Title

A Framework for Strategic and Equitable Multibenefit Land Repurposing to Sustain Food-Energy-Water Systems and Address Water Injustice in the San Joaquin Valley, California

Author

Espinoza, Vicky

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A Framework for Strategic and Equitable Multibenefit Land Repurposing to Sustain Food-Energy-Water Systems and Address Water Injustice in the San Joaquin Valley, California

A dissertation submitted in partial satisfaction of the requirements for the degree of
Doctor of Philosophy
in
Environmental Systems
by
Vicky Espinoza

Committee in charge:
Dr. Joshua Viers, Chair
Dr. Alvar Escriva-Bou
Dr. Erin Hestir
Dr. Josué Medellín-Azuara

2022

The dissertation of Vicky Espinoza is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Joshua H. Viers, Ph.D. Date

Alvar Escriva-Bou, Ph.D. Date

Erin Hestir, Ph.D. Date

Josué Medellín-Azuara, Ph.D. Date

University of California, Merced

2022

I dedicate this dissertation to

my parents, Sergio and Rocio
my sister, Leslie
my partner, Ali
and to the San Joaquin Valley community members and farmers that shared their lived experiences and visions for the future of water and land use in California

Dedico esta disertación a

mis padres, Sergio y Rocio
mi hermana, Leslie
mi pareja, Ali
y a los miembros de la comunidad y agricultores del Valle de San Joaquín que compartieron sus experiencias vividas y visiones para el futuro del agua y el uso de la tierra en California

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ACKNOWLEDGMENTS

I appreciate the funding support from the University of California Office of the President Water Security and Sustainability Research Initiative (MR-15-328473), California Energy Commission (300-15-004), US Department of Energy Clean Energy Research Center for Water and Energy Technologies (DE-IA0000018), US Department of Agriculture NIFA (2017-38422-27227, 2021-69012-35916, and 2021-67021-35344), and UCOP 2021-2022 President's Dissertation Year Fellowship at UC Merced, UC Merced Global Food Initiate Grow Grant Award, UC Merced Environmental Systems Summer Fellowship, and Graduate Group Recruitment Fellowship.

I am grateful to my advisor, Dr. Joshua Viers, for believing in and supporting my vision to develop a framework for equitable water and land use management through the engagement of underserved and underrepresented communities and farmers in the San Joaquin Valley. Thank you for challenging me to become a better critical thinker-doer and for believing in my mission.

I thank my doctoral committee for supporting my growth—Dr. Alvar Escriva-Bou, Dr. Erin Hestir, and Dr. Josué Medellín-Azuara.

I am grateful for collaborations at UC Merced with Leigh Bernacchi, Max Eriksson, Lorenzo Booth, Nick Santos, and Anna Rallings.

Thank you to the many mentors in my educational journey that have guided me and motivated me to pursue higher education in STEM—Dr. Leigh Bernacchi, Dr. Colleen Naughton, Dr. Duane Waliser, Dr. Marty Ralph, Dr. Mike DeFlorio, Dr. Bin Guan, Dr. Eugene Yan, Dr. Yan Feng, Dr. David Cook, Dr. Maria Prokopenko, Dr. Nicole Mölders, and Dr. David Sell.

I greatly appreciate the people that supported my efforts in developing equitable water and land use solutions through community and farmer engagement—Ann Hayden, Anna Schiller, Ana Lucia Garcia-Briones, Dr. Ruth Dahlquist-Willard, Graciela Gomez, Amanda Monaco, Breanne Ramos, Matt Angell, Laurel Angell, Breanne Vandenberg, Victor Hernandez, Adriana Renteria, Caitlin Joseph, Carmen Carrasco, Kara Heckert, Deborah Nares, Rasheed Hislop, Jaime Fanous, Paul Towers, Jean Okuye, Dave Thiel, Dr. Nell Green Nylen, and many others.

I have had the great pleasure of building a network of trust throughout my doctoral journey. I am grateful to Environmental Defense Fund, Merced County Farm Bureau, Community Alliance with Family Farmers, American Farmland Trust, East Merced Resources Conservation District, Madera/Chowchilla Resources Conservation District, Community Water Center, Leadership Counsel for Justice and Accountability, Self-Help Enterprises, Public Policy Institute of California, University of California Agriculture and Natural Resources, Water Solutions Network, California Department of Food and Agriculture, Cortez Growers Association, and USDA NRCS. Special thanks to California Ag Today, AgNet West, Water Wrights, Maven's Notebook, and Radio Bilingüe for supporting and disseminating CaliWaterAg resources.

I am enternally grateful to the community members and farmers that supported my research and extension efforts and shared their lived experiences with me. Thank you to my champion farmers and community members that helped spread the word about the bilingual workshops on SGMA and my trilingual YouTube channel, CaliWaterAg. Forward together!

Estoy agradecida con los miembros de la comunidad y los agricultores que apoyaron mis esfuerzos de investigación y extensión y compartieron sus experiencias vividas conmigo. Quiero agradecer a mis agricultores campeones que ayudaron a difundir los talleres bilingües sobre SGMA y mi canal trilingüe de YouTube, CaliWaterAg. Adelante juntos!

