Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California

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Abstract

We use the geo-referenced June Agricultural Survey of the U.S. Department of Agriculture to match values of individual farms in California with a measure of water availability as mediated through irrigation districts, and degree days, a nonlinear transformation of temperature, controlling for other influences on value such as soil quality, to examine the potential effects of climate change on irrigated agriculture in California. Water availability strongly capitalizes into farmland values. The predicted decrease in water availability in the latest climate change scenarios downscaled to California can therefore be expected to have a significant negative impact on the value of farmland.

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1 Introduction

Climatic variables such as temperature and precipitation are essential inputs to agricultural production. Different combinations and seasonal patterns have direct consequences on yields and hence profits. Following the pioneering study by Mendelsohn et al. (1994), we consider the potential impact of climate change on California agriculture, extending the earlier analysis with several new features.

In a semi-arid area like California, climate change is likely to affect agriculture in two distinct ways. One pathway is the direct effect of climate on crop growth, represented through the crop production function: changes in temperature, precipitation, solar radiation or atmospheric carbon dioxide may affect crop yield and the demand for water for irrigation. For example, an increase in precipitation during the growing season would reduce the demand for supplemental irrigation water, while an increase in temperature during the growing season would increase that demand. Another potential pathway is through the *supply* of water for irrigation. In California and some of the other western states, precipitation occurs almost entirely during the winter months (October - March), while the period when there is the greatest demand for water - urban as well as agricultural – is typically the late spring and summer (April - September); as a result, some form of storage is required to keep the runoff until when it is to be used. The snowpack in the mountains serves as an important source of natural storage that complements the man-made system of reservoirs in these regions. In California, for example, the total amount of water stored naturally in the state's snowpacks at the beginning of April in a "good" water year just about matches the total amount stored behind the state's major reservoirs; thus, the snowpack effectively doubles our ability to store water for warm-season uses. Current climate-change projections suggest that, by middle of the century, at a least a third of this storage in springtime snowpacks will be lost due to the increase in winter temperatures. Unless some man-made replacement storage is developed, this will cause a significant reduction in the total water supply available for use in California.

Because of the greater weight placed on urban uses, in California these effects are likely to fall disproportionately on agriculture.

Therefore, in order to assess the potential effect of climate change on the profitability of farming in a region that relies on supplemental irrigation, it is necessary to consider not only the direct effects of climate on crop yields and farm profit but also the effects of climate change on the effective water supply and the availability of water for agricultural users. The main innovation of this paper is that we explicitly account for both types of effects.

Although it is well understood in theory (see for example Burness and Quirk (1979) and (1980)), only a few empirical studies have examined whether and how access to irrigation water is capitalized into farmland value in practice, including Selby (1945), Hartman and Anderson (1962), Crouter (1987), and Faux and Perry (1999). The study by Selby uses aggregate data: the dependent variable is the countywide average value of irrigated land in 199 counties in 11 western states, which is examined as a function of the average cropping pattern, crop yield and cost of irrigation water in the county.[1] The other studies use individual farm-level observations. Hartman and Anderson (1962) consider land value in farm sales within a single irrigation district in Colorado as a function of the amount of water available from the irrigation district; Crouter (1987) considers land sales within a different irrigation district in Colorado; Faux and Perry (1999) consider land sales in four irrigation districts in Malheur County, Oregon. The first two of these studies find that water availability is a significant determinant of farmland value. However, all three of these studies cover a much smaller area than our sample, which extends to about 150 irrigation districts in 39 counties in California.[2] Our larger spatial coverage permits us to allow for the effect on farmland value of variables that are not likely to vary much within the small scale covered by these other studies. The only other study that incorporates surface water use on a larger scale relies on average farmland values in a county, where both dryland and irrigated farmland

[1] Renshaw (1958) also uses aggregate data and studies the average value of irrigated farmland in each of 34 Bureau of Reclamation projects as a function of cropping pattern.

[2] Our statistical analysis relies on 112 of those districts.

values are averaged (Mendelsohn and Dinar 2003). Rather than relying on data aggregated to the county level, we utilize the geo-referenced June Agricultural Survey that allows us to match farm-level data on the value of a farm with fine-scale climate and soil databases.

The other novel feature of this study is the use of degree days, a non-linear transformation of the temperature variable suggested by agronomic experiments to be a better predictor of plant growth.[3] We then employ the fine-scale climate data set to show how the degree days variables are correlated with undemeaned temperature and precipitation variables.

Our empirical analysis establishes a statistical link between farmland values and both water availability and climate, controlling for soil characteristics and population density as a key socio-economic influence on land value. We find that surface water availability and climate conditions clearly and robustly capitalize into farmland values. Since the most recent climate scenarios are now predicting a sharp increase in growing-season temperatures in California as a well as a potentially large decrease in available surface water, our results suggest a correspondingly large combined impact on farmland value.

The paper proceeds as follows: The next section explains the concept of degree days. Section 3 describes the unique dataset we use in this study. Section 4 describes and discusses our empirical results. Section 5 briefly considers the potential impact of climate change on agriculture in California, and Section 6 concludes.

2 Degree Days

Most of the agronomic literature argues that plant growth is only indirectly driven by temperature, and in a non-linear fashion. Plant growth is linear in temperature only within a certain range, between specific lower and upper bounds. These bounds underpin the concept of degree days. Degree days are defined as the sum of degrees above a lower baseline and

[3]The concept of degree days is introduced also in a study of potential climate impacts on the value of farmland in areas not primarily dependent on irrigation, but without the derivation presented in the next section (Schlenker et al. 2004).

below an upper threshold during the growing season. We follow the definition of Ritchie and NeSmith (1991) and use degree days $8-32°C$. Plant growth is approximately linear in the number of degree days in this range.[4]

For degree days $8-32°C$ we set the lower bound equal to $8°C$ and the upper bound to $32°C$. In other words, a day with a temperature below $8°C$ results in zero degree days; a day with a temperature between $8°C$ and $32°C$ contributes the number of degrees above $8°C$; and a day with a temperature at or above $32°C$ contributes 24 degree days. Degree days are then summed over all days in the growing season.

