Estimating Agricultural Acreage Responses to Input Prices: Groundwater in California

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1 Introduction

Water is arguably the most important input in California agriculture, and its importance has been highlighted by recent droughts. Farmers and researchers both have long been interested in the marginal value of agricultural water and its impact on production. However, due to a patchwork of legal doctrines, historic water rights, and the absence of any reliable market for agricultural water, estimates of water's value in California agriculture have been challenging to come by (Buck et al., 2014). However, producers in California generally have the option to pump groundwater as a source of last resort. This pumping is largely unregulated, and only recently has California's 2014 Sustainable Groundwater Management Act begun to impact farmers' behavior. Producers who rely on groundwater use energy (electricity or fuel) to pump water up from an underlying aquifer. Therefore, the cost structure for groundwater is straightforward: the deeper the well, the more expensive the water.

In this chapter, I exploit the insight that groundwater depth is an effective proxy for agricultural water costs on farms where groundwater pumping occurs. I use panel data on groundwater levels and field-specific land cover to estimate the effects of groundwater depth (and by extension the price of water) on land use decisions in Fresno County. I demonstrate that deeper groundwater levels decrease the likelihood of land being covered in annual crops and increase the likelihood of land being left fallow or in grassland.

I am not the first to tie groundwater levels to water costs; authors of previous studies have had the same insight (Schoengold & Sunding, 2014; Green et al., 1996). However, I add to the extant literature by using groundwater's physical characteristics as a source of plausibly exogenous variation. The classic simplification that an aquifer is like a bathtub ignores important hydrological facts. In particular, lateral groundwater movement is slow and leads to a nonuniform water table over space. Thus, even though the entire central valley of California is part of a single large aquifer system, different regions face differing well depths at any particular point in time. Simultaneously, lateral groundwater flow ensures that the groundwater depth at any one point is the result of aggregate groundwater pumping in the surrounding area, rather than the private pumping of a single landowner.

Using three distinct datasets, I compile a balanced panel of over 8000 agricultural fields in Fresno County for the years 2008 through 2016. (See Fig. 1 for a map of Fresno County within California.) For each parcel of land, I observe that year's land cover and a measure of groundwater depth from a nearby (less than 5 miles away) well. I then estimate an econometric model of the effect of groundwater depth on land cover that includes fixed effects for both parcels and years. This approach controls for any time-invariant characteristics of individual parcels as well as any widely shared annual shocks to either groundwater levels or land cover.

My identification assumption is that, conditional on the included fixed effects, variation in groundwater depth is as good as random. This is, perhaps unintuitively, a credible assumption in this setting. Since aggregate regional pumping determines groundwater levels and individual pumpers' impacts on aggregate pumping are quite

Fig. 1 Fresno County, California

small, it makes sense that observed groundwater levels are not determined by own-parcel land cover choices.

Although my analysis does not explicitly control for surface water use, this omission biases my findings toward zero and leaves me with conservative estimated effect sizes. Surface water in California is allocated according to the appropriative doctrine, meaning that surface water rights are tied to specific land parcels. By including parcel fixed effects, I am able to account for surface water access – a measure that is highly correlated with surface water use.

Previous literature on water resources in California agriculture has focused in large part on the adoption of efficient irrigation technologies. In their seminal paper, Caswell and Zilberman (1986) develop a theoretic framework relating land quality, well depth, electricity costs, and irrigation efficiency to technology adoption and production decisions. Dinar (1994) further explores such issues and expands the framework to include groundwater quality and other important agricultural characteristics. Green et al. (1996) apply microparameters at the field level to expand the empirical understanding of technology adoption behaviors. Unlike previous work that has focused on irrigation efficiency, this chapter instead explores how variations in (implicit) water prices affect crop choices and production decisions.

I find that increased groundwater depth reduces the likelihood that agricultural parcels will be planted to an annual crop and that this effect is pronounced for parcels that have recently been planted to an annual crop or left as fallow or grassland. Additionally, increased groundwater depth is correlated with an increased likelihood of fallowing land after growing annual crops and an increased likelihood of keeping land fallow or in grassland. Groundwater depth does not seem to have a meaningful effect on choosing to plant perennial crops, but it does seem to increase the likelihood that perennial crops stay planted.