Thank you to my parents, sister, partner, and friends for their support, patience, and love. Thank you for celebrating my successes and for giving me strength during the challenges. Fortunate to have the support of many and tenacity to push my limits and "dare mighty"!

CURRICULUM VITAE

VICKY ESPINOZA | Ph.D. Candidate

University of California Merced

E-mail: vespinoza2@ucmerced.edu

Telephone: (323) 547-5506

EDUCATION

University of California Merced Merced, CA

PhD, Environmental Engineering August 2022

University of Southern California Los Angeles, CA

Master of Science, Environmental Engineering May 2017

University of Chicago Chicago, IL

Bachelor of Science, Geophysical Sciences June 2013

RESEARCH EXPERIENCE

University of California Merced Merced, CA

Environmental Systems Group- Doctoral Dissertation *Present*

- Quantify the crop water use, crop revenue, and greenhouse gas emission discrepancies resulting from land-use misclassification in complex agricultural landscapes, like the San Joaquin Valley
- Identify sociohydrologically vulnerable regions in the San Joaquin Valley to inform where to strategize the transition of irrigated land to address Sustainable Groundwater Management Act targets by 2040
- Assess marginalized community and farmer land-use preferences to inform state land repurposing projects
- Extension work includes the creation of trilingual (English, Spanish, Hmong) resources for the CaliWaterAg YouTube channel and organizing workshops to inform underrepresented rural communities and small-scale farmers about groundwater law and the implications on their livelihoods

NASA Jet Propulsion Laboratory Pasadena, CA

Earth Sciences Division – Earth Science Research Assistant *June 2016 to August 2017*

- Incorporate global climate CMIP5 model simulation output into the Atmospheric Rivers Detection Algorithm to gain an understanding of atmospheric river trends with climate change effects globally
- Analyzed thermodynamic and dynamic changes of atmospheric rivers in a hypothetical aquaplanet simulation under climate change conditions

University of Southern California Los Angeles, CA

Environmental Engineering- Research Assistant *August 2015 to May 2016*

- Developed per-pixel classification of crops to help identify crop trends in Central Valley, CA, during drought conditions through the use of remote sensing and ground survey data

Argonne National Laboratory Lemont, IL

Earth Sciences Division- Research Assistant *June 2014 to June 2015*

- Researched extreme climate events; drought effects on hydropower generation, and flood risk assessment

- Utilized ArcGIS' Soil Water Assessment Tool (SWAT) to model future California drought effects on hydropower plant energy production
- Utilized HEC-HMS, HEC-RAS, and FLO-2D models for flood risk assessment for select nuclear power plants in the United States
- Wrote technical reviews for flood risk assessment of nuclear power plants in flood-prone regions

Pomona College Geology Department Claremont, CA
Laboratory Technician *June 2013 to June 2014*

- Researched climate change effects on marine mono-nitrogen oxides (NOx) through ancient/modern corals and marine samples
- Gathered marine particulate matter from a sonde at various water column depths at the San Pedro Basin to observe nitrogen cycling in the ocean
- Processed Neo-Archean to modern-day corals through acidification and crushing of samples and analyzed for mono-nitrogen oxides concentration detection

University of Alaska Fairbanks Geophysical Institute Fairbanks, AK
NSF REU- Atmospheric Science Intern *June 2012 to August 2012*

- Analyzed measurement concentrations of $PM_{2.5}$ and meteorological parameters over Fairbanks, AK, to interpret the cause(s) of the Fairbanks region exceeding the National Ambient Air Quality Standard (NAAQS) set by the EPA required by the Clean Air Act

Argonne National Laboratory Lemont, IL
Earth Sciences Division- Atmospheric Science Intern *June 2011 to August 2011*

- Developed 3D regional climate models with real-time meteorology—forward and backward trajectories of aerosol particles and modeled aerosol distribution and daily trends over India and China
- Climate models created contributed to the Ganges Valley Aerosol Experiment (GVAX) project and website

EXTENSION EXPERIENCE

Community and Small-Scale Farmer Engagement
San Joaquin Valley Network Building *Present*

- To date, I have engaged with more than 300 underserved community members and marginalized small-scale farmers in the San Joaquin Valley and have ~10 champion farmers that support my extension efforts
- I reach about 400 people between the CaliWaterAg trilingual YouTube channel (104 subscribers) and CaliWaterAg Facebook and Instagram platforms (~300 followers combined)
- To date, I have collaborated and or maintained a good relationship with the following community organizations in the San Joaquin Valley: Leadership Counsel for Justice and Accountability, Self-Help Enterprises, and Community Water Center
- To date, I have collaborated and or maintain a good relationship with the following agriculture and environmental organizations in the San Joaquin Valley: UC Agriculture and Natural Resources Small Farm Advisors, Community Alliance with Family Farmers (CAFF), American Farmland Trust, USDA Natural Resources Conservation Service- Modesto, Cortez Growers' Association, Farm Bureaus, California Almond Board, California Women for Agriculture, Merced Resource Conservation District, Madera/Chowchilla Resource

Conservation District, Environmental Defense Fund, The Nature Conservancy, Sustainable Conservation

