Title
Assessing the Resilience of Desert and Southern California Farming Systems to Water Scarcity

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Publication Date
2018

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
RIVERSIDE

Assessing the Resilience of Desert and Southern California Farming Systems to Water Scarcity

A Dissertation submitted in partial satisfaction of the
requirements for the degree of

Doctor of Philosophy

in

Environmental Sciences

by

Arisha Ashraf

March 2018

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ACKNOWLEDGEMENTS

Religion in modern society is admittedly a sensitive topic. Yet, this is the only place in this very long PhD journey where I can present my authentic self sans any citations of previous work. With that qualification, I thank God for giving me the daily, sometimes hourly, will to move forward, and surrounding me with great people.

Thanks to my advisor, Ariel Dinar, for being the best advisor in the world. That is not an academic statement at all (though it could be backed by previous research from his former students). Still, it is the only way I could account for his generous and patient support in time and resources throughout this process. His mentorship started even before I started UCR (and after I was accepted) when he chatted with me over the phone for 1.5 hours to ensure I was adequately prepared to enter graduate school. Who does that?!

I am grateful for the generous support from The John Randolph Haynes Foundation Doctoral Dissertation Grant Program, The Giannini Foundation, and the NIFA-funded multistate project (W3190). Several students and staff are partners/friends in my success: Towfiq Khan, Jessica Gonzalez, Amanda Tieu, Helen Huynh, Refat Amin, Jenessa Stemke, Cara Washington, Erik Dickson, Monobina Mukherjee, Jacob Gray, Abraham Juliot, John Herring, Shayna Conaway, Carol O'Brien, and Sherry Sereg.

Langston Montgomery, my love, how do I even begin? You put up with an often crabby (Cancerian to boot!), perpetually sweatshirt-clad partner who could not go anywhere on most weekends. You helped me with many of my data issues, and made me appreciate data analysis. Here's to marriage, Phase II iA, and our romantic weekend on

the beach learning R together! (Yes folks, data is part of our romance.) Am blessed for my stepson, Myles. His positive, infectious attitude on life makes me hopeful that Millennials will embrace technology to illuminate our world rather than harm it.

Shakila Ashraf, my Ammie, the most brilliant, beautiful and humble woman I know. As a young woman, she walked far to teach Urdu to college girls in Lucknow. She gave her salary and foregone rickshaw rupees to her parents to help fund her younger sisters' education. Yes, Ammie, I was listening. Your stories are etched in my heart. Aziz Ashraf, my Abbu, is the strongest person I know, and has a soft side reserved for his family. He washed my gym clothes when I was a bratty junior high girl who refused to get up and do it myself. Just one representative example of the type of father he has always been. Alia Ashraf, my sister and best friend. Amel Qudsia and Sarosh Qaiser, my best friends and sisters. I could go on about you guys, especially my Alia, but I do not want to appear too soft to the economists.

My closest kin: Khala Jaan, Apia Khala, Achikhala, Usman Bhai, Amir Bhai, Bheya, Baaji, Amnah Siddiqui, Asma Azim, Nancy Tseng, Asiya Merchant, Rashid Altafi, Langston Senior & Juanita Montgomery, Nicole & Randy Ellis, Zack & Nkeh Montgomery, Jacquelyne Moyers, Richard Ramon, Tanweer Ahmed, Tahsin & Yasmin Rizvi, Farhat & Syed Qaiser, Sharmin Raza, Monika Kerdeman, Susanne Grund. In memory of Shamsa Abbasi, Wasim Ahmed, Ahmed Sakr, Renee Qureshi, Maria Manfra, and Doris Bennett. And, here's to the kids: Aazim, Ayzah, Rayaan, Yusuf, Alena, Zidaan, Morgan, Emma, Ella, and Kai. Many more folks that only a database or the human heart could hold. Whoops, there is that soft side again.

Dedicated to two intellectual giants, my Abbu, Dr. Abdul Aziz Ashraf, and, my Khaloo Jaan, Dr. Sabihuddin Bilgrami.

ABSTRACT OF THE DISSERTATION

Assessing the Resilience of Desert and Southern California Farming
Systems to Water Scarcity

by

Arisha Ashraf

Doctor of Philosophy, Graduate Program in Environmental Sciences
University of California, Riverside, March 2018
Dr. Ariel Dinar, Chairperson

This study addresses the shortcomings in the literature by collecting primary farm-level data via a questionnaire for several productive regions of California that are often overlooked in agricultural analyses. Farm-level analyses help develop bottom-up incentives for adapting to climate change and addressing water scarcity. Because it is the localized climate directly observed by the economic agent, microclimate is more likely to impact production decisions than sub-regional averages. I study the impacts of change in microclimate on agricultural productivity in Desert and Southern California regions while controlling for other micro-level effects such as grower, farm, and water source characteristics. I also analyze the extent to which microclimate influences the adoption of two important water management strategies: soil moisture and salinity monitoring. In

addition, I analyze microclimatic impacts on productivity and land sales at the parcel-level.

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Chapter 1: Introduction

Increasing temperatures and higher variability in precipitation in California are part of a larger regional trend in the Western United States (Hoerling et al. 2013; Dettinger et al. 2011; Barnett et al. 2008; Groisman and Knight 2008; Trenberth et al. 2007). This is consistent with global trends that indicate that 2000-2010 has been warmer at the Earth's surface than any preceding decade since 1850 (Hartmann et al. 2013). Observed increases in temperature and precipitation extremes in semi-arid regions, such as Southern California, clearly translate into more severe future impacts than analogous trends in temperate regions, such as projections of increased frequency and duration of heat waves and droughts over the remainder of the current century (Hoerling et al. 2013; Mastrandea et al. 2011; Cayan et al. 2010; Seager et al. 2007).

Previous studies suggest that agriculture in the largely irrigated Western United States may not be as susceptible to precipitation trends as agriculture in the more temperate East (Schlenker and Roberts 2011; Schlenker, Hanemann and Fisher 2007). This holds for long-run mean precipitation conditions (i.e., precipitation normals). However, this conclusion minimizes the severity of the recent drought experienced in California with historically low precipitation and soil moisture levels (Williams et al. 2015; Griffin and Anchukaitis 2014). The recurrence and longer duration of droughts in California over the past two decades has greatly affected the agricultural industry, which, on average, uses about 80% of freshwater resources (Walthall et al. 2012). Figure 1.1 illustrates the percentage of California's area in drought from 2000-2016. Not only does this reveal the large spatial and temporal extent of the most recent drought, but the colors reveal the large area under extreme (red area) and exceptional (maroon area) drought from mid-2013 to 2017. The most immediate economic impacts are lost agricultural revenue emanating from fallowed acres and yield declines, and farm job losses for one of the most vulnerable socioeconomic groups. For example, the 2009 drought resulted in revenue losses of $370 million with fallowing of 285 thousand acres in the San Joaquin Valley, and almost 10 thousand farm jobs losses (Howitt, MacEwan, and Medellin-Azuara 2011).

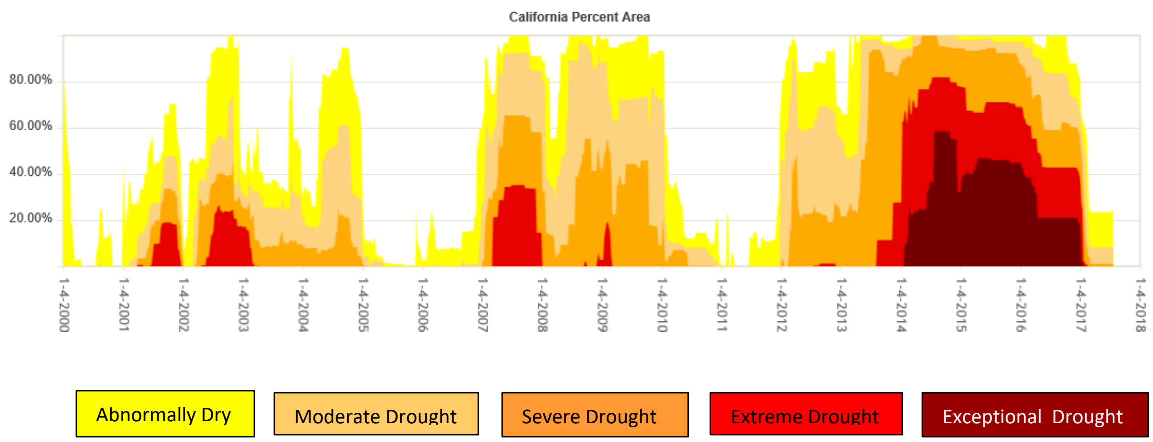

Figure 1.1: Spatial and Temporal Extent of Drought in California (2000-2016)
Source: National Drought Mitigation Center

Arguably the most important variables explaining how agriculture will be affected by climatic changes are those of human ingenuity at the farm level. Human ingenuity is simply another word for adaptation to climate change in order to minimize welfare losses. Thus, the overarching theme of our three subsequent analyses is quantifying grower responsiveness to farm-level microclimate in Southern California, our study area. Using original survey data, we study differential impacts of short-run weather and long-run climate—based on farm size, type, and water source—on productivity per acre and likelihood of adopting water management practices, which have not been studied in previous county-level analyses. Further, we are able to decompose water sources into price, pricing structure, frequency of rate increases, senior water rights, quality, and type of source (district and/or groundwater). In addition to studying farm-level productivity, we study short-run fluctuations in weather on likelihood of adoption of water management technologies and practices, and on parcel-level land sales.

Our contribution to the literature is based upon an original survey instrument we developed and disseminated to growers in the region (see Annex 3.4). The contact information was taken from the respective county Agricultural Commissioner Offices. This survey is comprised of 28 multiple choice and fill-in questions on grower, farm, and water source characteristics. This was disseminated via mail by a team of 3 undergraduate students, to growers in the study region, with a 14.6% response rate.

We focus on Southern California agriculture, specifically Imperial, Riverside, San Diego, and Ventura counties. The region is often overlooked as analyses tend to focus on the Central Valley, California's most productive agricultural region. Yet, there are several crops for which 50% or more of California's production originates in these four counties, including raspberries, lemons, flowers and foliage, avocado, and sudan hay. All of the state's date and sugar beet production originates in these four counties (CDFA 2015). Imperial, Riverside, San Diego, and Ventura counties are amongst the top 15 agricultural counties in the state, representing approximately 16% of statewide agricultural revenue (CDFA 2015). They also represent the diverse climate of the region with two coastal (San

Diego and Ventura), and two desert (Riverside and Imperial) counties. The 4 counties also vary in farm size with San Diego County having the largest share of farms under 10 acres, and, at the other extreme, Imperial County having the largest share of farms (32% of all Imperial farms) with 1000 or more acres (Figure 1.2). There is also a wide distribution in gross revenue across these counties (Figure 1.3).

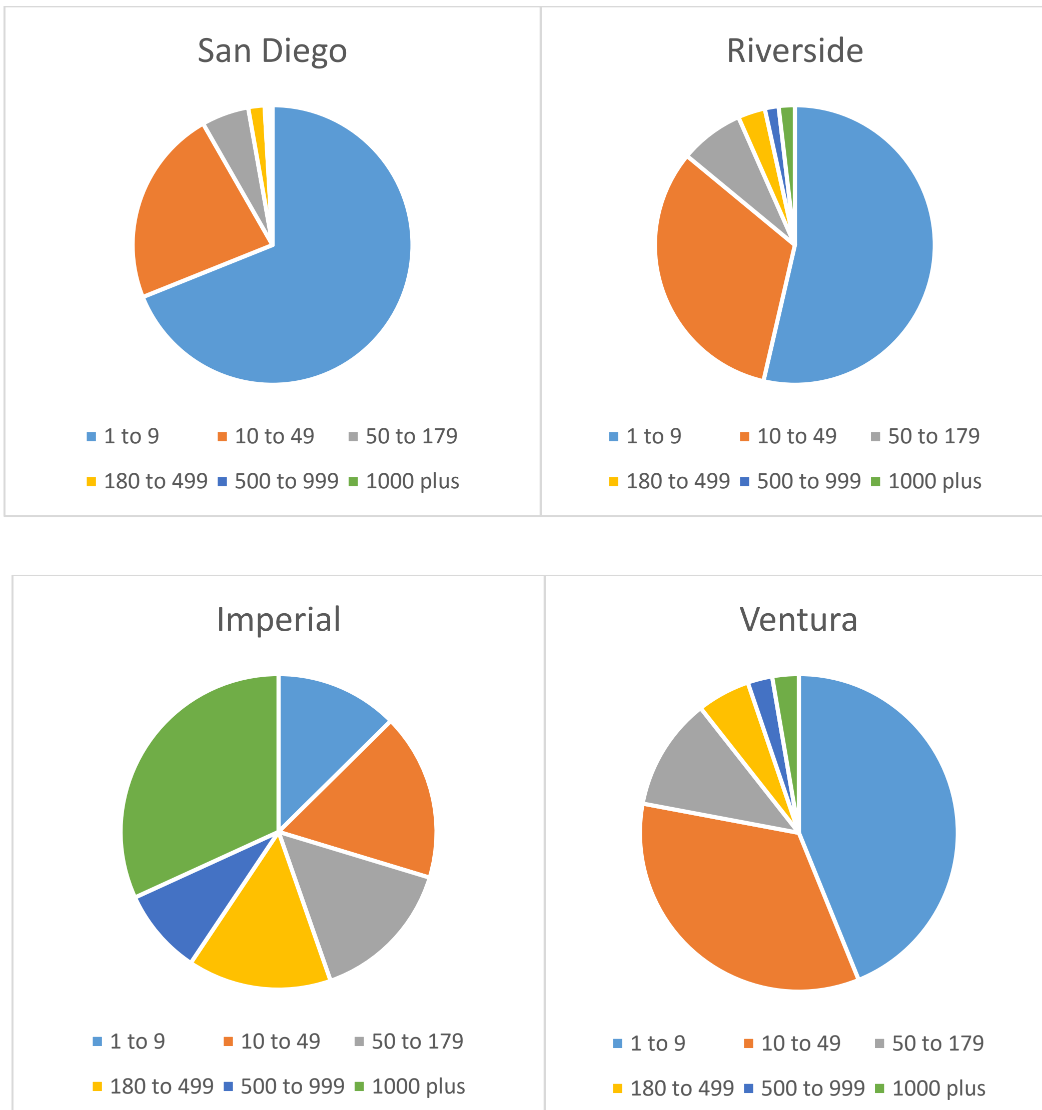

Figure 1.2: Distribution of Farm Sizes Across Study Region

Data Source: USDA Farm and Ranch Irrigation Survey, County Summary Highlights 2012

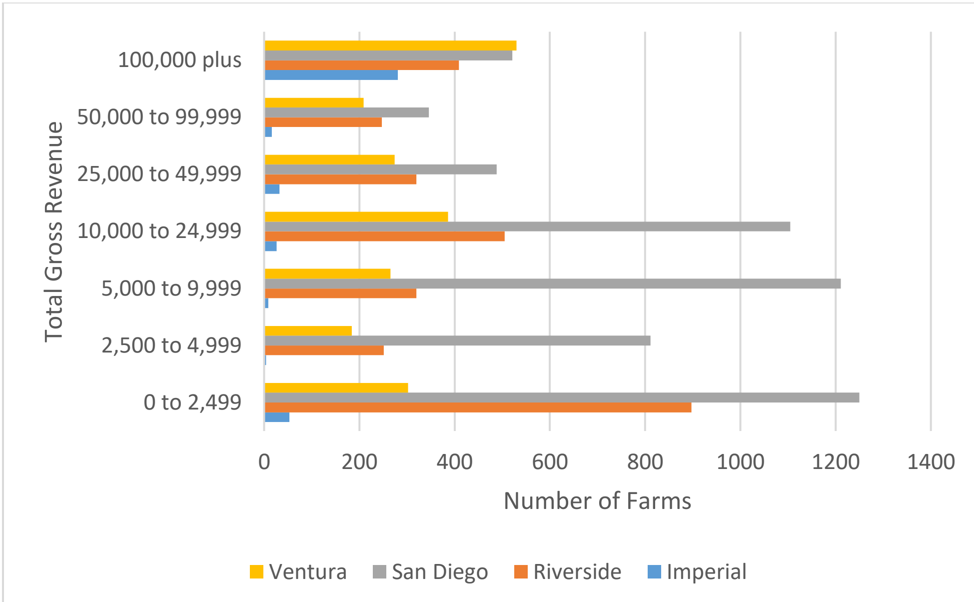

Figure 1.3: Number of Farms in Each Gross Revenue Category

Data Source: USDA Farm and Ranch Irrigation Survey, County Summary Highlights 2012

The dissertation is organized into 7 chapters, including this introductory chapter. Chapter 2 discusses the analytical framework and key hypotheses for the 3 subsequent analyses. Similarly, Chapter 3 discusses the data sources and variable transformations for each of the 3 analyses. It provides detail on our original survey research, as well as external data sources supplementing the survey data. Our empirical analyses are presented in chapters 4 - 6. Chapter 4 applies the Ricardian framework to quantify the marginal economic impact of human capital and farm-level variables on farm productivity under varying (with respect to the cross-section of farms) climatic, water source, and soil conditions. Chapter 5 also uses data from our questionnaire to examine choices of irrigation management technologies and practices by Southern California growers. Chapter 4 explores adaptation to climate change implicitly, whereas Chapter 5 explicitly evaluates two important irrigation management practices: soil moisture monitoring and salinity monitoring. Chapter 6 departs from our original survey data, and includes two analyses of short-run weather fluctuations with respect to parcel level data from the Riverside County Assessor's Office: (1) an exploratory panel analysis of farm sales, and (2) a Ricardian analysis on land values using the same dataset. Chapter 7 concludes the dissertation with broad policy implications of agricultural adaptation to climate change.

Chapter 2: Analytical Framework and Key Hypotheses

This chapter presents the analytical framework for the three complementary analyses in this study: (1) the Farm-Level Ricardian (Chapter 4), (2) the Discrete Choice of Adoption (Chapter 5), and (3) the Parcel-Level Models (Chapter 6). All three analyses illuminate our understanding of adaptive responses to climate change and drought. The first study implicitly models adaptation, while the latter two do so explicitly.

The Ricardian analysis quantifies the marginal economic impact of critical human capital (experience, education) and farm-level variables (percent income generated from agriculture, farm size, ownership) on farmland productivity under varying climatic, water source, and soil conditions. While previous studies have aggregated heterogeneous climates, water sources, and soil conditions at the county level (Deschenes and Kolstad 2011; Mendelsohn and Dinar 2003; Mendelsohn, Nordhaus and Shaw 1994), we examine the marginal economic impact of these variables at the farm-level.

The resilience of the agricultural sector will be determined by the ability of farmers to adapt to an increasingly warm and dry climate through adopting technologies and management practices. The discrete choice analysis examines the extent to which the probability of implementing two important water management practices—(1) soil moisture monitoring, and (2) salinity monitoring—is determined by a set of farm-level variables. This analysis tests many of the same variables in the Ricardian analysis with the addition of variables representing water scarcity perceptions and sources of information used for irrigation management. We also study the influence of short-run fluctuations in weather, in addition to the climate normals presented in the farm-level Ricardian analysis.

Using Riverside County as a case study, our third empirical chapter examines the impact of short-run fluctuations in weather on both the likelihood of land sale, and on productivity at the parcel level during 2000-2016. This period will fully capture two historic drought cycles: 2007-2009; and 2011-2016. The analyses of the Riverside County land sale examine to what extent certain categories of agricultural land are more vulnerable to sales or productivity loss during periods of drought (high temperatures and low precipitation captured by 5-year or 10-year averages) while controlling for soil characteristics (available water storage, drainage class), population, and access to reliable surface water from 4 major water districts (Coachella Valley Water District, Eastern Municipal Water District, Palo Verde Irrigation District, Western Municipal Water District).

Spatial Scale in County vs. Farm-level Analyses

Selection of spatial scale often guides the suite of explanatory variables included or, equally important, omitted, in a given analysis. Analogous to earlier studies on the effects of spatial scale on global climate model (GCM) projections, one may find inconsistent yield estimates between coarse and finer scale models (Adams, McCarl, and Mearns 2003). In addition, it may misrepresent the variability in the true model. This introduces the potential for measurement error on explanatory variables.

An immediate concern with aggregation at the county level is the omission of data on decision-maker/grower (e.g., experience, education), farm (e.g., farm size, farm type, percent agricultural income), and detailed water source attributes (e.g., number of water sources, surface or groundwater, senior water rights holder, water price). Excluding such information assumes a priori a limited role of the economic agent to influence farmland productivity. It also simplifies the inherent complexity in representing farm and water source characteristics. It is not for lack of explanatory power that these variables are excluded. It is more likely that they would have been studied had they been available in existing data sources. The USDA Farm and Ranch Irrigation Survey (FRIS), a major source of US agricultural data for economic analyses, does not provide these variables at the farm level to researchers. There is, however, little reason to assume that the climate, soil, and water variables in county-level studies are correlated with any of these micro-level variables, thus ruling out the potential bias in climate, soil, and water estimators.

Aggregation at the county level also leaves the model susceptible to measurement error on certain explanatory variables (e.g., microclimate and soil quality). Measurement error is defined as an imprecise measure of an economic variable, dependent or explanatory, which has a well-defined quantitative meaning (Woolridge 2006). [1] Following the classical errors-in variable (CEV) assumption, this could lead to estimators

[1] This situation is in contrast to a variable that cannot be directly quantified for which a proxy variable is used instead.

that are asymptotically inconsistent and biased downward in their respective probability limits (Woolridge 2006). [2]

The remaining sections in this chapter present the theoretical framework behind each of the 3 empirical analyses in this dissertation: (1) the Farm-Level Ricardian, (2) the Discrete Choice of Adoption, and (3) the Parcel-Level Models. Each subsection also includes hypotheses on the impact of climate and other key variables on the respective dependent variables (gross revenue per acre, likelihood of adoption, likelihood of land sale, land value per acre).

Farm-Level Ricardian Model

Following the classic paper by Mendelsohn, Nordhaus, and Shaw—MNS (1994), this study models farmland productivity using gross revenue per acre.[3] The Ricardian approach quantifies the impact of climate and other site-specific variables (e.g., soil

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[2] The proceeding proof follows from Woolridge (2006). Under the CEV assumptions, the observed value, x_1, is correlated with measurement error, m_1, such that

$$Cov(x_1, u - \beta_1 m_1) = Cov(x_1, u) - \beta_1 Cov(x_1, m_1) = -\beta_1 Cov(x_1, m_1) = -\beta_1 \sigma_{m_1}^2$$

Note that the observed value and error term, u, are uncorrelated following standard OLS assumptions. And, the final RHS term is derived from

$$Cov(x_1, m_1) = E(x_1, m_1) = E(x_1^* m_1) + E(m_1^2) = \sigma_{m_1}^2$$

where x_1^* is the true (unobserved) value such that $x_1^* = x_1 - m_1$. The proof of (in)consistency follows:

$$plim(\hat{}\beta_1) = \beta_1 + \frac{Cov(x_1 u - \beta_1 m_1)}{Var(x_1)} = \beta_1 \left(\frac{\sigma_{m_1}^2}{\sigma_{x_1^*}^2 + \sigma_{m_1}^2} \right) = \beta_1 \left(\frac{Var(x_1^*)}{Var(x_1)} \right)$$

By construction, $Var(x_1^*) < Var(x_1)$. Thus, the probability limit of the estimator is always closer to zero than the true value.

[3] We do not use profits as our dependent variable because of limited data on farm level operational costs. We also do not use land value per acre, as in the original MNS 1994 paper, because available data from the County Assessor does not represent market value. California Proposition 13 (People’s Initiative to Limit Property Taxation of 1978) caps the rate of private property appreciation at 2% annually.

quality, market access, population density) on farmland productivity. The approach exploits cross-sectional variation in climate (and these other variables) to determine the respective marginal impacts to farmland productivity, as represented by gross revenue. Two major assumptions of the Ricardian model are: (1) interest rate, rate of capital gains, and capital per acre are equal for all parcels (and thus for all growers); and (2) growers have fully adapted to local climatic, economic, and environmental conditions.

Farmland is a special case in which land rents are generally proportional to land productivity, which is represented by gross revenue per acre in our model. The value of a given farming practice changes in response to increasing temperature. Climate has a positive impact on productivity of a given agricultural activity up to a point where productivity reaches an optimum, after which changing climatic conditions (higher temperatures in Figure 2.1) introduces declining marginal productivity. At point C in Figure 2.1, a profit maximizing grower will switch to another activity rather than experience declining returns from the original one. Under the assumption that growers have fully adjusted or adapted to long-run conditions, gross revenue is equivalent to the envelope function, represented by the bold lines in Figure 2.1.

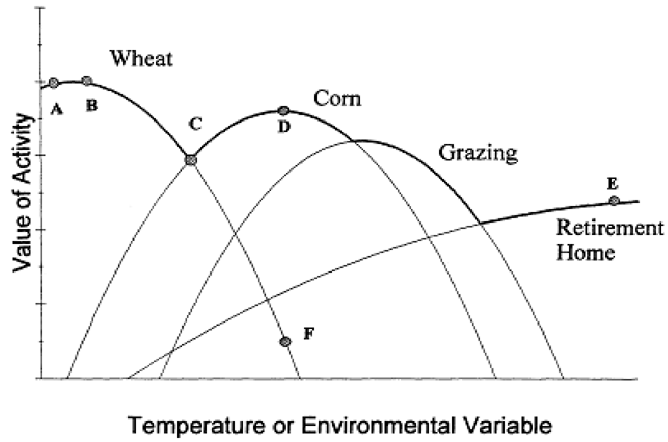


Figure 2.1: Crop Shifting as an Adaptation to Increasing Temperature

Source: Mendelsohn, Nordhaus, and Shaw 1994

Farmland value, *V*, for the i^{th} individual reflects the net present value of long run revenue generated from farming represented by Equation 2.1 (Mendelsohn and Dinar 2003):

$$\textbf{(2.1)} \qquad V_i = \int \left[\sum P_j Q_j(X, C, S, W, G, F) - \sum RX \right] e^{-\varphi t} dt$$

where *X* is a vector of purchased inputs required for the production of each crop, j, which we represent as irrigation technology;[4] *C* is a vector of climate variables (30-year normals for seasonal temperature minimums and maximums, and precipitation); *S* is soil quality (available water within the soil top 100 cm); *W* is a set of water source variables (e.g., surface or groundwater; salinity; senior water rights; water price); *G* is a vector of human capital variables (education, experience); *F* is a vector of farm characteristics (farm acreage, farm type, percent income generated from agriculture, ownership, zoning); and

[4] Ultimately, we find that irrigation technology is partitioned based upon crop choice. Thus, we do not include it in our final analysis.

R is a vector of input costs required for the production of each crop. φ is the discount rate.

Ricardian Model Hypotheses

There are general hypotheses that can be formulated based on previous work even though study areas in previous research have different climates, soils, and underlying mix of crops. We will infer these hypotheses, using the results in Chapter 4.

Climate Variables

We expect a nonlinear relationship (e.g., logarithmic, quadratic) between climate variables and gross revenue. This is consistent with the underlying nonlinearity in crop growth biology. It is also consistent with the detrimental yield effects of climate extremes, such as heavy rains, droughts, excess freezing, and heat waves (Mendelsohn and Dinar 2009:10-31).

It is expected that an increase in minimum temperature will have a negative marginal impact on gross revenue, particularly as many of the farms in the study region grow orchards. Increasing the minimum temperature is thought to have a negative impact on productivity because many tree crops require cooling at night, particularly during the cooler seasons (Lobell and Field 2011).

Increasing the maximum temperature is expected to exhibit a negative marginal impact as well (Deryng et al. 2014; Lobell and Field 2007). It will be interesting to explore which effect is stronger—higher minimum or higher maximum temperatures.

Grower characteristics (education, experience)

Educational levels are expected to have a hill-shaped relationship with productivity (Das and Sahoo 2012). We expect to observe an increasing trend until a Bachelor's degree. Education after a BA is expected to exhibit declining marginal benefits to farm productivity, as the opportunity cost of devoting this knowledge capital to farming relative to off-farm income (e.g., lawyers, medical doctors) becomes more expensive.

Years of growing experience is expected to have a positive marginal impact on productivity (Maddison et al. 2007). This is also expected to have a hill shape, with decreasing marginal productivity for increasing experience after a median level of experience.

