The Irrigation Problem: Climate, Agriculture, and Adaptation

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Abstract

The net effect of climate change on agricultural production in snowpack-dependent surface water (SDSW) systems is difficult to assess because of two countervailing factors. On one hand, SDSW systems tend to have a diverse crop mix, which provides a greater potential to adapt to a changing climate by switching crops. On the other, snowpack is expected to be significantly affected by warmer temperatures. A majority of the most influential papers on climate change impacts on agriculture focus on non-irrigated production in regions that produce only a few crops such as soy, corn, wheat, and cotton. Studies that have looked at irrigated production have not adequately delineated between ground and surface water dependent systems. We estimate the impact of projected climate on irrigated agriculture in the U.S. west of the 100 degree meridian, where average rainfall is 20 inches or less. We make two substantial contributions: (1) we use irrigated cash rents as the outcome, which reflect expectations about future profits but are not subject to the same fluctuations, (2) we use USGS estimates of water use for irrigation as in Mendelsohn and Dinar (2003), but focus exclusively on irrigated farms.

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Introduction

All agriculture depends on local climate conditions, but irrigated agriculture in the mountain and pacific regions of the United States[4] (the Mountain West) is unusual in that available water depends on snowpack that is generated in distant locations with different climates[5]. Reductions in snowpack shift the timing and reduce the supply of water. Yet surface water irrigation is also characterized by a diverse mix of often high value crops, affording producers an array of adaptation strategies that is not available to their dryland and groundwater-irrigating counterparts. In 2015, the Mountain West withdrew 57.7 million acre-feet of surface water for irrigation, 85 percent of the U.S. total. Surface water irrigation was the primary water source in every state in the Mountain West except California (US Geological Survey 2015). According to the 2017 Agricultural Census, farm output by farms with irrigation in the Mountain West was \$59.2 billion, almost a third of the \$193.5 billion of all U.S. agriculture output (USDA-NASS (2019)). Most research on the effects of climate on agriculture has excluded land west of the 100° meridian, focusing on rain-fed agriculture in regions that grow corn, soy, wheat, and cotton. But climate affects non-irrigated agriculture differently than irrigated agriculture (Schlenker, Hanemann, and Fisher 2005), especially in the West where water supply is largely dependent on snowpack. Although Schlenker, Hanemann, and Fisher (2007) study the relationship between water use, climate and yields in irrigation districutes in California, other studies have either not distinquished between irrigated and non-irrigated farms (Mendelsohn and Dinar 2003) or have focused on groundwater systems that specialize in a small number of grain crops [CITATION]. Because surface-water irrigated agriculture is also characterized by a Estimates that exclude surface-water irrigated agriculture may underestimate damages by not accounting for losses due to snowpack, while overestimating damages due to the negative effects of reductions in snowpack, while of warm-

[4]Defined by the USDA as Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.

[5]Groundwater irrigation draws primarily from aquifers, which recharge from precipitation that falls throughout the year. While aquifer recharge is affected by surface water flows and thus to some extent by snowpack, it is less directly related. We focus on surface water.

ing that result from reduced water supply uthe West capture at most two thirds of the effect of climate on agriculture.

In this paper we examine how climate affects surface-water irrigated agriculture in the West. Surface-water irrigation changes the relationship between climate and agriculture in at least two ways. First, irrigation provides a cooling effect that can reduce the negative impact of extreme temperatures. Increases in temperature that would otherwise reduce yields may not do so in irrigated areas. Second, water supply is largely a function of snowpack, which is expected to decrease in the West by XXX by XXX [CITATION]. We make three novel contributions. First, by estimating the impact of climate on irrigated and non-irrigated cash rents, we are able to distinquish differences in the response to climate. Most previous efforts have focused on yields, profits, or land values of both irrigated and non-irrigated farms, limiting to non-irrigated by focusing on United States east of the 100° meridian. Second, we account for water use and water availability through watershed-level snowpack, which is the primary determinant of water supply in the West. Finally, we examine the question of farm adaptation to climate in the irrigated West, an area that produces a wide variety of crops that allows for greater adaptation than eastern monoculture settings.

Climate impacts are often discussed in the context of a hill-shaped curve. An oft-depicted figure perhaps first seen in Mendelsohn, Nordhaus, and Shaw (1994) illustrates increasing outcomes (yields, profits, or land values) as temperature increases, with farmers employing adaptation strategies such as crop switching to maximize profits at different temperature levels. As temperatures pass a threshold, economic returns begin to decline as even hardier crops suffer from extreme heat and profitability declines. Figure 1 depicts this relationship in the West using growing degree days (GDD), an agronomic measure of temperature accumulation that strongly relates to yields (Schlenker and Roberts 2009). The mean irrigated and non-irrigated rent for each state is plotted against total growing season GDD. As GDD increases, irrigated cash rents also increase up to a point at which higher temperatures reduce profitability. Several states such as Idaho, Washington, and Oregon lie on the portion of the curve where increased temperatures increase the mean value of production, while higher temperatures in Arizona and California will decrease the mean value of production.

Previous studies have typically used yields (Schlenker and Roberts 2009; Burke and Emerick 2016), profits or sales (Burke and Emerick 2016; Deschênes and Greenstone 2007; Fisher et al. 2012), or land values (Mendelsohn, Nordhaus, and Shaw 1994; Mendelsohn and Dinar 2003) to estimate the effect of climate on economic returns to agriculture. Cash land rental rates have a number of advantages over these measures. First, while rents allow for the same profit-maximizing behavior that profits, sales, and land values capture, rents are reportedly separately for irrigated and non-irrigated land. As a result, rents allow for a precise estimate of the effect of climate on economic returns to *irrigated agriculture*, which the other ricardian outcomes cannot provide. Second, like land values, rents reflect long-term expectations about economic returns as determined by climate, whereas profits and sales reflect outcomes based on weather in a particular year. Moreover, profits and sales reflect other factors that affect the market for agricultural products, though these factors are attenuated by fixed effects. Rents are a better measure than land values because rents are the reported transaction value, while land values are reported estimates of the perceived value of land based on the current market[6]. Moreover, the rental market sees a considerably larger number of transactions. In 2014 the USDA conducted the Tenure, Ownership, and Transition of Agricultural Land (TOTAL) survey, estimating that rented farmland accounts for 39[7] percent of land in U.S. farms (rented cropland accounts for 54 percent of all cropland). Almost 70 percent of rented land is on a fixed-cash basis (as opposed to flexible cash or crop share). In contrast, only 2.3 percent of land in farms was expected to be sold on the market (as opposed to sale to a relative) over the five year period following the TOTAL survey. Most leases are ten years or less, suggesting that the rental market is substantially more thick.

In an early attempt to determine the effects of climate on agriculture, Mendelsohn, Nord-

[6]Specifically, the Census of Agriculture instructions state "Estimate the value of the land, houses, barns, andother buildings for each of the three listed categories if they were sold in the current market."

