CLIMATE, PRICES, AND FEDERAL PROGRAMS: CHOICES FOR IRRIGATED AGRICULTURE

by

Hannah Hansen

A Thesis Submitted to the Faculty of the

DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF SCIENCE

In the Graduate College

THE UNIVERSITY OF ARIZONA

2022

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

As members of the Master's Committee, we certify that we have read the thesis prepared by: Hannah Hansen
titled: Climate, Prices, and Federal Programs: Choice for Irrigated Agriculture

and recommend that it be accepted as fulfilling the thesis requirement for the Master's Degree.

Bonnie G Colby
_______________________________ Date: May 4, 2022
Bonnie Colby

Gary D Thompson
_______________________________ Date: May 4, 2022
Gary Thompson

_______________________________ Date: May 4, 2022
Daniel Scheitrum

Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

I hereby certify that I have read this thesis prepared under my direction and recommend that it be accepted as fulfilling the Master's requirement.

Bonnie G Colby
_______________________________ Date: May 4, 2022
Bonnie Colby
thesis committee chair
Agricultural & Resource Economics

Acknowledgements

The thoughtful and patient support of my thesis advisor, Dr. Bonnie Colby, and my other committee members, Dr. Gary Thompson and Dr. Daniel Scheitrum, made this work possible. I am grateful for all the hours my advisors have invested in me and my work. I would also like to thank the faculty and staff of the Department of Agricultural and Resource Economics at The University of Arizona for providing the base of knowledge required for this work and specific feedback and ideas regarding this study. These include Dr. Satheesh Aradhyula, Dr. Jeffrey Michler, Dr. Anna Josephson, Dr. George Frisvold, Dr. Tahidur Rahman, and Danielle Buhrow. A special thanks is owed to Dr. Russell Tronstad for sharing his expertise on federal cotton commodity programs and central Arizona agriculture. To Brian McGreal, thank you for laying the groundwork for this project and for your willingness to share your own knowledge of central Arizona agricultural water use. A team of faculty and students from the University of Arizona's hydrology department namely Dr. Laura Condon, Danielle Tadych, Matthew Ford, and Mekha Pereira also provided vital feedback and guidance throughout the course of this research. I especially owe thanks to Mekha for her assistance in using the GIS software to collect the land cover data necessary for my study as well as her camaraderie as we worked on similar studies. Various public and private agencies provided the necessary data and information for this project. I would not have made it to this point without the guidance of Dr. Ryan Fitch at The W. A. Franke College of Business at Northern Arizona University. Thank you for always keeping your office door open to me and assisting me through the graduate school application process. Without the contributions of those mentioned above, this work would not have been possible. I am especially grateful to them and the countless others who lent their support to me throughout this process. Lastly, I would like to thank my friends and family for their love and support throughout my life and graduate school. I owe the biggest thank you to my first and most important teacher, my mother, Katy Hansen at the Hansen Homeschool.

This project is jointly funded and made possible by two federal grants: 1) National Science Foundation – United States Department of Agriculture Award: Groundwater and the Future of Sustainable Agriculture – Balancing Economic, Energy, and Water Constraints on Food Production, and 2) National Ocean and Atmospheric Administration Regional Integrated Sciences and Assessments Award: Climate Assessment for the Southwest (CLIMAS).

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List of Acronyms and Initialisms

ACC – Arlington Canal Company
ADWR – Arizona Department of Water Resources
AF – Acre-feet
AMA – Active Management Area
APA – Arizona Power Authority
BAU – Business as usual
BMP – Best Management Practices
BWCDD – Buckeye Water Conservation and Drainage District
CAIDD – Central Arizona Irrigation and Drainage District
CAP – Central Arizona Project
CDL – Cropland Data Layer
CIS – Coupled infrastructure systems
CMID – Cortaro-Marana Irrigation District
CPI – Consumer Price Index
CRB – Colorado River Basin
DCP – Drought Contingency Plan
EIA – Energy Information Administration
ERS – Economic Research Service
EWG – Environmental Working Group
GMA – Groundwater Management Act
HID – Hohokam Irrigation District
LSDV – Least squares dummy variable
MAF – Million acre-feet
MSIDD – Maricopa-Stanfield Irrigation and Drainage District
MWD – Maricopa Water District
NASS – National Agricultural Statistics Service
NMIDD – New Magma Irrigation and Drainage District
OLS – Ordinary Least Squares
PADD – Petroleum Administration for Defense Districts
QCID – Queen Creek Irrigation District
RID – Roosevelt Irrigation District
RMA – Risk Management Agency
RWCD – Roosevelt Water Conservation District
SCIDD – San Carlos Irrigation and Drainage District
SGMA – Sustainable Groundwater Management Act
SRP – Salt River Project
STAX – Stacked Income Protection Plan
STID – San Tan Irrigation District
TID – Tonopah Irrigation District
USDA – United States Department of Agriculture
WTO – World Trade Organization
WWDT – West Wide Drought Tracker

Abstract

Drought has gripped the arid American West in the Colorado River Basin since 2000. The majority of water consumed in the region is used by agricultural irrigation. Farm operations in central Arizona rely on a combination of local surface water, groundwater, the mainstem of the Colorado River, and Colorado River water imported to central Arizona through the Central Arizona Project (CAP). Groundwater is particularly important to agricultural viability because of its widespread availability. In previous decades, the abundance of this resource caused pumping rates to exceed replenishment resulting in water table declines in central Arizona. CAP water was made available for crop irrigation under financial arrangements that made it affordable to farmers and CAP use replaced much of their groundwater pumping. The recent federal declaration of a Colorado River shortage may prompt farmers to supplement reduced surface water with more groundwater.

This study examines agricultural water use and crop mix selection in the major irrigation districts of central Arizona. It is important to study these decisions that affect the rate of groundwater consumption. Statistical models of crop mix and agricultural water deliveries are developed for a major Arizona crop, alfalfa, in the Phoenix, Pinal, and Tucson Active Management Areas (AMAs). Using panel data from 2008-2020, economic and climatic variables (crop prices, crop yields, water prices, temperature, and precipitation) are examined for effects on farmers' water application, acreage, and crop mix decisions. Contributions of this work include an analysis of the Tucson AMA, federal commodity programs, and temperature and precipitation effects. Climate, federal commodity payments, and the gross revenues of crops have significant impacts on central Arizona crop mix. Irrigation district water deliveries are affected by the climate and the gross revenue of cotton plus wheat. Findings from this study can help inform recommendations for managing the impacts of impending changes in central Arizona's agricultural CAP supplies.

Chapter 1: Introduction

In the arid American west, water is a scarce resource. Efficient and effective management is becoming more necessary in all sectors, as the region battles through a prolonged drought. Agricultural production is not exempt from water supply issues especially considering its majority share of total consumption. The agricultural sector consumes nearly three-fourths of Arizona's total water resources annually (Bae & Dall'erba, 2018). Typically, Arizona agricultural growers get their irrigation water from local surface water, groundwater, the mainstem of the Colorado River, and Colorado River water imported to central Arizona through the Central Arizona Project (CAP). The August 2021 federal Colorado River shortage declaration by the Bureau of Reclamation resulted in a 512,000 acre-feet (AF) reduction in Colorado River water deliveries to Arizona through the CAP. Central Arizona farmers will be the first to bear this water supply reduction and may supplement by using more groundwater. However, groundwater is already pumped at rates that exceed replenishment leading to a host of economic and environmental effects from overdraft in central Arizona. Water application and crop mix decisions affect the rate at which farmers may move to consume additional groundwater resources.

A study of agricultural water use in the arid central Arizona region is important because the decisions of these agricultural water users will affect future generations in both the urban and rural agricultural sectors. Within the CAP service region, groundwater still accounts for 40% of total water used (Ferris & Porter, 2021). Despite Arizona's Groundwater Management Act and limits on groundwater withdrawals, the lack of strict extraction rights that consider hydrologic conditions has led to an exploitation of the resource (Bruno & Jessoe, 2021). The overextraction of the resource leads to a range of externalities for groundwater users and non-users alike. High rates of extraction have caused water tables to decline, pumping costs to rise, and land to subside (Bruno & Jessoe, 2021). In certain parts of Maricopa and Pinal counties, land has subsided more than eighteen feet since the early 1900s (Yoo & Perrings, 2017). The environmental and financial impacts from land subsidence can be substantial as damage can occur to roads, buildings, and gas and water pipes (Yoo & Perrings, 2017).

This study starts with a brief description of the study area and the methods and data used to evaluate agricultural water use and crop mix decisions along with the key findings. The history of Arizona water policy and agricultural water use is discussed in a review of existing literature of Arizona water management. It then provides a review and summary of relevant economic literature on agricultural water management studies. Next, a conceptual model of agricultural production and irrigation water demand is developed to guide later econometric analysis. A discussion on the data and methods employed in this study follows. The next section details the final econometric models estimated and the results of these regressions. The study concludes with a discussion on the policy implications of the results found.

1.1 Study Area

Having established the challenges faced by arid agriculture, this study aims to examine the effects of economic and climatic variables on agricultural water and crop mix decisions in fourteen central Arizona irrigation districts in the Phoenix, Pinal, and Tucson Active Management Areas (AMAs). The irrigation districts located in the AMAs included in this study represent the largest and most significant irrigation districts in terms of planted acreage and water deliveries. Even within these fourteen largest irrigation districts there is a great diversity of size, policy structure, water sources, and end users (agricultural, municipal, industrial, etc.). Regardless of their differences, the irrigation districts share the common purpose of delivering water to individual water users within their boundaries. Irrigation district water demand can be thought of as the sum of all individual users' demand within the district. Since all irrigation districts within this study are located within one of three central Arizona AMAs, they are all subject to certain regulations under the Groundwater Management Act (GMA). Districts are required to submit annual water use reports detailing sources and deliveries to the Arizona Department of Water Resources (ADWR). ADWR makes these reports public allowing for this analysis. Irrigation districts outside of AMAs are not subject to the same water use reporting guidelines and therefore cannot be included in this study. The GMA of 1980 governs groundwater use in AMAs to try and slow the effects of groundwater overdraft. Irrigation districts are constrained by groundwater rights allocated under the GMA. They also notably source Colorado River through the CAP. This resource is now further constrained by federal drought declarations affecting growers' water sourcing decisions.

Not all irrigation districts in the state of Arizona and within the three AMAs of interest are included in this study. The districts chosen were included because they represent the majority of water deliveries and planted acreage in the study area. Only irrigation districts located within an AMA are included in this study because they are subject to water use reporting requirements that enable this study. This means that tribal agriculture and water use cannot be included because data are unavailable or limited due to different reporting requirements. The included irrigation districts also have access to Colorado River water delivered through the CAP giving them some flexibility in their water sourcing decisions. The Phoenix AMA contains thirty-nine irrigation districts, ten of which are included in this study (Arizona Department of Water Resources, 2020). The ten districts in order of size are Salt River Project, Roosevelt Water Conservation District, Roosevelt Irrigation District, Maricopa Water District, New Magma Irrigation and Drainage District, Buckeye Water Conservation and Drainage District, Queen Creek Irrigation District, Arlington Canal Company, Tonopah Irrigation District, and San Tan Irrigation District. These districts represent the majority of water deliveries and agricultural land in the Phoenix AMA. They exhibit a great range both in the size of districts and the agricultural water deliveries. The three smallest districts in terms of area in the study are located in the Phoenix AMA along with the biggest district, the Salt River Project (SRP) (Table 3). In total, these ten districts deliver a combined average of over 550,000 AF a year to agriculture each year. Some districts in the region have shifted from an agricultural focus to a more municipal centered focus as urbanization has taken over in the region.

The Pinal AMA is much more agriculturally focused and includes the two districts with the highest agricultural water deliveries. The three Pinal AMA districts in order of size are the Central Arizona Irrigation and Drainage District (CAIDD), Maricopa-Stanfield Irrigation and Drainage District (MSIDD), and Hohokam Irrigation District. The CAIDD and MSIDD together account for more agricultural water deliveries than the ten Phoenix AMA irrigation districts combined. The San Carlos Irrigation and Drainage District (SCIDD) is also located within the Pinal AMA but is ultimately excluded from the final econometric analysis as it is in a unique position because of its organizational purpose and the precarious nature of its main water source in San Carlos Lake. The structural differences between SCIDD and the other fourteen districts in this study are significant. The peculiarities of the SCIDD and its effect on water delivery and crop mix estimation is discussed in greater detail in Appendix A.2.

The Tucson AMA only has one irrigation district. The Cortaro-Marana Irrigation District (CMID) is one of the smaller districts included in this study with an average of 37,718 AF of agricultural deliveries each year.

Agricultural production in the study area is dominated by alfalfa and cotton. Table 4 shows the average acres and percentage of major crop categories planted in the fourteen irrigation districts examined in this study. The two most common crops display some differences that farmers must consider when determining crop mix. Alfalfa is the most commonly planted crop as its profitability has increased in recent years. It accounts for an average of 53% of all planted acres in the study region. Unlike many other crops which are planted annually, a stand of alfalfa is productive for 5-7 years with multiple cuttings within a season. Alfalfa must be irrigated year round making it one of the more water intensive crops in the region when considered alone. Its needs average 6 AF per acre per year (Erie et al., 1982). The perennial nature of alfalfa is important to remember when evaluating models of crop mix decisions, since only 15-20% of the total alfalfa acreage would be up for rotation in a given year. Alfalfa farmers may therefore have a lower level of flexibility compared to annual crop farmers. This effect is further discussed in Chapters 5 and 6.

The second most commonly planted crop, cotton, is less water intensive than alfalfa with an average need of 3.5 AF per acre per year. However, cotton is not grown year round and is often grown in rotation with another crop such as wheat which consumes 2 AF of water per acre per year (Ottman, 2015; Erie et al., 1982). When considering cotton and the crops it is planted in rotation with, its water needs are similar to alfalfa's. Cotton and winter wheat are considered together in the water delivery and crop mix models to reflect this aspect of agricultural planting decisions.

Other categories of crops grown in the study region include grains (corn, sorghum, barley, wheat), tree crops (especially nut trees), and other crops (melons, lettuce, etc.) (see Table 5 for cropping categories). In some irrigation districts, grains are grown at the same rate as cotton, and some are rotated on the same land as cotton. The CMID has the highest average share of grains planted. Even though these other crops affect agricultural water consumption in the study region, the study focus remains on alfalfa and cotton (in rotation with winter wheat) because of their consistent prevalence.

1.2 Data and Methods

In order to examine the agricultural water and crop mix decisions in central Arizona AMAs, this study uses annual state, county, and irrigation level economic and climatic data from 2008-2020. The ADWR posts the detailed annual reports of irrigation district water use that act as the source of water delivery data in this study. Information on the source types and end use categories are included allowing for the focus on agricultural water deliveries. The United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS), the CAP, the United States Energy Information Administration (EIA), and the New York Cotton Exchange provide crop price and input cost data. An important component of this study is the land cover data sourced from the USDA NASS's Cropland Data Layer (CDL). The CDL provides annual satellite records of land cover of the continental United States. Arizona cover has been available since 2008 which is the reason for this study period beginning in 2008. Climate effects are estimated separately through annual county average temperature and precipitation reported by the West Wide Drought Tracker which uses climate data from PRISM and the National Weather Service Cooperative Observer Network (West Wide Drought Tracker, 2022). Precipitation is especially important because it impacts soil moisture which affects crop yield (Earth Observing System, 2019). Another key variable included in this study is a measure for federal cotton commodity payments. The Environmental Working Group (EWG) collects county level crop insurance and federal farm payment program information from the USDA Risk Management Agency and summarizes it into basic program categories. A more detailed discussion of these data, their sources, and their construction follows in Chapter 4.

The estimated regressions in this study use the percentage of planted acreage with alfalfa to evaluate crop-mix decisions. Different iterations of the crop mix model are estimated to test the statistical significance of a combination of various economic and climatic effects including average annual precipitation and temperature, federal cotton commodity payments, crop prices, diesel prices, and crop gross revenues. The functional form of the models estimated is especially crucial to the effects of the crop mix models where the dependent variable is a proportion, continuous but bounded by zero and one. This study uses Ordinary Least Squares (OLS) regressions to estimate crop mix, but alternative logit models are considered and discussed further in Chapter 5.

OLS regressions are also used in the estimation of agricultural water delivery models. Many of the same independent variables are included in the water delivery models as in the crop mix regressions such as precipitation, temperature, diesel prices, crop prices, and gross revenues. Some additional variables (CAP water prices and crop acreage) are also evaluated. The details of model specifications are discussed in Chapter 5 and 6.

The diversity of irrigation district structures and sizes affects the efficiency of the OLS regression estimates. To deal with this issue, irrigation district level fixed-effects are employed through the demeaning approach. This approach uses “demeaned” observations where the irrigation district level mean is subtracted from each observation to focus on the trends over time and not differences between districts. This solves the issue of heteroskedastic error terms and accounts for time-invariant variation between irrigation districts. Further detail and explanation of this process is included in Chapter 6.

1.3 Key Findings

The results of the econometric models estimated in Chapters 5 and 6 of this study provide information on which economic and climate factors influence crop mix and agricultural water use decisions. The fixed-effects model results presented in this thesis are the most reliable, useful, and statistically significant of the various regression models estimated in this study.

In the percent alfalfa acreage model, all four independent variables, precipitation, federal cotton payments, gross revenue of alfalfa, and gross revenue of cotton plus wheat, are determined to be statistically significant at a minimum of a 90% confidence level. Variables are lagged by one year in the crop mix models, because farmers must make crop decisions at the beginning of the year before conditions become clear. As annual precipitation increases, the proportion of alfalfa planted also increases. Federal payments to cotton disincentivizes farmers from planting alfalfa and draw them to plant more cotton. An increase in the gross revenue of alfalfa indicates an increase in the percentage of alfalfa planted. Increases in the gross revenue of cotton and wheat has the opposite effect on the share of alfalfa acreage.

In the estimated water deliveries model, current year variables are included because of the more flexible nature of the water ordering schedule as farmers can adapt their water application rates over the growing season. Both temperature and precipitation are included as climatic measures but only precipitation is statistically significant predicting decreases in water deliveries as precipitation increases. It may be that precipitation, an indicator of soil moisture, is more impactful to agricultural decisions than temperature. CAP water prices do not have a significant effect on water deliveries indicating that farmers may have inelastic price elasticity of water demand. The gross revenue of alfalfa does not significantly affect agricultural water deliveries, but the gross revenue of cotton and wheat have a statistically significant positive effect. The implications of these results are further discussed in Chapters 6 and 7.

Chapter 2: Literature Review

This study of agricultural water use and crop mix decisions is informed by a review of recent economic literature on water policy, agricultural water use, and surface and groundwater demand studies. The chapter begins by providing a summary of the history and legal framework of water management and agricultural use in Arizona. An array of econometric literature on water cutbacks and groundwater management in the American West is next in the discussion. The inclusion of a novel federal cotton commodity variable is supported by literature on federal commodity programs. Also highlighted is the role the USDA Cropland Data Layer has begun to play in economic literature. Finally, the summary of the literature ends with sources that guided the modeling of fixed-effects. This chapter concludes with a discussion on the contributions from this work.

2.1 Arizona Water Policy

Arizona was granted Colorado River water rights in 1922 but was unable to use much of its 2.8 million acre-feet (MAF) allotments without the infrastructure to move the water inland where the greatest demand was. The Central Arizona Project (CAP) enables water to be moved from the western side of the state to central Arizona for urban and agricultural uses. The legislature that authorized the development of the CAP required that CAP water rights be junior to all existing rights meaning Arizona would be the first to bear delivery cuts in times of drought and shortage in the Colorado River Basin (CRB). Additionally, before construction was complete, the Secretary of the Interior required that Arizona adopt a statewide groundwater management code because of high overdraft (Shipman & Wilson, 2014). Between 1940-1953, Arizona groundwater overdraft averaged 2.3 MAF annually. The Groundwater Management Act (GMA) was passed in 1980 to curtail this type of overdraft and secure federal funding for the CAP. The GMA created Active Management Areas (AMAs) in zones where expansion of agriculture is prohibited, wells are regulated, sales of land must have a 100-year assured water supply, and a long-term groundwater management goal is set (Ferris & Porter, 2021). The 336 mile long CAP was completed in 1993 (Lahmers & Eden, 2018). The goal of the CAP was to prompt growers to use more renewable surface water, but high costs prohibited the switch until a target pricing scheme made the CAP water more affordable (Shipman & Wilson, 2014; York et al., 2020). The CAP delivers 1.6 MAF of Colorado River water to central Arizona each year

(Anderies et al., 2020). Arizona's remaining Colorado River allotment is used by agricultural and urban users along the Colorado River on the western side of the state. Arizona's total demand is typically 6.8 MAF annually (Anderies et al., 2020).

The four sectors of water use for monitoring under the GMA are: 1) indigenous water use (Indian), 2) non-Indian agriculture, 3) industrial uses, and 4) municipal uses (York et al., 2020). Agriculture is the greatest contributor to unreplenished groundwater use in the Phoenix, Pinal, and Tucson AMAs (Ferris & Porter, 2021). While agriculture, both Indian and non-Indian, uses the greatest share of water, it also contributes to return flows and recharges that are vital for state conservation goals (York et al., 2020).

Producers in central Arizona source their water from groundwater, surface water from the Salt and Gila Rivers, and Colorado River water delivered through the CAP (York et al., 2020). Groundwater provided 40% of water in the CAP service area in 2019 (Ferris & Porter, 2021). Historical irrigation use from 1975-1980 in the AMAs was used as the basis for quantified water rights under the GMA and granted an Irrigation Grandfathered Right to the farmer. Farmers may bank unused groundwater credits for future use.

Although there is a hydrologic connection between groundwater and surface water, Arizona has not managed the resources conjunctively. Groundwater was often managed through English common law traditions of granting rights to landowners above aquifers demonstrating beneficial use. Prior appropriation rights are granted for surface water. Indigenous peoples have recently begun to fight for quantified water rights in courts. Since indigenous people were the first to use the water, they are granted water rights with the most senior priority dates. These *Winters* rights cannot be forfeited for non-use either. Water may be leased off tribal lands in Arizona under the *Arizona Water Settlements Act of 2004*. Tribes receive 46% of CAP water in Arizona with nearly 100% going to agricultural uses, so these types of collaborations are vital to the Arizona economy as a whole (York et al., 2020).

Agricultural water users must comply with a water duty limit (base program) set by the Arizona Department of Water Resources (ADWR) that is reduced with each new management period (Ferris & Porter, 2021). The allotments were set above actual usage for many of the agricultural producers enabling them to bank their unused portion in flex credit accounts. By the end of the Second Management Plan, over 15 MAF had been banked in flex credit accounts by farmers. The Arizona State Legislature amended the GMA in 2002 to include a best management practices (BMP) program as a voluntary alternative to the Base Program requirements. Farmers could ignore the Base Requirement allotments by giving up their flex credit balances so long as the BMP program was found to be at least as water conserving (Bilby & Wilson, 2013). However, BMP farmers in the Phoenix AMA typically apply 18% more water than non-BMP farms (Ferris & Porter, 2021).

Groundwater regulations will become even more important as the Colorado River region is expected to face further strain on their water resources as demand grows with population growth and supply decreases due to climate changes and limited storage abilities. Arizona will be first to bear the reductions, especially in the agricultural sector as they are counted upon to adapt usage to protect municipal and industrial (M&I) uses (Bickel et al., 2019). Lahmers & Eden (2018) explore how these reductions will likely push central Arizona growers back to groundwater. Continued overdraft can lead to higher pumping and drilling costs for growers. Environmental consequences such as land subsidence, reduced aquifer storage capacity, damage to canals and well casings, and regional and local flooding may become more prominent (Lahmers & Eden, 2018).

Ferris and Porter (2021) describe the political history of the GMA. Its regulations have helped slow the effects of overextraction, but pumping rates are still unsustainable in general. The safe-yield goal for AMAs states AMAs should achieve a balance between the amount of groundwater withdrawn and the amount replenished by 2025. Ferris and Porter (2021) report that the AMAs will not be able to reach that goal in three years or sustain it. The GMA and the BMP program is evaluated by Bilby & Wilson (2013) using a case-study approach. The BMP was developed in collaboration with an informal group of ADWR staff, irrigation district managers, and farmers. Farmers must earn a total of ten enrollment points from the four BMP categories: Agronomic Management, Water Conveyance Systems, Farm Irrigation Systems, and Irrigation Water Management to qualify. Bilby and Wilson found that 70% of farmers needed no adjustments in their water management practices or irrigation systems to qualify for the BMP program. These farmers were often already using water conservation technologies and practices that qualified them for the BMP program and allowed them to circumvent the GMA water allotment requirements. Water savings through the BMP program therefore were negligible (Bilby & Wilson, 2013).

The effects of these negligible water savings are becoming evident in the Colorado River reservoirs. The Department of the Interior developed thresholds for tiers of drought as measured by the water levels in Lakes Powell and Mead in 2007. The Lower CRB states adopted the Drought Contingency Plan (DCP). Part of the DCP includes the introduction of a new "Tier Zero" drought declaration set at 332 meters above sea level. When Tier Zero is initiated, more severe water cuts are triggered. The goal of the DCP is to raise water levels through conservation efforts. The first Tier Zero shortage went into effect in August 2019 based on predicted water levels. Water availability was affected, and farmers had to deal with the new shortage (York et al., 2020). In August 2021, the US Bureau of Reclamation announced the first Level 1 shortage for Lake Mead. Arizona will see a 512,000 AF (18% of state's annual apportionment) reduction in deliveries in 2022 (Aaron & Bryant, 2021).

2.2 Central Arizona Agricultural Water Use

There is a long history of irrigated agriculture in Arizona dating back to 1200 BCE along the Santa Cruz River. Since then, indigenous communities have participated in irrigated agricultural activities (Lahmers & Eden, 2018). Colonial settlors gained greater shares of agricultural activities throughout the past two centuries. Today, agriculture consumes the majority (73%) of water available in Arizona. In 2010, total agricultural water use equaled 6 MAF (Bae & Dall'erba, 2018). Compared to other sectors within Arizona, $1 of agricultural production requires 43 times the amount of water needed for $1 of production in the industry and service sectors (Bae & Dall'erba, 2018).

Bae and Dall'erba (2018) simulate three scenarios with the goal of achieving 19% of water savings in Arizona agriculture. The approaches include improving irrigation efficiency, price increases, or reduced crop exports. Irrigation efficiency improvements are found to be the cheapest solution. In a real world setting, a combination of these three strategies may be employed in addition to other strategies not evaluated like changing crop mixes. The authors estimate water consumed by agriculture in the United States and the share of water that is then "virtually" traded through agricultural exports. Virtual water is defined by Bae and Dall'erba as the volume of water embodied in the production process of a good. Exported crops are not a significant share of good produced in Arizona (0.47%), but they account for 57.86% of overall water available through direct virtual water. Only 15.28% of Arizona's water stays in the state post-production even though 73.13% is used in agricultural production. Bae and Dall'erba (2018) develop an economic input-output model to calculate the virtual water flows associated with Arizona's (net) trade.