CaliWaterAg YouTube Channel *Present*

- Created a trilingual (English, Spanish, Hmong) YouTube channel for underrepresented communities and small-scale farmers to foster understanding of the Sustainable Groundwater Management Act (SGMA), its impacts on agriculture, and how communities can become involved
- The aim is to inform, empower, and involve underrepresented communities and small-scale farmers in SGMA groundwater sustainability planning and also include their voices in my doctoral community-informed land use repurposing model
- Currently on the CaliWaterAg channel: SGMA and land use series, drinking water issues in San Joaquin Valley's underserved communities, and tutorials (e.g., how to find your GSA, how to use Zoom on your phone or computer)

Latinx Community and Small-Scale Farmer Information Dissemination *Present*

- Disseminate farmer and community workshops, conferences, and other local opportunities in Spanish and English through social media platforms (i.e., Facebook, Instagram, LinkedIn, and Twitter), phone calls, and SMS texts
- Called and emailed more than 50 agricultural organizations and about five bilingual California newsletter/radio stations to help disseminate information on the trilingual CaliWaterAg YouTube channel created to inform and empower through knowledge California underserved communities and farmers

Water Solutions Network Cohort 4 *April to November 2021*

- Collaborate and co-develop water solutions in the Tule Lake Basin with key California water stakeholders
- Engage stakeholders across various sectors (e.g., Native American Tribal Groups, Environmental Justice Groups, farmers, local and state water agencies, environmental agencies) through phone interviews and web surveys to identify overlapping water goals and identify differences that could be bridged to facilitate equitable and representative water management

Community Land Use Preferences Survey *March to June 2021*

- Surveyed 32 disadvantaged, agricultural communities in the San Joaquin Valley via SMS distributed bilingual (Spanish and English) survey that resulted in 197 survey responses that provided community land-use preferences with insight on participant value on land use contributions to economic and community well-being
- The survey was conducted as a component of my doctoral dissertation and Strategic Alternative Land Use Transformation and Optimization (SALUTO) model partially funded by DOE US-China Clean Energy Research Center for Water-Energy Technologies (DE-IA0000018) and 2021-2022 President's Dissertation Fellowship, and a gift from the Environmental Defense Fund (EDF)
- The University of California Merced Review Board approved this project with all survey participants remaining anonymous (protocol # UCM2019-118)

Bilingual SGMA & Agricultural Land Repurposing Workshop *January 2021*

- Organized and presented at bilingual (Spanish and English) virtual workshops related to doctoral research on agricultural land repurposing and SGMA with Environmental Defense Fund

Community Engagement for Land Use Repurposing Model *January to July 2021*

- With a UC Global Food Initiative Grow Grant, I engaged 26 underserved communities (~100- 250 people) throughout the San Joaquin Valley to provide information to community members on how the Sustainable Groundwater Management Act (SGMA) could impact agriculture and rural communities
- Disseminated the trilingual CaliWaterAg YouTube channel community resource to address the information access inequity present in the San Joaquin Valley by placing ~260 flyers throughout markets, feed stores, postal offices, bus stops, community centers, and schools in 26 underserved, agricultural communities

INFEWS-ER Challenge Cohort *October 2020 to May 2021*

- In a group of 7 graduate students from around the nation and world, we analyzed how new permitting processes for the swine industry could lead to timely, effective, equitable management of swine production in North Carolina
- Interviewed about ten stakeholders in the North Carolina swine production industry (e.g., farmers, community members, biowaste technology developers, North Carolina policymakers) to understand the current swine permitting challenges and how changes in permitting could impact farmers and community members

Madera Small-Scale Farmer Advisory Group *2020-2021*

- Invited to collaborate with a group of small-scale farmer stakeholder groups (California Alliance of Family Farms, UC ANR, and Leadership Counsel) to identify issues marginalized small-scale farmers in Madera County, California, face in the Sustainable Groundwater Management Act (SGMA) process

San Joaquin Valley Grower SGMA Workshop *2019-2020*

- Created and organized workshops that inform marginalized small-scale farmers throughout the San Joaquin Valley about the potential impacts of the Sustainable Groundwater Management Act (SGMA) on agriculture and how they can participate in their local groundwater sustainability agencies
- The objective of the workshops is to inform, empower, and involve growers in SGMA-related decisions
- Two workshops presented to Spanish-speaking farmers in Merced/Stanislaus counties before COVID-19 restrictions; attendance of about ten people total

Merced County Cortez Grower's Association *2019-2020*

- Attend grower meetings to learn about issues Merced/Stanislaus County growers are facing, learn about seasonal practices, and build trust with growers
- Attend grower meetings every other week to talk to growers about SGMA and its potential impacts on agriculture, and give resources for how growers can become involved

U.S. Department of Agriculture Science Outreach Program *January-March 2020*

- Engage two 4th grade classes on hydroponics science once a week (~30 kids per class)
- Create 1-hour lesson plans that cover the definition of hydroponics, lab safety, how plants grow, comparing plant hydroponics vs. soil growth, developing a hypothesis, measuring plant growth, and reporting results
- Students in groups of five grew plants in hydroponic systems and soil to compare the difference in growth