[7]39 percent of land in U.S. farms is rented, 31 percent is rented by non-operators (Bigelow, Borchers, and Hubbs 2016).

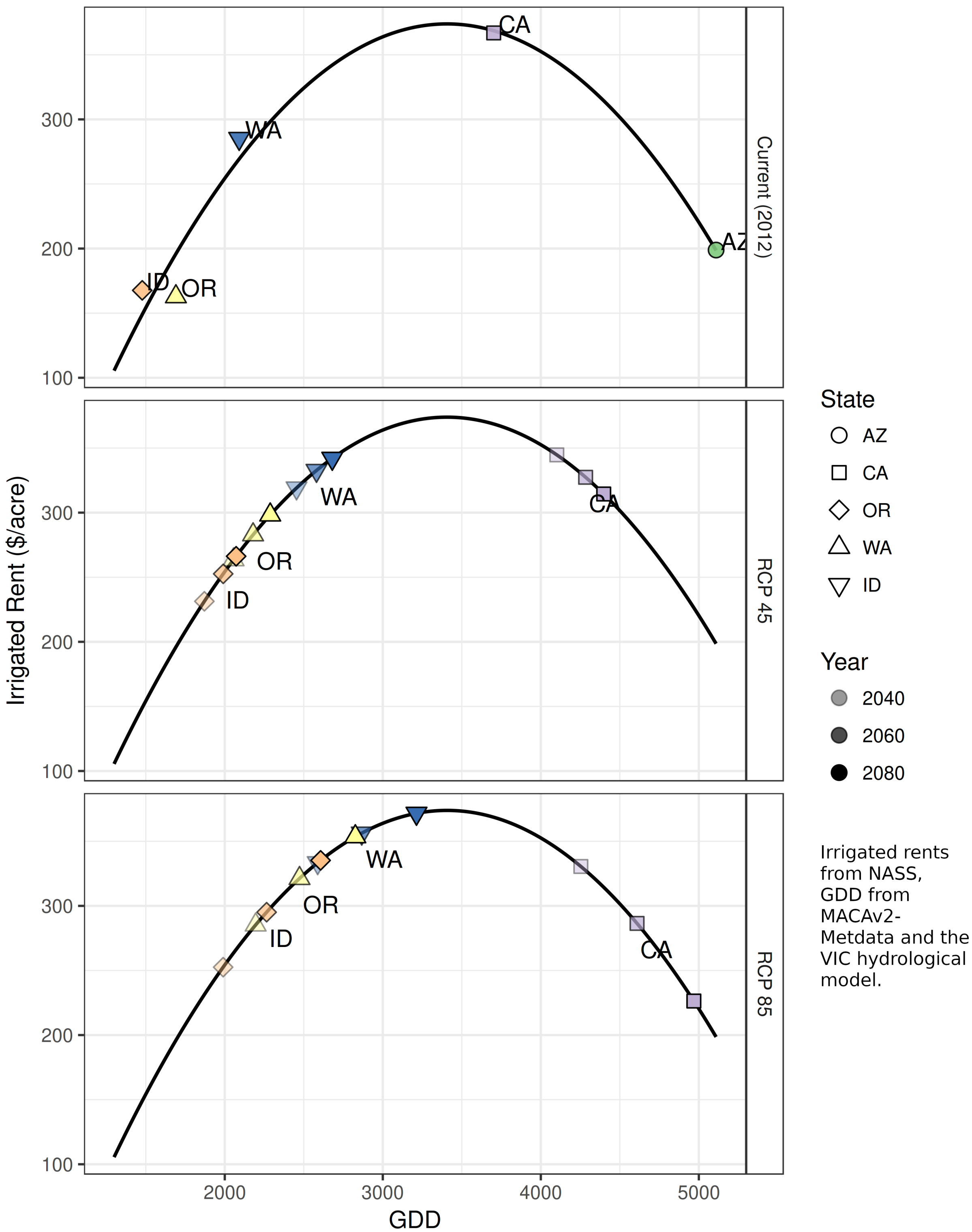

Figure 1: The quadratic relationship between temperature and irrigated cash rents. The first panel shows the relationship for historical climate centered on 2012. The second and third panels show projections for RCP4.5 and RCP 8.5 emissions scenarios.

haus, and Shaw (1994) use a reduced-form equation to investigate the relationship between monthly temperature and precipitation and farmland values for the entire U.S. Subsequent critiques pointed out three issues relevant to irrigation: (1) excluding water availability implicitly assumes climate has no effect on water available for irrigation (Darwin 1999a); (2) irrigation likely interacts with both temperature and precipitation, which may act as a substitute for precipitation and may also mitigate the negative effects of high temperatures (Schlenker, Hanemann, and Fisher 2005); and (3) water costs remain fixed (Schlenker, Hanemann, and Fisher 2005).

Mendelsohn and Dinar (2003) sought to account for the omitted effect of irrigation by including water use estimates from the United States Geological Service (USGS), but did not suggest a method for accounting for water availability based on future climate projections, and moreoever did not distinquish between irrigated and non-irrigated counties. Schlenker, Hanemann, and Fisher (2005) provide evidence that production in irrigated counties differs sufficiently differently from non-irrigated counties that they should be modeled separately. They also argue that the relationship between climate and irrigated agriculture should be based on irrigation districts, which account for a substantial number of irrigated acres in the West [DATA SOURCE]. Schlenker, Hanemann, and Fisher (2007) use farm-level data in California to estimate the effect of surface water availability on land values, where water availability is derived from irrigation district diversion records and depth to groundwater. However, they do not suggest a method of estimating future water availability.

We focus on the first issue of water availability and the second issue of potential interactions between irrigation, temperature, and precipitation. We also consider the question of adaptation by Burke and Emerick (2016). To address the first, we include watershed precipitation and snowpack, which is the supply source of surface water (and to some extent groundwater) for irrigation. Snowpack acts as storage, releasing water for irrigation as it melts in the spring. In particularly dry areas such as the southwest, snowpack can account for up to 75% of seasonal water supply (Hamlet et al. 2005; Elias et al. 2016). Snowpack is a function of temperature and precipitation; in warming areas it may both decrease in size and melt earlier than it has historically. As a result, irrigated agricultural production that depends on snowpack for water supply is affected not just by precipitation and temperature over the growing season, but also by precipitation and snowpack accumulated in winter months in the watershed.

We investigate the potential for irrigation to mitigate the negative effects of extreme temperatures by examining how watershed water availability affects the relationship between cash rents and temperature and precipitation. Producers may be able to use available water to cool plants during extreme temperatures, an effect we should see in the interaction between watershed snowpack and extreme temperature. Moreover, we should expect to find no such interaction for non-irrigated rents. Finally, precipitation cannot be used to cool during extreme temperatures, so should have no interaction either.