Pinal County is a major agricultural producer for both the state of Arizona and the entire U.S. It ranks in the top 2% of all U.S. counties in the total value of agricultural sales (Bickel et al., 2018). It should be noted that Arizona counties are typically much larger in size that those in other states. This is likely to inflate the national influence of agricultural production in central Arizona counties. In Maricopa County, agriculture was estimated to contribute $1.95B in 2015 (York et al., 2020). Because precipitation in the region is so scarce (8-10 inches per year), farmers rely on groundwater and surface water delivered through the CAP to irrigate. Agriculture used 96% of the Pinal County water through 2001-2005 (Bickel et al., 2019).

Pinal County's agricultural contributions are further analyzed by Bickel et al. (2018). Farms in Pinal County range from small family- or individually-owned operations to large scale corporate operations. These larger farms make up a smaller share of all farms (23%) but account for nearly all sales (98%). The construction of the CAP enabled the development of agriculture in Pinal County and helps it to continue to thrive as an agricultural powerhouse. Cotton is the top crop in Pinal County by acreage and value of sales. Pinal County produces 42% of Arizona's cotton and is ranked 5th in the nation for cotton and cottonseed sales. In 2016, the total estimated contribution from on-farm agriculture was estimated to be $1.1 billion, $908.1 million of which was in direct sales. Nine of the top twenty industries in Pinal County are agriculture or agriculture-related industries. Altogether, summing the direct, indirect, and induced effects, the total contribution of on-farm agriculture and agribusiness to Pinal County's output was nearly $2.3 billion in total sales in 2016 (Bickel et al., 2018).

Water use is an important input in agriculture and irrigation has become more efficient over time especially for the top crops. The irrigation application intensity (the amount of water applied per unit of land area) has continued to decrease in Arizona. The reduction in water consumption has not affected crop productivity which has actually increased (Bickel et al., 2018). Agricultural producers wield a great deal of power when it comes to decisions regarding the development of water infrastructure and regulations. York et al. (2020) show the current institutions are not effective in reaching water conservation goals using a socio-hydrological framework. Growers must make decisions according to the social and hydrological risks and institutions in their environment.

Irrigated agricultural water decisions in the arid southwestern US is the focus of a study by McGreal and Colby (2022). The two examine the drivers of water deliveries and irrigation intensity in twelve irrigation districts in two central Arizona AMAs. This includes the effects of climatic, economic, and remote sensed land cover variables. Alfalfa, cotton, and wheat are the most common crops planted in the region. McGreal and Colby use irrigation district level fixed-effects models to estimate water deliveries and irrigation intensity. The authors find that drought, cotton prices, and CAP water prices can all be significant in explaining water deliveries and irrigation intensity. Additionally, they name crop mix as one of the major determinants of water deliveries (McGreal & Colby, 2022).

2.3 Studies of Demand Responses to Surface Water Cutbacks

With the recent 512,000 AF reduction in Arizona's Colorado River surface water deliveries, central Arizona growers will be responsible for bearing the brunt of this cutback. The impacts of both hypothetical and actual surface water cutbacks have been examined by Anderies et al. (2020), Bickel et al. (2018), Bickel et al. (2019), and Goemans and Kelley (2022). This breadth of literature informs this work in how growers can be expected to react to cutbacks and the strategies they might employ to achieve consumption reductions.

Anderies et al. (2020) examine the effects from a decline in the CAP water deliveries in the Salt, Verde, and Aqua Fria basins in central Arizona. The authors use infrastructure management as a tool to reach groundwater neutrality introducing the concept of coupled infrastructure systems (CIS). The CIS includes hard infrastructure (pipes, dams, aqueducts, etc.), soft infrastructure (rules and norms), and natural infrastructure (aquifers, groundwater recharge basins, and river watersheds). Anderies et al. develop a dynamic model to review the relationships between the various water basins and sources in the Central Arizona Region and how interdependencies among different classes of infrastructure can impact regional climate responses. Instead of focusing on each industry's response individually, the authors present a collectively beneficial solution for all stakeholders together. They find that a 15% reduction of runoff from Lakes Powell and Mead trigger groundwater depletion rates equal to the volume of Lake Powell every half century (Anderies et al., 2020). The more collaborative a system is, the more resilient it is to drought.

In the previously mentioned Bickel et al. (2018) study, the authors evaluate the effects of a hypothetical 300,000 AF reduction of irrigation water in Pinal County. Farmers can respond through crop mix decisions by reducing acreage grown and harvested. Regardless of the crop fallowed, there will be decreased sales from decreased production. The economy is affected by lower spending on inputs and labor. Six fallowing scenarios are defined and examined with different mixes of wheat, cotton, and alfalfa acreage fallowed. Alfalfa crops require the most water applied so scenarios where alfalfa acreage is fallowed need the least total acres fallowed, but the gross sales for alfalfa were highest. These scenarios then have the biggest losses in the sales category. Fallowing only cotton generates the biggest losses to value added, labor income, and employment. Losses are smallest when all wheat crops and half of alfalfa crops are chosen for fallowing, but this is not a realistic solution.

Possible fallowing solutions are also explored in Bickel et al.'s (2019) evaluation of strategies for addressing surface water cutbacks in Pinal County. The authors employ rationing and input-output models to detail impacts on stakeholders throughout the economy. The rationing models introduced first require less complicated calculations and have modest data requirements lending them to be easier to interpret by non-economists. Bickel et al. build upon these models to develop the input-output model. These conceptual models are applied empirically to Pinal County. A reduction shock in the water supply is applied to evaluate the modeling approaches. A "putty-clay" production function approach (where producers face flexible and inflexible decisions) is the basis for rationing models. Growers respond to water cutbacks differently depending on the time frame. Fallowing decisions are easily made and implemented but shifting cropping patterns would take more forethought. The rationing models presented by Bickel et al. (2019) approach the fallowing decision by ranking the crops and fallowing those that do the worst. Rankings are based on gross revenue per AF of water or net income per AF of water. Gross revenues are easy to calculate, but net income provides a better measure of losses to both farmers and farm workers. Rationing models may not be sophisticated enough to give accurate estimations of the total amount of cropland fallowed, but they are reliable in telling which crops will face cutbacks first. If the gross revenue is the deciding factor for fallowing, Bickel et al. find wheat would be fallowed first then alfalfa. But it the production cost savings are considered, then producers would choose to fallow cotton acres first to achieve water savings (Bickel et al., 2019).

Goemans and Kelley (2022) investigate the different methods of water savings to free up water for farmers to engage in temporary transfers while considering risk impacts. The authors compare the expected profitability, risk premiums, and potential water savings for 13 different irrigated cropping activities in Colorado. Transfers of water from agriculture become increasingly necessary as urban centers grow. The temporary nature of these transfers can alleviate some of the negative environmental and socioeconomic impacts from permanent dry-up. Temporary water transfers allow water rights to remain attached to the land and holders retain ownership. Goemans and Kelley examine crop switching, harvest modifications, limited irrigation, and rotational fallowing as means to save water. Before crop production begins, the farmer must decide how to allocate their water to cropping and transfers by ranking a set of alternative irrigated cropping activities. Farmers may accept a transfer after choosing an activity that conserves water relative to the historic usage, but the joint profitability of the crop production and water transfer revenues must exceed that of cropping alone. Rotational fallowing was found to reduce risk exposure with relatively equal gross margins but had minimal water savings. Swapping corn for alfalfa also reduced farmer risk without diminishing profitability but again water savings were negligible. More profitable irrigated cropping activities had lower water savings. The inclusion of risk exposure was an important component to the calculation of breakeven water transfer values. Excluding the risk effects underestimated breakeven values by 4-55%. These findings imply that farmers should be compensated for the water they transfer and the risk they take on to do so. The transfer values should therefore exceed the foregone value of production.

2.4 Groundwater Background & Studies

Across the state of Arizona, corporate farms are building expensive wells to continue pumping groundwater from greater depths. Lawmakers have introduced bills to expand groundwater regulation beyond the AMAs but have not seen any success. Many local surface water sources for Arizona originate in these more rural areas like the Salt River in the White

Mountains so protecting these resources has implications for the Phoenix AMA and others (Aleshire, 2021).

The influence of the price of water on groundwater extraction is discussed by Bruno and Jessoe (2021). They conduct a meta-analysis of price elasticity of water demand and discuss the policy implications. The price elasticity of demand determines the price groundwater must be set at to reach sustainability goals. It is dependent on location for agricultural groundwater but Bruno and Jessoe report it ranges from -0.1 to 1.1. Optimal extraction depends on the rate of replenishment, depth to water table, and drought conditions. Overextraction of groundwater can lead to negative externalities for others (Bruno & Jessoe, 2021).

Land use choices and spacing can also impact groundwater extraction. Bourque et al. (2016) examine the spatial placements of groundwater conservation projects across Kern County, California to achieve recharge or biodiversity goals while minimizing costs. Their results show there is overlap between the land used to achieve groundwater conservation goals and biodiversity habitat targets. The costs and benefits of fallowing and artificial groundwater recharge are considered as two possible groundwater management strategies. Costs are defined as the cost of water recharge (or fallowing) plus the user-assigned cost for fragmented networks. They assume the average cost of purchasing surface water to be equal to $650/AF based on a 2015 survey of eighty Central Valley water districts. Bourque et al.'s target is 15% of total irrigation demand reallocated to groundwater basin recharge. It would be cost-effective to fallow 11% of Kern County's agricultural area. The effects of groundwater overdraft cost the California agricultural economy $247M and 1,815 jobs in 2016 (Bourque et al., 2019).

California's equivalent to Arizona's GMA is the Sustainable Groundwater Management Act (SGMA). MacEwan et al. (2017) examine the impact that the SGMA will have on groundwater extraction in California by creating a model that integrates a biophysical response function and a hydrologic model into an economic model of groundwater use and then apply it to the critically overdrawn Kings and Tulare Lake subbasins of California. Economic optimization guides water management decisions constrained by the hydrologic system. The authors find sustainable yield is less than historical average pumping. An average reduction of 14% across all three model regions would need to be achieved to reach sustainable yield. The present value of SGMA regulation is estimated to be a positive benefit of $249M. The policy implications follow that SGMA allows overall gains while achieving sustainability goals. However, these gains will not be distributed uniformly.

In California's Central Valley, Nelson et al. (2016) examine the linkage between surface water and groundwater and the potential impacts of ending long-term overdraft. The focus lies on economic and operational aspects including groundwater recharge, surface water pumping and diversions, water scarcity, and associated operating water scarcity costs. Nelson et al. (2016) analyze the long term effects of ending groundwater overdraft by describing an optimization modeling approach for the base overdraft and No Overdraft cases. They attempt to minimize the economic costs of water operations and shortages to estimate the minimum physically possible total cost of ending groundwater overdraft. Nearly all annual agricultural demands in Central Valley can be met when overdraft is allowed. When overdraft is restricted scarcity can increase costs by $50M total (Nelson et al., 2016).

2.5 Federal Commodity Programs

Cotton is eligible for a variety of subsidized federal commodity and insurance programs which can affect the pricing structure for cotton growers. The USDA's Risk Management Agency (RMA) administers the Federal Crop Insurance Program. The types of policies and crops eligible for coverage are decided by the RMA. Policies are available for more than 100 crops, but corn, cotton, soybeans, and wheat make up 2/3 of all acres enrolled (Environmental Working Group (EWG), 2022). Federal farm programs help agricultural producers manage the variations in agricultural production and profitability from year to year. There have been many iterations of federal commodity programs with different Farm Bills altering the eligibility and structure of payments and programs every few years (Evans, 2021).

The 2014 Farm Bill made major revisions to federal commodity payments. Cotton was affected by the elimination of direct and countercyclical payments and became eligible for the subsidized supplemental insurance program, the Stacked Income Protection Plan (STAX) (Glauber, 2018). Cotton was ineligible for the new Price Loss Coverage and Agricultural Risk Coverage programs that other commodities were eligible for. Even though the cotton industry lobbied for STAX, participation was low. Arizona has consistently had some of the highest levels of enrollment in STAX. The federal government has given $2.1 billion in average subsidy payments to cotton each year contributing to about 50% of the value of cotton production (Glauber, 2018).

Sall and Tronstad (2021) examine the crop insurance participation rates and the planted acreage responses to subsidized crop insurance programs for cotton producing counties across the US. Cotton can be grown in a variety of conditions and is resilient against drought. Yields will differ based on regions so Sall and Tronstad assume that the impact of the crop insurance will not be equally distributed. Crop insurance changes are important to examine because they can affect farmers' insurance participation and cropping decisions. In this study, Sall and Tronstad use county-level data from 645 cotton producing counties from 1996-2016. The authors simultaneously model the effects of insurance participation and acreage response at a national and four regional levels to reflect the simultaneous nature of the decision process for level of crop insurance and acreage allocated to cotton (Sall & Tronstad, 2021). Insurance participation was highest in the southeast (56.9%) followed by the southwest (54%), then the Delta (43.2%), and finally the west (37.8%). The southwest had the highest per unit subsidy rates at 5.4 cents per pound. A one percent increase in the prior-year rate of return leads to a 0.05% increase in insurance participation across the entire US. Low yield, higher risk counties (southeast and southwest) received higher subsidies per pound of production. Insurance participation was also higher in these regions. Insurance participation and planted acres have a positive and statistically significant relationship in the US. Across the board, Sall and Tronstad found that the elasticity of the percentage of cropland planted with insurance participation was negative and statistically significant (-0.578 in the US). They believe this suggests that cotton's acreage response is inelastic to insurance participation (Sall & Tronstad, 2021).

While Sall and Tronstad (2021) focus on the impact of commodity programs across the entire US, Reyes et al. (2020) study patterns and trends in crop insurance loss data for the eight Ogallala Aquifer states in the western High Plains region from 1989-2017. Understanding trends in crop insurance payments can help producers better manage their risk. Reyes et al. find crop insurance can be used as a proxy for agricultural impact from weather driven causes of loss (2020). The federal government covers 62% of producers' insurance premiums on average (Reyes et al., 2020). The authors also find drought and failure of irrigation supply were two of the top ten causes of agricultural loss receiving insurance payouts in the Ogallala Aquifer region

(2020). Cotton received 29% of indemnities in the region. High risk regions identified by Reyes et al. (2020) include counties where groundwater is used for agricultural irrigation and drought contributes to 40% of indemnities.

Frisvold (2016) compares water use and productivity in cotton production in the western US using data from 1984-2013. He includes a discussion of federal commodity programs effects on water use. The scale effects (total production), mix effects (which crops are grown), location effects (where crops are grown), and intensity (water use per acre) all impact the way federal commodity programs affect water use (Frisvold, 2016).

The impact on crop profitability is also examined by King et al. (2021). The authors find crop insurance has made certain crops more profitable and has prompted farmers to shift to these more profitable crops regardless of water use requirements. Government subsidies can contribute significant portions of farm income. Federal payments make up 20-46% of farm-related income on farms 4-404 hectares (ha) and 311% of farm related income on farms 04-3.6 ha (King et al., 2021). Larger farms are typically more profitable, but the majority still receive subsidy payments that contribute 15% of income (King et al., 2021).

2.6 Land Sensing Data in Economics (CDL)

The Cropland Data Layer (CDL) was developed by the US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) to present an annual and accurate measure of land cover (and importantly crop cover) across the US. The CDL crop cover data paints a picture of the state of agriculture in a region. Since it was implemented across the contiguous US in 2008, economists such as Wilson et al. (2016) and Ma et al. (2021) have begun to include this source in their analyses of agricultural water use.

Wilson et al. (2016) attempt to quantify future land-use related water demand in California under a ‘business-as-usual’ (BAU) scenario. Developed water use consumes 17.6% of CA water (Wilson et al., 2016). Analysis of land-use related estimates of future water demand is important in the creation of effective water resource management plans. Wilson et al. project land-use change over a 70 year period (1992-2062) in the Central California Foothills and Coastal Mountains and the Central California Valley. They model agricultural expansions and contractions, urbanization, land protection, and conversion from annual to perennial crops. The

USDA CDL was used to calculate average county applied water use for crops. An area-weighted average applied water use value was assigned to each CDL cropland class (Wilson et al., 2016). Wilson et al. (2016) find that between 2012-2062 under the BAU scenario, developed land cover is projected to increase by 62.9% with annual cropland declining a projected 30.3%. The result of this development would increase water demand by 1.8 billion cubic meters.

Ma et al. (2021) attempt to use an economic value estimation model to determine the value of Arizona's agricultural water use. Cropland Data Layers and meteorological data aid in their estimation. Previous methods for estimating the economic value of water required assumptions regarding crop production and labor choices and are more labor- and data-intensive. Ma et al. develop a framework that is more accessible across regions and easier to apply to regions without market price comparison data. Irrigation water's economic value is computed based on the net returns of agricultural crops irrigated and agricultural water used. Relevant components include gross revenues, variable costs, and net returns of irrigated crops, Arizona agricultural water use, and the economic value of agricultural water. The authors restrict the application of their framework to 12 major groundwater subbasins in Arizona that contribute nearly 90% of the state's major crops. Crops examined include barley, cotton, alfalfa, hay, durum wheat, and lettuce. The costs of production of these crops differ in each subbasin. In order to determine the crop types planted in the study period (2008-2016), the authors employed the use of the CDL from the USDA NASS. The estimated economic value of agricultural water for cotton is positive in the Gila Bend subbasin and negative in the East Salt River Valley, Maricopa-Stanfield, the West Salt River Valley, and Eloy subbasins (Ma et al., 2021).

2.7 Panel Data and Fixed-Effects Modeling in Agriculture

The fixed-effects framework recognizes the existence of fundamental differences between groups. Since it can be difficult to explicitly include all these differences within a model, the fixed-effects capture all time-invariant variables. In these types of regressions, the deviations from group-specific averages are used to measure influence on the dependent variable (Schlenker, 2010). Schlenker (2010) applies fixed-effects panel models to an analysis of crop yields and climatic responses. The benefit of such a model is its ability to overcome omitted variable bias by capturing all additive time-invariant influences (Schlenker, 2010). Including fixed-effects in the empirical modeling of irrigation districts will help control for structural differences between each district. This section details the uses of fixed-effects models in the agricultural setting.

Petrick and Zier (2012) use a panel dataset of 69 East German regions to test the effects of direct payments and rural development measures of the European Union's Common Agricultural Policy on employment in agriculture. They use four different estimators to eliminate the fixed-effects. They are the first to use these methods in an agricultural study. Excluding relevant control variables can bias results for panel data. This issue comes up because some control variables cannot be included if they are not easily recorded or readily available. Bias from heterogeneity can be eliminated through the use of fixed-effects if the effects of time-invariant characteristics can be linearly separated (Petrick & Zier, 2012). The traditional method of eliminating fixed-effects is to time demean the sample using the least squares dummy variable (LSDV) approach. The validity of this method is not confirmed with small samples, so Monte Carlo studies of small samples were used to build the "corrected LSDV" which outperforms other models in terms of bias and efficiency (Petrick & Zier, 2012). This method is preferred by Petrick and Zier. Another estimator developed by Blundell and Bond (1998) was found to be more efficient if lagged differences were included as instruments into a level equation of the dependent variable (Petrick & Zier, 2012).

Weather and climate changes can be expected to directly impact agriculture since weather is a direct input into the production function (Auffhammer & Schlenker, 2014). Sources of variation in econometric studies may stem from time-series variation, cross-sectional variation, or a combination of the two in a panel setting. Each of these three sources of variation have been used to link agricultural outcomes to weather. Auffhammer and Schlenker note that econometric studies often exclude control variables for all relevant dimensions of climate. If there is not a stationary relationship between the included and omitted variables, there will be prediction errors. The included variable would also capture some of the variation from the omitted variables. This challenge from panel data can be addressed through location fixed-effects to capture all time-invariant confounding factors (Auffhammer & Schlenker, 2014).

The impact of climate on agriculture is also analyzed by Blanc and Schlenker (2017) using panel models. The value of panel models in climate studies stems from their ability to account for locational climate differences across space and in variables such as soil quality that may also be correlated with climate (Blanc & Schlenker, 2017). The locational fixed-effects capture any time-invariant differences between groups and ensures that the deviations from the mean are not correlated with baseline spatial differences. Unobserved variables in a panel regression are controlled through the fixed-effects. Fixed-effects panel models cannot include variables that do not change with time because they are being captured through the fixed-effects. Group fixed-effects (for irrigation districts in the case of this work) capture variation from unobserved factors that are constant within each group over time. Including these fixed-effects is equivalent to a joint demeaning of the dependent and independent variables. Demeaning transforms a variable such as weather into shocks (deviations from the average). Independent variables are then random and exogenous solving the biased coefficient problem.

A benefit of the demeaning approach is the retention of more degrees of freedom in the statistical analyses. This is important for interpreting weather variables that are often highly correlated such as temperature and precipitation. More degrees of freedom are also helpful in estimating nonlinear climatic effects (Blanc & Schlenker, 2017). When the degrees of freedom are higher there is greater power to reject a false null hypothesis and find significant results (UT Austin, n.d.).

2.8 Contributions

The literature summarized in this chapter guided the research and modeling of this thesis. With the solid foundation of the literature examined above, this thesis work adds to the existing literature on Arizona crop mix and agricultural water delivery decisions. Of the literature discussed in this chapter, McGreal and Colby's analysis of water deliveries and irrigation intensity is most closely concerned with the focus of this work. Griffin (2005) presents a model for efficient water use by a single firm. This work provides the basis for the theoretical model of irrigation district water deliveries presented in Chapter 3 of this thesis. Griffin discusses how the prices of crops, water, and other inputs will affect the profitability of a farmer within an irrigation district and influence their production decisions. The analysis in the following chapters will cover three Arizona Active Management Areas including the Tucson AMA and the corresponding Cortaro-Marana Irrigation District. The effects of federal crop subsidies and insurance in economic literature have not been widely discussed so the inclusion of the novel federal cotton payment per acre variable may help guide further analyses of water and crop decisions. The Tucson AMA and federal cotton commodity payments were not considered by McGreal and Colby (2022). Climatic factors are known to influence water and crop choices by farmers. This work attempts to measure the individual impacts of both precipitation and temperature. Later chapters will also discuss the multiple approaches taken to account for irrigation district fixed-effects in models of crop mix and agricultural water deliveries.

Chapter 3: Theoretical Background for This Study

The conceptual modeling of this study begins with an examination of an individual agricultural water user's decision making process in order to maximize profits. Even though the empirical analysis presented in Chapter 5 focuses exclusively on irrigation district level decisions, the total water demand of each district is comprised of the sum of individual growers' demand. Therefore, one must understand the profit-maximizing decisions of agricultural growers first. Griffin (2005) provides a basic model of the profit-maximizing agricultural water user that is applied to farmers within an irrigation district for this study.

3.1 Profit-Maximization Model

Farmers in central Arizona can be modeled as striving for profit-maximization. A central Arizona farmer represents the agent in this model and produces an output of a single crop (alfalfa or cotton may be chosen as the model output), represented by Y in this model, dependent on their water delivery decisions and other production inputs. Water deliveries is denoted by W. Other inputs relevant to production could include labor, fertilizer, or energy costs and could be captured in a vector of agricultural inputs. However, to simplify the theoretical analyses, this model includes only one other choice input denoted by X. Climate variables can also be expected to influence agricultural output, but this is an exogenous factor outside of growers' control (Moore et al., 1994). As such, they are not considered in this theoretical model. Farmers can be expected to adapt to climatic variables which are later examined in the empirical models to follow in Chapter 5.

The farmer's production function for crop output Y is represented by the combination of the two inputs, W and X, such that $Y = f(W, X)$. A degree of substitutability between W and X exists for the farmer so they may choose varying amounts of each input in order to obtain output Y. For example, some growers may choose to use deficit irrigation of a certain crop such as alfalfa to remain in production at lower quantities while conserving water. The profit-maximizing farmer attempts to select the optimal levels of W and X with respect to profit.

The profit maximizing firm's production function must meet certain conditions. The first condition is that there must exist a positive marginal product defined by the first derivative of the production function ($\frac{\partial f}{\partial W}$) up to a point of water usage denoted $\overleftarrow{w}$. Additional water usage beyond this point would reduce production while raising water costs. A positive second derivative, $\frac{\partial^2 f}{\partial W^2}$ indicates increasing return to scale until point $\overrightarrow{w}$ (occurs before point $\overleftarrow{w}$) where decreasing returns to scale begin to occur when $\frac{\partial^2 f}{\partial W^2} < 0$.

The farmer's profit, (π) can be simply defined as the total value of output (*TVP*) less total operating costs (*TC*).

$$\pi = TVP - TC \qquad (1)$$

This framework can be expanded upon with certain assumptions to define and solve the farmer's profit-maximization problem. The farmer can be assumed to be a price taker within the market, meaning they are small enough that they do not have any influence over the price they receive for crop *Y*. The price farmers receive for crop *Y* is defined as p_Y dollars per unit. Similarly, the cost of input *X* is defined as p_X dollars per unit. The cost of water to the farmer is represented by the function *c(W)*. Farmers could face different cost function structures for their water. For example, a farmer might have access to a low cost water source only up to a limited quantity where they must then move up a tier to a higher costing water source. If, however, the cost of water is assumed constant the farmer would face a price of water, p_W, and the cost function would be defined as $c(W) = p_W \cdot W$. The first derivative is of the cost function is assumed to be positive ($\frac{dc}{dW} > 0$) meaning more water costs more.

Taking these assumptions into consideration, the *TVP* and the *TC* can be defined as:

$$TVP = p_Y \cdot f(W, X) \qquad (2)$$

$$TC = c(W) + p_X \cdot X \qquad (3)$$

Substituting equations (2) and (3) into equation (1) gives the following profit function.

$$\pi = p_Y \cdot f(W, X) - c(W) - p_X \cdot X \qquad (4)$$

A farmer maximizes equation (4) by selecting optimal quantities of *W* and *X*.

$$\max_{W,X} \pi = p_Y \cdot f(W, X) - c(W) - p_X \cdot X \qquad (5)$$

This is done by taking the partial derivatives of the profit function with respect to W and X to find the first order necessary conditions.

$$\frac{\partial \pi}{\partial W} = \frac{\partial [p_Y \cdot f(W,X) - c(W) - p_X \cdot X]}{\partial W} \qquad (6)$$

$$\frac{\partial \pi}{\partial X} = \frac{\partial [p_Y \cdot f(W,X) - c(W) - p_X \cdot X]}{\partial X} \qquad (7)$$

Equations (6) and (7) are then set equal to zero to determine the optimal levels of inputs. Because of the previous assumptions made about the production function, the profit function extrema found through this optimization problem can be assumed to be a maximum. The fixed optimal quantities of W and X are now defined as W^* and X^*. Considering these optimal levels of inputs in the derivatives in equations (6) and (7) yields:

$$p_Y \cdot f_W - c'(W^*) = 0 \qquad (8)$$

$$p_Y \cdot f_X - p_X = 0 \qquad (9)$$

Because the output price is included in both equations (8) and (9) they can be rearranged so that the output price is alone on the left hand side of each and then set equal to each other.

$$p_Y = \frac{c'(W^*)}{f_W} \qquad (10)$$

$$p_Y = \frac{p_X}{f_X} \qquad (11)$$

$$\frac{c'(W^*)}{f_W} = \frac{p_X}{f_X} \qquad (12)$$

The above equations represent the equality between the ratio of marginal cost to marginal productivity of each input and the output price. This occurs only under profit maximizing conditions. Equation (12) can be rearranged to find the rate of technical substitution which will be equal to the ratio of the marginal prices of the two inputs.

$$\frac{f_X}{f_W} = \frac{p_X}{c'(W^*)} \qquad (13)$$

The cost of input X, p_X, is a fixed value, and if the cost of water was also fixed at p_W, then the ratio of the marginal input prices would be the ratio of the input prices $\frac{p_X}{p_W}$.