2 Data

I utilize data from three sources. First, I use the Cropland Data Layer (CDL) to determine land cover and crop choice. Next, I use Common Land Units (CLUs) to determine individual agricultural field boundaries. Finally, I use data from the California Department of Water Resources to determine the depth to groundwater at various monitored wells. I describe each of these data sources below.

2.1 Cropland Data Layer

The Cropland Data Layer (CDL) is a pixelated grid, or raster, dataset of landcover in the United States collected and maintained by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). A satellite records the electromagnetic wavelengths of light reflected from different points on the earth's surface and uses a ground-tested algorithm to assign each pixel a single land cover type for the year. Pixels measure 30 meters by 30 meters, except for the years 2006–2009, when pixels measured 56 meters by 56 meters. The CDL provides remarkably high-resolution land cover data and is able to distinguish between many different types of vegetation. Figure 2 displays the CDL for Fresno County in 2016. Within the agricultural region of the county, the lighter gray pixels represent developed (urban) areas. The darker pixels represent prominent land covers, including grapes, almonds, cotton, and alfalfa. The color-coded image is available on request to the author.

One problem with using raw CDL data is that a 30-meter by 30-meter pixel is likely not the appropriate unit of analysis. Rather, economists are more interested in observing field-level crop choices. Additionally, although CDL data are quite accurate for primary row crops (Boryan et al., 2011), it is apparent that individual

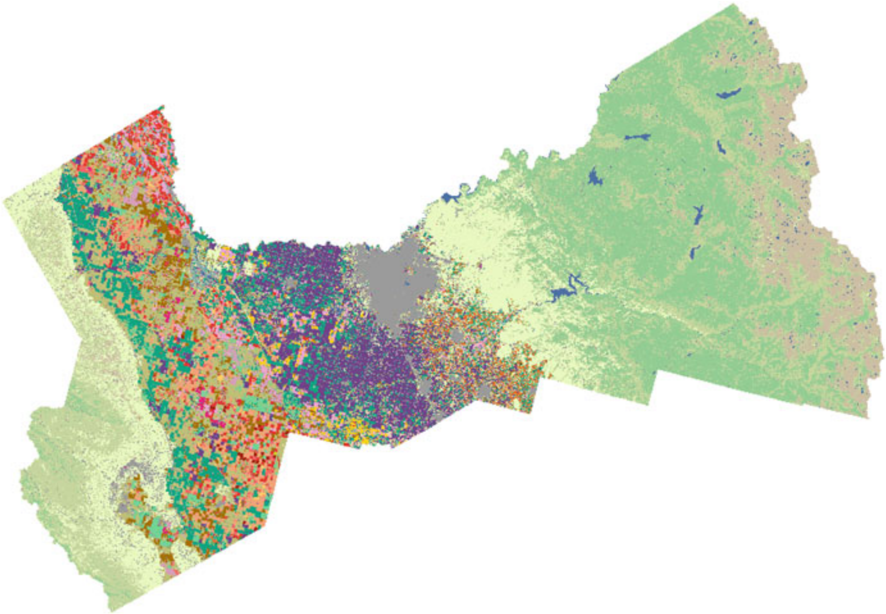

Fig. 2 Cropland Data Layer (CDL) – Fresno County, 2016. *Note:* This figure plots land cover for 30-meter by 30-meter pixels across Fresno County for the year 2016. (Source: NASS)

pixels are frequently mismeasured. For instance, upon visual inspection of a CDL image, it is not uncommon to observe what is clearly a large field of more than 100 pixels planted to one crop, with one or two pixels somewhere in the field reported as another crop. If analysis is conducted at the pixel level rather than the field level, such mismeasurements become a large concern. To address this concern, I exploit Common Land Unit data to construct field-level crop cover observations.

2.2 Common Land Unit

According to the Farm Service Agency (FSA) of the USDA, a Common Land Unit (CLU) is "an individual contiguous farming parcel, which is the smallest unit of land that has a permanent, contiguous boundary, common land cover and land management, a common owner, and/or a common producer association" (Farm Service Agency, 2017). Practically, a CLU represents a single agricultural field. Geospatial outlines, or shapefiles, of CLUs are maintained by the FSA but are not currently publicly available.