Expressing this more formally, degree days D are the expected degrees above a lower threshold b_1 and below an upper threshold b_2

$$D = \begin{cases} b_2 - b_1 & \text{if } t > b_2 \\ t - b_1 & \text{if } b_1 < t \leq b_2 \\ 0 & \text{if } t \leq b_1 \end{cases}$$

Hence the expectation over degree days is truncated at the two bounds b_1 and b_2. The probability that the average temperature t is between the two truncation points is given by

$$Prob(b_1 < t \leq b_2) = F\left(b_2\right) - F\left(b_1\right)$$

where F is the cumulative distribution of temperature with mean μ and standard deviation σ. In the case where this distribution is the normal distribution, the expected degree days

[4]Ritchie and NeSmith argues that temperatures above 34° have negative impacts on plant growth for dryland farming. However, since California is highly irrigated, we omit the degree days above $34°C$ from the analysis.

conditional on the fact that $t \in (b_1, b_2)$ is given using $\Phi()$ for the standard normal distribution.

$$
\begin{aligned}
\mathbb{E}[t - b_1 | b_1 < t \leq b_2] &= \int_{b_1}^{b_2} \frac{t - b_1}{\left[\Phi\left(\frac{b_2-\mu}{\sigma}\right) - \Phi\left(\frac{b_1-\mu}{\sigma}\right)\right]\sqrt{2\pi}\sigma} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt \\
&= \mu - b_1 + \frac{1}{\left[\Phi\left(\frac{b_2-\mu}{\sigma}\right) - \Phi\left(\frac{b_1-\mu}{\sigma}\right)\right]} \int_{b_1}^{b_2} \frac{t-\mu}{\sqrt{2\pi}\sigma} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt
\end{aligned}
$$

Using integration by substitution with $u = \frac{(t-\mu)^2}{2\sigma^2}$, the integral becomes

$$
\int_{\frac{(b_1-\mu)^2}{2\sigma^2}}^{\frac{(b_2-\mu)^2}{2\sigma^2}} \frac{\sigma^2}{\sqrt{2\pi}\sigma} e^{-u} du = \left[-\frac{\sigma^2}{\sqrt{2\pi}\sigma} e^{-u}\right]_{\frac{(b_1-\mu)^2}{2\sigma^2}}^{\frac{(b_2-\mu)^2}{2\sigma^2}} = \sigma \left[\phi\left(\frac{b_1-\mu}{\sigma}\right) - \phi\left(\frac{b_2-\mu}{\sigma}\right)\right]
$$

where $\phi()$ is the density function of the standard normal. Combining equations, we get

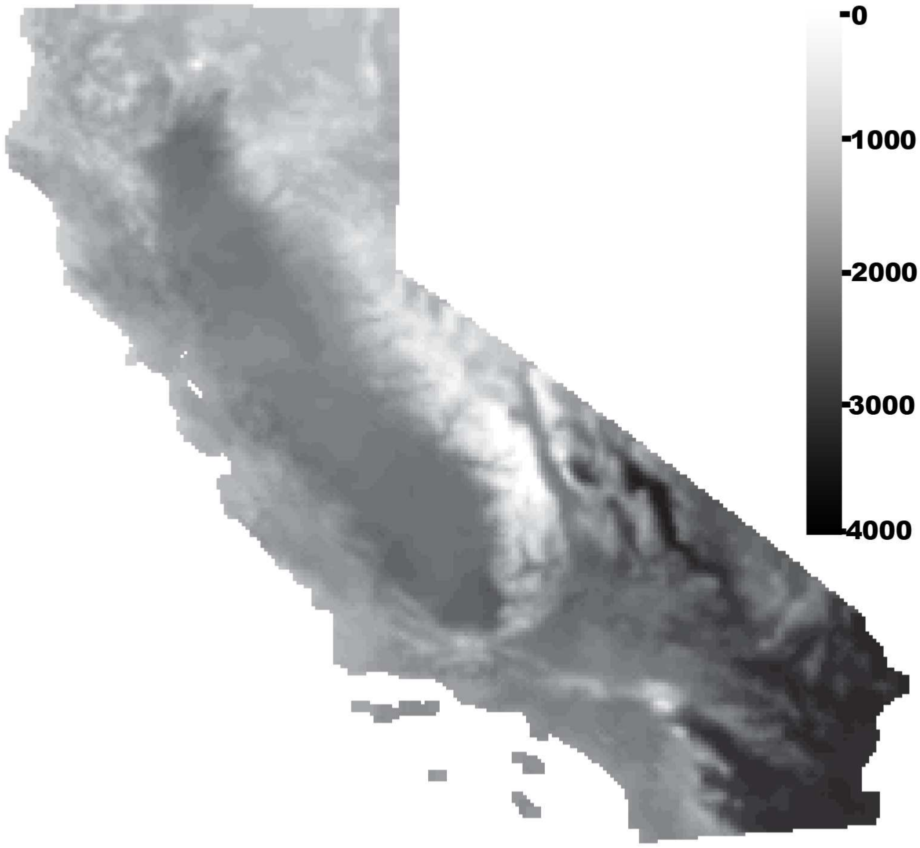
$$
\mathbb{E}[D | b_1 < t \leq b_2] = \sigma \frac{\phi\left(\frac{b_1-\mu}{\sigma}\right) - \phi\left(\frac{b_2-\mu}{\sigma}\right)}{\Phi\left(\frac{b_2-\mu}{\sigma}\right) - \Phi\left(\frac{b_1-\mu}{\sigma}\right)} + \mu - b_1
$$