While water availability sets irrigated agriculture apart from non-irrigated agriculture, irrigation also provides increased flexibility in crop choice. Agriculture in the eastern U.S. is heavily concentrated in Corn, Soybeans, Cotton, and Wheat, and production is often limited to a choice between those crops. Studies that exclude the West capture that lack of flexibility, which serves to mitigate any negative impacts from a changing climate. Recently Burke and Emerick (2016) and Mérel and Gammans (2018) have investigated the extent to which producers adapt to a new climate, finding limited evidence for adaptation. But they exclude the western U.S., where irrigation provides more opportunities for adaptation. A benefit of focusing on cash rents is that this flexibility is captured in expectations about future profits.

The problem of irrigation

The role of irrigation has been difficult to reconcile in the context of the climate-agriculture relationship. In the West, water supply is determined by a combination of man-made reservoirs and mountain snowpack, both of which may be hundreds of miles from where the water

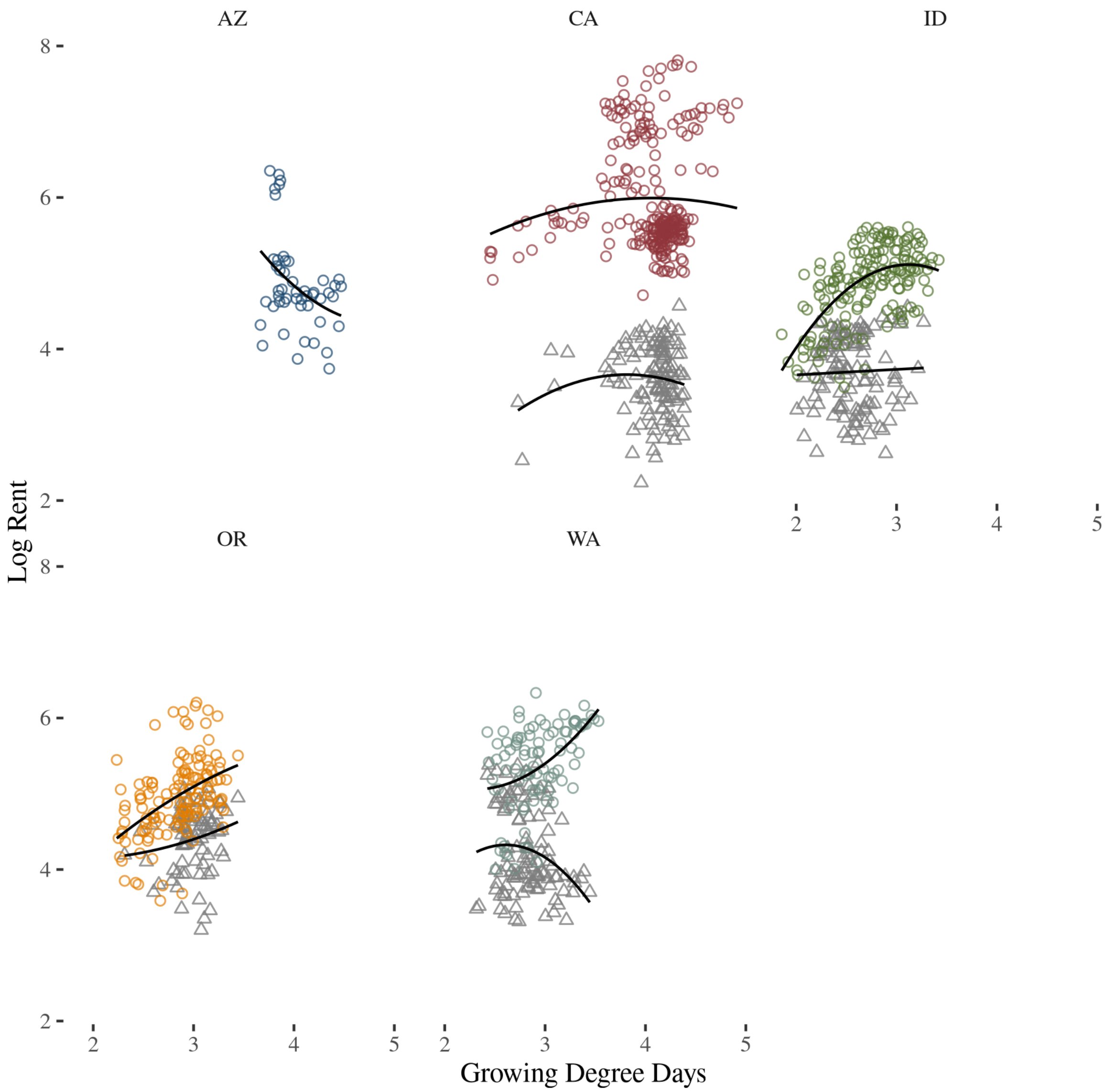

Figure 2: Temperature (growing degree days) affects irrigated and non-irrigated rents differently. In the arid West, the availability of water increases expected profits and reverses the relationship between temperature and rent. Irrigated rents are in color, non-irrigated in gray. Fits are quadratic in growing degree days. Data are pooled for years from 2008 to 2014.

is actually used. Indeed, Arizona receives 2.8 million acre-feet per year for consumptive use from the Colorado River, which is expected to decline by at least 10 percent by 2100 (Lahmers and Eden 2018). The water available in the Colorado River depeds on how climate affects snowpack in Colorado and Utah, not counties in Arizona.

Mendelsohn, Nordhaus, and Shaw (1994) estimated the relationship between climate and agriclulture for all U.S. agricultural counties without accounting for irrigation supply explicitly, arguing in a reply to comments (Mendelsohn and Nordhaus 1996) that water supply was dependent on climatic conditions and so was implicitly captured by changing county-level climate measures. Yet because the supply of water for irrigation originates outside of the county, it is dependent on climate conditions elsewhere. The omission of climate in those source regions leads to biased estimates on temperature and precipitation coefficients (Darwin 1999a, 1999b).

There is data from the USGS on water use (US Geological Survey 2015), though it is derived from a combination of theoretical crop requirements and satellite images rather than observation. Mendelsohn and Dinar (2003) extend the analysis in MNS by including water use as a covariate, measuring how variation in water use between counties affects farm values, but explicitly assuming that water supplies are perfectly inelastic, and thus eliminating what is perhaps the issue of most concern to irrigated agriculture in the West: the effect of climate on water supply.

An additional difficulty is accounting for the allocation of water supplies. Surface water supplies follow geographic rather than administrative boundaries. The precipitation in a watershed determines the water stored in snowpack and water available to refill reservoirs. In the West, that water is then allocated according to the priority date of rights. When there is a shortage of water, farmers with a more junior right (a later priority date) are restricted first. As a result counties whose farmers on average have a more junior right face a higher risk of not having water in a drought year. This difference in risk ensures that counties are heterogeneous how watershed-level water supplies affect them. A county with more junior rights in the same basin with the same total water supply faces a higher risk of curtailment[8] than a neighboring county with more senior rights.