Water source variables (senior water rights, type of water source, number of sources, tds, water price)

Unit water price exhibits a complex relationship with productivity per acre, and is given limited attention, so far, in Ricardian analyses of California agriculture (Schlenker, Hanemann, and Fisher 2007; Mendelsohn and Dinar 2003). High water price could be a limiting factor at the extensive margin (i.e., increasing the acreage), however price may influence intensive margin (i.e., increasing the productivity per unit acre) improvements based on empirical evidence on adoption of irrigation technologies in California (Green et al. 1996; Dinar, Campbell, and Zilberman 1992; Caswell and Zilberman 1985; Caswell 1982).

Senior water rights are expected to exhibit a positive relationship with productivity due to greater water security (Mukherjee 2013). Senior water rights holders in our sample also have the lowest water price per acre-foot.

It is expected that the number of water sources will have a positive impact on productivity, as growers are able to use an alternative source should the primary source become less reliable, have greater water security (Mukherjee and Schwabe 2014).

Salinity level in water (as represented by total dissolved solids in ppm) is expected to exhibit a negative relationship with productivity, particularly for growers with a high relative price of water and fewer water sources (Mukherjee and Schwabe 2014). Lower quality water requires more monitoring (as well as more leaching) in order to minimize crop damage, and this is costly as the price of water increases and fewer alternative sources are available.

Farm-level variables (ownership, percent income generated from agriculture, soil, farm type, county, zoning)

Percent ownership of land is expected to exhibit a positive marginal impact on productivity because there is more incentive to invest in productivity improving changes as a landowner (Maddison et al. 2007).

Percent of income generated from agriculture, is expected to exhibit a positive impact on productivity. Increasing percentage of income generated from agriculture increases the incentive to maximize output.

Soil quality, as measured through available water moisture in the top 100cm of the soil, is expected to exhibit a positive relationship with gross revenue per acre as higher quality soil improves productivity (Schlenker et al. 2007; Mendelsohn and Dinar 2003).

Orchards and vineyards tend produce higher values per acre (Mukherjee and Schwabe 2014), whereas field crops tend to produce the lowest.

Farms in San Diego County will exhibit a strong positive relationship with productivity relative to the other counties due to the high price of land and water, and high percentage of orchards and vineyards.

The relationship between agricultural zoning and gross margin is expected to be positive because farms in these areas have greater access to the agricultural industry (e.g., extension and industry experts, input suppliers, distribution companies) (Mukherjee 2013).

Discrete Choice of Soil Moisture and Salinity Monitoring Model

In addition to studying the impact of climate and other relevant variables on farmland productivity, we study the factors influencing the adoption of technologies to monitor soil moisture and salinity.[5] Adoption of climate-effective monitoring practices is particularly important as projections of prolonged drought continue throughout the current century. Most growers in our sample have already adopted micro-irrigation (micro-sprinkler, drip, sub-surface drip) practices for vegetables, orchards, and vineyards,

[5] We expect growers monitoring soil water moisture and salinity to have better information to make water-related decisions.

and extension experts suggest that consistent and/or sophisticated monitoring of growing conditions represents the next stage of irrigation efficiency adaptations (Gispert 2015).

Soil moisture monitoring practices help ensure precise frequency and duration of irrigations. Salinity monitoring affects water availability in both the short and long run. Too much leaching leads to water waste and, ultimately poor irrigation and economic efficiency. Too little leaching affects soil salinity and water quality at both the farm and basin level, and ultimately water availability at the farm-level in the long run.

We implement logistic regression, consistent with previous studies on technology adoption (e.g., Escalera, Dinar, and Crowley 2015; Mendelsohn, and Dinar 2003; Caswell and Zilberman 1985), to study the factors influencing adoption of at least one soil moisture monitoring practice (of the following: gravimetric approaches, tensiometers, gypsum blocks, and dielectric sensors), or at least one water salinity monitoring practice (of the following: water provider updates, handheld TDS/salinity meter, laboratory salinity assessments).

We expect that a profit-maximizing grower, *i*, will implement at least one soil (or salinity) monitoring practice. The perceived profit per acre to grower *i* of monitoring or not monitoring soil (where *j* is the binary probability {0,1}), is represented as:

$$\pi_{ij} = Q_{ij} + \varepsilon_{ij} \qquad \textbf{(2.2)}$$

where Q is the non-stochastic component of perceived profit, while the errors, ε_{ij}, represent the stochastic component. If the observations are indeed drawn at random, as in our survey sample, then it can be assumed that the error is an *iid* random variable (McFadden 1978). The reduced form of the value function is represented as:

(2.3) $$Q_{ij} = Q_{ij}^{*}(I, X, C, S, W, G, F) + \varepsilon_{ij} \quad \forall\, j \in \{0,1\}$$

where the vectors X, C, S, W, G, F are the same as in Equation 2.1, with the addition of a vector of perception and information source variables, I. Empirical evidence on California avocado growers suggests that receiving information from the UC Cooperative Extension positively influences the decision to improve irrigation efficiency (Escalera, Dinar, and Crowley 2015). There is also evidence that growers who feel threatened by current or recent drought are more likely to believe in the existence of future droughts (Diggs 1991; Taylor, Stewart, and Downton 1988). This study extends the previous research cited above by testing the probability of adopting soil moisture and salinity monitoring practices given a grower feels threatened by drought (Equations. 2.4 – 2.5):

(2.4) $$P_{i1} = \Pr(Q_{i1} > Q_{i0})$$

(2.5) $$P_{i1} = \Pr(\varepsilon_{i0} - \varepsilon_{i1} < Q_{i1}^{*} - Q_{i0}^{*}).$$

The binary probability of the i^{th} grower selecting at least one monitoring practice (moisture or salinity) is:

(2.6A) $$P_{ij} = \frac{e^{Q_{ij}+\varepsilon_{ij}}}{1 + e^{Q_{ij}+\varepsilon_{ij}}} \quad \forall j \in \{0,1\}$$

And, the multinomial logistic regression with four choices (implements both monitoring practices, implements neither practice, implements salinity monitoring only, implements soil moisture monitoring only) is represented as:

(2.6B) $$P_{ij} = \frac{e^{Q_{ij}+\varepsilon_{ij}}}{1 + \sum e^{Q_{ij}+\varepsilon_{ij}}} \quad \forall j \in \{1,2,3,4\}$$

Discrete Choice Model Hypotheses

Based on previous work, we identify below several hypotheses that will be inferred, using the results in Chapter 5.

Water price is expected to have a positive relationship with the probability of adopting at least one soil moisture or salinity monitoring technology (Dinar, Campbell, and Zilberman 1992; Caswell and Zilberman 1985, Caswell 1982).

Hotter/drier micro-climates are expected to have a positive impact on the adoption probability (Mendelsohn and Dinar 2003).

High-value crops are expected to be associated with higher values of adoption probability (Green et al. 1996; Dinar, Campbell, and Zilberman 1992; Caswell and Zilberman 1985).

Human capital variables such as education and experience may positively influence adoption probability exhibiting a hill shape (Schuck et al. 2005; Genius et al. 2014).

Receiving information from extension agents and other government sources is expected to have a positive impact on the probability to adopt soil moisture and salinity monitoring technologies (Escalera, Dinar, and Crowley 2015; Genius et al. 2014).

With respect to the multinomial logistic regression, we expect to identify micro-level variables that influence the adoption of both practices when one practice has been adopted. This is analogous to bundling complementary technologies (Fleischer, Mendelsohn, and Dinar 2011).

Water source type (district or groundwater) or number of water sources may influence the likelihood of adoption, analogous to the Ricardian literature (Mukherjee 2013).

Acreage is expected to have a positive impact on adoption probability, suggesting an economy of scale impact (Dinar, Campbell, and Zilberman 1992).

Growers with a higher percentage of income generated from agriculture will have more incentive to adopt monitoring practices (Dinar, Campbell, and Zilberman 1992).

Growers who rank drought as a top threat to water scarcity will be more likely to adopt water moisture and salinity monitoring (Schuck et al. 2005)

Soil quality is expected to have an inverse relationship with soil moisture monitoring, as poor quality soil will require more monitoring (Green et al. 1996; Caswell and Zilberman 1985). Analogously, a higher level of total dissolved solids (i.e., lower quality with respect to this metric) is expected to increase the likelihood of salinity monitoring. Crops that are more salt sensitive will increase the probability of salinity monitoring (Caswell et al. 2001).

Parcel-Level Models

The empirical studies in Chapter 6 depart from our 4-county questionnaire data, and narrow the focus from farm- to parcel-level. Using a dataset on 17 years (2000-2016) of agricultural parcel sales in Riverside County, we implement two analyses to test the impact of short-run weather fluctuations at the parcel level: (1) panel logistic regression model to study the factors influencing the likelihood of land sale, (2) Ricardian analysis of impacts and implicit adaptation. Among the menu of adaptation measures, leaving agriculture (whether through selling a subset of parcels or the entire farm) is an extreme form of adapting to climate extremes.

Previous work has focused on which factors influence the value (i.e., long-run productivity) of farmland (e.g., Mukherjee and Schawabe 2014; Mendelsohn and Dinar 2003; Mendelsohn, Nordhaus and Shaw 1994). It is equally important to understand what is influencing the sale of farmland in response to climatic shocks in the first place. We focus on Riverside County parcel sales from 2000-2016 to examine the following in a population averaged panel regression:

(2.7) $\Pr(sale_{it}|climate_{it}, soil_i, watdistrict_i, population_i, usecode_i, acre_i)$

where sale is a dichotomous variable representing whether a given agricultural parcel, *i*, in a given year, *t*, was sold or not. Weather is a vector of a 10-year (or 5-year) average of maximum or minimum temperatures, precipitation, and variability for a given parcel *i*, sold in year, *t*. Soil represents a vector of soil quality of parcel *i* (measured as available water moisture in the top 100cm of the soil; and slope gradient), watdistrict (dummy for 4 major water districts represented in our analysis) represents access to reliable water supply from a water institution, population is the municipal population in which parcel *i* is located, crop zone is the specific agricultural zoning as defined by Riverside County (Table 6.1), and acre is the size of parcel *i*.

In addition to land sales, we study the impact of short-run fluctuations of weather on farmland value using the Ricardian framework as in Equation 2.1. Since we are not using survey data, we do not have information on human capital variables. Thus, we return to the original Ricardian equation where land value is a vector of exogenous variables (Mendelsohn and Dinar 2003).

Parcel-Level Model Hypotheses

We identify below several hypotheses that will be inferred, using the results in Chapter 6.

We expect an increase in the short-run precipitation mean to increase likelihood of parcel sales and parcel value. This is because the short-run perception of drought reduces the profitability of farming.

We expect an increase in the 5-year coefficient of variation in precipitation to decrease likelihood of sales and parcel value. A larger coefficient of variation implies more extreme disparities in annual precipitation events associated with the drought.

It is expected that parcels located in areas experiencing the highest population growth are more likely to be sold and have the highest value (Platinga, Lubowski, and Stavins 2002).

We expect that soil quality will cause an increase in sales and value (Schlenker et al. 2007; Mendelsohn and Dinar 2003).

We expect that the number of sales in the urban districts (Western Municipal Water District and Eastern Municipal Water District) and that the value of parcels will be greater in these districts compared to non-urban districts. Land in urban water districts has higher development value (Platinga, Lubowski, and Stavins 2002).

In general, we expect sales and value to follow the same trend, i.e., variables that stimulate increasing sales will also stimulate increasing value.

To summarize, this chapter discusses the analytical framework and key hypotheses for the three complementary empirical analyses in this study (in chapters 4-6). The farm- and parcel-level Ricardian analyses examine the impact of both long-term (farm-level model) and short-term (parcel-level model) temperature and precipitation expectations on farmland productivity. Additionally, we explore how land sales may be related to farmland productivity and temperature/precipitation expectations. The discrete choice model explicitly studies potential adaptations of important irrigation monitoring practices.

Chapter 3: Data Collection and Variable Construction

This chapter details data collection methods, procedures, and data sources, as well as how key variables are constructed. The primary dataset for Chapters 4 and 5 was constructed using four methods: (1) a semi-structured survey instrument, (2) spatial GIS analysis (land value, climate, soil properties, groundwater, zoning) supplemented by Google Earth when spatial data were unavailable (3) other external sources (crop production and prices, and water prices), and (4) survey of water districts on rate structure. Survey design and implementation are discussed first, since this is our contribution to the dataset. This is followed by a description of external data sources, and survey of water districts. Following this, data sources for Chapter 6 are presented. This chapter concludes with a brief discussion of data collection challenges.

Survey Design

The impact on long-run productivity and adoption of advanced irrigation technology and other water management practices are inherently farm-level aspects. We collect our own data using a survey instrument. As Salant and Dillman (1994) suggest, a robust original data source is the foundation for a strong survey. Thus, as further justification for pursuing a survey method of data collection, we found an excellent spatial dataset from the respective county-level Agricultural Commissioners' Offices, which could be supplemented with important farm/farmer, water sources, and water management variables from our survey. And, it could be linked to existing spatial climate and soil data. In administering the survey, we went through several stages that are described below.

Pilot Survey

Prior to implementing the pilot survey, we received approval from the UCR Institutional Review Board.[6] There were two primary objectives to the pilot survey: (1) field-test survey questions, and (2) gauge response rate. Rather than rely on focus groups to field-test the survey questions, we chose to disseminate a pilot survey. The major benefit of sending a pilot survey is that we could potentially receive valuable input from respondents who could not participate in focus groups due to financial, time, or physical constraints. A second benefit was time savings in survey implementation. Focus groups require managing multiple schedules to find a convenient meeting time and place, and possibly funding travel and accommodation.

Although we planned to disseminate an online survey, we had not yet at that stage secured assistance from either Agricultural Extension or Farm Bureaus in each county to host our survey. In order to save time, we sent the pilot survey via postal ("snail") mail using contact information from the Agricultural Commissioner Pesticide Permit Database (i.e., our original dataset). An informal team of fellow graduate students and family/friends helped prepare the pilot phase mailings. Each mailing package included invitation letters (Annex 3.1), consent documents (Annex 3.2), first version of questionnaire (Annex 3.3), and a self-addressed return envelope.

[6] We were subsequently approved for amending the questionnaire prior to mailing the final survey.

Using a random-number function[7] in Microsoft Excel, we randomly selected 300 respondents in total from Riverside and San Diego counties. We selected these counties as they are representative of the type of agriculture found in the region (row and field crops, vineyards, and orange and avocado groves). Based on our discussions with extension experts,[8] we were sensitive to the potential apprehension with which Imperial County growers, in particular, would react to our survey. Growers in Imperial County have held senior water rights for over a century due to the Seven-Party Agreement.[9] They are aware that they have been criticized for using less efficient irrigation practices (e.g., flooding, gated pipe), and many fear that they will be mandated to change these practices (Bradshaw, 2014). Thus, they may be hesitant to providing any information on irrigation and other practices. In order to minimize Imperial growers' time burden, we chose to field test the survey on a potentially more receptive audience, and send only the final survey to Imperial. Since Ventura County has a relatively similar distribution of farm types as San Diego County (Figure 3.1), we also decided to exclude Ventura from the pilot.

The pilot survey consists of 20 questions, including grower characteristics (5), farm characteristics (3), water source characteristics (1), water management practices (4), perceptions of water scarcity (7), and an open-ended comment space at the end of the

---

[7] For uniform distribution on the interval [1, n), where n=total number of growers in each respective county dataset, we used: RAND( ) *(n-1) + 1. We copied this formula to 150 rows, and rounded up to the nearest whole number.

[8] These included Dr. Khaled Bali, who was at that time Director of UCCE Imperial County, and Dr. Oli Bacchi, Crop Extension specialist in the same county.

[9] Both Palo Verde Irrigation District and Coachella Valley Water District are also parties to this agreement. However, these growers do not represent all of farming in Riverside County whereas IID growers represent the majority of farming in Imperial County.

survey (Annex 3.3). The majority of these questions are multiple choice often with an "other" choice that included an option to write in a response that was not pre-determined. Eight questions are fill-in style.

We received a roughly 10% response rate from the pilot phase (n=31), and learned valuable lessons on question structure for preparing the final survey. First, there were far too many questions on water scarcity perceptions, which could be consolidated into fewer questions. Second, income questions were better placed at the end of the survey to minimize participant suspicion. We also discovered that both water source and crop questions needed to be simplified. We achieved this by only asking for water source rank and name, which could be used to search external data for total dissolved solids, water price, and (in the case of district water) percent of supplier revenue generated from selling water to agricultural consumers. We simplified the crop question to only ask for the top 3 highest value crops, based on feedback from survey respondents.

Final Survey Data Collection Plan

The final survey consisted of 28 questions (Annex 3.4). Questions associated with farm, farmer and water source characteristics were straightforward to construct (e.g., education, percent agricultural income, years of farming experience, water sources, acreage, crop type), and we used either fill-in or close-ended questions. Water management practices (e.g., irrigation, soil moisture monitoring, salinity monitoring, water scheduling, and water flow monitoring technologies) required reliance on previous surveys (FRIS 2013; Escalera, Dinar and Crowley 2015; Dinar and Campbell 1990) and help from agricultural extension and resource conservation experts.[10] Two questions on water scarcity perceptions were also included (Diggs 1991; Taylor, Stewart, and Downton 1988).

The original data collection method was an on-line survey via the Survey Monkey platform that would be disseminated by the respective Agricultural Extension agencies or Farm Bureaus for the four counties. The greatest strength of an on-line vs. mail-in survey is the time saving both in disseminating the survey and inputting/coding data. One also has the ability to "force" responses for the most critical data, thus reducing incomplete surveys (of course, too many of these questions may frustrate respondents and cause them to quit).

The Agricultural Extension agencies, Imperial County in particular, were hesitant to host a survey on their websites. Ultimately, the Farm Bureaus in Riverside and San Diego counties hosted our survey. After being hosted on the Riverside Farm Bureau site for one month, the survey only received two complete responses (and three incomplete ones). San Diego Farm Bureau did not directly host the survey on their website, but agreed to disseminate the survey via an email newsletter. This yielded two responses after one month. The pilot mail-in survey had a higher response rate than the on-line final version. Thus, we made a decision to implement a mail-in survey using the same dataset as from our pilot survey.

[10] Eta Takele, Jose Aguiar and Carmen Gispert from UCCE Riverside County; Paul Lake and Lance Anderson from the Resource Conservation Districts; Steve Pastor from Riverside Farm Bureau; and Khaled Bali from UCCE Imperial County.

We mailed the survey to 1277 potential respondents in a staggered sequence following the timeline in Figure 3.1. We mailed the entire list in Imperial and Riverside counties due to the relatively smaller number of growers. For San Diego and Ventura counties, we used a random number generator to randomly select 300 recipients from each county. The mailing packets contained: invitation letter, informed consent, survey, and self-addressed return envelope. We also offered a $25 incentive if we were to receive the survey by the two-month deadline stipulated in the informed consent. We had a dedicated team of three undergraduate students to assist with the initial and follow-up mailings. These students later assisted with data entry. We received 221 responses, of which 187 were valid, resulting in a 14.6% response rate.[11]

March – June 2015: Develop general understanding of survey design (question types, questionnaire structure; common sampling/measurement errors) and sampling strategies (Salant and Dillman 1994; CIMMYT 1993; Cohen and Cohen 1983). Read previous surveys (Escalera, Dinar, and Crowley 2015; CIMMYT 1993; Dinar and Campbell 1990).

June – August 2015: Pilot phase survey dissemination

August -- September 2015: Finalize survey based on pilot phase findings

September – October 2015: On-line survey dissemination

October – November 2015: Send Mail-in survey (due to poor response rate on-line) to Riverside and San Diego counties

January 2016: Send follow-up letter to non-respondents in Riverside and San Diego counties. Preliminary coding and database creation

February – April 2016: Send mail-in survey sent to Imperial County; continue data entry; send follow-up letter to Imperial county non-respondents

April – June 2016: Send mail-in survey sent to Ventura County; continue data entry; send follow-up letter to Ventura county non-respondents

Figure 3.1: Survey Milestones and Timeline

[11] Of the 221 responses received, we excluded nurseries, anonymous responses, and growers who did not sell commercially.

Questionnaire Dataset

The observations in the original dataset, used for the pilot and final surveys, were obtained from the County Agricultural Commissioners' Offices in Imperial, Riverside, San Diego, and Ventura counties via a Public Information Request Form. There is no formal name for this dataset, though it is informally called "Pesticide Permit Data". It represents agricultural entities who applied for Restricted Materials Permits at a given time. Conservative estimates suggest that these data represent roughly 75% of growers in each county (Mulherin, 2014). We used 2014 as our reference year, because we wanted to ask growers about the prior year when we started our analysis in mid-2015. The dataset includes contact information, location, and commodity information (crop type, planted acreage) at the agricultural field level (with site-ID) for each grower. Importantly, these excel data are linked to geospatial data.

These data are not linked to email addresses, preventing us from using the dataset in an on-line survey. As discussed earlier, our primary reason for abandoning on-line survey dissemination was the poor response rate. Additionally, the Agricultural Commissioner has GIS field boundaries for each farm, which allow us to accurately link land value, climate, and soil to specific agricultural fields. This will subsequently be explained in more detail.

Imperial County

The original dataset from Imperial County contained 312 entities. 87 entities were excluded as ineligible (uncultivated agriculture—6, research or management companies—54, non-agricultural use—22, misc--5). The survey was mailed to n=225 growers. The final survey sample size for Imperial County is n=30.

Riverside County

The original dataset from Riverside County contained 481 entities. Twenty-nine entities were excluded as ineligible (apiary--4, aquaculture--1, poultry--5, management companies--11, misc.--8). The survey was mailed to n=452 growers. The final survey sample for Riverside County is n=60.

San Diego County

The original dataset from San Diego County contained 2075 entities. In order to control for non-commercial farms, we excluded 890 growers with less than 5 acres.[12] We also excluded 17 other growers (apiary—3, management companies—5, water utilities—9). Thus, the cleaned dataset included 1168 entries, of which we randomly selected 300. The final survey sample for San Diego County is n=48.

Ventura County

The dataset from Ventura County was particularly noisy. Although we had requested only agricultural parcels, we received data on pest control, golf courses, water utilities, etc. After excluding 310 ineligible entities (pest control—35, management companies—45, parks—15, golf courses—23, utility—33, apiary—5, growers with less

[12] Even though we excluded growers with less than 5 acres, several respondents in San Diego County reported less than 5 acres on their surveys. This reveals a discrepancy between reported acres in the Agricultural Commissioner dataset, and actual planted acres.

than 5 acres—112, misc.—42), the size went down from 1170 entities to 860, of which we randomly selected 300. The final survey sample for Ventura County is n=49.

Farm Types Data

The Agricultural Commissioner Dataset provides information on the planted acreage of each crop on each field for each grower. We categorized each crop as either field/grain (G), nursery (N), vegetable (R), tree/orchard (T), vineyard (V), or a mix of more than one category (M) based on a field guide of California agriculture (Starrs and Goin 2010). After each crop was categorized, we calculated the percent of each crop category with respect to total planted acres on farm.[13] If 75% or more of the planted acreage was devoted to a particular crop category, then farm type was labeled as such.[14]

[13] Note that planted acres is different from the total farm acreage. It may be larger than the total acreage because of annual crop rotations. Or, it may be smaller when the entire field is fallowed.
[14] The USDA does not have a method to categorize farms with multiple crops. We use >/= 75% acreage as a conservative estimate, as 75% is commonly used to represent the mathematical majority.

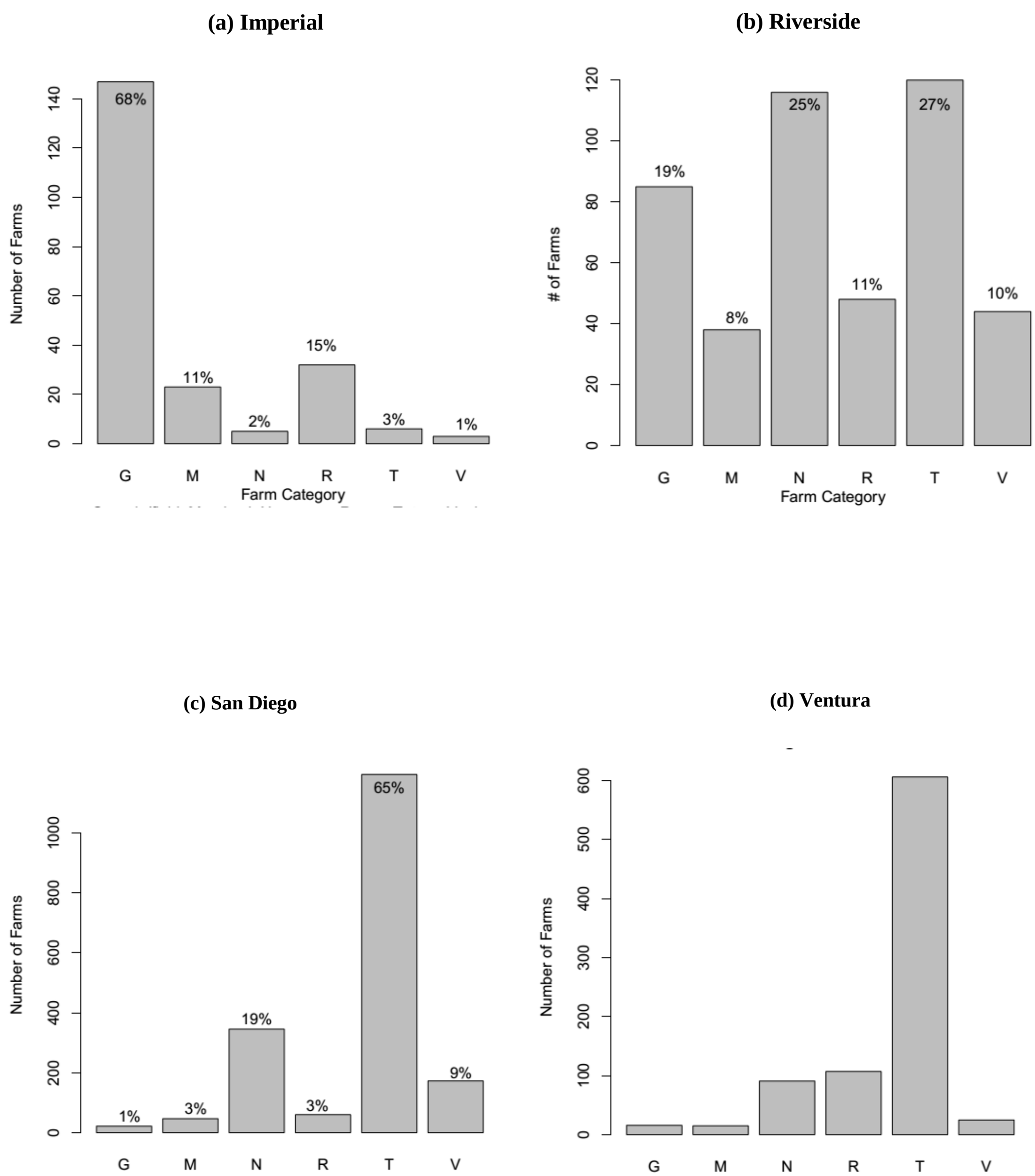


Figure 3.2: Distribution of Farm Types in the Original Dataset

Water Source Data

There are two broad categories of water sources in our sample: district water and groundwater. Water source names and relative importance were collected from the survey. More than half of growers (62%) have only a single water source, and this is most likely district water (Figures 3.3 and 3.4).

Figure 3.3: Histogram of Number of Water Sources

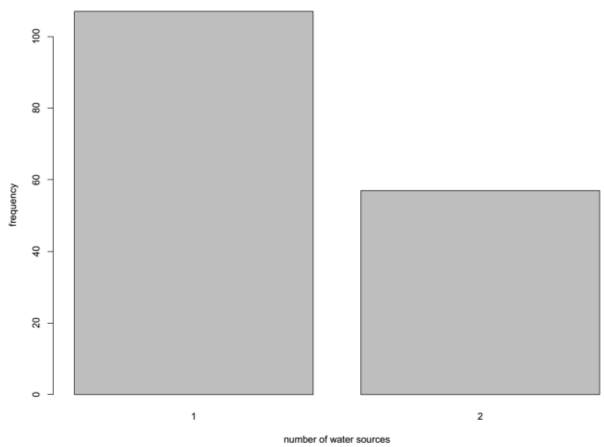
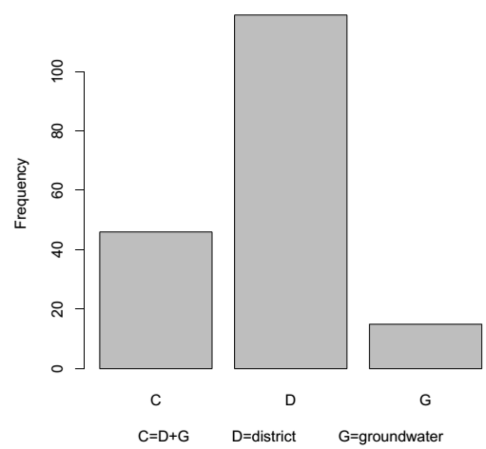


Figure 3.4: Histogram of Water Source Types



Water District Data

Water district variables (water price, salinity, percent revenue from agricultural accounts) were derived from Consumer Confidence Reports (CCRs), Annual Reports (ARs), and other supplemental documentation (Annex 3.5). Water district boundaries are represented in Figure 3.5.