Finally, the unconditional expectation becomes

$$
\begin{aligned}
\mathbb{E}[D] &= Prob(t \leq b_1)\mathbb{E}[D | t \leq b_1] + Prob(b_1 < t \leq b_2)\mathbb{E}[D | b_1 < t \leq b_2] + Prob(t > b_2)\mathbb{E}[D | t > b_2] \\
&= \sigma \left[\phi\left(\frac{b_1-\mu}{\sigma}\right) - \phi\left(\frac{b_2-\mu}{\sigma}\right)\right] + \left[\Phi\left(\frac{b_2-\mu}{\sigma}\right) - \Phi\left(\frac{b_1-\mu}{\sigma}\right)\right][\mu - b_1] \\
&\quad + \left[1 - \Phi\left(\frac{b_2-\mu}{\sigma}\right)\right][b_2 - b_1]
\end{aligned}
$$

A practical problem in implementing this calculation is that, while the degree day concept is based on an aggregation of daily temperatures, most of the available data on climate provide only observations on a monthly basis and hence only the monthly standard deviation σ_m is known. However, Thom (1954, 1966) develops the necessary relationship between daily and monthly variations in temperature under the assumption of normality. Later articles relax the normality assumption and compare monthly and daily observations at U.S. stations to generate better estimates. Moreover, as Lehman (1987) points out, the error associated with normal distribution is likely to be minor for the Central Valley of California, where most of

Figure 1: Number of Degree Days ($8°C - 32°C$) for the Months April Through September in California



our observations are situated.

We use a 103-year high-resolution temperature and precipitation climate data set for the coterminous United States, which is outlined in more detail in the data section below. We derived the sum of degree days during the main growing season, i.e., for the months of April through September using the 30 year temperature averages between 1960-1989. The results are displayed in Figure 1 for the sum of degree days for the months April through September.[5] The mountain range is clearly visible as higher altitudes have lower temperatures. On the other hand, the hottest temperatures can be found in Imperial Valley in Southern California that, unless irrigated, would become a dessert.

[5]Note that the maximum number of this range is given to be 4392, i.e., 183 days times 24 degree days per day.

One might wonder how the degree days variable compares to the monthly climate variables used in the original study by Mendelsohn et al. (1994), and also most recently by Schlenker et al. (2005).[6] We regress degree days $8-32°C$, as well as its squared term, on the sixteen climate variables in question; results are displayed in Table 1, columns 1 and 3 using all PRISM cells in California and columns 2 and 4 just the cells where the agricultural area is positive.[7] In all specification we adjust for the spatial correlation of the error terms following the non-parametric approach of Conley (1999). Omitting the spatial correlation of the error terms would underestimate the true variance-covariance matrix as the errors are assumed to be independent even though they are not. Intuitively, averaging several *unrelated* observations results in a much cleaner signal than if one were to average observations with highly correlated errors. The t-values are of course reduced once we adjust for spatial correlation, though most of the temperature coefficients remain significant.

In Schlenker et al. (2004), the study of the potential impact of warming on farmland values in the large area east of the 100^{th} meridian in the U.S., the historic boundary of land that can be farmed without irrigation, we have shown that the use of degree days yields estimates that are consistent with agronomic findings, and that these results are robust to changes in specification. Moreover, an encompassing test reveals that the five climatic variables degree days $8-32°C$, degree days $8-32°C$ squared, the square root of degree days above $34°C$, precipitation during the growing season, and precipitation squared, are better predictors of farmland values than the sixteen monthly climatic variables for dryland agriculture.[8]

While the degree days model for counties east of the 100^{th} meridian yields estimates that appear reasonable and in line with predictions (i.e., the quadratic form peaks at a

[6]These are average monthly temperature and precipitation in January, April, July and October.

[7]Shawn Bucholtz of the Economic Research Service at the United States Department of Agriculture was kind enough to provide us with processed LandSat satellite images of the agricultural area in each PRISM grid cell for the entire US.

[8]As note above, we do not include the variable degree days 34° in the current analysis as there is some controversy whether and at what point temperatures become harmful when sufficient water can be applied to a crop.

Table 1: Explaining Degree Days as a Function of Undemeaned Climate Variables

Variable	**Degree Days $8-32°C$**	**Degree Days $8-32°C$**	**Degree Days $8-32°C$ Squared**	**Degree Days $8-32°C$ Squared**
Constant	-1509	-1424	-551	352
	(14.44)	(24.26)	(1.04)	(1.06)
January Temperature	-13.5	-5.34	15.8	5.02
	(2.49)	(0.88)	(1.05)	(0.29)
January Temperature Squared	0.139	-0.435	-5.01	-4.19
	(0.33)	(1.12)	(5.11)	(3.49)
April Temperature	-28.6	31.7	-86.9	-7.77
	(2.42)	(1.72)	(2.23)	(0.08)
April Temperature Squared	3.08	1.07	11.8	10.5
	(9.51)	(1.55)	(7.07)	(2.89)
July Temperature	135	130	-26.1	-116
	(22.40)	(13.12)	(0.44)	(1.83)
July Temperature Squared	-0.876	-0.718	9.03	11.4
	(6.40)	(3.09)	(7.67)	(7.56)
September Temperature	82.3	23.3	-125	-197
	(3.74)	(0.90)	(2.32)	(1.21)
September Temperature Squared	-1.61	-2.02E-3	8.35	8.92
	(2.47)	(0.00)	(3.97)	(1.68)
January Precipitation	5.02	3.88	7.07	18.0
	(1.31)	(1.61)	(0.77)	(1.47)
January Precipitation Squared	-7.09E-2	-0.143	-9.33E-2	-0.750
	(0.98)	(2.03)	(0.42)	(2.07)
April Precipitation	-7.82	-4.86	-66.3	-21.6
	(0.79)	(1.16)	(1.38)	(0.97)
April Precipitation Squared	0.520	0.296	3.99	1.29
	(1.08)	(0.69)	(1.59)	(0.49)
July Precipitation	-34.8	-42.6	50.5	-273
	(2.51)	(3.15)	(0.94)	(3.93)
July Precipitation Squared	17.4	27.8	4.34	158
	(3.13)	(3.53)	(0.22)	(3.97)
September Precipitation	-11.6	0.567	22.8	3.19
	(1.20)	(0.11)	(0.61)	(0.13)
September Precipitation Squared	0.139	0.198	-2.42	2.48
	(0.28)	(0.52)	(1.01)	(0.95)
Subset	All Obs.	Agric. Obs.	All Obs.	Agric. Obs.
Number of Observations	23979	5899	23979	5899