Second Annual "Growing Together" Black Farmer Conference *February 2020*

- Attended the USDA organized conference held in Fresno, California, and engaged with black urban small-scale farmers to learn more about their water and agricultural challenges

- Disseminated information on the trilingual CaliWaterAg Youtube channel available for them to learn more about the implications of the Sustainable Groundwater Management Act at their convenience

Alpaugh and Allensworth Climate and Water Project *June 2019*

- Facilitated two days of a three-week program in which 8th and 9th-grade students from underserved communities develop interests in water, climate change, and scientific research by interviewing scientists at UC Merced
- Provided an overview of climate change and agriculture for students, answered interview questions, and guided student-led digital storytelling project

Community Water Center Community Engagement *2017-2019*

- Work in disadvantaged communities in the San Joaquin Valley on informing community members about the Sustainable Groundwater Management Act and its implications on the future of the San Joaquin Valley through workshops; 3 workshops of about 30 people each

Community and Small-Scale Farmer Invited Talks

- Invited speaker at Latinx Farmer Marketing and Organizing Event organized by Community Alliance with Family Farmers (CAFF), November 2021; provided an overview of the Sustainable Groundwater Management Act and answered questions related to the potential implications on agriculture and future water use
- Invited presentation for Central Valley Community Foundation and Joe Del Bosque organized by UC Merced presenting my community-informed doctoral research "Strategic Alternative Land Use Transformation & Optimization (SALUTO) Model," October 2021
- Invited presentation for UC Regents members organized by UC Merced presenting my doctoral research "Strategic Alternative Land Use Transformation & Optimization (SALUTO) Model," October 2021
- Invited presentation for American River Partners organized by Dr. Viers at UC Merced to present doctoral work on "Community-Informed Strategic Alternative Land Use Transformation & Optimization (SALUTO) Model," May 2021
- Invited Moderator for UC Merced's World Water Day "The Fight For Water": A Panel Discussion with Juan Carlos Oseguera, Joe Del Bosque, and Patrick Cavanaugh, March 2021
- Invited speaker at the 6th Annual Virtual Latino Farmer Conference organized by the USDA Natural Resources Conservation Service (NRCS) and the National Center for Appropriate Technology (NCAT), January 2021; presented in Spanish, "Los Impactos del Sobregiro de Agua Subterránea en la Agricultura"
- Invited Speaker at Virtual EcoFarm Conference, January 2021; presented in Spanish "Los Impactos del Sobregiro de Agua Subterránea: Un Ejemplo de California"
- Invited Panelist at Women for the Land Learning Circle- Planning for Resilience in California's San Joaquin Valley Virtual Workshop in English organized by American Farmland Trust, September 2020
- Invited speaker alongside Christina Babbitt (Environmental Defense Fund) at the USDA funded Water for Ag Engagement Webinar series, April 2020 and presented "Engaging Farmers and Communities in Response to California's Sustainable Groundwater Management Act"
- Invited speaker at the 5th Annual Latino Farmer Conference organized by USDA NRCS and NCAT in Tulare, January 2019; presented "Las Implicaciones de la Ley de Gestión Sostenible de las Aguas Subterráneas (SGMA) en Los Agricultores"

Local, State, and Federal Policymaker Engagement

San Joaquin Valley Farmland Transitions Project *Present*

- Invited member of the stakeholder advisory group for the project-by-project partners: Ellen Hanak (PPIC Water Policy Center), Sarah Moffat (Central Valley Community Foundation), and Laura Ramos (California Water Institute, Fresno State University)
- The stakeholder advisory group will meet four times over the next two years with the project team to provide suggestions and feedback, in meetings generally lasting 2–3 hours

Reedley College AgTech x Education Conference *August 2021*

- Engaged with AgTech entrepreneurs and learned about the challenges and opportunities at the intersection of AgTech and Education
- Engaged with Secretary Karen Ross (California Department of Food and Agriculture) and talked about my doctoral research, community engagement, and challenges that marginalized small-scale farmers face

Engage Local Irrigation and Conservation Districts *2019- Present*

- Engage with San Joaquin Valley irrigation districts, like Turlock Irrigation District/GSA and McMullin Area GSA, to inform them of the trilingual (Spanish, Hmong, and English) CaliWaterAg YouTube channel I created that includes a series on the Sustainable Groundwater Management Act that could be of use to their constituents
- Attend Merced and Madera/Chowchilla Resource Conservation District meetings and present to members on doctoral work on "Community-Informed Strategic Land Repurposing Model" and SGMA

California Agricultural Laborers Immigration Reform Workshop *September 2019*

- Engaged with Costa, Pannetta, Cox, and Lofgren on my doctoral work on "Community-Informed Strategic Land Repurposing Model" and learned from agricultural laborers about the challenges they face without immigration protection

University of California 10th Annual Graduate Research Advocacy Day *March 2019*

- Accompanied Vice Provost and Graduate Dean Marjorie Zatz to meet state leaders and talk about community informed doctoral research—Frank Bigelow (R-Madera) and Rudy Salas Jr. (D-Bakersfield) and Senator Andreas Borgeas (R-Fresno), as well as representatives from the offices of assembly members Heath Flora (R-Ripon), Joaquin Arambula (D-Delano) and Adam Gray (D-Merced) and senators Anna Caballero (D-Merced) and Melissa Hurtado (D-Sanger)