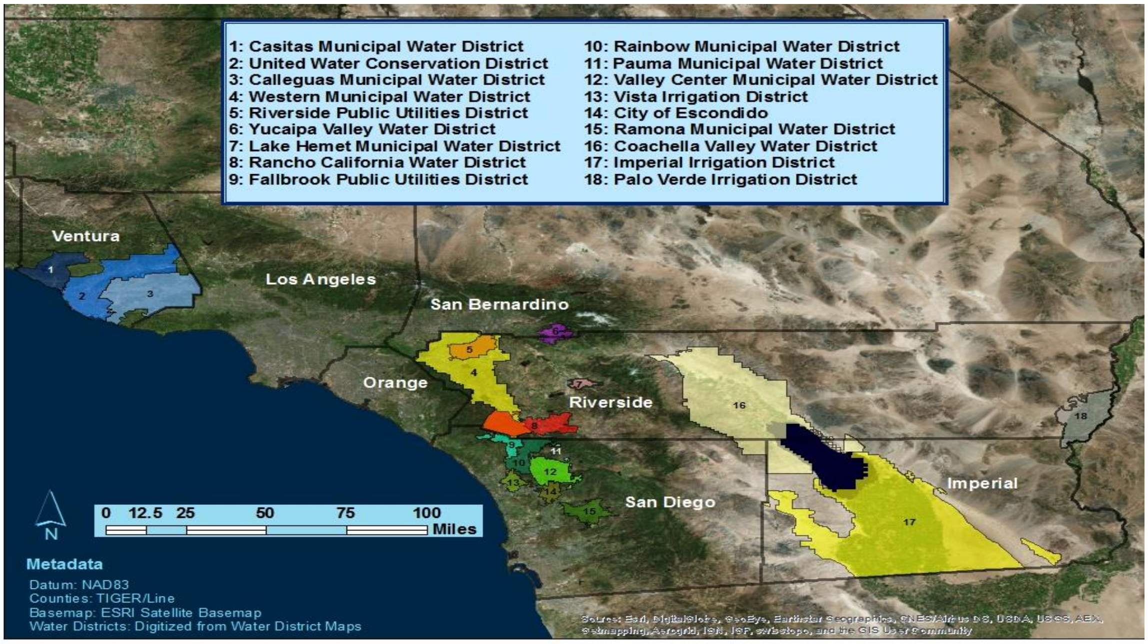


Figure 3.5: Water Districts Represented in Survey Sample

Note: This map was created in ArcMap using water service area maps for the 18 water agencies represented in different colors to make them more visible. We could not locate service maps online for Bard Water District or Gage Canal.

water providers in the dataset for that county. They include Imperial Irrigation District (IID), which provides the majority of water to the predominantly agricultural county. IID, a member of the 1931 Seven-Party Agreement, receives all of its water from the Colorado River via the All-American Canal. Bard Water District also provides water to smaller growers in the region.

San Diego County has several small (relative to IID) water districts servicing agriculture. These are, in decreasing order of survey representation, Rainbow Valley Water District, Valley Center Municipal Water District, Ramona Valley Water District, Rancho California Water District, Fallbrook Public Utilities, City of Escondido, and Vista Irrigation District.

Riverside County is relatively more complex in agricultural water distribution, where two districts (Coachella Valley Water District and Palo Verde Irrigation District) hold senior water rights to the Colorado River via the Seven Party Agreement. Other districts represented in the survey include Western Municipal Water District, Rancho California Water District, Riverside Public Utilities, Eastern Municipal Water District (reclaimed water), and Lake Hemet Municipal Water District. Though it is not considered a water agency, Gage Canal also represents an important source of agricultural water from the Santa Ana River for citrus growers in the city of Riverside.

Ventura County is arguably the most complex county with respect to agricultural water. There are 3 major wholesalers in the county: United Conservation District (associated basin: Santa Clara River), Casitas Municipal Water District (Ventura River), and Calleguas Municipal Water District (Calleguas Creek). Ventura County also has a proliferation of smaller entities that are either Mutual Water Companies or Private Water Companies. The former are commonly owned by their shareholders, while such ownership is not necessary in the latter. Mutual Water Companies are loosely regulated by the Public Utilities Commission, while Private Water Companies are not. The majority of mutual water companies receive water from the nearest groundwater basin (Detmer, 2016), thus we derive total dissolved solids information based on the nearest groundwater well, as explained in the proceeding section on groundwater data. We still code mutual water companies as water districts because, even though these are smaller than the other water districts represented in this study, they still represent institutions with governing rules for members (North 1990). Mutual water companies represented in our survey include Farmers Irrigation, Del Norte Mutual Water Company, Fillmore Irrigation Company, Crestview Mutual Water Company, Southside Improvement Company, and La Loma Ranch Mutual Water Company. In addition to wholesalers and mutual/private water companies, mid-sized water districts also operate in Ventura County. Those represented in our survey include Camrosa Water District, Ventura County District 1, Ventura County District 19, and the City of Simi Valley.

Groundwater Data

Total dissolved solids (TDS) in ppm is used as a measure of water quality, where higher tds values imply lower water quality. It is calculated in ArcMap using USGS Groundwater Ambient Monitoring and Assessment (GAMA) reports for Riverside, San Diego, and Ventura counties (Goldrath et al. 2009; Montrella et al. 2009; Wright et al. 2005)[15]. Maps of sample wells from these reports were converted to ArcMap documents, and TDS data (also in these reports) were linked to each sample well. The centroid location of respondents using groundwater as their primary water source was linked to the sample well maps using inverse distance weighting. Inverse distance weighting is a spatial interpolation technique in ArcMap that averages the values in the neighborhood of each data point, giving a decreasing weight as distance increases. This resulted in a given respondent's TDS value equal to a weighted average of surrounding sample wells represented in the USGS data (Annex 3.6).

[15] Imperial County does not have any respondents using groundwater.

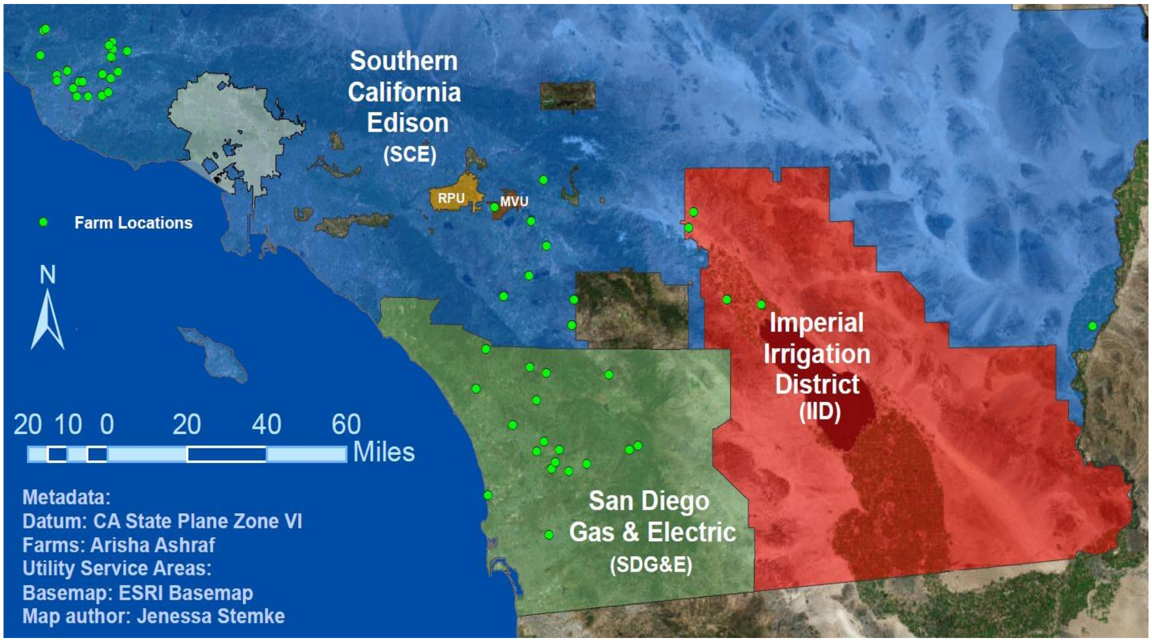


Figure 3.6: Electric Utility Providers Servicing Respondents (green points) with Groundwater

Source: This map was created from SCE, IID, and SDG&E service area maps.

Groundwater price is assumed to equal the marginal extraction cost, which in turn, is assumed to equal electricity cost of pumping groundwater.[16] Equation 3.1 represents the electricity cost for lifting one acre-foot of water, p_{gw},[17] (Peacock 1996):

$$p_{gw} = 1.024 g_h p_u \qquad \textbf{(3.1)}$$

where g_h is the pumping height in feet, and p_u is the unit price of electricity per kWh. Groundwater height is also calculated using inverse distance weighting from the same GAMA monitoring wells used for TDS calculation (Annex 3.6). The nearest electric

[16] Due to the static nature of our analysis, marginal user cost is assumed to be constant.

[17] The constant 1.024 is the ratio of 1 acre-foot of water in lbs (=2.719x10^6 lbs) and 1 kWh (=2.655x10^6 ft-lbs).

utility provider to each relevant respondent is found using the service maps from utility providers available online (Annex 3.7). And, once an electric utility provider is identified, the electricity price per kWh is used to calculate the cost per acre-foot of water pumped.

Crop Salt Tolerance

We classify crops in our data as sensitive, moderate sensitive, moderate tolerant, and tolerant, based on Tanji and Kielen (2002). Due to the low number of crops in our sample classified as moderate sensitive or moderate tolerant, we combine these categories into a general "moderate" category. We utilize a lowest-common-denominator approach to classify farms, where the existence of a salt-sensitive crop renders the entire farm salt sensitivity. Thus, we select the highest sensitivity among all crops listed in the survey to represent the sensitivity of the farm. We do not include weights by area because these are qualitative categories.

Climate Data

Following the practice of previous hedonic property studies in California, climate data were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Group housed in Oregon State University (Mukherjee and Schwabe 2014; Deschenes and Kolstad 2011; Schlenker, Hanemann and Fisher 2007). These are spatially interpolated datasets collected from a range of climate monitoring networks, which provide more intra-county variability than the limited number of California

Irrigation Monitoring Information System (CIMIS) weather stations[18] (PRISM Climate Group 2016). We used a 30-year average monthly climate normals (1981-2010) for maximum daily temperature (tmax) and minimum daily temperature (tmin) measured in Celsius. To clarify, tmax (tmin) implies the monthly average of the daily maximum (minimum) temperature, and not the maximum (minimum) temperature recorded each month. We also include the 30-year normal for precipitation (ppt), which represents the total monthly rainfall and snowmelt in millimeters averaged over the 30-year period.[19]

GIS files of the national climate data were downloaded at a resolution of 800m, and clipped to represent the 4-county region of analysis. The polygon data in the Agricultural Commissioner files was first converted to points. Using the Extraction tool in ArcMap, climate data values were assigned to these points. Due to limited "within-field" variability of climate variables, the centroid point value was assigned to each field. We then took a weighted average of the field-level data in order to determine the farm-level climate normal.

Soil Moisture Capacity

We included a variable representing soil moisture defined as available water storage (0-100 cm). This is the total volume of water (in centimeters) that could be available to plants when the soil, inclusive of rock fragments, is at field capacity for the top 100 cm of the rootzone (NRCS n.d.). Soil data was constructed from USDA NRCS

[18] For example, in Riverside County, there are no stations with 30-year normal data from 1984-2014. And, only nine stations have data from 2000-2014.
[19] Note that precipitation is a sum of total rainfall and snowmelt for each month, whereas temperature is the average daily temperature for each month.

Geospatial Data Gateway shapefiles by performing a spatial intersect between NRCS and Agricultural Commissioner field boundary shapefiles in GIS, similar to the land value calculation. Thus, it is not the centroid value, but a weighted average of soil moisture at the field level. For farms with multiple fields, a second weighted average is calculated at the farm level. Across all 4 counties, 72 respondents were not included in the NRCS Geospatial Data. For these respondents, we had to manually input latitude and longitude information obtained from Google Earth into the Web Soil Survey online (USDA 2016).

Previous models that have included multiple soil variables (Schlenker, Hanemann, and Fisher 2007; Mendelsohn and Dinar 2003; Mendelsohn, Nordhaus and Shaw 1994) have also had larger sample sizes, roughly 10 orders of magnitude greater than our sample. We were more parsimonious in representing soil quality in order to avoid over-fitting our models. Available water storage captures that aspect of soil quality that is most relevant for irrigation management purposes, namely soil moisture capacity.

Crop Price Data

Data on crop prices is necessary for the gross revenue analysis. Yield data for the top 3 crops on each farm was taken from our survey, and this was subsequently multiplied with crop price data from the county-level 2014 Crop Reports, compiled by the respective Agricultural Commissioners' offices. Total revenue was divided by total yield (tons) to generate a price per ton. If this data was unavailable for a given crop, the USDA NASS Quarterly Agricultural Price Reports for 2014 were consulted.

Zoning Data

Zoning data were obtained from the Planning Departments in each county. These data include zoning codes and maps. The codes for Agricultural zoning are presented in Annex 3.8. We coded each field as 1=inside agricultural zone, and 0=outside agricultural zone based on whether the field centroid was in an agricultural zone. Latitude and longitude from Google Earth was used for San Diego County respondents whose GIS data were unavailable.

Water Agency Surveys

We developed a 5-question survey for the water districts in our survey area primarily to ask how long their current pricing structure for agricultural clients was in place and how frequently they had increased their water price for agricultural clients in the past decade. Two undergraduate students emailed and telephoned 27 water agencies for these data (Annex 3.9).

Data Sources for Chapter 6

Data on all existing agricultural parcels from 2000-16 is from the Riverside County Assessor Office, which includes use code and acreage. Data on actual agricultural parcel sales is from ParcelQuest, a subscription-based website that is used by the majority of County Assessors in the state. 5-year (and 10-year) climate variables are derived from the PRISM Group GIS data in an analogous fashion to our survey. Soil quality data are collected from the NRCS SSURGO spatial data, as with our survey data. We use the following soil files: az656, ca678, ca679, ca680, ca681, ca695, and ca777. Water district service maps are taken from the Riverside County Open Data Warehouse Major Water Districts spatial data. Population data is derived from the US Census and Riverside County Open Data Warehouse. To account for parcels that are not directly located in a major urban center, we divide the population rate and mean variables by a distance factor (i.e., equal to the number of miles the parcel is located from the nearest urban center). This equals 1 if a given parcel is within or less than 1 mile away from the nearest urban center.

Data Challenges

Constructing a complex dataset is a time-consuming endeavor. Using a paper survey compounded this challenge as we manually input all survey data. Some questionnaires were only partially complete when mailed back to us. Some growers were not producing commercially, others were coded as tree crops when in reality these were nursery trees. And, we ultimately excluded all nurseries from our dataset because these do not rely on the soil or, in the case of indoor nurseries, on climate, in the same way as conventional, open-space crops.

In addition to missing or irrelevant data from the questionnaires, the spatial datasets also created a few challenges. First, the spatial data from the Agricultural Commissioner on field boundaries was quite noisy, including multiple permit years with slightly different acreages for identical crop fields. The same polygons were redrawn on top of one another in ArcMap several times. We corrected for this by selecting 2014 as the reference permit year. Even after doing this, several growers who were in the 2014 excel file originally requested from the Agricultural Commissioner were missing 2014 spatial data. To correct for this, we used the next chronological year of spatial data.

We experienced a similar challenge with the Assessor Data. Only Assessor Parcel Numbers (APN) were included in the spatial data, and not land values. Thus, we had to separately purchase land value data for agricultural parcels from the respective Assessor offices. These data also introduced missing values since not all APNs in the spatial data were available in the land value data. Agricultural Commissioner spatial data for San Diego County presented the greatest challenge. Several growers in the original dataset were missing completely from the spatial data. We used the physical address of the farm/grove/vineyard to find the centroid latitude and longitude in Google Earth prior to geospatial analysis. Additionally, several respondents were not represented in the soil shapefiles. We supplemented this data with the Web Soil Survey as discussed in the soil moisture data section of this chapter. Overall, we addressed these data collection challenges in the most efficient and robust means at our disposal in order to minimize respondent attrition.

Chapter 4: Farm-level Ricardian Model

We begin with our first of three empirical chapters. The Ricardian framework allows one to exploit cross-sectional differences in key production variables to approximate the marginal impact of climate, at a given time period. Previous studies have aggregated data at the county level, which involves strong simplifying assumptions of county homogeneity in farmer characteristics, water source, soil type, irrigation technology, and other key inputs. Perhaps most relevant for an analysis on climate impacts, such data aggregation assumes a homogeneous county climate.

Using data from our farm questionnaire, we study the impacts of change in microclimate on agricultural productivity in Desert and Southern California regions while controlling for other micro-level effects such as grower, farm, and water source characteristics. We define microclimate as the average climate of all cropped fields on a given farm.[20] Figure 4.1 illustrates our survey region and respondent distribution. What is the marginal impact of these micro-level variables on productivity after long-run adaptations by the grower are taken into account? To what extent do such variables, which provide more accurate representation of both the grower and farm, help explain the variation in gross revenue per acre in Desert and Southern California agriculture? We explore these questions using two, non-linear specifications of the farm-level value function with respect to climate: log-log and quadratic transformation.

[20] Note that in Chapter 6, microclimate is defined at the parcel level since that is our unit of analysis.

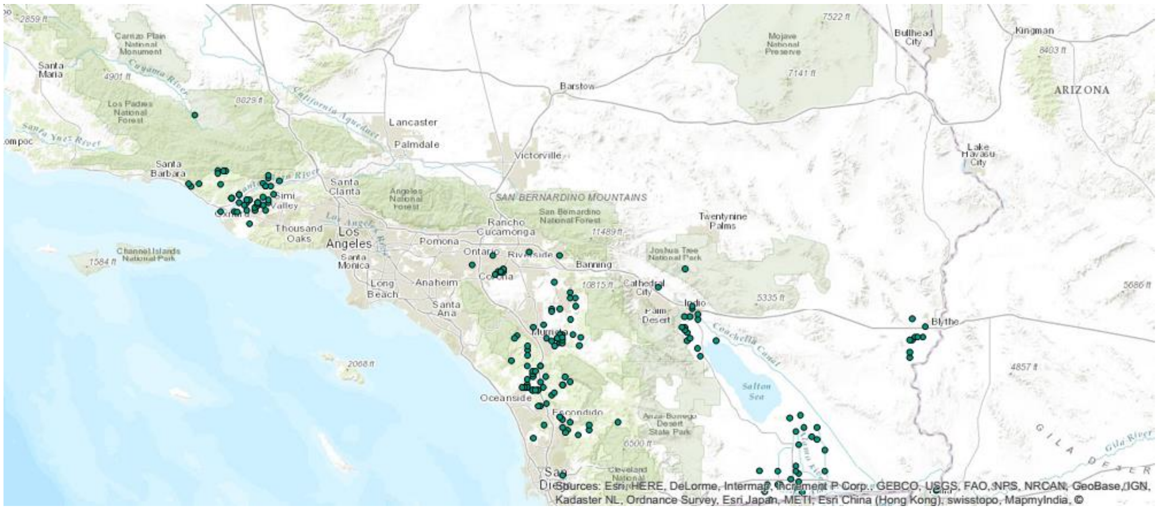


Figure 4.1: Survey Respondent Map

Literature Review

The Ricardian specification (Chapter 2 presents the theoretical framework) allows us to implicitly capture long-run production decisions, many of which are the result of complex historical relationships with local climate, water, and soil conditions. This is particularly true in Southern California where growers in the hottest regions tend to have access to senior water rights. Mendelsohn, Nordhaus and Shaw (1994) is one of the first studies to elegantly represent economic decision-making by the grower while analyzing the impacts of climate change on US agriculture.[21] Cross-sectional differences in climate across 2933 US counties reveal the relative contribution of temperature and precipitation normals to farm productivity. Ultimately, these authors find that previous studies overestimate the loss in agricultural profits as they do not allow for reasonable

[21] Johnson and Haigh (1970) is an earlier hedonic property study incorporating climatic impacts.

adjustments to baseline production practices that incur substantial losses under a changing climate.[22]

Although previous Ricardian studies account for responsiveness to climatic change, most studies do not include characteristics of the decision-makers on farm, which are likely to directly influence productivity. This is not to say that socioeconomic variables are entirely excluded from earlier analyses. Previous Ricardian models have included a limited number of socioeconomic variables (various measures of population, income per capita, farm wages) wrapped up at the county level (Schlenker, Hanemann, and Fisher 2007; Mendelsohn and Dinar 2003; Mendelsohn, Nordhaus, and Shaw 1994). These studies have found that population density, particularly urban population density, has a relatively strong, positive impact on land value, while population density squared and population growth rate have negative impacts. Income per capita also has a positive impact on productivity. However, these are ultimately measures of market access and not ability of the economic agent to influence productivity as, at the aggregate county level, total population, urban population, and income per capita may all capture level of urbanization. We study characteristics such as education, farming experience, farm ownership, farm size, and water price. We represent urbanization, using a zoning variable.

[22] More colloquially, they are improving upon the "dumb farmer" scenario in which the farmer makes no adjustments in crop mix, fallowed land, or adopted technology to mitigate the damages from a changing climate.

Microclimate is important to study because it is the localized climate directly observed by the economic agent (i.e., grower), and thus more likely to impact production decisions rather than county averages. Microclimate is defined as a set of local atmospheric conditions that differs across space, where climate difference could be less than a degree, and the spatial distance could be a few feet.[23] Climate variables in many previous studies represent county averages (Deschenes and Kolstad 2011; Mendelsohn and Dinar 2003; Mendelsohn, Nordhaus, and Shaw 1994). However, some studies incorporate microclimate at different spatial scales (Mukherjee 2013; Schlenker, Hanemann and Fisher 2007). Mukherjee (2013) uses a sub-county scale by connecting farm parcels to the nearest California Irrigation Management Information System (CIMIS) weather station. Schlenker, Hanemann and Fisher (2007) use spatially interpolated PRISM data at the centroid of each farm in their dataset.[24] We define microclimate at the agricultural field level, using PRISM data to generate the centroid value of each field. We then take the weighted average of all fields in the farm.

We include a climate variability measure to capture large differences in monthly climate variables observed within a year. Thus, our variability measure captures climate extremes across seasons. In their study of US counties, Mendelsohn et al. (2007) find that inter-annual temperature variance (1988-2002) for April and July have lower marginal impacts on productivity than variance of April and July temperature normals. However, inter-annual temperature variance has a greater impact on productivity in October than

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[23] As stated earlier, we use the average of all cropped fields within a farm to quantify farm-level microclimate.

[24] See Data Sources (Chapter 3) for more information on PRISM data.

the temperature normal. This finding suggests that growers are expecting more predictability (i.e., lower variance) in fall temperatures. Mendelsohn and Dinar (2003) also account for inter-annual variability in their model of US agriculture. Temperature variability has a lesser impact than the respective climate normals in January and October, while it has greater impact in July.

Descriptive Statistics

In this section, we briefly analyze several farm-level variables from our survey sample. While several of these variables do not reveal a statistically significant relationship with our primary measure of productivity (i.e., gross revenue per acre), they provide an important socioeconomic snapshot of our survey sample. For the subsequent discussion, we implement mosaic plots, which are powerful tools for visualizing the distribution of categorical variables. This descriptive analysis is supplemented with summary statistics in Table 4.1.

The average grower has about 27 years of experience and obtained a Bachelor's degree in their education. He owns more than half of his property (66%) and farms an average of 649 acres. Roughly 25-50% of his income is derived from farming. Figure 4.2 illustrates how farm characteristics (e.g., farm type and percent income from agriculture) are distributed with respect to gross revenue per acre. Vegetable farms (=R) have the highest median value with respect to revenue per acre relative to other farm types, even higher than orchards (=T) and vineyards (=V). Notably, the mean gross revenue per acre for the ≥75% category (=4) is highest relative to other categories. However, growers with <25% income from agriculture (=1) have the second highest gross revenue per acre.

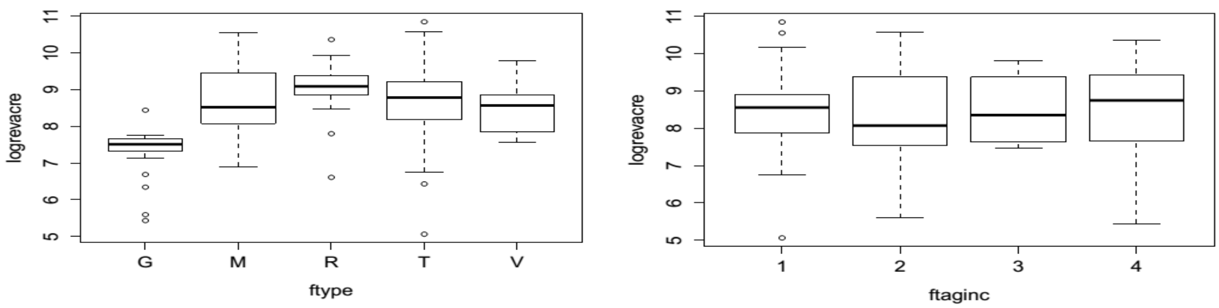


Figure 4.2: Farm Type (ftype) on Left, and Percent Income from Agriculture (ftaginc) on Right

Education and Experience

The left panel in Figure 4.3 represents the distribution of education categories across the four counties. While a large proportion of growers hold a Bachelor's degree across all counties, Imperial County has the largest proportion (74% of all Imperial growers in the sample). However, the proportion of post-graduate degrees is lowest in Imperial, whereas postgraduate degrees are highest in San Diego County (50% of all San Diego growers within our sample). The right panel indicates that Imperial County growers have the highest median years of experience, whereas San Diego County growers have the lowest. Additionally, Ventura County has the highest variance in years of growing experience.

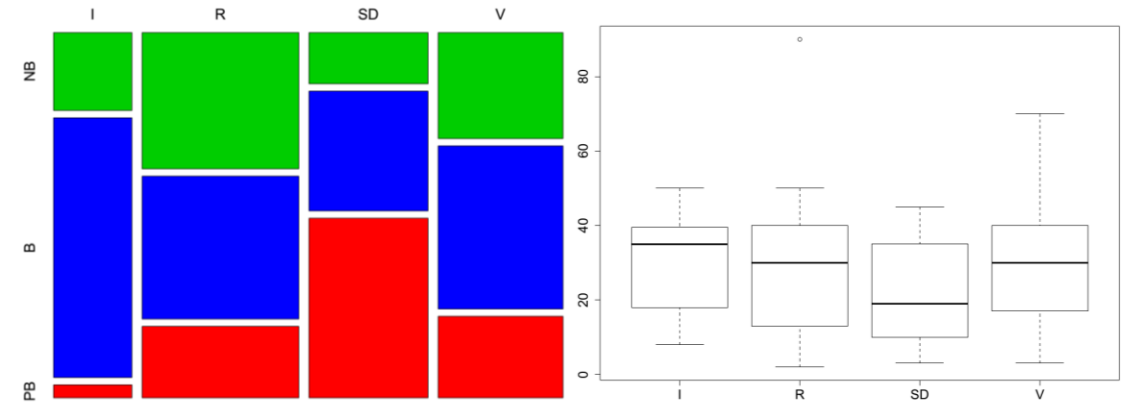


Figure 4.3: Distribution of Grower Education (left) and Experience in Years (right) by County

Notes: (1) NB=Education less than Bachelors, B=Bachelors, PB=Education higher than Bachelors;
(2) I=Imperial, R=Riverside, SD=San Diego, V=Ventura

Climate

Annex 4.1 presents a correlation matrix, which reveals a high degree of correlation between the seasonal climate variables. In order to limit multicollinearity problems and increase the degrees of freedom (given our relatively small sample size), we use annual climate variables in our empirical models. Annual minimum temperature is the mean of monthly minimum temperature normals, which are, in turn, the mean of daily minimum temperature normals. The range of annual minimum temperatures (in °C) for the sample is [2.69, 23.29]. Annual precipitation is the sum of total annual precipitation (in mm), with a range of [50.46, 607.94]. We also study the effects of climate variability within year using the coefficient of variation for each grower.