I utilize CLU data for California obtained from the website GeoCommunity. These data contain shapefiles from the mid-2000s and are the most recent version publicly accessible. In my analyses, I implicitly assume that individual CLUs do not change over time – a reasonable assumption given the FSA definition. The FSA does adjust individual CLU definitions on a case-by-case basis, if necessary, but I assume these adjustments to be negligible as in previous similar studies (Hendricks et al., 2014).

I overlay the CDL raster data with CLU shapefiles. Upon visual inspection, the fit is quite good: CLU boundaries line up with crop changes in the CDL, CLU boundaries largely do not exist for nonagricultural areas, and geographical features such as waterways are visible. One concern is that many CLUs are quite small, and this is particularly pronounced in areas near urban sprawl. Therefore, to maintain confidence that the fields I study are actually "fields" in the way we think of them, I drop all CLUs with an area of less than 5 acres from my dataset.

To assign each CLU a single crop cover, I calculate the modal value of the raster pixels contained within each CLU shapefile. I then assign that modal value to the entire CLU. This procedure enforces the assumption that each field (CLU) is planted to a single crop. However, this is not strictly true. Figure 3 reports the proportion of modal values within each CLU in my final dataset. Reassuringly, most fields are dominated by their modal CDL value.

Finally, for each CLU shapefile, I construct a centroid for the field. I then use these CLU centroids to calculate distances from each field to the nearest well in my data.

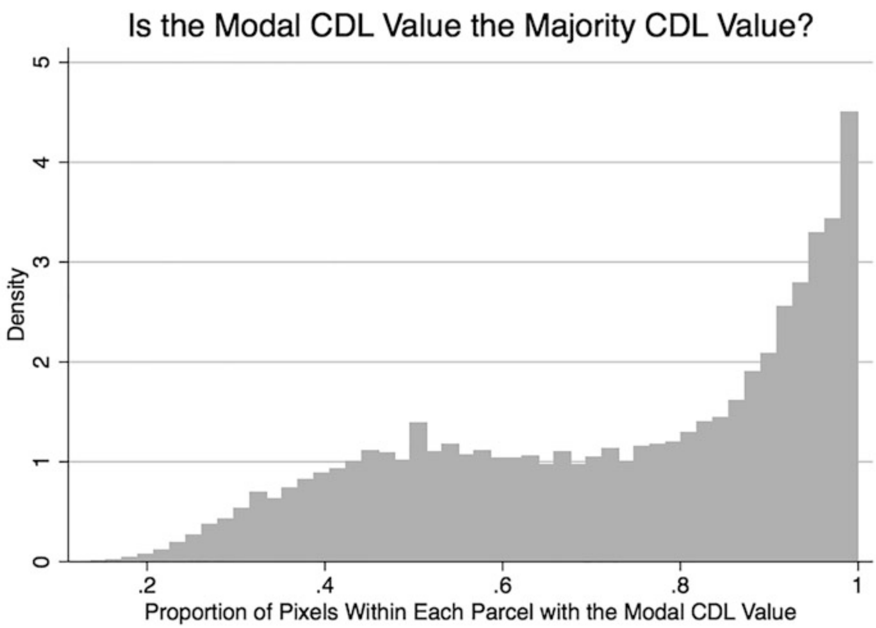

Fig. 3 Modal CDL values. *Note:* This figure plots a histogram of the proportion of CDL pixels in each CLU parcel in my final dataset that share the modal CDL value

2.3 Groundwater Depth

I obtain data on groundwater depth from the California Department of Water Resources. Specifically, I begin with the universe of well depths available as of March 2017. I then restrict my data to only those wells in Fresno County that have at least annual readings dating back to 2007. This leaves me with 47 unique wells. I then calculate an annual average groundwater depth for each well, leaving me with a balanced panel of 47 wells with annual observations from 2007 to 2016. These wells include those in the California Statewide Groundwater Elevation Monitoring (CASGEM program) as well as other wells that voluntarily report data.

Figure 4 summarizes groundwater depth readings over time for the 47 wells in my dataset. Several observations are worth noting. First, there is a wide range of groundwater depths within Fresno County, even in a single year. In 2015, for instance, there is a nearly 500-foot difference between the deepest groundwater level and the shallowest, while the average depth is around 175 feet. Second, there is meaningful year-to-year variation in groundwater levels: the average annual depth fluctuates between about 150 and 175 feet. Third, from 2011 to 2016, the figure shows groundwater depth increasing for many wells. This fits with anecdotal observations that farmers relied on increased groundwater withdrawals during these years as California experienced a prolonged drought.