Policymaker Invited Talks

- Invited speaker request by Pablo Garza (Chief Consultant at the Assembly Water, Parks and Wildlife Committee) to speak on behalf of my doctoral work with small-scale farmers in the San Joaquin Valley at the State of California joint informational meeting with the Committee of Agriculture and the Water, Parks and Wildlife Committee, 2021
- Invited Panelist alongside Felicia Marcus (William C. Landreth Visiting Fellow, Stanford University Water in the West Program), Clifford Lee (Deputy Attorney General (Retired), California Department of Justice), and Valerie Kincaid (Partner, O'Laughlin & Paris LLP) moderated by Nell Green Nylen (UC Berkeley School of Law) on "Learning From Our Dry History: Lessons for a Drought-Prone California" at the Environmental Law Conference at Yosemite (virtual), 2021
- Invited Panelist along with Anna Schiller (Environmental Defense Fund), Amanda Monaco (Leadership Counsel for Justice and Accountability), and Emily Finnegan (Local Government Commission) moderated by Danielle Dolan (Local Government Commission) on "Session 16: Community-Driven Solutions to Coordinate Land Use Planning and Groundwater Management" at the American Water Resources Association Virtual Conference, 2021

- Invited speaker alongside Camille Pannu (UC Irvine Law) and Cristal Gonzalez (Clean Water Action) on "The Human Right to Water and Environmental Justice Panel" hosted by the Latinx Law Student Association and The Water Law Society, Univ. of the Pacific McGeorge School of Law, 2021
- Invited Panelist alongside Amanda Monaco (Leadership Counsel for Justice and Accountability), Kristin Dobbin (UCLA), Max Gomberg (State Water Resources Control Board) moderated by Nell Green Nylen (UC Berkeley School of Law) on "Achieving Water Justice in a Changing Climate" at the California Water Law Symposium, 2021
- Invited speaker to present doctoral research "Strategic Alternative Land Use Planning for Climate Smart Communities and Groundwater Sustainability," to the State Water Resources Control Board, 2020
- Clinton Global Institute University Fellow doctoral work feature "Strategic Alternative Land Use Planning for Climate Smart Communities and Groundwater Sustainability," Washington D.C. Virtual Presentation, 2020
- Invited speaker to present to Maria Herrera (California Water Commission) on doctoral work, "Strategic Alternative Land Use Planning for Climate Smart Communities and Groundwater Sustainability," 2020
- Invited Panelist at the 2019 Congressional Hispanic Caucus Institute Leadership Conference on "Climate Smart Approaches to Resilient Food-Energy-Water Systems in California," Washington D.C., 2019
- Next Generation Delegate featured speech, "Imagine: A story of San Joaquin Valley Disparity at the Chicago Council on Global Affairs, 2019

TEACHING EXPERIENCE

University of California Merced Merced, CA

ENGR 180 Spatial Analysis and Modeling- Lecturer *Summer 2021*

- An asynchronous 8-week course with 27 undergraduate level students
- Developed material for remote live lectures three times per week that incorporated interactive tools (e.g., Mentimeter polls and pop quizzes), created short, pre-recorded material to accompany remote live lectures, developed homework assignments, quizzes, midterm exams, and organized course reading material
- Held office hours and organized laboratory assignments and final project with the teaching assistant

Environmental Engineering- Teaching Assistant *2017 - 2018*

- Water Resources Planning and Management (~30 undergraduate level students under Dr. Viers)

Guest Lectures at UC Merced *2017- Present*

- ENGR 180 Spatial Analysis and Modeling (Dr. Fernandez-Bou) *Spring 2021*
  - Lecture on remote sensing applications in Google Earth Engine (~30 undergraduate students)
- ENVE 140 Water Resources Planning and Management (WRPM) (Dr. Viers) *Winter 2019*
  - Lecture on groundwater trading (~20 undergraduate students)
- ENVE 140 Water Resources Planning and Management (Dr. Viers) *Winter 2019*
  - Groundwater lecture (~20 undergraduate students)
- ENVE 140 Water Resources Planning and Management (Dr. Medellin-Azuara) *Fall 2018*
  - California Water Management (~20 undergraduate students)

University of Southern California Los Angeles, CA

Environmental Engineering- Teaching Assistant *August 2015 to May 2017*

- Energy and the Environment (90 students, mix of Ph.D. and Master's level students)
- Introduction to Environmental Engineering (22 students, undergraduate level students)

MENTORSHIP EXPERIENCE

UCLA Ecology & Evolutionary Biology (EEB 183; Dr. Lipman) *January to March 2021*

- Oversaw a team of five undergraduate students that were conducting a geospatial analysis to analyze the demographics of unrepresented "white areas" in the San Joaquin Valley as part of their EEB 183-course project
- Prepared weekly meeting materials and tutorials on ArcGIS software for geospatial analysis