Notes: Table lists regression coefficients and t-values in brackets. Coefficients for the last two columns are divided by 1000 for easier exposition. Temperature are in degree Celsius, precipitation in cms. All t-values are corrected for the spatial correlation of the error terms using Conley's non-parametric approach. We use a Barlett window of 5 degrees in both latitude and longitude, which translates into a cutoff point of approximately 350 miles. The first and third column use all PRISM cells in California in the estimation, while the second and fourth only rely on the cells with positive agricultural area.

level deemed optimal by field experiments), the sixteen monthly variables often switch signs (Kaufmann 1998). Darwin (1999) criticizes the use of these variables for giving counter-intuitive results. Several of the quadratic functional forms have a positive squared term, suggesting temperature / precipitation extremes are value-maximizing. Even for hill-shaped relationships the peak levels sometimes appear inconsistent with agronomic findings.

Later on in section 4 we obtain coefficient estimates on the degree days variables that are again in line with agronomic predictions.[9] On the other hand, a comparable regression using the sixteen monthly climate variables gives mixed results.[10]

Table 1 suggests an explanation for why some of the variables appear to have the counter-intuitive U-shaped relationship. If the true relationship between farmland value and degree days is positive in the linear and negative in the squared term of degree days, then the reduced-form relationship between farmland value and temperatures will be a composite of the relationships in Table 1. All coefficients in the regression explaining degree days will be multiplied by a positive constant, while all coefficients in the regression explaining degree days squared will be multiplied by a negative constant, and the composite result is hence indeterminate as long as the two coefficients are of the same sign.[11]

One striking feature of Table 1 is that some of the signs switch when the analysis is shifted from all PRISM cells to cells with positive agricultural area. This suggests that

[9]As noted above, we do not include degree days $34°C$ in the regression as there is disagreement at what point temperature become harmful if sufficient water can be applied.

[10]For example, optimal temperatures are $7.6°C$, $20.6°C$, $21.4°C$ in January, April, and July, while September temperatures are U-shaped. The problem with these monthly climate variables is that they account for only three of the six months that characterize the growing season for most crops (April - September). On the other hand, if one used the monthly climate variables for every month in the growing season, let alone every month in the year, there would be serious multicollinearity. The problem was recognized in the 1960s when there was a discussion in the agricultural economics literature of the need to find an index for weather. Johnson and Haigh (1970) uses principal components to reduce the dimensionality of monthly temperature and precipitation data in a hedonic study of agricultural land values; Doll (1967) uses regression to create a weather index for studying the crop yield response to weather; Oury (1965) uses an index of aridity for fitting a crop production function.

[11]For example, the coefficient on April temperature squared is positive and statistically significant in the both regression equations (for degree days and degree days squared). If farmland values are a quadratic function of degree days, i.e., are increasing in degree days and decreasing in degree days squared, the reduced form equation regressing farmland values on April temperature squared is a composite of a positive and negative term.

the relationship between degree days and the undemeaned climate variables is not uniform in California. For example, (Lehman 1987) points out that the relationship between mean temperatures and the variance thereof is spatially disperse, yielding different reduced form relationships for various spatial areas.[12]

3 Data

Farmland Values

The Ricardian approach to farmland valuation, as originally suggested in Mendelsohn et al. (1994) relies on the observation that the value of land in equilibrium should equal the discounted stream of future cash flows. If the price of farmland were higher than the discounted stream of future profits, it would be better to sell the farmland and invest the proceeds in Treasury bonds yielding a stream of interest payments. Farmers will sell their land until the price falls to the point where it equals the discounted stream of future cash flows. On the other hand, if the price of farmland were below the discounted value of future cash flows, arbitrageurs would buy the land and drive up the price until it is back in equilibrium. In an efficient market the value of land is therefore directly related to the maximum attainable profit.[13]

