERA5-Land. Daily aggregated values for all variables under both VIC and PRMS forced with Daymet were obtained from Kao et al. (2024) [77]. Both products are only available through December 31, 2019.

Raw values were aggregated into metrics described in Table B8. Annual precipitation reflects cumulative values over the water year, April 1 SWE values are instantaneous estimates of SWE on that day. Crop-specific growing seasons are not used in this analysis due to considerable crop variability across the study domain and uncertainty in how climate change will alter phenology [82]. Instead, we define growing season as April 1 through September 30 based on institutional water delivery schedules [83], which reflect when producers must make planting decisions based on anticipated water availability. We validate this assumption using biophysical growing season estimates [84] in which the average day of the growing season begins April 1 and ends October 20, which is after the end of the water year, as shown in Table B13.

4.2.3 Validation and Benchmarking

To assess product skill for 950 watersheds in the study domain, we benchmarked April 1 SWE against Snow Data Assimilation System (SNODAS) [85], consistent with work in the WUS [86]. For runoff, we benchmarked estimates of annual runoff (calendar year) against observed streamflow in

247 western watersheds overlapping with the study domain from the Catchment Attributes for Large
Sample Studies (CAMELS) database [87]. We also compared VIC and PRMS performance directly
using estimates of runoff and SWE from identical Daymet forcings.

Skill for both SWE and runoff was assessed using percent bias (PBIAS), relative root mean square
error (rRMSE), Kling-Gupta Efficiency (KGE), and R^2 . Satisfactory runoff and SWE performance
was defined following community standards reported in Table 8 of Moriasi et al. (2015) ([88]).

All products showed satisfactory runoff skill, but ERA5-Land demonstrated substantially superior
SWE performance (KGE = 0.47, PBIAS = -11.27%, $r^2 = 0.72$) compared to alternatives (KGE
 ≤ 0.15), consistent with recent benchmarking [32]. Full results are presented in Figure C2 and
Figure C1. Regional summaries are provided in Table B1 and Table B2.

While runoff skill differences were incremental, ERA5-Land’s substantially superior SWE
performance led us to use it for our snow-focused study.

4.3 Socio-Economic Data

4.3.1 Data Sources

Agricultural land use by crop type from 2008-2023 was obtained from the USDA’s Crop Data Layer
(CDL) [38]. Data on irrigated, non-irrigated, and pasture land rental rates were obtained from annual
USDA surveys conducted between 2008 and 2023 [39].

Cash rent values are the price paid by a producer to lease land from a landowner. Unlike farmland
asset prices (i.e., market value of agricultural real estate including the land itself and its structures),
which can be influenced by speculative factors or non-agricultural uses (e.g., urbanization or antici-
pated land use change), rental rates provide a more direct measure of the economic returns specific
to farming. Determined in competitive rental markets, cash rental rates incorporate key factors such
as expected land productivity, crop prices, and input costs, effectively capturing the opportunity
cost of land for agricultural use. In land market equilibrium, cash rental rates reflect the economic
surplus earned from the marginal acre of cropland and can serve as a proxy for profits earned from
land in an area with inelastic land supply [26, 27].

Population data were obtained from the National Cancer Institute’s US County Population
Database (1992-2023) [89]. We also identified watersheds that intersected with high farming
concentration counties as defined by USDA in 2025 [65].

4.3.2 Data Processing

CDL extraction followed the same process as gridded hydroclimate products. Consistent with best-
practices reported by [90], we then calibrated extracted pixel area values with published error

statistics [38] to correct for systematic under- or over-mapping bias in the CDL. Using this technique, if a crop is hypothetically under-mapped by 20% in a watershed, each pixel’s area value is adjusted upward (e.g., a 30m pixel of 900 m² of that crop becomes 1,125 m²) so that summed totals match the reference data.

We then assign bias-corrected CDL acreage assigned to crop categories based on high, moderate, and low water-need categories using a two-step procedure designed to reflect conditions in the WUS. First, we compile observed seasonal ET totals from the U.S. Bureau of Reclamation’s AgriMet network [91], which provides crop-specific annual ET estimates across Idaho, Wyoming, Oregon, California, Washington, Montana, and Utah. Where AgriMet crop curves are available, we use the crop-level mean of reported annual ET totals as an empirical indicator of relative crop water demand. Second, for crops not represented in the AgriMet ET totals, we rely on published crop water requirement parameters from FAO-56 [92]. Specifically, we assign each crop a representative mid-season crop coefficient (K_c) and a representative growing-season length (days), and construct a relative water-requirement proxy defined as $K_c \times \text{season-days}$. We then combine information from both sources to assign crops into ordinal water-need groupings. ET estimates and water-requirement proxies are available in Table B10 and Table B11, respectively. Crop water use requirements are outlined in Table 1.

The USDA [39] provides county average rental rates per acre for irrigated and non-irrigated cropland as well as pastureland. For our analysis, we convert these rates into 2020 USD per hectare using the Consumer Price Index from the U.S. Bureau of Labor Statistics [93].

4.4 Future Climate Projections

4.4.1 CMIP6 Projection Dataset

Future hydroclimate projections of precipitation, SWE, temperature, and runoff were obtained as summaries at the HUC8-scale from the CMIP6-based SECURE Water Act Section 9505 Assessment dataset developed by Oak Ridge National Laboratory (ORNL, [77]). Future climate is simulated under four distinct shared socio-economic pathways (SSPs) using seven CMIP6 GCMs [94]:

- **SSP1-2.6 (low emissions):** Sustainable pathway with strong mitigation efforts,
- **SSP2-4.5 (middle-of-the-road):** Moderate emissions with balanced mitigation and adaptation,
- **SSP3-7.0 (high emissions):** Fragmented world with weak cooperation and high emissions,
- **SSP5-8.5 (very high emissions):** Fossil-fuel intensive development with rapid growth.

GCMs were selected to minimize overlap in climate responses and historical performance across CONUS [95, 96] and span a range of warming and precipitation responses (C6). Projections were downscaled using the Double-Bias Corrected Constructed Analogs (DBCCA) method [97], which

preserves large-scale GCM climate change signals while improving agreement with historical observations [96]. Downscaled forcings were then used to drive calibrated VIC and PRMS hydrologic models [77], methodologically consistent with the Daymet-VIC and Daymet-PRMS observational products.

Using a time-slice approach [98], we quantify changes over 2060-2099 relative to a 1980-2019 baseline under four SSPs. The seven-GCM ensemble projects area-weighted WUS warming of 1.9°C (IQR 1.7–2.0°C) under SSP1-2.6, 2.7°C (2.6–3.1°C) under SSP2-4.5, 3.9°C (3.4–4.0°C) under SSP3-7.0, and 4.5°C (4.3–5.0°C) under SSP5-8.5 relative to 1980–2019. Additional information can be found in [subsection A.2](#).

4.4.2 Bias Correction and Delta-Change Methodology

Systematic errors in GCM outputs relative to historical observations are a known issue and there are many methods for reducing the impact of these errors. Because our analysis focuses on mean seasonal and annual conditions rather than extremes, we employed a delta-change method [99, 100] that preserves changes in the mean while correcting systematic biases. This approach has been widely used in large-scale climate impact assessments [101].

We apply the delta-change method by estimating changes between historical (1980–2019) and future (2060–2099) simulations from each GCM and applying the resulting change factors to the observational baseline. This procedure is performed independently for each watershed and observational product across all GCM-SSP combinations.

We estimated bias-corrected temperature in each watershed ($\mathbf{T}_{fut,bias}$) using [Equation 1](#) [99–101]:

$$\mathbf{T}_{fut,bias,d} = \mathbf{T}_{hist,obs,d} + (\bar{\mathbf{T}}_{fut,sim,m} - \bar{\mathbf{T}}_{hist,sim,m}) \quad (1)$$

where $\mathbf{T}_{hist,obs,d}$ is the observed temperature from each product described in [subsubsection 4.2.1](#) for each day (d) in the historical baseline period (1980-2019), $\bar{\mathbf{T}}_{fut,sim,m}$ is the mean simulated temperature for the month (m) corresponding to a given day (d) in the future period (2060-2099), and $\bar{\mathbf{T}}_{hist,sim,m}$ is the mean simulated temperature for the month (m) corresponding to a given day (d) in the baseline period (1980-2019). Each GCM-SSP pair represents an individual simulation.

For precipitation, SWE, and runoff ($\mathbf{X}_{fut,bias}$), bias-corrected values were obtained using [Equation 2](#) [99–101]:

$$\mathbf{X}_{fut,bias,d} = \mathbf{X}_{hist,obs,d} \times \left(\frac{\bar{\mathbf{X}}_{fut,sim,m}}{\bar{\mathbf{X}}_{hist,sim,m}} \right) \quad (2)$$

where $\mathbf{X}_{hist,obs,d}$ is the observed variable $\mathbf{X}$ (e.g., precipitation, SWE, or runoff) from each product for each day (d) in the historical baseline period (1980-2019), $\bar{\mathbf{X}}_{fut,sim,m}$ is the mean projected value of the variable X for m corresponding to a given d in the future period, and $\bar{\mathbf{X}}_{hist,sim,m}$ is

the mean simulated value of the variable X in m corresponding to a given d in the baseline period. To avoid large change factors when dividing by very small numbers, we set values for SWE below 5 mm to 0.

Delta-change methods are well-established for meteorological variables like precipitation and temperature [99–101], but comparatively less guidance exists for their application to derived hydrologic variables such as SWE and runoff. Bias-correcting only precipitation and temperature would require re-running hydrologic models with corrected forcings, which would effectively decouple the climate and hydrologic projections and introduce inconsistencies with the ORNL dataset’s integrated modeling framework.

We therefore apply the delta-change method uniformly to all variables (precipitation, temperature, SWE, and runoff), maintaining consistency between meteorological forcings and hydrologic responses. This approach preserves the physically-consistent relationships between climate drivers and hydrologic outcomes simulated by the VIC and PRMS models within the ORNL framework.

4.5 Statistical models

Using hydrologic, climatic, and demographic data, we employ two reduced form modeling approaches to identify key drivers of observed changes in agricultural land use by crop type and rental rates: (1) an annual model using panel fixed effects and (2) a long-term model using long differencing.

4.5.1 Annual Model: Panel Fixed Effects Estimation

To assess how changes in hydroclimatic conditions impact cropping decisions in the short-term, we first estimated the following econometric specification that provides estimates of annual impacts:

$$y_{it}^{(k)} = \mathbf{X}_{it}\boldsymbol{\beta}^{(k)} + \alpha^{(k)}P_{it} + \theta_i + \gamma_{rt} + \varepsilon_{it}, \quad k = 1, \dots, K \quad (3)$$

where $y_{it}^{(k)}$ is the natural log of total area under agricultural use category k for watershed i in year t , $\mathbf{X}_{it}$ is a vector of hydrologic and climatic variables, and P_{it} is population. Our chosen variables aimed to capture how agricultural land use decisions are driven by population and expectations of snowpack, growing season temperature, runoff, and precipitation (as measured by 5-year rolling means). We also included squared terms for each climate variable to capture nonlinearities and an interaction term between temperature and runoff. Equation 3 is estimated separately for $K = 6$ land uses: total irrigated cropland, land with high-, moderate-, and low-water use crops, perennial crops, and grass pasture. We also estimated the same model with cash rents for irrigated, dryland, and pasture land as the outcome variables.

415 The term θ_i is a watershed fixed effect that captures unobserved heterogeneity that is constant
 416 over time but varies across basins. This could include geographic, economic, or social characteristics
 417 that are unique to each basin but do not change over the period of study. The term γ_{rt} is a HUC6-
 418 by-year fixed effect that controls for common shocks that affect all watersheds during year t within
 419 HUC6 r , such as abrupt changes in input and output prices or reservoir levels that may be localized
 420 to a specific region. Lastly, ε_{it} is the idiosyncratic error term. Standard errors are clustered in
 421 two dimensions: within watersheds and within HUC6 basins-by-year. Clustering within watersheds
 422 addresses the issue of autocorrelation over time. This is critical because land use within a watershed
 423 is influenced by past events and conditions, leading to a natural correlation in observations across
 424 different years within the same watershed. Clustering within HUC6 basins-by-years aims to account
 425 for the spatial correlation that may exist across different watersheds within a larger basin. Watersheds
 426 within the same larger basin are likely to experience similar economic and hydrologic conditions,
 427 leading to potential correlations in their economic outcomes. This specification aims to isolate the
 428 impact of hydrologic conditions on land use outcomes by controlling for unobserved confounders
 429 that could bias the estimates. It allows for a causal interpretation of the estimated parameters $\beta^{(k)}$
 430 under the assumption that all other factors that could influence the outcome are either controlled
 431 for by the fixed effects or captured by the error term.

432 **4.5.2 Long-term Model: Long Difference Estimation**

433 Although [Equation 3](#) is a commonly used econometric approach to assess the impacts of climate
 434 change on agricultural productivity, there is some debate about its applicability for estimating long-
 435 term climate impacts [[14](#), [102](#), [103](#)]. By absorbing time-invariant climate factors, fixed effects may
 436 not account for adaptation and only capture responses to weather shocks, which may not be identical
 437 to permanent shifts in climate [[104](#)].

438 To accurately assess the economic implications of *climate change*, as opposed to weather, it
 439 is important to estimate the net impacts of adaptation efforts undertaken by economic agents to
 440 counteract negative climate effects. Thus, an alternative to the panel fixed effects approach, dubbed
 441 "long differencing," models the change in the long-term average of an economic outcome as a function
 442 of the change in average climate [[102](#)]. This approach seeks to account for adaptation by examining
 443 changes over extended periods, which should capture the effects of longer-term adjustments that
 444 agents might make in response to persistent changes in the environment. Importantly, the long
 445 differences approach is particularly well-suited for estimating the impact of hydroclimate change
 446 on rental rates, as it can reveal impacts to the annual profitability of agricultural production after
 447 considering long-run adaptation efforts. We therefore also employed a long differences approach using

the same data as in Equation 3, which can be represented as follows:

$$\bar{y}_{i,b} - \bar{y}_{i,a} = (\theta_{i,b} - \theta_{i,a}) + \beta(\bar{\mathbf{X}}_{i,b} - \bar{\mathbf{X}}_{i,a}) + \alpha(\bar{P}_{i,b} - \bar{P}_{i,a}) + \varepsilon_{it} \quad (4)$$

where $\bar{y}_{i,b}$ and $\bar{y}_{i,a}$ represent the average values of y_{it} over the periods 2019-2023 and 2008-2012, respectively. Similarly, $\bar{\mathbf{X}}_i$ and $\bar{P}_i$ denote the average values of the explanatory variables over the same periods. For Equation 4, we no longer take the natural log of land area as the data is much less skewed after averaging and differencing. The seven-year gap between the end of the first period (2012) and the start of the second period (2019) provides time for agricultural producers to adjust production practices and land use decisions, and for climate-driven changes in expected profitability to be reflected in land rental rates through leasing markets. As with the fixed effects approach, Equation 4 inherently controls for unobserved factors that are constant over time, as $\theta_{i,b} - \theta_{i,a}$ cancels out. Prior to estimation, all variables were centered and scaled before squaring and interacting.

While the fixed effects model provides robust causal inference by controlling for unobserved heterogeneity, it may not fully capture the economic responses to long-term changes in climate. Specifically, fixed effects estimates are primarily driven by interannual weather fluctuations, and while they offer insight into year-over-year responses to weather shocks, they may fail to reflect the true impact of *climate change*, which unfolds gradually over longer periods. In contrast, the long differencing approach allows us to capture how producers adapt their behaviors in response to persistent, long-term changes in environmental conditions. By examining changes in land use and rental rates over extended periods, we better account for the gradual adaptation processes that may occur as agents respond to new climate norms. Considering such adaptive responses improves assessment of climate change impacts, as such actions may partially mitigate negative effects predicted by short-term models. Therefore, long differencing offers a more accurate reflection of climate change impacts, as it incorporates both direct climatic effects and the adaptive behaviors of economic actors over time.

4.6 Impact Estimation

4.6.1 Historical and Future Impacts

To estimate the impacts of past and future hydroclimatic change on agricultural land use and land value, we applied the estimated coefficients from the long difference models introduced in Equation 4 to both historical climate and population data prior to our observed study period and to the projected climate data under seven GCMs. Due to data limitations on end-of-century population projections,

we omit the impact of population growth on future agricultural outcomes and focus solely on the impact of hydroclimatic change.

Before applying the coefficients, we calculated changes in the averages of the climate and hydrology variables ($\bar{\mathbf{X}}$) for each HUC8 (i) under each future GCM (m) relative to the observed period from 2008-2023 (*obs*): $\Delta \mathbf{X}_i^m = \bar{\mathbf{X}}_i^m - \bar{\mathbf{X}}_i^{obs}$. Similarly, for the historical period (*hist*) we calculated $\Delta \mathbf{X}_i^{hist} = \bar{\mathbf{X}}_i^{obs} - \bar{\mathbf{X}}_i^{hist}$. The change in future outcome variable was thus calculated as $\Delta y_i^m = \Delta \mathbf{X}_i^m \hat{\beta}$, where $\hat{\beta}$ is the estimated coefficient corresponding to the outcome variable. The change in historical outcome is $\Delta y_i^{hist} = \Delta \mathbf{X}_i^{hist} \hat{\beta}$. We calculated future and historical level outcomes (defined as $y_i^m = \bar{y}_i^{obs} + \Delta y_i^m$ and $y_i^{hist} = \bar{y}_i^{obs} + \Delta y_i^{hist}$ respectively) for all variables: total irrigated cropland, land with high-, moderate-, and low-water use crops, land with grass pasture, and irrigated, dryland, and pasture rental rates.

4.6.2 Total Economic Value Estimation

To assess the total economic impact of climate change, we combined level outcome predictions from Equation 4 of agricultural area and rental rates into a single measure of total change in rental rates. This measure reflects overall changes in profitability and depends on the amount of agricultural land in different crop types and the amount that remains economically viable overall. Specifically, for each HUC8 watershed i we calculated an average total current value ($\bar{V}_i$) over the observed 2008-2023 period as:

$$\bar{V}_i = \bar{R}_{i,I} \times (\bar{A}_{i,H} + \bar{A}_{i,M}) + \bar{R}_{i,D} \times \bar{A}_{i,L} + \bar{R}_{i,P} \times \bar{A}_{i,P}, \quad (5)$$

where $\bar{A}_{i,H}$, $\bar{A}_{i,M}$, $\bar{A}_{i,L}$, and $\bar{A}_{i,P}$ represent the average areas in hectares for high-, moderate-, and low-water use crops, and pasture land, respectively, and $\bar{R}_{i,I}$, $\bar{R}_{i,D}$, and $\bar{R}_{i,P}$ represent average rental rates for irrigated, dryland, and pasture cropland in 2020 \$USD per hectare during the 2008-2023 observed period. The sum of land areas times their respective per-hectare rental rates represents the total exchange value of all agricultural land at current rental rates that depend in part on the productivity of available land. This definition of value differs from a welfare value that considers the difference between the marginal willingness to pay for land and its opportunity cost.