Equation 8 can be rearranged such that output price multiplied by the marginal product of water is equal to the marginal cost of water:

$$p_Y \cdot f_W = c'(W^*)$$

This reflects that under optimal profit-maximizing choices, the marginal value product of water is equal to the marginal cost of water. This type of relationship can be assumed to exist for all choice inputs.

$$MVP_W = MC_W \qquad (14)$$

This section developed the grower's crop production and profit functions with a focus on a conceptual model of profit maximization for a single output, multiple inputs case, with a focus on the irrigation water input. The next section examines the drivers of irrigation water demand based mainly on crop mix decisions such as which crops to plants and how many acres to allocate to each crop.

3.2 Drivers of Irrigation District Water Demand

The demand for irrigation water is a derived demand, based on the net returns from agricultural products produced (Scheierling et al., 2006). This section develops a conceptual model of water demand by identifying and describing the main drivers of irrigation water demand as informed by the literature, drawing on Schoengold, Sunding, and Moreno (2006).

Schoengold et al. (2006) use a panel dataset of individual land sections to derive an agricultural water demand function. They define water use at a particular location at a given point in time as a function of water price, time dependent variables, land quality variables, and predicted land allocation. With a clearly defined crop production function, one may derive the water demand function through the value of the marginal product of water (Schoengold et al., 2006). This framework guides the development of the conceptual models for water demand in this thesis, which focuses on irrigation district level water demand, modeled as the sum of member growers' demand.

3.2.1 Time Dependent Variables

Some drivers of water demand change over time but not across irrigation districts. Input prices are one such variable. The irrigation districts in central Arizona all face the same CAP water price, which does change year to year. Besides surface water, farmers may also pump groundwater. The costs for using groundwater can be reflected in energy costs used to pump groundwater. Electricity costs are highly subsidized, with prices locked in under lengthy contracts in central Arizona irrigation districts, but fuel prices can act as a proxy for other on farm energy costs as a time-variant driver of water demand. This is discussed further in Chapter 4.

3.2.2 Spatial Characteristics

Growers across central Arizona are also subject to drivers of water demand that vary over location and sometimes over time as well. These spatial characteristics variables are especially significant because of the diversity of irrigation districts within this study. Even within an AMA, irrigation districts may experience differences in spatial characteristics affecting which types of crops may be grown, which irrigation systems can be used, and the relative profitability of each crop and irrigation system (Schoengold et al., 2006). This is evident in different crop mixes between the three AMAs. Alfalfa is the dominant crop in the Phoenix and Tucson AMA irrigation districts, but in the Pinal AMA, cotton and alfalfa are more evenly planted. The locational characteristics that are time invariant are captured in irrigation district fixed-effects explained further in Chapter 6.

Environmental variables that change over time and location can be used to reflect soil and topography characteristics that impact crop mix and irrigation choices. In this study, average county temperature and average county precipitation are used to reflect differences between irrigation districts.

3.2.3 Predicted Land Allocation Among Crops

Land allocation refers to crop cover (crop mix) choices made by farmers within an irrigation district. Crop cover is a function of its own that impacts water demand decisions. Acres planted of crop *C* in irrigation district *i* at time *t* is represented by A_{cit}. The decision of how much of a crop to plant is influenced by the prices of all crops and federal commodity payments (vector $\boldsymbol{P}$), expected climate and weather conditions (*temp* and *precip*), cost of water (p_W), cost of other on farm energy (proxied by diesel prices, p_E) and unique irrigation district characteristics (vector $\boldsymbol{D}$).

$$A_{cit} = f(\boldsymbol{P}_t, temp_{it}, precip_{it}, p_{Wt}, p_{Eit}, \boldsymbol{D}_{it}) \qquad (15)$$

3.3 Irrigation Water Demand Model

With the drivers of the derived demand for irrigation water examined, a conceptual model of water demand may be defined. Water demand (measured in acre-feet) in irrigation district *i* and time *t*, represented by W_{it}, is established as a function of the above time dependent variables (*TD*), spatial characteristics (*SC)*, and predicted land allocation (*A*). The final form is shown in equation (20).

$$W_{it} = f(TD_t, SC_{it}, A_{cit}) = f(\boldsymbol{P}_t, temp_{it}, precip_{it}, p_{Wt}, p_{Eit}, \boldsymbol{D}_{it}) \qquad (16)$$

This model includes all the common drivers of water demand included in recent agricultural economics literature on irrigation water demand. The conceptual work presented in this chapter guides the econometric analysis presented in Chapter 5.

Chapter 4: Data

The data included in this thesis are obtained from a variety of sources to construct the final panel dataset used in the empirical analysis presented in Chapter 5. There are fourteen irrigation districts included in the study across three Active Management Areas (AMAs) (Phoenix, Pinal, and Tucson). The time frame of this study is from 2008-2020. Because the Cropland Data Layer (CDL) for Arizona only goes back to 2008, that year must act as the lower boundary. The upper boundary, 2020, is the latest year in which there are available data for all economic and climatic variables. Contributions to the literature on crop mix and water delivery predictions stem from the inclusion of variables representing federal commodity payments for cotton and specific climatic variables (temperature and precipitation). The data used represent a mix of state, county, and irrigation level data. The final panel dataset is composed of 182 observations. This chapter will detail the sources of data, collection and cleaning procedures, and major trends including the significant variables chosen for the final empirical models.

4.1 Water Use Variables

Because all the irrigation districts in this study are located within the regulatory boundaries of AMAs, they are required to submit annual water usage reports to the Arizona Department of Water Resources (ADWR). These reports are available on the AWDR's Online Data Repository. From these annual reports, one can obtain the data on irrigation water deliveries to each district and the sources of water (groundwater, surface water, CAP water, in-lieu water[1]).

The data obtained through the ADWR reports serve as the dependent variable for the agricultural water deliveries model. Water deliveries can vary drastically between irrigation districts and years. For example, as Table 1 indicates, the smallest annual water delivery occurred in the San Tan Irrigation District (STID) in 2016 with only 267 AF delivered. While the biggest agricultural delivery of 338,502 AF (Central Arizona Irrigation and Drainage District (CAIDD) in 2011) is 3 orders of magnitude greater. The average trends across AMAs in water deliveries to agriculture can be observed in Figure 1. Irrigation district-specific agricultural deliveries are shown in Figure 2-4. The CAIDD and Maricopa-Stanfield Irrigation and Drainage District (MSIDD) deliveries are consistently more than 100,000 AF greater than other district

[1] In-lieu water is renewable water delivered to a recipient who holds a groundwater right but agrees to replace pumping with the in lieu water. This creates groundwater savings (ADWR, 2022).

deliveries. The fixed-effects strategy employed in Chapters 5 and 6 helps combat this issue of different annual water deliveries between districts. Total water deliveries across all fourteen irrigation districts have been on the decline (Figure 1).

A strong correlation (0.966) exists between agricultural water deliveries and planted area across the entire study. The correlation between water deliveries and planted area in individual irrigation districts is weaker (Table 2). The effects of this correlation can be seen in the results of the agricultural water deliveries models. Variables representing crop acres have extremely strong explanatory power.

4.2 Land Cover Measure

The USDA NASS publishes the Cropland Data Layer (CDL) each year. The CDL uses remote sensing to report land cover across the contiguous United States. The resolution is $900m^2$ pixels and there are approximately 4.5 pixels within an acre. To make interpretation more meaningful, these pixels are converted to acres. Crop cover is the main purpose of the CDL, but it also measures other land cover types including developed area, fallowed, lands, open water, grassland, forest, and other non-cropped land covered. The CDL captures land cover images daily in order to obtain a usable image once every two weeks throughout the growing season. Its main focus is large area summer crops, but it can also capture crops grown in rotation by verifying with Farm Service Agency farmer reports. If the CDL does determine a field is planted in rotation, it will be categorized into a double crop grouping. Cotton and alfalfa acres are reported with over 90% accuracy in Arizona (USDA NASS, 2022).

Irrigation district shapefiles from ADWR can be integrated with CDL raster data to obtain measures of crop cover within an irrigation district. This process is completed for each irrigation district for each year within the study period. Tables 3 and 4 report the average size and crop cover for each irrigation district. The crop variables are grouped according to their CDL category and can be seen in detail in Table 5. Because cotton and alfalfa are so vital to central Arizona agriculture, these crops are examined alone. Figures 5-7 show the proportion of acres planted with alfalfa by county separated into three groups based on average proportion to allow for better observation of trends. The share of cotton acres by irrigation district is reflected in Figures 8-10. The average trends across all fourteen irrigation districts for alfalfa, cotton, and grains (corn, sorghum, barley, durum wheat, winter wheat) are reflected in Figure 11. Alfalfa has the highest percentage of planted acres followed by the grain category.

4.3 Economic and Climatic Variables

The USDA NASS reports annual survey data on crop yields and prices at the county and state level. This resource provides the alfalfa, cotton, and wheat yields for the three counties in the study region (Maricopa, Pima, and Pinal). Alfalfa yields are reported in tons per acre, cotton yields are reported in pounds per acre, and wheat yields are reported in bushels per acre. All winter wheat yield and price data needed for this study are reported at the state level. Certain year observations for yield are unavailable for winter wheat, alfalfa, and cotton. The USDA stopped reporting county-level yields for alfalfa in 2018 but has continued to report state level yields. Pima county is also missing observations for alfalfa and cotton in other years. The procedure to fill missing crop yield observations is addressed in Appendix A.1 and Table A1. Figures 12 & 13 show the annual trends in alfalfa and cotton yields for each of the three counties examined. Figure 14 shows the state level annual winter wheat yield trends.

State level crop prices received are also reported through the USDA NASS for alfalfa, cotton, and winter wheat. The USDA NASS may withhold data when the privacy of individual operations may be inferred because they might have been one of a few or the only producer in the county that year. When this occurs and the annual value is not available as is the case of upland cotton in 2015 and 2016, this is corrected by averaging the existing monthly prices received for that year. To allow for comparison across years and to account for inflation all monetary variables are adjusted using the Consumer Price Index (CPI) from the US Bureau of Labor Statistics. Real prices are generated using 2020 as the base year and will thus be referred to as 2020\$. The real Arizona alfalfa prices are reported in 2020\$ per ton in Figure 15. The average price is just over \$200 per ton. The winter wheat price is reported in dollars per bushel in Figure 16. The average price fluctuates around \$5.25 per bushel.

Because cotton is eligible for many different federal commodity payments, the price received reported by the USDA NASS is not an accurate estimate for the price farmers can expect to receive. A good proxy for price is the Expected December Futures price for cotton. The Futures price on the last Friday in February is used since this is about the time when farmers must finalize their cropping decisions for the season. The source for transcription of the

December Futures price is futures.tradingcharts.com from 2008-2020. These prices are reported in cents per pound but are converted to dollars per pound in this study and can be observed in Figure 17. Cotton Futures reach a peak of $1.40 per pound in 2011 but prices have been on the decline since then.

The USDA NASS annual crop yields and annual prices (USDA NASS for alfalfa and winter wheat and December Futures for cotton) are multiplied for each crop and county in each year in the study period to create a gross revenue variable. The county gross revenue for alfalfa is shown in Figure 18. Because cotton and winter wheat are often grown in rotation, the gross revenues of these two crops are added for each year to get a measure of gross revenue for cotton plus winter wheat. Figure 19 shows the combined cotton and wheat county gross revenue. Even though the price variables included within this study only vary by year, the gross revenues of cotton and alfalfa will vary between irrigation districts due to differences in county yield. For the most part, the gross revenue of alfalfa closely tracks the same trends and dollars per acre values as the gross revenue of cotton plus wheat. This is apparent in Figure 20 which shows the annual average gross revenue across all three counties of alfalfa compared to that of cotton plus wheat. Gross revenue measures are included instead of simply prices because they introduce more variability with the crop yield measures. Additionally, the price of alfalfa has been found to be insignificant in explaining variation in water deliveries in the literature (McGreal, 2021).

The Bureau of Reclamation administers the Central Arizona Project (CAP) which provides low cost Colorado River water to central Arizona water users. These CAP prices are much easier to obtain and interpret than cotton prices. Annual fee schedules are published by CAP each year that include fees for the current year and future fee projections. Prices are set to cover delivery costs and the repayments costs for the federal loan to complete the CAP (CAP, 2022). Farmers are aware of the CAP water price they will face years in advance. These fees are at the state level and reported as dollars per acre-foot of water delivered and are adjusted to 2020$ before inclusion in this study. The real CAP prices are reflected in Figure 21. The average price is $64 per AF. CAP prices were steadily increasing until they leveled out in 2015 at a peak $82 per AF. Since 2017, prices have been on the decline.

Energy (specifically electricity) costs also play a role in crop mix and production decisions. Power is needed to pump groundwater from wells. Even though energy is an important input in agricultural crop production, the irrigation districts in this thesis have contracts with the Arizona Power Authority (APA). APA provides highly subsidized electricity through the Western Area Power Administration to these irrigation districts. Rates for agricultural uses can be as low as $0.06 per kilowatt hour (McGreal & Colby, 2022). Since farmers are not bearing the full cost of power and do not expect price changes year to year, another measure that can represent energy costs must be used. US diesel prices can act as a proxy for other on farm energy costs in agricultural production (Scheitrum, 2022). The US Energy Information Administration (EIA) releases annual diesel prices for five districts across the US. Arizona is located within the West Coast region (Petroleum Administration for Defense District (PADD) 5). The final variable uses the PADD5 No 2 Diesel Retail Prices for 2008-2020 in dollars per gallon adjusted to 2020$. Diesel prices fluctuate frequently between $2-4 per gallon as can be seen in Figure 22.

This study examines the effect of climatic variables separately instead of using a drought indicator index to reflect climate behavior. The West Wide Drought Tracker (WWDT) which uses climate data from PRISM and the National Weather Service Cooperative Observer Network reports the temperature and precipitation measures that act as the climatic variables in this study. Annual values for each county are calculated by averaging monthly values reported by WWDT. Temperature is reported in Fahrenheit and precipitation is reported in inches. Both current year and a one-year lagged temperature and precipitation variables are explored in the course of defining the final empirical models of crop mix and water deliveries. Using temperature and precipitation instead of a climate index allows interpretation of the specific effects from these climatic variables separately. Precipitation may affect crop mix and water delivery decisions because of its relationship with soil moisture. As precipitation increases, so does soil moisture which is an important condition for plant growth (Sehler et al., 2019; Earth Observing System, 2019). Figure 23 shows the average annual county temperature across the study period and Figure 24 shows the average annual precipitation. Weather trends are similar between the three counties of interest. Maricopa has a slightly higher average temperature which may be a result of the urban heat island effect.

4.4 Federal Commodity Payments Measure

The Environmental Working Group (EWG) obtains county level crop insurance information from the USDA Risk Management Agency through the Freedom of Information Act.

Their Farm Subsidy Database categorizes payment data by a variety of levels including state, county, category, program, crop insurance, commodity payment, top recipients, etc. Annual county data for all federal cotton payments from 2008-2019 are collected. Payment programs are irregular across the years because federal farm bills change the structure of payment programs every five years or so. Some payment categories are so irregular they are excluded from this study when calculating the total payments to cotton for each county. The Other Payments category is not included because payments are made to this category sporadically and it is not clear which programs fall into this miscellaneous category. Counter-cyclical payments are also excluded from the total payments. EWG only reports payments within this program category from 2002-2010. From 2008-2009, the counter-cyclical payments to Maricopa and Pinal Counties were much larger than any other payment category. These payments were not tied to planted cotton acres and are not likely to influence cropping decisions (Tronstad, 2022). The counter-cyclical program was also the cause of a trade dispute against the United States brought to the World Trade Organization (WTO) by Brazil in the 2000s. Brazil argued that US agricultural federal farm programs gave US producers an unfair advantage and were inconsistent with the US's WTO commitments (Office of the US Trade Representative, 2014). Counter-cyclical payments were ended as a result of this dispute (Tronstad, 2022). Because of these reasons, counter-cyclical payments are left out of this study. Since the events of Brazil's case against US federal cotton programs, a shift has occurred to creating payment programs for cottonseed which result in payments to farmers similar to those before the WTO dispute (Sall & Tronstad, 2021).

Federal cotton payments may not be directly tied to acres planted and therefore would not directly influence the year to year planting decisions. However, farmers are paid according to their base acres which is sporadically adjusted. Because farmers do not know in which years, their cotton base will be readjusted, they are incentivized to maintain their cotton acreage to insure they will continue to receive payments should the base be readjusted (Tronstad, 2022).

At the time of this empirical analysis, EWG has not yet published 2020 federal cotton payments and put a pause on fulfilling data sharing requests (Leary, 2022). The procedure for estimating 2020 payments is detailed in Appendix A.1. Figure 25 shows the total real federal cotton commodity payments (without exclusion of categories) by county for all programs.

Following a peak in payments in 2009, total federal subsidies for cotton take a steady decline. Pima county payments are far smaller than those paid to Maricopa and Pinal. The three do not start to merge until the last few years. Even though Pinal County has more cropland than Maricopa County, the payments for these two counties closely mirror each other.

A per acre cotton commodity measure for each county is explored as the choice variable form. This variable is calculated by summing the annual irrigation district cotton acres by county. Then the total real federal payments to cotton are divided by the total county cotton acres for each of the three counties included in this study. This helps control for some of the variation in payments that would occur with fluctuations in cotton acreage. Payments per acre trends are displayed in Figure 26. From 2008-2013, Maricopa payments per acre are significantly higher than either Pima or Pinal. Pima County does not receive any payments from 2017-2019.

4.5 Choice Variables

Not all the variables covered in this chapter are selected for the final empirical models used to predict crop cover and agricultural water deliveries. Appendices A.2 and A.3 explore the alternative models considered. Of the climatic variables explored, average county precipitation lagged by one year is significant in explaining variation in crop mix decisions. Current year temperature and precipitation are both included in water delivery models and significant under certain conditions. Instead of including crop prices, this study uses the gross revenue of alfalfa and the gross revenue of cotton plus wheat. The gross revenue measures combine the variability from state level crop prices and county level crop yields. Federal payments for cotton are significant when predicting alfalfa acres. The price of CAP water ultimately does not have an influence in predicting grower water deliveries. Chapter 5 discusses the empirical models estimated in more detail and Chapter 6 explains the implications of the results.

Chapter 5: Empirical Models

The data discussed in Chapter 4 are included in statistical analyses informed by the conceptual model developed in Chapter 3. Initial rounds of statistical analyses employ Ordinary Least Squares (OLS) regressions. This chapter describes the preliminary independent variables tested for statistical significance to determine which are meaningful in predicting percent alfalfa acreage and agricultural water deliveries. Potential alternative functional forms for the percent alfalfa model with a limited dependent variable and their strengths and weaknesses are described. Robustness checks are conducted on the OLS regressions and find the variances of error terms from these regressions may be heteroskedastic. The consequences and corrections to heteroskedasticity are discussed.

5.1 Empirical OLS Regressions

The percentage of alfalfa is the dependent variable in the crop mix model for multiple reasons even though there may be some potential drawbacks. Firstly, alfalfa is one of the most prominent crops in the study region averaging 53% of planted acreage. It is also a crop that is in the ground year round. Alternative crops such as cotton are planted seasonally in rotation with another crop such as winter wheat. Potential measurement errors in the Cropland Data Layer (CDL) from the seasonal nature of cotton is a concern. The CDL categorizes cotton as a singular crop, and within double-cropping categories in rotation with other crops. Alfalfa on the other hand is in the ground all year lending confidence to the CDL acreage measures for this crop. Because alfalfa is the only crop grown in a field in a year, one does not need to consider the implications from additional crops grown in a rotation. One of the weaknesses of using alfalfa acres as the dependent variable in the crop mix model is the life of the plant. A stand of alfalfa may be productive for 5-7 years so planting decisions do not occur annually. Instead, it can be expected that only 15-20% of the total alfalfa acres in a given year is considered for changes in crop cover. Crop mix is estimated using OLS, but the dependent variable is different because it is constructed by dividing alfalfa acres in an irrigation district by the total planted acres in the same district in a given year. This gives a dependent variable that is a proportion, continuous between zero and one as represented in equation (17). The implications of a proportional dependent variable are discussed further in section 5.3 of this chapter.

$$\frac{alfalfa\ acres_{it}}{total\ planted\ acres_{it}} = percent\ planted\ alfalfa_{it} = PPA_{it} \qquad (17)$$

The definition of the crop mix dependent variable allows for the specification of the model for percent alfalfa acreage. Here, the share of alfalfa acreage in irrigation district *i* in year *t* is predicted dependent on climatic and economic variables.

$$PPA_{it} = \alpha_{PPA} + \beta_1 temp_{at-1} + \beta_2 precip_{at-1} + \beta_3 FedCottonPayments_{at} + \beta_4 GrossRevAlfalfa_{at-1} + \beta_5 GrossRev(Cotton + Wheat)_{at-1} + e_{it} \qquad (18)$$

Included in this model of alfalfa acreage are lagged climatic variables for county *a,* temperature (*temp*) and precipitation (*precip*). The federal cotton commodity payments variable (*FedCottonPayments*) is estimated with current year payments. Current year payments are used for federal commodity payments because while they do impact cotton planting decisions, the effect is more of an indirect effect. Year to year cotton acres planted do not typically affect annual payments, but farmers want to plant cotton to keep their acreage up in case the base acres eligibility is reset that year. Finally, the gross revenues of alfalfa (*GrossRevAlfalfa*) and of cotton plus wheat (*GrossRev(Cotton+Wheat)*) are included and also lagged. The independent variables' explanatory power and significance in this preliminary OLS model are discussed in the next section.

Recall the conceptual model of water demand represented in equation (16) derived in Chapter 3.

$$W_{it} = f(TD_t, SC_{it}, A_{cit}) = f(\boldsymbol{P}_t, temp_{it}, precip_{it}, p_{Wt}, p_{Eit}, \boldsymbol{D}_{it}) \qquad (16)$$

This conceptual model guides the empirical modeling of agricultural water deliveries in this section. Irrigation district agricultural water deliveries (*AWD*) measured in AF in irrigation district *i* in year *t* are also estimated using OLS.

$$AWD_{it} = \alpha_D + \delta_1 temp_{at} + \delta_2 precip_{at} + \delta_3 CAP_t + \delta_4 diesel_t + \delta_5 GrossRevAlfalfa_{at} + \delta_6 GrossRev(Cotton + Wheat)_{at} + \delta_7 AlfalfaAcres_{it} + \delta_8 CottonAcres_{it} + e_{it} \qquad (19)$$

The water deliveries model includes explanatory variables that are not included in the crop mix model. These variables are CAP water prices (*CAP*), the cost of diesel (*diesel*), and measures of crop cover within an irrigation district (*AlfalfaAcres* and *CottonAcres*).

5.2 Significant OLS Independent Variables

The life cycle and rotational timeline for alfalfa crops may dampen the effects of any of the explanatory variables in the regressions run. Even with this consideration, the percentage alfalfa models perform generally well. Preliminary models with cotton acreage as the dependent variable have lower explanatory power within districts and fewer statistically significant independent variables compared to the percentage alfalfa models. The signs on significant estimated coefficients do not align with economic theory at times (Tables A4, Appendix A3).

The prices of crops are expected to influence cropping choices because of their effect on profitability. This assumption does not hold in the case of alfalfa prices. In multiple preliminary model specifications, the price of alfalfa is not statistically significant in explaining variation in alfalfa acreage. This result is also present in McGreal and Colby's (2022) estimation of central Arizona agricultural water deliveries and irrigation intensity. The multi-year life-cycle of an alfalfa stand, and planting decision timing weaken the effect on alfalfa price in a specific year. Lagging the alfalfa prices by a longer period to reflect the life cycle of alfalfa is not suitable because a portion of the total acreage will come up for replanting each year. The insignificant statistical effect of alfalfa prices carries over to the gross revenue variable in certain model specifications.

On the other hand, cotton prices are found to be statistically significant in crop mix models. Recall from Chapter 4 how cotton market prices differ from the price received by farmers. As such, the December Futures price for cotton is included in the crop mix regressions in the gross revenue measure. Cotton is also eligible for federal farm program payments which influence grower revenues. A relative annual index for total payments is tested along with a per acre measure. Because the per acre measure accounts for fluctuations in total payments stemming from cotton acres planted, it is the preferred federal commodity payment variable. The final federal cotton commodity variable also dropped two program payment categories because of concerns about measurement and influence on acres planted, as discussed in Chapter 4.

It is possible there could be a relationship between federal commodity payments for cotton and the December Futures cotton price. This study examined the relationship between these two variables through their correlation coefficient. Including two or more variables that are highly correlated in a regression can cause standard errors to be inflated leading to wide confidence intervals and small t-statistics (Williams, 2015). However, this is not the case with these two variables that contribute to farmer revenue. The correlation coefficient between December Futures and the federal cotton commodity payments is 0.199. Typically, correlation coefficients greater than 0.7 are considered strong and cause for concern. Since the December Futures price for cotton and federal cotton subsidies are not highly correlated, both can be included in the same regression. Both are often significant with expected signs in the same model. These variables increase cotton revenues and drive farmers toward planting cotton and away from alfalfa.

These price variables are also considered in the crop mix and water deliveries models through the gross revenue variables described in Chapter 4. The gross revenue variables account for annual variations in the state price for alfalfa and winter wheat and the December Futures price for cotton along with the county level time-variant changes in crop yield (for alfalfa and cotton). Even though alfalfa prices alone are not statistically significant, when combined with alfalfa yields, they do have an impact on the percentage of alfalfa planted. A higher alfalfa gross revenue prompt farmers to increase alfalfa acreage. The opposite effect is present for the gross revenue of cotton plus wheat. Unlike the gross revenue of alfalfa, the gross revenue of cotton and wheat also positively influences agricultural water deliveries.

The impact of energy costs and difficulty in finding a variable to capture that cost component was discussed in Chapter 4. Regional diesel prices are tested as a viable proxy explanatory variable in various different preliminary model specifications. In nearly all regressions, diesel prices are not found to be statistically significant. Because the diesel prices do not seem to impact crop mix or water delivery decisions, this variable is not included in any final models. It may be that diesel prices are not a good proxy for on farm energy costs in agricultural crop mix and water delivery decisions. Further research into measures of energy costs should be conducted before determining the effect on the production of crops and water deliveries.

Unlike electricity costs, where there is not a clear time-varying measure to evaluate, the price of surface water for growers is easily included in models of water deliveries. The Central Arizona Project (CAP) water prices are hypothesized to impact agricultural water delivery decisions by central Arizona growers. The current year price is used in regressions because prices are posted years in advance giving growers insight into future trends and time to adapt.

One would expect an increase in the price of CAP water to reduce agricultural deliveries. This result is present in many of the preliminary models lending to the inclusion of the variable in the final model specification. CAP water prices are not found to be statistically significant in the final fixed-effects model.