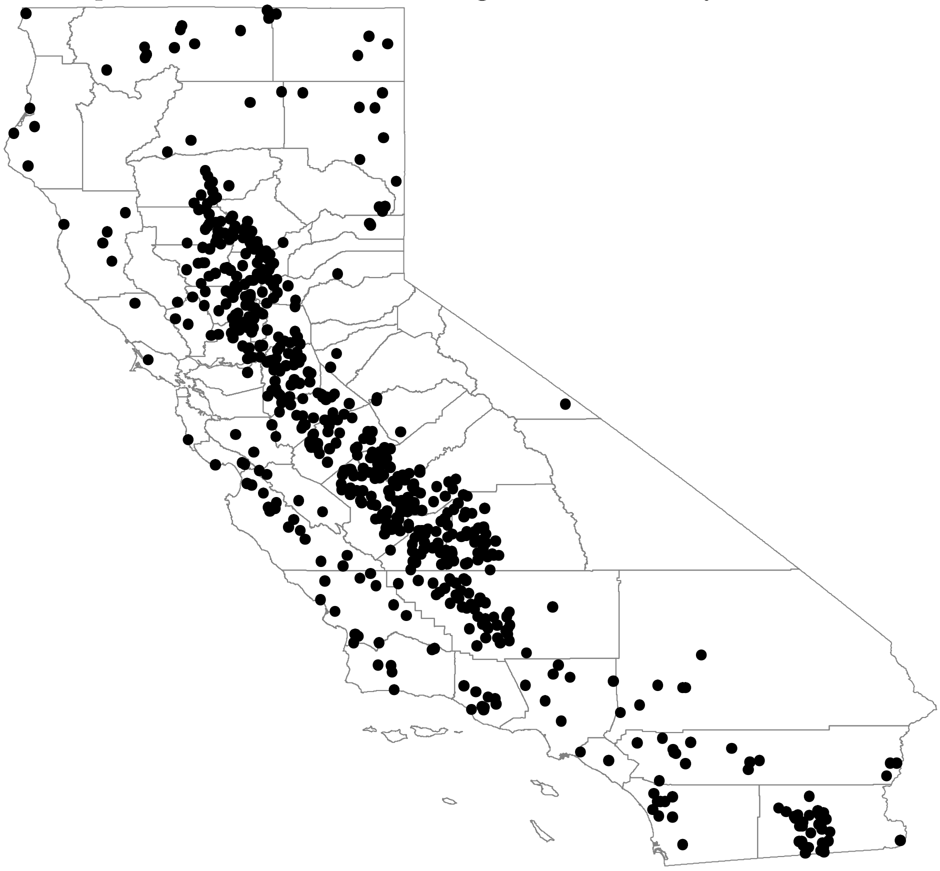
The dependent variable in a Ricardian analysis therefore is farmland value. Our analysis uses individual farm-level observations from the June Agricultural Survey. This survey is conducted in June of each year to forecast the planted area of most crops. The survey is split into two parts: the first is a random sample of the Census of Agriculture, while the second is a stratified sample of farms based on geographic location. We rely on the second part as it is a geo-referenced sample of all farms, i.e., USDA randomly selects latitude and longitude combinations and records all farms in that one square-mile section.[14] We use the

[12]Recall that the variance of temperatures enters the inverse Mills ratio when we derive degree days.

[13]This argument was first advanced by Renshaw (1958), who proposed using the differential increase in farmland values as a way to measure the economic benefits from irrigation projects.

[14]It is hence possible to have several observations for each longitude-latitude pair.

Figure 2: Sample Locations of the June Agricultural Survey in the Years 1998-2003



Notes: Figure displays the sample locations of the June Agricultural Survey as dots. County boundaries are added in grey.

reported farmland value per acre in our analysis. Our data set includes observations for the years 1998-2003, and all farmland prices were adjusted by the GDP implicit price deflator to be in 2000 dollars. Figure 2 displays the sample location for the state of California.

Climate Variables

We use a 103-year high-resolution temperature and precipitation climate data set for the coterminous United States. This small-scale climate series was developed by the Spatial Climate Analysis Service at Oregon State University for the National Oceanic and Atmospheric Administration. Researchers at Oregon State developed the PRISM model that is employed by almost all professional weather services and regarded as one of the most reliable interpolation procedures for climatic data on a small scale.[15] We derived the sum of degree days during the main growing season, i.e., for the months of April through September as outlined in Section 2 above using the 30 year temperature averages between 1960-1989.

Other Control Variables

Our study area, shown in Figure 2, comprises over 90% of the irrigated farmland in California, including the Central Valley, the Imperial Valley, and several of the coastal valleys. Total agricultural water use in California amounted to about 33 million acre feet (MAF) in 2000. Of this, about 20 MAF is surface water diversions from rivers etc, and the rest is supplied by pumping groundwater. About 7 MAF of the surface water is supplied through water service contracts to irrigation districts by two major water projects, the federal Central Valley Project (CVP), operated by the US Bureau of Reclamation, and the State Water Project (SWP) operated by the State Department of Water Resources (DWR). In addition, many irrigation districts own water rights to divert water from rivers. Furthermore, about 15% of the irrigated acreage in the Central Valley is farmed by individual farmers not organized in irrigation districts who obtain their water from their own groundwater wells.[16] In this study we focus on the farms that lie within 112 irrigation districts; these account for about 55% of the irrigated acreage in California.[17]

[15] The PRISM run we use gives monthly minimum and maximum temperature values as well as precipitation estimates on a 2.5 mile x 2.5 mile grid for the contiguous United States.

[16] Farmers in a substantial number of irrigation districts also have their own wells and obtain a portion of their water through self-supplied groundwater.

[17] The remainder are not included because water supply data was missing or incomplete. The irrigation

Our measure of access to irrigation water in this study is average surface water deliveries per acre in each district over the period from 1992 to 2002.[18] These data were pieced together from a variety of sources, including the annual operations reports from the CVP and the SWP, data published by the Association of California Water Agencies, and data in the files of the regional DWR offices.[19] The water delivery data are an ex post measure of surface water availability. In future work we intend to include an estimate of the irrigation districts' ex ante expectations, as of the time of crop planting, regarding how much water will be available for delivery during the balance of the growing season.

Another possible measure of access to irrigation water is the average water right per acre of the district, but this information is often both hard to obtain and unreliable. A single irrigation district may hold tens of water rights, and these are kept in paper files which have not been computerized or synthesized, and are available with limited access in the offices of the State Water Resources Control Board; the system is designed for inspecting individual water rights but not for the mass screening of several thousand water rights. Furthermore, the water right can often be a misleading indication of access to water. In the case of water service contracts, for example, the SWP is in the position of having signed contracts to deliver 4.2 MAF, but has a firm supply of only about 2.5 MAF. With regard to rights for surface water diversion, in many cases the existing rights have not been perfected and the face value of the water rights along a stream may exceed the normal flow; without some process of quantification, the amount of water to which access is provided by the right is highly uncertain.[20]

We also obtained observations on more than 15,000 groundwater wells in the Central

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district boundaries were obtained from DWR.