Data

We focus on counties in the West with cash rent data available from the USDA-NASS Cash Rents Survey (National Agricultural Statistics Service, n.d.). The Cash Rents Survey was conducted annually from 2008 to 2014 and bi-annually beginning in 2016 and reports the mean county rent for irrigated, non-irrigated, and pasture land for all counties with at least 20,000 acres of cropland and pasture. Land rented on a non-cash basis is not included. For each county, we also use data from the Census of Agriculture [AgCensus] on acres, land rents, profits, net farm income, and land and building rent (available every five years from 1982 to 2017)[9]. County demographic information on population, housing units, and income are from the U.S. Census[10]. United States Census Bureau (2017) provides static county characteristics on land area, water area, and the latitude and longitude of the county centroid.

Historical and projected climate measures consist of daily measures of minimum and maximum temperature and total precipitation on a 6-kilometer resolution latitude-longitude gridded data set. Historical climate data is from the VIC model [CITATION] and covers the period from 1979-2016 over 102,268 grid points that includes all points in counties with centroids west of the 100° meridian. Projected climate is from the MACAv2-METDATA (Abatzoglou 2011) and covers 30,140 grid points in Washington, Idaho, Oregon, and California from 2016-2099[11]. To capture the uncertainty in projected climate, we use six climate models[12] that encompass a range of assumptions. Each model projects climate data for four

[8] Curtailment is the process by which the right to use water is temporarily reduced or suspended so that more senior rights holders are ensured their water.

[9] NASS data are retrieved from Quick Stats using the `R` package `rnassqs` (Potter 2019).

[10] Retrieved using the `R` package `censusapi` (Recht 2017).

[11] The MACAv2-METDATA are derived from global climate model (GCM) data from the Coupled Model Intercomparison Project 5 (CMIP5, Taylor, Stouffer, and Meehl 2012) and statistically downscaled using a modification of the Multivariate Adaptive Constructed Analogues (MACA, Abatzoglou and Brown 2012) method with the METDATA (Abatzoglou 2011) observational data set as training data.

[12] The climate models are: bcc-csm1-1, BNU-ESM, CanESM2, CNRM-CM5, GFDL-ESM2G, and GFDL-

representative concentration pathways (RCPs), each of which reflect atmospheric carbon concentration levels relative to pre-industrial levels. The RCPs are 2.6, 4.5, 6.0, and 8.5, of which we include the 4.5 and 8.5 scenarios[13].

In our model, county-level agricultural outcomes are a function of climate as measured by county temperature and precipitation over the growing season as well as watershed-level precipitation from December to August and snow-water equivalents (SWE) from December to April. For each grid point and year in our climate data, we calculate the length of the growing season as the number of days from the last day with a temperature below 0°C in the spring to the first day below 0°C in the fall. Precipitation is the total accumulated precipitation over the growing season. SWE is estimated as a function of temperature and precipitation following [CITATION], where sufficiently cold temperatures convert precipitation to snow.

Previous studies have accounted for temperature in a number of ways. Mendelsohn, Nordhaus, and Shaw (1994) used monthly averages of temperature, but recent studies have focused on the agronomic measure of degree days, a measure of temperature accumulation in which only temperatures above and below a threshold are counted (Schlenker, Hanemann, and Fisher 2007). Growing degree days (GDD) are a frequently used specific case of degree days and are measured as the temperature-weighted sum of time spent between 8°C and 32°C over the growing season. Heating degree days (HDD) are similarly defined for temperatures over 34°C. Following the model suggested by Schlenker, Hanemann, and Fisher (2006), we calculate both GDD and HDD, as well as the degree days for each temperature increment as in Schlenker and Roberts (2009).

We use the Gridded Soil Survey Geographic (gSSURGO) Database (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture 2018) to create county-level soil attributes. gSSURGO is the most detailed soil geographic data available and contains classifications for the suitability of irrigated and non-irrigated agriculture.

ESM2M.

[13]We selected 4.5 and 8.5 for brevity's sake and also because we are considered to be beyond the 2.6 scenario.

We spatially merge the soil data to the climate latitude/longitude grid, obtaining measures of moisture capacity, permeability, salinity, slope length, wetlands, flood fraction, and fraction clay and sand.

To create county-level climate and soil variables, we calculate the mean of each variable over grid points for which at least 1% of land within 3km is classified as agricultural. As a reuslt county-level measures of growing season, GDD, and precipitation capture the climate relevant to agricultural portions of the county rather than urban or mountainous areas. For watersheds, the entire basin precipitation and SWE that determine total water available so we average over all grid points in each watershed. For counties that lie within multiple watersheds, we calculate the average of watershed variables weighted by the area of each watershed within the county.

The resulting data set consists of county-level climate variables from 1948 to 2016 and projected 30-year climate normals for 2040 (2025-2055), 2060 (2045-2075), and 2080 (2065-2095) as well as agricultural variables for every five years from 1982 to 2017 and yearly measures of irrigated and non-irrigated rents and demographic variables from 2008-2017. Soil variables are time-invariant. In our main analysis there are 142 counties with irrigated land rents and 118 counties with non-irrigated land rents.

Irrigated and non-irrigated rents, profits, and land values

County-level agricultural outcomes used in previous studies do not differentiate between irrigated and non-irrigated farmland. As a result studies have relied on a combination of strategies for distinguishing between irrigated and non-irrigated counties. The prevalent strategy has been to omit the region of the U.S. west of the 100° meridian entirely and focus on dryland agriculture [Burke and Emerick (2016); CITATIONS]. Alternatively, Segerson and Dixon (1999) suggest defining an irrigated county as one in which 10 percent of total agreage is irrigated. Schlenker, Hanemann, and Fisher (2005) vary that value in their analysis, selecting and comparing models with irrigated and non-irrigated counties to test whether

Table 1: Data Summary

Variable	Mean	SD	Min	Max	Hist
DDay Mod	2.04	0.77	1.06	4.44	
Housing Density	0.44	0.1	0.29	1.01	
ln Irr Rent	5.28	0.77	3.46	7.7	
Pop Density	219.14	507.85	0.52	3884.06	
Precip	28.01	22.21	3.12	117.49	
Soil Flood Prone	0.25	0.25	0	1	
Soil Frac Clay	0.19	0.22	0	1	
Soil Frac Sand	0.032	0.074	0	0.61	
Soil K Factor	0.33	0.07	0	0.5	
Soil Moisture	0.17	0.03	0.088	0.27	
Soil Permeability	1.99	1.33	-0.24	9.53	
Soil Salinity	0.031	0.075	0	0.64	
Soil Slope Length	492.87	333.46	0	1631.17	
Soil Wetland	0.039	0.042	5e-05	0.27	
sqrt DDay High	0.12	0.12	0.0031	0.59	
SWE	20.49	8.7	3.9	27.92	
Urban	0.13	0.34	0	1	
Water Use	3	1.83	0.61	16.33	
Watershed Precip	59.63	14.18	24.26	70.91	

the difference in the response to climate between irrigated and non-irrigated agriculture is significant. Our analysis, but focusing on irrigated and non-irrigated county cash rents, is the first analysis we are aware of that can differentiate without approximating with composite measures of agricultural outcomes.