Next, for each GCM, we calculated an expected total exchange value ($\hat{V}_i$) as:

$$\hat{V}_i^m = \max(\hat{R}_{i,I}^m, \hat{R}_{i,D}^m) \times (\hat{A}_{i,H}^m + \hat{A}_{i,M}^m) + \hat{R}_{i,D}^m \times \hat{A}_{i,L}^m + \hat{R}_{i,P}^m \times \hat{A}_{i,P}^m, \quad (6)$$

where $\hat{A}_{i,H}$, $\hat{A}_{i,M}$, $\hat{A}_{i,L}$, and $\hat{A}_{i,P}$ represent the projected level outcomes for area in hectares for high-, moderate-, and low-water use crops, and pasture land, respectively, and $\hat{R}_{i,I}$, $\hat{R}_{i,D}$, and $\hat{R}_{i,P}$ the projected rental rates for irrigated, dryland, and pasture cropland. For the projected estimation, we assumed that if $\hat{R}_{i,D} > \hat{R}_{i,I}$, that is if the projected dryland rental rate is greater than the projected

irrigated rental rate within a HUC8, then irrigated cropland converts to dryland. The total change in agricultural land rental rate within each watershed was thus calculated as:

$$\Delta V_i = \hat{V}_i - \bar{V}_i \quad (7)$$

To calculate the total projected change across the WUS, we then summed ΔV_i across all watersheds.

To characterize the consistency of projected impacts across agriculturally important regions, we evaluated projected changes in exchange value across 28 climate futures (7 GCMs $\times$ 4 SSPs) for all watersheds intersecting high-farming-concentration counties described in [subsection 4.3](#). For each watershed, outcomes are summarized using the 10th, 50th (median), and 90th percentiles across all climate futures. We assume that greater agreement across climate models and emissions scenarios regarding the severity of future impacts can support spatial prioritization for adaptation and resource allocation.

4.7 Robustness checks

The long-difference specification allows land use and rental rate responses to reflect adjustment and adaptive behavior, rather than short-run weather shocks. However, this approach comes at a cost. By collapsing the panel structure into differences across two multi-year periods, the long-difference model is effectively cross-sectional, with identifying variation coming from approximately 950 HUC8 watersheds, depending on the dependent variable. In this setting, it is reasonable to expect that coefficient estimates may be sensitive to alternative modeling choices, data products, or sample construction.

To assess the stability of our results, we conduct a series of robustness checks that examine how estimated effects respond to changes in the underlying climate and hydrologic inputs, the projected data products used for future scenarios, climate variable definitions, and the inclusion or exclusion of watersheds with distinct water-supply characteristics. Where applicable, we also implement these robustness checks for the annual (panel fixed effects) model.

4.7.1 Alternative Climate and Hydrologic Inputs

To assess the robustness of estimated model parameters to the choice of underlying hydroclimate data, we re-estimated both the annual panel and long-difference models using multiple climate and hydrologic products. This exercise characterizes parameter uncertainty arising from differences in products, bias correction, and hydrologic modeling assumptions, and ensures that our results are not driven by idiosyncratic features of any single data product. Specifically, we estimated models

536 using three alternative observational datasets that differ in both meteorological forcing and hydro-
537 logic representation: ERA5-Land, Daymet coupled with VIC, and Daymet coupled with PRMS (see
538 [subsection 4.4](#)). Although WLDAS was included in our initial benchmarking analysis, we excluded
539 it from this robustness exercise due to poor historical performance ($KGE = -0.04$ for SWE), which
540 raises concerns about its suitability for training statistical response models.

541 By re-estimating model coefficients across these alternative input datasets, we evaluated the
542 stability of estimated relationships between climate and land use and rental rates to measurement
543 and modeling choices embedded in the observed hydroclimate data. Consistency of results across
544 products provides confidence that estimated responses reflect underlying economic and biophysical
545 mechanisms rather than spurious variation introduced by any specific data-processing pipeline.

546 Differences in temporal coverage across observational datasets also require adjustments to model
547 specification. The Daymet-based products are available through 2019, whereas ERA5-Land extends
548 through 2024. To ensure consistency across training datasets in the long-difference specification,
549 we therefore defined the pre-period as 2008–2012 and the post-period as 2015–2019 for all models
550 estimated using alternative climate and hydrologic inputs. This differs from the main results of
551 the paper, which used 2008–2012 versus 2019–2023. Although this adjustment shortens the middle
552 window under which adaptive behavior can be captured, it allows for a direct comparison of coefficient
553 estimates across input datasets. Comparing results from this specification to the main results also
554 provides an implicit robustness check on sensitivity to the choice of differencing years, allowing us
555 to assess whether estimated responses are driven by particular endpoint selections rather than by
556 underlying climate–land-use relationships.

557 Overall, estimated climate–land-use and climate–rent responses are highly stable across alterna-
558 tive observational climate and hydrologic input datasets. As shown in [Figure C8](#), [Figure C9](#), and
559 [Figure C10](#), coefficient magnitudes, signs, and confidence intervals are mostly consistent across mod-
560 els trained on ERA5-Land, Daymet–VIC, and Daymet–PRMS, with only modest variation across
561 products.

562 4.7.2 Sensitivity to Projected Climate and Hydrologic Products

563 To characterize uncertainty in future outcomes arising from alternative representations of climate
564 and hydrologic change, we project each statistically estimated model onto the full set of projected
565 hydroclimate products described in [subsection 4.4](#). This yields 504 distinct projections (3 training
566 datasets $\times$ 3 observational baselines $\times$ 7 GCMs $\times$ 4 SSPs $\times$ 2 hydrologic models), spanning variation
567 in emissions pathways, climate model structure, downscaling products, and hydrologic modeling
568 frameworks. This exercise allows parameter estimates derived from one historical data product to be
569 evaluated under alternative future hydroclimate realizations. As a result, some projections involve

mismatches between the observational baseline used for estimation and the dataset used to generate future conditions. The goal is not to construct internally consistent baseline–future trajectories, but rather to assess whether projected responses exhibit anomalous behavior under specific combinations of climate forcings, hydrologic models, or emissions scenarios.

Figure C11 summarizes the resulting distribution of projected changes in total agricultural land value across SSPs and projected hydroclimate products. Across scenarios, projected outcomes are highly consistent across models trained on different historical input datasets, while substantially greater variation emerges across emissions pathways and projected hydroclimate realizations. This pattern indicates that uncertainty in future outcomes is driven primarily by differences in projected climate and hydrologic conditions rather than by sensitivity of estimated responses to alternative historical data products. Importantly, the magnitudes of these projected results are highly similar to the main projections in Figure 3C, despite using a different post-period as discussed above.

4.7.3 Excluding Watersheds with Major Water Infrastructure

Water management in the study domain is complex and can involve significant water transfer and reservoir storage. These complexities are widely acknowledged but remain challenging to address given constraints on data, modeling capabilities, and information about operations [79, 105]. To assess the robustness of our results to these dynamics, we re-estimated our models across all input datasets after excluding watersheds influenced by documented interbasin water transfers (IBTs) [105]. We identified 94 HUC8 watersheds with recorded IBTs that include both a documented flow rate and operational start date (see Table B12). This exclusion is conservative: only seven of these IBTs began operation during the study period (2008–2024), while the remaining transfers predate the analysis and are already absorbed by watershed fixed effects. We assume these watershed are also equipped with significant infrastructure to support IBTs.

For our primary model specifications, this challenge is partially mitigated because most major water infrastructure in the WUS was built decades ago (e.g., California State Water Project in the 1960s–70s, Colorado-Big Thompson Project in the 1930s–1950s) [106]. Our panel regression framework includes watershed fixed effects, which absorb time-invariant characteristics such as average reservoir storage capacity and access to interbasin transfers. As a result, estimated coefficients reflect responses to hydroclimatic variation conditional on the presence of existing infrastructure, rather than assuming natural flow conditions.

However, fixed effects cannot fully account for time-varying infrastructure operations or nonlinear interactions between water management and changing climate conditions. Reservoir releases, interbasin transfers (IBT), and allocation priorities may evolve in response to drought, policy changes, or competing demands, potentially dampening or reshaping observed climate responses over time.

Because large-scale water infrastructure can itself function as an adaptation mechanism, estimated climate sensitivities may differ systematically between basins with and without such features.

Excluding watersheds influenced by documented interbasin transfers yields coefficient estimates that are highly consistent with those obtained from the full sample. As shown in [Figure C12](#), [Figure C13](#), and [Figure C14](#), both annual and long-difference models exhibit similar magnitudes, signs, and confidence intervals when basins with major water infrastructure are removed.

4.7.4 Excluding Groundwater-Dependent Watersheds

Access to groundwater represents an additional adaptive margin that may affect observed responses to hydroclimatic change. To evaluate the sensitivity of our estimates to groundwater access, we identify watersheds with substantial dependence on groundwater for irrigation supply using the USGS irrigation water-use reanalysis data spanning 2000–2020 [107]. These data are reported at the HUC12 level and were aggregated to the HUC8 scale by summing surface and groundwater irrigation withdrawals across constituent HUC12 watersheds. We classify a HUC8 watershed as groundwater-dependent if at least 75% of average annual irrigation withdrawals are sourced from groundwater. This criterion identifies 192 HUC8 watersheds in the study domain.

Groundwater use can substitute for declining surface runoff, buffer temperature-driven water stress, and relax short-run water constraints faced by irrigated agriculture. These mechanisms may interact with climate conditions and evolving groundwater institutions in ways that are not fully captured by watershed fixed effects. Watersheds with substantial groundwater reliance may exhibit systematically different land-use and rental-rate responses than surface-water-dominated watersheds. In particular, groundwater access can attenuate sensitivity to surface-water availability, while regulatory frameworks governing extraction—such as California’s Sustainable Groundwater Management Act (SGMA)—have changed during the study period and may introduce time-varying constraints.

Excluding watersheds with substantial reliance on groundwater for irrigation does not materially change estimated climate sensitivities. As shown in [Figure C15](#), [Figure C16](#), and [Figure C17](#), coefficient estimates from models across all input datasets excluding groundwater-dependent basins closely track those from the full sample across both land-use and cash-rent outcomes.

4.7.5 Degree-day (DD) Specifications

We also evaluate robustness to alternative temperature representations by re-estimating models using growing and harmful DD metrics in place of our baseline nonlinear temperature specification. DD measures are widely used in agronomic and economic analyses because they map directly to crop-specific thermal thresholds. However, prior work shows that in fixed-effects econometric settings, estimated climate responses are generally robust to the precise functional form of temperature as

long as sufficient nonlinear flexibility is allowed [108]. We treat the degree-day models as a sensitivity check, and regression results for these specifications for the long-term model are available in Table B14.

Across specifications, the direction of estimated temperature effects remains broadly consistent with the baseline results, and interactions between temperature and runoff continue to appear statistically significant in many cases. However, recent evidence suggests that DD specifications perform worse than flexible nonlinear alternatives when predicting aggregate economic outcomes in settings with heterogeneous crop mixes [108], in part because degree-day measures require the choice of a fixed thermal cutoff (often data-driven and crop-specific) while our outcomes reflect composite responses across multiple crops .

4.8 Limitations

Several limitations and caveats apply to the methods presented here. First, the length of our analysis is constrained to 2008-2023 by data availability from the USDA CDL [38] and irrigated cash rent survey values [39], and population data [89]. As more data become available, the models developed here can be further refined and improved upon. Second, there is some existing debate about whether the econometric methods used in this study fully account for producer adaptation [14, 103]. To accurately assess the economic implications of climate change it is important to estimate the net impacts of adaptation efforts undertaken by economic agents to counteract negative climate effects [109]. Third, we assume the relationship between hydroclimate and agricultural choices and outcomes can be represented by a model that is linear in parameters. This rules out impacts driven by threshold behavior. However, a linear model provides an efficient unbiased estimate of average effects. Although linear in parameters, our specifications include polynomial terms and interactions that permit curvature, heterogeneous marginal effects, and model-implied optima without introducing discontinuities. Fourth, we do not consider how impacts are distributed across producer groups, potentially minimizing the recognition of inequities in losses.

Our approach could be coupled with recent national-scale research on how the shocks and losses associated with climate change disproportionately disadvantage certain racial and ethnic groups [110]. This avenue for future research can improve understanding of these impacts and, critically, investigate how they can be managed. Fifth, using past variability and producer responses to predict future impacts presents significant challenges. Our approach could overestimate economic impacts if producers adapt to changing conditions using strategies not employed in the past, such as agrivoltaics, switching to new water-efficient crop varieties, or increasing storage capacity although this is limited if insufficient water is available to recharge them [111, 112].

Results could also understate impacts if water scarcity leads to institutional changes that prioritize urban water demands over agricultural ones. Lastly, our analysis is limited by its reliance on runoff estimates within HUC8 watersheds, without incorporating water transfers or deliveries from other watersheds. For example, droughts in the Colorado River headwaters that impact Southern California producers are not directly modeled in our approach. While our use of HUC8, HUC6-by-year, and state fixed effects control for abrupt changes in runoff, water stored in reservoirs, or interbasin transfers, this approach prevents us from explicitly estimating their effects. As a result, our models may not fully capture the broader regional impacts of hydrologic variability and the interconnected nature of water systems in the WUS. Future work incorporating explicit data on interbasin transfers and reservoir operations could improve understanding of these dynamics and their economic consequences for agriculture.

5 Tables

Table 1: List of crops by water use category.

Water Use	Crops
High Water Needs	Alfalfa, Rice, Cotton, Sugarcane, Greens, Lettuce, Broccoli, Tomatoes, Turnips, Carrots, Cauliflower, Celery, Cucumbers, Eggplants, Garlic, Gourds, Honeydew Melons, Onions, Peppers, Asparagus, Cabbage, Cantaloupes, Watermelons, Pumpkins, Radishes, Squash, Sugarbeets
Moderate Water Needs	Wheat, Corn, Sorghum, Chick Peas, Other Small Grains, Lentils, Barley, Buckwheat, Dry Beans, Potatoes, Durum Wheat, Flaxseed, Millet, Oats, Peanuts, Peas, Rape Seed, Rye, Sweet Potatoes, Safflower, Soybeans, Speltz, Sunflower, Triticale
Low Water Needs	Camelina, Canola, Clover/Wildflowers, Mustard, Switchgrass, Vetch
Perennials	Almonds, Apples, Apricots, Avocados, Blueberries, Cherries, Citrus, Oranges, Olives, Pecans, Pistachios, Plums, Pomegranates, Walnuts, Grapes, Peaches, Pears, Prunes, Cranberries, Caneberries, Nectarines, Strawberries

Table 2: The impact of temperature, runoff, and snow-water equivalent (SWE) on irrigated cropland area and cash rental rates for the Annual (Equation 3) and Long-term (Equation 4) models. For columns (1)–(3), the dependent variable is $\ln(\text{crop area})$, so coefficients are semi-elasticities (approximately percent changes in area for a one-unit change in the explanatory variable). For columns (4)–(6), the dependent variable is $\Delta \text{ crop area}$ (hectares). For columns (7)–(8), coefficients are changes in $\Delta \text{ cash rent}$ (dollars). Additional modeled outcomes and controls for precipitation and population are omitted from this table, but are available in Table B3 and Table B4. Implied optima for temperature and runoff can be calculated from the estimated linear and quadratic terms, evaluated at mean values of interacting variables.

Variable	Annual Model			Long-term Model				
	Total (1)	HWU (2)	MWU (3)	Total (4)	HWU (5)	MWU (6)	Irr. Rent (7)	Dry Rent (8)
Temp. ($^{\circ}\text{C}$)	1.16*** (0.252)	0.870*** (0.268)	1.16*** (0.259)	-2,228.1 (7,958.3)	1,829.6 (2,174.3)	-4,057.7 (6,820.8)	-165.5* (94.6)	-30.3** (15.3)
Temp. Sq.	-0.039*** (0.006)	-0.039*** (0.007)	-0.030*** (0.006)	-149.2 (273.3)	-264.5** (125.1)	115.3 (162.9)	-1.80 (2.24)	-0.275 (0.386)
Runoff (10^8 m^3)	0.008 (0.035)	0.042 (0.040)	0.003 (0.035)	969.7 (1,612.0)	1,911.2*** (410.7)	-941.5 (1,400.0)	35.9 (31.1)	-15.0*** (4.91)
Runoff Sq.	0.0001 (0.0002)	-1.03×10^{-5} (0.0002)	0.0001 (0.0002)	3.41 (10.7)	-11.0*** (3.55)	14.4 (9.78)	-0.105 (0.390)	0.037 (0.055)
Temp. $\times$ Runoff	-0.0006 (0.002)	-0.002 (0.002)	-0.0008 (0.002)	-83.7** (35.3)	-42.6* (20.3)	-41.1 (33.9)	-3.04** (1.55)	1.03*** (0.227)
Apr. 1 SWE (10^8 m^3)	0.045*** (0.015)	0.038** (0.018)	0.041** (0.021)	-111.9 (1,291.5)	-520.3 (383.0)	408.3 (1,176.1)	-2.63 (21.0)	-3.19 (3.39)
<i>Fixed effects:</i>								
HUC8	Yes	Yes	Yes					
HUC6-by-Year	Yes	Yes	Yes					
State				Yes	Yes	Yes	Yes	Yes
Observations	15,200	15,200	15,200	950	950	950	837	693
R ²	0.982	0.976	0.977	0.275	0.229	0.258	0.211	0.245
Within Adjusted R ²	0.019	0.020	0.008	0.031	0.108	0.008	0.028	0.067

Observations for columns 1–3 correspond to HUC8-years; columns 4–8 correspond to HUC8s.
Clustered standard-errors in parentheses: HUC8 and HUC6-by-Year for Equation 3, State for Equation 4.
Significance codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

6 Figures

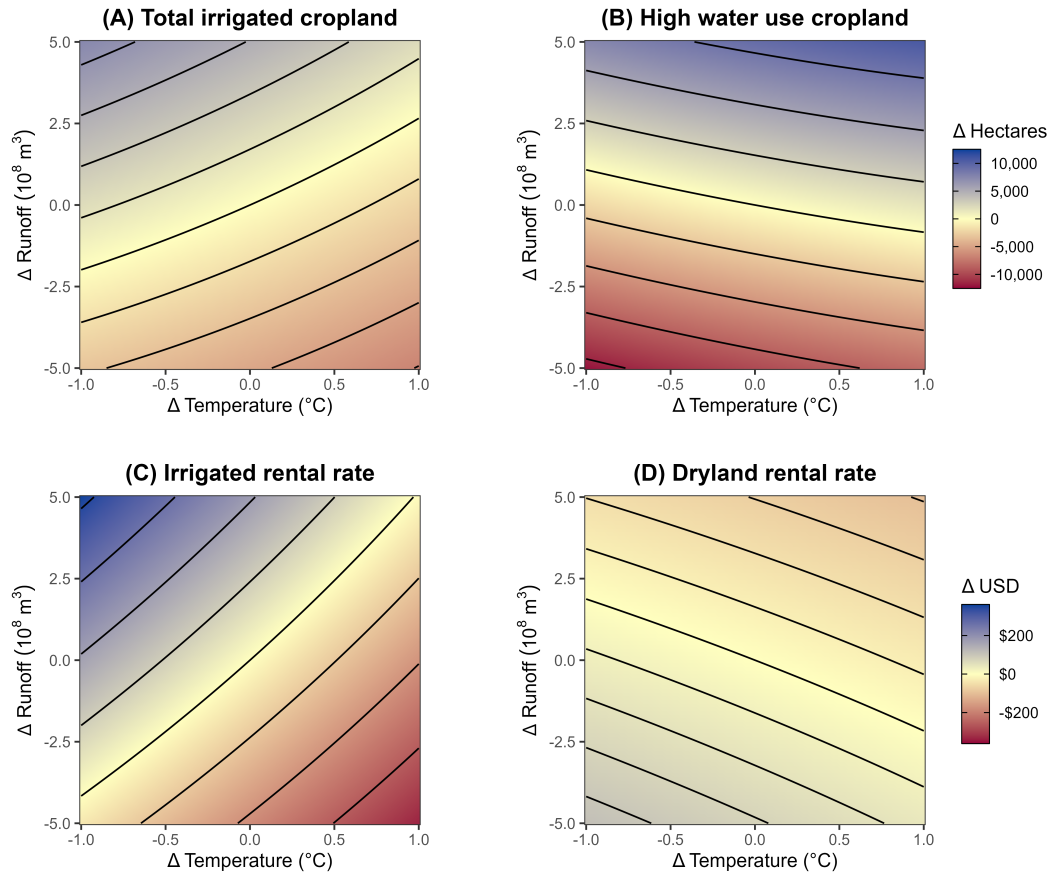


Fig. 1: Estimated impacts of simultaneous changes in growing-season temperature and runoff on agricultural land use and land rental rates. Each panel shows the predicted change in the outcome as a function of changes in growing-season temperature (horizontal axis, $^{\circ}\text{C}$) and annual runoff (vertical axis, 10^8 m^3), holding other covariates constant. Panels correspond to (A) total irrigated cropland area, (B) high water use cropland area, (C) irrigated cropland rental rates, and (D) dryland cropland rental rates, all based on long-difference regression estimates from the long-term model (see Table 2). Color gradients indicate the magnitude and sign of the predicted effect, where warmer colors denote reductions and cooler colors denote increases relative to the baseline. Black contour lines connect combinations of temperature and runoff changes that yield equal predicted impacts, illustrating the interaction between climate variables. The tilted contour lines indicate that the marginal effect of temperature depends on runoff availability, with greater water availability partially mitigating temperature-driven losses in irrigated outcomes.