[18]In this analysis, we limit our sample to years after 1992 when the Central Valley Improvement Act was passed that allocated more water to instream environmental uses and limited the amount of water that can be exported at the pumping plants in the Delta. However, we also conducted an analysis using average deliveries between the years 1982-2002 and found little difference in the results.

[19]We also obtained some data from these sources on the retail prices for irrigation water charged by the districts, but the price data are less complete than the delivery data.

[20]In future work, we hope to be able to develop some more useful information on the effective supply of water covered by districts' water rights

Valley. Groundwater is a virtually unregulated resource and in many areas it provides a substitute for surface water in the event of a shortage. The depth of groundwater varies significantly spatially and also temporally both between years and between months within a year. We calculate the average well depth in the month of March, the beginning of the growing season, for each of the years 1990 to 1998 and then average the depths over these years. The groundwater depth at each farm location is derived as a weighted average of all well locations, where the weight is the inverse of the distance of each well to the farm to the power of 2.14, the exponent that minimizes the sum of prediction errors from cross-validation. In the cross-validation step each well is sequentially excluded from the data and the depth is calculated using all remaining wells. The square of the difference between interpolated depth and actual depth is summed over all well locations.

There are several soil data bases of potential interest to our analysis. In order of increasing detail they are the (i) National Soil Geographic (NATSGO) Data Base that relies on the National Resource Inventory (United States Department of Agriculture 2000), (ii) State Soil Geographic (STATSGO) Data Base (United States Department of Agriculture 1994) and (iii) Soil Survey Geographic (SURGO) Data Base (United States Department of Agriculture 1995). While SURGO is the most detailed soil database, designed to allow erosion management of individual plots, there is no uniform reporting requirement. Instead we use the more aggregated soil database STATSGO that groups similar soils into polygons for the entire United States. Average soil qualities are given for each polygon. While this soil database gives a first approximation of the actual average soil qualities, significant heterogeneity could remain.

Finally, farmland close to urban areas has an inflated value compared to farmland elsewhere because of the option value of the land for urban development (and also, perhaps, because of superior access to urban consumers). Plantinga et al. (2002) examine the effects of potential land development on farmland prices and find that a large share of farmland value, more than 80% in major metropolitan areas, is attributable to the option to develop the land for urban uses. The City and County Data Book lists population density and income per capita on a county level. However, given that our analysis relies on individual geo-referenced farm-level data, we construct a variable to approximate population pressure that is on a smaller scale than the county-level aggregates of the City and County Data Book. We derive the gravitational population pressure by calculating the weighted sum of the population in each Census Tract. The total number of people in each of the roughly 65,000 tracts is weighted by the inverse of the squared distance between the farm and the centroid of each tract in meters (U.S. Census Bureau 2002).

4 Empirical Analysis

In this section we highlight the importance of access to water as a determinant of farmland values. The expectation is that more abundant and more secure access to water should result in higher farmland values.[21]

Table 2 presents our estimates for the hedonic regression with farmland value per acre as the dependent variable. We use a random effects model to allow farmland with identical longitude / latitude pairs to be correlated. As mentioned earlier, the June Agricultural Survey randomly selects a longitude/latitude pair and then samples *all* farms within the 1-square mile section around that location. It is hence possible to obtain several observations for the same longitude/latitude pair.[22]

The estimates in Table 2 are based on observations with a farmland value below $15,000

[21]This is the core assumption of Huffaker and Gardner (1986), Whittlesey and Herrell (1987), Crouter (1987), and Gardner and Huffaker (1988).

[22]As noted earlier, the standard OLS estimate underestimates the true variance-covariance matrix. OLS assumes all errors to be independent, even though they are in fact correlated. It is not uncommon in hedonic studies for variables to be statistically significant yet to switch signs between alternative formulations of the model. This could occur in a case like the present one, where the error terms are not i.i.d. Similarly, Moulton (1986) points out that treating grouped data as independent can underestimate the true variance-covariance matrix. One of his examples is a hedonic regression study of housing in the greater Boston area where he finds that the standard OLS variance-covariance matrix underestimates the true variance-covariance matrix by a factor of between 1.3 and 2.4. The effect of the understatement of the variance-covariance matrix is to overstate the significance of the regression coefficients.

Table 2: Hedonic Regression of Farmland Value ($ per acre, 2000) using Degree Days.

Variable	Coefficient	t-Value
Constant	1365	(0.38)
Thousand Degree Days ($8-32°C$) April-September	5493	(2.48)
Thousand Degree Days ($8-32°C$) April-September Squared	-1112	(2.78)
Precipitation April - September (Feet)	3591	(0.78)
Precipitation April - September (Feet) Squared	-75.3	(0.02)
Percent Clay (Percentage Points)	-70.2	(3.75)
K-Factor of Top Layer	-29.7	(1.00)
Minimum Permeability of All Layers (Inches / Hour)	-130	(1.13)
Average Water Capacity (Inches / Inch)	-70.8	(1.01)
Percent High Class Soil (Percentage Points)	5.95	(1.27)
Population Density	30.1	(2.32)
Depth to Groundwater (Feet)	-1.47	(0.37)
Federal + Private Water (Acre-feet / Acre)	656	(4.62)
Number of observations	2555	

Notes: Table list coefficient estimates from a random-effects model and t-values in parenthesis. Sample includes observations with farmland values below $15,000 and water prices below $20 per AF.

per acre.[23] Including higher value observations in the analysis increases the R-square of the regression, but the variable with the greatest explanatory power becomes population density. At the same time the confidence levels for soil quality and water availability are reduced. Farmland with values above $15,000 per acre is generally close to urban areas and the value of this land reflects what is happening in the urban land market and the value of the future potential to develop this land for urban use, not what is going on in the local agricultural economy. Including these observations creates large outliers and results in estimates that are mainly driven by the outliers.[24]

The coefficients on the climatic variables appear reasonable. The result for degree days implies that the quadratic form peaks at 2469 degree days for a six-month period. This is consistent with the agronomic literature which indicates degree days requirements of this

[23]Our main results are insensitive to the cutoff point. For example, if we choose cutoff points of $10,000 and $20,000, the optimal number of degree days becomes 2201 and 2473, respectively. The value of surface water availability becomes $538 and $723 per acre-feet. Only 4% of the area in our sample has a value above $15,000.