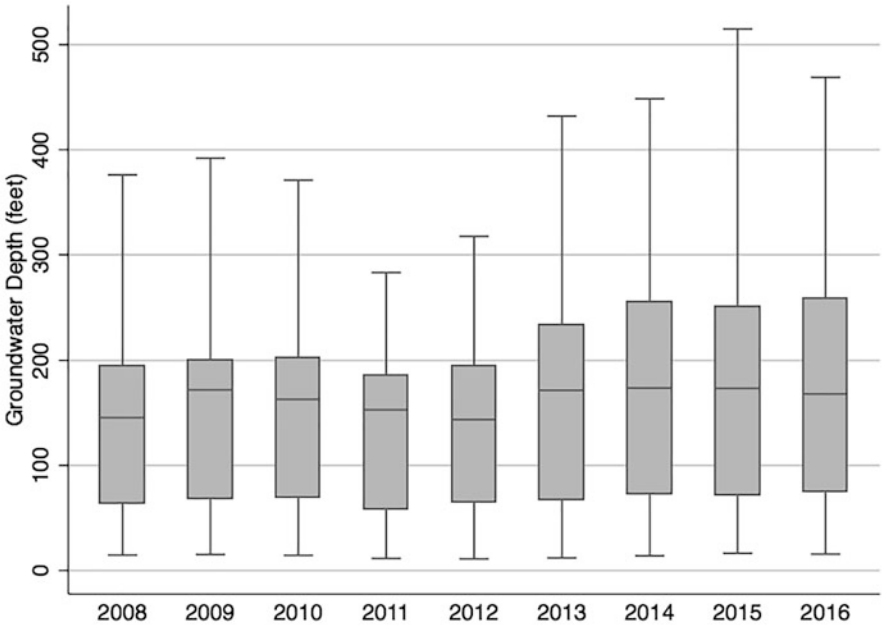

Fig. 4 Groundwater depth over time. *Note:* This figure plots annual summaries of the groundwater depths measured at each of the 47 wells in my dataset

2.4 Final Dataset and Summary Statistics

To construct the final dataset for use in my econometric analysis, I restrict my sample to only those CLU parcels within 5 miles of a well. Figure 5 plots this subset of parcels and the 47 wells. This sample restriction prevents me from attributing groundwater readings from too far away to a particular field that may experience different local groundwater levels due to slow lateral groundwater flow. I then match each CLU parcel to its nearest well and use the annual readings from that well as a proxy for that parcel's true (unobserved) groundwater depth.

Figure 6 presents a histogram of the distance of each CLU parcel in my dataset to its nearest well. The distribution of distances is roughly uniform except for distances less than one mile, which are less prevalent. This is encouraging evidence that distance-to-well is unlikely to drive my results in any systematic way.

Next, I classify each CLU parcel's land cover into one of seven categories: annual crop, perennial crop, water, developed (urban), forest or wetland, fallow or grassland, and missing or undefined. Then, for each year, I determine a parcel's land cover category in the previous year. This ultimately yields a balanced panel of 8804 agricultural fields with annual land cover observations from 2008 to 2016.

Table 1 summarizes the annual percentage of CLU parcels in each category of land cover from 2008 to 2016. The overall proportion of observations in each land

Fig. 5 Final dataset. *Note:* This figure plots the 47 Fresno County wells used in my analysis, as well as the Fresno County parcels no more than five miles from these wells. These are the parcels included in my econometric analysis