Irrigated and non-irrigated (and pasture) cash rents per acre were introduced as a question on the USDA's June agricultural land survey in 2008 and are reported every year through 2017 with the exception of 2015. Total cash rent, revenues, farm value, expenses, and net farm income reported as part of the USDA Census of Agriculture taken every five years on years that end in a 2 or a 7, are reported as totals rather than per acre[14], and do not distinquish between irrigated and non-irrigated farms or farmland. While a number of papers have made use of these latter measures (Mendelsohn, Nordhaus, and Shaw 1994; Mendelsohn and Dinar 2003; Schlenker, Hanemann, and Fisher 2005; Deschênes and Greenstone 2007; Fisher et al. 2012), the inability to distinguish between irrigated and non-irrigated land has made understanding the relationship between climate and irrigated agriculture difficult, though it is clear that that relationship is different that of non-irrigated agriculture (Schlenker, Hanemann, and Fisher 2005).

If census outcomes for all farms in a county serve as proxies for effects on irrigated farms, we should expect strong correlation between them to increase as the percentage of agricultural land in a county that is irrigated increases. In Figure 3 we fit a quadratic curve to the correlation between log census outcomes and log irrigated cash rents for four commonly used outcomes: farm values, net farm income, profits, and rental value of land and buildings. At low levels of irrigation, correlation is low, but improves substantially for all measures except profits. Census outcomes are most similar to irrigated cash rents when the percent of agricultural acres that are harvested and irrigated approaches 70 percent. As a result, researchers trying to capture the relationship between irrigated outcomes and explanatory variables are faced with a tradeoff between better approximating the true outcome as mea-

[14]With the exception of land values for which both total and per acre values are reported.

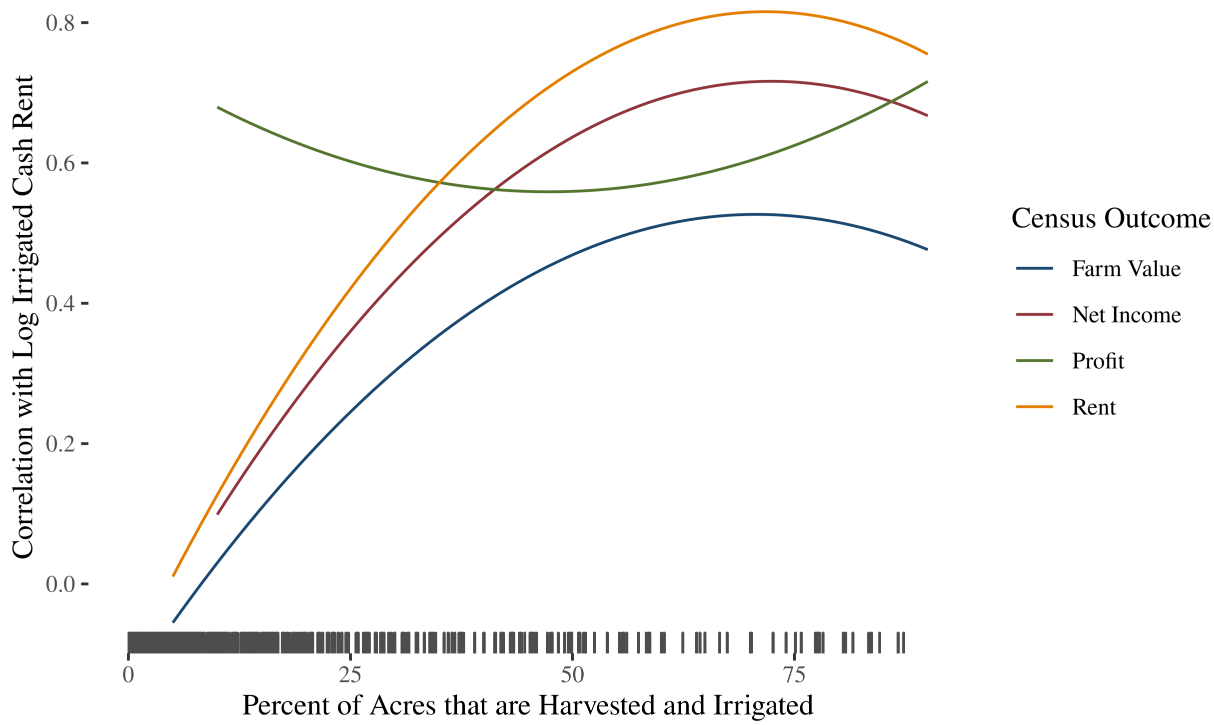

Figure 3: Correlation between census outcomes and irrigated cash rents as the percent of irrigated harvested crop acres. Trends are a quadratic fit to the empirical distribution. Outcomes and acres are from the 2012 Census of Agriculture. Irrigated cash rents are from the 2012 Cash Rent Survey. The rug displays the number of observations.

sured by irrigated cash rents and the loss of information due to excluding counties with lower rates of irrigation. This is particularly true since irrigation only comprises a small fraction of total acres in the majority of counties with a reported irrigated cash rent.

Climate specifications in yields and ricardian outcomes

Although quadratic specifications of climate variables are

Specifications matter. Quadratic specifications have been used for most of the ricardian approaches based on land values or profits [Mendelsohn, Nordhaus, and Shaw (1994); Mendelsohn and Dinar (2003); SchlenkerETAL2005], and capture the general shape of the response while providing for nonlinearity. Yet the quadratic specification seems insufficiently flexible in the presence of threshold effects that result in sharp decline in yields (Schlenker, Hanemann, and Fisher 2006; Schlenker and Roberts 2009).

Cooper, Nam tran, and Wallander (2016) a flexible fourier transform

Roberts and Schlenker (2011) Berry, Roberts, and Schlenker (2014)

Rents and temperature

An important aspect of studying the relationship between climate and agriculture has been determining how best to specify temperature. Early studies used average monthly temperature (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005), but more recent efforts have used the concept of degree days. Degree days are the time spent during the growing season integrated over temperature, such that

$$\text{dday} = \int_{t_0}^{t_{max}} g(t)f(t),$$

where t is temperature, $f(t)$ is the time-distribution of temperature during a growing season, and $g(t)$ is a function of temperature. The "growing degree day" (gdd), a common agronomic measure, is a special case in which $g(t) = t \forall t \in [8, 32]$ and zero otherwise. Degree days are typically modeled piecewise, with a squared term, or both. Schlenker and Roberts (2009) use a piecewise formulation to estimate the degree day response of corn, soy, and cottton yields, finding strong nonlinearities above thresholds that vary from 29^∘C to 32^∘C. However, farmers may mitigate any negative temperature effects by switching to other crops or making investments in cooling infrastructure. Irrigation increases the range of strategies that farmers have, both by providing a cooling effect and by increasing the range of crops that can be grown.