The literature on agricultural water deliveries that informs this study report the power of crop mix and acres in predicting water deliveries. Cropland Data Layer (CDL) measures are a major determinant of agricultural water deliveries (McGreal & Colby, 2022). With these results in mind, preliminary water deliveries regressions included CDL crop acreage variables. The regressions with CDL variables have high explanatory power. Nearly all variation in agricultural water deliveries is captured by the CDL variables and most other variables are found to be statistically insignificant. Because of how influential crop mix and acreage are in determining water deliveries, these types of CDL variables are excluded from the final model specification of crop mix. This allows some of the other independent variables to recapture some of the explanatory power. Excluding CDL variables also reduces the chance of overfitting the regressions.

The logic for evaluating climatic impacts separately through temperature and precipitation was covered in Chapter 4. The timing of these two variables differs between the crop mix and water deliveries models. Precipitation and temperature are lagged by one year in the crop mix models because planting decisions are made at the beginning of the year. Farmers do not have perfect foresight regarding weather trends and are unlikely to make decisions based on weather forecasts. They must rely on past weather events and trends to determine cropping decisions. Temperature is included in preliminary crop mix models, but its insignificance leads to its exclusion from the final model. Precipitation is often significant in preliminary regressions. Lagged precipitation acts as a proxy for soil moisture which is more likely to influence farmers' planting decisions at the start of the year (Sehler et al. 2019).

Whereas farmers must make cropping decisions each year prior to the beginning of the planting cycle year and are then locked in on their choices, there is greater flexibility when it comes to agricultural water deliveries and the quantity of water applied per acre. Water orders are made throughout the growing season. Because of the year-round nature of water application decisions, farmers can be expected to possess the ability to react to current temperature and precipitation conditions. Even though central Arizona is an arid region, precipitation is found to be statistically significant in explaining variation in water deliveries. When precipitation increases, water deliveries decrease. The opposite would be expected for temperature. As weather gets hotter, one would believe farmers to increase their agricultural water deliveries. Temperature and precipitation are included in the final water deliveries model defined in Chapter 6. Temperature, though significant in preliminary OLS models (Table 7), is not found to be significant in the final model (Table 10).

With the discussion of possible independent variables completed in this section, the next section focuses on an analysis of the statistically significant variable coefficients. It also considers a possible alternative functional form for the alfalfa acreage model.

5.3 Econometric Analysis and Functional Form

Certain independent variables stand out in the alfalfa crop mix and the agricultural water deliveries regressions because they are consistently statistically significant with coefficients that align with basic economic expectations. The final OLS regressions include these choice variables. The results and implications of these OLS regressions are presented in this section.

In the basic OLS percentage alfalfa model including lagged precipitation, federal cotton payments per acre, and the lagged gross revenues for alfalfa and cotton plus winter wheat, only the estimated coefficient for lagged precipitation is statistically significant. The full regression results are presented in Table 6. The negative sign of the coefficient indicates that an increase in annual precipitation would decrease alfalfa acreage in the next year. This result does not immediately make sense because alfalfa is a water intensive crop that one would expect would benefit from higher precipitation and soil moisture. Additionally, the explanatory power of this model is extremely low with an R^2 of 0.0702. The low R^2 and insignificant coefficients may be the result of violations of important OLS assumptions. Robustness checks are conducted in the next section to determine the validity of the OLS percentage alfalfa model.

Like the alfalfa OLS model, the agricultural water deliveries model has a low R^2 of 0.1230 and only one out of five independent variables has a statistically significant estimated coefficient (Table 7). Water deliveries are regressed on the current year temperature and precipitation, CAP water price, and gross revenues of alfalfa and cotton plus winter wheat.

Temperature is found to be statistically significant but the negative sign on the coefficient is troubling. The model predicts that an increase in temperature decreases water deliveries to agriculture when one would assume the opposite to be true. As with the percentage alfalfa model, robustness checks are completed to validate the results of this OLS water deliveries model.

Both the water deliveries and crop mix models are estimated using OLS. OLS regressions can still be used to predict crop mix even with a limited dependent variable by using robust standard errors. Although, the models could predict values outside of the boundaries of the dependent variable in the percentage alfalfa models because it is bounded by zero and one. Alternative functional forms are considered, but OLS is still a valid estimator for proportional dependent variables through the use of robust standard errors with results that are easier to interpret (Lewis & Linzer, 2005). Papke and Wooldridge develop a method modeling fractional dependent variables which they then apply to a data set of employee participation rates in 401(k) pension plans (1996). In Papke and Wooldridge's model, their dependent variable is bounded between zero and one, as is the case in this study's model of percentage of planted acres with alfalfa. The authors propose the use of a generalized linear model (GLM) linked to a logit function (1996). The logit link function initiates a logit transformation of the dependent variable, and the binomial family can be used even if the dependent variable is continuous (Baum, 2008). Instead of performing the necessary transformations manually, the GLM technique in Stata can be used to generate predictions and transform them back into the units of the response variable automatically (Baum, 2008). Maximum likelihood models and seemingly unrelated regression estimation (SURE) methods have been also used to estimate consumer demand models with limited dependent variables (Thompson, 2022; Morley 1997; Heien & Wesseils, 1990). Because the OLS regressions are easier to interpret, they are applied to this analysis of crop mix with the awareness that predicted values might exceed the boundaries.

5.4 Robustness Checks

With the choice variables and functional form determined, robustness checks can now be completed on the estimated models. The OLS models estimated rely on the assumption that the variance of the error term is constant (homoskedasticity). Even if this assumption is violated and heteroskedasticity is present among the error terms, the OLS estimates are still unbiased.

However, they will no longer have the smallest variance meaning tests of significance are biased (Williams, 2020). Heteroskedastic errors are of concern in this study because the irrigation districts within the study area are structurally different. These differences could cause OLS regressions to generate heteroskedastic errors. As such, it is important to confirm the suspicion of heteroskedasticity with robustness checks. The first rough test for heteroskedasticity in a model is an observation of a plot of the residuals plotted against fitted values. Ideally, one should observe residuals with even widths across the plot. Figures 27 and 28 show the residuals plots for the alfalfa acres and water deliveries models. The residuals in Figure 28 for the water deliveries model do not display constant variance. On the other hand, the residual plot for the percentage planted alfalfa model in Figure 27 shows residuals that are more evenly distributed. It may be that district structural differences more greatly affect water deliveries than crop mix. If the plot shows some residuals higher than others (as is the case in the water deliveries model), more formal tests may be conducted such as the Breusch-Pagan Test for Heteroskedasticity. This test compares fitted values to residuals errors to determine if constant variance of the errors terms is present. The null and alternative hypotheses are as follows:

$$H_0: Errors\ are\ homoskedastic$$

$$H_1: Errors\ are\ not\ homoskedastic$$

A rejection of the null hypothesis implies heteroskedastic errors. This is then corrected by employing robust standard errors and through district fixed-effects. The Breusch-Pagan test for both models is conducted with the results reported in Table 8. The assumption of homoskedastic errors is rejected for the water deliveries model with a high χ^2 of 47.39 and a p-value approaching zero, but the same cannot be said for the percent planted alfalfa model. The small χ^2 of 0.26 in this model and corresponding p-value of 0.6108 do not warrant cause for concern from heteroskedastic errors. This result is consistent with the visual inspection of Figure 27. Regardless of these findings, both models are estimated using fixed-effects for completeness in the next chapter.

Chapter 6: Econometric Results

With the basic OLS model specifications and the process of robustness checks covered in Chapter 5, this chapter focuses on the final models of percent alfalfa acreage and agricultural water deliveries. To correct for the potential heteroskedastic errors detected in Chapter 5, the final models employ fixed-effects through demeaning to control for irrigation district level structural differences. Lastly the interpretations of the results and coefficients from the final fixed-effects models are discussed.

6.1 Fixed-Effects Models

This chapter presents the final choice models informed by the preliminary OLS model estimates and analysis in Chapter 5. As discussed, this study estimates a model of the percentage of planted acreage in alfalfa and a model of agricultural water deliveries. Recall the construction of the dependent variable in equation (17) for the crop mix model. The choice model estimates the percentage of planted acreage covered with alfalfa in irrigation district *i* in year *t*.

$$PPA_{it} = \alpha_{PPA} + \beta_1 precip_{at-1} + \beta_2 FedCotPay_{at} + \beta_3 GrossRevAlfalfa_{at-1} + \beta_4 GrossRev(Cotton + Wheat)_{at-1} + e_{it} \quad (20)$$

The alfalfa crop mix decisions estimates depend on last year's precipitation in county/AMA a. Federal cotton payments per acre in county a in year *t* also influence the crop mix decisions. The last two independent variables included are the gross revenue of alfalfa and of cotton plus winter wheat in county a in year *t-1*. Recall, that variables are lagged in the crop mix model because farmers make their planting decisions early in the year and must rely on the previous years' trends. Finally, a constant (α_{PPA}) and error term (e_{it}) are included.

Shifting to the agricultural water deliveries model, the model is presented with some similarities, but also vital differences.

$$AWD_{it} = \alpha_D + \delta_1 temp_{at} + \delta_2 precip_{at} + \delta_3 CAP_t + \delta_4 GrossRevAlfalfa_{at} + \delta_5 GrossRev(Cotton + Wheat)_{at} + e_{it} \quad (21)$$

Here, the dependent variable is total agricultural water deliveries in acre-feet to irrigation district *i* in year *t*. Independent variables in the water deliveries model are estimated with the current year values because growers submit orders throughout the year and have greater flexibility to react to changing conditions. Precipitation and the gross revenues of alfalfa and cotton plus winter wheat are included in both models. The water deliveries model deviates from the percentage alfalfa model with the inclusion of temperature and the CAP water costs. With the variables in both models defined, the next section discusses the process of including fixed-effects to correct for the heterogeneity detected in robustness checks in Chapter 5.

6.2 Demeaning Approach to Fixed-Effects

Group-specific fixed-effects can eliminate group-specific unobserved heterogeneity and provide unbiased estimates of independent variables (Bruder & Ludwig, 2014). One approach is to demean variables by subtracting the group-specific (irrigation district) average value of a given variable in a district from each individual observation in that district. The resulting variables have a mean of zero within each district. The demeaning approach allows focus on variation over time but ignores variation across irrigation districts that are unchanging over time. Model estimates are then based on the within district variation over time and irrigation district specific heterogeneity will no longer disturb the estimation (Bruder & Ludwig, 2014). One can distinguish *between* and *within variation*. Group differences are captured in the between variation. This is generally of lesser importance than the within variation generated by changes over time within a group. The within variation measures variation of the demeaned data (Bruder & Ludwig, 2014). In McGreal and Colby (2022), the authors measure the explanatory power of their model of irrigation district water deliveries through the R^2 *Within* and the R^2 *Between*. The R^2 *Within* captures variation in the dependent variable within an irrigation district over time. Variation between irrigation districts is measured by the R^2 *Between* but this is of less interest.

Bruder & Ludwig (2014) present the Least Squares Dummy variable (LSDV) regression as an alternative method to controlling for group heterogeneity. By including *N-1* dummy variables for groups you can control for structural time-invariant differences. McGreal and Colby consider this approach but choose to use the demeaning approach to fixed-effects to preserve degrees of freedom in their analysis. Though mathematically the same as LSDV, the demeaning approach helps to avoid potential “overfitting” due to dummy variables (McGreal and Colby, 2022).

The final models presented in this chapter follow McGreal and Colby’s methodology to control for district fixed-effects by demeaning variables. Preliminary models are estimated using the LSDV approach, but the models are overfitted, explaining nearly all the variation in the dependent variable with R^2 values equal to 0.98 or higher (degrees of freedom equal 176). Excluding the district level dummy variables results in models with lower explanatory power indicating that irrigation district structural differences are extremely important in explaining differences in crop mix and water deliveries. Even though the demeaned fixed-effects models do not have as high R^2 value as the LSDV models, the explanatory power increases compared to the OLS models without any fixed-effects. The final percentage alfalfa model estimated in Table 9 has an R^2 *Within* of 0.2285 and an R^2 *Between* of 0.5246. This means this model of crop mix decisions is able to explain variation between irrigation districts better than it is able to explain variation within a district over time. Table 10 shows the results for the agricultural water deliveries model and the corresponding R^2 *Within* of 0.2886 and R^2 *Between* of 0.1786. The water deliveries model predicts variation in a district over time at about the same level as the percentage alfalfa model, but its power to explain differences between district deliveries is much lower. Just as robustness checks for heteroskedasticity are conducted for the OLS models, a Wald Test for Groupwise Heteroskedasticity is completed for the fixed-effects models estimated in this chapter with the following null and alternative hypotheses (where σ^2 is the variance).

$$H_0\colon \sigma_i^2 = \sigma^2 \ for \ all \ i$$

$$H_1\colon \sigma_i^2 \neq \sigma^2 \ for \ all \ i$$

Both the alfalfa and water deliveries models are found to have groupwise heteroskedastic errors (Table 8). As such the models are estimated using robust standard errors. The models estimated with robust standard errors are reported in Tables 9 and 10 and are discussed in greater detail in the next section.

6.3 Interpretations and Implications of Significant Variables

Now that the explanatory power of the final models for percentage planted alfalfa and agricultural water deliveries has been discussed, this section focuses on the specific coefficient estimates and the implications of these results. A consistent finding is that the fixed-effects models perform better than the OLS regression from Chapter 5.

6.3.1 Percent Planted Alfalfa Model

The fixed-effects alfalfa regression presents multiple differences from the OLS regression in Chapter 5, both in explanatory power and statistically significant coefficients (Table 9). The first significant variable in the percentage planted alfalfa model is lagged average county precipitation. Recall that this independent variable is also statistically significant in the OLS regression in Chapter 5 but has a negative estimated coefficient (Table 6). The positive sign of this coefficient indicates that increases in precipitation in a given year leads to a higher percentage of alfalfa acreage planted in the next year. A one inch increase in the average monthly precipitation would increase the estimated proportion of alfalfa by 0.05. The implications of this rather large positive coefficient are not clear. For one, recall the discussion in Chapter 5 about alfalfa cropping decisions. Only 15-20% of all alfalfa crops can be expected to change in a given year based on the productive life of the crop. However, greater precipitation in past years leads to greater soil moisture (Sehler, 2019). This creates conditions that are more favorable to the crops (Earth Observing System, 2019). Alfalfa is one of the more water intensive crops so greater soil moisture may encourage farmers to plant more of this crop. When compared to cotton in a 12 month rotation with other crops, the difference in alfalfa water needs is modest.

The federal cotton payments per acre are statistically significant in the fixed-effects model, a difference from the OLS regression. The negative sign of this coefficient aligns with basic economic theory that as the price of competitive goods increases, supply for the other good decreases. Growers with the ability to plant cotton are incentivized through federal farm program payments to decrease their alfalfa acreage since this crop is not eligible for federal payments. The size of this coefficient and the other economic variables are smaller than the effect from precipitation. A dollar increase in the federal payments per acre would decrease the estimated proportion of alfalfa by 0.0001.

The lagged gross revenues of alfalfa and of cotton plus wheat also become significant when fixed-effects are included in the model estimation. The magnitude of the effects of alfalfa's gross revenue and cotton plus wheat's gross revenue are equivalent in size to the estimated coefficient of federal cotton payments per acre. The estimated coefficient for the gross revenue of alfalfa in this model is positive which conforms to standard economic expectations. The negative sign on the cotton and wheat gross revenue variable also aligns with expectations. As alfalfa earns more money and cotton and wheat earn less, growers will be more likely to plant alfalfa.

6.3.2 Agricultural Water Deliveries Model

Shifting the discussion to the model of agricultural water deliveries, the fixed-effects model also performs better than the OLS model with the same explanatory variables (Table 9). An interesting result is that the insignificant and significant climatic variables in the two models flip when fixed-effects are included. Temperature is insignificant, and precipitation become significant. The negative sign aligns with the expectation that more precipitation would decrease the need for irrigation water. However, the large magnitude of this coefficient is cause for concern. It would not be unexpected for larger irrigation districts with higher annual agricultural water deliveries to experience variations of 10,000 AF in a year. For some of the smaller irrigation districts, total annual deliveries do not even reach that amount. The size of precipitation's estimated coefficient is more than 30 times the size of average deliveries to the smallest district STID.

The price of CAP water is not statistically significant. This suggests that farmers are not responsive to changes in water price. Another insignificant variable is the gross revenue of alfalfa. Prices of alfalfa (insignificant in other studies, McGreal, 2021) are used in the construction of this variable, so this result is not particularly surprising.

On the other hand, the gross revenue of cotton plus wheat is statistically significant. The estimated positive effect states a dollar per acre increase in the gross revenue of cotton plus wheat leads to a 19 AF increase in agricultural water deliveries in an irrigation district. As crops become more profitable, one expects farmers would choose to increase their water deliveries to ensure high yields of such crops.

One other troubling aspect of the agricultural water deliveries model is the size of the estimated constant (92,476 AF). About half of the irrigation districts included in this study do not have any annual agricultural deliveries close to that figure while the two biggest districts consistently use more than double this amount of water. It seems that even with the district level fixed-effects through demeaning, the range of deliveries to districts negatively impacts model results. This inflated estimated constant is not present in the water deliveries model estimated with SCIDD (Appendix A.2, Table A3). This interesting result is discussed further in Appendix A.2.

This chapter has detailed the final fixed-effects models estimated in this study and the interpretations of the statistically significant estimated coefficients. The next chapter discusses the policy implications of these results.

Chapter 7: Conclusion and Policy Implications

It is clear that Arizona and the arid American West are in a growing predicament with their current water challenges. Hotter drier weather conditions are impacting snowpack melt times leading to diminished Colorado River flows. Arizona is experiencing a long-term period of aridification that may become permanent (Ferris & Porter, 2021). The dire nature of this situation is highlighted by the Bureau of Reclamation's Tier 1 water shortage declaration reducing Colorado River water available to Arizona and other lower basin states and Mexico. Before the CAP was completed to deliver Colorado River water to central Arizona, growers relied on groundwater and some local surface water. Groundwater still composes nearly half the water used in the CAP region (Ferris & Porter, 2021). While the availability of CAP water has led to increasing water levels in central Arizona, it is now possible that central Arizona growers may need to supplement decreased surface water sources with more groundwater. This is a troubling scenario when the agricultural sector is already the largest contributor to unreplenished groundwater use in the Phoenix, Pinal, and Tucson AMAs (Ferris & Porter, 2021).

Even with the current regulations in place in central Arizona through the GMA, groundwater is still pumped in an unsustainable manner (Ferris & Porter, 2021). This issue will likely worsen with the Colorado River water cutbacks. This study is important because the findings helped to determine drivers of agricultural water use and crop mix decisions. These factors influence the rate farmers will move back to groundwater when surface water fails to meet their supply needs.

In some ways, urbanization has helped Arizona's water situation. When high water use agricultural lands are converted for urban development, water use becomes less intensive and declines on said parcel. Nearly 200,000 acres of agricultural land have been retired from production in the Phoenix AMA since 1985. Considering that Arizona agriculture consumes an average of 4.2 AF/acre this is an estimated reduction of over 800,000 AF per year (Frisvold, 2015). Population in Arizona's capital city, Phoenix, increased 120% in the same time period while municipal water demand only grew by 70%. Improvements in efficiency have also been achieved through urban and agricultural conservation efforts and technology adoption. These reductions in demand are important, but alone are not enough to help AMAs reach sustainable groundwater levels (Ferris & Porter, 2021).

Water managers have begun to explore further solutions for the water situation faced by central Arizona. Investments by municipal water providers in treatment plants to augment supply through reclaimed water have totaled billions of dollars (Ferris & Porter, 2021). Reclaimed water is widely used as an irrigation source in the urban setting for fields, parks, and golf courses. In Phoenix, this reclaimed water is delivered to the Palo Verde Nuclear Generating Station as a cooling source (Tenney, 2018). Reclaimed water and unused CAP water have been used to artificially recharge aquifers across central Arizona. The Arizona Water Banking Authority has banked nearly 4.5 MAF for future Arizona use (Arizona Water Banking Authority, 2022).

This study aims to determine drivers of central Arizona crop mix selection and agricultural water use. It began with an introduction to the current conditions facing agricultural water users in fourteen irrigation districts in three central Arizona AMAs. With the supply of agricultural water affected by the 512,000 AF Colorado River shortage, agricultural production can be expected to also be impacted. Farmers may switch to less water intensive crops, fallow their lands, or supplement with additional groundwater resources. Chapter 2 provided a history of Arizona's water policy and agricultural water use trends. The economic literature on agricultural water demand also discussed in Chapter 2 informed the conceptual model of agricultural production and water demand developed in Chapter 3. Agricultural production is used to derive the demand of irrigation water. This conceptual model was then incorporated with the data discussed in Chapter 4 for the empirical analysis presented in Chapter 5 and 6.

The final fixed-effects percentage alfalfa model estimated in Chapter 6 finds that climatic and economic conditions do affect crop mix decisions. Lower precipitation is found to decrease the share of alfalfa planted in the study region. Perhaps as drought conditions persist in central Arizona, farmers may begin to plant less water intensive crops. Alternatively, alfalfa farmers can adopt a deficit irrigation strategy where they apply less than optimal levels of irrigation water to harvest lower yields without needing to completely fallow acreage. Alfalfa is a resilient crop and can return to maximum yield levels when the correct water intensity is applied even after periods of deficit irrigation (Hanson et al., 2007; Lindenmayer et al., 2011). This work focused on crop acreage and irrigation water deliveries under normal application conditions. Future research might examine less water intensive crops and trends in their acreage or water deliveries under deficit irrigation strategies across central Arizona. While the federal cotton commodity payments are not based directly on acres planted each year, these programs still seem to have an impact on crop mix decisions. Consistent results appear in cotton and alfalfa models finding that increases in these payments are associated with increased cotton acres, while also decreasing alfalfa acres. The gross revenue potential of a crop is also important in production decisions. If alfalfa's gross revenue decreases, the percentage of acreage planted with alfalfa declines. Increases in the gross revenue of cotton plus winter wheat also lead to an estimated decrease in the proportion of alfalfa acres. Changes in the proportion of alfalfa acreage can be expected to occur at slower rates than those of annual crops like cotton. These results can inform agricultural producers and policymakers about ways to influence crop mix which is one of the biggest drivers of agricultural water use.

Besides changing the cropping patterns in central Arizona, other factors influence agricultural water use according to regression results from Chapter 6. The climate is found to influence water deliveries. The negative impact of precipitation was more consistently statistically significant, but under certain models, temperature is found to affect water deliveries. If drought conditions persist, one can expect agricultural growers to increase their agricultural water deliveries. Policymakers and water managers should consider long-term solutions opposed to quick fixes since these climate conditions are not expected to improve in the coming years.

Another important result from the agricultural water deliveries model is the insignificance of the CAP price of water. As CAP water becomes scarcer with federal Colorado River drought declarations, water managers may be restricted in their ability to use price increases as a tool to decrease water demand. The current cost of pumping groundwater does not reflect the actual social costs of extractions. If policymakers could capture the total social cost of groundwater pumping through increased electricity costs or stricter regulations, extraction might decline to more sustainable levels, but that is reliant on the assumption of price elasticity of water demand. The pumping cost of groundwater is especially important in determining the rate of substitution between surface water and groundwater. While this work attempts to estimate future agricultural water deliveries to central Arizona, the share of water resources will depend on the costs of surface water and groundwater. Growers will substitute surface water with groundwater as long as they have the rights to pump and it is economically feasible.

The focus of crop mix selection in this study is important to economic literature. McGreal and Colby (2022) find crop mix to be a major determinant of agricultural water use in central Arizona. This result is confirmed in preliminary OLS water delivery models. The final model presented in Chapter 6 presented factors that are found to be statistically significant in predicting the share of alfalfa planted. This model could be adapted through future research for other significant Arizona crops to get a more complete look at Arizona's agricultural impacts.

The contributions of this work extend to the use of remote sensed land cover data provided through the CDL. The CDL has only been available in the entire contiguous United States since 2008, so it has not been widely explored in agricultural economic literature. The empirical analysis in Chapter 5 uses these data in three main ways. Firstly, total planted area and specific crop acreage are employed in different forms in the dependent variables. Initial OLS water deliveries models included alfalfa and cotton acreage as explanatory variables. CDL variables were dropped from the final water deliveries models because of their extreme power to explain the variation in deliveries. Finally, the CDL's land cover data were incorporated with the EWG cotton commodity payments to create a per acre payment variable that is included in the final crop mix model.

While this work was able to identify certain drivers of agricultural water demand and crop mix selection by central Arizona agricultural growers, certain questions remain that provide areas for future research work. The highly subsidized and time-invariant nature of electricity costs for irrigation districts prevent the inclusion of such a metric in econometric analysis of water demand. But basic economic production theory supports the inclusion of a measure of energy costs in agricultural production and water demand estimations. Diesel prices were tested as a proxy for other on farm energy costs in the econometric analysis presented in Chapters 5 and 6 but were not found to be significant in this work. Future research could focus on how best to include energy costs in models of agricultural production and in water demand econometric analysis.

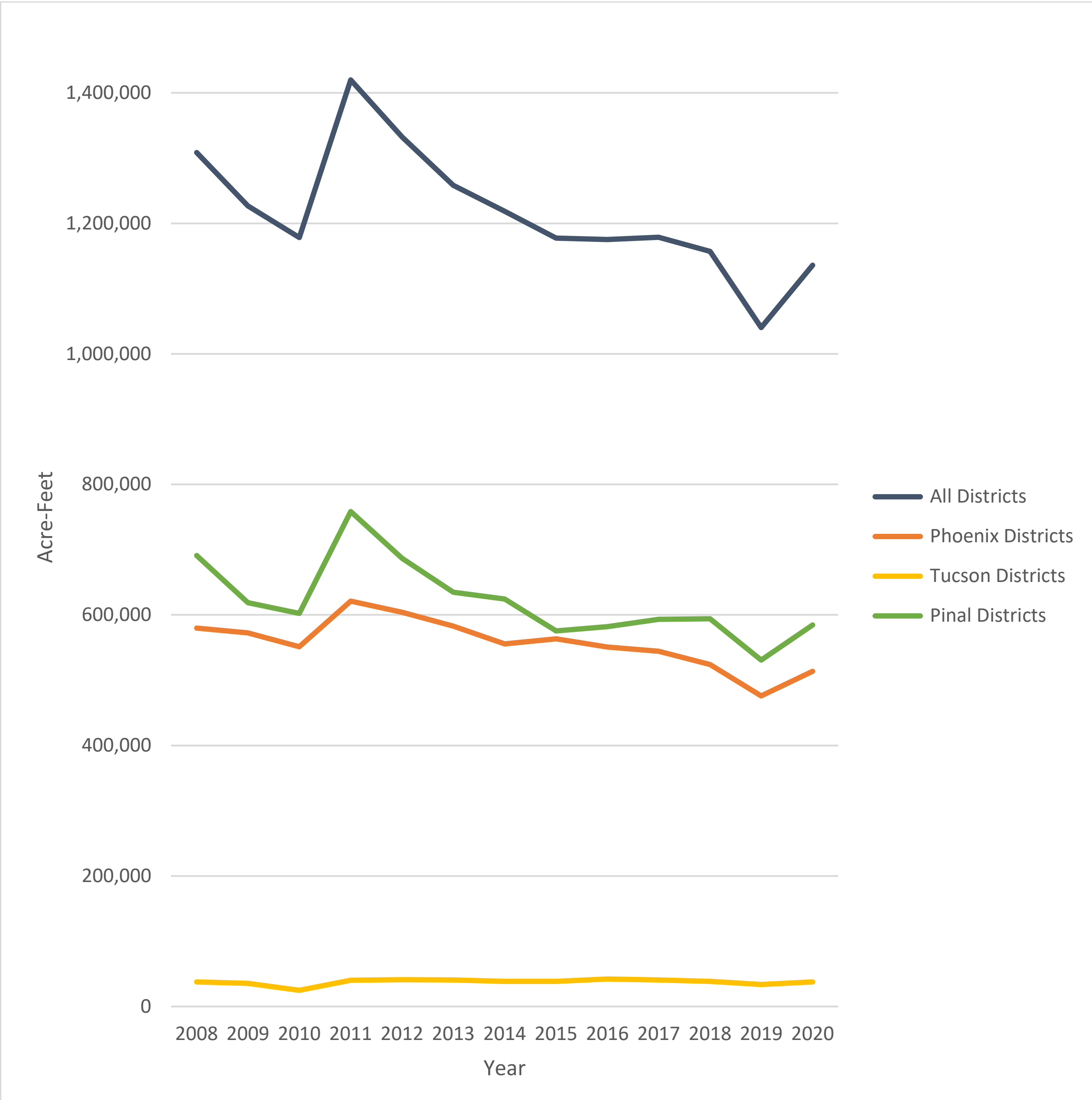
The inclusion of the EWG cotton commodity payment data is another contribution of this work. Federal commodity payments contribute to farmer revenue and significantly impact share of crop acreage as found by models in Chapter 5 and 6. The impact of federal cotton commodity programs on central Arizona crop mix decisions is discussed in detail in this study, but the complexity and diversity of these programs remains to be fully examined. Cotton is not the only commodity eligible for federal payments; subsidized insurance policies are available for over 100 crops in the US (EWG, 2021). Even within the cotton programs, changes occur about every five years with new iterations of federal farm bills that change payment structures. Further research questions regarding the impacts of federal crop commodity payments are abundant.