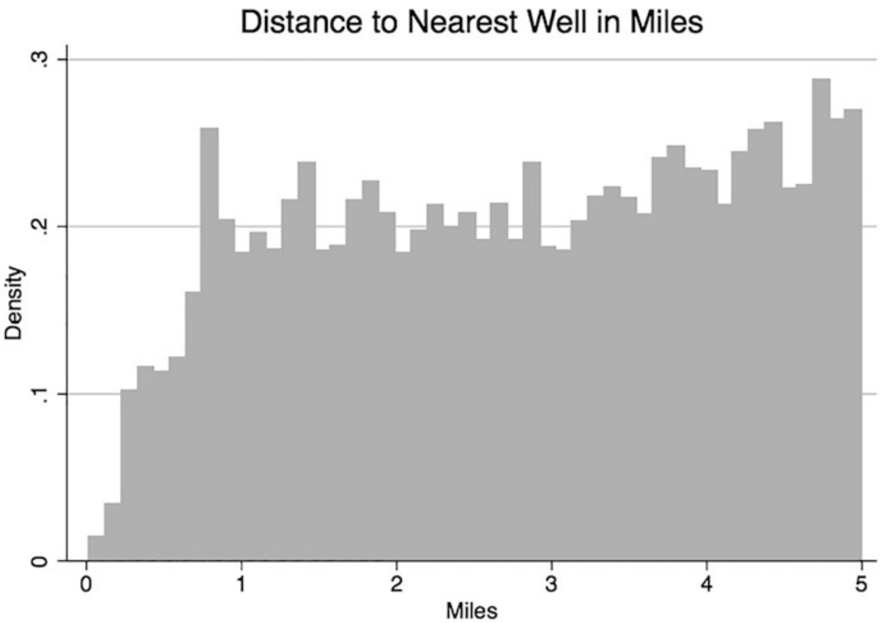

Fig. 6 Distance to nearest well. *Note:* This figure plots a histogram of the distance from each CLU parcel centroid in my final dataset to its nearest well

Table 1 Annual aggregate land cover, percent of total

	Year								
Land cover	2008	2009	2010	2011	2012	2013	2014	2015	2016
Annual crop	32.16	36.74	36.95	35.09	33.41	32.61	29.40	22.57	23.36
Perennial crop	39.97	25.41	29.04	41.98	41.30	46.10	45.26	45.90	46.43
Water	0.49	0.70	0.45	0.58	0.65	0.68	0.66	0.65	0.62
Developed (urban)	2.27	2.67	1.90	2.04	1.98	1.93	2.92	2.76	2.70
Forest or wetland	0.31	1.43	1.31	0.08	0.12	0.05	0.05	0.06	0.03
Fallow or grassland	24.65	32.89	30.21	20.09	22.41	21.57	21.57	27.93	26.70
Missing or undefined	0.16	0.15	0.14	0.14	0.14	0.15	0.15	0.14	0.14

Note: This table records the proportion of CLU parcels in my final dataset with each of the eight categories of land cover for each year between 2008 and 2016. By far the most common categories are annual crops, perennial crops, and fallow or grassland

cover category is relatively stable over time, but there is also discernible year-to-year variation. The three most common land cover categories are annual crop, perennial crop, and fallow or grassland. Annually, more than 95% of CLU parcels are in one of these three categories. Therefore, in my subsequent analyses, I focus on land use transitions between these categories.

Table 2 summarizes the unconditional probabilities of CLU parcels transitioning between annual crops, perennial crops, and fallow or grassland between any 2 years.

Table 2 Unconditional land cover transition probabilities

	Current land Cover		
Previous land cover	Annual crop	Perennial crop	Fallow or grassland
Annual crop	75.39	9.28	15.00
Perennial crop	6.32	84.31	8.22
Fallow or grassland	16.83	15.05	66.01

Note: This table records the unconditional probability of a CLU parcel having a particular land cover given its previous land cover. I focus on the three most common land covers: annual crop, perennial crop, and fallow or grassland. All numbers are percentages

Notably, this table does not control for any possible determinants of these transitions and merely summarizes my dataset. In my empirical analyses, I estimate how groundwater depth affects the probabilities of these transitions.

3 Empirical Strategy

My goal is to estimate the effect of groundwater depth on the probability that land cover transitions between any two categories. Conceptually, increased groundwater depth results in more expensive water if that water is pumped from aquifers. Therefore, one would expect relatively deeper groundwater levels to cause farmers to transition from relatively more water-intensive land uses to relatively less water-intensive land uses. Between annual crops, perennial crops, and fallow or grassland, the third category is the least water intensive. Thus, one would expect deep groundwater levels to increase transitions to fallow or grassland.