We repeat Schlenker and Roberts's (2009) analysis with respect to rents and census outcomes in the context of irrigation. [RESULTS TO BE DISCUSSED HERE.]

Rents, snowpack, and water supply

[DISCUSSION AND ANALYSIS TO BE ADDED]

Empirical Approach

A farmer's willingness to pay to rent land is the sum of discounted expected future profits, which are a function of location-specific characteristics such as weather, water availbility, and soil. Some of these vary in time, such that the profit in county i and year t is approximated by

$$\pi_{it} = \beta X_{it} + \theta_i + \nu_{it},$$

where θ_i is the location-specific fixed effect and X_{it} is a vector of time-varying characteristics. This is the approach used in more recent literature (Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Fisher et al. 2012; Burke and Emerick 2016).

However, rents are the sum of discounted expected future profits, so they depend on expectations about time-varying characteristics rather than realizations in a particular year. As a result a fixed-effects model would capture the response that rents have to annual variation in weather, but would not provide estimates of the effect of climate. We define the relationship between weather and climate as in Mérel and Gammans (2018) and Burke and Emerick (2016), where weather w_{it} in a given location and time is a random variable centered on climate μ_i such that $\mathbb{E}\left[w_{it}|\mu_i\right] = \mu_i$ and the sample analogue of μ_i is $\bar{X}_i$, the average of weather over time. We hypothesize that rents reflect average weather and other time-varying characterisitics at a location, but not fluctuations from year to year, such that

$$y_{it} = \beta \bar{X}_i + \theta_i + \nu_{it}.$$

The difficult is in defining θ_i. In a cross-sectional analysis, we can set $\theta_i = \alpha_0 + \S_i$, where S_i with a set of characteristics that are relevant to rents, such as soil moisture and salinity. This is the approach taken by Mendelsohn, Nordhaus, and Shaw (1994), Mendelsohn and Dinar (2003), and Schlenker, Hanemann, and Fisher (2005). This specification captures the spatial variation across counties, but is subject to the bias introduced by omitted variables not included in θ_i. We cannot account for such bias by letting $\theta_i = \alpha_i$ as in a fixed-effects model since the model would be unidentified. Instead we use a random effects within between (REWB) specification, which makes use of variation within and between locations (Bell, Fairbrother, and Jones 2018). For county i and year t, we model rents as

$$y_{it} = \beta_1(X_{it} - \bar{X}_i) + \beta_2\bar{X}_i + \beta_3 Z_i + \varepsilon_{it},$$

where β_1 represents the average effect of deviations from the mean ox X, i.e. the "within" or "fixed" effects, and β_2 represents the average effect of deviations in the mean of X between counties, i.e. the "between" effect. β_3 is the effect of other location specific variables such as soil and demographic characteristics.

Empirical Results

The results of our primary regressions are shown in Table 1. Standard errors are adjusted for spatial correlation (Conley 1999; Conley and Molinari 2007), but results are similar for robust standard errors clustered by state. Irrigated cash rents increase with higher GDD, and are negatively affected by HDD, consistent with previous literature and theory on the effect of temperature on agricultural profitability. However, irrigated rents are not affected by county precipitation, which makes intuitive sense since the primary source for water is irrigation. In contrast, non-irrigated rents are strongly affected by precipitation but not by GDD.

One of the goals of this paper is to develop a method for accounting for water availability that can be derived from projected climate models to allow for estimates of future impacts. Our results suggest that watershed level percent snow is a suitable measure of water avail-

Table 2: Irrigated rents reflect the effect of water use on temperature.

	Log Irrigated Rent	
	Base Model	Water Avail.
GDD	1.971**	2.051**
	(0.836)	(0.848)
GDD sq	−1.591*	−1.519*
	(0.840)	(0.859)
sqrt HDD	−0.402***	−0.412***
	(0.129)	(0.136)
Precipitation	−0.098	0.065
	(0.251)	(0.239)
Precipitation sq	−0.013	−0.064
	(0.182)	(0.173)
Basin Precip		−1.977
		(1.808)
Basin Precip sq		1.694
		(1.868)
Snow-Water Equiv.		3.734**
		(1.749)
Snow-Water Equiv. sq		−4.119**
		(1.680)
Observations	140	140
Log Likelihood	-109.159	-103.917
Akaike Inf. Crit.	268.319	265.833
Bayesian Inf. Crit.	337.586	345.183

Note: *p<0.1; **p<0.05; ***p<0.01
Regressions are generalized least squares with standard errors adjusted for spatial correlation.

ability. It has a positive effect on irrigated cash rents, which should be expected if snowpack works as storage for water used in irrigation. But in addition, it has no effect on non-irrigated rents, which we should expect since non-irrigated agriculture is not making use of irrigation water. Finally, the significance doesn't hold if we use the smaller-scale HUC 4 watershed boundaries.

The availability of water for irrigation may also allow producers to reduce the negative effects of high temperatures through cooling. In Table 2 we display interactions between temperature variables and watershed measures of water availability as well as precipitation. For irrigated rents, the interaction between HDD and snowpack is significant and positive, suggesting that water availability as measured by watershed snowpack mitigates some of the negative impacts of extreme temperatures. In addition, precipitation has a positive effect when interaction terms are included and the coefficient for GDD increases while the coefficient for HDD becomes significantly more negative. For non-irrigated rents the impact of HDD is also much more negative when interaction terms are included. The impact of GDD decreases with an increase in precipitation, and the impact of both GDD and HDD is reduced with an increase in watershed snowpack [WHY?].

Discussion and Next Steps

Much of this paper is on solid footing, but several things have to condensed and presented. We have analyzed the effects of temperature on outcomes from the perspective of the distribution of hours at each degree of temperature, as in Schlenker and Roberts (2009). A more thorough discussion of this needs to be included. In addition, we have compard a number of modeling specifications via AIC, and a discussion of that process needs to be included as well. We would also like to include results for the Mountain West region, and perform some robustness checks.

The treatment of water supply could be expanded. At the least it seems like an investigation of the relationship between county water use and basin-wide SWE may be useful,

Table 3: Non-irrigated rents depend solely on precipitation.