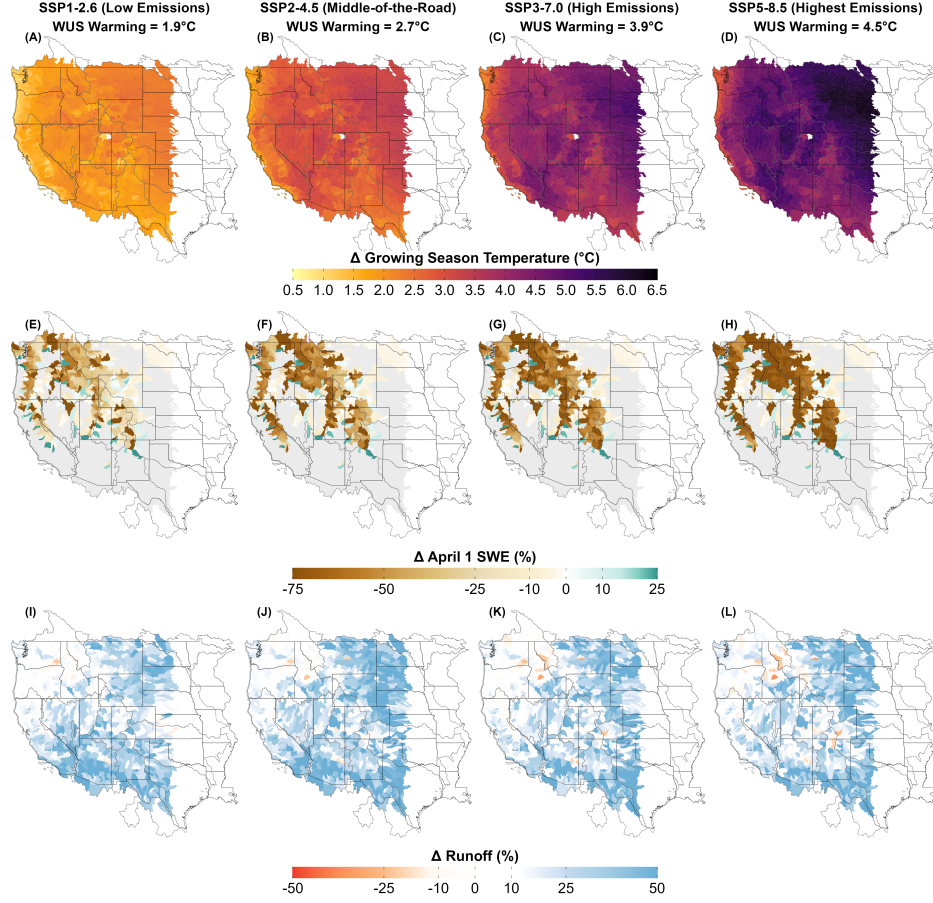


Fig. 2: Projected multi-model ensemble median changes in growing season temperature (A-D), April 1 SWE (E-H), and 5-year mean annual runoff (I-L) under four CMIP6 SSPs. Future values (2060-2099) are reported relative to baseline (1980-2019). Area-weighted WUS warming based on mean annual temperature from the seven-GCM ensemble is 1.9 $^{\circ}\text{C}$ (IQR: 1.7–2.0 $^{\circ}\text{C}$; SSP1-2.6), 2.7 $^{\circ}\text{C}$ (2.6–3.1 $^{\circ}\text{C}$; SSP2-4.5), 3.9 $^{\circ}\text{C}$ (3.4–4.0 $^{\circ}\text{C}$; SSP3-7.0), and 4.5 $^{\circ}\text{C}$ (4.3–5.0 $^{\circ}\text{C}$; SSP5-8.5). Median April 1 SWE losses range from -24.6% (IQR -30.7% to -20.7%) under SSP1-2.6 to -41.8% (IQR -44.6% to -41.6%) under SSP5-8.5, and intermediate losses of -34.5% (SSP2-4.5) and -36.9% (SSP3-7.0). Nine coastal, transboundary, and lacustrine watersheds are not shown.

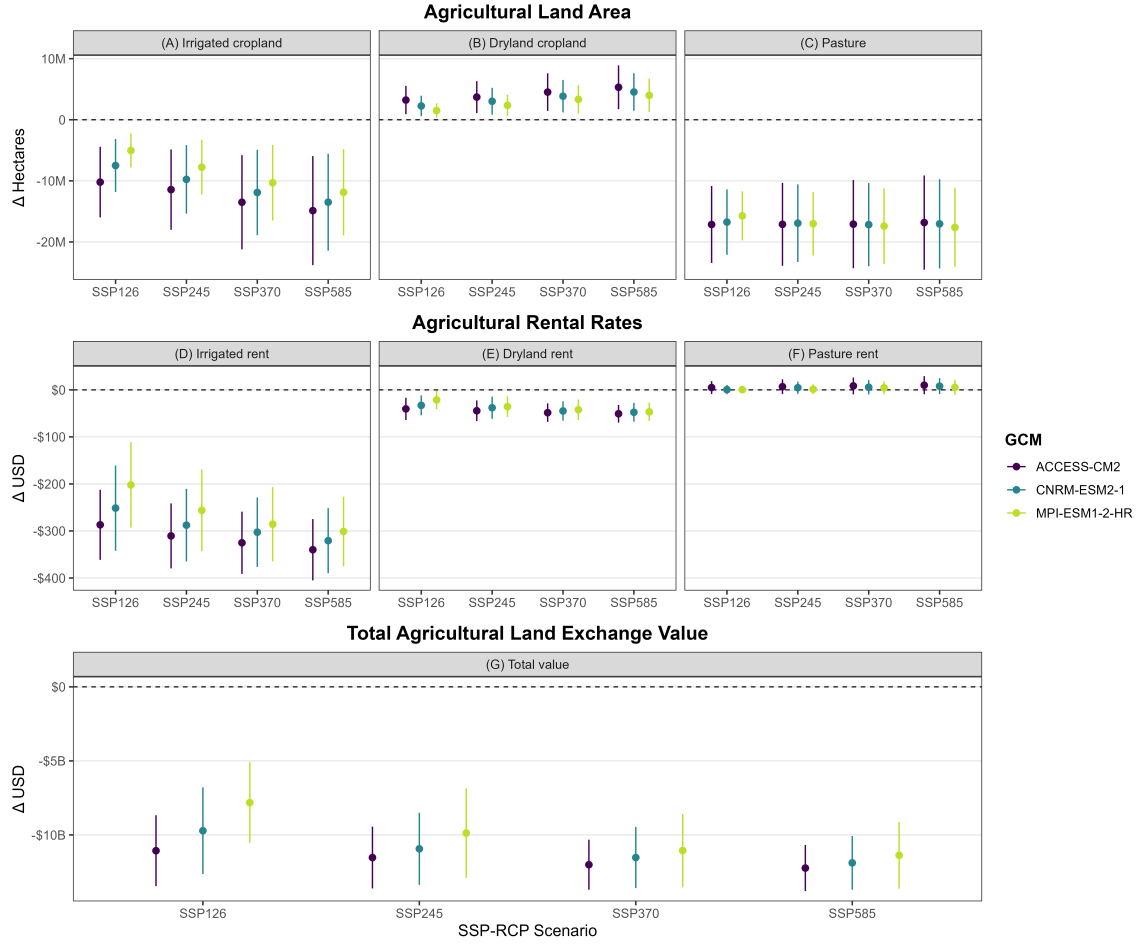


Fig. 3: Projected changes in agricultural land use, rental rates, and total agricultural exchange value across the western United States under alternative SSP-GCM combinations using long-term model estimates. Panels (A)–(C) report changes in land area (hectares) for irrigated cropland, dryland cropland, and pasture, respectively. Panels (D)–(F) report changes in average per-hectare rental rates (USD) for irrigated, dryland, and pasture land. Panel (G) aggregates these components into total agricultural exchange value (USD). Points represent model-based projections, and vertical bars denote 95% bootstrapped confidence intervals. The horizontal dashed line in each panel indicates no change relative to the observed baseline. Results shown here highlight a representative subset of climate models and outcomes; corresponding projections for all seven GCMs and all land use outcomes are reported in [Figure C5](#).

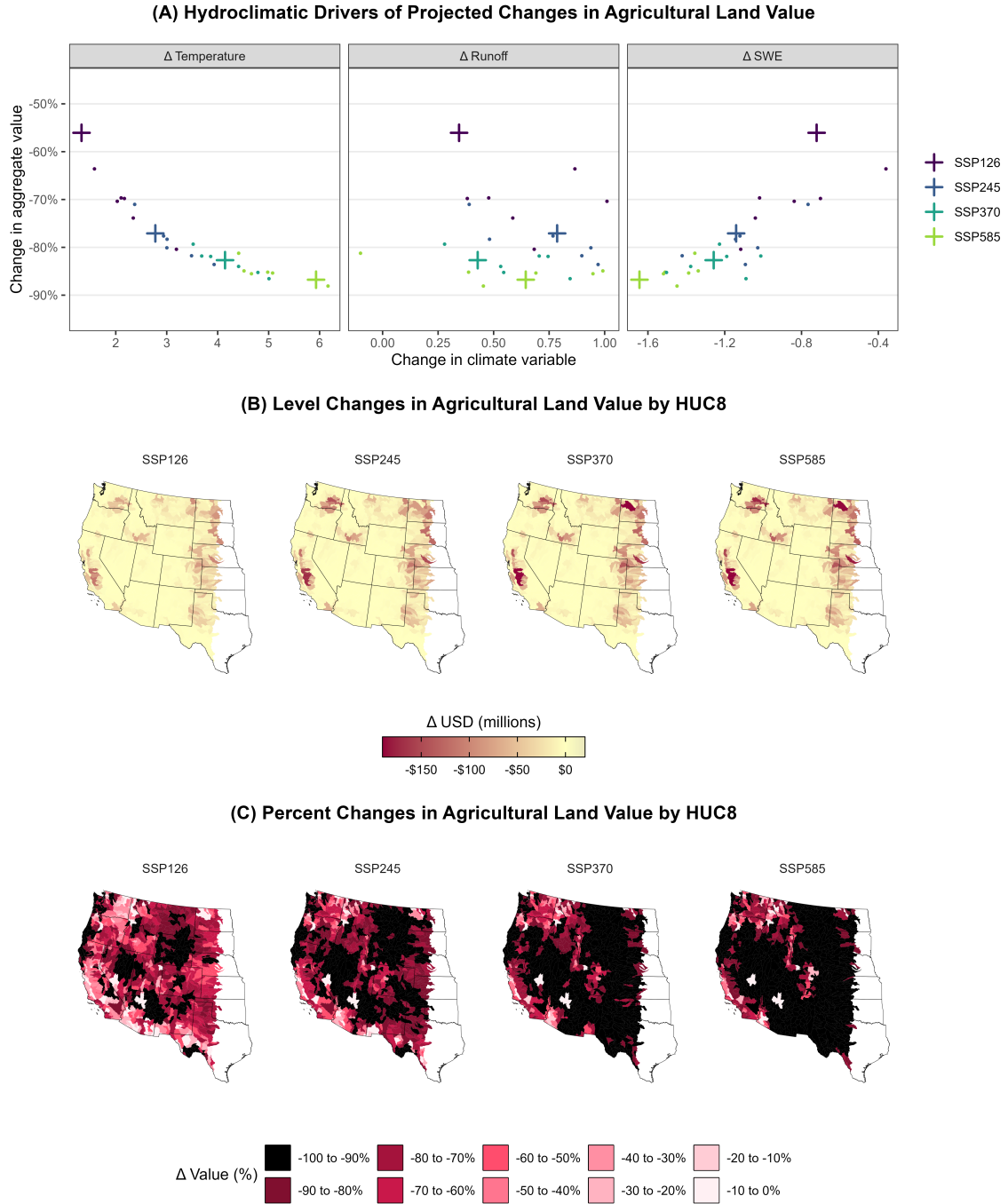


Fig. 4: Projected changes in total agricultural land exchange value under future hydroclimatic conditions in the western United States (2060-2099 relative to 2008-2023). Panel (A) relates projected percentage changes in aggregate agricultural land value to changes in key hydroclimatic variables across seven GCMs and four SSP-RCP scenarios. Points represent GCM–SSP combinations, with starred markers indicating the representative GCM selected for each SSP displayed Panel (B) and (C). Panels (B) and (C) map the spatial distribution of projected changes in agricultural land value at the HUC8 watershed scale for the selected GCM–SSP combinations.

7 Acknowledgments

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Appendix

Appendix A Supplemental Text

A.1 Out-of-Sample Validation for Long-Difference Models

We assess external predictive performance of the long-difference (LD) models using an out-of-sample (OOS) validation exercise. The LD models are first estimated using non-overlapping historical averages from 2008–2012 (“pre” period) and 2013–2017 (“post” period). For each hydrologic unit, we construct long differences in irrigated land use, cash rents, and hydroclimatic covariates across these periods and estimate the LD specification with state fixed effects.

Out-of-sample performance is evaluated using a subsequent validation window, and we construct analogous long differences between 2013–2017 and 2018–2022 and apply the estimated LD coefficients to predict changes over this later period. Predicted changes are then added to observed 2013–2017 levels to recover out-of-sample predictions of average outcomes in 2018–2022. Model performance is assessed by comparing predicted and observed outcome levels in the validation period. [Figure C18](#) displays observed versus predicted values for total irrigated cropland (OOS $R^2 = 0.991$) and irrigated cash rents (OOS $R^2 = 0.924$).

However, it is important to clarify the interpretation of this validation exercise. The LD framework is not designed for short-horizon or high-frequency prediction, and conventional cross-validation approaches are not well suited to models that rely on averaging outcomes and covariates over long time horizons. The primary objective of the LD approach is to identify long-run relationships between hydroclimate and economic outcomes by filtering out transitory shocks and short-run noise, rather than to optimize predictive accuracy per se. As a result, the high OOS fit in levels should be interpreted with caution: predicted outcomes are constructed by adding model-implied long-run change components to recent observed means, which mechanically improves fit relative to purely level-based forecasting.

DBCCA has been shown to compare well against observations across CONUS, although it can overestimate the frequency of hot extremes [96]. Because our analysis emphasizes mean annual and growing-season conditions aggregated over 30-year periods, potential biases in short-duration extremes are expected to have limited influence.

A.2 Product Details

Observed Product Details WLDAS is the highest resolution of all products used and was designed for the WUS with stakeholders. Despite having explicit focus on groundwater management and a record extending back to 1979, WLDAS performs poorly with regard to total precipitation estimation in dry regions [113]. ERA5-Land exhibits less random error than other precipitation products in the WUS [114]. However, some analyses suggest it may underestimate snow when compared against passive microwave products [115]. More recent benchmarking indicates passive microwave products may introduce anomalous trends in mountainous regions and finds that ERA5-Land demonstrates superior skill in snow estimation [32]. Daymet, which is used to force both the VIC and PRMS models [77], outperforms coarser datasets in some regional analyses but struggles in higher-elevation arid and topographically complex terrain characteristic of the WUS where station density is low [116].

Hydrologic Model Details Daymet forcings are used to drive two different hydrologic models, VIC and PRMS. Both of these models have documented limitations relevant to our study domain. VIC is a widely-used[34] semi-distributed hydrologic model that simulates water and energy balance processes using meteorological forcing, producing estimates of runoff, snowmelt, and other variables [117]. PRMS is a deterministic, distributed-parameter, process-based model that divides watersheds into hydrologic response units to simulate daily water and energy balance components [78].

Key differences between the models include runoff generation mechanisms and snowpack representation. VIC simulates saturation excess as the primary process and estimates SWE using elevation bands with temperature lapse rates, while PRMS uses energy-balance-driven snowpack dynamics and simulates surface runoff, interflow, and baseflow through separate reservoir representations.

Limitations for VIC include limited subsurface representation, sectoral water use, groundwater pumping, reservoir operations, and environmental flow requirements [118]. PRMS is also limited in its representation of groundwater, water management, and lateral flow between model units [78].