[24]We also experimented with using median regression to estimate the hedonic farmland value equation and found that this produced similar results which were very stable and almost insensitive to the cutoff point.

order of magnitude for several important crops grown in the Central Valley.[25] Since many tree crops need cool nights, increasing temperatures substantially above the required degree days to grow a crop can only be harmful.[26] Precipitation is expected to be valuable and is indeed positive, but not statistically significant. Precipitation during the summer months is very limited in California, with most districts receiving only an inch or two of rain.

The sign of the regression coefficient on water availability in Table 2 makes intuitive sense: the availability of surface water is valuable.[27] However, two points should be noted. First, the coefficient on average water delivery measures the capitalized value not of one acre foot of water per acre in a single year but rather of the long-run annual availability of one acre-foot per acre. Second, what is capitalized is the net value - i.e. the marginal value of water minus the retail cost to the farmer. By way of illustration, if the *gross* capitalized value of an acre-foot of water were \$1000 per acre-foot, yielding an annual value of, say \$50 per acre-foot (using a discount rate of 5%), and the annual delivery cost to the farmer were \$20, the *net* capitalized value of the water would be \$600 per acre-foot.[28] We therefore test the sensitivity of our results to variations in water price by excluding irrigation districts with high prices from the analysis to get a better estimate of the net value of water. Restricting

[25]The degree day requirement are somewhat crop-specific, with various lower and upper bounds. As a means of illustration, the growing period for corn is about 120 days, or roughly two-thirds of the six-month period April-September. A proportional number of degree days would be 1640, which is close to reported requirements. For further comparison of degree days and other temperature variables see Schlenker et al. (2004).

[26]A map showing the number of degree days in California is depicted above in Figure 1. As mentioned above, we did not include degree days $34°C$ as there is some dispute at what point temperatures become harmful if a plant is highly irrigated. (The $34°C$ was obtained from dryland agriculture. Accordingly, if we include the variable, it is negative but insignificant with a t-value of 1.05.

[27]We assume that the errors of our hedonic farmland equation are $i.i.d$ on a per-acre basis. If this assumption is appropriate, the standard errors will be estimated correctly. Since we are dealing with individual farmland data and not county averages, no weighting is required. One might wonder whether the variance of the errors is smaller for larger farms. We hence estimate a random-effects model with heteroscedastic random effects. Since the number of observations per group is limited, it is difficult to estimate the group-specific variance precisely. The noise is so large that we obtain several group-specific variances that are negative, which is theoretically infeasible. Alternatively, we apply White's consistent estimator in the second stage, which reduces the t-value on water availability from 4.62 to 4.18. The degree days variable remains significant as well.

[28]At this point we are not including prices as an explanatory variable in the regression equation because our price data are still very incomplete.

the sample to observations that have prices less than \$30, \$40, \$50, and \$60, changes the per acre value of an acre-foot from \$656 in Table 2 to \$450, \$434, \$365, and \$324 respectively as the hedonic regression only picks up the net benefit of the water availability. The optimal number of degree days changes slightly to 2470, 2460, 2544, and 2511, respectively. The linearity of the coefficient on water availability is confirmed when we include dummies for different ranges of water availability.[29]

The sample includes districts with no access to surface water; these are farming areas that depend exclusively on groundwater.[30] The coefficient on groundwater depth is negative, suggesting that greater depth is less desirable as it results in higher pumping cost. However, the coefficient is not statistically significant.

Soil variables have intuitive signs; yet only the variable clay content is statistically significant at conventional levels. Higher clay percentages are undesirable as they imply drainage problems, especially in the west side of the Central Valley. Higher values of the variable K-factor indicate increasing erodibility of the top soil. The water capacity of soil indicates how much water it can hold. While a large water capacity is good for dryland farming where the water should stay in the root zone, it can be damaging in irrigated agriculture as it indicates drainage problems. The fraction of soil that is considered top soil has a beneficial effect on farmland values. Finally, as expected, population density has a strong influence on land prices: this variable is significant and of a large magnitude compared to the sample mean. The potential to sell agricultural land for urban development is often the most profitable option for farmers.

Hedonic regressions rely on a cross-section and hence are prone to misspecification and

[29]There is one exception: The category of districts with more than 5AF has a negative sign. However, Glenn-Colusa Irrigation District is the only district that has more than 5 acre-foot per acre in our sample, and hence we are picking up some unique feature of this district with the dummy variable. When we checked the sensitivity of our results to including/excluding a single district at a time, the only one with a large impact is Glenn-Colusa. We therefore exclude the district from the previous analysis as we fear that there is something distinctive about this district that is not presently captured in our data.

[30]It should be noted that the pumping of groundwater is *not* monitored in California and therefore there is little reliable data on the amount of groundwater that is actually pumped by farmers.

omitted variable bias (Mundlak 1961, Deschenes and Greenstone 2004). However, in the following we show that the estimate on surface water availability is insensitive to the inclusion and exclusion of all the other control variables. While there is no direct way to test for omitted variable bias, this is at least comforting as it implies that omitted variable would have been correlated with surface water availability and farmland values, but *not* any of the other control variables. In case the omitted variable were correlated with one of the other controls as well, excluding it should significantly shift the parameter estimate on water availability.