It is less clear, however, whether annual or perennial crops as a category are more water intensive. A relevant concern here is the option value involved in this trade-off. For instance, an almond farmer with an orchard of relatively young trees has a strong incentive to keep her trees watered, even in a drought. However, at some point, an old and less productive orchard becomes less lucrative to irrigate than an annual crop that does not require as much water. On the other hand, a farmer who currently farms an annual crop may balk at investing in a perennial crop when groundwater levels are sufficiently deep. In short, deep groundwater levels are likely to increase annual crop cover. However, it is unclear what effect they would have on perennial crop cover.

To estimate groundwater depth's effect on land cover transitions, I estimate the fixed effects model specified in Eq. (1) on different subsets of my data. In each regression, the outcome variable LandCover_{it} is one of several different binary variables signifying a particular land cover category, such as annual crop or perennial crop. Subscript i indexes different CLU parcels and subscript t indexes year. The variable $\text{GroundwaterDepth}_{it}$ represents the groundwater depth in feet as measured at the well nearest to field i in year t. I include a constant term β_0, a CLU parcel fixed effect α_i, and a year fixed effect γ_t. The error term is ε_{it}, and standard errors are clustered at the CLU parcel level to allow for correlation in a single field's land cover decisions over time.

$$\text{LandCover}_{it} = \beta_0 + \beta_1 \text{ GroundwaterDepth}_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

To clarify how I implement my empirical strategy, consider the following example. To determine the effect of groundwater depth on the transition probability from annual crop cover to perennial crop cover, the outcome variable LandCover_{it} would be defined as the binary variable Perennial that takes on a value of 1 for parcel i in year t if it is in a perennial crop land cover in year t, and 0 otherwise. I then estimate specification (1) on all observations in my data for which the prior year's land cover was annual crop.

To consider β_1 as a causal effect in my regressions, I rely on the identifying assumption that groundwater depth is as good as random after accounting for parcel and year fixed effects. More precisely, I assume that groundwater depth for a particular field is uncorrelated with the error term ε_{it} after accounting for α_i and γ_t. This assumption would clearly be incorrect if groundwater were a private good – that is, both excludable and rival. However, groundwater is a common pool resource: rival but not perfectly excludable. Any one farmer's groundwater depth is ultimately determined by the aggregate pumping of those farmers nearby, and any one farmer's contribution to aggregate pumping is assumed to be small enough to be insignificant. In other words, I identify β_1 using deviations from annual location-specific average groundwater levels, which I assume to be as good as random and driven by idiosyncratic aggregate pumping levels.

My empirical approach does not explicitly control for access to surface water for irrigation. Surface water rights are certainly relevant and can affect both groundwater pumping and crop cover. However, since California follows the appropriative doctrine for surface water rights, these rights are legally tied to individual parcels of land (Wilkinson, 1992). Therefore, parcel fixed effects should capture the overall effect of having access to some level of water rights. Additionally, unobserved surface water use biases my estimates toward zero insofar as a farmer with no need to pump groundwater would not change her land use decisions at all in response to changes in groundwater levels. Although it would be possible to more explicitly consider surface water rights with additional data, such an exercise is beyond the scope of this chapter.

4 Results

Over 95% of my observations fit into three land cover categories: annual crop, perennial crop, and fallow or grassland. Consequently, I focus my analysis on transition probabilities between these three categories. This leads me to estimate specification (1) nine times to fill a 3×3 transition matrix.

Table 3 Conditional land cover transition probabilities

	Current land cover		
Previous land cover	Annual crop	Perennial crop	Fallow or grassland
Annual crop	85.72	8.76	5.51
Perennial crop	5.65	81.84	10.66
Fallow or grassland	25.25	14.19	57.18

Note: This table records the conditional probability of a CLU parcel having a particular land cover given its previous land cover, controlling for field fixed effects and year fixed effects. Specifically, this table reports the values of $\hat{\beta}_0$ recovered by estimating Eq. (1). I focus on the three most common land covers: annual crop, perennial crop, and fallow or grassland. All numbers are percentages