Future Product Details GCMs include ACCESS-CM2 [119], BCC-CSM2-MR [120], CNRM-ESM2-1 [121], EC-Earth3 [122], MPI-ESM1-2-HR[123], MRI-ESM2-0 [124], and NorESM2-MM [125], which were selected to ensure minimal overlap in their climate responses and modeling errors when representing historical climate in CONUS [95, 96]. GCMs, are characterized relative to ensemble median warming and precipitation increase across the study domain per range from above-median warming with above-median wetting (NorESM2-MM, MRI-ESM2-0, ACCESS-CM2, EC-Earth3),

above-median warming with below-median wetting (MPI-ESM1-2-HR), to below-median warming with below-median wetting (CNRM-ESM2-1, BCC-CSM2-MR).

We access three temporal windows from Kao et al. [77]: observational baseline runs (1980-2019) using Daymet meteorological forcings, GCM historical simulations (1980-2019) using downscaled CMIP6 outputs to validate model performance, and GCM future projections (2060-2099) using downscaled CMIP6 outputs under four SSP scenarios. All simulations use identical VIC and PRMS model configurations and spatial aggregation to HUC8 watersheds.

A.3 Growing Season Definition

The institutional growing season definition (April 1 - September 30) used in our analysis aligns with independent biophysical estimates. Table B13 shows growing season characteristics calculated by defining growing season as the period from when Growing Degree Days exceed 300 to the first killing frost after day-of-the-year (DOY) 200 [84]. Consistent with this approach [84], we use GRIDMET [126]. Using the period from 2000-2019, the mean biophysical growing season in our study domain runs from DOY 90 (March 31) to DOY 295 (October 22), closely bracketing our April 1 (DOY 91) - September 30 (DOY 273) institutional definition.

A.4 Results for perennial crops

Results for perennial crops are highly sensitive to whether California is included in our sample. In the baseline long-difference specification and associated future projections, we estimate large and statistically significant increases in land allocated to perennial crops, with projected changes ranging from approximately 150% to over 600% relative to observed baselines. To assess the external validity of these results, we conducted a sensitivity analysis excluding HUC8 watersheds located within California, which account for a disproportionate share of perennial crop production in the WUS. As shown in Table B15, omitting California reduces the magnitude of the estimated temperature coefficients by nearly 10x. Once these observations are removed, the estimated projections on perennial crop area by end of century attenuate sharply toward zero.

We interpret this as evidence that projected expansion of perennial crops is not a generalized response to hydroclimatic change across the WUS, but rather reflects unique conditions of highly specialized perennial-producing regions. Because perennial systems are characterized by long-lived capital investments, region-specific water institutions, and crop portfolios that are not easily extensible to other basins, we place limited confidence in the external validity of these estimates.

Appendix B Supplemental Tables

Table B1: SWE benchmarking results broken out by HUC2 Region.

Model	Region	SWE Performance Metrics (median [IQR])					
		PBIAS	rRMSE	KGE	R^2		
Daymet-PRMS	09 Souris-Red-Rainy	-91.23 [20.55]	1.51 [0.29]	-0.30 [0.32]	0.45 [0.12]		
Daymet-PRMS	10 Missouri River	-41.89 [75.68]	1.14 [0.75]	0.09 [0.74]	0.56 [0.53]		
Daymet-PRMS	11 Arkansas-White-Red	-72.92 [54.83]	1.37 [0.50]	-0.17 [0.58]	0.40 [0.46]		
Daymet-PRMS	13 Rio Grande	-63.74 [75.08]	1.32 [1.32]	0.22 [0.68]	0.76 [0.26]		
Daymet-PRMS	14 Upper Colorado	-22.58 [48.55]	0.64 [0.72]	0.41 [0.55]	0.67 [0.39]		
Daymet-PRMS	15 Lower Colorado	-22.92 [109.89]	1.31 [0.97]	0.18 [0.67]	0.72 [0.51]		
Daymet-PRMS	16 Great Basin	-52.99 [56.97]	1.15 [0.90]	0.01 [0.66]	0.29 [0.50]		
Daymet-PRMS	17 Pacific Northwest	-46.95 [49.27]	0.74 [0.72]	0.26 [0.63]	0.60 [0.36]		
Daymet-PRMS	18 California	-55.73 [51.71]	1.11 [0.68]	-0.04 [0.63]	0.61 [0.62]		
Daymet-VIC	09 Souris-Red-Rainy	-69.50 [1.63]	1.11 [0.07]	0.09 [0.01]	0.78 [0.08]		
Daymet-VIC	10 Missouri River	-76.94 [21.56]	1.12 [0.43]	-0.05 [0.47]	0.64 [0.47]		
Daymet-VIC	11 Arkansas-White-Red	-76.18 [11.49]	1.11 [0.24]	0.02 [0.21]	0.75 [0.40]		
Daymet-VIC	13 Rio Grande	-82.34 [18.32]	1.38 [0.98]	-0.10 [0.41]	0.68 [0.16]		
Daymet-VIC	14 Upper Colorado	-78.60 [24.26]	0.96 [0.61]	-0.05 [0.46]	0.65 [0.34]		
Daymet-VIC	15 Lower Colorado	-91.73 [20.10]	1.76 [0.78]	-0.20 [0.41]	0.56 [0.82]		
Daymet-VIC	16 Great Basin	-76.64 [24.77]	1.23 [0.69]	-0.06 [0.48]	0.47 [0.53]		
Daymet-VIC	17 Pacific Northwest	-47.48 [46.62]	0.72 [0.58]	0.32 [0.46]	0.64 [0.33]		
Daymet-VIC	18 California	-70.85 [47.37]	1.11 [0.58]	-0.04 [0.55]	0.66 [0.41]		
ERA5-Land	09 Souris-Red-Rainy	-22.11 [13.38]	0.57 [0.21]	0.72 [0.16]	0.85 [0.07]		
ERA5-Land	10 Missouri River	-10.92 [44.65]	0.75 [0.62]	0.48 [0.52]	0.68 [0.35]		
ERA5-Land	11 Arkansas-White-Red	109.88 [220.14]	2.57 [2.88]	-0.84 [2.36]	0.51 [0.56]		
ERA5-Land	13 Rio Grande	-36.01 [46.12]	1.17 [1.73]	0.14 [0.86]	0.54 [0.79]		
ERA5-Land	14 Upper Colorado	4.12 [64.81]	0.66 [0.91]	0.54 [0.68]	0.81 [0.17]		
ERA5-Land	15 Lower Colorado	-44.24 [80.36]	1.26 [0.66]	0.02 [0.44]	0.75 [0.55]		
ERA5-Land	16 Great Basin	-12.18 [48.77]	0.92 [0.94]	0.44 [0.51]	0.83 [0.23]		
ERA5-Land	17 Pacific Northwest	-2.29 [47.40]	0.56 [0.73]	0.57 [0.51]	0.71 [0.26]		
ERA5-Land	18 California	-27.95 [52.44]	1.04 [1.08]	0.39 [0.91]	0.74 [0.45]		
WLDAS	09 Souris-Red-Rainy	-94.03 [12.75]	1.55 [0.15]	-0.39 [0.32]	0.32 [0.30]		
WLDAS	10 Missouri River	-91.53 [30.54]	1.40 [0.64]	-0.34 [0.42]	0.28 [0.38]		
WLDAS	11 Arkansas-White-Red	-86.00 [24.79]	1.34 [0.54]	-0.36 [0.51]	0.37 [0.35]		
WLDAS	13 Rio Grande	-76.94 [34.32]	1.44 [1.27]	-0.03 [0.67]	0.33 [0.51]		
WLDAS	14 Upper Colorado	-71.67 [37.59]	0.96 [1.08]	-0.06 [0.66]	0.30 [0.43]		
WLDAS	15 Lower Colorado	-96.38 [11.89]	1.81 [0.67]	-0.42 [0.41]	0.25 [0.43]		
WLDAS	16 Great Basin	-73.49 [30.50]	1.24 [0.83]	0.03 [0.62]	0.58 [0.44]		
WLDAS	17 Pacific Northwest	-47.91 [37.54]	0.80 [0.77]	0.21 [0.47]	0.32 [0.33]		
WLDAS	18 California	-26.78 [71.85]	1.02 [0.90]	0.36 [0.71]	0.58 [0.39]		

Table B2: Runoff benchmarking results broken out by USGS Hydrologic Region.

Model	USGS Region	Runoff Performance Metrics (median [IQR])			
		PBIAS	rRMSE	KGE	R^2
ERA5-Land	05 Hudson Bay/Upper Mississippi	158.29 [60.00]	1.95 [0.79]	-0.77 [0.90]	0.64 [0.06]
ERA5-Land	06 Missouri	3.85 [58.23]	0.74 [0.52]	0.35 [0.58]	0.44 [0.24]
ERA5-Land	07 Lower Mississippi	74.75 [152.04]	1.11 [1.34]	-0.18 [1.80]	0.30 [0.18]
ERA5-Land	08 Western Gulf of Mexico	143.37 [208.02]	1.61 [1.52]	-0.93 [1.19]	0.42 [0.13]
ERA5-Land	09 Colorado	-11.41 [46.84]	0.68 [0.72]	0.41 [0.56]	0.59 [0.34]
ERA5-Land	10 Great Basin	-15.08 [131.42]	0.86 [0.90]	0.24 [1.04]	0.66 [0.16]
ERA5-Land	11 Pacific slope CA	-26.29 [37.72]	0.50 [0.61]	0.46 [0.52]	0.92 [0.08]
ERA5-Land	12 Pacific slope WA/Upper Columbia	-27.27 [30.46]	0.36 [0.16]	0.53 [0.23]	0.80 [0.29]
ERA5-Land	13 Snake	11.21 [29.15]	0.22 [0.25]	0.73 [0.31]	0.83 [0.08]
ERA5-Land	14 Pacific slope OR/Lower Columbia	-32.10 [28.18]	0.37 [0.21]	0.49 [0.31]	0.77 [0.25]
PRMS	05 Hudson Bay/Upper Mississippi	-60.61 [9.16]	1.10 [0.10]	-0.29 [0.10]	0.07 [0.13]
PRMS	06 Missouri	-32.40 [31.36]	0.61 [0.49]	0.38 [0.38]	0.52 [0.30]
PRMS	07 Lower Mississippi	-12.63 [35.75]	0.57 [0.26]	0.35 [0.29]	0.60 [0.22]
PRMS	08 Western Gulf of Mexico	-54.26 [54.77]	0.74 [0.21]	0.13 [0.45]	0.55 [0.20]
PRMS	09 Colorado	-21.04 [51.19]	0.50 [0.71]	0.47 [0.50]	0.76 [0.19]
PRMS	10 Great Basin	-0.42 [134.13]	0.87 [1.02]	0.10 [0.69]	0.73 [0.11]
PRMS	11 Pacific slope CA	-5.47 [38.11]	0.53 [0.41]	0.54 [0.58]	0.83 [0.11]
PRMS	12 Pacific slope WA/Upper Columbia	-2.17 [29.52]	0.24 [0.18]	0.63 [0.35]	0.59 [0.40]
PRMS	13 Snake	-1.59 [19.22]	0.19 [0.16]	0.79 [0.19]	0.78 [0.13]
PRMS	14 Pacific slope OR/Lower Columbia	2.53 [22.75]	0.19 [0.13]	0.71 [0.21]	0.82 [0.24]
VIC	05 Hudson Bay/Upper Mississippi	2.62 [27.43]	0.72 [0.25]	0.52 [0.10]	0.51 [0.14]
VIC	06 Missouri	-10.20 [30.48]	0.55 [0.59]	0.48 [0.49]	0.56 [0.37]
VIC	07 Lower Mississippi	-7.02 [26.53]	0.39 [0.13]	0.69 [0.20]	0.68 [0.23]
VIC	08 Western Gulf of Mexico	-40.14 [36.84]	0.56 [0.16]	0.34 [0.31]	0.63 [0.24]
VIC	09 Colorado	1.74 [53.46]	0.48 [0.73]	0.56 [0.38]	0.81 [0.19]
VIC	10 Great Basin	20.18 [200.99]	0.87 [1.87]	0.23 [2.01]	0.65 [0.24]
VIC	11 Pacific slope CA	-3.40 [51.99]	0.48 [0.65]	0.52 [0.70]	0.85 [0.14]
VIC	12 Pacific slope WA/Upper Columbia	3.20 [26.40]	0.20 [0.12]	0.67 [0.32]	0.59 [0.51]
VIC	13 Snake	15.07 [37.20]	0.22 [0.25]	0.71 [0.26]	0.87 [0.07]
VIC	14 Pacific slope OR/Lower Columbia	4.84 [25.14]	0.19 [0.19]	0.72 [0.21]	0.83 [0.20]
WLDAS	05 Hudson Bay/Upper Mississippi	182.17 [44.55]	2.00 [0.45]	-0.89 [0.50]	0.71 [0.07]
WLDAS	06 Missouri	36.07 [88.41]	0.76 [0.69]	0.03 [0.68]	0.43 [0.28]
WLDAS	07 Lower Mississippi	677.79 [1762.90]	7.00 [17.93]	-6.12 [19.10]	0.50 [0.04]
WLDAS	08 Western Gulf of Mexico	82.71 [143.81]	1.02 [1.45]	-0.20 [2.08]	0.59 [0.19]
WLDAS	09 Colorado	61.70 [86.37]	0.79 [1.00]	0.21 [1.13]	0.68 [0.37]
WLDAS	10 Great Basin	140.03 [272.24]	1.74 [2.92]	-0.76 [3.10]	0.74 [0.27]
WLDAS	11 Pacific slope CA	28.24 [81.44]	0.42 [0.78]	0.60 [0.75]	0.89 [0.07]
WLDAS	12 Pacific slope WA/Upper Columbia	-7.95 [28.24]	0.22 [0.11]	0.59 [0.25]	0.52 [0.32]
WLDAS	13 Snake	10.16 [29.87]	0.24 [0.22]	0.65 [0.48]	0.69 [0.18]
WLDAS	14 Pacific slope OR/Lower Columbia	-0.23 [21.80]	0.21 [0.12]	0.73 [0.22]	0.69 [0.29]

Table B3: Regression output for Equation 4 including all coefficient estimates and modeled outcomes. Coefficients are in hectares for Δ crop area outcomes and in USD for Δ cash rent outcomes.

Model:	Agricultural Land Use (Δ hectares)						Cash Rental Rates (Δ USD)		
	Total (1)	High Water (2)	Moderate Water (3)	Low Water (4)	Perennials (5)	Pasture (6)	Irrigated (7)	Dryland (8)	Pasture (9)
Growing Season Temp.	-2,228.1 (7,958.3)	1,829.6 (2,174.3)	-4,057.7 (6,820.8)	2,162.9 (2,252.6)	-5,267.1 (3,080.8)	-96,702.7** (36,980.3)	-165.5* (94.6)	-30.3** (15.3)	0.682 (5.79)
Growing Season Temp. Sq.	-149.2 (273.3)	-264.5** (125.1)	115.3 (162.9)	-2.71 (31.1)	380.4 (224.2)	1,877.3 (1,159.7)	-1.80 (2.24)	-0.275 (0.386)	-0.150 (0.140)
Runoff	969.7 (1,612.0)	1,911.2*** (410.7)	-941.5 (1,400.0)	202.8 (474.9)	-1,367.8* (718.5)	1,433.9 (11,917.2)	35.9 (31.1)	-15.0*** (4.91)	-6.79*** (1.89)
Runoff Sq.	3.41 (10.7)	-11.0*** (3.55)	14.4 (9.78)	7.16 (11.9)	4.09 (4.02)	39.8 (141.6)	-0.105 (0.390)	0.037 (0.055)	-0.011 (0.022)
Temp. $\times$ Runoff	-83.7** (35.3)	-42.6* (20.3)	-41.1 (33.9)	-4.86 (18.4)	66.9** (29.3)	217.8 (208.7)	-3.04** (1.55)	1.03*** (0.227)	0.628*** (0.086)
Growing Season Precip.	-1,319.8 (803.7)	-1,578.6*** (369.9)	258.8 (659.2)	945.2 (970.8)	1,161.3* (635.7)	6,573.1 (11,605.5)	-41.8*** (15.2)	2.69 (2.49)	-1.58* (0.903)
Growing Season Precip. Sq.	4.57 (4.37)	7.26** (2.62)	-2.69 (2.99)	-11.9 (12.0)	-6.45* (2.96)	-79.9 (91.9)	0.246* (0.132)	-0.048** (0.024)	0.009 (0.008)
Apr. 1 SWE	-111.9 (1,291.5)	-520.3 (383.0)	408.3 (1,176.1)	-440.7 (315.0)	883.4 (675.9)	-7,848.5 (5,892.4)	-2.63 (21.0)	-3.19 (3.39)	-3.67*** (1.32)
Population	-0.055** (0.023)	-0.011 (0.006)	-0.045** (0.018)	0.001 (0.003)	0.017 (0.014)	0.120* (0.067)	-0.0005 (0.0005)	-5.85×10^{-5} (8.66×10^{-5})	5.44×10^{-5} (3.2×10^{-5})
<i>Fixed effects:</i>									
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950	950	950	712	688	950	837	693	856
R ²	0.27497	0.22885	0.25770	0.31182	0.23765	0.45380	0.21080	0.24500	0.18421
Within Adjusted R ²	0.03070	0.10788	0.00771	0.05930	0.14431	0.04527	0.02778	0.06711	0.10078

Clustered (State) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B4: Regression output for Equation 3. For columns 1–6, the dependent variable is $\ln(\text{crop area})$, so coefficients are semi-elasticities (approximately percent changes in area for a one-unit change in the explanatory variable). For columns 7–9, coefficients are changes in cash rent (USD) per unit change in the explanatory variable.