There exists a lack of available water use data on irrigation districts outside the AMAs. Agricultural production occurs throughout the state of Arizona, but irrigation districts outside of AMAs in areas such as Yuma are not subject to the same water use reporting requirements. Therefore, the question of whether the results found in this study hold in irrigation districts outside of central Arizona AMAs remains unanswered.

There is clearly lots of work to be done by Arizona water managers, policymakers, and agricultural growers. Strides have been made in the last century to better manage the state's scarce water resources. The Groundwater Management Act slowed the expansion of groundwater use in the most critically over pumped regions and has decreased the total amount of groundwater extracted in key areas of the state. The CAP opened up a whole new water source through the Colorado River to further decrease the state's reliance on groundwater. The management of the state's water portfolio requires water managers and policymakers to understand the drivers of water demand. This work helps identify such drivers from agricultural production to contribute to that goal of efficiently and effectively managing a resource that grows scarcer each day.

Figures

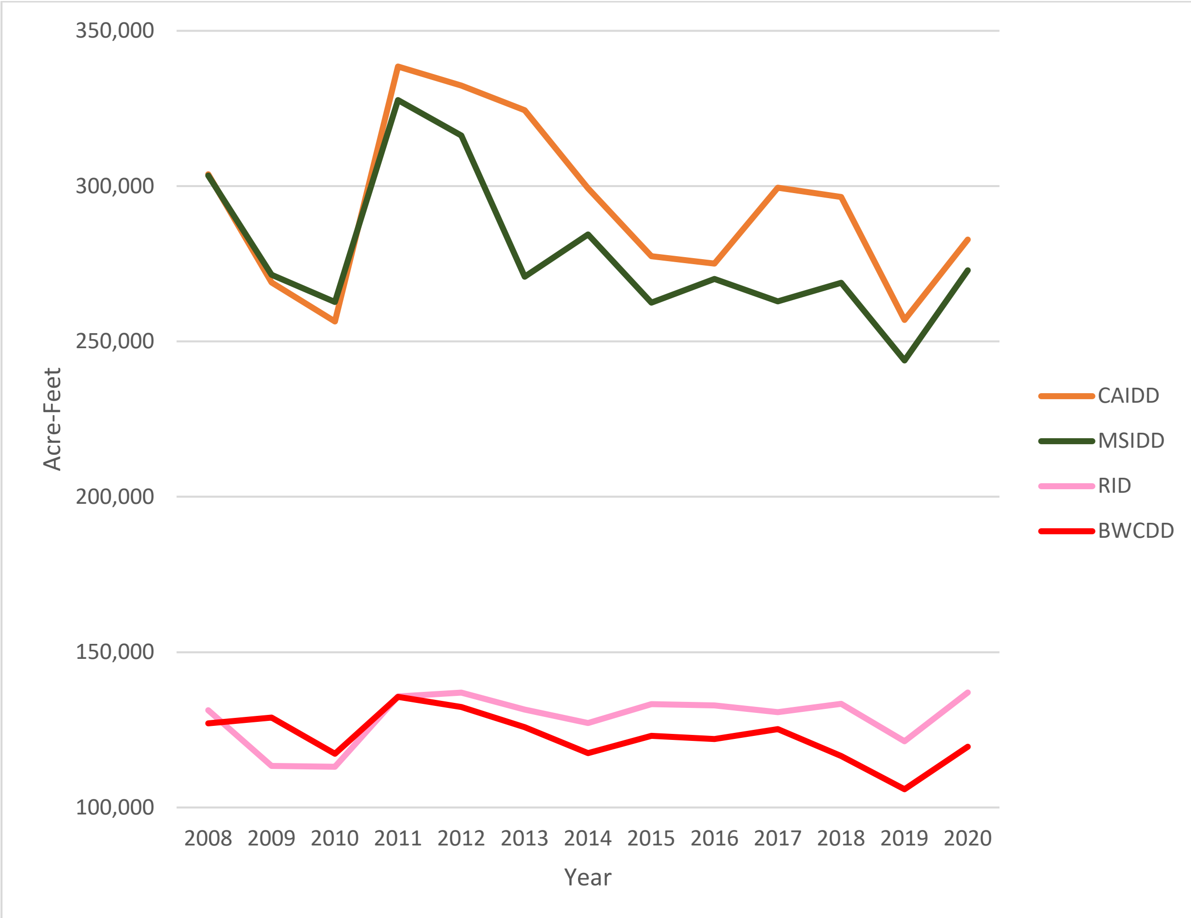
Figure 1: Total Water Deliveries to Agriculture by AMA



Data Source: ADWR

Notes: The sum of annual water deliveries for irrigation districts is calculated for each AMA and across the entire study region.

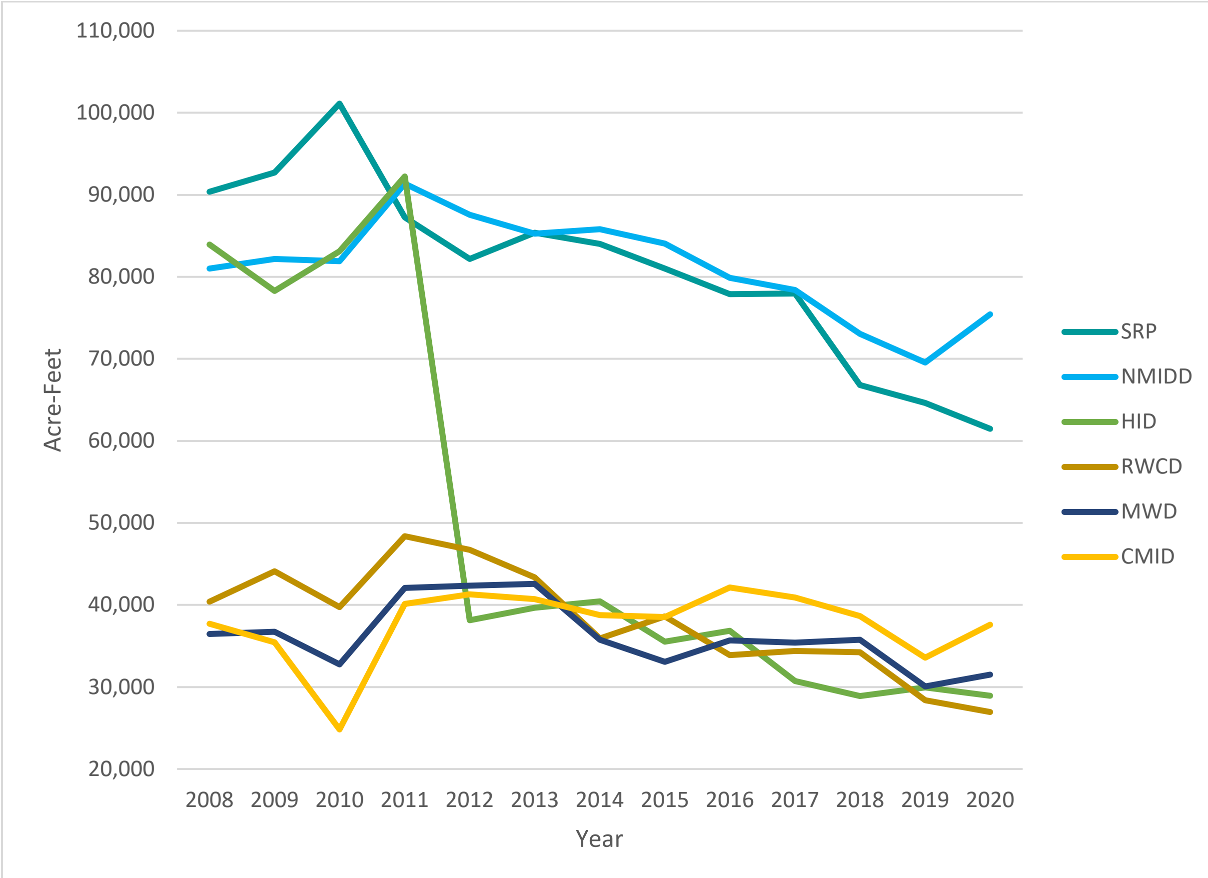
Figure 2: Water Deliveries to Agriculture by Top Four Districts



Data Source: ADWR

Note: These four districts have the highest average agricultural water deliveries.

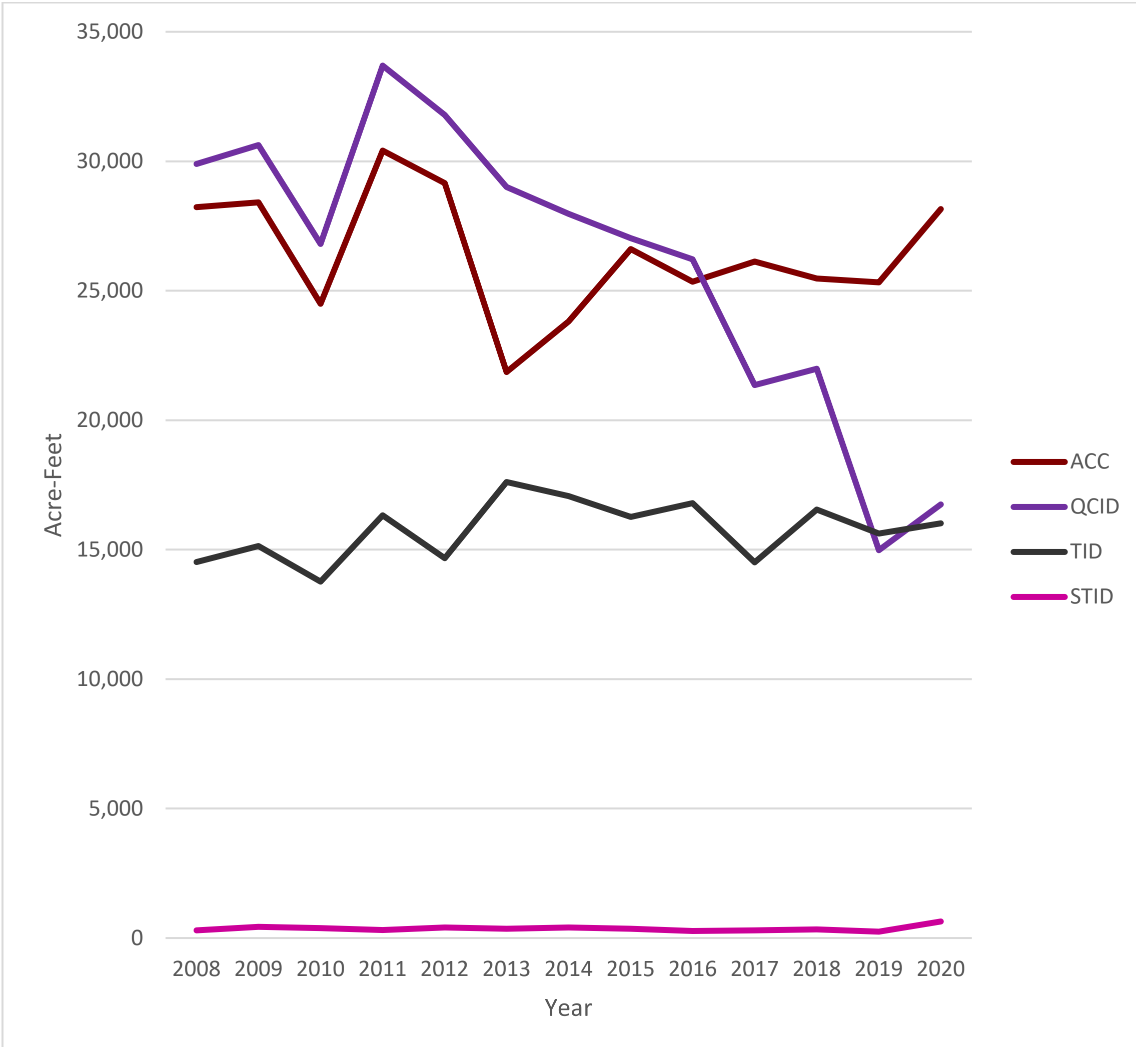
Figure 3: Water Deliveries to Agriculture by Middle Six Districts



Data Source: ADWR

Note: These six districts have the middle average agricultural water deliveries.

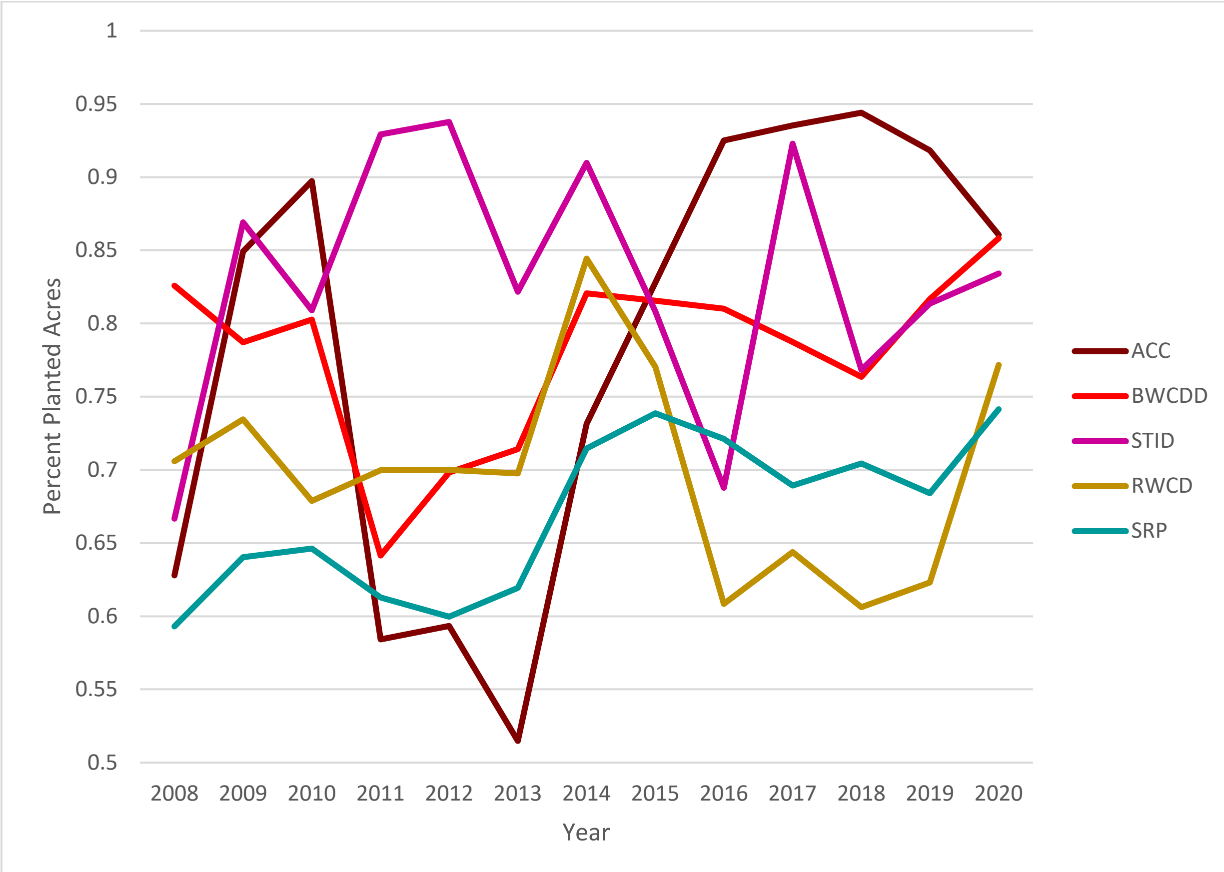
Figure 4: Water Deliveries to Agriculture by Bottom Four Districts



Data Source: ADWR

Note: These four districts have the lowest average agricultural water deliveries.

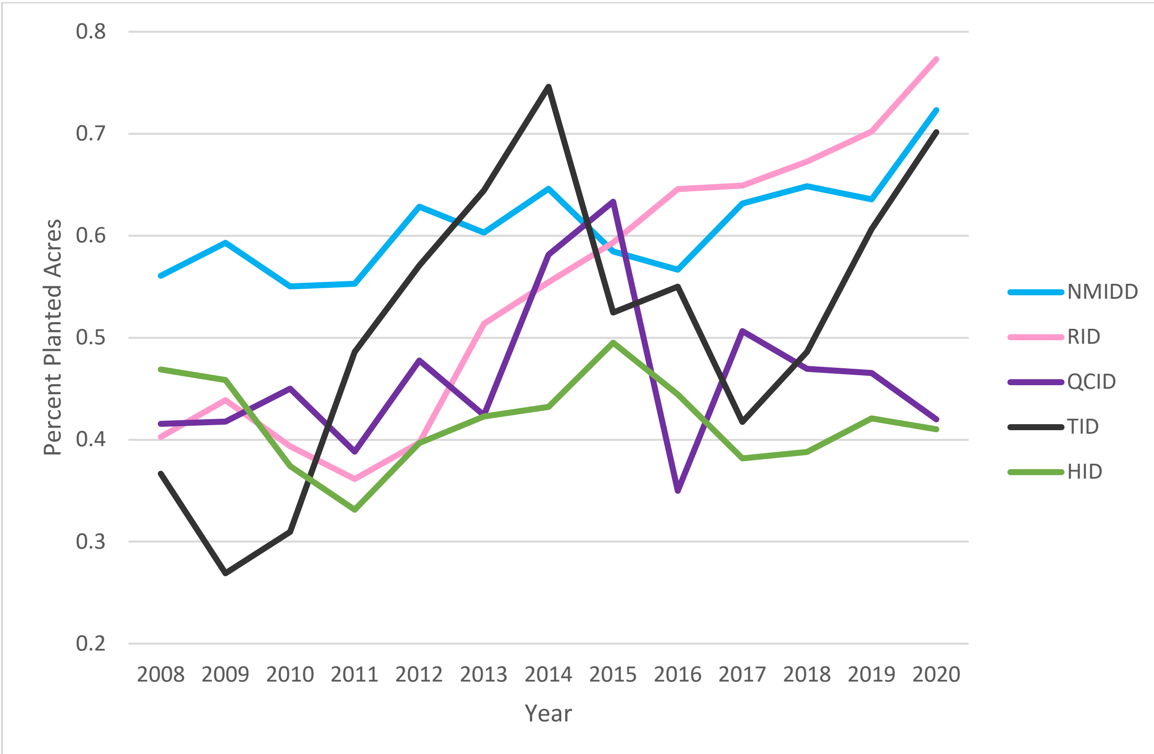
Figure 5: Share of Alfalfa Planted by Top Five Districts



Data Source: USDA NASS Cropland Data Layer

Note: These five districts have the highest average alfalfa percent planted.

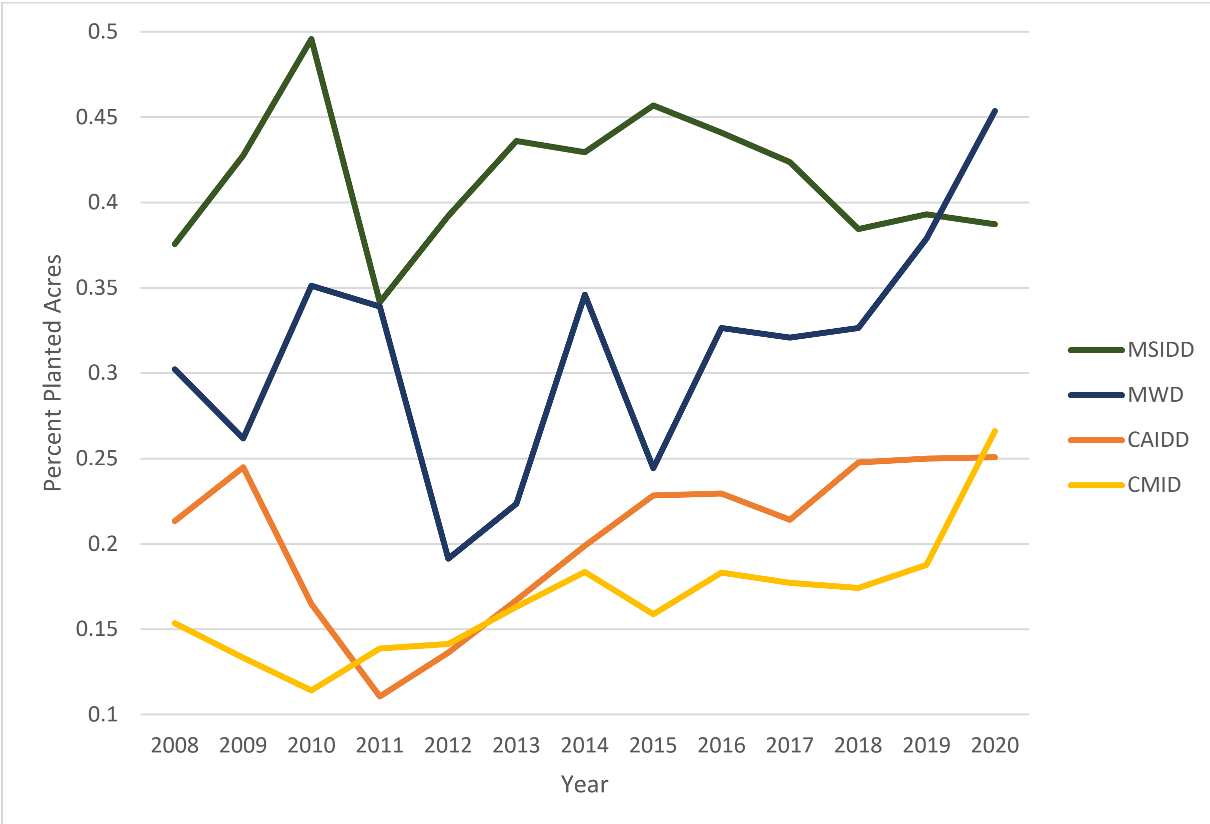
Figure 6: Share of Alfalfa Planted by Middle Five Districts



Data Source: USDA NASS Cropland Data Layer

Note: These five districts have the middle average alfalfa percent planted.

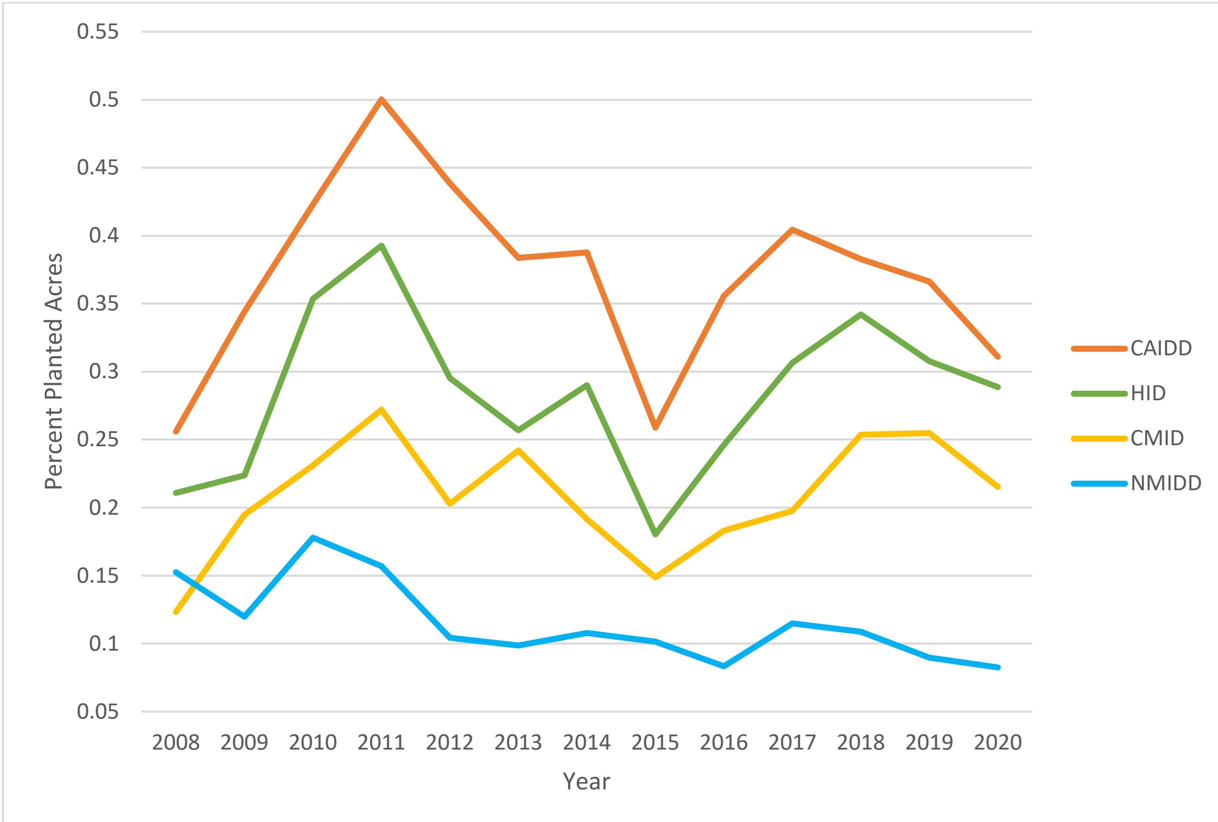
Figure 7: Share of Alfalfa Planted by Bottom Four Districts



Data Source: USDA NASS Cropland Data Layer

Note: These four districts have the lowest average alfalfa percent planted.