The graphs in Figure 4.4 illustrate the distribution of minimum temperature and precipitation variables (annual means and coefficient of variation-CV) accounting for the five farm types in our sample. Grain/field crops farms (colored in black) have the smallest temperature and precipitation range as illustrated by the cluster of black points. It is also apparent that tree crops farms (colored in blue) make up the largest percentage in our dataset, with a relatively large distribution of climate values. However, it is clear that tree crops clustered around lower temperatures and higher levels of precipitation. Vegetable farms (green), vineyards farms (cyan), and mixed farms (red) fall somewhere in between tree and field/grain farms in the various graphs in Figure 4.4.

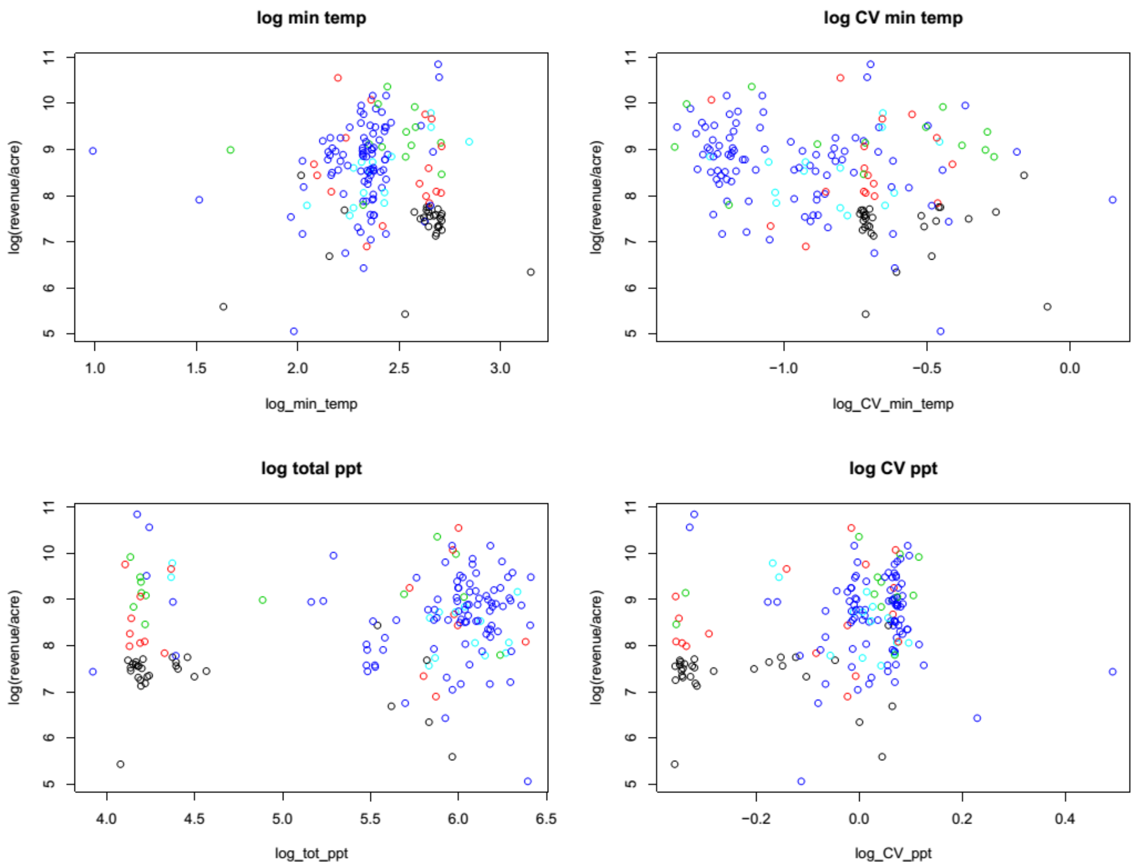


Figure 4.4: Relationship of Gross Revenue and Climate Variables by Farm Type

Note: Color Coding of Farm Types Follows: Black=Grain/Field, Red=Mixed, Green=Row/Vegetable, Blue=Tree, Cyan=Vineyard

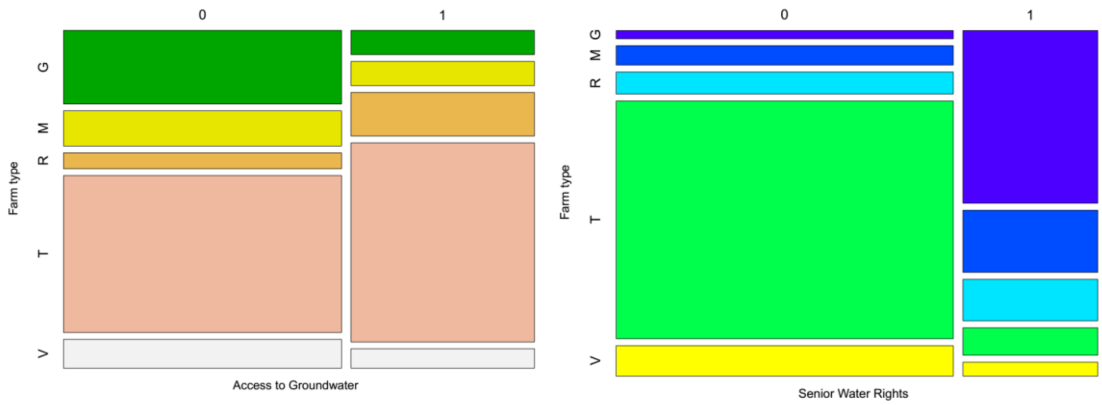


Figure 4.5: Distribution of Groundwater (left) and Senior Water Rights (right) by Farm Category

Notes: (1) y-axis=farm type: V=vineyard, T=tree, R=vegetable, M=mixed, G=field/grain
(2) x-axis: left panel=Access to Groundwater; right panel=Senior Water Rights

Water Sources

Figure 4.5 illustrates the distribution of farm types between two water source variables: access to groundwater (left panel) and senior water rights (right panel). Tree crops farms have the best access to groundwater, whereas field crop farms have the best access to senior water rights.

Variable Construction and Transformation

Gross Revenue

Several Ricardian studies have used revenue or gross revenue as the dependent variable in addition to or in lieu of land value (Deschenes and Kolstad 2011; Mendelsohn et al. 2007; Mendelsohn, Nordhaus, and Shaw 1994). Due to the implications of Proposition 13 in California, assessed land value does not accurately represent market value of land unless the property has been recently sold or transferred.[25] As such, we use gross revenue per acre as an alternative measure of agricultural productivity for the reference year of 2014. However, use of gross revenue is an annual measure and does not represent long-term productivity.

Yield data for the 3 highest value crops (across all 2014 seasons) for each grower is derived from our questionnaire. We requested the top 3 crops from each grower in order to maintain questionnaire consistency across all counties, minimize survey length, and ensure completion of the questions by the respondents. Requesting yield data for all crops would be infeasible for growers in Imperial and Riverside counties, where quite a large number of crops are grown annually on each farm. Figure 4.6 illustrates that we have a rich distribution of crops in our sample. We use equation (4.1) to obtain gross revenue per acre on farm (using the three main crops grown on each farm):

$$(4.1) \qquad \left(\sum_{i}^{3} g_i p_i\right) \Big/ a_i \qquad \forall i \in \{1,2,3\}$$

where g is total yield in tons for the i^{th} crop, p is the price[26] per ton for the i^{th} crop, and a is the total acreage of the i crops. We emphasize that this is not the total farm acreage.

[25] California Proposition 13 (People's Initiative to Limit Property Taxation), enacted in 1978, restricts annual increases of assessed value to 2% per year or less.

[26] Chapter 3 provides details on crop price data sources.

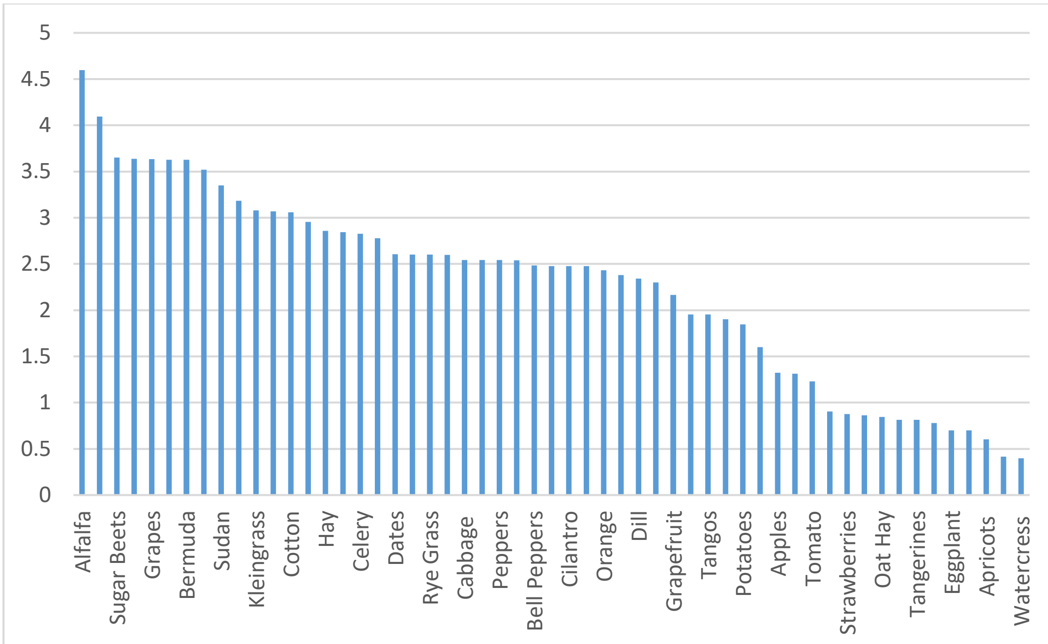


Figure 4.6: (log) Crop Acreage in Dataset

Multiple Imputation of Agricultural Income Variable

Percent income derived from agriculture is an important variable, as it captures a given grower's level of investment in his/her farm. Even though we created broad categories for this variable (divided in quartiles), this was a sensitive question for 15 growers who left it blank. We use multiple imputation to keep the percent income from agriculture variable in our analysis and avoid list-wise deletion (King et al. 2001; Rubin 1976). We use the Amelia package in R where the underlying algorithm for imputing missing values is expectation maximization using maximum likelihood estimation. In the first step, the (expected value of the) log likelihood is evaluated using current estimates for the parameters. The second step maximizes this likelihood function to generate new parameters, which then update the first step, and so forth. Several imputed datasets are generated from this iterative process (we use the standard number of m=5 imputed datasets), and the expected value of a given missing value is the mean of this value across the m imputed datasets.

Empirical Framework

Based on the literature reviewed and discussed earlier, the following empirical models are estimated. The dependent variable, *y*, represents gross revenue per acre (Equations 4.2-A and 4.2-B below). The dependent variables are explained and presented with their descriptive statistics in Table 4.1 below.

$$(4.2-\mathrm{A}) \quad \log(\mathrm{y}) = \beta_0 + \beta_1 logwatprice + \beta_2 rate\_frequency + \beta_3 deficit + \beta_4 ftypeR + \beta_5 ftypeM + \beta_6 ftypeT + \beta_7 ftypeV + \beta_8 aginc2 + \beta_9 aginc3 + \beta_{10} aginc4 + \beta_{11} gwater + \beta_{12} logCVannmax + \beta_{13} logAVGannmax + \beta_{14} seniorwat$$

$$(4.2-\mathrm{B}) \quad y = \gamma_0 + \gamma_1 watprice + \gamma_2 rate\_frequency + \gamma_3 deficit + \gamma_4 own + \gamma_5 ftypeR + \gamma_6 ftypeM + \gamma_7 ftypeT + \gamma_8 ftypeV + \gamma_9 aginc2 + \gamma_{10} aginc3 + \gamma_{11} aginc4 + \gamma_{12} ANNppt + \gamma_{13} AVGwinterppt^2 + \gamma_{14} acre + \gamma_{15} seniorwat$$

As Figure 4.7 illustrates, gross revenue per acre has a right-skewed distribution that can be addressed by using log transformation. We also explore (log-log) quantile regression to control for the heterogeneous farm types in our sample. We do not find the coefficients at the 25^{th}, 50^{th}, or 75^{th} quantiles to be statistically different from the log-log OLS specification.

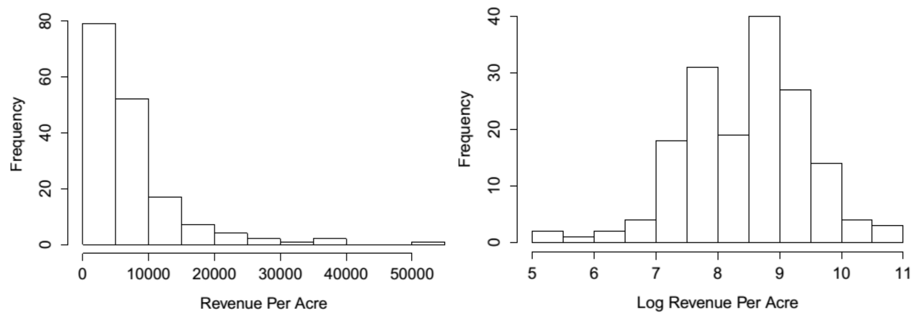


Figure 4.7: Distribution of Gross Revenue per Acre

Discussion of Results

We study the impact of climate on marginal productivity of farmland using a large set of micro-level variables collected from our questionnaire. The right-skewed distribution of the dependent variable improves with natural log transformation (Figure 4.7), and indeed the log-transformed specification (Table 4.2) results in greater explanatory power relative to the quadratic counterpart.[27] We interpret log-transformed coefficients as elasticities, i.e., percentage change in the geometric mean of the dependent variable with 1% unit increase in the geometric mean of a given independent variable (Wooldridge 2006).[28] We removed one outlier from the regression (Cook's Distance=0.18), which improved the robustness of the overall model and reduced the RMSE. We subsequently discuss only the results from the log-transformed specification as this is the more robust of the two specifications.

[27] The log transformed model has almost 3 times the explanatory power based on the F-statistic.
[28] Recall, the geometric mean is the nth root of a product of n numbers.

Table 4.1: Descriptive Statistics for Ricardian Dataset

Variable	Mean (n=165)[a]	Range [Min, Max]	Type	Description
Logrevacre	8.44 (0.996)	[5.06, 10.85]	continuous	natural log transformation of per acre revenue in 2014$
Revacre	7268.92 (7609.71)	[158.3, 51435.9]	continuous	per acre revenue in 2014$ based on top 3 crops
County	--		factor, 4 levels	county fixed effect for Imperial, Riverside, Ventura, & San Diego. Imperial is the benchmark.
Acre	648.78 (1437.61)	[0.25, 10625]	continuous	total planted acres on a given farm
Water deficit	0.40 (0.49)	[0,1]	factor, 2 levels	Did the grower experience a water shortage in 2014?
Gwater	0.39 (0.49)	[0, 1]	factor, 2 levels	Does the grower have access to groundwater? This does not mean that groundwater has to be the primary water source.
Seniorwat	0.29 (0.45)	[0, 1]	factor, 2 levels	Does the grower belong to a district with senior water rights? 1=yes
Edu	---		factor, 3 levels	NB= No Bachelors; B=Bachelors; PB=Post Bachelors
Exp	27.59 (15.45)	[2, 90]	continuous	Years of growing experience
Own (land)	0.66 (0.47)	[0, 1]	factor, 2 levels	Does the grower own all of her property? 1=yes
Agzone	0.75 (0.44)	[0, 1]	factor, 2 levels	Does 75% or more of the acreage classify as agricultural zone? 1=yes
CVannmin	0.45 (0.15)	[0.25, 1.16]	continuous	Standard deviation of each month divided by annual mean
CVannppt	0.97 (0.13)	[0.70, 1.63]	continuous	Standard deviation of each month divided by annual mean
AVGannmin	11.25 (2.58)	[2.69, 23.29]	continuous	12-month average minimum temperature normal (1981-2010)
annppt	308.93 (175.24)	[50.46, 607.94]	continuous	Total annual precipitation for normal (1981-2010) in mm
aws0100	10.79 (4.10)	[2, 18]	continuous	weighted average of available water supply in the top 100cm of soil
rate_frequency	6.48 (4.52)	[0, 13]	continuous	Number of times water rate has increased over the past 10 years

Variable	Mean (n=165)[a]	Range [Min, Max]	Type	Description
ftype	--		factor, 5 levels	G=field crops; R=vegetable/row; V=vineyard; T=orchard; M=mixed. G is the benchmark.
price_structure	0.26 (0.44)	[0, 1]	Factor, 2 levels	Does the water district (or electric provider) have a tiered pricing structure? 1=yes
watprice	434.12 (530.54)	[20, 2498.08]	continuous	Water price per acre foot.
tds	722.46 (281.16)	[189.46, 1597.88]	continuous	Total dissolved solids in ppm
aginc	2.35 (1.37)	[1, 4]	factor, 4 levels	percentage of income from farming. 1=[0,0.25); 2=[0.25, 0.5); 3=[0.5,0.75);4=[0.75,1]. Level 1 is the benchmark.

[a]Notes: Standard errors appear in parentheses. This includes all variables tested in the empirical model

Table 4.2: Log of Gross Revenue per Acre Regression Results

Dep. Var.= log(gross revenue per acre)[a]	Coefficient	Robust[b] St. Err.	t-value	p-value
constant	5.180	0.950	5.45	0.000
Percent Agricultural Income:				
(Baseline= <25%)				
25 - 49%	0.342	0.208	1.65	0.101
50 - 74%	0.652	0.194	3.36	0.001
75 - 100%	0.538	0.165	3.26	0.001
water deficit	-0.212	0.141	-1.50	0.136
access to groundwater	0.520	0.142	3.67	0.000
senior water rights	1.309	0.285	4.59	0.000
log(water price per acre-foot)	0.284	0.081	3.52	0.001
water price increase frequency	0.032	0.020	1.57	0.118
log(annual min temp normal)	0.272	0.305	0.89	0.374
log(variation in annual min temp normal)	-0.602	0.270	-2.23	0.027
Farm Type:				
(Baseline=orchard)				
mixed	-0.290	0.314	-0.92	0.358
vegetable crop	0.209	0.239	0.88	0.382
field crop	-1.581	0.299	-5.29	0.000
vineyard	-0.296	0.158	-1.87	0.063
n	164			
F-stat	18.45			
p-value of F-stat	0.000			
Adjusted R^2	0.494			
Standardized RMSE[c]	0.088			

a: All log transformations are natural log
b: Huber-White sandwich estimator
c: Root Mean Square Error is standardized by dividing by the mean of the dependent variable

Table 4.3: Gross Revenue per Acre (Quadratic in Climate Variables) Regression Results

Depen. Var. = gross revenue per acre	Coefficient	Robust St. Err.[a]	t-value	p-value
constant	-10233.050	3722.020	-2.750	0.007
Percent Agricultural Income:				
(Baseline= <25%)				
25 - 49%	1875.710	2180.650	0.860	0.391
50 - 74%	4178.280	1719.180	2.430	0.016
75 - 100%	5535.320	1621.570	3.410	0.001
Farm Type:				
(Baseline=field crop farms)				
mixed crop	7057.030	2133.460	3.310	0.001
vegetable crop	9863.760	2424.630	4.070	0.000
orchard	7462.620	3271.550	2.280	0.024
vineyard	4009.940	2939.280	1.360	0.175
deficit supply	-1610.700	1050.390	-1.530	0.127
senior water rights	9205.510	3380.560	2.720	0.007
Own (land)	3603.460	1408.260	2.560	0.012
water price per acre-foot	2.010	1.230	1.630	0.104
water price increase frequency	296.680	148.960	1.990	0.048
annual precip. normal	11.760	16.280	0.720	0.471
square annual precip. normal	-0.090	0.020	-0.370	0.710
acre	-1.120	0.420	-2.650	0.009
N	164			
F-stat	6.400			
p-value of F-stat	0.000			
Adjusted R^2	0.300			
Standardized RMSE[b]	0.920			

a: Huber-White sandwich estimator.

b: Root Mean Square Error is standardized by dividing by the mean of the dependent variable.

Both variability and mean climate conditions are included in the regression results in Table 4.2 as this gives more accurate measures of the respective partial effects (Mendelsohn et al. 2007). One of our most important results is the negative and statistically significant impact of increased variability in the average monthly minimum temperature normal. For example, a 5% increase in variability results in a 3% decline in gross revenue per acre.[29] This result captures fluctuations in long-run (i.e., 30-year) minimum temperature expectations across a given year. There are several negative implications associated with an increase in variability. It implies that certain seasons are experiencing extremes in heat or cooling, which are detrimental to crop growth (Mendelsohn and Dinar 2009). Thus, an increase in variability may be correlated with a decline in annual predictability. And, if a grower is unable to accurately predict seasonal climate from year-to-year, they are less likely to develop an optimal seasonal production/adaptation plan. Variability also makes it difficult for the average grower to follow a consistent production plan throughout the year. There are costs associated with adjusting production practices on a seasonal basis, such as adding more fertilizer, cover, or even fallowing a portion of the land. In the case of permanent crops (i.e., trees and vineyards), additional costs are incurred from damage to the plant or fruit during hotter seasons.

[29] $\beta_i = -0.602$ (where i=log(CVmin)). A 5% increase in variability implies $1.05^{-0.602} = 0.971$. This is roughly a 3% decline in gross revenue per acre. Please refer to Table 4.2 for coefficient value.

The data present a counterintuitive relationship mean annual daily (minimum and maximum) temperatures (Figure 4.4).[30] Although the positive marginal effect is not statistically significant for either temperature normal, it may reveal a complex relationship amongst productivity, temperature, and senior water rights, given that some of the most productive regions are in the desert (Coachella, Blythe, Imperial County). The potentially negative impact of high temperatures is likely offset by a reliable and cost effective water supply. However, even a superior water supply is unable to offset the negative impact of seasonal variability in minimum temperature on gross revenue per acre. The negative impact of variability in minimum temperature also captures the extremes in heat, which are dampened in the annual mean.

Consistent with our hypothesis, neither total annual precipitation nor variability in annual precipitation significantly impacts productivity. Southern California growers have adjusted to the largely semi-arid climate, particularly as no grower in our sample relies solely on rainwater for irrigation. We find that growers who perceive to be experiencing a water shortage have roughly 20% ($e^{-0.212}$) less productivity per acre than growers who do not have this perception as represented by the deficit supply variable.[31]

The marginal impacts of water source characteristics reveal important findings. Four water variables capitalize, to varying degrees, into gross revenue per acre. Contrary to our hypothesis, water salinity does not have a statistically significant impact. Relative

[30] Please note that only the data and results for the minimum temperature normal are presented in Figure 4.4 and Table 4.1, respectively.
[31] At a 14% significance level.

to non-rights holders, growers with senior water rights have 3.7 times ($e^{1.309}$) the level of productivity per acre. Senior water rights holders (Imperial Irrigation District, Palo Verde Irrigation District, Coachella Valley, and Bard Water District) also have the lowest water prices in our sample, ranging from $20-33 per acre-foot.[32] Even accounting for this, water price exhibits a positive (and significant) relationship with gross revenue per acre. For example, a 5% increase in water price results in a 1.4% increase in productivity per acre. This suggests that access to senior water rights may capture more than a low price, and likely captures the value of holding priority water rights. This finding may also suggest that, ceteris paribus, a higher water price motivates growers to improve water efficiency. We also find that increasing the frequency of price increases by one unit, increases productivity per acre by 3.3% ($e^{0.032}$).[33] This suggests that sending growers a signal of scarcity, such as more frequent price increases, growers respond positively by improving their productivity per acre. Access to groundwater also exhibits a positive and statistically significant relationship with productivity per acre. Growers with access to groundwater have 68% ($e^{0.520}$) higher productivity per acre than those without. This is lost likely due to the fact that groundwater provides growers with a more secured supply of water.

We also find that county fixed effects are not statistically significant, and farm type better captures the sub-groups within the dataset. As expected, farm type has a relatively large and significant impact on productivity. We use orchards as the baseline category. As expected, field crops are less productive than orchards. This is quantified as

[32] One grower receives water from Bard Water District, which gives priority to Native American growers. This price is even more subsidized at $5/acre-foot.
[33] At an 11% level of significance.

80% ($e^{-1.581}$) less productive, based on our sample. We also find that vineyards are 74% ($e^{-0.296}$) less productive per acre than orchards. Assuming that income derived from agriculture is proportional to the amount invested in the farming enterprise, one would expect higher productivity per unit area as the percentage of income from agriculture increases. This is consistent with our results, although our results suggest declining marginal productivity per acre of this investment. That is, growers earning nearly all of their income from agriculture are 71% ($e^{0.538}$) more productive than growers earning less than the baseline (i.e., 25% income from agriculture). And, growers earning half to ¾ of income from agriculture are 92% ($e^{0.652}$) more productive than the baseline.

Growing experience and education do not reveal a significant relationship with productivity per acre. These variables may be better explored in a more homogenous analysis, i.e., one that focuses on a single farm type or agricultural income strata. Soil quality is not significant likely because fertilizer and other amendments substitute for soil quality. Additionally, it may already be captured by the farm type since marginal lands tend to grow field crops.

Conclusions

Farm-level analyses are instrumental in developing bottom-up incentives for adapting to climate change and addressing water scarcity. We find a significant relationship between grower productivity and climate and water source variables. As our results suggest, growers may need more predictability ability with respect to seasonal maximum temperature variability. Education and grant programs could target technologies and practices that help growers achieve this predictability, exploiting free-access data such as the California Irrigation Management Information System (CIMIS). We also find evidence that water price and the frequency with which this price is increased serve as incentives for increasing productivity per acre. This may not apply to senior water rights holders who continue to face a highly subsidized water price. We do not find a significant relationship between farm-level productivity and most of the grower and farm characteristics tested. This is likely due to the heterogeneity of farm types represented and relatively small sample size.

Chapter 5: An Analysis of Choice in Soil and Salinity Monitoring Technologies

In this chapter, we use data from our survey instrument to examine choices of irrigation management technologies by Southern California growers. The previous chapter explores adaptation to climate change implicitly, whereas this chapter explicitly evaluates the determinants of adaptation by adopting two important irrigation management practices: soil moisture monitoring and salinity monitoring.

There are several reasons growers monitor soil moisture. Most immediately, it allows them to learn if they are applying an excessive volume of water, which is particularly important when they are testing new crops or crop varieties. Related to this, it provides growers information on the optimal amount of time lapse between irrigations under climatic conditions that are changing the timing and duration of the growing season (Cayan et al. 2010). Additionally, soil moisture monitoring provides information on distribution uniformity, which is a measure of how evenly water reaches each plant or a portion of the field in a given irrigation boundary (Escalera, Dinar, and Crowley 2015; Burt et al. 1997). Distribution uniformity is a key factor in ensuring that crop yield meets industry criteria (e.g., size, weight, color) relatively uniformly (Mission RCD, No date), and ultimately is a measure of efficiency. Based on discussions with extension specialists and previous survey research in California (Aguiar 2015; Gispert 2015; Escalera, Dinar, and Crowley 2015; USDA 2013), we constructed a list of soil moisture technologies. This was later refined after analyzing the results from our pilot survey. Ultimately, we included two less sophisticated soil moisture-monitoring approaches (i.e., gravimetric approaches using auger, cap or an oven; and tensiometers) and two more sophisticated methods (i.e., gypsum block and dielectric sensors).[34]

Monitoring the salinity of irrigation water and soil extract also serves multiple purposes. Growers want to be sure the salinity of the irrigation water is viable for the crops they grow. This requires regular monitoring as salinity levels fluctuate seasonally and through time. Salt accumulation in the soil must also be monitored as high concentrations of certain ions could inhibit plant germination and create drainage problems (Burt and Styles 2011, Tanji and Kielen 2002). Salt accumulation in the soil is sometimes even caused by fertilizer application. Salinity monitoring also serves the purpose of potentially reducing sub-optimal leaching. If a grower leaches too much then water is obviously wasted. However, if a grower leaches too little, water is also wasted through the production of a poor quality crop (where this water could have been allocated to other crops of presumably higher quality) and excess concentration of ions in the soil for the next round of crops. We implemented an analogous strategy as we did when developing the soil moisture-monitoring list, relying on extension specialists, previous survey research, and our pilot survey. Our survey included three salinity monitoring practices in order from least to most sophisticated: (1) consulting with water provider for information on salinity in water supply; (2) using a handheld salinity monitor or pen; and (3) sending water and soil samples to a lab.

[34] We also included an "other" category in the survey for both soil moisture and salinity practices in addition to the ones we defined.