Model:	Agricultural Land Use (log)						Cash Rental Rates		
	Total (1)	High Water (2)	Moderate Water (3)	Low Water (4)	Perennials (5)	Pasture (6)	Irrigated (7)	Dryland (8)	Pasture (9)
5-Year Mean Temp. (°C)	1.16*** (0.252)	0.870*** (0.268)	1.16*** (0.259)	-1.37*** (0.361)	0.492 (0.321)	-1.33** (0.645)	120.2 (68.8)	-18.8 (19.1)	-1.72 (4.86)
5-Year Mean Temp. Sq.	-0.039*** (0.006)	-0.039*** (0.007)	-0.030*** (0.006)	0.050*** (0.010)	-0.005 (0.007)	0.011 (0.013)	0.463 (1.66)	0.099 (0.492)	-0.043 (0.120)
5-Year Mean Runoff (10^8 m^3)	0.008 (0.035)	0.042 (0.040)	0.003 (0.035)	-0.112* (0.061)	0.050 (0.053)	-0.139* (0.085)	11.8 (12.2)	2.13 (3.66)	-0.321 (1.39)
5-Year Mean Runoff Sq.	0.0001 (0.0002)	-1.03×10^{-5} (0.0002)	0.0001 (0.0002)	0.0004 (0.0003)	-0.0004 (0.0003)	0.0003 (0.0005)	0.042 (0.082)	-0.003 (0.014)	0.0001 (0.006)
Temp. $\times$ Runoff	-0.0006 (0.002)	-0.002 (0.002)	-0.0008 (0.002)	0.006* (0.003)	-0.002 (0.003)	0.006 (0.004)	-0.527 (0.771)	-0.101 (0.201)	0.036 (0.082)
5-Year Mean Prcp. (10^8 m^3)	-0.028* (0.015)	-0.038** (0.016)	0.0002 (0.017)	0.011 (0.034)	0.014 (0.023)	-0.061 (0.040)	14.1* (8.20)	0.972 (0.982)	-0.079 (0.356)
5-Year Mean Prcp. Sq.	0.0001 (0.0001)	0.0002 (0.0001)	-6.74×10^{-6} (0.0001)	-0.0002 (0.0002)	-6.56×10^{-5} (0.0002)	0.0002 (0.0003)	-0.101 (0.064)	-0.008 (0.008)	-0.002 (0.003)
Apr. 1 SWE (10^8 m^3)	0.045*** (0.015)	0.038** (0.018)	0.041** (0.021)	-0.011 (0.026)	-0.0001 (0.022)	0.041 (0.053)	11.9* (4.82)	-1.20 (1.76)	-0.119 (0.460)
Population	-1.36×10^{-7} (1.12×10^{-6})	1.28×10^{-6} (1.51×10^{-6})	-6.68×10^{-7} (1.07×10^{-6})	3.09×10^{-7} (1.75×10^{-6})	2.52×10^{-6} (1.63×10^{-6})	$6.31 \times 10^{-6**}$ (2.79×10^{-6})	-0.0009 (0.0007)	-0.0002* (0.0001)	-3.86×10^{-5} (4.09×10^{-5})
<i>Fixed effects:</i>									
HUC8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HUC6-by-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (HUC8-years)	15,200	15,200	15,200	11,392	11,008	15,200	10,290	8,147	11,270
R ²	0.98191	0.97568	0.97749	0.90958	0.95617	0.91781	0.93896	0.92013	0.90738
Within Adjusted R ²	0.01940	0.01956	0.00792	0.00848	0.00098	0.00334	0.00371	0.00635	0.00082

Clustered (HUC8 & HUC6-by-Year) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B5: Backcasted changes (1980–2007 relative to 2008–2023) in agricultural land use (ha), rental rates (2020 \$USD per ha), and aggregate land value driven (2020 \$USD, billions). Point estimates are shown with corresponding 95% confidence intervals.

Outcome	Point Estimate	Lower Bound	Upper Bound
High water use cropland	1,968,403	1,112,965	2,818,198
Moderate water use cropland	212,557	-742,220	1,238,716
Low water use cropland	-59,854	-98,075	158,420
Perennials	-587,324	-711,873	-437,724
Grass pasture	-25,317,639	-13,858,871	-11,256,409
Total irrigated cropland	1,532,653	240,929	2,380,112
Irrigated rent	\$111.51	\$33.08	\$201.16
Dryland rent	\$18.42	\$6.66	\$30.50
Pasture rent	-\$1.68	-\$4.66	\$2.71
Total agricultural land value	\$3.63	\$0.98	\$7.15

Table B6: Summary statistics for agricultural land use (ha), rental rates (2020 \$USD per ha), and aggregate land value (2020 \$USD, millions) over 2008-2023.

Variable	Obs (HUC8s)	Mean	Std. Dev.	Median	Min	Max
Total Irr. Cropland	950	33,880	63,834	4,240	0	582,668
High Water Use	950	8,144	19,767	1,769	0	196,054
Moderate Water Use	950	25,736	56,031	1,030	0	556,491
Low Water Use	712	816	4,772	4	0	96,704
Perennials	688	2,605	13,763	8	0	185,218
Grass Pasture	950	43,139	59,829	22,193	8	476,424
Irrigated Rent	908	\$458.32	\$624.11	\$280.89	\$72.98	\$5,784.62
Dryland Rent	802	\$91.18	\$64.34	\$73.11	\$11.61	\$539.86
Pasture Rent	930	\$28.99	\$30.28	\$20.06	\$2.76	\$219.46
Total agricultural land rental value	950	\$14.86	\$32.02	\$2.37	\$0	\$259.89

Table B7: Projected changes in agricultural area and rental rates by GCM and SSP. Area changes are in hectares; rental-rate changes are in USD.

GCM	Agricultural Land Use (Δ ha)				Rental Rates (Δ USD)		
	HWU	MWU	LWU	Pasture	Dry	Irrig.	Pasture
SSP1-2.6							
ACCESS-CM2	-6,062	2,469	2,937	-38,012	-50.2	-332	1.48
BCC-CSM2-MR	-4,497	1,260	1,454	-34,140	-29.4	-268	-1.03
CNRM-ESM2-1	-5,157	1,825	1,966	-36,658	-39.4	-289	-1.23
EC-Earth3	-5,384	1,869	2,142	-36,010	-41.0	-304	0.929
MPI-ESM1-2-HR	-3,857	1,032	1,162	-33,383	-22.4	-226	0.107
MRI-ESM2-0	-5,112	1,745	1,928	-36,021	-38.5	-283	0.252
NorESM2-MM	-5,098	1,621	1,900	-35,479	-37.5	-305	0.480
SSP2-4.5							
ACCESS-CM2	-6,478	3,040	3,505	-38,880	-53.4	-349	2.36
BCC-CSM2-MR	-5,916	2,320	2,708	-38,251	-46.9	-329	1.05
CNRM-ESM2-1	-6,003	2,254	2,736	-37,136	-46.8	-333	1.51
EC-Earth3	-6,315	2,761	3,105	-37,649	-50.7	-337	2.73
MPI-ESM1-2-HR	-5,268	1,805	2,131	-37,352	-42.5	-299	-0.413
MRI-ESM2-0	-5,945	2,398	2,700	-37,675	-48.6	-325	0.816
NorESM2-MM	-5,768	2,157	2,538	-37,258	-47.6	-320	1.48
SSP3-7.0							
ACCESS-CM2	-6,900	4,006	4,386	-39,190	-56.9	-358	2.79
BCC-CSM2-MR	-6,660	3,580	3,916	-39,491	-54.8	-350	2.32
CNRM-ESM2-1	-6,576	3,327	3,662	-39,111	-53.5	-346	1.08
EC-Earth3	-6,862	4,018	4,085	-38,985	-56.4	-353	2.46
MPI-ESM1-2-HR	-6,200	2,758	3,131	-39,299	-50.9	-335	0.924
MRI-ESM2-0	-6,376	2,944	3,275	-38,557	-52.3	-341	1.19
NorESM2-MM	-6,397	3,074	3,452	-39,072	-53.7	-341	1.81
SSP5-8.5							
ACCESS-CM2	-7,243	5,314	5,218	-39,057	-58.9	-368	3.31
BCC-CSM2-MR	-6,903	4,228	4,325	-39,684	-56.3	-356	2.62
CNRM-ESM2-1	-7,002	4,198	4,380	-39,234	-55.9	-357	2.37
EC-Earth3	-7,237	5,052	4,955	-38,537	-57.8	-362	3.81
MPI-ESM1-2-HR	-6,513	3,622	3,854	-40,519	-55.3	-346	0.365
MRI-ESM2-0	-6,764	3,640	3,949	-38,844	-55.2	-351	2.85
NorESM2-MM	-6,785	3,793	4,099	-38,845	-56.0	-352	4.11

Table B8: Summary of data sources.

Variable	Product	Spatial Res.	Temporal Res.	Temporal Extent	Source
<i>Hydroclimate - Observational</i>					
Precipitation SWE Temperature Runoff	ERA5-Land	9 km	Daily	1980-2023	Reanalysis
Precipitation SWE Temperature Runoff	WLDAS	1 km	Daily	1980-2023	Data Assimilation
Precipitation SWE Temperature Runoff	Daymet-VIC	~4 km	Daily	1980-2019	Hydrologic Model
Precipitation SWE Temperature Runoff	Daymet-PRMS	~4 km	Daily	1980-2019	Hydrologic Model
<i>Hydroclimate - GCM Simulations</i>					
Precipitation SWE Temperature Runoff	CMIP6 + VIC/PRMS (7 GCMs, historical)	~4 km	Daily	1980-2019	Downscaled GCM
Precipitation SWE Temperature Runoff	CMIP6 + VIC/PRMS (7 GCMs × 4 SSPs)	~4 km	Daily	2060-2099	Downscaled GCM
<i>Socio-Economic</i>					
Land Use	CDL	30 m	Annual	2008-2023	Satellite
Rental Rates	NASS	County	Annual	2008-2023	Survey
Population	NCI	County	Annual	1975-2023	Census

Table B9: Summary of Variables, Metrics, and Calculation Methods

Variable	Metric	Calculation Method / Note
Runoff	Annual Runoff	Cumulative maximum runoff per year
	April 1 Runoff	Runoff on April 1, measured as cumulative
	Fraction of Cool Season Runoff	Ratio of Accumulated April 1 runoff to annual runoff
	Day Corresponding to 25% Annual Runoff Volume	Day when cumulative runoff reaches 25% of annual
	Day Corresponding to 50% annual runoff volume	Day when cumulative runoff reaches 50% of annual
	Mean 30-Year Annual Runoff	30-year averages of above metrics by HUC8
	Rolling 5-Year Mean Annual Runoff (Current Year and Prior 4 Years)	5-year rolling mean, calculated per HUC8
Precipitation	Annual Precipitation	Cumulative maximum precipitation per year
	April 1 Precipitation	Precipitation on April 1, measured as cumulative
	Fraction of Cool Season Precipitation	Ratio of Accumulated April 1 precipitation to annual precipitation
	Day Corresponding to 25% Annual Precipitation Volume	Day when cumulative precipitation reaches 25% of annual volume
	Day Corresponding to 50% Annual Precipitation Volume	Day when cumulative precipitation reaches 50% of annual
	Mean 30-Year Annual Precipitation	Yearly averages per HUC8
	Rolling 5-Year Mean Annual Precipitation (Current Year and Prior 4 Years)	5-year rolling mean, calculated per HUC8
SWE	Annual SWE	Maximum SWE per year
	April 1 SWE	SWE on April 1

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Variable	Metric	Calculation Method / Note
	Fraction of Cool Season SWE	Ratio of April 1 SWE to annual SWE
	Day Corresponding to 25% Annual SWE Volume	Day when SWE reaches 25% of annual SWE
	Day Corresponding to 50% Annual SWE Volume	Day when SWE reaches 50% of annual SWE
	Mean 30-Year Annual SWE	Yearly averages per HUC8
	Rolling 5-Year Mean Annual SWE (Current Year and Prior 4 Years)	5-year rolling mean, calculated per HUC8
Temperature	Annual Temperature	Mean temperature per year
	Planting Season Temperature	Average temperature between waterdays 151-184
	Growing Season Temperature	Average temperature after waterday 184
	Growing Degree Days (GDD)	Sum of daily temperatures between 0°C and 31.999°C during growing season
	Extreme Heat Days (EHD)	Count of days with temperature >32°C during growing season
	Mean 30-Year Annual Temperature	Yearly averages per HUC8
	Rolling 5-Year Mean Annual Temperature (Current Year and Prior 4 Years)	5-year rolling mean, calculated per HUC8

Table B10: Observed mean annual crop evapotranspiration (ET) totals from the U.S. Bureau of Reclamation AgriMet network. Values represent crop-level averages of reported seasonal ET totals across western irrigated production regions and are reported in inches.

Crop	Average ET (inches)
Alfalfa (Mean)	35.7
Alfalfa (New Plant)	47.3
Alfalfa Hay (Mean)	27.1
Asparagus	32.4
Bean	17.1
Beet	23.6
Beets	22.6
Blue Grass	18.2
Blueberries	29.8
Broccoli	24.6
Cabbage	15.3
Carrot Seed	11.1
Carrots	10.3
Cherries	29.0
Cherry	42.9
Concord Grapes	27.2
Cranberries	23.0
Dry Beans	19.9
Field Corn	25.3
Garlic	26.3
Grass Seed	11.9
Grass Seed fall	8.9
Hay (Mean)	40.0
Hazelnuts	42.3
Hops	36.1
Lawn	34.1
Lentils/Peas	11.6
Lettuce	11.0
Melon	16.8
Melons	17.2
New Mint	25.4
Onion	25.9
Onions	26.7
Orchard	46.1
Pasture	28.3
Peaches	30.6
Peas	13.4
Peppermint	23.2
Potatoes	24.4
Rape	15.0
Rapeseed	19.6
Rapeseed fall	17.4
Safflower	26.9
Shepody Potatoes	25.1
Spearmint	22.9
Spinach	16.2
Spring Corn	21.6
Spring Grain	22.8
Squash	21.5
Stawberries	27.6
Sugar Beet Seed	29.1
Sugar Beets	30.0
Sweet Corn	22.2
Winter Grain	23.6

Table B11: Crop water requirement parameters derived from FAO-56. The relative water requirement proxy is constructed as the product of the representative mid-season crop coefficient (K_c) and the mean growing-season length (days). Units are index values used for ordinal classification.

Crop	K_c	Season Length (days)	$K_c \times \text{Days}$
Sugarcane	1.25	317.5	396.9
Alfalfa	1.20	232.5	279.0
Garlic	1.00	240.0	240.0
Cotton	1.20	187.5	225.0
Flaxseed	1.10	185.0	203.5
Tomatoes	1.152	157.5	181.4
Durum wheat	1.15	157.5	181.1
Wheat	1.15	157.5	181.1
Triticale	1.15	155.0	178.3
Lentils	1.10	160.0	176.0
Peppers	1.052	165.0	173.6
Switchgrass	0.95	180.0	171.0
Rye	1.05	160.0	168.0
Speltz	1.10	150.0	165.0
Soybeans	1.15	142.5	163.9
Barley	1.15	135.0	155.3
Oats	1.15	135.0	155.3
Safflower	1.07	142.5	152.5
Honeydew melons	1.05	140.0	147.0
Watermelons	1.05	140.0	147.0
Rice	1.20	120.0	144.0
Eggplants	1.05	135.0	141.8
Clover	0.90	150.0	135.0
Onions	1.00	135.0	135.0
Carrots	1.05	125.0	131.3
Celery	1.05	125.0	131.3
Sunflower	1.00	127.5	127.5
Sorghum	1.00	125.0	125.0
Millet	1.00	122.5	122.5
Wildflowers	0.90	135.0	121.5
Cauliflower	1.05	112.5	118.1
Dry beans	1.15	102.5	117.9
Cucumbers	1.00	117.5	117.5
Corn	1.20	95.0	114.0
Peas	1.10	102.5	112.8
Broccoli	1.05	105.0	110.3
Canola	1.00	107.5	107.5
Gourds	1.00	107.5	107.5
Lettuce	1.00	107.5	107.5
Rapeseed	1.00	107.5	107.5
Chickpeas	1.00	102.5	102.5
Buckwheat	1.15	85.0	97.8
Vetch	0.90	105.0	94.5
Camelina	1.00	92.5	92.5
Mustard	1.00	90.0	90.0

Table B12: HUC8 watersheds excluded in interbasin water transfer (IBT) sensitivity analysis. Watersheds identified from Siddik et al. (2023) as containing documented interbasin water transfers. All models were run both with and without these watersheds to assess sensitivity of results to water management infrastructure.

State(s)	HUC8	Watershed Name
CA	18020162	Upper Putah
CA	18050001	Suisun Bay
CA	18030003	Middle Kern-Upper Tehachapi-Grapevine
CA	18070102	Santa Clara
CA	18090206	Antelope-Fremont Valleys
CA	18030009	Upper Dry
CA	18040001	Middle San Joaquin-Lower Chowchilla
CO	10190004	Clear
CO, WY	10190007	Cache La Poudre
CO, WY	10180010	Upper Laramie
NV, UT	16020306	Southern Great Salt Lake Desert
NV, UT	16020308	Northern Great Salt Lake Desert
CO	11020001	Arkansas Headwaters
CO	14010003	Eagle
NE	10180014	Lower North Platte
ID	17040208	Portneuf
NV	15010011	White
NV	16060008	Spring-Steptoe Valleys
CA	18090208	Mojave
CO	10190001	South Platte Headwaters
CO	10190002	Upper South Platte
ND	10130101	Painted Woods-Square Butte
ND	10130201	Knife
CO, NM	14080104	Animas
CA	18020111	Lower American
CA	18020129	South Fork American
CA	18030004	Upper Poso
CA	18030005	Upper Deer-Upper White
CA	18030006	Upper Tule
CA	18030007	Upper Kaweah

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State(s)	HUC-8	Watershed Name
CA	18030012	Tulare Lake Bed
CA	18040003	San Joaquin Delta
CA	18040013	Upper Cosumnes
CA	18050002	San Pablo Bay
CA	18050003	Coyote
CA	18050004	San Francisco Bay
CA	18060002	Pajaro
AZ	15020008	Middle Little Colorado
AZ	15060106	Lower Salt
ND	10110101	Lake Sakakawea
CA	18040009	Upper Tuolumne
ID, UT	16010202	Middle Bear
CO	14020006	Uncompahgre
CA	18090103	Owens Lake
AZ, CA, NV	15030101	Havasu-Mohave Lakes
CO	10180001	North Platte Headwaters
CO	10190005	St. Vrain
CO	11020006	Huerfano
CO	13010003	San Luis
CO	13010004	Saguache
CA	18070203	Santa Ana
AZ	15070102	Agua Fria
OR	17090011	Clackamas
OR, WA	17070101	Middle Columbia-Lake Wallula
CN, WA	17020006	Okanogan
WA	17030003	Lower Yakima
CO	14010002	Blue
CO	14010004	Roaring Fork
CO	14020002	Upper Gunnison
CO	14020003	Tomichi
CO	14020005	Lower Gunnison

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State(s)	HUC-8	Watershed Name
CO, UT	14030002	Upper Dolores
ID	17040212	Upper Snake-Rock
ID	17050101	C.J. Strike Reservoir
UT	14060004	Strawberry
UT, WY	16020101	Upper Weber
CO	14080102	Piedra
CO, UT	14080202	McElmo
UT	16020203	Provo
AZ	15060203	Lower Verde
CO, WY	10180002	Upper North Platte
UT	16020202	Spanish Fork
CO, UT	14010005	Colorado Headwaters-Plateau
CO, NM	14080101	Upper San Juan
CO	13010001	Rio Grande Headwaters
UT	14060009	San Rafael
UT	16030004	San Pitch
CA	18020163	Lower Sacramento
CA	18040012	Upper Mokelumne
CA	18040006	Upper San Joaquin
CO	14010001	Colorado Headwaters
OR, WA	17080001	Lower Columbia-Sandy
ND	9020202	Upper Sheyenne
MT, ND	10060005	Charlie-Little Muddy
CO	14050001	Upper Yampa
CO, UT	14030001	Westwater Canyon
AZ	15030105	Bouse Wash
AZ	15030204	Bill Williams
AZ	15050100	Middle Gila
AZ	15070201	Lower Gila
AZ, CA, MX	15030107	Lower Colorado
AZ, MX	15030108	Yuma Desert

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State(s)	HUC-8	Watershed Name
AZ, CA	15030104	Imperial Reservoir
AZ	15070101	Lower Gila-Painted Rock Reservoir

Table B13: Summary statistics of start date, end date, and season length (day of year) across HUC8 watersheds. Results follow Volk et al. [84] for the study area from using gridMET daily temperature data [126]. Growing season start was calculated as the first day reaching 300 cumulative growing degree days (base 0°C), and end was identified as the first killing frost (-2°C) occurring after calendar day 200).