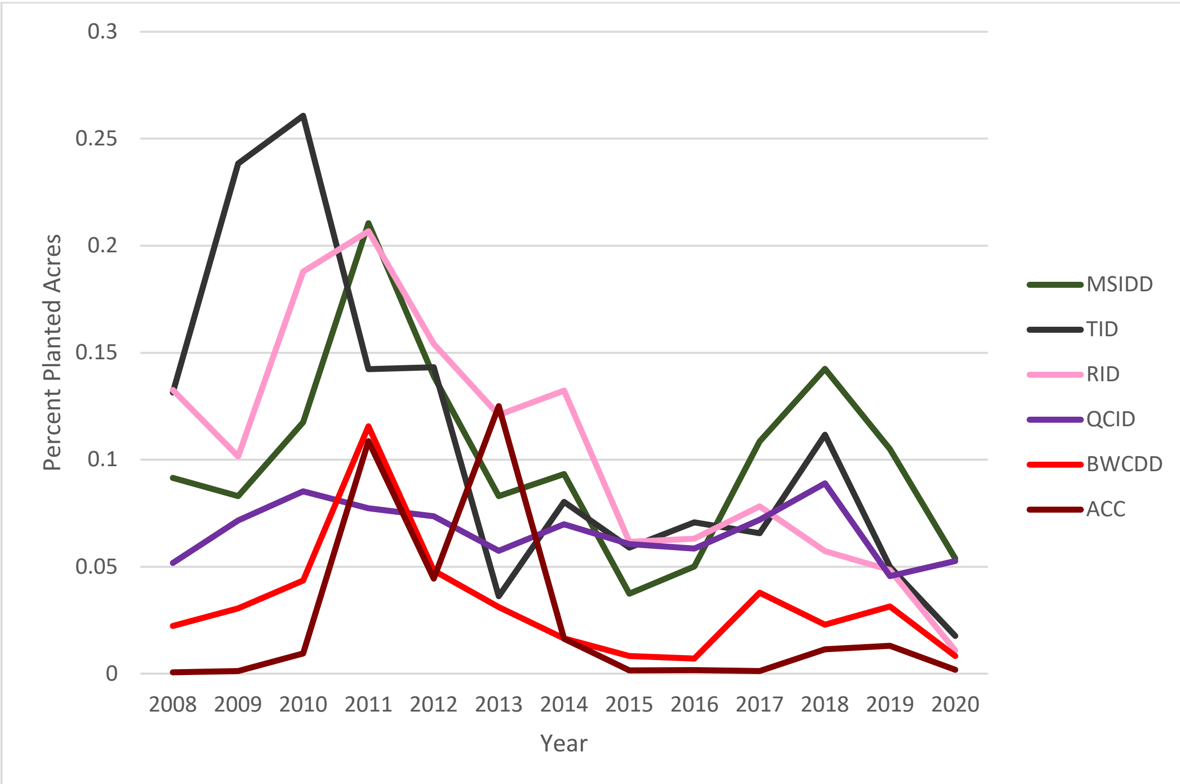
Figure 8: Share of Cotton Planted by Top Four Districts



Data Source: USDA NASS Cropland Data Layer

Note: These four districts have the highest average cotton percent planted.

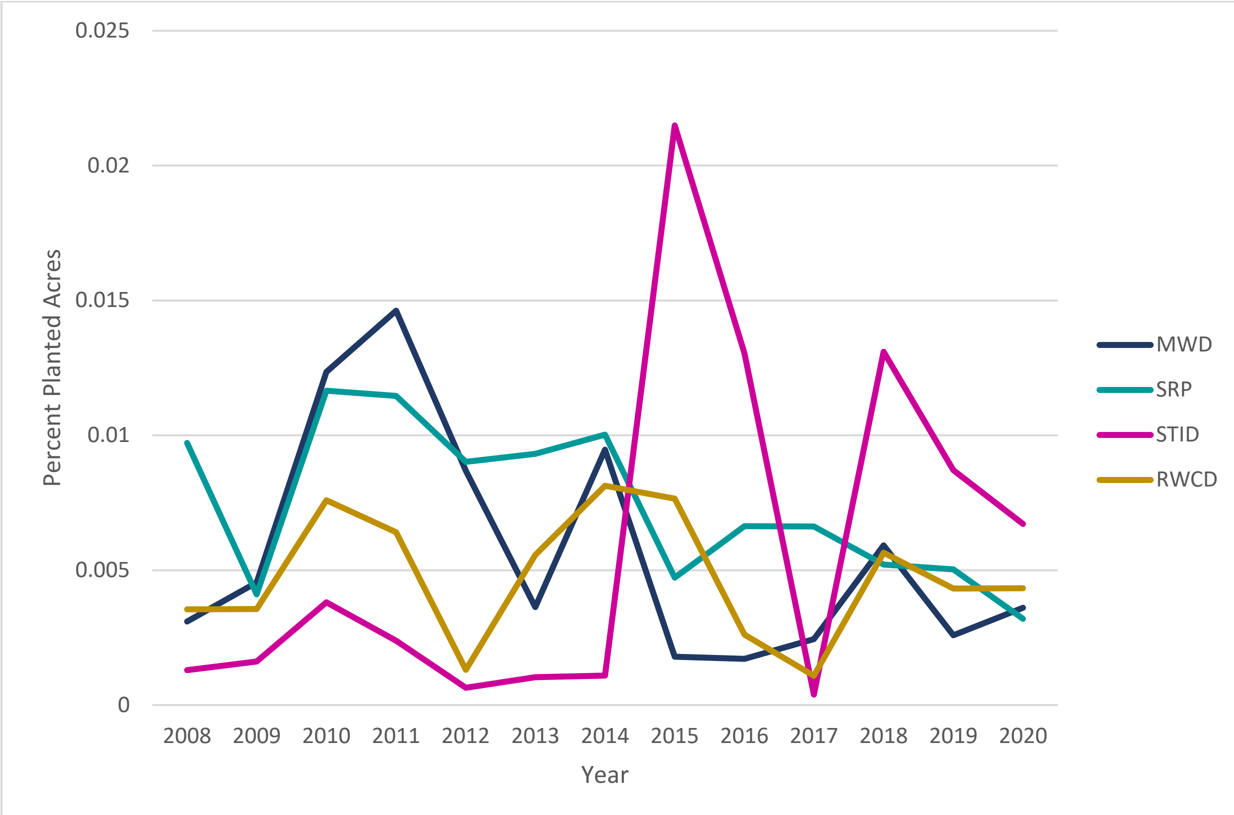
Figure 9: Share of Cotton Planted by Middle Six Districts



Data Source: USDA NASS Cropland Data Layer

Note: These six districts have the middle average cotton percent planted.

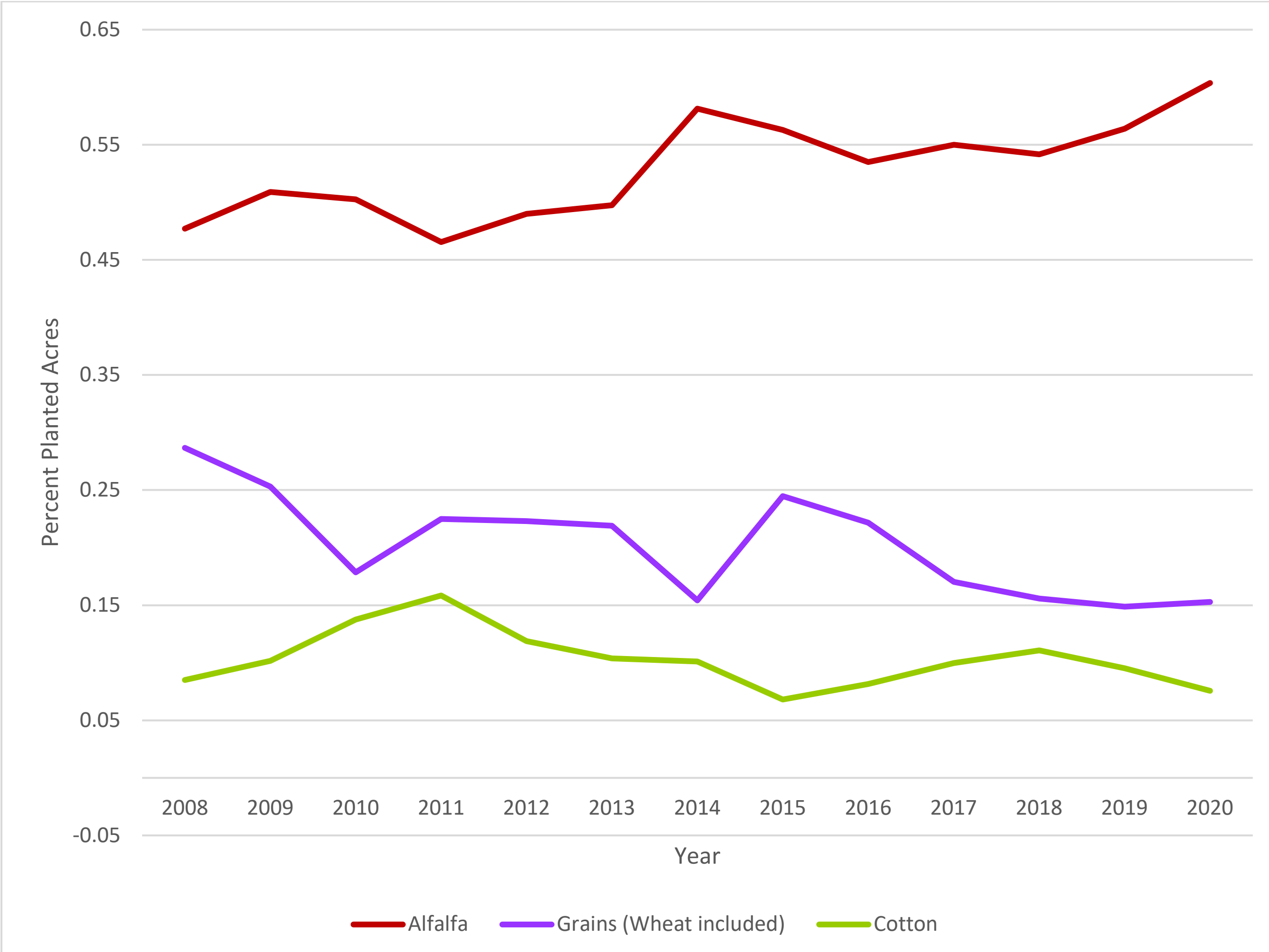
Figure 10: Share of Cotton Planted by Bottom Four Districts



Data Source: USDA NASS Cropland Data Layer

Note: These four districts have the lowest average cotton percent planted.

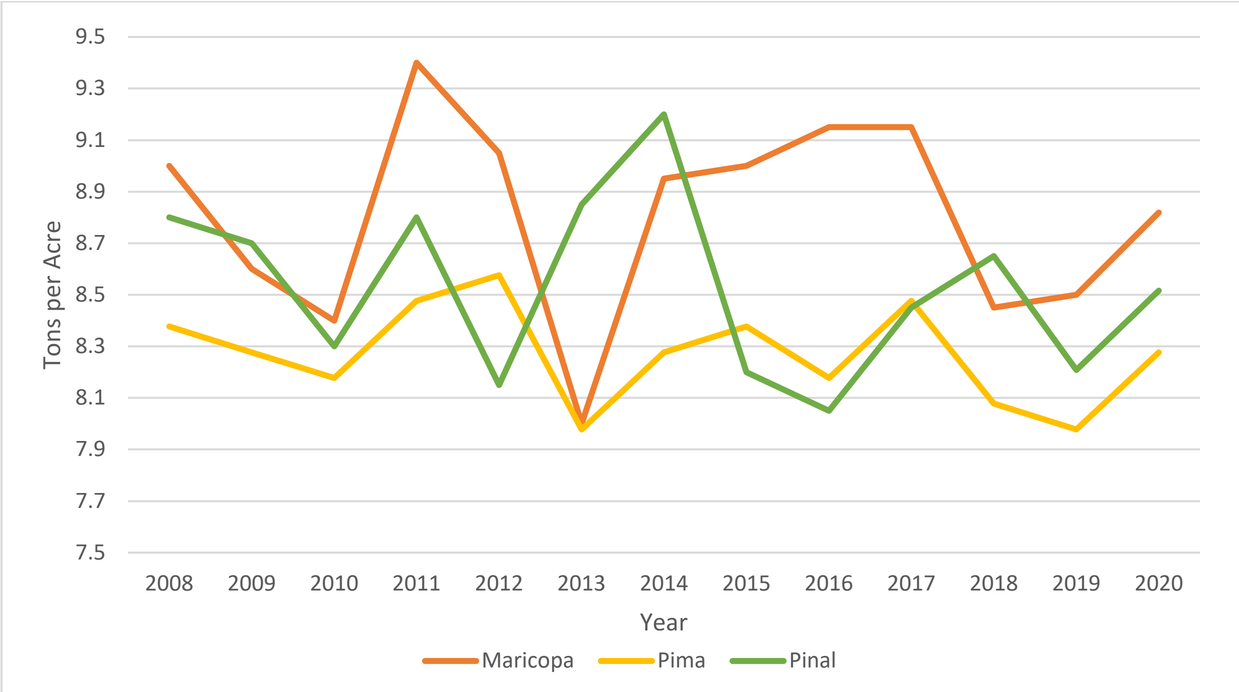
Figure 11: Average Share of Major Crops Planted by All Districts



Data Source: USDA NASS Cropland Data Layer

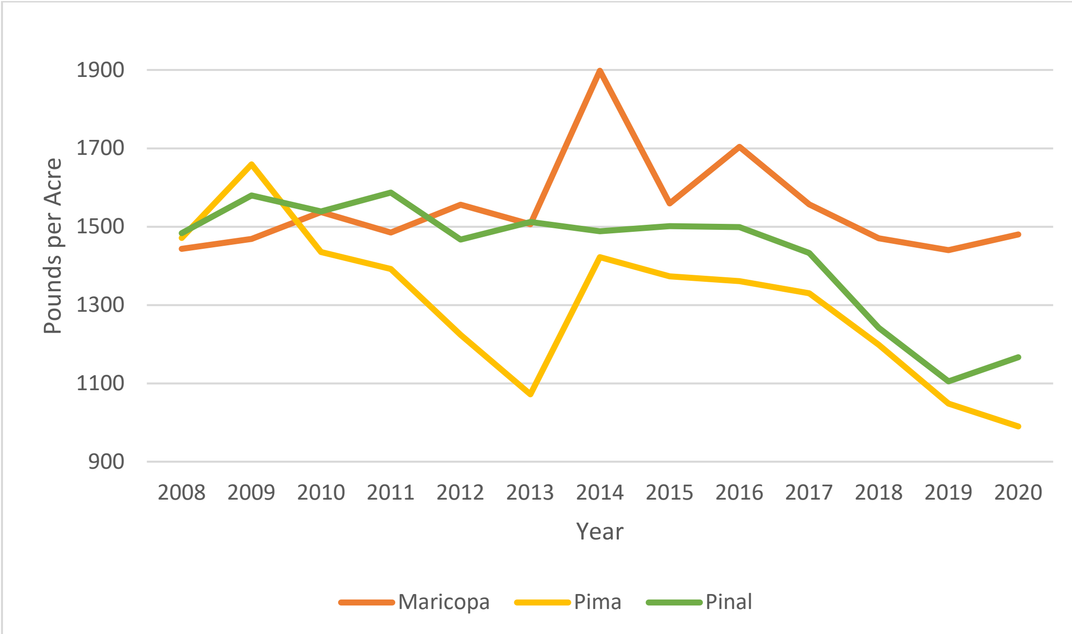
Note: The average share of each crop grouping is calculated across all fourteen districts.

Figure 12: County Alfalfa Yields



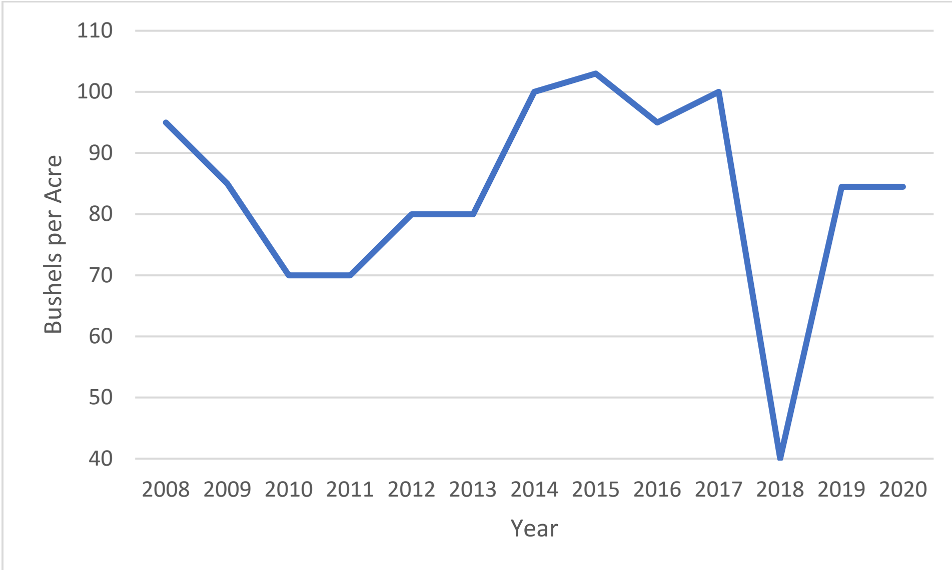
Data Source: USDA NASS

Figure 13: County Cotton Yields



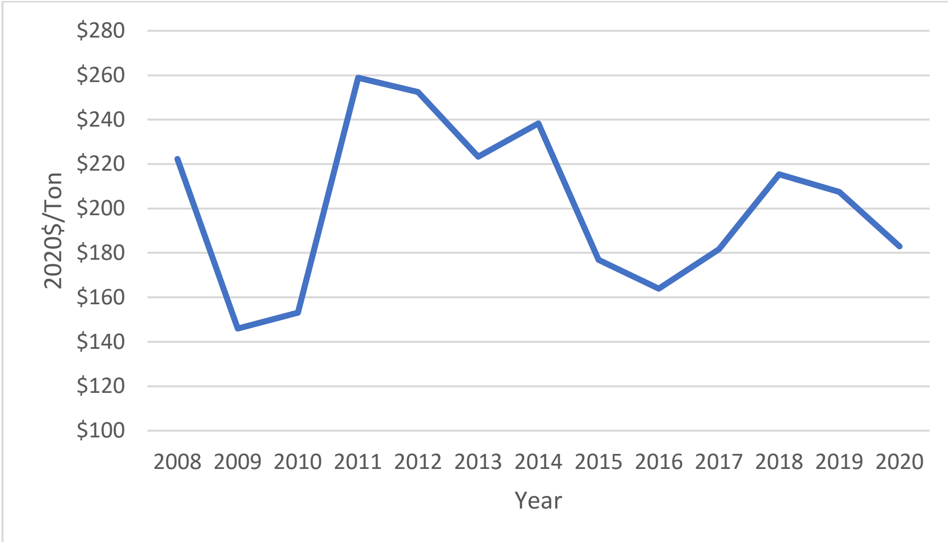
Data Source: USDA NASS

Figure 14: Arizona Winter Wheat Yields



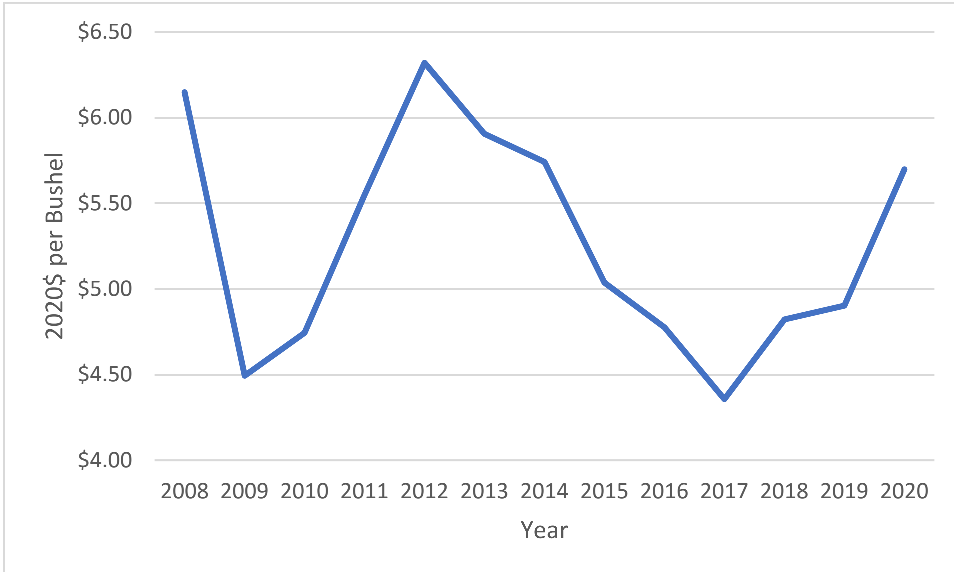
Data Source: USDA NASS

Figure 15: Real Arizona Alfalfa Prices



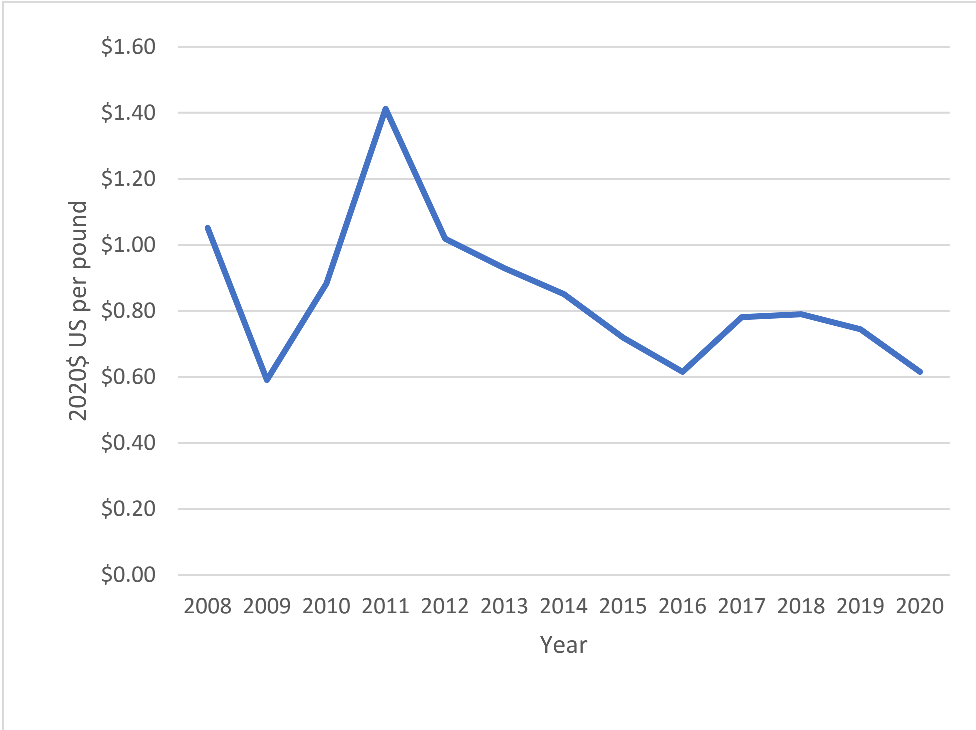
Data Source: USDA NASS

Figure 16: Arizona Winter Wheat Price



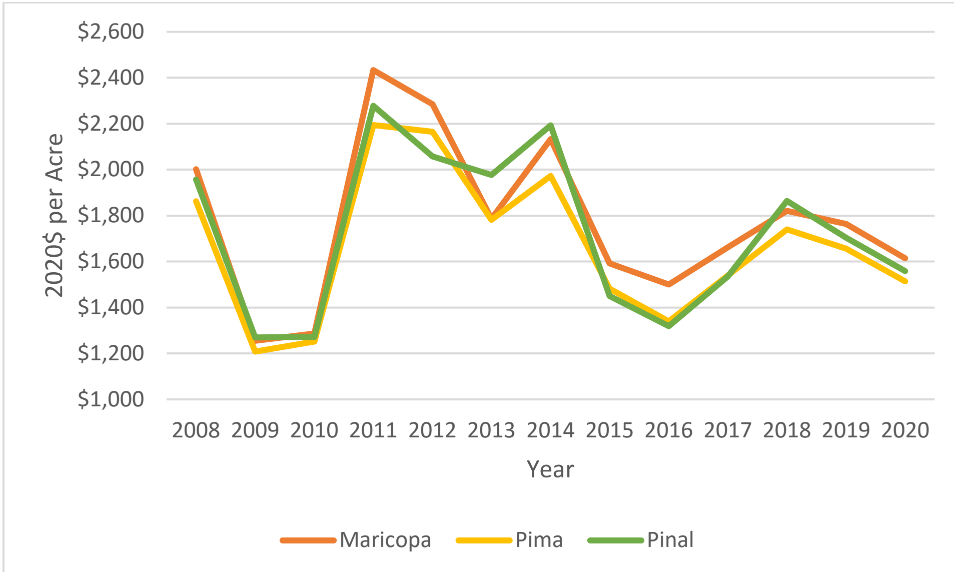
Data Source: USDA NASS

Figure 17: Real Cotton December Futures



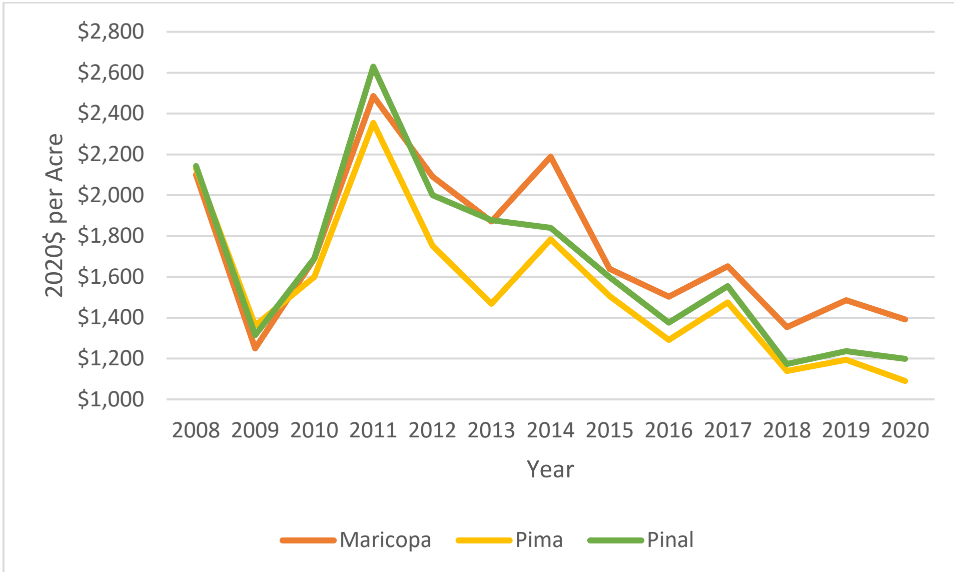
Data Source: New York Cotton Exchange

Figure 18: Real Alfalfa County Gross Revenue



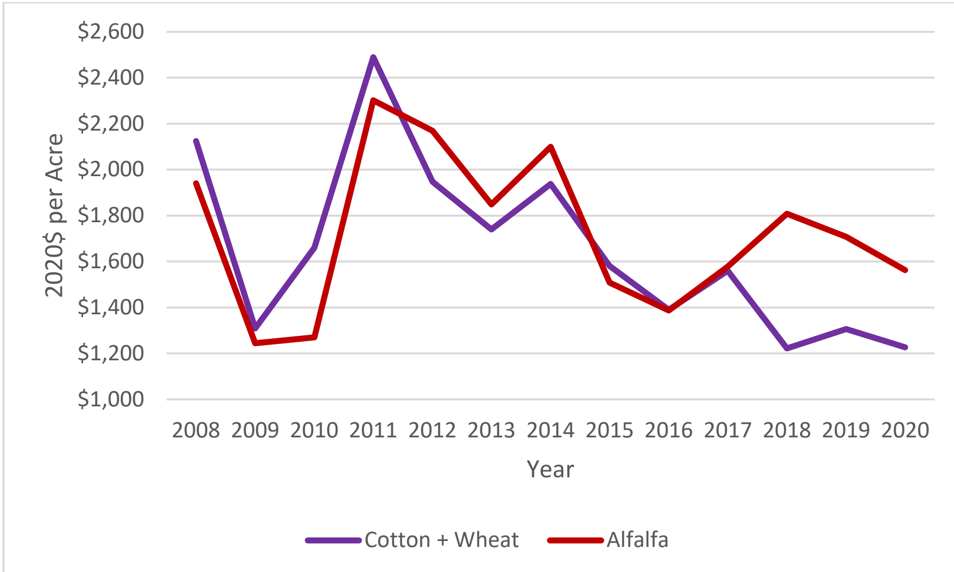
Data Source: USDA NASS

Figure 19: Real Cotton + Wheat County Gross Revenue



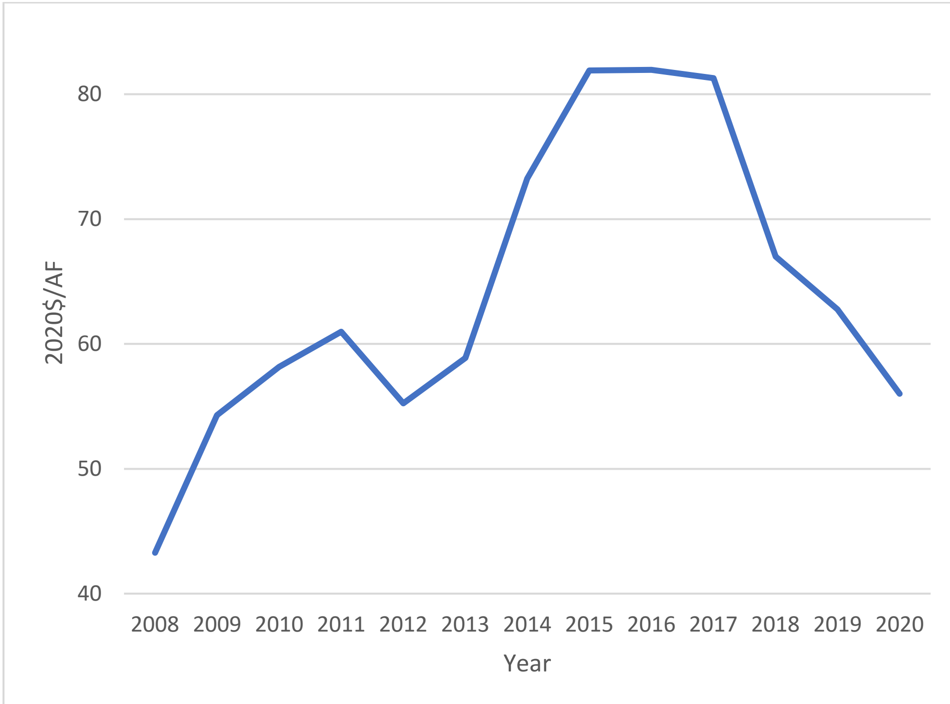
Data Source: USDA NASS and New York Cotton Exchange