Using an approach suggested by Leamer (1983) we estimate the robustness of our results to varying modeling assumptions by taking permutations of our set of independent variables. While it is somewhat ad hoc to rerun models with all possible combinations of the independent variables, this sensitivity analysis, presented in Table 3, indicates that our main estimates are robust across different modeling assumptions. Specifically, we use three sets of permutations: (i) all possible combinations of the five soil variables; (ii) soil variables as well as the location variables population density and depth to groundwater; (iii) all the variables in (ii) plus the four climatic variables. Since we allow each of the n variables under consideration to be included or excluded in the model, there are 2^n possible combinations. The results of the possible combinations on our variables of interest (the value of surface water availability) are given in Table 3. The inclusion or exclusion of soil and location variables appears to have a very limited effect on the estimates. This result gives us some confidence that there are no omitted soil or location variables that might seriously bias our estimates.[31] Similarly, excluding the climatic variables has limited effect on the coefficient estimate of water availability, suggesting that there is not a strong link between climate and surface water availability. Instead it is our hypothesis that the first farmers who settled in California chose plots close to major waterways that facilitate irrigation.[32]

[31] If a soil variable of great importance had been omitted, one would expect it to be somewhat correlated with the other soil variables, rendering our results sensitive to the inclusion or exclusion of soil variables.

[32] One potential concern is that water availability might be correlated with soil quality, i.e., the first settlers

Table 3: Sensitivity of Coefficient Estimate on Surface Water Availability to Different Model Specification

Possible Permutations Between the Following Variables	Number of Models	Coefficient Estimates Mean	Min	Max	σ
Soil variables	32	674	646	712	16
Soil and location variables	128	649	569	712	29
Soil, location, and climatic variables	2048	731	568	852	61

The soil variables are (i) Percent Clay, (ii) K-Factor of Top Layer, (iii) Minimum Permeability of All Layers, (iv) Average Water Capacity, and (v) Percent High Class Soil. The location variables are (i) Population Density, (ii) Depth to Groundwater. The climatic variables are (i) Degree Days, (ii) Degree Days Squared, (iii) Precipitation, and (iv) Precipitation Squared.

5 Potential Impacts on Farmland Value

In this section we briefly speculate on potential impacts of climate change on the average value of farmland in California. There is no claim of definitive empirical results, as these must wait on the development of more complete and accurate data on water rights, prices and deliveries and perhaps also more detailed climate and streamflow projections. Initially, climate scientists speculated that the increase in annual precipitation under most major climate scenarios would moderate the pressure on water resources. However, recent hydrological studies for moderate-temperate climates utilizing a smaller geographic scale discovered that despite the possible modest increase in annual precipitation, the runoff during the main growing season, i.e., between April and August in the Northern Hemisphere, might actually decrease as a seasonality effect dominates the annual effect (Lettenmaier and Sheer 1991, Hamlet and Lettenmaier 1999, Leung and Wigmosta 1999). Gleick and Chalecki (1999) conclude that "some consistent impacts have been identified [...] among the most important is the shift

with the oldest and largest water rights chose plots with the best soil and hence water availability could be correlated with unobserved soil characteristics. This would bias our estimates on the value of water availability upwards. However, as indicated in the text, it appears likely that the first settlers mainly chose plots close to major waterways. Since the Central Valley is comprised of former lake beds with relatively homogenous soils, the distance to the nearest river is usually not a proxy for soil quality. Hence we use this variable in a Durbin-Wu-Hausman endogeneity test, and find no evidence that water availability is endogenous.

in the timing of runoff that results from changes in snowfall and snowmelt dynamics". The idea is that more precipitation will fall as rain, rather than snow, during the winter rainy season (relative to the pre-warming pattern), and runoff from a melting snowpack will occur earlier in the spring. Both changes will mean reduced runoff in late spring and early summer. The decrease in water availability when it is needed most, during the growing season, will increase the demand for irrigation (McCabe Jr. and Wolock 1992), putting more pressure on river and groundwater systems. The predicted decrease in water availability depends on the seniority of water rights. More senior rights holders are likely to be served first and are hence less prone to a decrease in water availability. For the same reason, junior right holders will face potentially large reductions in availability. Given that the estimated value is $568 to $852 per AF for cheap water over the various model permutations in Table 3, a reduction of as much as one or two AF per acre, not implausible according to the most recent climate change scenarios downscaled to California (Katherine Hayhoe et al. 2004), would result in a decrease in the value of the affected farmland of as much as $1,700 per acre (high per AF value, two AF). Since the area-weighted per acre value of all observations in our sample is $4,177, this clearly represents a very substantial impact.

6 Conclusions

This paper studies how surface water availability, soil characteristics, and climatic variables capitalize into farmland values, and how these values would be affected by changes in the climatic variables. Using a micro-level data set of individual farms in California we find a major effect of water availability on farmland values, controlling for other influences.

Our estimate of the value of surface water is highly statistically significant and robust under a wide set of modeling assumptions. Permutations over all possible combinations of control variables yield coefficient estimates that are confined to a fairly narrow range, suggesting that our results a not driven by a particular modeling assumption. Predicted changes in water availability due to climate change hence have the potential to severely impact the value of farmland.

The other climate variable, degree days, is also statistically significant, even under the random-effects model, and the estimates on the linear and quadratic terms imply an optimal number of degree days that is consistent with agronomic findings.

Perhaps the most important caveat to the analysis of this paper is that results on the impact of changes in surface water availability must be regarded as preliminary because the data here are complex, and we are continuing to develop finer and more accurate measures, including some measure of the seniority of water rights. In addition, since the analysis relies on cross-sectional data it does not pick up any potential changes not reflected in the data, most notably changes in prices, technology, CO_2 fertilization, or the potential reduced water-requirements through CO_2 fertilization.

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