Year	Mean			Median			Number of HUC8s		
	Start (DOY)	End (DOY)	Length (days)	Start (DOY)	End (DOY)	Length (days)	Start	End	Length
1980	94	293	192	109	289	180	950	935	888
1981	87	296	197	94	292	192	950	918	843
1982	100	290	181	108	283	172	950	930	874
1983	95	290	187	101	277	166	950	925	876
1984	98	289	180	109	273	158	950	935	862
1985	96	284	185	104	274	171	950	941	915
1986	80	290	201	81	284	196	950	917	863
1987	90	296	195	101	288	183	950	942	853
1988	93	297	190	101	292	177	950	941	841
1989	93	288	189	99	287	184	950	938	890
1990	–	–	–	–	–	–	0	0	0
1991	93	287	190	97	288	186	950	929	903
1992	83	287	196	89	283	191	950	936	877
1993	97	285	182	110	282	170	950	940	907
1994	89	294	200	96	293	190	950	936	895
1995	88	286	184	86	275	178	950	904	826
1996	90	285	187	95	281	180	950	913	876
1997	93	297	192	97	286	182	950	933	848
1998	93	301	188	103	290	177	950	944	791
1999	92	289	186	98	275	172	950	932	865
2000	86	285	193	93	273	179	950	932	897
2001	96	292	191	103	283	176	950	918	895
2002	96	293	182	101	285	174	950	924	834
2003	85	291	198	89	288	189	950	936	872
2004	87	295	202	92	295	198	950	931	883
2005	87	294	202	94	291	189	950	926	894
2006	88	291	192	100	286	181	950	940	852
2007	88	295	199	92	289	191	950	936	870
2008	101	296	184	111	286	171	950	940	866
2009	91	290	189	100	281	172	950	938	865
2010	95	303	203	104	300	195	950	942	900
2011	101	296	187	104	292	180	950	942	881
2012	86	296	196	92	287	190	950	932	830
2013	97	292	188	103	281	173	950	942	892
2014	87	303	198	92	305	202	950	937	813
2015	75	309	225	77	307	224	950	938	843
2016	81	304	212	84	302	205	950	934	834
2017	84	297	198	88	286	189	950	929	818
2018	88	296	196	94	287	186	950	919	846
2019	95	289	187	104	282	173	950	928	889
Mean	91	293	193	97	287	183	926	909	844

Table B14: Long-difference regression results using growing and extreme degree days. Coefficients are in hectares for Δ crop area outcomes and in USD for Δ cash rent outcomes.

Model:	Agricultural Land Use (Δ hectares)						Cash Rental Rates (Δ USD)		
	Total (1)	High Water (2)	Moderate Water (3)	Low Water (4)	Perennials (5)	Pasture (6)	Irrigated (7)	Dryland (8)	Pasture (9)
Growing Degree Days (GDD)	-13.0 (9.55)	-22.9*** (5.24)	9.88 (7.94)	11.1 (8.38)	17.3* (8.19)	71.3 (141.1)	0.812 (0.746)	-0.011 (0.066)	0.023 (0.029)
Extreme Degree Days (EDD)	-751.4** (265.7)	-473.1* (248.9)	-278.4** (98.3)	-91.2 (79.3)	674.3 (452.1)	-724.9 (2,861.2)	-10.2 (14.7)	-0.879 (1.24)	0.062 (0.136)
Runoff	842.8 (1,497.6)	1,397.3* (662.0)	-554.5 (1,181.4)	72.4 (549.2)	435.8 (480.8)	14,546.0 (11,315.0)	28.5 (22.7)	-11.2 (7.46)	-5.94* (3.32)
Runoff Sq.	3.03 (18.0)	-9.38 (7.35)	12.4 (13.8)	7.27 (12.6)	-7.01 (7.89)	-66.9 (150.2)	-0.037 (0.154)	0.042 (0.081)	0.013 (0.021)
GDD $\times$ Runoff	-0.352* (0.185)	-0.111 (0.135)	-0.241 (0.174)	0.009 (0.078)	0.098 (0.142)	-2.72 (1.57)	-0.023* (0.011)	0.005 (0.003)	0.003* (0.002)
EDD $\times$ Runoff	-178.6* (100.1)	-161.9** (74.6)	-16.7 (33.5)	6.30 (4.90)	168.7*** (48.9)	253.0 (381.3)	-3.82*** (1.31)	-0.157 (0.332)	-0.250 (0.178)
Annual Precipitation	-497.3 (761.4)	-1,140.4** (479.3)	643.1 (477.2)	991.4 (977.2)	166.1 (103.6)	8,299.9 (10,558.2)	14.4** (5.75)	6.48 (5.66)	-0.165 (0.843)
Annual Precipitation Sq.	-2.28 (6.72)	3.86 (3.13)	-6.15 (4.40)	-11.8 (11.4)	-0.339 (0.783)	-71.9 (90.0)	-0.092* (0.048)	-0.068 (0.054)	0.0002 (0.006)
April 1 SWE	-522.0 (917.7)	-402.9 (388.3)	-119.1 (786.1)	-236.2 (178.4)	254.7** (107.5)	-7,357.4 (5,872.7)	3.48 (23.9)	-1.60 (7.96)	-3.26 (1.90)
Population	-0.034* (0.017)	0.003 (0.007)	-0.036** (0.013)	-0.0005 (0.003)	0.012 (0.010)	0.225** (0.103)	-0.0004 (0.0005)	-6.24×10^{-5} (0.0001)	4.04×10^{-5} (4.66×10^{-5})
<i>Fixed effects:</i>									
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950	950	950	712	688	950	837	693	856
R ²	0.33336	0.30139	0.27003	0.29227	0.28499	0.43853	0.21083	0.22147	0.18882
Within Adjusted R ²	0.03928	0.13925	0.00131	0.05505	0.20305	0.01752	0.02661	0.03658	0.10478

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B15: Long-difference perennials model with and without California. Coefficients report changes in perennial crop area (hectares).

	Full sample	Excluding California
Δ Growing season temperature	-5,267.1 (3,080.8)	-858.6* (335.0)
Δ Growing season temperature ²	380.4 (224.2)	27.4* (11.6)
Δ Runoff	-1,367.8 (718.5)	-180.8 (146.9)
Δ Runoff ²	4.09 (4.02)	0.944 (0.681)
Δ Temperature $\times$ Runoff	66.9* (29.3)	6.55 (6.13)
Δ Precipitation	1,161.3 (635.7)	11.2 (56.5)
Δ Precipitation ²	-6.45 (2.96)	-0.209 (0.398)
Δ April 1 SWE	883.4 (675.9)	183.2 (93.5)
Δ Population	0.0168 (0.0136)	0.000644 (0.00197)
State fixed effects	Yes	Yes
Observations	688	562
Number of states	13	12
Adjusted R^2	0.214	0.025
Within R^2	0.156	0.034
RMSE	5,114	683

Clustered (state) standard errors in parentheses

*Significance: * $p < 0.05$, ** $p < 0.01$*

Model	Watersheds	Runoff Performance Metrics (median)			
		PBIAS	rRMSE	KGE	R ²
Daymet-PRMS	247	-10.38	0.43	0.5	0.7
Daymet-VIC	247	0.85	0.36	0.6	0.72
ERA5-Land	247	-14.66	0.48	0.44	0.69
WLDAS	247	20.1	0.44	0.41	0.64

Fig. C1: Results of runoff benchmarking, color coded by criteria thresholds proposed by Moriasi et al. (2015). Red indicates insufficient or unsatisfactory skill and green satisfactory skill. Saturation reflects the magnitude of skill.

Model	Watersheds	SWE Performance Metrics (median)			
		PBIAS	rRMSE	KGE	R ²
Daymet-PRMS	653	-44.8	0.99	0.15	0.57
Daymet-VIC	654	-69.56	1.05	0.03	0.64
ERA5-Land	699	-11.45	0.78	0.47	0.72
WLDAS	697	-66.61	1.23	-0.04	0.34

Fig. C2: Results of SWE benchmarking, color coded by criteria thresholds proposed by Moriasi et al. (2015). Red indicates insufficient or unsatisfactory skill and green satisfactory skill. Saturation reflects the magnitude of skill.

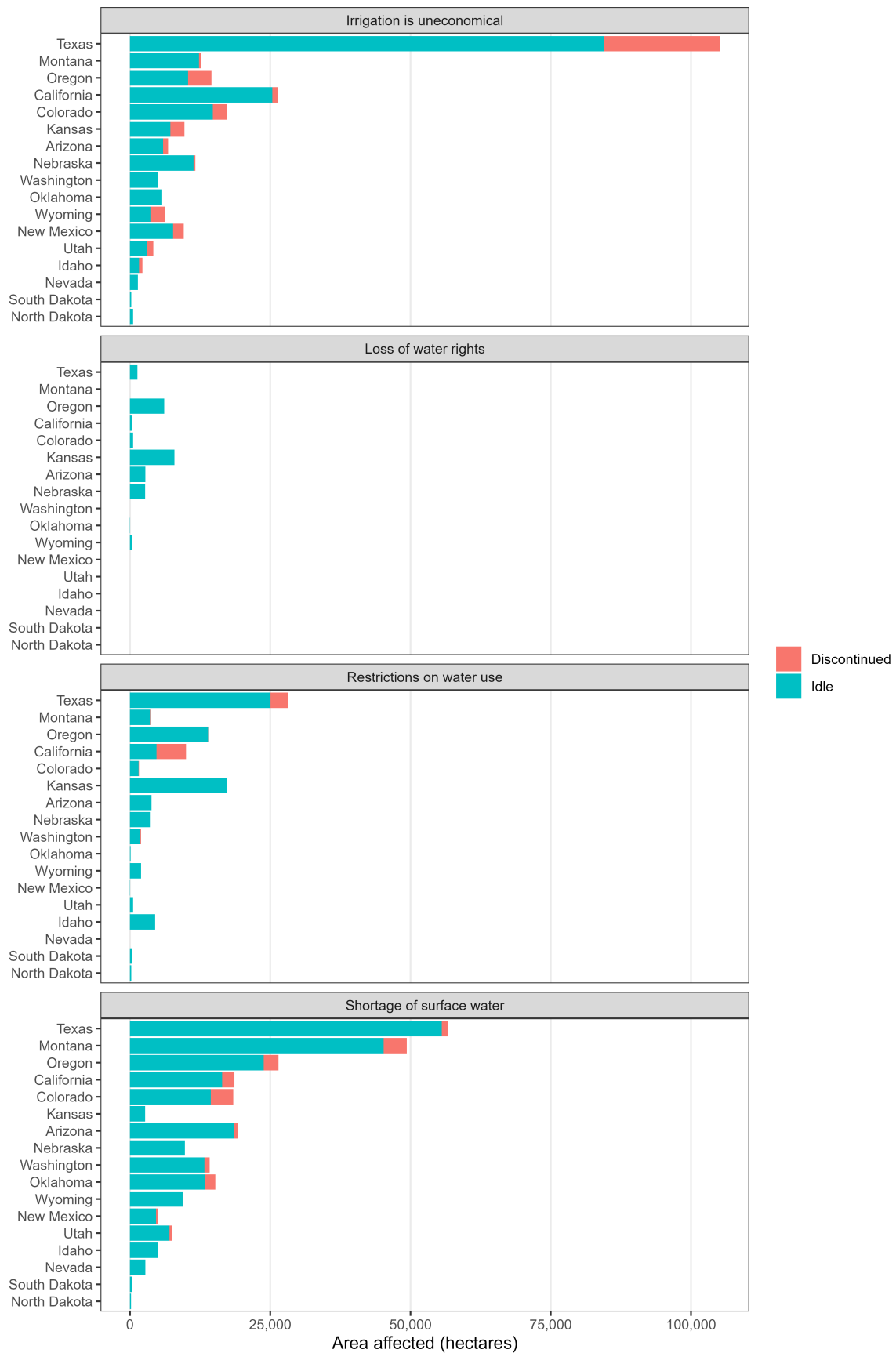


Fig. C3: Reported area of previously irrigated land (2018) that is currently idle or discontinued across the WUS, by primary reason for irrigation discontinuation, based on the 2023 USDA Census of Agriculture Irrigation and Water Management Survey.

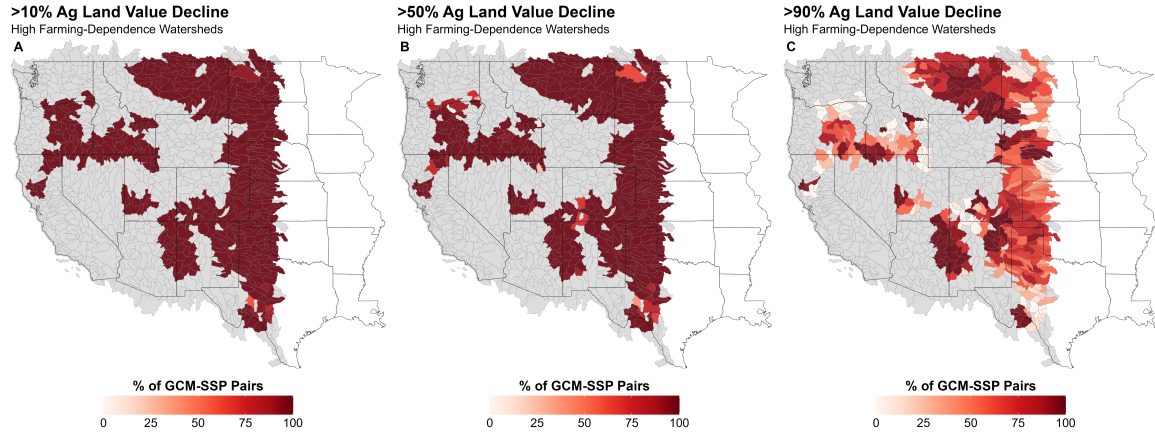


Fig. C4: Consistency of projected agricultural land value declines across climate scenarios in high farming-dependence watersheds. Panels show the percentage of GCM-SSP pairs projecting land value declines exceeding (A) 10%, (B) 50%, and (C) 90% relative to 2008–2023 averages. High farming-dependence watersheds are identified by intersection with USDA ERS farming-dependent counties [65]. Projections are derived from VIC-based hydroclimatic inputs. Darker shading indicates greater scenario agreement, with watersheds where a high percentage of scenarios exceed a given threshold representing more robust signals of loss. Grey watersheds indicate areas outside the farming-dependence classification.

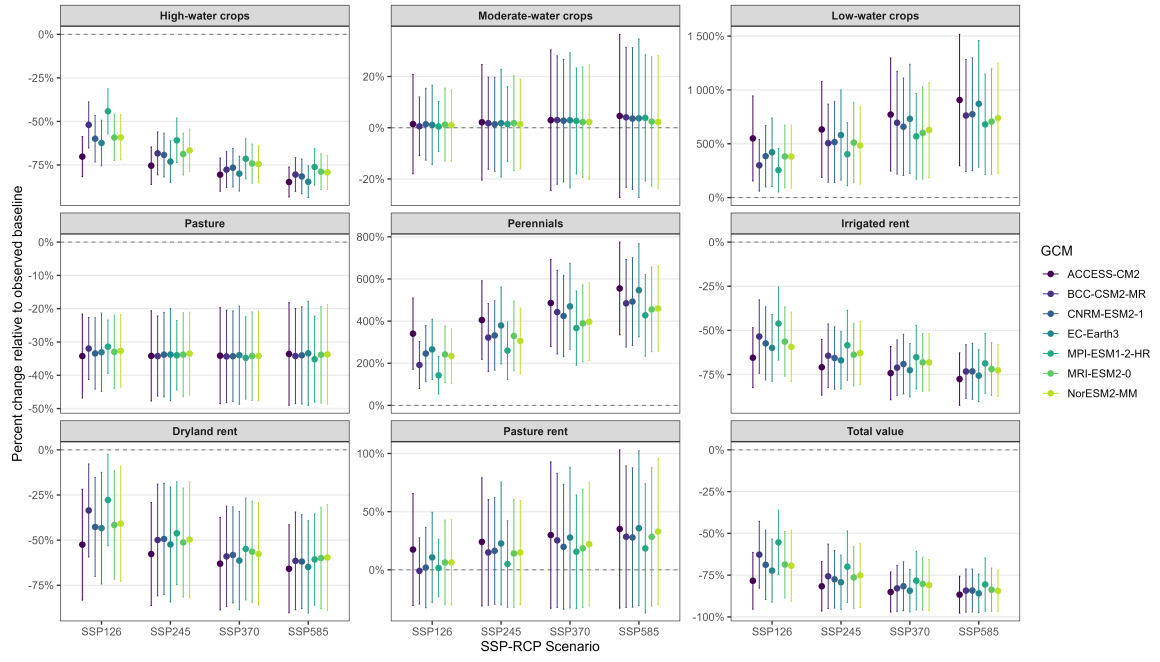


Fig. C5: Projected impacts (% changes) on agricultural land use, rental rates, and total agricultural exchange value across the western United States.