We have three key objectives in this chapter. First, we are interested in incorporating the diverse institutional arrangements, climate, land quality, and crop choices of agricultural counties in Southern California into a single, meaningful analysis. Figures 4.4 and 4.5 in the previous chapter illustrate the diverse climate, water institutions, and farm types in our sample. Previous adoption studies in California have focused on the Central Valley, which tends to have more homogenous growing conditions relative to Southern California (Osgood 1999; Green, Sunding, Zilberman and Parker 1996; Dinar, Campbell and Mendelsohn 1992; Putler and Zilberman 1988; Caswell and Zilberman 1985; Caswell 1982).

Second, we are interested in the extent to which adoption of water management technologies represents adaptation to an increasingly warm and dry climate. Monitoring practices represent the next generation of efficient on-farm water management (Gispert 2015). These require growers to be more pro-active in scheduling irrigations (in the case of soil moisture monitoring), and in minimizing wasteful leaching practices (in the case of salinity monitoring).

Finally, we are interested in the extent to which growers may bundle water management practices to maximize benefits (Fleischer, Mendelsohn and Dinar 2011). Specifically, we explore the extent to which microclimate and other control variables influence the decision to jointly adopt oil moisture and salinity monitoring. We evaluate this by implementing a multinomial logistic regression.

This chapter starts with a review of the adoption literature, followed by a discussion of key variables and descriptive statistics. We then discuss the basic empirical models and the various permutations. This is followed by a discussion of results. We conclude with broad policy recommendations to be discussed in more detail in the final chapter of the dissertation.

Literature Review

The next generation of efficient water management moves beyond installing an irrigation system to actively monitoring water use (Gispert 2015). However, few studies focus on factors influencing adoption of monitoring technologies. As discussed in this section, previous studies focus on the adoption of irrigation systems.

Semi-arid conditions, coupled with being the national leader in agricultural production, mean that California growers are generally receptive to optimizing water use (Walthall et al. 2012; Jackson et al. 2012). California was the first US state to run trials on drip irrigation, and berry farmers in San Diego County were the first to adopt this technology (Caswell 1982). During the late 1970s, subsurface drip irrigation was the latest technology to improve water application and reduce water waste. In her empirical analysis of subsurface drip adoption amongst perennial crop growers in the San Joaquin Valley, Caswell (1982) finds that water cost and farm type are significant in predicting the likelihood of adopting drip relative to traditional irrigation technology (furrow and flood). Caswell and Zilberman (1985) extend this analysis to include sprinkler irrigation, and confirm the previous results that water cost and farm type are significant in increasing the likelihood of adopting more efficient (drip or sprinkler) relative to traditional technology. Caswell and Zilberman (1985) also find that water source, specifically groundwater relative to surface water, increases the likelihood of adopting either sprinkler or drip irrigation. At the time of their analysis, many water districts did not have the appropriate infrastructure to deliver pressurized water needed for the newer technologies.

Green et al. (1996) compare three technologies in their survey of San Joaquin Valley: two mature technologies (furrow and high-pressure sprinkler) and a new one (drip). They find that the adoption of high-pressure sprinkler has similar characteristics to that of furrow, suggesting that the former may also be nearing the end of its product life cycle. For example, it is statistically unlikely that higher water costs would lead to adopting high-pressure sprinkler. As expected, crop choice positively and significantly influences the decision to adopt drip, with the adoption likelihood higher in citrus, deciduous fruit, and vineyards relative to truck crops. Both an increase in slope and soil quality (permeability) positively and significantly impact adoption of drip.

Water price is an important metric and, indeed, policy instrument with respect to irrigation technology adoption, but it tends to capture more than drought-related scarcity (e.g., fixed and variable costs related to daily operations). When measuring the extent to which such adoption represents adaptation to climate change, it is thus important to control for climate, as done in subsequent studies. Dinar, Campbell, and Zilberman (1992) also find that water cost and farm type increase the likelihood of adopting modern (drip or sprinkler) technology at both the farm and field levels. In addition, they find that acreage has a positive and significant impact at the field level, indicating that economies of scale exist at the field level. They also include climate variables (7-year weather data on temperature and precipitation) in their analysis. Schuck et al. (2005) also study irrigation technology adoption as an adaptation to climate change. While they do not include climate variables in their analysis, they evaluate irrigation technology adoption (sprinkler or gated pipe versus gravity systems) amongst Colorado growers immediately following a historic drought. They find that growers who switch irrigation systems following the drought were more likely to switch from gravity to gated pipe rather than gravity to sprinkler. This is an example of how growers tend to minimize the cost of transitioning to a new technology rather than maximize benefits from saving the most water possible by adopting the most efficient technology. There is also an income effect to this finding, as those who adopted gated pipe instead of sprinkler tended to have lower income. Schuck et al. (2005) also found that level of education had a positive and significant impact on adoption of sprinkler during the drought. Leasing land had a negative and significant impact on adoption of sprinkler. Mendelsohn and Dinar (2003) run individual logistic regressions on percent cropland irrigated by a given technology across a large sample of US counties. They find that the likelihood of adopting gravity and drip irrigation is significant with high temperatures, while there is a significant negative relationship with sprinkler systems and high temperatures. Higher precipitation increases the likelihood of adopting sprinkler, but at a declining rate. Increasing allocation of surface water also increases the likelihood of adopting sprinkler irrigation, while higher soil salinity levels increase the likelihood of adopting drip systems. At the nation-state scale, Su and Moaniba (2017) find that innovations in climate-technology may be driven by anthropogenic climate change. Specifically, they find that the number of climate-patents is positively associated with GHG emissions from certain fuel sources.

Studies also find a significant relationship with adoption of efficient irrigation technologies and sources of information, particularly information from agricultural extension. Escalera, Dinar, and Crowley (2015) study the adoption of a broad range of soil monitoring technologies among California avocado growers. They find that the likelihood of adopting tensiometers to monitor soil moisture is positively and significantly related to receiving farming information from University of California Cooperative Extension. Genius et al. (2014) study adoption of drip or sprinkler amongst olive growers in Crete. They find that extension services (public and private) and social networks significantly increase the rate at which either of these technologies are adopted. In addition, measures of human capital (age, education) also have a significant impact on increasing the adoption rate.

Key Variables and Descriptive Statistics

The dataset used for the analysis in this chapter is larger than that used for the Ricardian model (Chapter 4) with a total of n=187 observations. In spite of a larger number of observations, the summary statistics of this dataset are similar to that presented in Table 4.1, and will not be alluded to further in this chapter. For detailed summary statistics for this chapter, please refer to Annex 5.1. Prior to analyzing the distribution of water management practices, we examined the distribution of micro-irrigation (e.g., micro-sprinkler, drip, sub-surface drip) across our sample.[35] We initially hypothesized that a sufficient number of high value crop growers would still be using traditional methods (e.g., furrow and flood), and we could study characteristics of adopting micro-irrigation practices in high value crops. We also hypothesized that this variable would be continuous from [0,1] suggesting that growers may not homogenously adopt one type of irrigation method. Our hypotheses proved invalid on both counts. As Figure 5.1 illustrates, micro-irrigation is relatively neatly partitioned according to farm type, particularly with field crops (=G), orchards (=T), and vineyards (=V). And, growers in our sample generally do not use different irrigation practices on different crops.[36] This is not to say that they may not use different methods across the life-cycle of a crop, but this aspect is out of the scope of our analysis.

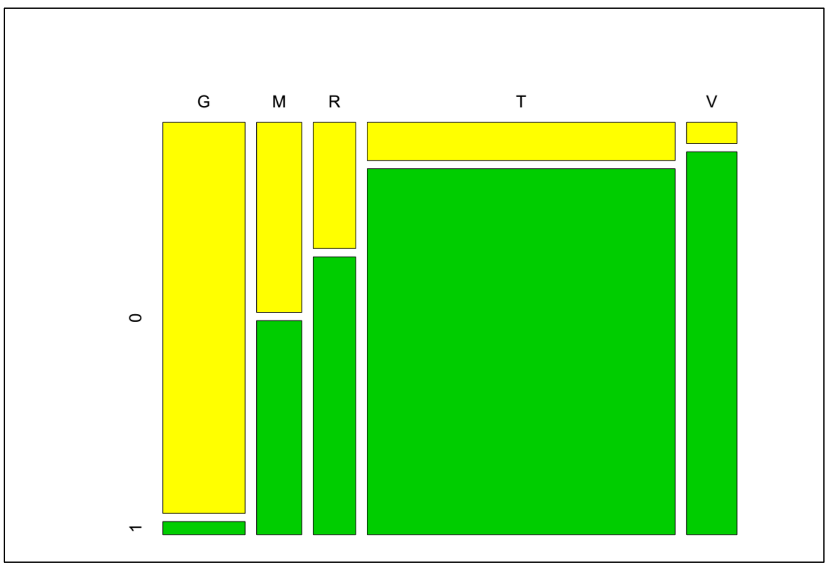


Figure 5.1: Distribution of Micro-irrigation Technology by Farm Type
Note: Green=Adopted micro-irrigation; Yellow=Did not adopt micro-irrigation

[35] To create our micro-irrigation variable, we calculated the percent acreage devoted to micro-irrigation practices (micro-sprinkler, drip, sub-surface drip) with respect to total acreage devoted to the top 3 crops.
[36] Six growers had decimal values for this variable (ID#: 50; 97; 113; 158; 174; 175), and we rounded these values accordingly.

Dependent Variables for Binary Logistic Regressions

Figure 5.2 illustrates that individual water management practices amongst growers in our sample are not widespread. Studying adoption of any of these practices individually may lead to a loss of power. Instead, we follow Caswell et al. (2001) and define adoption of soil moisture (or salinity) monitoring as the use of at least one of the soil (or salinity) technologies we identify in our survey (including an "other" category to capture any technology we may have missed). As such, our analysis does not distinguish between growers who may be using more than one monitoring technology, or may be using one technology more frequently than another grower using the same technology.

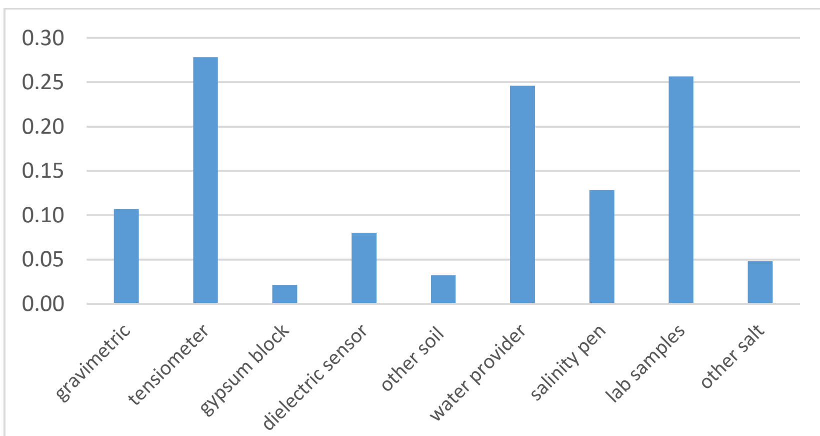


Figure 5.2: Relative Frequency of Different Soil Moisture and Salinity Monitoring Practices

Figure 5.3 illustrates that mixed (=M) farm types and orchards (=T) have the greatest proportion of growers using soil monitoring practices, whereas orchards have the greatest proportion of growers using salinity monitoring practices.

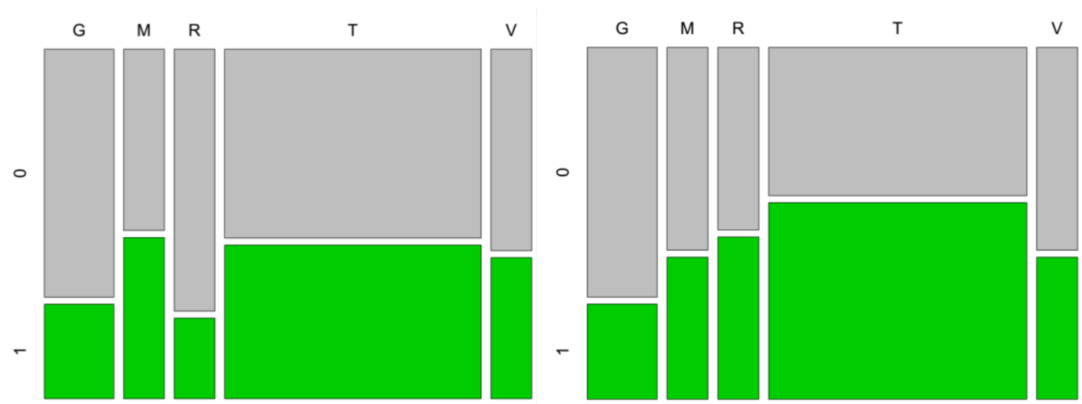


Figure 5.3: Soil Monitoring (left) and Salinity Monitoring (right) with Respect to Farm Types

Correlation coefficient between dependent variables: ρ = 0.426

Green= Adopted monitoring **Gray= Did not adopt monitoring**

Dependent Variable for Multinomial Logistic Regression

The dependent variable for the multinomial logistic regression represents four levels of choice: (1) implements both monitoring practices, (2) implements neither practice, (3) implements salinity monitoring only, (4) implements soil moisture monitoring only (Figure 5.4). This sorts the data differently from the individual binary logistic regressions in that it distinguishes between selecting only one practice (soil or salinity monitoring) and selecting both.

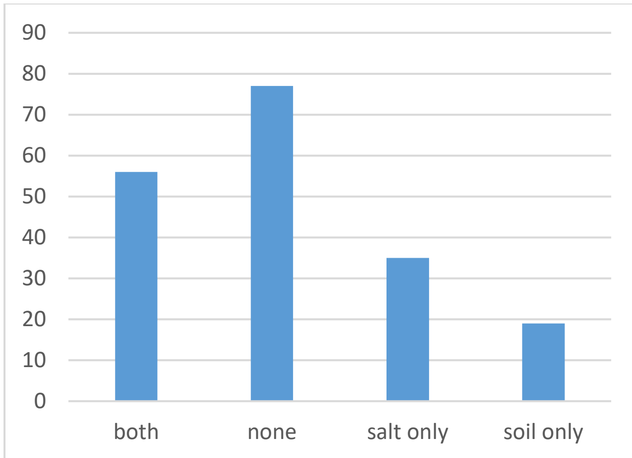


Figure 5.4: Relative Frequency of Multinomial Logit Categories

Other Key Variables

As with the soil and salinity monitoring technologies, we created categories for primary threats to water scarcity and primary source of information from extension experts, previous surveys, and our pilot survey. We found that population growth and drought are the top concerns amongst growers in our sample. Both population growth and drought are irreversible trends that affect the sustainability of agriculture in the region. These may incentivize growers to improve productivity through intensive margin improvements such as soil moisture and salinity monitoring. Intensive margin adaptations are those that improve the efficiency per unit area compared to extensive margin adaptations that improve efficiency of the total planted area. We also found that industry and social networks (i.e, friends and neighbors who are also farmers) are the primary sources of information.

Figure 5.5: Primary Threat to Water Supply

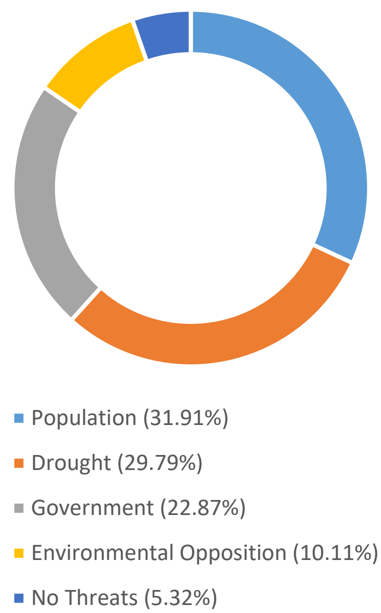
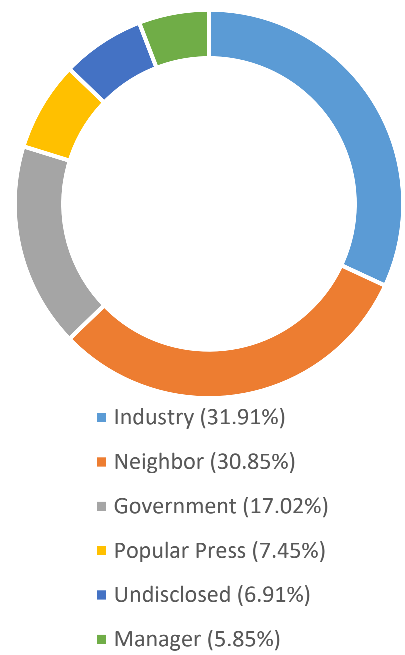


Figure 5.6: Primary Information Source



Variable Transformations

We also performed multiple imputation[37] for the percent agricultural income (aginc) variable, which is missing 23 values out of a total dataset of 187, or we would lose 12% of our dataset if we used list-wise deletion.

Empirical Specifications

Binary Logistic Regressions

We test several permutations of the following general logistic specification (Equation 5.1):

[37] As in Chapter 4, this was implemented via an expectation maximization algorithm using the Amelia package in R.

$$(5.1)\quad \ln\left(\frac{p}{1-p}\right) = \theta_0 + \theta_1 ftypeR + \theta_2 ftypeM + \theta_3 ftypeT + \theta_4 ftypeV + \theta_5 aginc2 + \theta_6 aginc3 + \theta_7 aginc4 + \theta_8 watprice + \theta_9 annmax_{normal} + \theta_{10} annmax_{5yr} + \theta_{11} annmax_{10yr} + \theta_{12} acre + \theta_{13} wsource + \theta_{14} rate_{frequency} + \theta_{15} salt_{tolerance} + \theta_{16} govt_{info} + \theta_{17} saltmon$$

where p is the probability of adopting at least one soil moisture monitoring technology. *There is an analogous equation for salinity monitoring*. The coefficient for any given independent variable, x_i, represents how the likelihoods (of using at least one soil moisture monitoring device versus using none) change with a 1-unit increase in x_i while holding all other variables constant. The coefficient for a log (base k)-transformed variable, x_j, represents how the likelihood ratio changes with a k-fold increase in x_j. Note that the results in Tables 5.1 and 5.2 present likelihood ratios, and not the coefficients.

Multinomial Logistic Regression

The multinomial logistic regression has four categories: (1) implements both monitoring practices, (2) implements neither practice, (3) implements salinity monitoring only, (4) implements soil moisture monitoring only. It is represented as follows (Equation 3):

$$(5.2)\quad \ln\left(\frac{p_j}{p_k}\right) = \alpha_0 + \alpha_1 ftypeR + \alpha_2 ftypeM + \alpha_3 ftypeG + \alpha_4 ftypeV + \alpha_5 aginc2 + \alpha_6 aginc3 + \alpha_7 aginc4 + \alpha_8 watprice + \alpha_9 annppt_{5yr} + \alpha_{10} CVannppt_{5yr} + \alpha_{11} acre + \alpha_{12} wsource + \alpha_{13} rate_{frequency} + \alpha_{14} salt_{tolerance} + \alpha_{15} govt_{info}$$

where the subscript, k, represents the baseline, and subscript, j, represents the 3 choices other than the baseline.

Discussion of Results

Based on Chi-Square tests on the Wald statistics, the fit for both the soil moisture and salinity models is significantly different from the respective null models. The McFadden R^2 for both models is somewhat below the standard acceptable range of [0.20, 0.40] (Hensher and Stopher 1979). We use a natural log transformation on the acreage variable due to the large range in values [0.25, 10625], and find that the transformed variable is statistically significant. A 2.7-fold increase in acreage increases the likelihood of adopting soil moisture and salinity monitoring by 40% and 45%, respectively. This is consistent with our hypothesis that farms with more acres will, on average, be more likely to adopt monitoring practices. The "acreage effect" may be more relevant for small- and medium-sized farms since it takes an almost 3-fold increase to increase the likelihood of adoption. Indeed very large farms also tend to derive 75-100% of their income from farming activities, and we do not find a significant relationship with monitoring activities in these farms. Farms with 50-74% income from agriculture are 4.2 times more likely to adopt soil moisture monitoring than those with less than 25% agricultural income. And, farms with 25-49% income from agriculture are 2.6 times more likely to adopt salinity monitoring relative to those with less than 25% agricultural income.[38]

[38] At an 11% level of significance.

Table 5.1: Adoption of Soil Moisture Monitoring

depvar=soil moisture monitoring	Odds Ratio	Robust Std. Error	z	P>|z|
Constant	0.009	0.0185	-2.38	0.017
farm type (baseline=tree)				
mixed	0.687	0.437	-0.59	0.555
vegetable	0.161	0.130	-2.26	0.024
field	0.222	0.159	-2.10	0.035
vineyard	1.132	0.664	0.21	0.832
%age income from agriculture (baseline=less than 25%)				
25 – 49	1.703	0.926	0.98	0.328
50 – 74	4.246	2.705	2.27	0.023
75 – 100	1.168	0.697	0.26	0.795
ln (acre)	1.408	0.182	2.65	0.008
access to groundwater	0.974	0.386	-0.07	0.948
govt primary source of info	3.117	1.353	2.62	0.009
water rate frequency	1.090	0.062	1.51	0.131
ln (ppt 5-year mean)	1.637	0.570	1.42	0.157
ln (ppt 5-year variation)	2.015	2.922	-2.38	0.017
n=187				
McFadden R^2	0.15			
Sensitivity	48.00%			
Specificity	87.50%			

Table 5.2: Adoption of Salinity Monitoring

depvar=salinity monitoring	Odds Ratio	Robust Std. Error	z	P>|z|
Constant	0.001	0.002	-2.87	0.004
farm type: (baseline= tree)				
mixed	0.544	0.369	-0.90	0.370
vegetable	1.111	0.949	0.12	0.902
field crop	0.589	0.496	-0.63	0.530
vineyard	1.202	1.031	0.21	0.830
%age income from agriculture: (baseline=less than 25%)				
25 - 49	2.588	1.566	1.57	0.116
50 - 74	1.007	0.642	0.01	0.991
75 - 100	1.352	0.781	0.52	0.602
access to groundwater	1.314	0.551	0.65	0.516
govt primary source of info	2.888	1.511	2.03	0.043
crop salt tolerance: (baseline=moderate tolerance)				
sensitive	2.876	1.897	1.60	0.190
tolerant	2.176	2.074	0.82	0.414
ln (acre)	1.466	0.179	3.14	0.002
water rate_frequency	1.157	0.063	2.66	0.008
ln (ppt 5-year mean)	2.372	0.992	2.07	0.039
ln (ppt 5-year variation)	7.719	11.199	1.41	0.159
n=187				
McFadden R^2	0.17			
Sensitivity	65.93%			
Specificity	70.83%			

Farm type is a significant predictor of adopting at least one soil monitoring practice. Relative to orchards (i.e., baseline), vegetable and field crop farms are 84% and 76% less likely to adopt soil moisture monitoring. Additionally, growers who primarily receive their information from state and federal institutions (e.g., UCCE, NRCS, CDFA) are roughly 3 times more likely to adopt either monitoring practice than those who receive from other sources (e.g., neighbors, industry, popular press, farm managers). Contrary to our hypothesis, poor soil moisture quality (i.e., available water supply) is not a significant predictor of soil moisture monitoring. This may suggest that the underlying soil quality has little to do with actual moisture retention due to the large quantity of amendments growers add to soils.

Access to groundwater, number of water sources, or type of water source (district, groundwater, or both) do not significantly predict adopting either monitoring practice. We did not find a significant relationship between the level of total dissolved solids in irrigation water and adoption of salinity monitoring. This is contrary to our hypothesis that growers with higher salinity levels would be more likely to adopt salinity monitoring. However, when we included a variable on salt tolerance of the plant, we discovered why we may have observed this contradiction. Growers are concerned about the specific tolerance of their crops rather than broadly concerned about salinity levels. We found that growers with sensitive crops were almost 3 times more likely to adopt salinity monitoring than growers with moderate crops.[39]

[39] At a 19% level of significance.

Perhaps the most counter-intuitive result from our analysis is that water price is not a significant predictor of adopting at least one of these practices, which is contrary to the empirical evidence on irrigation technology adoption in the literature. However, when we included a variable on the frequency with which the water price has increased over the past decade, we found that a one-unit increase in frequency of rate increase (i.e., adding one more time the rate was increased over the past decade), a grower is 9% and 16% more likely to, respectively, adopt soil moisture and salinity monitoring. We do not observe a significant relationship with any of the climate normals, but find a significant relationship with short-run (5-year mean) total annual precipitation. The results in Tables 5.1 and 5.2 suggest that a positive increase in the precipitation mean results in positive likelihood of adopting either monitoring practice.[40] Additionally, the coefficient of variation across 5 years of precipitation also positively influences adoption of either monitoring practice.[41] It is counter-intuitive that we do not observe a significant relationship with human capital (education and growing experience). Perhaps education is a more important variable in developing countries (Maddison, Manley, and Kurukulasuriya 2007) where it is equated with access to information. Experience may be reflected across different time horizons based on farm type, i.e., it may take longer to acquire experience for more complex farm systems with multiple crops. Additionally, perceptions of water scarcity do not significantly impact the likelihood of adopting either

[40] The 5-year precipitation mean is significant at the 16% level with respect to adoption of soil moisture monitoring.
[41] The 5-year coefficient of variation is significant at the 16% level with respect to salinity monitoring.

of these practices. This may suggest that growers are monitoring soil moisture and salinity to improve crop health rather than optimize water use.

Due to the issue of endogenous regressors, we could not test our theory of "bundling" both monitoring practices with binary logistic regression. The multinomial logistic regression is more informative in identifying factors that influence adoption of both types of monitoring practices (Table 5.3). We find that percent of income derived from agriculture, farm type, and using government institutions as the primary source of information may increase the likelihood of jointly adopting both monitoring practices. We use "both practices" as the baseline in order to compare this to the implementation of "soil only" or "salt only". Due to the overlap in confidence intervals of these variables across the different categories, we cannot distinguish the effects of a single category relative to the baseline. A 2.7-fold increase in the 5-year precipitation mean results in roughly a 64% decline in likelihood that neither practice is being implemented, or that only soil moisture monitoring is implemented (with respect to baseline. The effect of variability is more modest.

Table 5.3: Multinomial Logistic Regression

Dep. Var. = monitor	Odds Ratio	Robust St. Err.	z	Pr>|z|
both	(base outcome)			
none				
constant	1338.092	2.498	2.88	0.004
aginc				
25-49%	0.284	0.654	-1.93	0.054
50-74%	0.256	0.777	-1.76	0.079
75-100%	0.589	0.709	-0.75	0.456
access to groundwater	0.856	0.495	-0.32	0.753
govt primary info source	0.217	0.598	-2.56	0.011
farm type (baseline=tree):				
mixed	1.908	0.707	0.91	0.361
vegetable	8.125	1.065	1.97	0.049
field	8.846	0.89	2.45	0.014
vineyard	1.448	0.691	0.54	0.592
ln (acre)	0.631	0.167	-2.75	0.006
water rate frequency	0.814	0.064	-3.24	0.001
ln (ppt 5-year mean)	0.372	0.439	-2.25	0.024
ln (ppt 5-year variation)	0.028	1.868	-1.91	0.056
salt monitoring only				
constant	16.760	3.068	0.92	0.358
aginc				
25-49%	0.220	0.796	-1.90	0.057
50-74%	0.033	1.262	-2.71	0.007
75-100%	0.525	0.657	-0.98	0.327
access to groundwater	0.864	0.520	-0.28	0.779
govt primary info source	0.320	0.605	-1.89	0.059

	Odds Ratio	Robust St. Err.	z	Pr>|z|
farm type (baseline=tree):				
mixed	0.178	1.109	-1.56	0.12
vegetable	6.398	0.998	1.86	0.063
field	1.761	1.116	0.51	0.612
vineyard	0.584	0.929	-0.58	0.562
ln (acre)	0.992	0.174	-0.04	0.965
water rate frequency	0.880	0.088	-1.45	0.148
ln (ppt 5-year mean)	0.596	0.535	-0.97	0.333
ln (ppt 5-year variation)	0.057	2.12	-1.35	0.176
soil monitoring only				
constant	86.747	4.026	1.11	0.268
aginc				
25-49%	1.119 E-07	0.906	-17.67	0
50-74%	0.199	1.217	-1.33	0.185
75-100%	0.253	1.223	-1.12	0.262
access to groundwater	0.559	0.868	-0.67	0.503
govt primary info source	0.254	0.881	-1.56	0.12
farm type (baseline=tree):				
mixed	0.164	1.61	-1.12	0.261
vegetable	0.729	1.425	-0.22	0.825
field	0.564	1.409	-0.41	0.685
vineyard	1.933	1.277	0.52	0.606
ln (acre)	1.171	0.224	0.71	0.479
water rate frequency	0.762	0.110	-2.48	0.013
ln (ppt 5-year mean)	0.352	0.768	1.36	0.173
ln (ppt 5-year variation)	0.005	2.329	-2.25	0.024
n=187				
log pseudolikelihood	-192.76			
McFadden R2	0.19			
Wald chisq(39)	1487.84			
Prob>chisq	0			

Conclusions

Growers who monitor soil moisture and salinity monitoring are more likely to receive their information from government institutions, yet this is not where the bulk of growers receive their information. According to Figure 5.6, more than half of growers in our sample receive information from industry or friends/neighbors who are also farmers. This suggests that government programs may benefit from strategic partnerships with industry and small farmers' groups. Such programs may also need to reach out to annual crop growers, and generally lower value crop growers. These crops tend to represent more acreage, and therefore represent an untapped opportunity. Finally, monitoring practices do not seem to be a conscious attempt by the grower to combat an increasingly warm and dry climate. Forging this connection may increase the number of growers implementing these practices, particularly as almost 1/3 of growers in our sample view drought as their primary threat to water security (Figure 5.5).