	Log Non-Irrigated Rent	
	Base Model	Water Avail.
GDD	−0.710	−0.493
	(0.669)	(0.687)
GDD sq	1.050	0.825
	(0.704)	(0.725)
sqrt HDD	−0.156	−0.144
	(0.108)	(0.112)
Precipitation	0.569***	0.570***
	(0.182)	(0.194)
Precipitation sq	−0.341**	−0.335**
	(0.144)	(0.153)
Basin Precip		1.927
		(2.077)
Basin Precip sq		−1.975
		(1.883)
Snow-Water Equiv.		0.959
		(2.407)
Snow-Water Equiv. sq		0.093
		(2.628)
Observations	118	118
Log Likelihood	-59.369	-56.027
Akaike Inf. Crit.	166.738	168.054
Bayesian Inf. Crit.	228.531	238.967
Note:	*p<0.1; **p<0.05; ***p<0.01	

especially if there is a better model specification that allows for county-specific responses to basin-wide precipitation. I think this is possible through the interaction of county identifiers and basin SWE. An alternative is to include variation in SWE as a measure of uncertainty.

The discussion should also include the economic response of shifting SWE levels in a basin. Basin-wide, trading of water to the extent that is possible will allow for adjustment to higher marginal value uses. This is particularly true within watersheds and within use categories (i.e. agriculture to agriculture).

We also wish to use the Census of Agriculture to perform a long-term panel data analysis and long-differences analysis as in Burke and Emerick (2016). These regressions have also already been run, but need to be discussed and tabled. This comparison would allow us to discuss results for irrigated rents in the context of possible omitted variable bias.

Current results are for a panel approach using MLE, which in Conley and Molinari (2007) does not perform as well as GMM. It would be worthwhile repeating the analysis under GMM estimators.

Empirical Distribution of Rents

More to be discussed here evaluating the empirical distribution of rents and how they change over time to consider whether our model specification is correct.

Spatial and Temporal Correlation

Investigation of spatial and temporal correlation. A bootstrapped Moran's I test for spatial correlation is significant, suggesting that standard errors should be adjusted for spatial correlation.

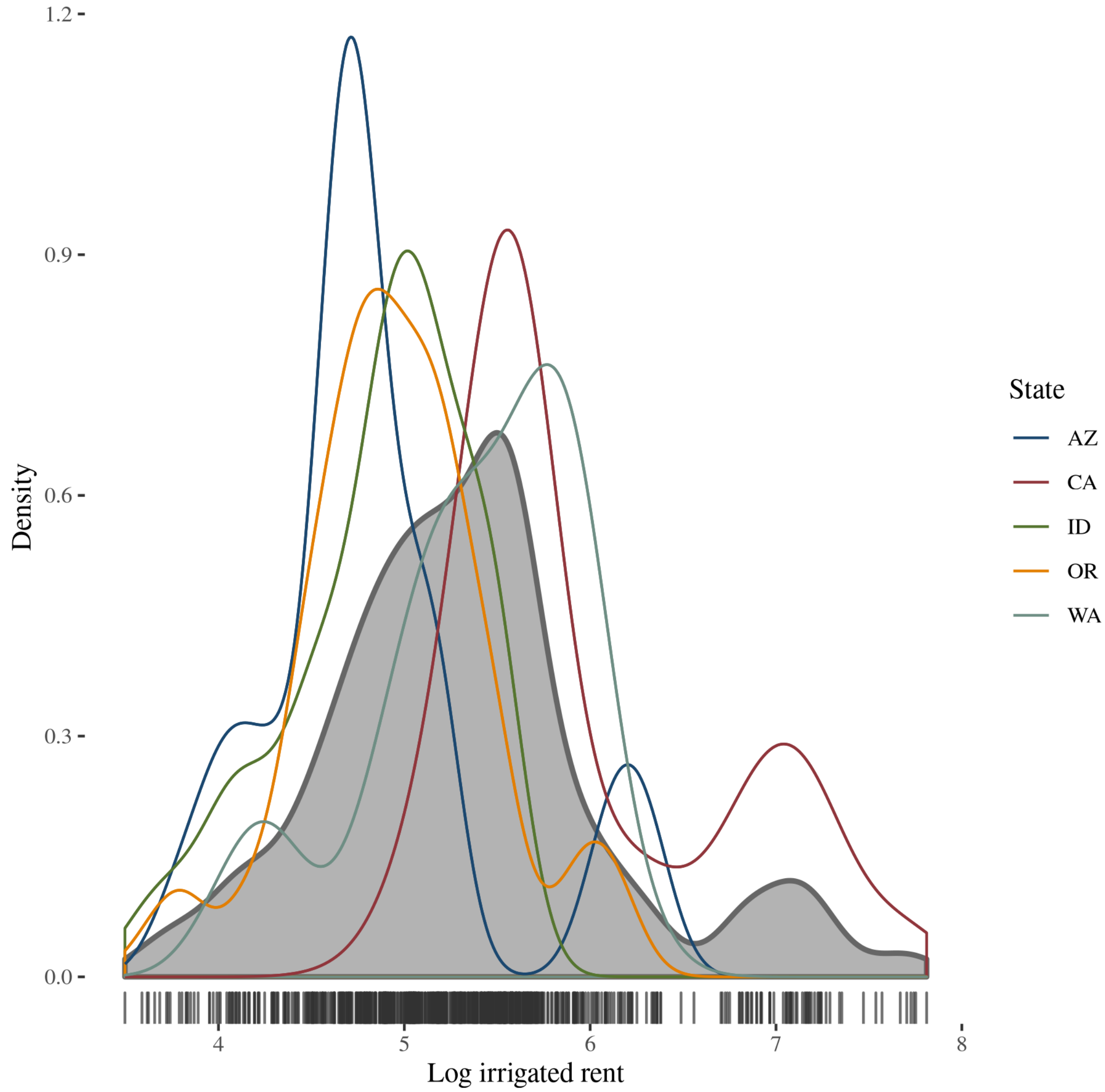

Figure 4: Distribution of log irrigated cash rent by state. Pooled distribution is in grey, with the rug indicating observations. Pooled logged rents are roughly normally distributed, though somewhat bimodal in Arizona, California, and Oregon.