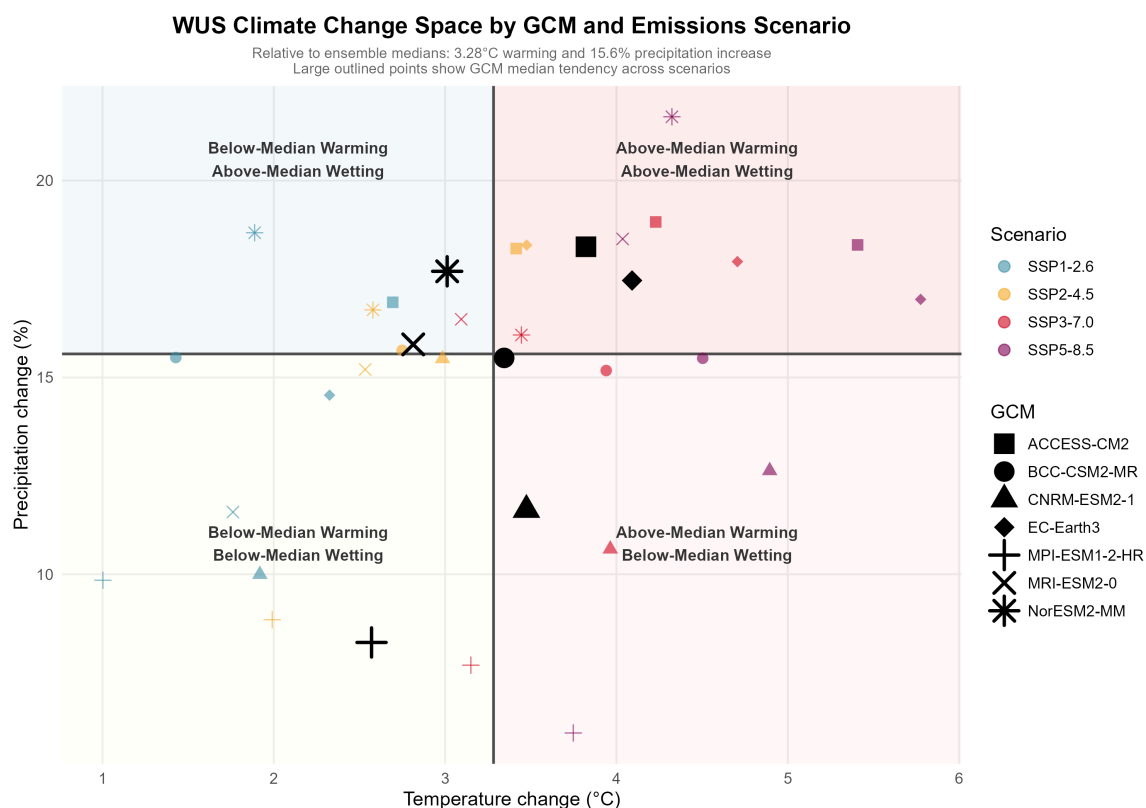


Fig. C6: Projected changes in mean annual temperature and precipitation (2060–2099 relative to 1980–2019) across seven CMIP6 GCMs and four SSP scenarios. Each point represents one GCM–SSP pair (28 total), positioned relative to ensemble median warming (3.28°C) and precipitation increase (15.6%) shown by black crosshairs. Large outlined symbols show GCM median tendencies across all SSPs. Quadrants indicate above- and below-median warming and wetting conditions. GCMs span a range from below-median warming with below-median wetting (CNRM-ESM2-1, BCC-CSM2-MR) to above-median warming with above-median wetting (NorESM2-MM, MRI-ESM2-0, ACCESS-CM2, EC-Earth3). This diversity of climate futures enables assessment of agricultural impact robustness across plausible end-of-century conditions.

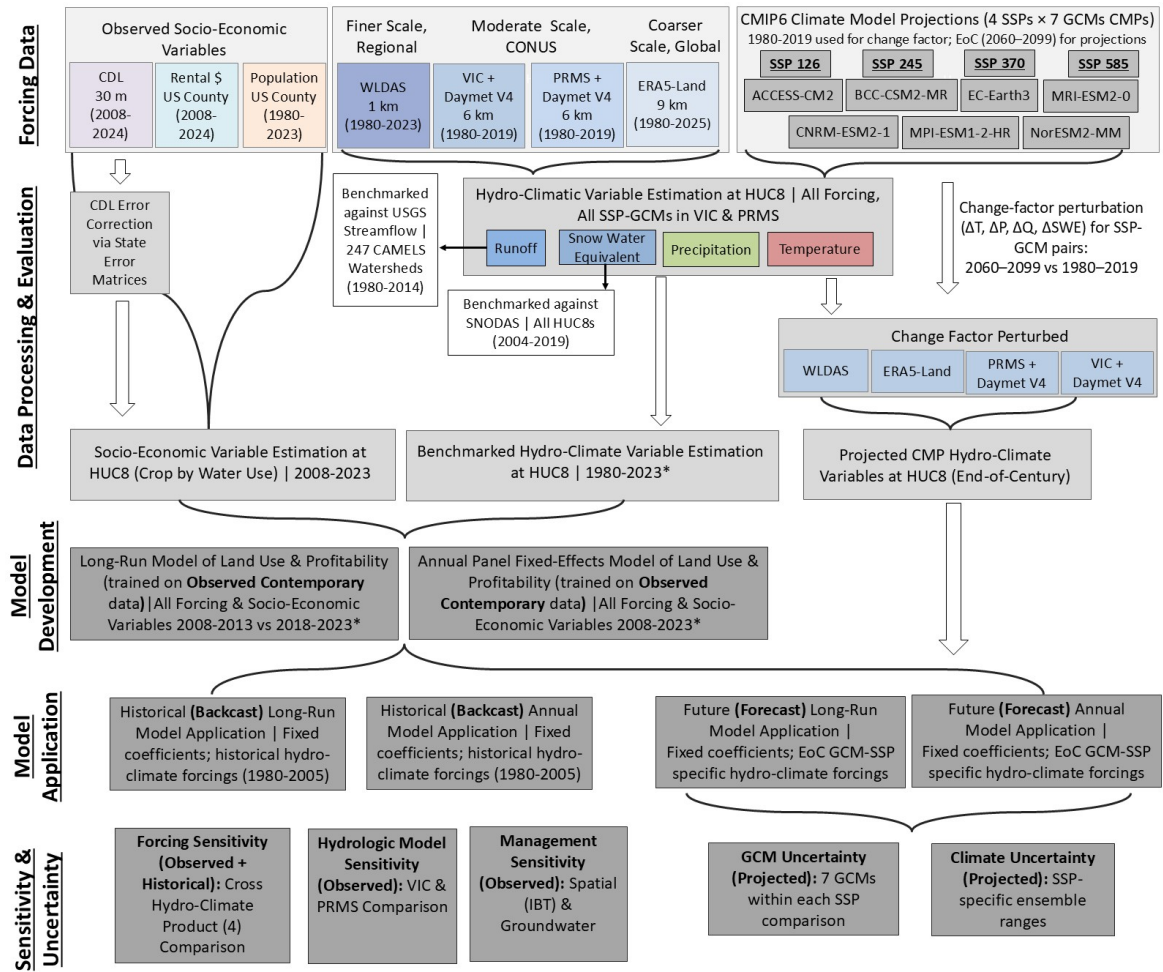


Fig. C7: The workflow links observed socio-economic data, multi-scale hydro-climate forcing products, and CMIP6 climate model projections to estimate land-use and rental-rate responses at the HUC8 scale. Observed socio-economic variables (cropland by water use, rental rates, and population) are harmonized with hydro-climatic forcings spanning regional to global scales (WLDAS, VIC-Daymet, PRMS-Daymet, ERA5-Land) and benchmarked against USGS streamflow (CAMELS) and SNODAS snow water equivalent. Annual hydro-climatic variables (runoff, snow water equivalent, precipitation, and temperature) are estimated for all HUC8 watersheds under observed conditions and used to train both long-run and annual fixed-effects panel models of land use and profitability. End-of-century projections are generated using a change-factor approach applied to CMIP6 GCM-SSP combinations (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5), producing projected hydro-climate forcings for 2060–2099 relative to a 1980–2019 baseline. Historical backcasting and future forecasting applications enable decomposition of forcing, hydrologic model, management, GCM, and scenario uncertainty.

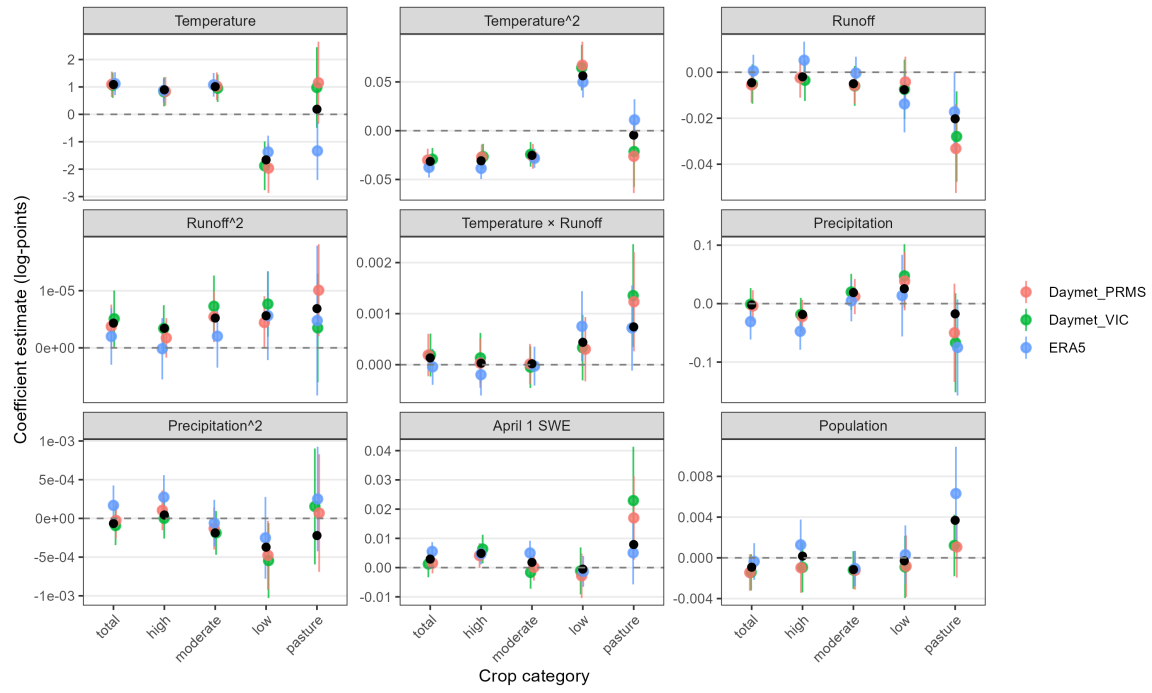


Fig. C8: Coefficient stability across alternative climate and hydrologic input datasets for the annual land-use models. Panels correspond to climate, hydrologic, and population covariates. Points show estimated coefficients and 95% confidence intervals from models trained on ERA5-Land, Daymet-VIC, and Daymet-PRMS. Black points show the arithmetic mean of coefficient estimates.

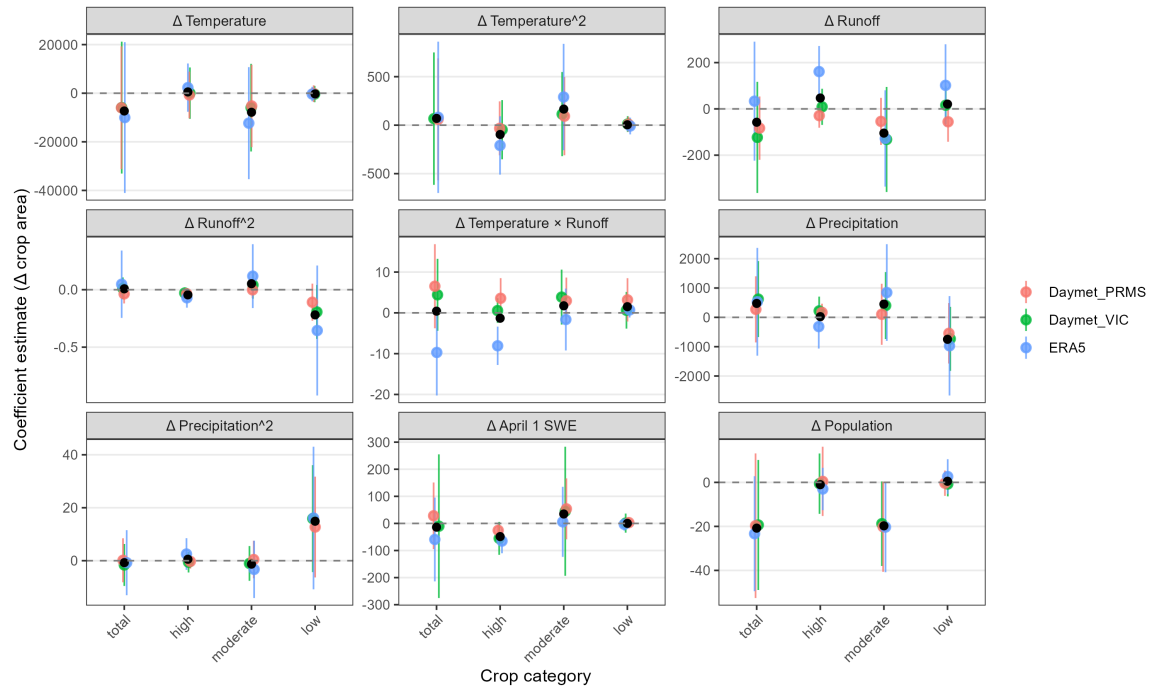


Fig. C9: Coefficient stability across alternative climate and hydrologic input datasets for the long-term land-use models. Panels correspond to climate, hydrologic, and population covariates. Points show estimated coefficients and 95% confidence intervals from models trained on ERA5-Land, Daymet-VIC, and Daymet-PRMS. Black points show the arithmetic mean of coefficient estimates.

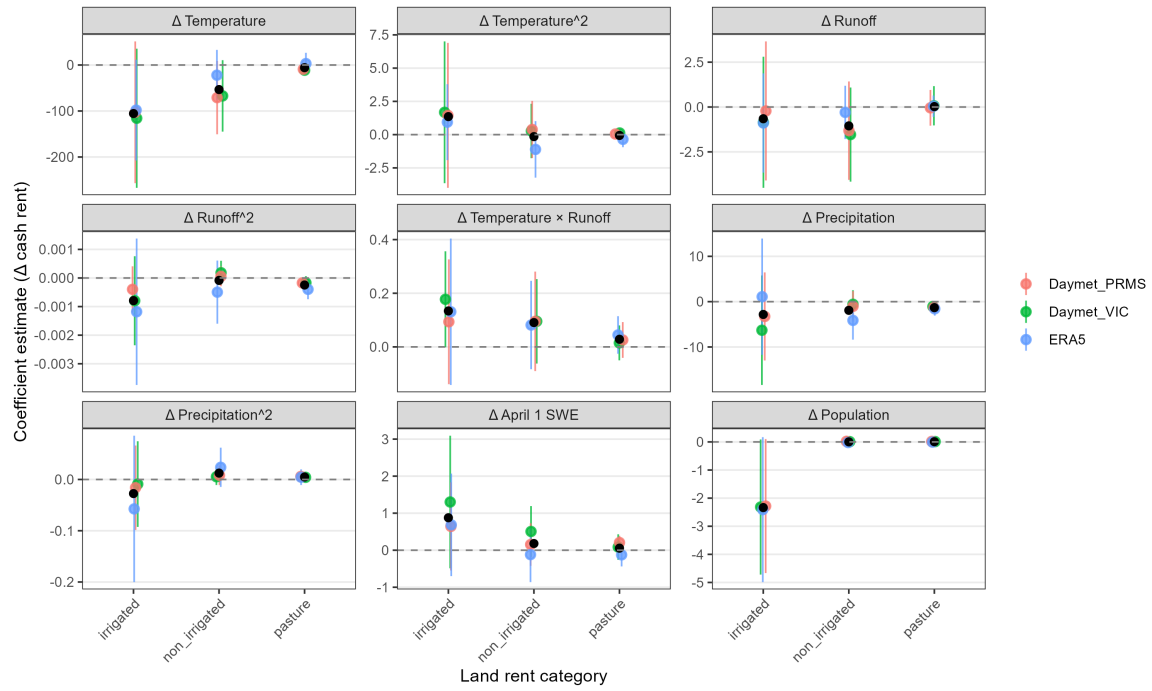


Fig. C10: Coefficient stability across alternative climate and hydrologic input datasets for the long-term cash rent models. Panels correspond to climate, hydrologic, and population covariates. Points show estimated coefficients and 95% confidence intervals from models trained on ERA5-Land, Daymet-VIC, and Daymet-PRMS. Black points show the arithmetic mean of coefficient estimates.

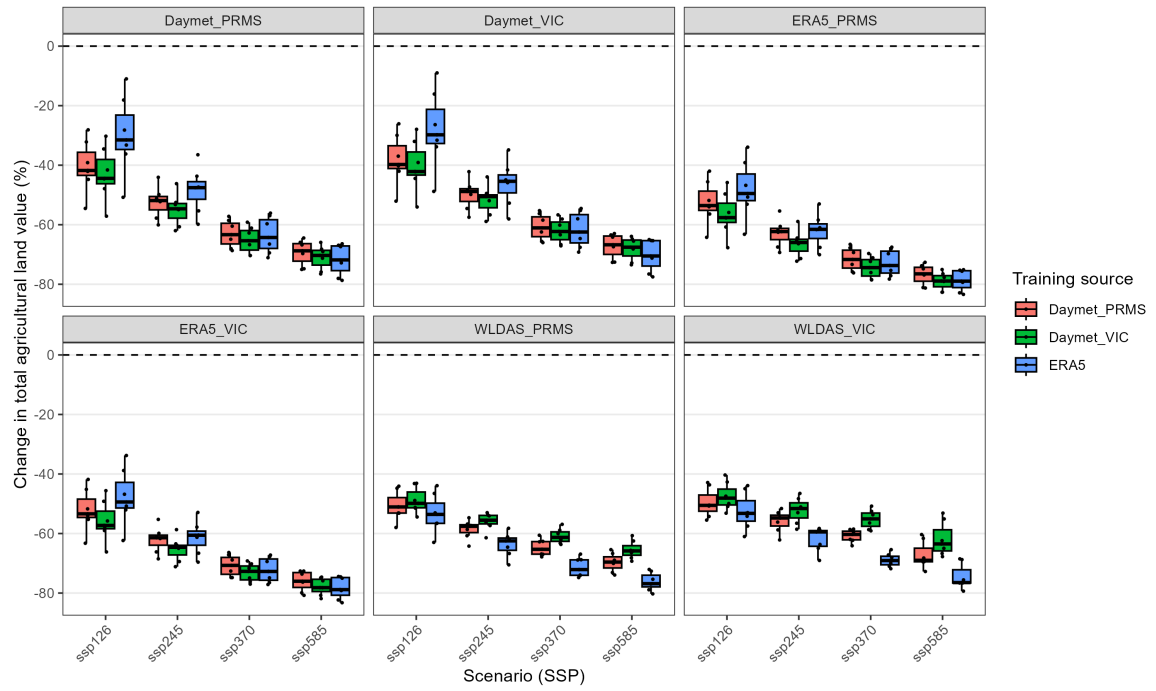


Fig. C11: Projected changes in total agricultural land value under alternative climate and hydrologic projections. Panels correspond to projected hydroclimate datasets, while colors indicate the historical product used to estimate model parameters. Box-plots show the range of outcomes across all GCMs for a given scenario. Across scenarios, variation in projected outcomes is dominated by differences in emissions pathways and projected hydroclimate realizations, with relatively limited sensitivity to the choice of historical training dataset.