Chapter 6: The Impact of Short-Run Weather Fluctuations on Farmland Sales and Values: Case Study of Riverside County

In this chapter, we study the impact of climate on the likelihood of land sale and land value in two complementary analyses. We focus on Riverside County for these analyses because it presents the greatest within-county variation in crop mix, climate, and water district characteristics within our 4-county study region. Riverside County has a complex relationship amongst quality farmland (i.e., good soil), senior water rights, urbanization, and high value crop production. In these ways, it is a microcosm of the future threats to the sustainability of agriculture in California.

The first empirical analysis is on the extent to which climate impacts the likelihood of agricultural land sales. This is particularly challenging to study because agricultural land is not sold very often. On average, 3-5% of agricultural parcels are sold in the US annually (Gloy et al. 2011). Climate *extremes*, such as drought, are more likely to influence the likelihood of a land sale than *average* climate conditions. Thus, the time horizon for the analysis (2000-2016) includes two major drought events (2007-09; 2011-16). We note that there are two types of land sales: one in which agricultural land is sold to another agricultural producer; and another in which agricultural land is sold to non-agricultural users. While climate extremes potentially influence both types of land sales, this chapter focuses on land that remains in agricultural production after it is sold. Indeed, more studies exist on the sale of agricultural land for non-agricultural uses (Hoppe and Korb 2006; Zollinger and Krannich 2002; Kimhi and Bollman 1999). Agriculture-to-agriculture land sales are less understood, warranting further analysis. This analysis is also warranted because there is limited understanding of the extent to which microeconomic variables influence the likelihood of land sales of both types. Previous work on agricultural land sales has focused on macroeconomic variables (Devadoss and Manchu 2007; Huang et al. 2006; Just and Miranowski 1993).

In the second empirical analysis, we return to the Ricardian framework to assess the extent to which short-run shocks, such as the droughts experienced in California from 2007-09 and 2011-2016, influence the value of the farming enterprise. We depart from the basic assumption of the Ricardian model that long-run climate patterns (as represented by 30-year normals) are the sole climatic effect on farmland value. Long-run averages minimize the contribution of extreme events. Yet, the recent California droughts are more severe than many experienced over the historical record, with projections for increased frequency and duration of these events (Hartmann et al. 2013). For example, the precipitation level from 2012-14 was the lowest of any 3-year running average on record (Williams et al. 2015). Further, 2012-14 represents the most severe reduction in soil moisture for California of any 3-year period over the past 1200 years (Griffin and Anchukaitis 2014). In addition to meteorological evidence, perceptions of the severity of drought events may be more prevalent. Our survey research indicates that almost 1/3 of growers in our southern California 4-county sample view drought as the primary threat to their water security.

Controlling for land quality, access to reliable water, and urban growth, we evaluate the impact of short-run temperature and precipitation (mean and variability) characteristic of the recent extreme drought conditions in California. We are cognizant of the extent to which the housing market crash in 2007-2008 may have impacted non-agricultural land values, though some argue that historically low interest rates may have caused farmland values to remain relatively high (Nickerson et al. 2012). This may suggest a dampened or ambiguous effect of the housing crisis on farmland values, allowing us to study climatic and weather impacts. Riverside County witnessed a drop in both county-wide agricultural revenue and farmland sales during the period of the housing crisis (Figures 6.1 and 6.2).

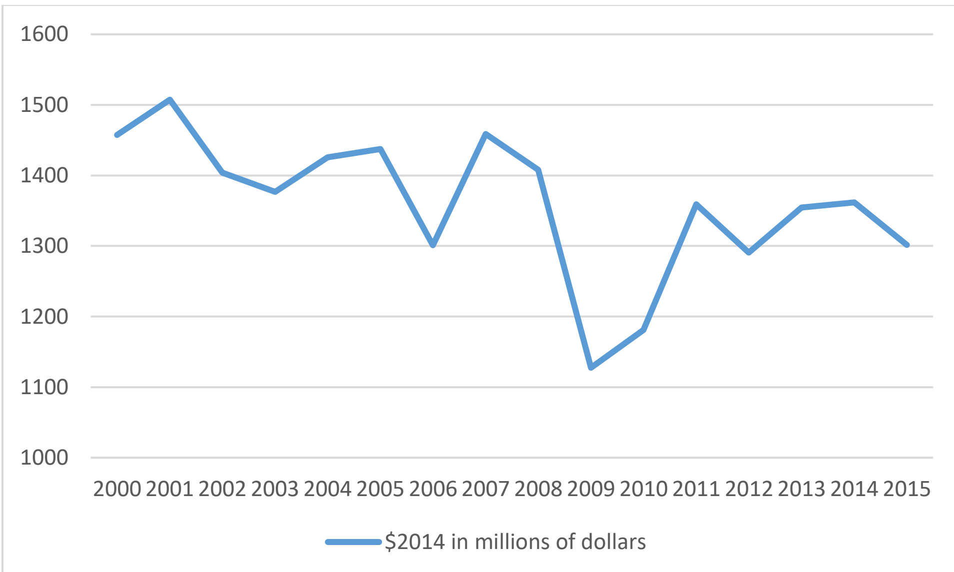


Figure 6.1: Total Gross Revenue from Agriculture in Riverside County (2000-2015)
Data Source: Riverside County Agricultural Commissioner Reports

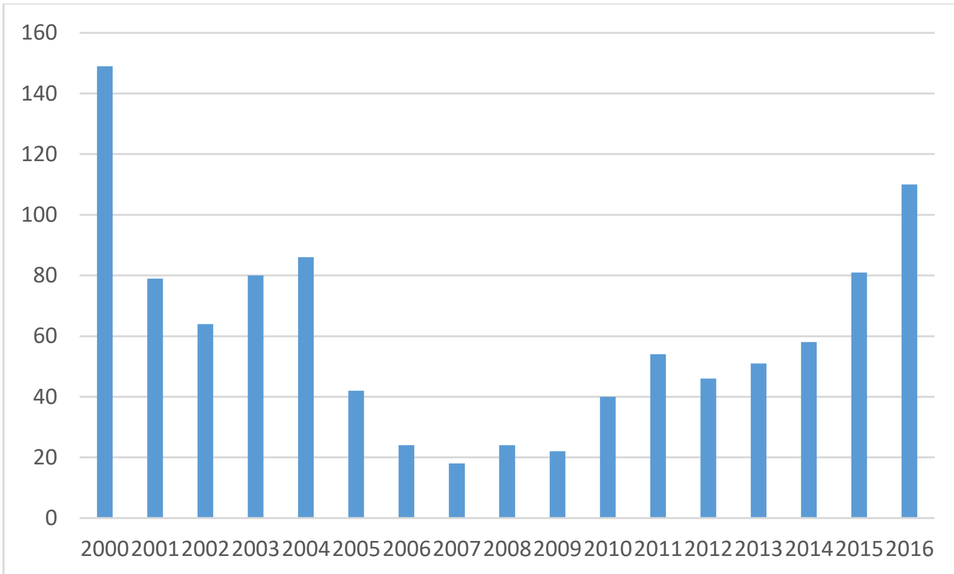


Figure 6.2: Total Parcels Sold in Dataset (2000-2016)

We begin with an exploratory analysis of land sales, analyzing the extent to which land sales are impacted by short-run fluctuations in weather. Our dataset represents parcels that have remained in agricultural production across a 17-year period (2000-2016) with access to irrigation water from 4 major districts (Coachella Valley Water District, Eastern Municipal Water District, Palo Verde Irrigation District, Western Municipal Water District). This is followed by an analysis of the impact of these short-run fluctuations on land values using the same dataset. This ensures that parcels in our dataset are being purchased for agricultural use rather than conversion to other uses. Our purpose here is to study farmland value, rather than capture the value of alternative land uses.

We conclude the chapter by discussing results from both analyses on the extent to which short-run weather fluctuations affect the probability of selling, and value of, agricultural land. While this chapter is ultimately focused on quantifying the impact of short-run weather fluctuations on parcel-level land value, we also explore how the likelihood of this sale may be connected to these same fluctuations in short-run weather. This has not been studied previously, and we present preliminary thoughts on how land sales may be linked to farmland values.

Literature Review

Positive expectations about the future viability of farming drive capital investment and potentially reduce land sales. Wheeler et al. (2012) survey Murray Darling Basin farmer attitudes to having their children take over farming operations following the historic drought. They find that farmers who plan to have their children inherit their farm are more likely to have made irrigation efficiency improvements and less likely to have sold any land in the prior 5 years. Zollinger and Krannich (2002) survey Utah growers to determine the factors influencing their expectation to sell land for non-agricultural uses. They find that increased profitability over the past five years has a significant negative influence on the expectation to sell land, while the perception of increased urbanization exerts a significant positive influence.

Deschenes and Kolstad (2011) study how weather and expectations on weather influence farmland productivity in California across a 20-year period. They assume that such expectations are derived from observing past weather, and thus include a 5-year moving average in their time-series model. Although none of their weather variables (5-year averages or annual) are significant, their study provides general intuition on the magnitude of these variables. The magnitude of the expected degree-day variable is larger than the annual average, suggesting that changes in expectation are more costly than annual weather changes.

This section has highlighted micro-level analyses of likelihood of selling farmland. These studies differ from the subsequent analysis on likelihood of land sales because these do not include climatic impacts. Additionally, these focus on agricultural land sales for non-agricultural uses whereas our study focuses on agriculture-to-agriculture land sales. This section also highlights land value studies that focus on short-run fluctuations in weather, which we build upon for the subsequent Ricardian analysis. More detailed review of the Ricardian literature is presented in Chapter 4.

Empirical Specifications

Exploratory Land Sales Analysis

Studying the likelihood of US farmland sales is complicated by the fact that very few such sales take place in a given year relative to the total number of agricultural parcels. Approximately 3-5% of agricultural parcels are sold in the US in a given year (Gloy et al. 2011). On average, 6% of parcels in our panel dataset were sold annually from 2000-2016. We explored the extent to which the land sales are influenced by ex **(6.2)** temperature and precipitation as measured by coefficient of variation on 5- or 10-year expectation periods. The population-averaged panel model, where *q* is probability of a land sale, is represented as:

$$log\frac{q}{1-q} = \alpha_0 + \alpha_1 ppt\_mean_{t-k} + \alpha_2 ppt\_cv_{t-k} + \alpha_3 tmax\_cv_{t-k} + \alpha_4 pop\_rate_{t-k} + \alpha_5 sq\_pop\_rate_{t-k} + \alpha_6 use\_citrus + \alpha_7 use\_irrigated + \alpha_8 use\_vineyard + \alpha_9 use\_date + \alpha_{10} district\_EMWD + \alpha_{11} district\_PVID + \alpha_{12} district\_WMWD + \alpha_{13} year + u_t \tag{6.1}$$

Variable descriptive statistics and definitions are presented in Table 6.1. The subscript (t-k) is added to time lagged variables, where t = current year and k represents the number of lagged years (5 or 10).

Ricardian Analysis

In addition to land sales, we study the impact of short-run fluctuations in weather on farmland value using the Ricardian framework. The empirical equation is represented as:

$$\log(\text{sale\_acre\_2014}) = \sigma_0 + \sigma_1 ppt\_mean_{t-k} + \sigma_2 ppt\_cv_{t-k} + \sigma_3 tmax\_cv_{t-k} + \sigma_4 pop\_rate_{t-k} + \sigma_5 sq\_pop\_rate_{t-k} + \sigma_6 use\_citrus + \sigma_7 use\_irrigated + \sigma_8 use\_vineyard + \sigma_9 use\_date + \sigma_{10} district\_EMWD + \sigma_{11} district\_PVID + \sigma_{12} district\_WMWD + \sigma_{13} year + u_t \tag{6.2}$$

Once again, the subscript (t-k) is added to time lagged variables, where t = current year and k represents the number of lagged years (5 or 10).

Table 6.1: Variable Description and Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Description
Acre	28.65	37.1	0.19	466	parcel acreage
sale_year	NA	NA	2000	2016	year parcel sold
sale_acre_2014	20510.52	17985.44	60.82	80157.45	sale price per acre in $2014
Slopegradd	12.35	15.1	1.00	53.00	soil slope gradient
Usecode	2.38	1.06	1.00	5.00	type of agricultural use, 5 levels
District	NA	NA	NA	4.00	water district, 4 levels
pop_rate_10	0.12	0.14	-0.04	1.06	population rate 10 years prior to sale
pop_mean_10	4.3	6.68	0.15	30.56	population mean 10 years prior to sale divided by 10,000
ppt_mean_10	220.96	162.87	49.39	638.75	annual precipitation mean 10 years prior to sale
ppt_cv_10	0.56	0.12	0.41	0.97	annual precipitation variation 10 years prior to sale
tmax_mean_10	28.54	3.32	23.24	32.43	annual maximum temp. mean 10 years prior to sale
tmax_cv_10	0.02	0.01	0.01	0.04	annual maximum temp. variation 10 years prior to sale
tmax_mean_5	28.54	3.36	22.96	32.61	annual maximum temp. mean 5 years prior to sale
tmax_cv_5	0.02	0.01	0.00	0.05	annual maximum temp. variation 5 years prior to sale
ppt_mean_5	199.73	150.3	27.28	626.10	annual precipitation mean 5 years prior to sale
ppt_cv_5	0.57	0.18	0.13	1.32	annual precipitation variation 5 years prior to sale
pop_rate_5	0.07	0.49	-6.58	0.95	population rate 5 years prior to sale
pop_mean_5	4.61	6.92	0.16	31.62	population mean 5 years prior to sale divided by 10,000
ppt_normal	234.32	169.64	75.48	544.14	30-year precipitation normal
tmax_normal	28.51	3.19	23.68	32.00	30-year annual maximum temp. normal
sq_pop_rate_5	0.24	2.51	0.00	43.34	square of population rate 5 years prior to sale
sq_pop_rate_10	0.03	0.08	0.00	1.12	square of population rate 10 years prior to sale

Dataset and Variable Construction/Transformation

Dataset

The annual parcel data (Assessor Parcel Number, Crop Zone, Sale Year, Sale Value) comes from the Riverside County Assessor and ParcelQuest, as stated in Chapter 3. There are 985 parcel sales that include land value within the 4 major water districts in this analysis. This translates into 16,785 observations (985x17) for the land sales model. ParcelQuest includes a greater number of observations of sales than of value associated with these sales. However, we chose to use observations in dataset, which have both sales and value of sales, in order to make the two analyses more comparable even if this meant fewer observations in the land sales analysis.

Variable Construction/Transformation

Climate variables are central to our analysis and are represented as follows:

(6.3)
$$E(x_{i,t}) = \frac{1}{k}\sum_{j=t-k}^{t-1} x_{i,j}$$

(6.4)
$$CV(x_{i,t}) = \frac{k}{(k-1)^{1/2}} \frac{\left(\sum_{j=t-k}^{t-1}(E(x_{i,t}) - x_{i,j})^2\right)}{\sum_{j=t-k}^{t-1} x_{i,j}}$$

where x_i represents either the annual precipitation or maximum temperature. Year of sale is t, and k is either 5 or 10 depending on whether a 5 or 10-year lag is represented. The 5- and 10-year values for precipitation and temperature were calculated using the annual average for daily maximum temperature and total annual precipitation (mm) from the PRISM Group (see Chapter 3).

We do not include temperature mean values in the regression because of the high degree of correlation with precipitation mean values.[1] Even though temperature is an important variable when studying drought, Williams et al. (2015) suggest that precipitation is the primary driver of drought.[2] Further, our descriptive statistics indicate that there is more variance between the precipitation normal and 5- and 10-year mean precipitation values than the analogous maximum temperature normal and maximum temperature 5- and 10-year means.

Population growth rate, γ_1, for the i[th] parcel, represents the slope of the line through the 5- or 10-year period prior to the year of sale as follows:

(6.5) $$pop_i = \gamma_{i,0} + \gamma_{i,1} year$$

where *pop* is the population and *year* is the given year of this population. The slope is taken at 5 or 10 years prior to the year of sale. For example, if the year of sale is 2000, then the 5-year population rate is calculated using annual population data for 1995-1999.

[1] For example, the correlation between the maximum temperature normal and precipitation normal is -0.97.
[2] Williams et al. (2015) found that anthropogenic warming contributed to 8-27% of the drought anomaly from 2012-14.

Table 6.2: Population-Averaged Panel Land Sales Analysis

Dependent variable = likelihood of land sale	Odds Ratio	Robust Std. Err.	z	P>|z|
(Intercept)	0.075	0.313	-8.28	0
ppt_mean_5	1.000	0.001	-0.36	0.717
tmax_cv_5	0.002	7.196	-0.88	0.379
ppt_cv_5	1.137	0.296	0.43	0.665
pop_rate_5	0.676	0.105	-3.72	0
sq_pop_rate_5	0.961	0.017	-2.35	0.019
Land Use Code:				
(Baseline=Avocado)				
Citrus	0.790	0.129	-1.84	0.066
General Irrigated	0.815	0.151	-1.35	0.176
Vineyard	0.669	0.153	-2.63	0.009
Date	0.785	0.184	-1.31	0.189
Water District:				
(Baseline=CVWD)				
EMWD	1.154	0.169	0.84	0.398
PVID	0.828	0.087	-2.18	0.029
WMWD	1.075	0.160	0.45	0.655
Year Dummies:				
(Baseline=2008)				
2000	4.145	0.207	6.89	0
2001	2.219	0.222	3.58	0
2002	1.889	0.208	3.05	0.002
2003	2.026	0.207	3.42	0.001
2004	2.489	0.185	4.94	0
2005	1.797	0.185	3.16	0.002
2006	1.163	0.192	0.79	0.432
2007	0.718	0.218	-1.52	0.129
2009	0.748	0.209	-1.39	0.164
2010	1.038	0.198	0.19	0.851
2011	1.315	0.193	1.42	0.155

	Odds Ratio	Robust Std. Err.	z	P>|z|
2012	1.616	0.189	2.54	0.011
2013	1.606	0.210	2.26	0.024
2014	1.730	0.197	2.79	0.005
2015	2.479	0.221	4.11	0.000
2016	2.667	0.247	3.98	0.000
Wald chi2(28)	252.42			
Prob > chi2	0			

Table 6.3: Parcel-level Ricardian Analysis

Dependent variable = log land sale per acre	Coefficient	Robust Std. Error	t value	Pr(>|t|)
(Intercept)	8.312	0.773	10.756	< 2.2e-16
ppt_mean_5	0.004	0.001	4.803	1.82E-06
tmax_cv_5	-33.887	12.167	-2.785	0.005
ppt_cv_5	-0.820	0.320	-2.563	0.011
pop_rate_5	0.617	0.256	2.415	0.016
sq_pop_rate_5	0.116	0.044	2.634	0.009
Land Use Code:				
(Baseline=Avocado)				
Citrus	0.773	0.202	3.836	0.000
General Irrigated	1.051	0.256	4.113	4.24E-05
Vineyard	0.772	0.258	2.991	0.003
Date	1.495	0.338	4.418	1.11E-05
Water District:				
(baseline=CVWD)				
EMWD	-0.247	0.313	-0.789	0.430
PVID	-1.245	0.169	-7.381	3.41E-13
WMWD	0.266	0.299	0.890	0.374
Year Dummies:				
(Baseline=2008)				
2000	0.971	0.711	1.367	0.172
2001	1.461	0.732	1.995	0.046
2002	1.450	0.731	1.985	0.047
2003	1.527	0.686	2.226	0.026
2004	1.409	0.698	2.019	0.044
2005	1.480	0.727	2.037	0.042
2006	1.090	0.785	1.390	0.165
2007	1.575	0.689	2.287	0.022
2009	1.354	0.708	1.914	0.056
2010	0.995	0.693	1.436	0.151
2011	1.263	0.703	1.797	0.073
2012	1.037	0.718	1.444	0.149
2013	1.509	0.709	2.128	0.034

	Coefficient	Robust Std. Error	t value	Pr(>|t|)
2014	1.162	0.695	1.673	0.095
2015	2.026	0.730	2.774	0.006
2016	2.030	0.744	2.730	0.006
Fstat	14.903			
pval (Fstat)	2.20E-16			
Average MSE from cross-validation	0.79			

Discussion of Results

We test the impact of 5 and 10 year lags of weather on both the likelihood of sale and value of farmland. We focus on the precipitation mean, as this has the greater contribution to drought relative to temperature (Williams et al. 2015). As previously discussed, the high degree of correlation (i.e., $\rho = -0.97$) between precipitation and maximum temperature means would introduce multicollinearity if both were included in our analyses. In addition to including the mean precipitation values, we test the impact of short-run (5 or 10 year) temperature and precipitation variability on likelihood of sales and land sale value.

None of the climate variables studied impact the likelihood of selling farmland in Riverside County from 2000-2017. The 5-; 10-; and 30- (normal) year mean precipitation also do not impact farmland value. This is similar to the results in Deschenes and Kolstad (2011). However, short-run precipitation variability has a significant influence on farmland value. A unit increase in the 5-year precipitation coefficient of variation reduces the value of farmland by 56% per acre.

Population rate exhibits a significant relationship with both likelihood of land sales and land value. For example, a unit increase in the 5-year population rate decreases the likelihood of selling farmland by 32%, and increases farmland value by 85%. The exact relationship varies across model specifications, but remains significant. Further, population rate exhibits a U-shaped relationship with likelihood of land sales and a hill-shaped relationship with land value. The U-shaped pattern is explained by the relationship found between urbanization and land value dynamics. Urbanization naturally follows from population increase, and urbanization tends to increase the value of farmland (Platinga, Lubowski, and Stavins 2002). This may provide incentives to growers to hold on to their land, rather than selling it. However, the marginal productivity of farmland continues to decline with increasing urban encroachment (square of population rate). And, this makes selling farmland more attractive.

Citrus and vineyard are less likely to be sold than avocado, while all land uses (citrus, general irrigated, vineyard, and date) tend to be more valuable per acre than avocado. The significance of citrus and vineyards tends to vary across model specifications, although that of general irrigated agriculture and dates remains robust across these specifications. At the water district level, the results suggest that more valuable farmland is more likely to be sold. Coachella Valley Water District has the most valuable farmland compared to the other 3 districts. This suggests that, controlling for other factors, the characteristics of a given water district may add significant value and may be sold to achieve a positive return rather than minimize a loss.

Conclusions

Based on our two analyses, we suggest that the relationship between likelihood of farmland sales and farmland value is attribute specific. That is, factors that influence the likelihood of land sale (e.g., land use) may not increase land value, as we had originally hypothesized. Our results suggest that short-run fluctuations in precipitation reduce the value of farmland. This suggests that the droughts experienced during this period may have influenced expectations on the future viability of farming in Riverside County.

Water district influences likelihood of land sales and land value in the same direction. In particular, Coachella Valley Water District has higher sales and value relative to Palo Verde Irrigation District, the other district in Riverside County holding senior water rights. This suggests that expectations on the viability of farming in Coachella Valley Water District are higher even relative to Palo Verde Irrigation District. Other attributes, such as land use, influence farmland sales likelihood and land value in opposite directions. For example, avocado sales relative to other land uses (citrus and vineyard) increased during this period, whereas land value for avocado declined relative to these other uses. This suggests that avocado orchards may have been sold in Riverside County during the study period due to declining value both relative to other agricultural uses and due to precipitation variability associated with the drought.

The relationship between land sale and value is, as suggested earlier, attribute-specific. Higher (lower) land value does not necessarily result in a higher (lower) likelihood of land sale. And, our preliminary results do not reveal a direct relationship between precipitation extremes (mean or variability) and likelihood of land sale. We have some indirect evidence that increasing likelihood of sale of avocado parcels may be related to declining land value. And, declining land value is, on average, related increasing precipitation variability. Studying the extent to which selling avocado parcels may represent an adaptation to extreme weather (or climate) is an important area of future research. Avocados are amongst the most valuable crops with respect to gross revenue per acre. However, as the frequency and duration of drought persists in Southern California, we may witness more avocado land being sold not only to other agricultural producers, but to non-agricultural users as well. In addition, farm survey research would benefit from including questions on dates of actual parcels sold and purchased. This could provide more insight into the microeconomic influences on the likelihood of land sales.

Chapter 7: Conclusions and Policy Implications

Resilience to water scarcity is fundamentally related to grower responsiveness to the external environment. We have quantified grower responsiveness to farm- and parcel-level microclimate in two desert (Imperial and Riverside) and two coastal (San Diego and Ventura) counties in Southern California, using primary survey data (Annex 3.4). Our metrics include gross revenue per acre (Chapter 4), likelihood of technology adoption (Chapter 5), land value per acre (Chapter 6), and likelihood of land sale (Chapter 6). Although we study several grower and farm characteristics, climate, water source, farm type, and share of income from agriculture are the most robust variables in our farm-level analyses. The results of the parcel-level analyses of Riverside County in Chapter 6 suggest that short-run variability in annual precipitation may have negatively impacted land value over the past 17 years, though a relationship with precipitation variability and the likelihood of land sale during this same period is not supported by our results.

Our analysis of grower responsiveness begins with a farm-level Ricardian model using several micro-level variables collected from our survey instrument (Chapter 4). We study the climatic impact on gross revenue per acre in 2014, which is an annual measure of farmland productivity. In Chapter 5, we evaluate the extent to which adoption of irrigation management practices (soil moisture monitoring and salinity monitoring) represents adaptation to an increasingly warm and dry climate. These monitoring practices require growers to be more pro-active in scheduling irrigations (in the case of soil moisture monitoring), and minimizing inefficient leaching practices (in the case of salinity monitoring), and thus represent the next generation of on-farm water management advances. The parcel-level analysis of Riverside County in Chapter 6 includes two complementary analyses: (1) an exploratory analysis of the extent to which likelihood of land sales are impacted by short-run fluctuations in weather; and (2) an analysis of the impact of these short-run fluctuations on land values. These studies focus on adaptation to extreme climatic events, such as the droughts experienced in Southern California from 2007-2009 and 2011-2016. We introduce two sets of dynamic variables into the analysis: climate and population. Not only do we explore the extent to which these dynamic variables individually impact parcel sales and value, but we explore a preliminary relationship between likelihood of a sale and the relative value of the parcel.

In addition to our empirical analyses, we learned how to construct a complex spatial dataset from primary data (our questionnaire) and existing public data sources on agricultural land values, climate, soil, groundwater, zoning, and utility boundaries. Chapter 3 provides detail on the questionnaire development as well as these multiple external data sources. Ultimately, the benefits of creating a rich dataset outweighed the cost in time.

There are several farm-level policy implications, based on our analysis of the original survey data:

We observe a connection between soil moisture/salinity monitoring and short-run precipitation. The 5-year total annual precipitation mean and 5-year total annual precipitation variability are both significant in both our binary logistic regression analyses. The positive relationship between the precipitation mean and adoption (of either monitoring practice) is counter-intuitive. We would expect this relationship to be negative because a decrease in precipitation associated with the drought would influence growers to monitor water quantity/quality if this grower were using monitoring as an adaption to the drought. We also observe a positive relationship with 5-year total annual precipitation variability, as we expected if monitoring were truly an adaptation to the drought. It is challenging to reconcile these seemingly contradictory results, and ultimately we are cautious about drawing a strong conclusion either way. Precipitation is a complex phenomenon, and further analysis with a larger sample may be necessary. Farm type and percentage of income generated from agriculture may be stronger determinants of adoption. Adoption that is not consciously tied to perceived changes in climate is often called "autonomous adaptation" (Janowiak et al. 2016; Stein et al. 2014; Anwar et al. 2013). This is often observed in the short-run as relatively quick-fixes to production plans. Given projections of increased frequency and duration of droughts during the current century, growers will develop the most effective, cost-minimizing strategies if they are intentionally addressing these long-run climatic changes today. Almost 1/3 of growers in our sample view drought as their primary threat to water security, and a greater link between monitoring and drought mitigation may even increase the level of adoption in the short-run. In addition to UC Cooperative Extension (UCCE) programs, there are several competitive grants (CDFA State Water Efficiency and Enhancement Program, NRCS Environmental Quality Incentives Program, NRCS Conservation Innovation Grants) that could incentivize growers to think in these intentional terms. As such, monitoring soil moisture and salinity could be a gateway into managing for long-run climatic changes.