Undergraduate Google Earth Engine Fallowing Project *2018-2020*

- Oversaw a team of four undergraduate researchers that conducted a geospatial analysis to identify fallowed lands by parsing and analyzing satellite imagery via the Google Earth Engine API
- Developed project timeline and implementation plan that resulted in time-series of satellite imagery and fallowed land identification through machine-learning methods in Google Earth Engine API

University of Southern California's Science Outreach Program *August 2015- May 2017*

- Taught grade school students in disadvantaged elementary schools near USC a wide range of science topics through visual and engaging experiments

University of Southern California's Joint Program (Math Tutor) *January - May 2016*

- Tutor mathematics at disadvantaged K-12 schools surrounding USC

Argonne National Laboratory's Women in Science and Technology *June 2014- June 2015*

- Planned STEM outreach events for high school girls from Chicago's low-income communities
- Helped the largest event bringing together underserved high school girls interested in STEM, *Girls Do Hack*

JOURNAL PUBLICATIONS

In-Prep

- **Espinoza, V.** and Viers, J.H. (In-Prep) The paradox of production: surface water supply drives agricultural productivity but not prosperity in California's San Joaquin Valley.
- **Espinoza, V.**, Bernacchi, L., Eriksson, M., Schiller, A., Hayden, A., Viers, J.H. (In-Prep) From fallow ground to common ground: Reconciling future land use perspectives in the San Joaquin Valley. Journal of Environmental Management.
- **Espinoza, V.**, Booth. L., Viers, J.H. (In-Prep) Land Use Misclassification Results in Water Use, Economic Value, and GHG Emission Discrepancies for California's High Intensity Agriculture.

Published

- Fernandez-Bou, A.S., Ortiz-Partida, J.P., Pells, C., Classen-Rodriguez, L.M., **Espinoza, V.**, Rodríguez-Flores, J.M., Booth, L., Burmistrova, J., Cai, A., Cairo, A., Capitman, J.A., Cole, S., Flores-Landeros, H., Guzman, A., Maskey, M.L, Martínez-Escobar, D., Sanchez-Perez, P.A., Valero-Fandiño, J., Viers, J.H., Westerling, L., and Medellín-Azuara, J. 2021. Regional Report for the San Joaquin Valley Region on Impacts of Climate Change. California Natural Resources Agency. Publication number: SUM-CCCA4-2021-003. In Review.
- Rallings, A.M., Clifton, B., **Espinoza, V**., Hao, Z., Chen, W., Duan, W., Peng, Q., Luo, P., and Viers, J.H.. 2021. Regional Hydrologic Classification for Sustainable Dam Operations in China: Exploratory Applications in the Yangtze River Basin. Journal of the American Water Resources Association 1– 14. doi.org/10.1111/1752-1688.12966.

- Hao, Z., Rallings, A.M., **Espinoza, V.**, Luo, P., Duan, W., Peng, Q., Gao, Y., Viers, J.H., Flowing from East to West: A bibliometric analysis of recent advances in environmental flow science in China, Ecological Indicators, Vol.125,2021,107358, doi.org/10.1016/j.ecolind.2021.107358.
- Fernandez-Bou A.S., Ortiz-Partida J.P., Classen-Rodriguez L.M., Pells C., Dobbin K.B., **Espinoza V.**, Rodríguez-Flores J.M., Thao C., Hammond Wagner C.R., Fencl A., Flores-Landeros H., Maskey M.L., Cole S.A., Azamian S., Gamiño E., Guzman A., Alvarado A.G.F., Campos-Martínez M.S., Weintraub C., Sandoval E., Dahlquist-Willard R.M., Bernacchi L.A., Naughton C.C., DeLugan R.M., and Medellín-Azuara J. (2021) 3 Challenges, 3 Errors, and 3 Solutions to Integrate Frontline Communities in Climate Change Policy and Research: Lessons From California. Front. Clim. 3:717554. doi: 10.3389/fclim.2021.717554.
- Massoud, E.; Massoud, T.; Guan, B.; Sengupta, A.; **Espinoza, V.**; De Luna, M.; Raymond, C.; Waliser, D. Atmospheric Rivers and Precipitation in the Middle East and North Africa (MENA). Water 2020, 12, 2863. doi.org/10.3390/w12102863
- Massoud, E.C., **Espinoza, V.**, Guan, B., Waliser, D.E. (2019). Global Climate Model Ensemble Approaches for Future Projections of Atmospheric Rivers. Earth's Future, Vol. 7, Issue 10, 1136-1151. doi.org/10.1029/2019EF001249
- Medellín-Azuara, J., Sumner, D.A., Pan, Q.Y., Lee,H., **Espinoza**, V., Cole, S.A, Bell, A., Davila Olivera, S., Viers, J.H., Herman, J., Lund, J.R.. (University of California, Davis and University of California, Merced). 2018. Economic and Environmental Implications of California Crop and Livestock, Adaptation to Climate Change. California Natural Resources Agency. Publication number: CCCA4-CNRA-2018-018.
- **Espinoza, V.**, Waliser, D. E., Guan, B., Lavers, D. A., & Ralph, F. M. (2018). Global analysis of climate change projection effects on atmospheric rivers. Geophysical Research Letters, 45, 4299–4308. doi.org/10.1029/ 2017GL076968