Figure 20: Average Real Gross Revenue Across Maricopa, Pima, and Pinal Counties



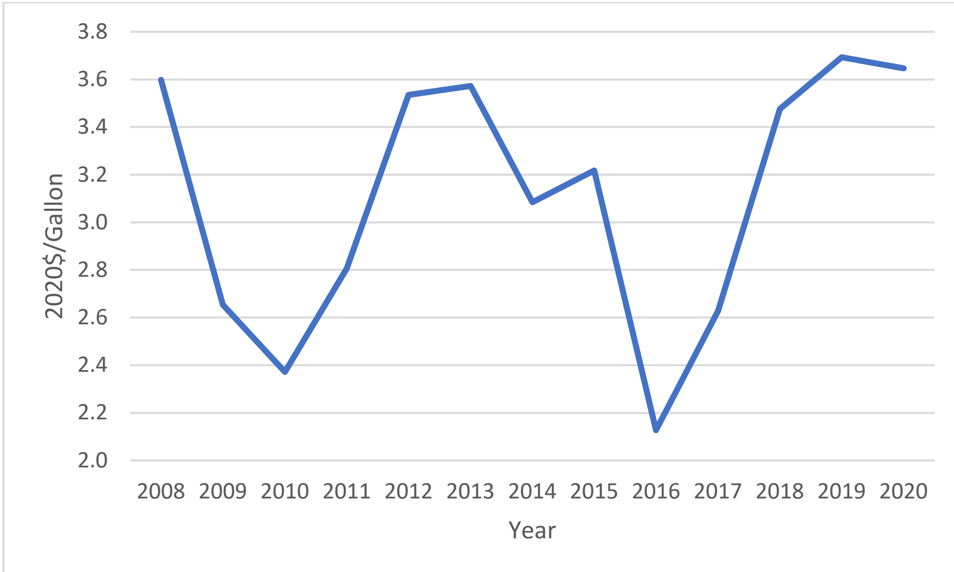
Data Source: USDA NASS and New York Cotton Exchange

Figure 21: Real CAP Water Prices



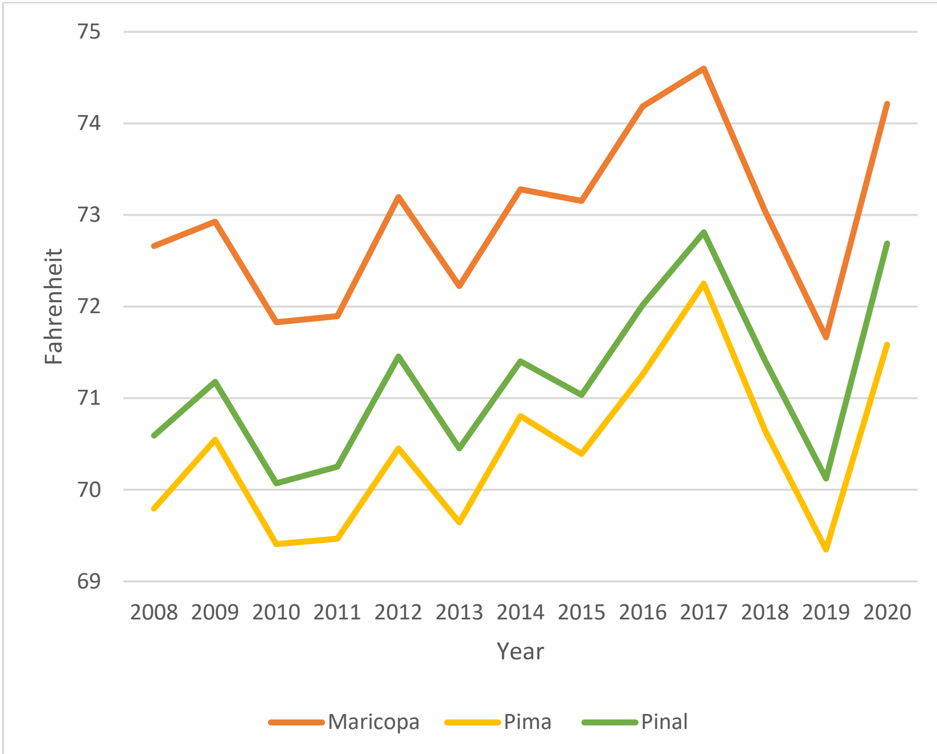
Data Source: CAP

Figure 22: Real Diesel Prices



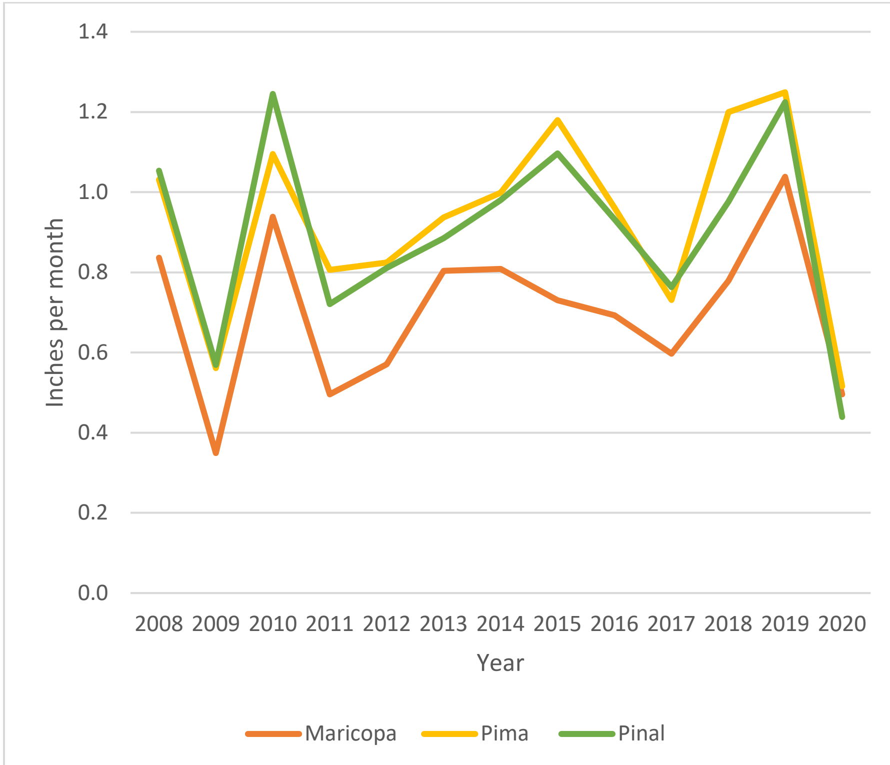
Data Source: US Energy Information Administration

Figure 23: Average County Temperature



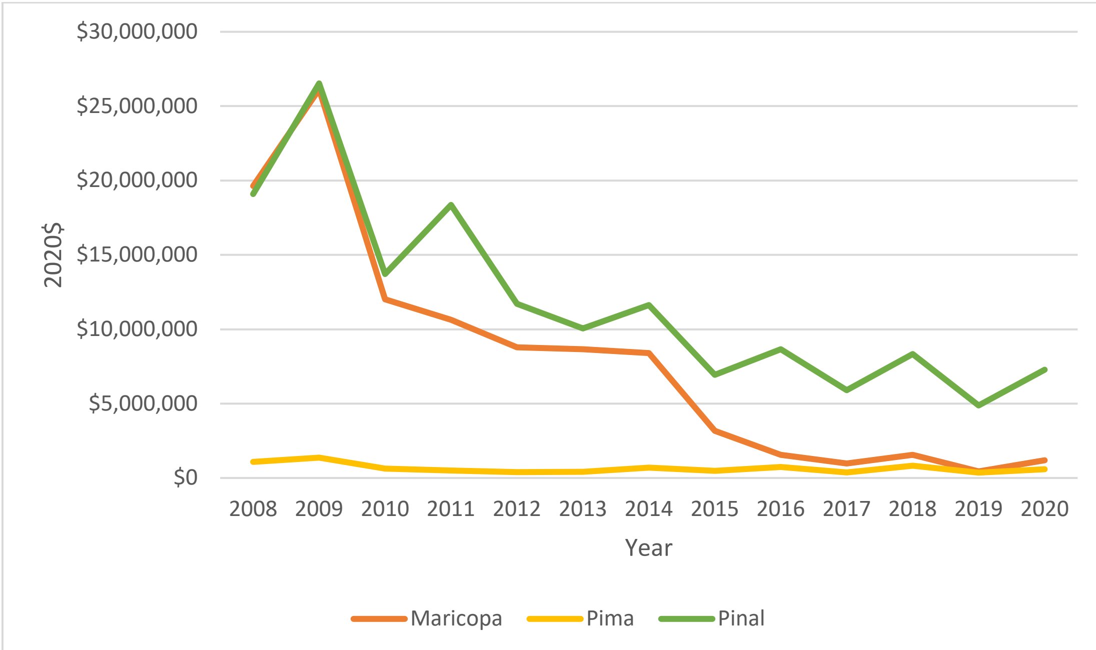
Data Source: West Wide Drought Tracker

Figure 24: Average County Precipitation



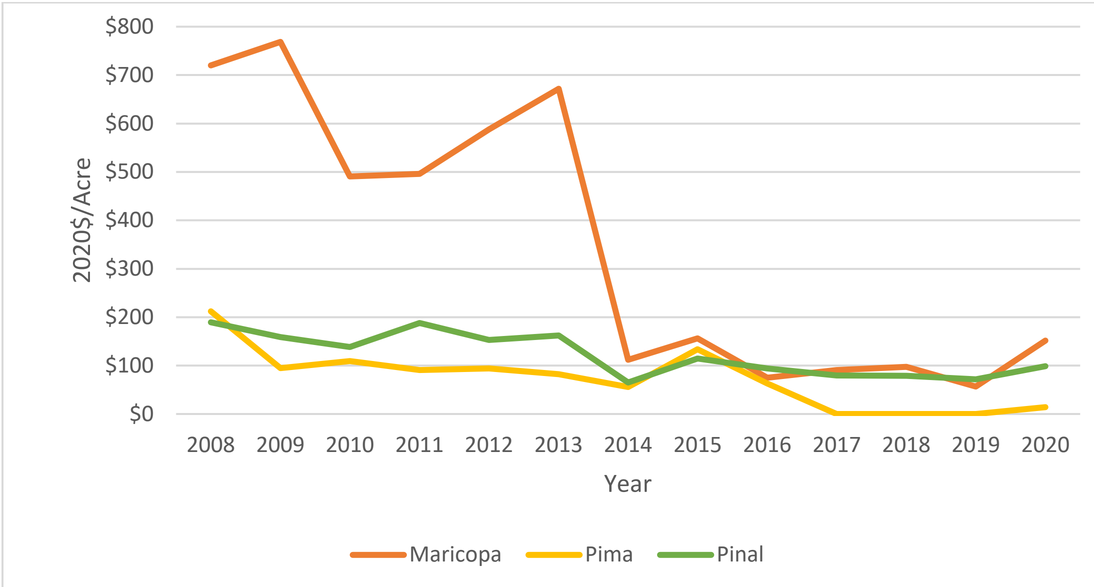
Data Source: West Wide Drought Tracker

Figure 25: Total Real Federal Cotton Commodity Payments



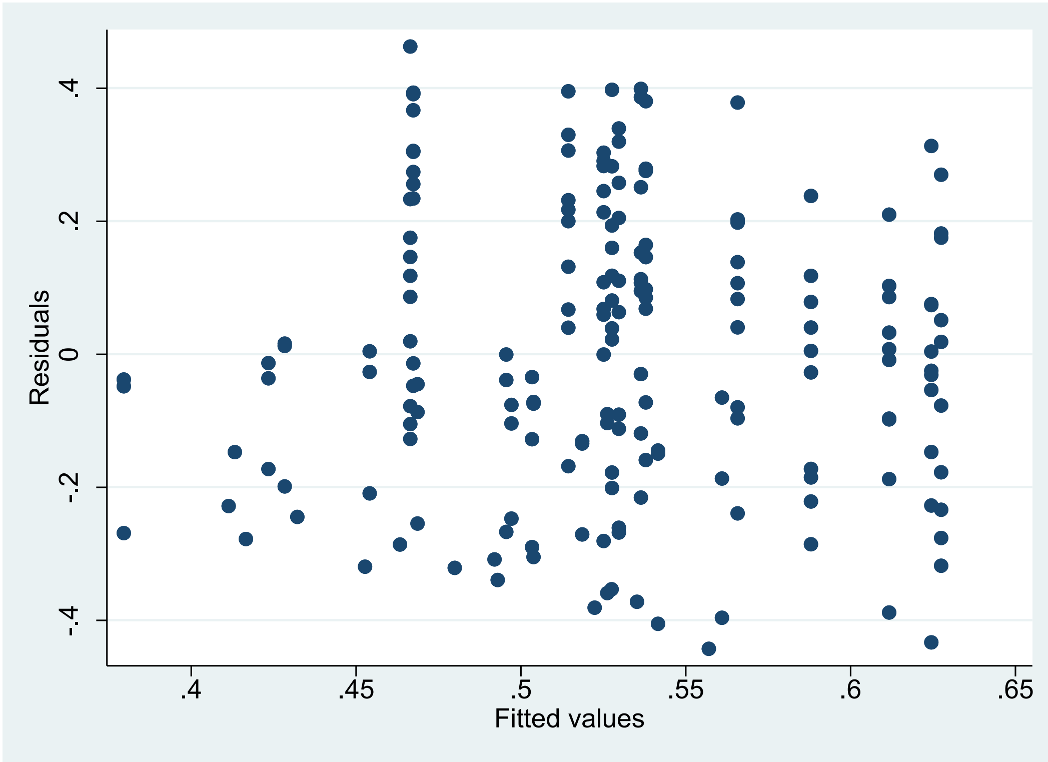
Data Source: EWG

Figure 26: Total County Cotton Payments Per Cotton Acre



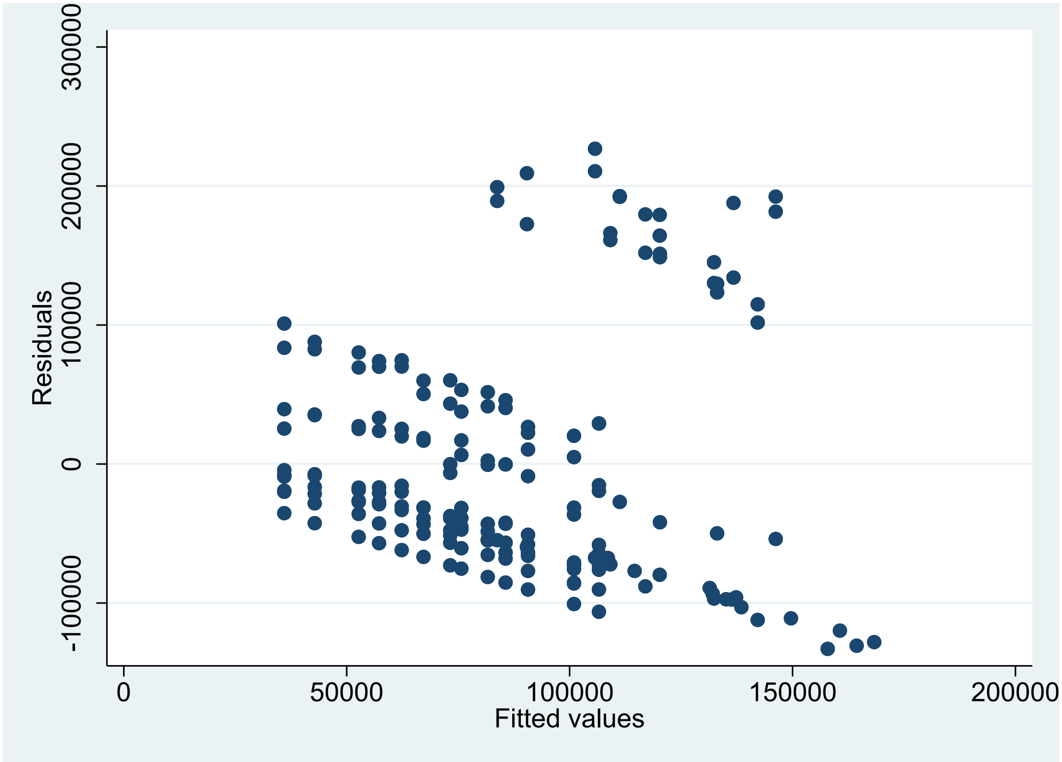
Data Source: EWG

Figure 27: Residuals – Percentage Planted Alfalfa



n = 182

Figure 28: Residuals – Agricultural Water Deliveries



n = 182

Tables

Table 1: Summary Statistics – Water Deliveries

	Water Deliveries	**Agricultural Water Deliveries**
Unit of Measure	acre-feet	acre-feet
Mean	126,216	86,851
Min	247	247
Max	593,828	338,502
Standard Deviation	150,344	90,151

n = 182

Table 2: Correlation Between Agricultural Water Deliveries and Planted Area by District

District	**Correlation Coefficient (Ag Water & Planted Area)**
Arlington Canal Company	-0.0726
Buckeye Water Conservation and Drainage District	-0.1762
Central Arizona Irrigation and Drainage District	0.3778
Cortaro-Marana Irrigation District	0.1343
Hohokam Irrigation District	0.5980
Maricopa-Stanfield Irrigation and Drainage District	0.3358
Maricopa Water District	0.1225
New Magma Irrigation and Drainage District	0.2420
Queen Creek Irrigation District	0.6695
Roosevelt Irrigation District	0.3854
Roosevelt Water Conservation District	0.5077
Salt River Project	0.7149
San Tan Irrigation District	-0.0382
Tonopah Irrigation District	0.1912
Overall	0.9662

Table 3: Summary Statistics – Irrigation Districts

District	AMA	Average Ag Deliveries (AF)	Total Acres	Average Planted Acres
Arlington Canal Company	Phoenix	26,417	5,481	3,894
Buckeye Water Conservation and Drainage District	Phoenix	122,838	21,905	16,422
Central Arizona Irrigation and Drainage District	Pinal	293,259	108,913	69,697
Cortaro-Marana Irrigation District	Tucson	37,718	20,692	8,773
Hohokam Irrigation District	Pinal	49,745	28,371	21,281
Maricopa-Stanfield Irrigation and Drainage District	Pinal	278,310	103,622	58,328
Maricopa Water District	Phoenix	36,172	36,350	7,442
New Magma Irrigation and Drainage District	Phoenix	81,195	27,199	17,461
Queen Creek Irrigation District	Phoenix	26,007	20,278	6,629
Roosevelt Irrigation District	Phoenix	129,057	39,207	23,684
Roosevelt Water Conservation District	Phoenix	38,084	41,550	7,815
Salt River Project	Phoenix	80,988	257,710	16,729
San Tan Irrigation District	Phoenix	367	3,446	428
Tonopah Irrigation District	Phoenix	15,757	4,142	3,271

n = 13 for each irrigation district

Table 4: Summary Statistics – Crop Cover by Irrigation Districts

District	Average Alfalfa Acres	Average Cotton Acres	Average Grains Acres	Average Trees Acres	Average Pasture Acres	Average Other Crops Acres	Average Fallowed Acres
ACC	3,061 (79%)	142 (4%)	296 (8%)	2 (<1%)	4 (<1%)	391 (10%)	303
BWCDD	12,802 (78%)	713 (4%)	1,800 (11%)	3 (<1%)	4 (<1%)	1,101 (7%)	1,238
CAIDD	14,222 (20%)	40,320 (58%)	11,841 (17%)	878 (1%)	378 (1%)	2,246 (3%)	20,261
CMID	1,464 (17%)	4,315 (49%)	2,882 (33%)	8 (<1%)	10 (<1%)	104 (1%)	1,653
HID	8,875 (42%)	8,064 (38%)	3,859 (18%)	22 (<1%)	10 (<1%)	455 (2%)	4,561
MSIDD	24,115 (41%)	10,483 (18%)	18,772 (32%)	248 (<1%)	326 (1%)	4,492 (8%)	25,766
MWD	2,305 (31%)	208 (3%)	2,311 (31%)	2 (<1%)	81 (1%)	2,551 (34%)	6,417
NMIDD	10,636 (61%)	3,136 (18%)	2,657 (15%)	9 (<1%)	12 (<1%)	1,017 (6%)	3,434
QCID	3,082 (46%)	1,349 (21%)	1,755 (26%)	61 (1%)	30 (<1%)	352 (6%)	2,689
RID	12,956 (55%)	4,088 (17%)	5,385 (23%)	<1 (<1%)	11 (0%)	1,244 (5%)	5,612
RWCD	5,464 (70%)	197 (3%)	1,462 (19%)	103 (1%)	143 (1%)	445 (6%)	3,367
SRP	11,182 (67%)	1,917 (11%)	2,396 (14%)	151 (1%)	112 (1%)	972 (6%)	6,144
STID	354 (83%)	20 (4%)	23 (6%)	14 (3%)	7 (1%)	10 (2%)	595
TID	1,682 (51%)	448 (14%)	990 (30%)	0 (0%)	8 (0%)	143 (4%)	300

n = 13 for each irrigation district. Percentage of planted acres in paratheses

Table 5: Cropland Data Layer Variables

Variable	**CDL Category**
Alfalfa Area	Alfalfa
Cotton Area	Cotton
Grains Area	Corn, Sorghum, Barley, Durum Wheat, Winter Wheat
Trees Area	Citrus, Pecans, Pears, Pistachios, Olives, Oranges, Grapes
Pasture Area	Grassland/Pasture
Other Crop Area	Cantaloupes, Watermelon, Rye, Spring Wheat, Lettuce, Other Hay (not Alfalfa), Oats, Dry Beans, Potatoes, Carrots, Chickpeas, Millet, Broccoli, Cabbage, Honeydew, Double Croppings
Fallowed Area	Fallow/Idle Cropland
Developed Area	Developed Open Space, Low Development, Medium Development, High Development

Table 6: OLS Percent Planted Alfalfa Model Results

	Percent Alfalfa
R^2	0.0702
n	182
Lagged Precipitation	-0.2524*** (0.0843)
Federal Cotton Payments per Acre	0.00003 (0.00007)
Lagged Alfalfa Gross Revenue	0.00006 (0.00007)
Lagged Cotton + Wheat Gross Revenue	-0.00003 (0.00007)
Constant	0.6665

Standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table 7: OLS Water Deliveries Model Results

	Water Deliveries
R^2	0.1230
n	182
Temperature	-29,599.19*** (7,202.59)
Precipitation	-30,950.36 (39,620.38)
CAP Water Price	905.16 (626.95)
Alfalfa Gross Revenue	6.27 (29.66)
Cotton + Wheat Gross Revenue	-6.97 (27.15)
Constant	2,196,832

Standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table 8: Tests for Heteroskedasticity

Model	Test	χ^2	p-value	Reject at 5%?	Reject at 10%?
Percent Alfalfa Model	Breusch-Pagan	0.26	0.6108	NO	NO
Water Deliveries	Breusch-Pagan	47.39	< 0.0001	YES	YES
Percent Alfalfa FE Model	Wald Test for Groupwise Heteroskedasticity	1,163.30	< 0.0001	YES	YES
Water Deliveries FE Model	Wald Test for Groupwise Heteroskedasticity	2,198.59	< 0.0001	YES	YES

Table 9: Fixed-Effects Percent Planted Alfalfa Model Results

	Percent Alfalfa
R^2 Within	0.2285
R^2 Between	0.5246
n	182
Lagged Precipitation	0.0531* (0.0252)
Federal Cotton Payments per Acre	-0.0001*** (0.00004)
Lagged Alfalfa Gross Revenue	0.00007** (0.00002)
Lagged Cotton + Wheat Gross Revenue	-0.00004* (0.00002)
Constant	0.4864

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table 10: Fixed-Effects Water Deliveries Model Results

	Water Deliveries
R^2 Within	0.2886
R^2 Between	0.1786
n	182
Temperature	-195.94 (822.79)
Precipitation	-13,822.73*** (3,478.73)
CAP Water Price	-73.06 (62.66)
Alfalfa Gross Revenue	-5.02 (6.86)
Cotton + Wheat Gross Revenue	19.02*** (6.25)
Constant	92,475.54

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

A Appendices

A.1 Data Notes

Whenever possible, it is preferred to use raw data in the construction of the dataset used in these analyses. However, some variables required cleaning, fill, and variable construction procedures before being included in models. This section details the data work undertaken to ensure inclusion in the final models. Procedures are separated by major variable categories/sources. Table A1 shows the observations for each variable that are filled using the following estimation procedures.