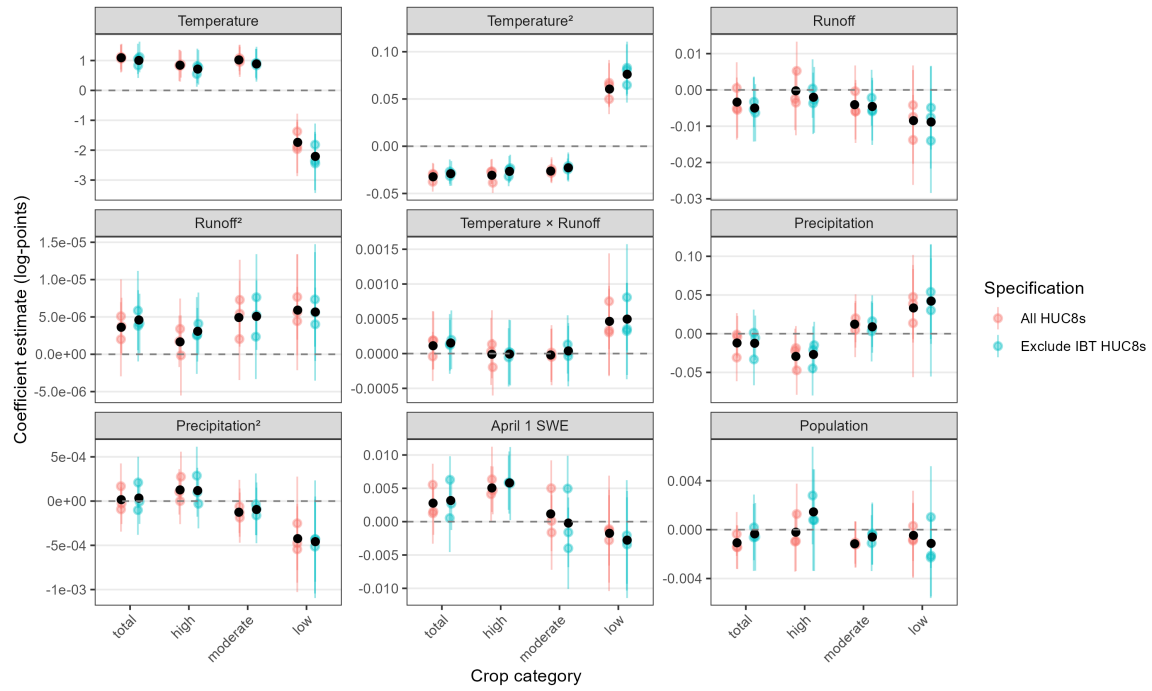


Fig. C12: Coefficient stability for the annual land-use models when **excluding watersheds with major interbasin water transfers**. Panels correspond to climate, hydrologic, and population covariates. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins with documented interbasin transfers. Black points show the arithmetic mean of coefficient estimates across all input datasets.

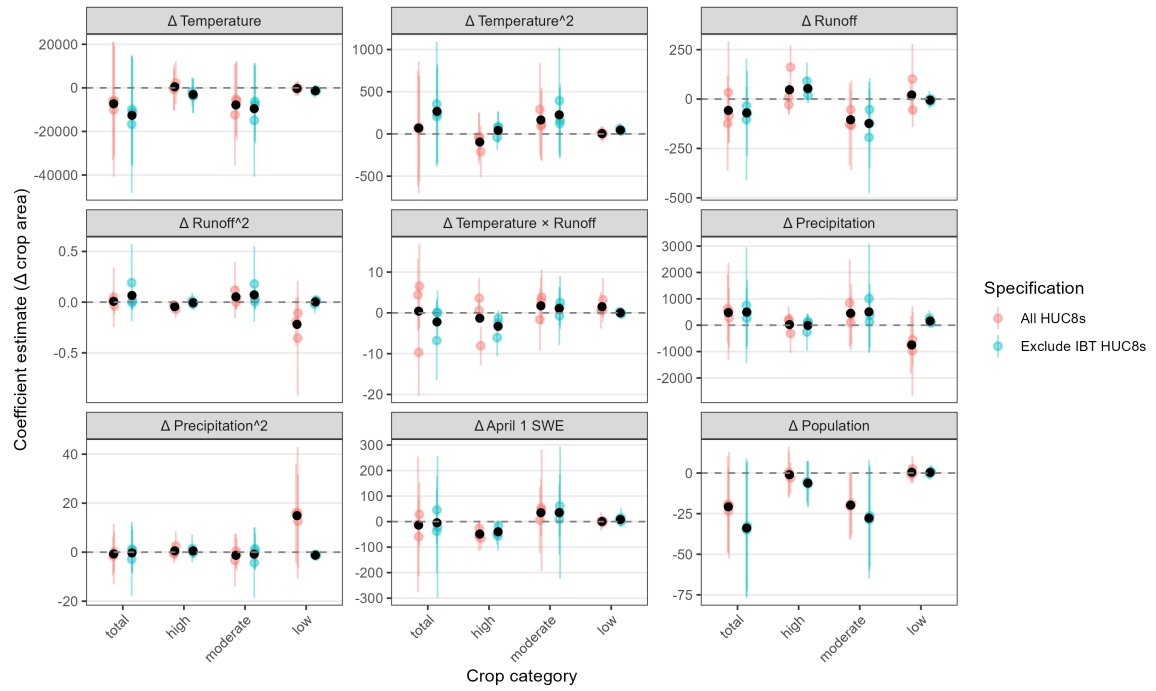


Fig. C13: Coefficient stability for the long-difference land-use models when **excluding watersheds with major interbasin water transfers**. Panels correspond to changes in climate, hydrologic, and population variables. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins with documented interbasin transfers. Black points show the arithmetic mean of coefficient estimates across all input datasets.

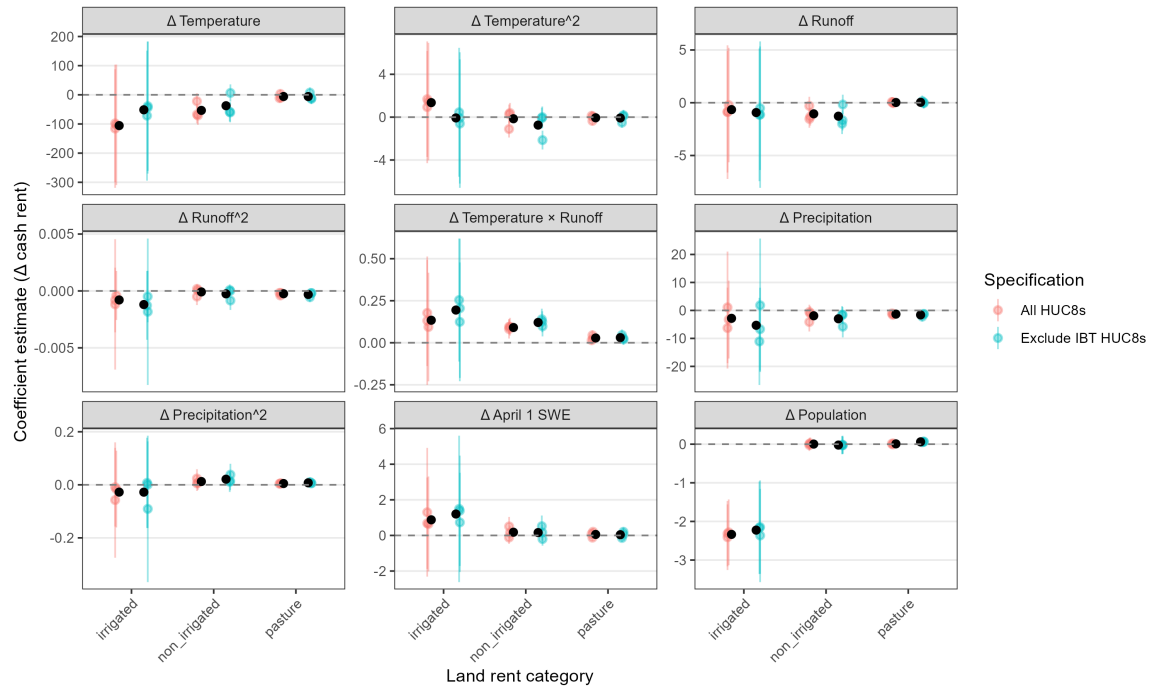


Fig. C14: Coefficient stability for the long-difference cash-rent models when **excluding watersheds with major interbasin water transfers**. Panels correspond to changes in climate, hydrologic, and population variables. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins with documented interbasin transfers. Black points show the arithmetic mean of coefficient estimates across all input datasets.

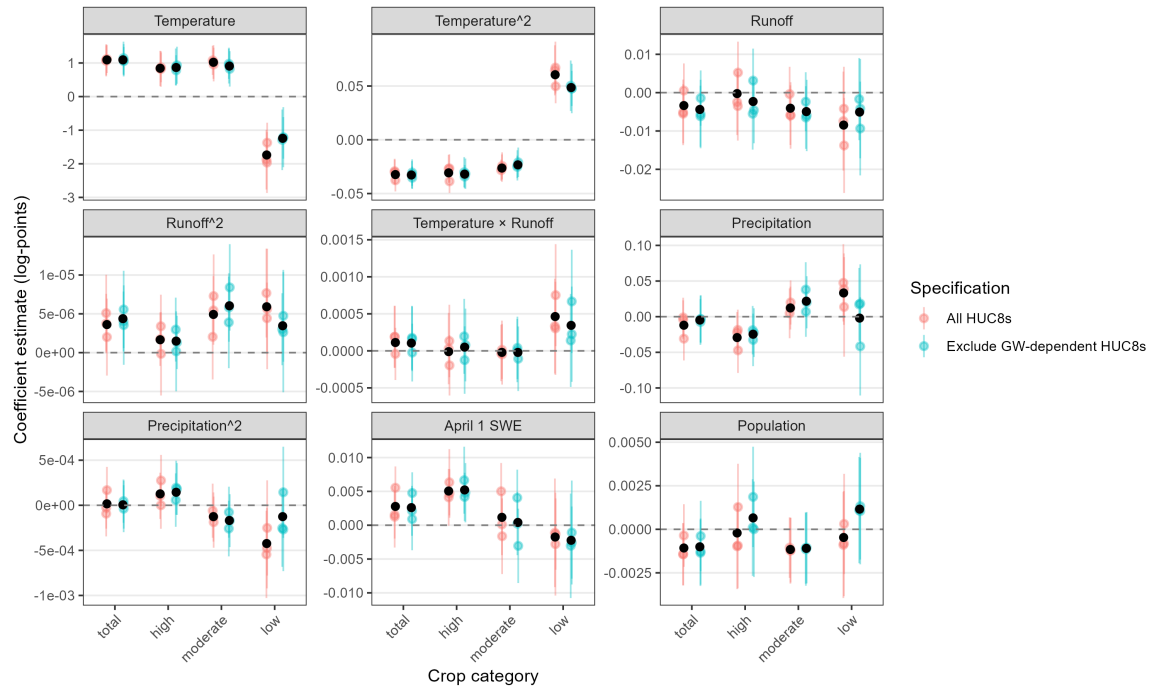


Fig. C15: Coefficient stability for the annual land-use models when **excluding groundwater-dependent watersheds**. Panels correspond to climate, hydrologic, and population covariates. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins where groundwater accounts for at least 75% of irrigation withdrawals. Black points show the arithmetic mean of coefficient estimates across all input datasets.

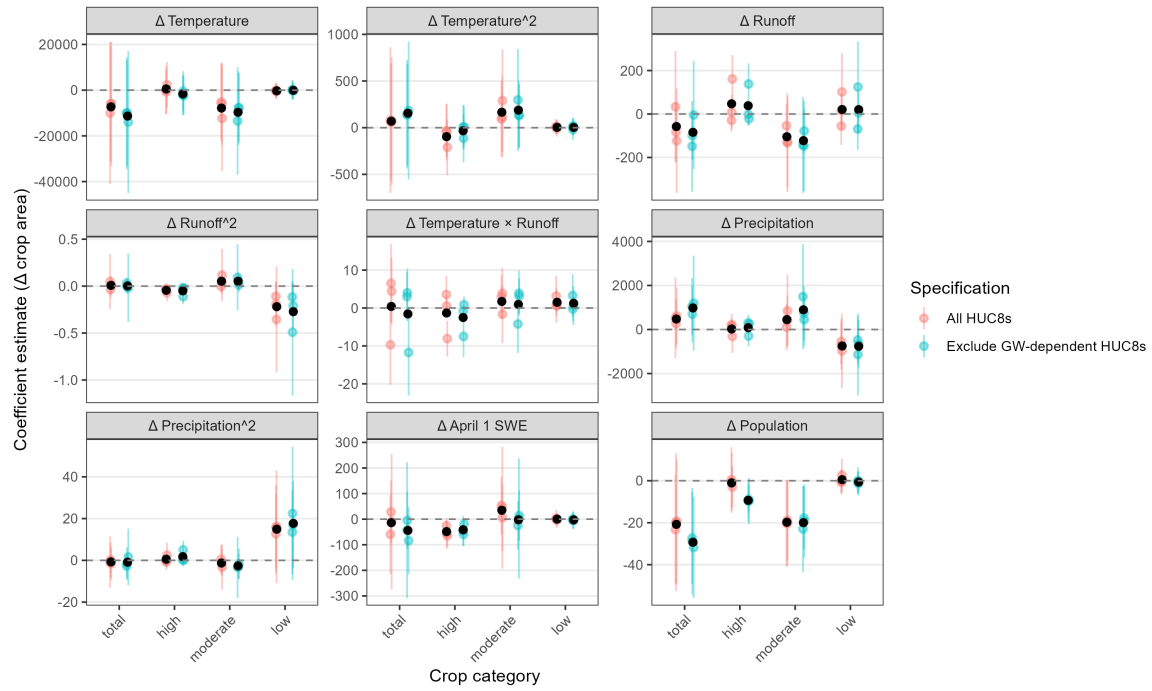


Fig. C16: Coefficient stability for the long-difference land-use models when **excluding groundwater-dependent watersheds**. Panels correspond to changes in climate, hydrologic, and population variables. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins where groundwater accounts for at least 75% of irrigation withdrawals. Black points show the arithmetic mean of coefficient estimates across all input datasets.

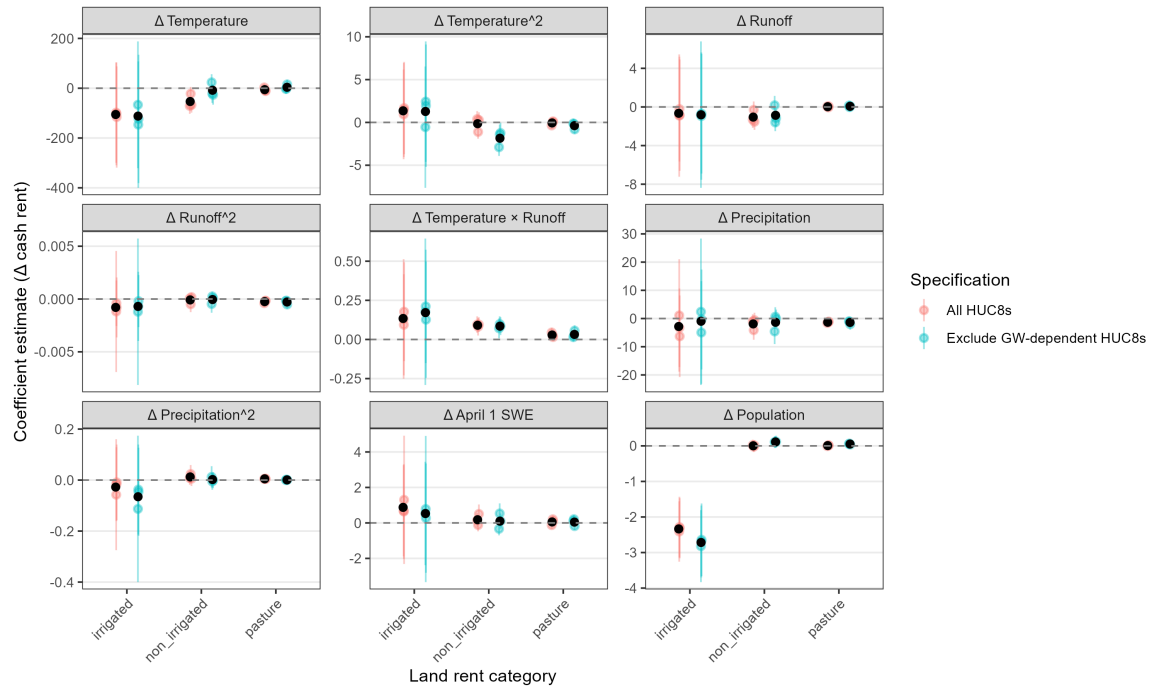


Fig. C17: Coefficient stability for the long-difference cash-rent models when **excluding groundwater-dependent watersheds**. Panels correspond to changes in climate, hydrologic, and population variables. Points show estimated coefficients and 95% confidence intervals from specifications estimated on the full sample of HUC8 watersheds and on the restricted sample excluding basins where groundwater accounts for at least 75% of irrigation withdrawals. Black points show the arithmetic mean of coefficient estimates across all input datasets.

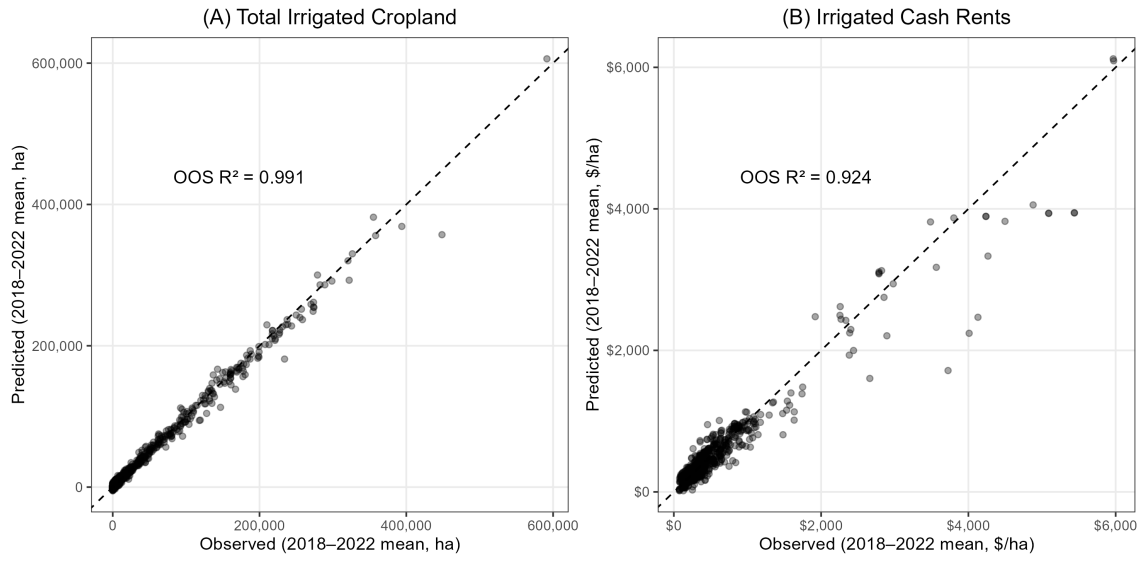


Fig. C18: Out-of-sample validation of long-difference models. Panel (A) compares observed and predicted levels of total irrigated cropland, and Panel (B) compares observed and predicted irrigated cash rents. In both panels, predictions are generated using long-difference models estimated on changes between 2008–2012 and 2013–2017, then applied out of sample to predict changes between 2013–2017 and 2018–2022. Each point represents a hydrologic unit; the dashed line denotes the 45-degree line corresponding to perfect prediction.

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