SUBMITTED CONFERENCE ABSTRACTS

- **Espinoza, V.** and Viers, J.H., Water Access and Sovereignty Inequities in San Joaquin Valley, California's Local Water Governance, American Water Resources Association Spring Conference, 2022
- **Espinoza, V.** and Viers J.H., San Joaquin Valley Irrigation District Vulnerability to Groundwater Overdraft Based on Surface Water Allocation and Consumptive Water Use, AGU Fall Meeting Abstracts, 2020
- Waliser, D.E, Guan, B., Goodman, A., DeFlorio, M., Gibson, P., **Espinoza, V.,** Atmospheric Rivers (ARs): Weather & Water Extremes that Shape Our Global Climate, JPL Executive Committee Presentation, 2019
- **Espinoza, V.** and Viers J.H., San Joaquin Valley Irrigation District Vulnerability to Groundwater Overdraft Based on Surface Water Allocation and Consumptive Water Use, AGU Fall Meeting Abstracts, 2019
- Massoud, E., Guan, B., **Espinoza, V.**, Waliser, D.E., Constraining Future Projections of Atmospheric Rivers Using a Multiobjective Model Evaluation Framework, 99th American Meteorological Society Meeting, 2019
- **Espinoza, V.** and Viers, J.H., Spatially and Temporally Based Sensitivity Analysis of Land Fallowing and Alternative Land Use Near Disadvantaged Communities in Kern County, California, USA, AGU Fall Meeting Abstracts, 2018

- Nover, D., **Espinoza, V.**, Luo, P., Viers, J.H., Rallings, A., The potential for environmental flows to support the sustainable management of hydropower modified river systems in China, AGU Fall Meeting Abstracts, 2018
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- Waliser, D.E., DeFlorio M., Guan, B., **Espinoza, V.**, Ralph, M., Jones, J., Entin, J., AR Prediction for the Western US in the Context of Global Weather/Climate Models, Western States Water Council, 2017
- Espinoza, V., Waliser, D.E., Guan, B., Lavers, D.A., Projections of Climate Change Effects on Global Atmospheric River Landfalls, AGU Fall Meeting Abstracts, 2016
- Yan, E., Tidwell, V.C., Bizjack, M., **Espinoza, V.**, Jared, A., Modeling the vulnerability of hydroelectricity generation under drought scenarios, AGU Fall Meeting Abstracts, 2015

RESEARCH PRESENTATIONS

- **Espinoza, V.**, "Community- Informed Strategic Alternative Land Use Transformation and Optimization (SALUTO) Model for Climate Smart Communities And Groundwater Sustainability," UC Merced's Research Week Virtual Reception for Community-Engaged Research, March 2021
- **Espinoza, V.**, Viers, J.H., "San Joaquin Valley Irrigation District Vulnerability to Groundwater Overdraft Based on Surface Water Allocation and Consumptive Water Use," Poster session at American Geophysical Union 2020, Virtual
- **Espinoza, V.**, Viers, J.H., "Spatially and Temporally Based Sensitivity Analysis of Land Fallowing and Alternative Land Use Near Disadvantaged Communities in Kern County, California, USA," Poster session at American Geophysical Union 2018, Washington, D.C.
- **Espinoza, V.**, "California Drought Impacts on Agricultural Regions," Speaker for UC Merced Blum Center Summer Institute 2018, Merced, CA
- **Espinoza, V.**, Waliser, D. E., Guan, B., Lavers, D. A., "Projections of Climate Change Effects on Global Atmospheric River Landfalls," Poster session at American Geophysical Union 2016, San Francisco, CA
- **Espinoza, V.**, Waliser, D. E., Guan, B., Lavers, D. A., "Projections of Climate Change Effects on Global Atmospheric River Landfalls," Speaker at International Atmospheric Rivers Conference 2016, San Diego, CA
- **Espinoza, V.** and Sanders, K.T. "A Geospatial Energy Analysis of Groundwater Pumping During the Recent California Drought," Speaker at ASCE Environmental Water Resources Institute 2016, Palm Beach, FL
- Yan, E., Tidwell, V.C., Bizjack, M., **Espinoza, V**., Jared, A., "Modeling the Vulnerability of Hydroelectricity Generation Under Drought Scenarios," Poster session at American Geophysical Union 2015, San Francisco, CA

OTHER PRESENTATIONS

- **Espinoza, V.**, "Expanding Knowledge Reach Beyond Academic Audiences- Science of Storytelling," UC Merced HSRI Social Media Workshop, November 2019