Irrigation District Annual Water Use

All irrigation districts' annual reports are available except for the 2008 Cortaro-Marana Irrigation District annual report. The missing water deliveries data for this year is estimated by the average of the other available years. When the annual report is available, the best source for deliveries is the Schedule D1S which reports the summaries of deliveries by source and type. Some irrigation districts do not include the Schedule D1S in their report. When that is the case, the next best action is to manually sum all deliveries to water rights beginning with '58-' (farm-owned irrigation grandfathered rights), '57-' (district-owned irrigation grandfathered rights), or '88-' (irrigation rights on a farm registered as having "Best Management Practices") on the Schedule D, but this method is not preferred as it is tedious and prone to human error (McGreal, 2021). The San Carlos Irrigation and Drainage District (SCIDD) does not include either the Schedule D1S or Schedule D in their annual reports. Because the SCIDD represents such a large proportion of water deliveries in the Pinal AMA, it is still included in the preliminary models of this work, but ultimately excluded because of major structural differences. It is discussed further in Appendix A.2. "Total Water Delivered To Lands" acts as a fair proxy for total water deliveries to SCIDD. The sum of CAP, allocated surface water, pumped water, and natural flows is used as the proxy for agricultural water deliveries in SCIDD (McGreal, 2021).

EWG Commodity Data Cleaning and Variable Construction

Environmental Working Group (EWG) subsidy data for Arizona counties is reported through 2019. To fill the missing 2020 observation of cotton commodity payments, the average value for 2016-2019 for each county is taken. As with all other monetary variables, commodity payments are corrected for inflation using the CPI for 2020.

A relative index was considered as an alternative federal cotton commodity variable. The relative index for each county shows how payments have changed over time since 2008. It is unaffected by fluctuating participation rates but does not account for acres planted. First, each year's real total payments were divided by the 2008 payment. This lets 2008 equal 1.0 in the index. Values greater than 1.0 indicate an increase in payments compared to 2008 and the opposite is true for values less than 1.0. This procedure is repeated for each of the three counties (Maricopa, Pinal, and Pima). This preliminary variable was abandoned for the preferred per acre commodity payment variable.

ERS Data Summary & Procedures

To construct the index reflecting costs of cotton production, the Value of Production less Operating Costs for the Fruitful Rim cotton from 2008-2020 is first adjusted to 2020$. Using these real dollar values for the value of production less operating cost, the construction procedure of a relative index is similar to the one constructed for the EWG commodity payments. Each year's real value of production is divided by the 2008 value of production. The 2008 index value equals 1.0. Index values greater than 1.0 indicate greater values of production compared to 2008.

USDA NASS Crop Yields

County crop yields for cotton and alfalfa are two of the variables considered for inclusion but ultimately not chosen for the final model specifications. They are used in the gross revenue measure. For the most part, annual county yields are available for both crops across the study region. Some missing years occur. To combat this issue of missing county alfalfa yields for 2019 and 2020, the percentage of county yields as state yield for each year is taken. This gives an annual proportion of state yields for each county. Then take the average of the annual proportions from 2012-2018 for Maricopa, Pima, and Pinal separately. That average county proportion is multiplied by the state level to get an average of the final two years yields. Pima county also has missing observations in 2008, 2013, and 2014. These missing values are filled by using the same procedure for estimation of 2019 and 2020 values for all counties. Upland cotton yields data are reported through 2020, but just as with the alfalfa yield data from NASS, Pima county is missing observations for cotton yields for 2015, 2017, 2018, and 2019. The same process as the alfalfa estimation is used but for cotton in Pima county by taking the average proportion of all available years in Pima county from 2008-2020. The average cotton yield proportion is then multiplied with the state yield to estimate the Pima county cotton yield.

Winter wheat is examined in rotation with cotton. County level winter wheat yields are not reported by the USDA NASS so state level yields are used instead. The 2019 and 2020 winter wheat yield values are not reported by the USDA NASS. These observations are estimated using the average yield values from 2015-2018. This means that the values for 2019 and 2020 are equal.

USDA NASS Crop Prices

Arizona winter wheat prices are reported through the USDA NASS. The state level price is not available from 2011-2014 to preserve farmer privacy. It is also unavailable in 2019 and 2020. The average wheat price is available for all years in the study and is used to help estimate the winter wheat price. The proportion of winter wheat prices to wheat prices is calculated for years with available winter wheat price data. These percentages are averaged across all available years. This average proportion of wheat price is multiplied by the state wheat price to estimate the winter wheat price in years where it is not reported.

Table A1: Missing Observations Filled

Year	Cotton Payments	Maricopa Alfalfa Yield	Pima Alfalfa Yield	Pinal Alfalfa Yield	Pima Cotton Yield	AZ Winter Wheat Yield	AZ Cotton Price	AZ Winter Wheat Price	CMID Water Deliveries
2008			X						X
2009									
2010									
2011								X	
2012								X	
2013			X					X	
2014			X					X	
2015					X		X		
2016							X		
2017					X				
2018					X				
2019		X	X	X	X	X		X	
2020	X	X	X	X		X		X	

A.2 San Carlos Irrigation and Drainage District Inclusion Effects

The San Carlos Irrigation and Drainage District (SCIDD) is very different from all other irrigation districts included in this study. This section details differences in results when SCIDD is included in the estimated models. In McGreal and Colby's (2022) study of central Arizona irrigation districts' water deliveries and irrigation intensity, SCIDD is excluded because of structural and functional differences. The SCIDD's main purpose is to deliver Gila River water from San Carlos Lake, a reservoir that has been hit hard by reduced water supply in recent years (McGreal and Colby, 2022; Tronstad, 2022). Cotton farmers in SCIDD have been responsible for a large share of Arizona indemnity claims because the failure of their water supply preventing planting. These factors are considered in this study by estimating irrigation district crop mix and water deliveries with SCIDD included and excluded. Differences arise in both models mainly in the form of weather variables. This is not particularly surprising because of the precarious situation SCIDD and their reservoir water source have been in in recent years. Ultimately, the differences between SCIDD and the fourteen irrigation districts in this study lead to the exclusion of SCIDD from the final model results.

The final choice alfalfa model results in Table 9 are estimated without the inclusions of the SCIDD. Results between the two alfalfa models estimated without SCIDD and with SCIDD are mostly consistent. Table A2 shows the results for the SCIDD percentage alfalfa fixed-effects model. The R^2 *Within* of 0.2201 and the R^2 *Between* of 0.5271 are nearly equivalent to the model results in Table 9. The most noticeable difference between the alfalfa models is the insignificance of precipitation when estimating with SCIDD included in the dataset. This result persists in multiple variations of the crop mix models.

The results for the SCIDD water deliveries model are contained in Table A3. The two water deliveries models estimated with and without SCIDD have the same statistically significant variables, precipitation and gross revenue of cotton + wheat; however, the level of significance is greater when SCIDD is excluded. Both the R^2 *Within* and the R^2 *Between* are higher. In preliminary OLS water deliveries models, some differences in variable significance did exist. For example, when the ratio of gross revenue lagged variable is included, temperature instead of precipitation is significant in the SCIDD model. The size of estimated coefficients also changes between models. In the SCIDD water deliveries model, the constant is estimated as

38,281 AF which is much lower than the constant estimated in the model in Table 9 (92,476 AF). These differences between models are likely a consequence of the obvious structural differences and issues with water supply security between SCIDD and other irrigation districts.

Table A2: Fixed-Effects Percent Planted Alfalfa Model Results (SCIDD)

	Percent Alfalfa
R^2 Within	0.2201
R^2 Between	0.5271
n	195
Lagged Precipitation	0.0433 (0.0251)
Federal Cotton Payments per Acre	-0.0001*** (0.00004)
Lagged Alfalfa Gross Revenue	0.00006** (0.00002)
Lagged Cotton + Wheat Gross Revenue	-0.00004* (0.00002)
Constant	0.4845

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table A3: Fixed-Effects Water Deliveries Model Results (SCIDD)

	Water Deliveries
R^2 Within	0.2746
R^2 Between	0.1297
n	195
Temperature	573.02 (1,126.20)
Precipitation	-10,327.81** (4,791.38)
CAP Water Price	-138.75 (88.93)
Alfalfa Gross Revenue	-8.59 (7.15)
Cotton + Wheat Gross Revenue	21.34*** (5.84)
Constant	38,281.4

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

A.3 Alternative Variables and Models Considered

Bt cotton costs

Bt cotton plants are a variety of cotton that has been genetically modified to make it more resistant to pests such as the bollworm and budworm. Sall and Tronstad (2021) include a variable for the cost of Bt cotton per acre in their econometric analysis of federal crop subsidy programs. This variable is explored as a possible explanatory variable. The Mississippi State University achieve of Beltwide Cotton Crop Loss database includes annual estimates of losses from cotton insect pest and acreage and price of Bt cotton in each state. This resource is used to collect Arizona's annual price of Bt cotton measured in the cost of Bt cotton per acre. As with all monetary variables, it is adjusted to 2020$. Due to the low occurrence of Bt cotton in the study region, it was ultimately excluded from all final models.

USDA Economic Research Service – Cotton Value of Production and Costs

The USDA Economic Research Service (ERS) reports annual estimates for costs and returns of twelve major commodities (cotton included) in the US and major production regions. These estimates are based on special Agricultural Resource Management Surveys conducted every 4-8 years and adjusted twice each year with estimates of annual price, acreage, and production changes. The ERS then reports the operating costs, allocated overhead, value of production, prices, yields, and quantities sold of each commodity (Padilla, 2020). This cost component is explored as a possible variable in the econometric models for water deliveries and crop mix decisions. The majority of Arizona (including the counties of interest in this study) is located within the Fruitful Rim region. The Fruitful Rim contains the greatest share of large and very large family and nonfamily farms. It accounts for 8% of US croplands and 22% of production. Cotton, fruits, vegetables, and nursery farms dominate the region (ERS, 2000). The USDA ERS Commodity Costs and Returns website reports the Cotton Costs and Returns data (ERS, 2022). The construction of an index of the value of production less the operating cost is the same as the procedure used for county yields as explained in Appendix A.1. The average difference between the estimated values for cotton and the actual available Pima cotton yields is less using the USDA NASS state yields (-7%) than the ERS regional yield (23%). The cotton yield estimates derived from the USDA NASS state yields is preferred. Because the ERS only reports commodity costs and returns at the regional level, the index values are the same for each county and irrigation district only varying across time. The index shows changes in the value of production less operating costs relative to the 2008 value. Any value greater than 1.0 indicates an increase in the real value less operating costs compared to 2008. Each years' value of production less operating cost has been greater than the 2008 value as seen in Figure A1. The regional spatial scale of this variable and the lack of an equivalent alfalfa measure are the main reasons for its exclusion from the body of this work.

Table A4: Alterative Fixed-Effects Percent Planted Cotton Model Results (Gross Revenues)

	Percent Cotton
R^2 *Within*	0.1753
R^2 *Between*	0.6901
n	182
Lagged Precipitation	-0.0237 (0.0173)
Federal Cotton Payments per Acre	-0.0006* (0.00003)
Lagged Alfalfa Gross Revenue	0.0001*** (0.00003)
Lagged Cotton + Wheat Gross Revenue	0.00006** (0.00002)
Constant	0.2809

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table A5: Preliminary Fixed-Effects Precent Planted Alfalfa Model Results

	Percent Alfalfa
R^2 *Within*	0.2234
R^2 *Between*	0.5297
n	182
Lagged Precipitation	0.0492* (0.0261)
Federal Cotton Payments per Acre	-0.0001** (0.00004)
Lagged Gross Revenue Ratio	0.0597** (0.0262)
Constant	0.4448

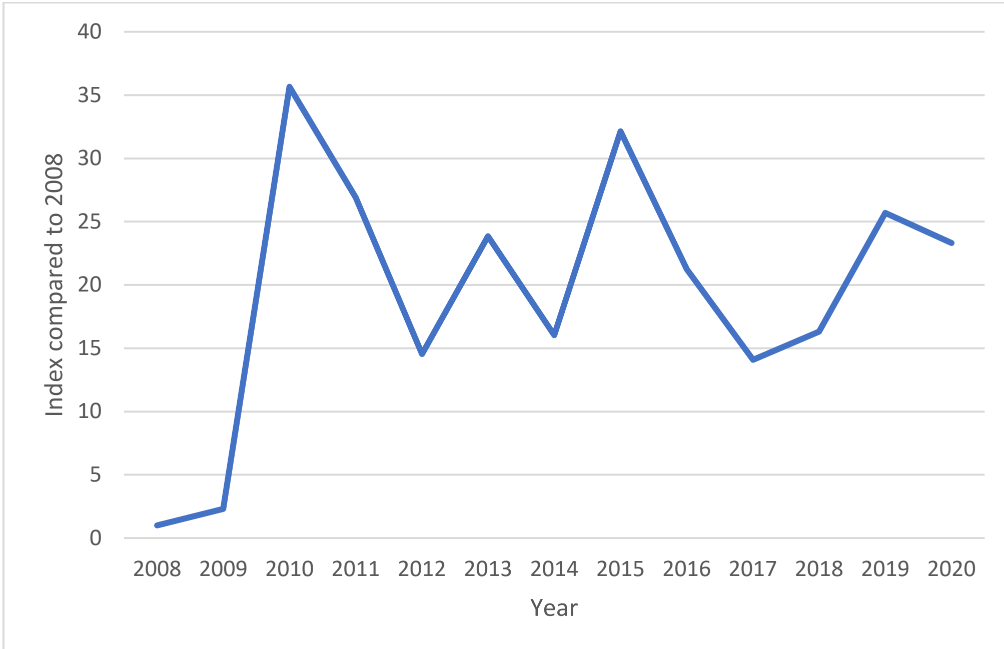
Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Table A6: Preliminary Fixed-Effects Water Deliveries Model Results

	Water Deliveries
R^2 Within	0.2113
R^2 Between	0.1980
n	182
Temperature	-386.04 (570.95)
Precipitation	-16,177.58*** (4,441.73)
CAP Water Price	-140.60* (77.11)
Gross Revenue Ratio	-17,591.97** (6,203.82)
Constant	161,285.1

Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

Figure A1: Real Value of Production less Operating Cost Index for Cotton



Data Source: USDA Economic Research Service

A.4 Meetings and Contacts

Mekha Pereira, Research Assistant
University of Arizona, Department of Hydrology and Atmospheric Sciences
mekhapereira@email.arizona.edu
January 28, 2022 – In person meeting
Topics: USDA NASS data, CropScape data and scripts, climatic variables from West Wide Drought Tracker.

Ashley Hullinger, Program Director, Water RAPIDS
University of Arizona, Water Resources Research Center
hullinger@arizona.edu
February 7, 2022 – In person meeting
Topics: Collaboration with DRPWRC, Implications of findings for rural communities and drought planning, visualization and mapping of data and trends.

Caroline Leary, General Counsel
Environmental Working Group
cleary@ewg.org
February 22, 2022 – Email
Topics: EWG data request and inquiry regarding 2020 cotton subsidy data.

Daniel Scheitrum, Assistant Professor
University of Arizona, Department of Applied Economics and Policy Analysis
dpscheitrum@arizona.edu
March 9, 2022 – Zoom meeting
Topics: Energy costs and diesel fuel costs from the U.S. Energy Information Administration as a proxy, interpretation of district dummies in fixed-effects models, logit regressions.

Gary Thompson, Professor and Department Head
University of Arizona, Department of Applied Economics and Policy Analysis
March 22, 2022 – In person meeting
gdthomps@email.arizona.edu
Topics: Modeling functional form and interpretations. Federal crop commodity variable. Crop mix dependent variable.

Russell Tronstad, Professor and Extension Specialist
University of Arizona, Department of Applied Economics and Policy Analysis
April 4, 2022 – In person meeting
tronstad@ag.arizona.edu
Topics: Federal commodity program payments for cotton and their influence on crop mix decisions.

References

Aaron, P., & Bryant, B. (2021). Reclamation announces 2022 operating conditions for Lake Powell and Lake Mead. *US Bureau of Reclamation*.

Aleshire, P. (2021). White Mountains well positioned for next crisis – water shortage. *White Mountain Independent*.

Anderies, J. M., Smith-Heisters, S., & Eakin, H. (2020). Modeling interdependent water uses at the regional scale to engage stakeholders and enhance resilience in Central Arizona. *Regional Environmental Change*, *20*(3), 1-16.

Arizona Department of Water Resources (2020). Irrigation districts within the active management areas.

Arizona Department of Water Resources (2022). Online data repository – annual water withdrawal and use report irrigation district summary.

Arizona Water Banking Authority (2022). Water Storage.

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, *46*, 555-561.

Bae, J., & Dall'erba, S. (2018). Crop production, export of virtual water and water-saving strategies in Arizona. *Ecological Economics*, *146*, 148-156.

Baum, C. F. (2008). Stata tip 63: Modeling proportions. *The Stata Journal*, *8*(2), 299-303.

Bickel, A. K., Duval, D., & Frisvold, G. (2018). Contribution of on-farm agriculture and agribusiness to the Pinal County economy. *University of Arizona, Cooperative Extension: Tucson, AZ, USA*.

Bickel, A. K., Duval, D., & Frisvold, G. B. (2019). Simple Approaches to Examine Economic Impacts of Water Reallocations from Agriculture. *Journal of Contemporary Water Research & Education*, *168*(1), 29-48.

Bilby, D. B., & Wilson, P. N. (2013). Regulatory capture? Arizona's BMP water conservation program. In *Western Economics Forum* (Vol. 12, No. 1837-2016-151811, pp. 29-37).

Blanc, E., & Schlenker, W. (2017). The use of panel models in assessments of climate impacts on agriculture. *Review of Environmental Economics and Policy, 20(2)*, 258-279.

Bourque, K., Schiller, A., Angosto, C. L., McPhail, L., Bagnasco, W., Ayres, A., & Larsen, A. (2019). Balancing agricultural production, groundwater management, and biodiversity goals: A multi-benefit optimization model of agriculture in Kern County, California. *Science of the total environment*, *670*, 865-875.

Bruder, J., & Ludwig, V. (2014). Fixed-effects panel regression. *The SAGE Handbook of Regression Analysis and Causal Inference*.

Bruno, E. M., & Jessoe, K. (2021). Using Price Elasticities of Water Demand to Inform Policy. *Annual Review of Resource Economics*, *13*.

Central Arizona Project (2022). Water Rates.

Earth Observing System (2019). Soil Moisture Control: An Essential Farming Constituent.

Economic Research Service (2000). Farm Resource Regions. *Agricultural Information Bulletin Number 760.*

Economic Research Service (2022). Commodity Costs and Returns.

Environmental Working Group (EWG) (2021). Farm Subsidy Database.

Erie, L., O. French, D. Bucks, & K. Harris (1982). Consumptive use of water by major crops in the southwestern United States. *US Department of Agriculture Economic research Service Conservation Research Report Number 29*, 42.

Evans, R. (2021). Husker study links crop insurance premium subsidies to fewer, larger farms. *Nebraska Today*.

Ferris, K., & Porter, S. (2021). Myth of Safe-Yield: Pursuing the Goal of Safe-Yield Isn't Saving Our Groundwater. *Arizona State University Kyl Center for Water Policy at Morrison Institute*.

Frisvold, G. (2015). Developing sustainability metrics for water use in Arizona small grain production. *Final report to the Arizona Grain Research and Promotion Council.*

Frisvold, G. B. (2016). Trends and patterns of water use in US cotton productions. *University of Arizona*.

Glauber, J. W. (2018). Unraveling Reforms? Cotton in the 2018 Farm Bill. *American Enterprise Institute.*

Goemans, C. & Kelley T. (2022). Comparative Profitability of Irrigated Cropping Activities for Temporary Water Transfers under Risk Aversion. Forthcoming in the *Journal of Agricultural and Resource Economics.*

Griffin, R.C. (2005). Chapter 2: Optimal Allocation and Development. *Water Resource Economics: The Analysis of Scarcity, Policies, and Projects.* The MIT Press.

Hanson, B., Putnam, D., & Snyder, R. (2007). Deficit irrigation of alfalfa as a strategy for providing water for water-short areas. *Agricultural water management*, *93*(1-2), 73-80.

Heien, D., & Wesseils, C. R. (1990). Demand systems estimation with microdata: a censored regression approach. *Journal of Business & Economic Statistics*, *8*(3), 365-371.

King, S. L., Laubhan, M. K., Tashjian, P., Vradenburg, J., & Fredrickson, L. (2021). Wetland conservation: challenges related to water law and farm policy. *Wetlands*, *41*(5), 1-17.

Lahmers, T., & Eden, S. (2018). Water and irrigated agriculture in Arizona. *Arroyo. University of Arizona Water Resources Research Center, Tucson, AZ.*

Leary, C. (2022). Private Communication, see Appendix A.4.

Lewis, J. B., & Linzer, D. A. (2005). Estimating regression models in which the dependent variable is based on estimates. *Political analysis*, *13*(4), 345-364.

Lindenmayer, R. B., Hansen, N. C., Brummer, J., & Pritchett, J. G. (2011). Deficit irrigation of alfalfa for water-savings in the Great Plains and Intermountain West: A review and analysis of the literature. *Agronomy Journal*, *103*(1), 45-50.

Ma, M., Gao, S., Lu, Y., & Yao, Y. (2021). Economic value of agricultural water use for Arizona. *The International Journal of Electrical Engineering & Education*, 0020720920984685.

McGreal, B. (2021). Effects of Economic and Climate Factors on Central Arizona Agricultural Water Use. (Master's Thesis, University of Arizona).

McGreal, B., & Colby, B. (2022). Modeling Effects of Economic and Climatic Factors on Arid Agricultural Water Use. Working Paper.

MacEwan, D., Cayar, M., Taghavi, A., Mitchell, D., Hatchett, S., & Howitt, R. (2017). Hydroeconomic modeling of sustainable groundwater management. *Water Resources Research*, *53*(3), 2384-2403.

Mississippi State University, Department of Biochemistry, Molecular Biology, Entomology & Plant Pathology (2022). Cotton Crop Loss Data.

Moore, M. R., Gollehon, N. R., & Carey, M. B. (1994). Multicrop production decisions in western irrigated agriculture: the role of water price. *American Journal of Agricultural Economics*, *76*(4), 859-874.

Morley, C. L. (1997). An evaluation of the use of ordinary least squares for estimating tourism demand models. *Journal of travel research*, *35*(4), 69-73.

Nelson, T., Chou, H., Zikalala, P., Lund, J., Hui, R., & Medellín–Azuara, J. (2016). Economic and water supply effects of ending groundwater overdraft in California's Central Valley. *San Francisco Estuary and Watershed Science*, *14*(1).

Office of the United States Trade Representative (2014). United States and Brazil Reach Agreement to End WTO Cotton Dispute.

Ottman, M. J. (2015). Planting dates for small grains in Arizona. *University of Arizona Cooperative Extension,* 2.

Padilla, S. (2020). A Look at USDA, Economic Research Service's Commodity Costs and Returns Data. *USDA, Economic Research Service*.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, *11*(6), 619-632.

Petrick, M., & Zier, P. (2012). Common Agricultural Policy effects on dynamic labour use in agriculture. *Food policy*, *37*(6), 671-678.

Reyes, J., Elias, E., Haacker, E., Kremen, A., Parker, L., & Rottler, C. (2020). Assessing agricultural risk management using historic crop insurance loss data over the Ogallala aquifer. *Agricultural Water Management*, *232*, 106000.

Sall, I., & Tronstad, R. (2021). Simultaneous Analysis of Insurance Participation and Acreage Response from Subsidized Crop Insurance for Cotton. *Journal of Risk and Financial Management*, *14*(11), 562.

Scheierling, S. M., Loomis, J. B., & Young, R. A. (2006). Irrigation water demand: A meta-analysis of price elasticities. *Water resources research*, *42*(1).

Scheitrum, D. (2022). Private Communication, see Appendix A.4.

Schlenker, W. (2010). Crop responses to climate and weather: cross-section and panel models. In *Climate Change and Food Security* (pp. 99-108). Springer, Dordrecht.

Schoengold, K., Sunding, D. L., & Moreno, G. (2006). Price elasticity reconsidered: Panel estimation of an agricultural water demand function. *Water resources research*, *42*(9).

Sehler, R., Li, J., Reager, J. T., & Ye, H. (2019). Investigating relationship between soil moisture and precipitation globally using remote sensing observations. *Journal of Contemporary Water Research & Education*, *168*(1), 106-118.

Shipman, T. D., & Wilson, P. N. (2014). *The Formative Political Economy of the Central Arizona Groundwater Replenishment District* (No. 1535-2016-132149).

Tenney, W. (2018). 6 Things You Need To Know About Your Wastewater. *Arizona Municipal Water Users Association*.

The University of Texas at Austin. (n.d.). Degrees of Freedom.

Thompson, G. (2022). Private Communication, see Appendix A.4.

TradingCharts.com (2022). Futures – Cotton #2 Historical Prices/Charts.

Tronstad, R. (2022). Private Communication, see Appendix A.4.

US Bureau of Labor Statistics (2022). Consumer Price Index.

US Department of Agriculture, National Statistics Service (2022). CropScape and cropland data layer – metadata.

US Department of Agriculture, National Statistics Service (2022). QuickStats.

US Energy Information Administration (2022). Petroleum & Other Liquids.

Williams, R. (2015). Multicollinearity. *University of Notre Dame*.

Williams, R. (2020). Heteroskedasticity. *University of Notre Dame*.

Wilson, T. S., Sleeter, B. M., & Cameron, D. R. (2016). Future land-use related water demand in California. *Environmental Research Letters*, *11*(5), 054018.

West Wide Drought Tracker (2022). Temperature and Precipitation. https://wrcc.dri.edu/wwdt/time/

Yoo, J., & Perrings, C. (2017). An externality of groundwater depletion: land subsidence and residential property prices in Phoenix, Arizona. *Journal of Environmental Economics and Policy, 6*(2), 121-133.

York, A. M., Eakin, H., Bausch, J. C., Smith-Heisters, S., Anderies, J. M., Aggarwal, R., ... & Wright, K. (2020). Agricultural water governance in the desert: Shifting risks in central Arizona. *Water alternatives*, *13*(2).