More than half of the growers in our sample receive their farming information from industry or friends/neighbors (Figure 5.5). Yet, based on the results from our logistic regression, growers who primarily receive their information from state and federal institutions are roughly 3 times more likely to adopt either monitoring practice than those who receive from other sources (e.g., neighbors, industry, popular press, farm managers). This suggests that government programs may benefit from strategic partnerships with industry and small farmers' networks, without compromising their neutral political role. UCCE and NRCS, in particular, may be able to streamline and leverage their water conservation initiatives with other state government institutions (e.g., California Department of Food and Agriculture, California Department of Water Resources, California Environmental Protection Agency, California Energy Commission, California Department of Energy).

Water price and frequency of water price increases may influence growers to be more productive. Our results from the farm-level Ricardian model suggest that a 5% increase in water price increases gross revenue per acre by 1.4%.[1] We also study how frequently water price has increased over the past decade. We find that increasing the number of times the price has increased by one unit (e.g., from once to twice over the past decade), increases productivity per acre by 3.4%. This suggests that water price may

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[1] All results from the farm-level Ricardian analysis reported in this chapter refer to the log-log specification.

direct growers to produce higher value crops. Future research on the role of price increases and frequency of these increases for lower value crop farms is important. The challenge is that crops with the lowest value per acre (i.e., field crops) tend to be produced in districts with senior water rights, which do not regularly implement water price increases (e.g., Imperial Irrigation District, Palo Verde Irrigation District, and Bard Water District). Notably, although Coachella Valley Water District holds senior water rights, they have increased agricultural water price 4 times over the past decade.

As expected, field crop growers have low productivity per acre. Relative to orchards (i.e., baseline), field crop farms garner almost 80% less revenue per acre. Field crop farms are 41% and 78% less likely to adopt salinity and soil monitoring practices, respectively. Adaptation programs may need to reach out to lower value crop growers. These crops tend to represent more acreage, and therefore represent an untapped opportunity.

Public data sources are noisy and incomplete. In constructing our dataset, we benefitted greatly from the spatial data from several generous agencies (Agricultural Commissioners, Assessors, NRCS). We also lost both time and data due to poor quality data, which these agencies dedicate valuable resources to collect. Most surprising was the lack of standardization in parcel identification numbers between files from the same agency (e.g., excel file records did not completely match with GIS file records). There may be a role for academics in setting standards or creating repositories of quality data.

It is more challenging to identify policy implications for the land sales analysis in Chapter 6 since only 3-5% of agricultural parcel are sold in the US annually (Gloy et al. 2011). We can, however, understand factors influencing sales, and the extent to which parcel-level land value exhibits an analogous relationship with these factors:

Short-run precipitation variability has a significant influence on parcel value. Based on our results, a unit increase in the 5-year precipitation coefficient of variation reduces the value of farmland by 56% per acre in our Riverside County sample. This is consistent with the negative impact of the annual variability in the maximum temperature normal on farm-level productivity per acre (Chapter 4), though we are cautious to directly compare the two analyses. Broadly, the parcel- and farm-level analyses suggest that variability in weather/climate negatively impact productivity per acre, whether annually or seasonally.

Population rate exhibits a significant relationship with both land sales and value. For example, a unit increase in the 5-year population rate decreases the likelihood of selling farmland by 32%, and increases farmland value by 85%. This may suggest pursuing synergies in urban and agricultural planning.

Water district type positively influences both land sales and value. In particular, Coachella Valley Water District has higher sales and value relative to Palo Verde Irrigation District, the other district in Riverside County holding senior water rights. Higher farmland values in Coachella Valley Water District may partially be attributed to their proactive irrigation efficiency measures over the past 20 years, as well as increasing water price more frequently than other districts that hold senior water rights.

Avocado land sales may reflect an adaptation to drought during this period. Avocado sales relative to other land uses (citrus and vineyard) increased during this period, whereas land value for avocado declined relative to these other uses. This suggests that avocado orchards have been sold in Riverside County during the study period due to declining valuation both relative to other agricultural uses and due to precipitation variability associated with the drought.

Broadly, factors that influence the likelihood of selling land may not increase land value, as we hypothesized. The results from the two analyses in Chapter 6 suggest that the relationship between farmland sales and farmland value is attribute specific. Population influences sales and value in the opposite direction, whereas water district and land use attributes influences sales and value in the same direction.

Even with limited resources, we were able to collect complete data on 187 growers. This suggests that growers are responsive to providing information to universities. We included a comments page in our survey, which we did not evaluate in our empirical analyses. Many of the comments suggested these individuals were receptive to information that would help them with their production plans (e.g., comparative analyses of rootstocks), but they did not know how to find or even translate the information. One grower even commented, “We are not your farmers. You are our research university.” There is high potential to foster a positive relationship with growers both directly and, indirectly, through extension research. Perhaps growers could serve as partners in collecting quality data (likely anonymously) that would prove invaluable to academic research.[2]

Caveats and Possible Future Work

We did not anticipate the large share of tree crop growers in our sample. This suggests that such growers are both more abundant, and likely more responsive to surveys. Coupling this with the results from Chapter 6, which reveal that avocado parcels were most devalued and more likely to be sold in Riverside County, warrants a focused analysis on tree crop growers. It also warrants a separate analysis of field crop growers. More data, both across time and space, is needed to evaluate the likelihood of land sale and the potential implications of climate change. As analytics become increasingly accessible, it will be interesting to evaluate the adoption of these data tools (particularly those monitoring climate and weather) and the extent to which productivity is affected.

[2] Large companies, such as DuPont and John Deere, already use sensors and GPS to collect detailed data from farmers. Even start-up, such as the Farmers Business Network, provides pricing and other data to growers.

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ANNEX 3.1 PILOT PHASE INVITATION LETTER

Dear {blank},

I received your contact information from the Public Records Department of the County Agricultural Commissioner's Office. I am writing from the University of California, Riverside to request your participation in a brief survey on farming practices in Riverside County. It is part of my Ph.D. dissertation research with the Department of Environmental Sciences, under the mentorship of Professor Ariel Dinar. With over $1.3 billion in gross agricultural production value in 2013, it is clear that Riverside farmers are among the most productive in California. Riverside farmers have developed some of the most resilient farming systems in the nation in spite of being located in the desert.

As a student of agricultural economics, I am interested in learning about your farming experience. Most people will agree that several factors affect farmland value, such as soil quality, proximity to urban centers, and, to some extent, climate. It is less obvious how irrigation technologies and management practices may influence land value. Common sense suggests that there is an indirect relationship through improving land quality. Could certain practices directly improve land value? Once I am finished with my research, I will provide you with my best response to this question based on rigorous and unbiased research.

My survey is made up of general questions on farm size, crops planted, irrigation technologies, and management practices. I am only requesting the most general level of information. I am not requesting crop variety, brand of technologies, or any other detailed proprietary information. I also ask general questions on how the drought may have affected you. Even then, I assure you that individual responses will not be published. My analysis is on the aggregate results from all of the surveys.

I would like to emphasize that, under the University of California System, we are committed to protecting your privacy. Your individual information will only be known to my 5-person research team. This team is made up of: Professor Ariel Dinar, 3 undergraduate research assistants, and myself. We will not share your individual information with the government, private companies, or any other entity or person.

Please feel free to email or call with any questions.

Sincerely,

Arisha Ashraf

ANNEX 3.2 PILOT PHASE CONSENT DOCUMENT

Document of Consent: *Please **read and sign** this document before proceeding with the survey.*

What is the purpose of the study?

This study will help me understand how Southern California farmers have maintained successful farming systems in spite of the often harsh climate, particularly during the current drought. I am interested in how farming practices (e.g., irrigation, soil monitoring, leaching, etc.) are connected to farm performance, as measured by production value. The results from my research will ultimately inform state policy on the benefits of existing farming practices in the region. There are no right or wrong answers for this survey, and I am not making any recommendations to you. You are the experts!

What are my rights during the survey?

Responding to the survey is voluntary. You may quit the survey at any point.

Will I receive compensation for completing the survey?

No, you will not receive any compensation for completing this survey.

How will my privacy be protected?

Your information will be password protected and only accessible by project staff (Arisha Ashraf, Ariel Dinar, and an undergraduate assistant). Your survey is assigned an ID# so that your individual contact information (including farm name and any other information that may reveal your identity) is stored separately from the rest of the survey questions. Your individual responses will not be published, even without your name. We will only publish aggregate results.

What if I have questions about the survey?

You have the right to ask, and have answered, any questions about the survey. If you have questions at any time you should contact Arisha Ashraf by phone or email.

What if I have questions about my rights as a survey participant?

All research with human volunteers is reviewed by a committee that works to protect your rights and welfare. If you have questions or concerns about your rights as a survey participant you may contact, anonymously, if you wish, our Principal Human Research Review Board Analyst.

Participant's Agreement:

By checking the box below, I indicate that: (1) I have read the information provided above, and (2) I voluntarily consent to participate in this survey.

☐ Yes, I agree to participate.

☐ No, I do not agree to participate.

______________________________________ __________________

Participant Signature Date

ANNEX 3.3 PILOT PHASE QUESTIONNAIRE

Please note that the survey structure and format has been abbreviated for the Annex.

1. What is your annual farm income bracket?
    a. Less than $20K
    b. 20,000 – 39,999
    c. 40,000 – 74,999
    d. 75,000 – 149,999
    e. 150,000 – 300,000
    f. Over 300,000
2. What is the highest level of education you have attained?
    a. Did not complete high school
    b. High school diploma
    c. Bachelor’s degree or 4 years of active military duty
    d. Graduate school
    e. Postgraduate
3. Which percentage of your income is generated from farming?
    a. Less than 25%
    b. 25 - 49%
    c. 50 – 74%
    d. 75 – 100%
4. Do you own or lease your farming operation?
    a. Own
    b. Lease
5. What is the your approximate total land value?
6. How many acres is your farming operation?
7. How many years of farming experience do you have?
8. What are all of your water sources, and how many acre-feet of water do you consume from each source?
9. Have you ever experienced any water reduction during your time farming this property? Yes No
10. If yes to Q.9, please describe when and why:
11. What do you believe are the biggest threats to your water supply?
    a. I do not believe there are any threats to my water supply.
    b. Urban population growth
    c. Drought in California
    d. Drought along the Colorado River
    e. Heat waves
    f. Government Regulations
    g. Other (please explain)
12. If you did not answer “a” to question 11, please rank your top 3 concerns in Q 11.
13. Please rank your concern with water scarcity affecting crop production prior to the drought:
    a. It was not a concern
    b. It was somewhat of a concern
    c. It was an important concern
    d. It was my top concern
14. Please rank your concern with water scarcity affecting crop production during the drought:

a. It was not a concern
b. It was somewhat of a concern
c. It was an important concern
d. It was my top concern

15. Please rank your concern with water scarcity affecting crop production during potential future droughts:
    a. It was not a concern
    b. It was somewhat of a concern
    c. It was an important concern
    d. It was my top concern
16. Please list your top 3-5 crops based total annual revenue for each season:

    FALL SEASON

Crop	**Acres Planted**	**Water application technology**	**How many years have you used this technology?**

Note that only the FALL SEASON table is printed in Annex 3.3. WINTER, SPRING and SUMMER tables were printed in the original pilot survey.

17. How do you currently schedule your irrigations? Do you use CIMIS or any other irrigation scheduling software?
18. Have you attended any farm workshops on water conservation over the past 3 years?
19. Do you currently use any of the following water conservation methods:
    a. Change mix of crops planted to reduce water use
    b. Fallow part of my crop land
    c. Implement pressurized irrigation systems
    d. Implement run-off recovery systems
    e. Plant transplants
    f. Other (please explain)
20. What are your main barriers for implementing water conservation practices:
    a. Many of the technologies are too expensive
    b. I do not have the time to learn about new farming practices
    c. I know about these practices, but I believe there is no way these will benefit me
    d. I do not know about these practices
21. Additional Comments:

ANNEX 3.4 FINAL SURVEY DOCUMENTS

Dear {blank},

I received your contact information from the Riverside County Agricultural Commissioner's Office. This is part of my PhD research in Agricultural Economics at UC Riverside. I am studying the relationship between farm performance and various farming practices, including irrigation, leaching, soil monitoring.

Your participation is critical to developing the most accurate picture of farming in Southern California. I would like to emphasize that I am a Southern Californian, and the main reason I chose this topic was that I noticed a gap between the research that goes on in the university system and farmer needs. Cooperative Extension addresses this gap, but it is still important that the universities directly reconnect with farmers.

As the Consent Document guarantees***, no individual information will be published nor will it be shared with any person or entity outside my research team***. This research team is made up of myself, my primary advisor (Dr. Ariel Dinar), and an undergraduate Research Assistant (Jessica Gonzalez).

For your convenience, I have included a print copy and self-addressed stamped envelope. The survey takes about 20 minutes to complete. I assure you that it looks longer than it is partly because I used big font, and partly because most of these are quick questions. Unlike superficial surveys from private companies which may only be 4 or 5 questions long, I would like to understand your unique situation with more depth. This requires more questions, but not as many as the US Department of Agriculture or government surveys.

If you prefer, you could take the survey on-line on the Riverside Farm Bureau's website under "What's New?". I would also be happy to chat with you over the phone or in-person. I value your time, and look forward to receiving your survey.

Hope you and your family have a Happy Thanksgiving.

Kind regards,

Arisha Ashraf, PhD candidate

Enc.

Tel:
Email:

<u>Document of Consent</u>: *Please **read and sign** this document before proceeding with the survey.*

Thank you for considering participation in my survey. You probably take several surveys, and I appreciate your time. This survey is part of my PhD research in Agricultural Economics for the University of California, Riverside on farming practices in Southern California.

Simply stated, I am a Southern Californian who would like to get to know my farmers. Unfortunately, California farmers have been disconnected from the urban/suburban populations they serve. They have also been disconnected from the research going on in the university system. Your participation is one, modest effort to bridge these gaps. Thanks again for your time!

What is the purpose of the study? This study will help me understand how Southern California farmers have maintained successful farming systems in spite of the often harsh climate, particularly during the current drought. I am interested in how farming practices (e.g., irrigation, soil monitoring, leaching, etc.) are connected to farm performance, as measured by production value. The results from my research will ultimately inform state policy on the benefits of existing farming practices in the region. There are no right or wrong answers for this survey, and I am not making any recommendations to you. You are the experts!

What are my rights during the survey? Responding to the survey is voluntary. You may quit the survey at any point.

Will I receive compensation for completing the survey? ***You have the option of receiving $25 if we receive your completed survey by <u>September 15, 2016</u>.*** If you wish to waive this option, please check the appropriate box at the end of this survey. Your check will be mailed 6-8 weeks after receiving your completed survey.

How will my privacy be protected? Your information will be password protected and only accessible by project staff (Arisha Ashraf, Ariel Dinar, and an undergraduate assistant). Your survey is assigned an ID# so that your individual contact information (including farm name and any other information that may reveal your identity) is stored separately from the rest of the survey questions. Your individual responses will not be published, even without your name. We will only publish aggregate results.

What if I have questions about the survey? You have the right to ask, and have answered, any questions about the survey. If you have questions at any time you should contact Arisha Ashraf by phone or email.

What if I have questions about my rights as a survey participant? All research with human volunteers is reviewed by a committee that works to protect your rights and welfare. If you have questions or concerns about your rights as a survey participant you may contact, anonymously, if you wish, our Principal Human Research Review Board Analyst.

Participant's Agreement: By checking the box below, I indicate that: (1) I have read the information provided above, and (2) I voluntarily consent to participate in this survey.

☐ Yes, I agree to participate.

☐ No, I do not agree to participate.

☐ ***Only for those who agree to participate***: I do not wish to receive the $25.

Participant Signature: Date:

FINAL SURVEY: Note formatting has been modified for this annex.

1. In your opinion, what are the top 3 threats to your water supply? To save yourself time, please rank only the top 3, with 1=top threat, and so on.

____ I do not believe there are any threats to my water supply. Please move to Q2.

Rank

____ Lack of federal or state government planning for alternative water sources
____ California or Colorado River drought
____ Competition for water from non-agricultural population
____ Competition for water from other farmers
____ Environmental movement opposed to desalination
____ Delta smelt (fish) issue
____ Other (Briefly describe):

2. Compared to an average water year, did you experience a lower water supply in 2014?
   a. Yes
   b. No

3. In the past 3 months, how have you received new information on farming practices? Please rank your top 3 choices only, with 1=greatest benefit, and so on.

   Rank
   ____ Popular media outlets (via TV, internet, radio)
   ____ Social media outlets
   ____ Friends and neighbors who are also farmers
   ____ Farm manager
   ____ Irrigation industry or trade association publications (print or on-line)

   ____ Cooperative Extension (UCCE), Natural Resource Conservation Service (NRCS), US Dept. of Agriculture (USDA) or other government publications (print or on-line)

   ____ Irrigation industry or trade association events
   ____ UCCE, USDA or other government events
   ____ Other

4. Please list all of your water sources in order of importance. Combine all of your individual wells under one source. *Use the list to the right to save time.*

   Water source #1:

   Water source #2:

   Water source #3:

ANSWER CHOICES FOR Q. 4
A = Well water B = Coachella Valley Water District C = Eastern Municipal Water District (Reclaimed water) D = Gage Canal E = Imperial Irrigation District F = Palo Verde Irrigation District G = Western Municipal Water District H = Rancho California Water District I = Other

5. <u>For well water only</u>: what is the approximate total dissolved solid (TDS)? For your convenience, a conversion table is to the right**.**
   A. Less than 300 ppm
   B. 300-600 ppm
   C. 601-900 ppm
   D. Greater than 900 ppm

CONVERSION TABLE
1 mg/L = 1 ppm 1 mg/mL = 1000 ppm 1 dS/m = 640 ppm (for less than 5 dS/m) 1 dS/m = 800 ppm (for 5 dS/m or greater)

6. How do you manage drainage water? *Please select <u>all</u> that apply*.
   A. This is managed by my irrigation or drainage district.
   B. Evaporation ponds
   C. Lateral drainage tiles
   D. Use of salt tolerant crops
   E. Use of irrigation technology that produces less drainage
   F. Fallowing portion of my land where drainage is poor
   G. Other (please specify):

7. How do you decide when to schedule water use? To save yourself time, please rank only those choices that apply. 1=most important, and so on.

   Rank
   ____ I do not have a choice. I can only schedule water use when it is delivered or made available by my irrigation water supplier. ***<u>Please select this choice only if you cannot use any methods below.</u>***
   ____ Personal calendar schedule
   ____ Condition of crop (observation or experience)
   ____ Feel of soil
   ____ When neighbors begin to irrigate
   ____ Use of soil moisture-sensing devices (e.g., gypsum block, tensiometer, etc.)

____ Use of plant moisture-sensing devices (e.g., pressure/chamber bombs, IR thermometer, etc.)
____ Use of irrigation scheduling services, including commercial and government
____ Use of reports on crop-water evapotranspiration (ET) via internet, print, radio sources
____ Computer simulation models (not from a commercial service)

8. For all: Roughly how many total planted acres was your farm/grove/nursery in 2014?
9. For tree crops: Roughly how many total trees did you have in 2014?
10. How frequently do you (or your farm manager) use the following to monitor TDS or salinity?

	Never	**Every week**	**Every 1-3 months**	**Every 4-6 months**	**Every 7-12 months**
I observe how my crops are growing under current conditions.	○	○	○	○	○
I check with my water provider.	○	○	○	○	○
I use a handheld TDS/salinity meter.	○	○	○	○	○
I send water samples to a lab.	○	○	○	○	○
Other (please specify below)	○	○	○	○	○

11. Please list your top 3 crops *based on value in 2014*, starting with the most valuable. For nursery crops, please list general categories

	Name	**Planted Acres**	**Duration of growing season (e.g., Nov-Feb)**
Crop #1			
Crop #2			
Crop #3			

12. *Approximately*, what was your total yield for each crop in 2014?

ANSWER CHOICES FOR Q.13
A = Gravity system (furrow or flood)
B = Micro-sprinkler
C = Surface drip system
D = Subsurface drip system
E = Drip tubing (**for greenhouse/nursery**)
F = Overhead misters (**for greenhouse/nursery**)
G = Boom irrigation (**for greenhouse/nursery**)
H = hand-watering by dragging a hose (**for greenhouse/nursery**)
I = Gated pipe
J = Center pivot system
K = Linear/hand move system
L = Other (**Please write in next to the crop #)**

13. How do you irrigate your top crops? Please select a letter from the table on your right, or write in the name if you select "other".

Crop #1:

Crop #2:

Crop #3:

14. Approximately how many *years* have you been using each technology?
Crop #1:

Crop #2:

Crop #3:

15. If you selected FURROW or FLOOD system, please select which type. *If not, please skip to the next question*.
    A. Down rows/furrow from open ditches
    B. Down rows/furrow from poly pipe, lay-flat tubing, or above-/underground pipe
    C. Controlled flooding within field borders from open ditches
    D. Controlled flooding within field borders from poly pipe, lay-flat tubing, or above-/underground pipe
    E. Uncontrolled flooding (e.g., pasture or rangeland) including open discharge from a well or pump

16. If you selected FURROW or FLOOD system, do you have a tail-water recovery system?
    A. Yes
    B. No
17. *For ROW or FIELD crops*: Roughly how many total acre feet of water did you apply to each crop category *during the growing season in 2014*? If it is easier to present this information in another time horizon (i.e., weekly or monthly), please specify time horizon.
Crop #1:

Crop #2:

Crop #3:

18. *For TREE (non-nursery) crops*: Roughly how many total gallons of water did you apply *during the 2014 growing season*? If it is easier, how many gallons of water did you apply per tree per week *during the 2014 growing season*?
Crop #1:

Crop #2

Crop #3:

19. *For NURSERY crops: Roughly how many total acre-feet of water did you apply to each crop category in 2014? You may also report the water usage on a monthly basis, if it is easier.*
Crop #1:

Crop #2:

Crop #3:

20. *Please skip this question if you do not use drip or sprinkler systems*. How frequently do you (or your farm manager) use the following methods to monitor your water pressure?

	Never	**Every week**	**Every 1-3 months**	**Every 4-6 months**	**Every 7-12 months**
Adjust lateral hose bibs	○	○	○	○	○
Check pressure regulator at *initial* water line	○	○	○	○	○
Check pressure regulators *along lateral lines*	○	○	○	○	○
Other (please specify below)	○	○	○	○	○

21. How frequently do you (or your farm manager) use the following methods to monitor soil moisture?

	Never	Every week	Every 1-3 months	Every 4-6 months	Every 7-12 months
Hand feel/appearance of soil	○	○	○	○	○
Gravimetric (e.g., auger, cap, oven)	○	○	○	○	○
Tensiometer	○	○	○	○	○
Gypsum block	○	○	○	○	○
Dielectric sensors	○	○	○	○	○
Other (please specify below)	○	○	○	○	○

22. How frequently do you (or your farm manager) use the following methods to monitor your water use?

	Never	Every week	Every 1-3 months	Every 4-6 months	Every 7-12 months
Review my water bill	○	○	○	○	○
Walk lateral lines to check that crops are irrigated uniformly	○	○	○	○	○
Check the flow meter at the *initial* water line	○	○	○	○	○
Check the flow meters *along lateral lines*	○	○	○	○	○
For well water only: I use a tool to measure water table height	○	○	○	○	○
Other (please specify below)	○	○	○	○	○

23. In your opinion, how important is each monitoring method (questions 10, 20, 21, 22) for scheduling irrigations? Please rank, with 1= most important, and so on. Or, check the appropriate spaces below.

_____ All monitoring methods are *equally* important.
_____ *None* of these are important for scheduling irrigations.

Rank

_____ TDS/salinity monitoring (Q. 10)
_____ Water pressure monitoring (Q. 20)
_____ Soil moisture monitoring (Q. 21)
_____ Water use/flow monitoring (Q. 22)

24. How many years of farming experience do you have:
    a. At this property: ______________________________
    b. In total: ______________________________

25. Which percentage do you own versus lease this property?
    a. Own: _______________
    b. Lease: _______________

26. What is the *highest* level of education you have attained?
    a. High school
    b. Associate's Degree
    c. Bachelor's Degree
    d. 4 years active military duty
    e. Master's Degree
    f. Doctor of Philosophy

27. What is your before-tax income bracket (farm + non-farm)?
    a. Less than $50,000
    b. $50,000 to $99,999
    c. $100,000 to $149,999
    d. $150,000 to $199,999
    e. $200,000 or greater
    f. Decline to respond

28. Which percentage of your before-tax income is generated from farming?
    a. Less than 25%
    b. 25 to 49%
    c. 50 to 74%
    d. 75 to 100%
    e. Decline to respond

End of survey. Thank you for your time.

ANNEX 3.5 WATER DISTRICT DATA SOURCES

District Name	TDS (ppm)	% Ag	watprice	Source notes
Palo Verde Irrigation District	744	90	$26.74/acre-foot	watprice: Very unclear how water price is determined. Due to lack of info, we assumed water price is comparable to the other two senior water rights holders in the sample (i.e., CVWD & IID). They have a water toll and a tax bill--each is sent out twice a year. TDS: They don't treat canal water for salinity. So, just use the Colorado River numbers from IID. % Ag: Via phone call with Jessica and Shirley Nash
Coachella Valley Water District	744	80	$33.48/acre-foot	watprice: This doc has water price: http://www.cvwd.org/DocumentCenter/View/895 TDS: They don't treat canal water for salinity. So, just use the Colorado River numbers from IID. %AG: This is based on the 2015-16 Annual Review. It includes domestic (83,869 af) and canal (327,010 af) only. This does not include wastewater or non-potable water sources--these would probably just increase ag % anyway.
Eastern Municipal Water District (reclaimed water)	NA	65	171.06	watprice: http://www.emwd.org/services/customer-service-billing/rates-and-fees/recycled-water-rates I took the 2015 avg of 3 categories: R432, R43W, R442. TDS: no info in 2015 CCR. Email Kevin P. on 12/05/16 %AG: Report of recycled water system, EMWD
Gage Canal	NA	100	$1.26 per 100 cubic feet	Difficult to contact. Those who answered phone did not want to share information. %ag: I assume that all recipients are ag since it originated as an irrigation canal for citrus growers in Riverside: http://www.parks.ca.gov/?page_id=22584 watprice: I used the same rate as Riverside Public Utilities since they help manage Gage Canal.
Western Municipal Water District	356	11	$1.47 per 100 cubic feet	TDS: 2015 CCR, pg. 4; watprice: This is the average of 8 categories of 2014 water rate taken from Table 1, pg 9 of the following doc: http://wmwd.com/DocumentCenter/View/1597 %Ag: saved in email folder

ANNEX 3.5 WATER DISTRICT DATA SOURCES CONTINUED

District Name	TDS (ppm)	% Ag	watprice	Source Notes
Rancho California Water District	560	36.3	$563.45/acre-foot	**TDS:** 2015 CCR, pg 6; **%AG**: ask Refat for the source; **watprice:** Annual Financial Report, Table 9 pg 78--took 2014 average of Ag & Ag/Domestic for both Rancho and Santa Rosa Divisions for TIER I only
Riverside Public Utilities	363	18	$1.26 per 100 cubic feet	**TDS:** Water Quality Report 2015; pg 2, **%AG:** 2014-15 Financial Report has vague pie chart on pg. 129; **watprice**: http://www.riversideca.gov/utilities/pdf/2014/Water-Schedule-WA-3-effective-04-22-2014.pdf Note that I did not include the monthly meter charge from this doc.
Lake Hemet Municipal Water District	280	24.55	$588.33/af	**TDS:** 2015 CCR, pg 1; **%AG**: The percentage refers to groundwater. Do they have other sources?; **watprice**: 2016 Rate Schedule --took average of IR1, IR2, IR3 https://www.lhmwd.org/files/Rate%20Sheet%20Updated%2007_01_2016.pdf
Imperial Irrigation District	744	97	$20/acre-foot	**watprice:** http://www.iid.com/water/about-iid-water **TDS:** 2010AR given by Suzanne Faubl. The Salinity of Colorado River water delivered to IID users has averaged 744 ppm over the last 21 years (1990-2010) **%AG**: 2010 AR
Bard Water District	744	90	$5/acre-foot	All data obtained by calling Bard Water District
United Water Conservation District (PTP)	1102	100	$289/af	**TDS:** Based on conversation w/Dan Detmer, most of the PTP water comes from the Oxnard Basin. Used 2003 Bulletin 118, pg 171 for average TDS of Oxnard Plain: http://www.water.ca.gov/groundwater/bulletin118/docs/Bulletin_118_Update_2003.pdf **%AG:** Note it is 100% using PTP, which is the only retail consumer. I am not including ag that is wholesaled to other districts or mutuals. **Watprice**: email from Dan Detmer saved in Water District email folder. 2016 price.