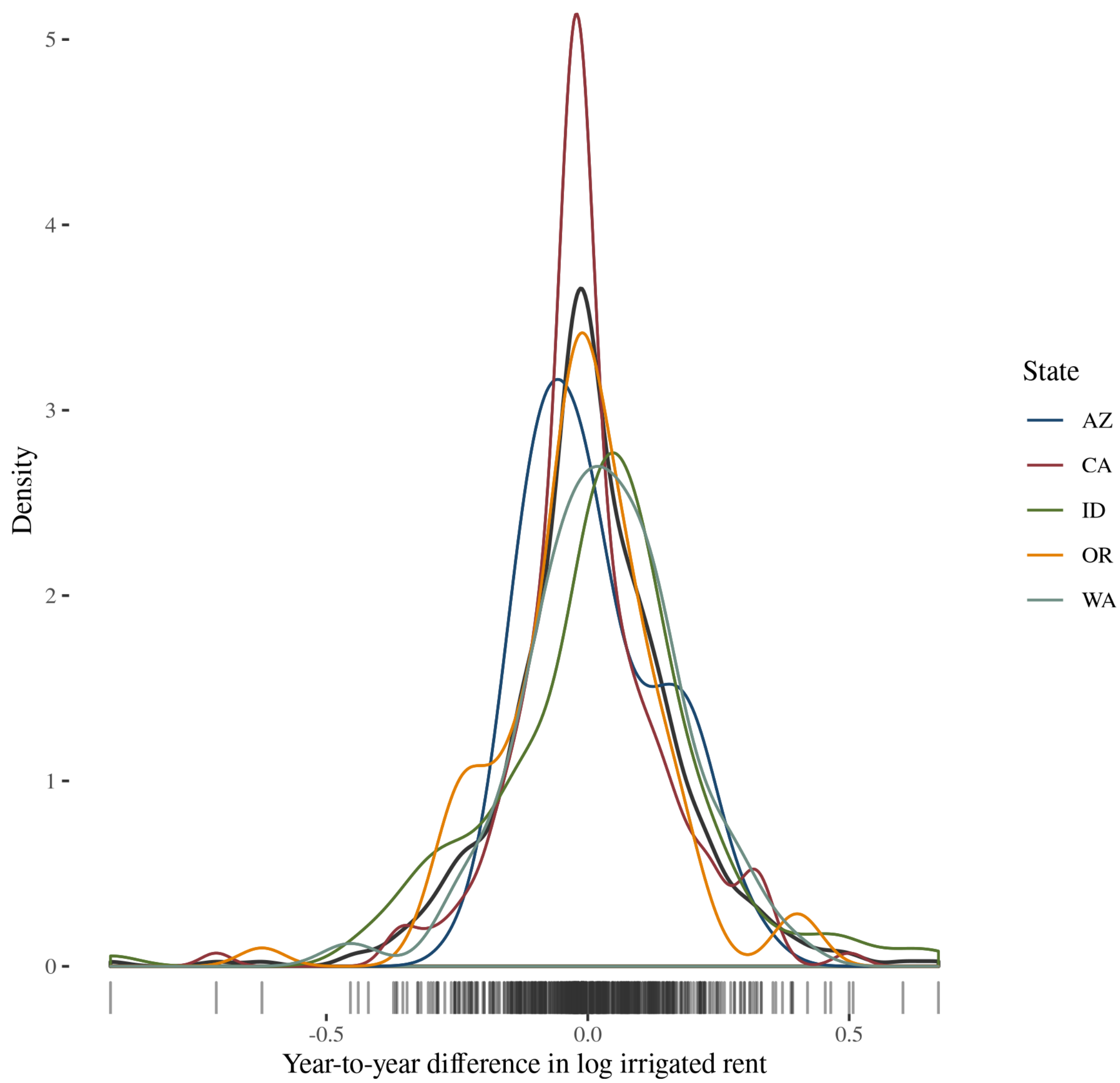

Figure 5: Distribution of annual difference in log irrigated cash rent. Pooled distribution is the heavy grey line. The rug indicates observations.

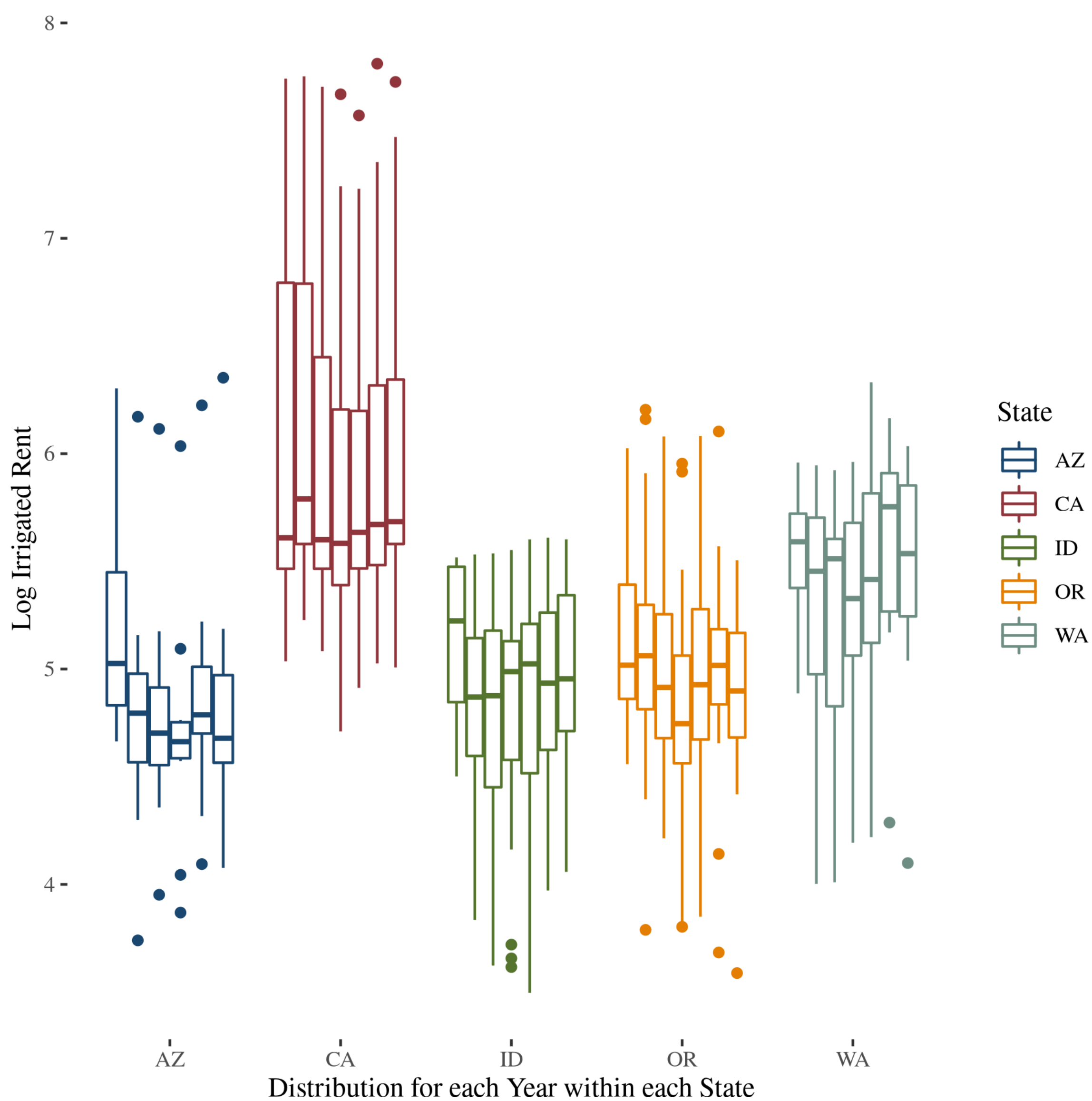

Figure 6: Distribution of log irrigated cash rent by year within each state from 2009 to 2014. Data suggest little evidence of a time trend but significant state clustering effects.

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