Table 4 Effect of groundwater depth (feet) on transition probabilities

	Current land cover		
Previous land cover	Annual crop	Perennial crop	Fallow or grassland
Annual crop	−0.061***	0.003	0.056***
	(0.009)	(0.004)	(0.008)
	$n = 25{,}795$	$n = 25{,}795$	$n = 25{,}795$
Perennial crop	0.005*	0.019***	−0.018***
	(0.003)	(0.005)	(0.004)
	$n = 30{,}964$	$n = 30{,}964$	$n = 30{,}964$
Fallow or grassland	−0.062***	0.006	0.065***
	(0.008)	(0.006)	(0.010)
	$n = 19{,}706$	$n = 19{,}706$	$n = 19{,}706$

Note: This table reports the effect of an additional foot of groundwater depth on the probability (percent chance) that a CLU has a particular land cover. Specifically, this table reports the values of $\hat{\beta}_1$ recovered by estimating Eq. (1) using various subsets of my data. These effects can be directly compared to the conditional transition probabilities reported in Table 3. Standard errors are reported in parentheses and are clustered at the CLU level. The number of CLU observations included in each regression is given by n. *$p < 0.1$, **$p < 0.05$, *** $p < 0.01$

To begin, I report the estimated $\hat{\beta}_0$ coefficients from these nine regressions in Table 3. Table 3 should be considered as a companion to Table 2 in that they both report transition probabilities between different land cover categories. However, Table 3 controls for parcel and year fixed effects, resulting in "conditional" transition probabilities. The three largest differences between the two sets of transition probabilities are that, after controlling for fixed effects, (1) annual crop cover is more likely after annual crop cover, (2) annual crop cover is more likely after fallow or grassland cover, and (3) fallow or grassland cover is less likely after fallow or grassland cover.

Next, Table 4 reports the effects of groundwater depth on the transition probabilities contained in Table 3. Each of these reported coefficients can be interpreted as the effect of an additional foot of groundwater depth on the relevant transition probability. For instance, consider a parcel that had an annual crop land cover in the previous year (i.e., look at the first row of Table 4). Increasing the groundwater depth for that parcel by 100 feet would decrease the likelihood that parcel would have an annual crop land cover this year by 6.1% (column one) and increase the likelihood the parcel would be fallow or grassland this year by 5.6% (column three).

The results reported in Table 4 paint a relatively clear picture that largely matches expectations. Groundwater depth reduces the likelihood that parcels will be planted to an annual crop, and this effect is especially large and statistically significant for parcels that have been recently planted to an annual crop or left as fallow or as grassland. Conversely, groundwater depth increases both the likelihood of fallowing land after growing annual crops and the likelihood of keeping land fallow or in grassland. Groundwater depth seems not to have a profound effect on the choice of whether to plant perennial crops, except to increase the likelihood that perennial crops stay planted. This fits with the idea that the dominant force with perennial crops is an option value determination that relies on the large fixed cost associated with many perennial crops.

5 Conclusion

My results support the prediction that farmers, when facing relatively more expensive sources of agricultural water, will transition to less water-intensive land uses. For an increase in groundwater depth of 100 feet, the likelihood that a parcel previously covered with an annual crop will be fallowed in the next year increases by 5.6%. Given that the conditional probability of this land use transition is only 5.5% to begin with, groundwater levels (and hence water costs) can have large and meaningful impacts on land use decisions.

To put my findings into perspective, Martin et al. (2011) note that each additional 100 feet of groundwater depth requires approximately 0.9 more gallons of diesel fuel to pump an acre-inch of water. At a diesel cost of $2.50 per gallon, an approximately $27/acre-foot increase in the cost of agricultural water would have similar effects to those reported in Table 4.

Future research can improve upon these results by expanding the geographic scope of the analysis, adding an evaluation of surface water rights, and disaggregating land cover categories into more precise definitions (nut trees vs. fruit trees vs. vegetables vs. grapes vs. field crops, etc.). Even without these steps, however, this chapter demonstrates how the depth of groundwater wells can inform policy debates about the value of agricultural water in a setting where such valuations are hard to come by.

California is currently implementing groundwater sustainability plans mandated by the Sustainable Groundwater Management Act (Wardle et al., 2021). As these efforts progress, policymakers are hoping to overcome the persistent market failures that plague common pool resources through trading mechanisms or other approaches (Bruno & Sexton, 2020). This chapter emphasizes that, as water in California becomes scarcer and more costly, we will see producers shift their crop choices in response.

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