ANNEX 3.5 WATER DISTRICT DATA SOURCES CONTINUED

District Name	TDS (ppm)	% Ag	watprice	Source Notes
Casitas Municipal Water District		80	$1.23/hundred cubic feet	**TDS:** 2015 CCR; **%AG**: This is 80% of retail accounts. Info is from Ron Merckling email stored in Water District email folder. **watprice**: 2013 rate document. This is an average of all 4 agricultural categories.
Camrosa Water District	725	40	$1053/af	**TDS:** 2015 CCR; **Other Notes:** Arroyo Santa Rosa Basin, pg 68 of Purveyor Report; **%AG**: Agricultural Water Management Plan **watprice:** same doc as %AG. I took the average of 6 categories from pg. 15 of this doc: Ag Irrigation MWD Full Service Rate, Ag Irrigation MWD Tier 2 Rate, Non-potable Commerical Ag, Blended Non-potable Ag MWD Full Service Rate, Blended Non-potable Ag MWD Tier 2 Rate, and Recycled Commercial Ag. 1 af = 435 hcf
California Water Service Company	576	<10	$2.01/100 cubic feet	**TDS:** 2015 CCR; **%AG**: 2006 Purveyor's Report. **Watprice**: 2006 Purveyor's Report **Other Notes:** Thousand Oaks Basin, pg. 58 of Purveyor Report
Del Norte Mutual Water Company		>50	$144.20/af	**TDS:** Las Posas Basin (see VenturaBasins worksheet for source) **watprice**: average of 3 lift zones in 2006 Purveyors Report **Other Notes:** North Las Posas Basin, pg 116 Purveyors Report; %AG: Purveyor Report shows that ag represents about 38% of connections. Assuming that each ag account uses at least twice as much as the domestic accounts (conservative assumption), then this is about 50% ag usage.
Fillmore Irrigation Company		86	$145/af	**TDS:** Fillmore Basin (see VenturaBasins for source) **Other Notes:** Fillmore Basin, pg 132; **%AG**: Based on conversation with Chris Woodard; **watprice:** based on conversation with Chris Woodard

ANNEX 3.5 WATER DISTRICT DATA SOURCES CONTINUED

District Name	TDS (ppm)	% Ag	watprice	Source Notes
Ventura County District 19	697.5	28	roughly $245/af	**TDS:** 2015 CCR, **watprice**: price in 2006 dollars **%ag**: As of 01/08/17, I used the percentage of ag connections in 2006 Purveyor Report since no info on ag revenue available. Anne Dana email did not work. Try calling general number listed if time permits. **Other Notes:** North Las Posas Basin, pg 344 of Purveyor Report
Crestview Mutual Water Co.		9.30	$1466.33/af	**TDS:** Average Pleasant Valley + Las Posas (see VenturaBasins for source) **Other Notes:** Pleasant Valley Basin/Las Posas **%AG**: Robert Eranio gave me this info over the phone watprice: Per discussion w/Robert Eranio. They charge per 1000 gallons at three Tiers of usage ($3, $6, $8). Mr. Eranio suggested that most people stick to Tiers 1 and 2 levels of usage. So, the average per 1000 gallons between Tiers 1 and 2 is $4.5. This is roughly $1466.33/af.
Southside Improvement Co. (Bardsdale Water Co.)		100	$115/af	**TDS:** Fillmore Basin (see VenturaBasins for source) **watprice:** Spoke to Richard Salberg; **%AG:** Purveyors Report; **Other Notes:** Fillmore Basin, pg 290 of Purveyors Report
Ventura City District 1/Ventura County Water Works District 1	430	25	$926.76/af	**TDS:** 2015 CCR pg 4; **%AG:** 2015 Agricultural Water Mgmt Plan + 2015 UWMP; **watprice**: Taken from 2013 rate document. Average of "current" Tier 1 and 2 ag rates. **Other Notes**: North Las Posas Basin, pg 336 of Purveyor Report
La Loma Ranch Mutual Water Company		<10	1324	**TDS:** Las Posas (see VenturaBasins for source) **%AG:** Purveyor Report says zero ag connections**; watprice:** 2017 water rate doc--average of combined rates for tiers 1 and 2 **Other Notes**: North Las Posas Basin, pg 168 of Purveyor Report
Farmers Irrigation		100	70.86	**TDS**: Santa Paula Basin (see VenturaBasins for source) **watprice**: Purveyors report states water price of $44 dollars/AF in 1994. Using inflation rate of 2.3%/annually, this is $70.86 in 2015. **Other Notes:** Santa Paula Basin, pg130 of Purveyor Report

ANNEX 3.5 WATER DISTRICT DATA SOURCES CONTINUED

District Name	TDS (ppm)	% Ag	watprice	Source Notes
Alta Mutual Water Company	165	100	$295/af	**TDS:** 2015 CCR; pg 3. **watprice**: email from Gerardo Claudio. **Other Notes:** Mound and Santa Paula Basins, pg 30 of Purveyor Report
Ventura County District No.8(City of Simi Valley)	439.5	2	1324	**TDS**: (i) denotes for treated water **watprice**: 2017 Calleguas rate document--average of combined tier 1 and 2 rates **%ag:** 2006 Purveyor Report. I took the percentage of ag connections since revenue data was unavailable. **Other Notes:** Simi Valley Basin, pg 338 of Purveyor Report
Valley Center Municipal Water District	647	70	$1383.33/acre-feet	**TDS**: 2015 CCR; %AG: 2015 UWMP; **watprice**: http://www.vcmwd.org/Portals/0/PDF/Finance/ScheduleOfRates.pdf
Ramona Municipal Water District	668.5	27	2125.73/AF	**TDS: 2015 CCR; %AG:** 2010 UWMP; **watprice**: Based on Jessica's notes. 1 unit=748 gallons and 1AF=435.6 units. Price per unit for untreated water=$4.88 (not including $1.02 pumping charge). Several questions on watprice: (1)is pumping cost per unit? (2) What is TSWR? This is $3.96/unit (3) why do they specify "untreated" water? is this purple pipe? (4) Where does the district get its ag water? Probably the same thing as question 3.
Rainbow Municipal Water District	647	60	1454.90/AF	**TDS**: 2015 CCR; **%AG**: Rainbow Municipal Water District Potable Water Cost of Service Study NOV 10, 2015; **watprice**: The first 10 units of water are $3.31 per unit. 11-26 units are at $3.48 per unit. And 27 or more are at $3.24 per unit. I took the average of all 3 tiers to get $3.34/unit. Again 1AF=435.6 units
Pauma Valley Water District	527	97	$1226/AF	**TDS**: There are 2 water districts report in Pauma Valley: 1. Yuima Municipal Water District ccr and 2. Rancho Pauma Mutual water company CCR **% Ag:** Well_water_and_conservation_techniques_help_Yuima_.html **watprice:** YMWD Water Rates

ANNEX 3.5 WATER DISTRICT DATA SOURCES CONTINUED

District Name	TDS (ppm)	% Ag	watprice	Source Notes
Vista Irrigation District	649.5	6	$3.99/100 cubic feet	**TDS**: 2016 CCR; **%AG:** Brent Reyes email to Jessice in Water District email folder. **watprice**: see Brent Reyes email to Jessica. I average Ag Domestic and SAWR ag rates in the rate document attached to his email
City of Escondido Water	640	14.5	$3.31 per 1,000 gallons	**TDS**: 2015 CCR; **%AG**: City of escondida 2010 water and wastewater rate study report **watprice:** Escondido Water, Utilities, Rates and Fees Schedule 2014
Fallbrook Public Utilities	647	40	$3.28/1,000 gallons	**TDS**: 2016 CCR; **%AG**: 2015 UWMP **watprice:** FPUD Current Water Rates 2016

ANNEX 3.6 GROUNDWATER TDS AND DEPTH

ID	County	Longitude	Latitude	IDW_TDS	WellDepth
198	V	-119.163	34.311	1563.995	598.528
170	V	-118.922	34.373	1004.152	296.630
169	V	-119.024	34.240	1438.462	619.336
181	V	-119.227	34.457	696.000	693.000
202	V	-118.922	34.426	987.029	201.266
196	V	-119.063	34.291	1193.161	618.077
194	V	-119.048	34.290	1222.135	622.853
157	V	-119.237	34.375	860.089	439.948
10	R	-117.008	33.773	297.770	547.015
3	SD	-116.643	33.091	189.458	267.038
219	V	-118.920	34.400	998.014	175.964
191	V	-118.962	34.245	1585.949	543.175
153	SD	-116.829	33.044	257.516	283.194
185	V	-119.217	34.463	696.000	698.000
182	V	-118.962	34.318	1202.884	588.729
100	R	-117.084	33.671	453.350	426.300
167	V	-119.118	34.326	1472.775	601.070
186	V	-118.935	34.258	1597.876	507.102
161	V	-118.936	34.414	1052.488	182.425
205	V	-118.895	34.327	1126.205	507.628
203	V	-118.926	34.305	1147.153	660.706
62	R	-116.073	33.578	241.079	487.907
197	V	-119.117	34.324	1477.080	615.407
116	SD	-116.990	32.804	934.323	486.185
29	SD	-117.045	33.084	1149.146	218.006
124	SD	-117.269	33.424	423.011	484.966
127	SD	-116.905	33.016	630.383	247.044
109	R	-117.023	33.990	221.554	509.226
82	R	-116.887	33.592	519.515	366.973
15	R	-117.195	33.600	409.149	464.708
74	R	-116.897	33.507	520.675	291.933
117	SD	-116.980	33.025	921.769	212.371
209	SD	-117.048	33.254	740.570	235.619
159	V	-118.855	34.398	911.844	274.095
164	V	-119.160	34.290	1546.463	474.845
17	R	-116.389	33.832	266.260	550.526
28	R	-117.077	33.854	225.618	572.459
171	SD	-117.310	33.290	1262.325	153.952
208	SD	-116.607	33.105	158.197	251.949
195	V	-118.928	34.375	1025.453	277.161
168	V	-119.072	34.240	1329.318	761.321
103	R	-116.897	33.507	520.675	291.933
160	V	-119.090	34.269	1277.925	724.331

ID	County	Longitude	Latitude	IDW_TDS	WellDepth
53	R	-117.237	33.900	386.473	555.584
187	SD	-117.255	32.935	1223.183	269.586
92	R	-116.368	33.887	1004.727	528.694
154	SD	-116.948	33.088	789.676	135.078
211	SD	-116.734	33.342	276.518	325.744
151	SD	-117.013	33.117	951.476	203.663
22	R	-116.223	33.594	551.827	494.618
214	SD	-117.007	33.345	818.860	149.712
212	SD	-117.150	33.171	1205.571	194.604
210	SD	-117.077	33.366	636.485	148.498
111	SD	-116.963	33.047	871.150	196.985

ANNEX 3.7 ELECTRICITY PRICES

Utility Company	Cost per kWh (kilowatt hour)
San Diego Gas & Electric	$/kWh Summer - Tier 1 0.20837 Tier 2 0.42970 Winter - Tier 1 0.19252 Tier 2: 0.39701
Riverside Public Utilities	Summer - Tier 1(0-750 kWh): 0.1035 Tier 2(751-1500 kWh): 0.1646 Tier 3(1500> kWh): 0.1867 Winter -Tier 1(0-350 kWh): 0.1035 Tier 2(351-750 kWh): 0.1646 Tier 3(750> kWh): 0.1867
Southern California Edison	**Tier 1:** 16 cent per kWh, **Tier 2:** 25 cent per kWh
Imperial Irrigation District	9.52 cent per kWh
Los Angeles Department of Water and Power	13.03 cents per kWh
Moreno Valley Utility	15.98 cents per kWh

ANNEX 3.8 AGRICULTURAL ZONING CODES

County	Zoning Code	Description
San Diego County	A70	Limited Agriculture, The A70 Use Regulations are intended to create and preserve areas intended primarily for agricultural crop production. Additionally, a limited number of small farm animals may be kept and agricultural products raised on the premises may be processed. Typically, the A70 Use Regulations would be applied to areas throughout the County to protect moderate to high quality agricultural land. E.g. Horticulture (all types), Tree Crops, Row and Field Crops
	A72	General Agriculture, The A72 Use Regulations are intended to create and preserve areas for the raising of crops and animals. Processing of products produced or raised on the premises would be permitted as would certain commercial activities associated with crop and animal raising. Typically, the A72 Use Regulations would be applied to areas distant from large urban centers where the dust, odor, and noise of agricultural operations would not interfere with urban uses, and where urban development would not encroach on agricultural uses. E.g. Horticulture (all types), Tree Crops, Row and Field Crops
	S80	Open Space Use, The S80 Open Space Use Regulations are intended to provide for appropriate controls for land generally unsuitable for intensive development. Typically, the S80 Use Regulations would be applied in both urban and rural environments to hazard or resource areas, public lands, recreation areas, or lands subject to open space easement or similar restrictions. Uses permitted within the S80 Use Regulations include those having a minimal impact on the natural environment, or those compatible with the hazards, resources, or other restrictions on the property. Various applications of the S80 Use Regulations with appropriate development designators can create or protect areas of very large residential parcels, agricultural areas, recreation areas, or limited use areas having identified hazards or resources.
San Diego (City)	AG-	The purpose of the AG zones is to accommodate all types of agricultural uses and some minor agricultural sales on a long-term basis. Nonagricultural uses are limited in the AG zones in order to strenghten the presence and retention of traditional agricultural uses.
	AG-1-1	Requires minimum 10-acre lots
	AG-1-2	Requires minimum 5-acre lots

	AR-	The purpose of the AR zones is to accomodate a wide range of agricultural uses while also permitting the development of single dwelling unit homes at a very low density. The agriculutral uses are limited to those of low intensity to minimize the potential conflicts with residential uses. This zone is applied to lands that are in agricultural use or that are undevloped and not apprporaite for more intense zoning. Residiential development opportunities are permitted with a Planned Development Permit at various densities that will preserve land for open space or future devlopment at urban intensities when and where appropriate.
	AR-1-1	Requires minimum 10-acre lots
	AR-1-2	Requires minimum 1-acre lots
Riverside	A-1	Light Agriculture. One-family dwellings. Light agriculture, animal husbandry, farm animals (Max. 5 animals per acre). Agricultural mobile homes for owner/farm worker with Plot Plan approval. Kennels/catteries pursuant to provisions of Sec. 18.45 (pg. XVIII - 119). Menagerie, feed store, farm labor camp, and mobile home park with an approved Conditional Use Permit. Minimum Lot: 20,000 sq. ft
	A-2	Heavy Agriculture. One-family dwelling. Agriculture, animal husbandry, farm animals (Max. 5 animals per acre), agricultural mobile homes for owner/farm worker with Plot Plan approval. Kennels/catteries pursuant to provisions of Sec. 18.45 (pg. XVIII-119). Lodge hall, feed store, private school, church, real estate office, with approved Plot Plan. Menagerie, farm labor camp, dairy farm, winery, composting facility with an approved Conditional Use Permit. Minimum Lot: 20,000 sq. ft
	A-D	Agriculture Dairy. Dairy farming, one-family dwellings in conjunction with a dairy operation, general agriculture, kennels/catteries pursuant to Sec. 18.45 (pg. XVIII -119), and farms for rabbits, fish , frogs, chinchilla, and other small animals. Grazing of farm animals (Max. 5 per acre). Agricultural mobile homes with approved Plot Plan. Abattoirs with approved Conditional Use Permit. Minimum Lot: 20 acres
	A-P	Light Agriculture with Poultry. One-family dwelling. Farms for commercial egg production and poultry. Fish, frogs, chinchilla, and other small animals. Nurseries, greenhouses, orchards, and field crops, packing and processing in connection with farm operations. Grazing of farm animals (Max. 5 animals per acre). Agricultural mobile home with approved Plot Plan. Minimum Lot: 5 acres

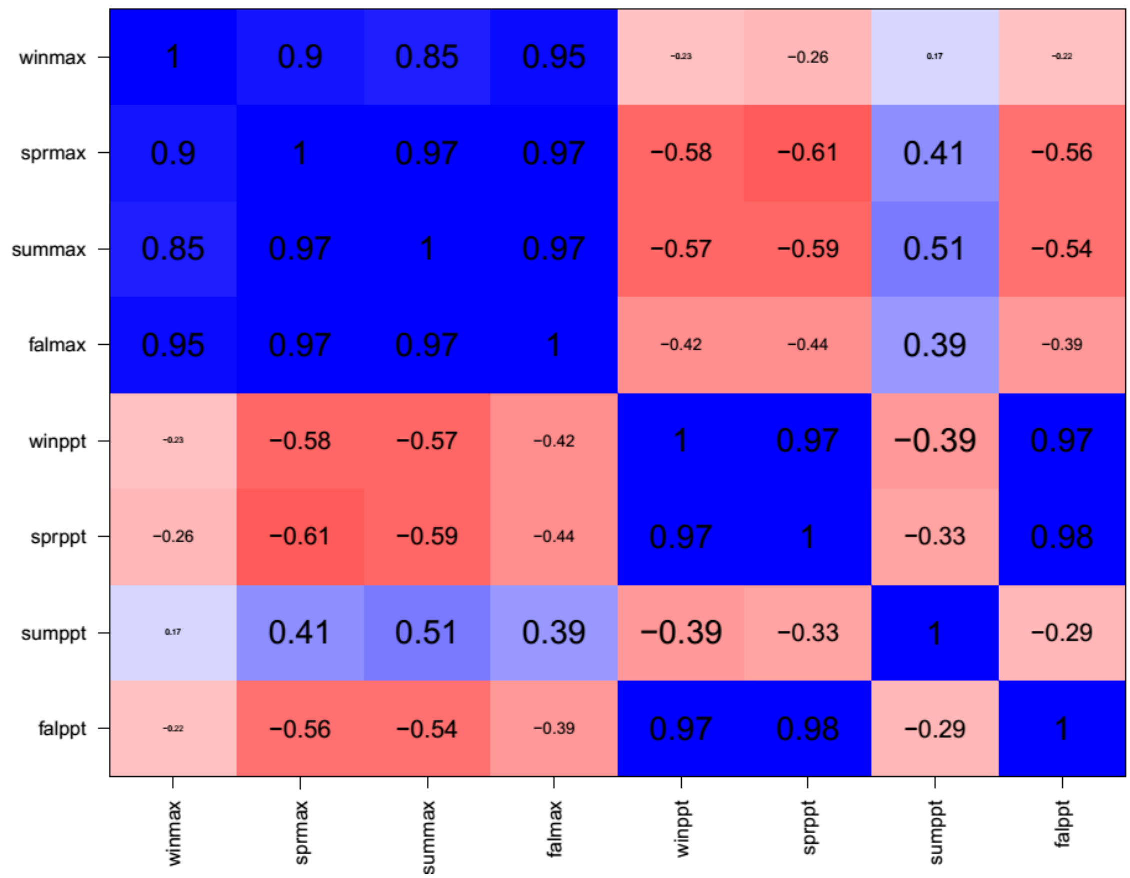
	R-A	Residential Agriculture. One-family dwellings. Mobile home on permanent foundations on lots less then 2 ½ acres. Noncommercial keeping of horses, cattle, sheep, and goats on lots over 20,000 sf. and 100 ft. in width. Two such animals on each 20,000 sf. up to 1 acre, and two such animals on each additional acre. Some agricultural uses, and limited noncommercial animal husbandry, 4-H projects. Agricultural mobile homes permitted for owner/farm worker for each 10 acres being farmed. Mobile home parks with approved conditional use permit. Churches with approved public use permit. Minimum Lot: 20,000 sq. feet
	R-R	Rural Residential. One-family dwelling, mobile homes, light agriculture, animal husbandry, farm animals, (Max. 5 animals per acre), kennels/catteries pursuant to provisions of Section 18.45 (pg. XVIII-119). Minimum Lot: 1/2 acre
	S-P	Specific Plan. Residential, commercial, manufacturing, open space, public facilities, health, and community facilities, agricultural uses pursuant to the permit requirements outlined in the adopted specific plan. If the specific plan does not specify a procedure, the use shall be subject to the most restrictive permit procedures contained in any zoning classification where the use is listed.
Imperial	A-1	Limited Agriculture. The purpose of the A-1 designation is to designate areas and allow uses that are suitable for larger residential living environments. The uses are generally limited to those typical of and compatible with quiet residential neighborhoods. The minimum lot size shall be one-half acre (net), unless required to be larger by other regulatory requirements, such as health and safety standards. The minimum lot size in the A-1 zone may be reduced if public infrastructure including sewer and potable water are available from either a district or a city. The A-1 designation is only allowed within urban designated areas as reflected on the land use diagram of the county general plan. Agricultural crops, private greenhouses and horticultural collections, flowers and vegetable gardens, fruit trees, nut trees, vines and nurseries for producing trees, vines and horticultural stock.
	A-2 & A-2-R	The purpose of the A-2 (general agriculture), (forty (40) acre minimum) zone is to designate areas that are suitable and intended primarily for agricultural uses (limited) and agricultural related compatible uses. All agricultural and grazing uses, including breeding and/or grazing of animals

	A-3	The purpose of the A-3 (heavy agriculture) (forty (40) acres or larger typical) zone is to designate areas that are suitable for agricultural land uses; to prevent the encroachment of incompatible uses onto and within agricultural lands; and to prohibit the premature conversion of such lands to nonagricultural uses. It is a land use that is to promote heaviest agricultural uses in the most suitable land areas of the county. Uses in the A-3 zoning designation are limited primarily to agricultural related uses and agricultural activities that are compatible with agricultural uses.
	AM-1	The purpose of the AM-1 (agriculture related light industrial) zone is to: Provide a zone that is consistent with the intent of the general plan to protect agriculture and at the same time allow limited but compatible industrial uses within the agriculture land use categories; Provide areas that are suitable for agricultural related light industrial land uses, yet are still compatible with and create no adverse impacts on adjacent agricultural land uses; Provide an opportunity for existing industrial uses, or for existing M-1 and M-1-N zones to become consistent with the general plan without becoming pre-existing nonconforming uses.
	AM-2	The purpose of the AM-2 (agricultural related industrial) zone is to: Provide a zone that is consistent with the intent of the general plan to protect agriculture and at the same time allow limited but compatible and consistent agricultural related industrial land uses within the agricultural land use categories as defined in the general plan; Provide uses that are suitable for agricultural related medium intensity industrial land uses, yet are still consistent with the general plan and compatible with the agricultural land uses in the vicinity, that are intended not to create adverse impacts on adjacent agricultural land or adjacent infrastructure; Provide an opportunity for existing Industrial uses or for existing M-2 and M-2-N zones to become consistent with the General Plan without becoming pre-existing, nonconforming uses; Provide an opportunity for on-farm processing of agricultural related products and produce that while industrial in nature, can be safely, effectively done within the agricultural designated land uses without adversely affecting either the surrounding agricultural land uses and without becoming a detriment on planned industrial areas.
Ventura	AE	Agriculturual Exclusive. The purpose of this zone is to preserve and protect commercial agricultural lands as a limited and irreplaceable resource, to preserve and maintain agriculture as a major industry in Ventura County and to protect these areas from the encroachment of nonrelated uses which, by their nature, would have detrimental effects upon the agriculture industry.
	RA	Rural Agricultural. The purpose of this zone is to provide for and maintain a rural setting where a wide range of agricultural uses are permitted while surrounding residential land uses are protected.

ANNEX 3.9 WATER DISTRICT SURVEY RESULTS

District Name	Price Structure	If tiered, for how long?	Times increased ag wat price in past 10 years?
Alta Mutual Water Company	Flat	NA	3
Bard Water District	Flat	NA	0
California Water Service Company	Tier	2008	4
Camrosa Water District	Flat	NA	7
Casitas Municipal Water District	Flat	NA	4
City of Oceanside	Flat	NA	11
Coachella Valley Water District	Flat	NA	4
Crestview Mutual Water Company	Tier	1995	8
Del Norte Mutual Water Company	Flat	NA	5
Eastern Municipal Water District (reclaimed water)	Tier	2009	9
Fallbrook Public Utilities	Flat	NA	10
Farmers Irrigation	Flat	NA	2
Fillmore Irrigation Company	Tier	2006	5
Gage Canal	Flat	NA	2
Imperial Irrigation District	Flat	NA	0
La Loma Ranch Mutual Water Company	Flat	NA	2
Lake Hemet Municipal Water District	Flat	NA	3
Palo Verde Irrigation District	Flat	NA	1
Rainbow Municipal Water District	Tier	2009	13
Ramona Municipal Water District	Flat	NA	10
Rancho California Water District	Tier	2007	10
Riverside Public Utilities	Flat	NA	0
United Water Conservation District (PTP)	Flat	NA	10
Valley Center Municipal Water District	Flat	NA	10
Ventura County District 19	Tier	2011	9
Vista Irrigation District	Flat	NA	9
Western Municipal Water District	Flat	NA	5
San Diego Gas and Electric	Flat	NA	9
Southern California Edison	Flat	NA	9

ANNEX 4.1 CORRELATION MATRIX OF CLIMATE VARIABLES



ANNEX 5.1 VARIABLE DESCRIPTIONS FOR CHAPTER 5

	mean (sd)	min	max	type	description
soilmon	0.4 (0.49)	0	1	factor, 2 levels	Does grower use at least 1 soil moisture practice?
saltmon	0.49 (0.5)	0	1	factor, 2 levels	Does grower use at least 1 salinity practice?
county				factor, 4 levels	county fixed effects; Imperial is benchmark
acre	748.84 (2266.63)	0.25	25000	continuous	total planted acres as stated in the survey
ftype	3.35 (1.24)	1	5	factor, 5 levels	G=field; R=vegetable; V=vineyard; T=orchard; M=mixed. G is benchmark
exp	27.47 (15.7)	1	90	continuous	years of growing experience
own	0.68 (0.47)	0	1	factor, 2 levels	Does the grower own all of her property? 1=yes
aginc	2.34 (1.36)	1	4	factor, 4 levels	percentage of income from farming. 1=[0,0.25); 2=[0.25, 0.5); 3=[0.5,0.75);4=[0.75,1]. Level 1 is the benchmark.
edu	1.97 (0.74)	1	3	factor, 3 levels	NB= No Bachelors; B=Bachelors; PB=Post Bachelors. B is benchmark
aws0100	10.94 (4.27)	2	23.8	continuous	soil available water supply in top 100cm
deficit	0.41 (0.49)	0	1	factor, 2 levels	Did grower experiencing water shortage in 2014?
wsource				factor, 3 levels	G=groundwater; D=district water; C=ground+district. D is benchmark.
seniorwater	0.27 (0.44)	0	1	factor, 2 levels	Does grower belong to a district with senior water rights?
tds	715.13 (266.93)	189.46	1597.88	continuous	total dissolved solids (ppm) in primary water supply
watprice	443.51 (533.47)	5	2498.08	continuous	water price per acre foot
AVGannmin	11.22 (2.52)	2.69	23.29	continuous	12-month average minimum temperature normal (1981-2010)
winterppt	58.68 (34.32)	9.2	118.9	continuous	3-month average maximum temperature normal (1981-2010)
CVannmin	0.44 (0.14)	0.23	1.16	continuous	Standard deviation of each month divided by annual mean
CVannppt	0.97 (0.14)	0.66	1.63	continuous	Standard deviation of each month divided by annual mean
threat				factor, 5 levels	P=population, D=drought, G=govt, E=enviro opposition, N=no threats. P is benchmark.
info				factor, 6 levels	I=industry, N=neighbor, G=govt, P=pop press, U=undisclosed, M=manager. N is benchmark.
agzone	0.75 (0.43)	0	1	factor, 2 levels	Does 75% or more of the acreage classify as agricultural zone? 1=yes
tdscuts	2.41 (1.08)	1	4	factor, 4 levels	Level1=(189, 560]; Level2=(560, 698]; Level3=(698,744]; Level4=(744, 1598]