AWARDS/HONORS

- UC Merced Grad Slam 3rd Place Winner *2022*
- UC President's Dissertation Fellow *2021-2022*
- UC Merced Grad Slam Top 10 Finalist *2021*
- UC Merced Global Food Initiate Grow Grant Award Recipient *2021*
- Partnership with Environmental Defense Fund *2020*
- UC Merced Environmental Systems Summer Fellowship *2020*
- Clinton Global Institute University Fellow *2020*
- Switzer Foundation Fellowship Finalist *2019 & 2020*
- USDA-CAMINOS Graduate Fellow *2019*
- Next Generation Delegate at the Chicago Council on Global Affairs *2019*
- Graduate Student Representative for Graduate Research Advocacy Day *2019*
- Clean Energy Research Center for Water-Energy Technologies (CERC WET) Graduate Fellowship *2017-2019*
- Imagine H_2O Water Innovation Policy Program Fellow *2018*
- Graduate Group Recruitment Fellowship *2017-2018*
- NSF Research Experiences for Undergraduates (REU) *2012*
- University of Chicago Dean's List *2009*

MEDIA COVERAGE *2017-Present*

- NGO Groundwater Collaboration and Clean Water Action Blog: http://cagroundwater.org/?p=961
- Environmental Defense Fund feature of Espinoza's San Joaquin Valley community engagement work: http://blogs.edf.org/growingreturns/2021/01/07/california-land-and-water-decisions-equity/
- Espinoza's CaliWaterAg incorporated into Groundwater Exchange, educational SGMA websites: English https://groundwaterexchange.org/sgma-videos-in-english/ & Spanish https://groundwaterexchange.org/videos-de-sgma-en-espanol/
- Espinoza's CaliWaterAg featured in Brown and Caldwell's Water News (Dec. 2020), Maven's Notebook, 2020; California Ag Today Radio (2020); AgNet West (2020) Water Wrights (2020): https://agnetwest.com/bilingual-sgma-video-series-foster-better-understanding/; https://agnetwest.com/new-addition-made-to-bilingual-sgma-video-series/; https://waterwrights.net/2020/08/28/caliwaterag-youtube-channel/
- UC Merced News; Espinoza at Chicago Council on Global Affairs Next Generation Delegate, 2019: https://news.ucmerced.edu/news/2019/grad-student-represents-valley-global-food-security-symposium
- UC Merced News Graduate Research Advocacy Day with Dean Zatz (Sacramento): https://news.ucmerced.edu/news/2019/graduate-students-make-case-research-capitol
- 2019 USDA Fellows: https://www.appliedarts.txstate.edu/Announcement/2019-USDA-Fellows.html

- Imagine H2O fellowship & Global Climate Action Summit 2018: https://news.ucmerced.edu/news/2018/uc-climate-change-research-one-focus-global-summit-new-reports
- NASA JPL News on Atmospheric Rivers 2018: https://www.jpl.nasa.gov/news/news.php?feature=7141
- NASA JPL News Intern Highlight 2018: https://www.jpl.nasa.gov/edu/news/2018/10/4/rolling-on-the-science-of-an-atmospheric-river

SKILLS

- Critical Thinking, Problem Solving, Effective Communication, Public Speaking, Scientific Publication Reviews, Scientific Journal Publication Writing, Data Management, Teamwork, Self-management, Organizational, Project Management, Grant Writing, Science Education Multilingual Tool Development (e.g., informational flyers, YouTube videos, and workshops)

Languages: Spanish (Fluent written and spoken) and English (Fluent written and spoken)

Applications: ESRI software (ArcMap and ArcPro), R, MatLab, iMovie, Garage Band, Microsoft Suite (Word, Excel, PowerPoint), GrADS, ArcGIS Soil Water Assessment Tool (SWAT), FLO-2D, HEC-HMS, HEC-RAS, Model for Ozone and Related Chemical Tracers (MOZART) model, Goddard Chemistry Aerosol Radiation and Transport (GOCART) model, WRF-Chem with MOZART gas-phase chemistry mode

ABSTRACT

Global food security is a rapidly emerging concern with climate change and increasing population growth. This dissertation research assessed components critical to inform the strategic transition of irrigated agricultural lands to meet policy targets and sustain food-energy-water systems worldwide by focusing on the San Joaquin Valley, California. This region is not only a global leader in the agricultural sector but is an exemplary representation of regions facing water stress, population growth, and environmental injustice. It is also amidst its trials and tribulations regarding sustainable water policy and management. The newly implemented Sustainable Groundwater Management Act (SGMA) establishes targets for groundwater utilization to address reduced surface water supply and groundwater overdraft. In the San Joaquin Valley, more than 10-15% of irrigated agricultural land is projected to go out of production within the next 10 to 20 years to sustain California's water supplies (Hanak et al., 2017). However, a significant question addressed in this project is how we transition agricultural land to address groundwater overdraft and minimize socioeconomic and environmental impacts on disenfranchised and underserved communities and farmers. While this reduction in irrigated acreage will help lessen groundwater overdraft as per SGMA, the reduction will also result in socioeconomic and environmental impacts on disadvantaged communities and marginalized farmers that rely on agriculture for their livelihood. The dynamics between land use and the direct and indirect implications of agricultural land use transitions remain unknown. The components of this dissertation aim to minimize the impacts of agricultural land use transitions under SGMA to those most impacted and often left out of the water and land use decisions—underserved communities and farmers. This doctoral dissertation has the following objectives:

1) Identify San Joaquin Valley community land use preferences.
2) Assess irrigation district overdependence on groundwater to identify where to focus agricultural land use transition efforts.
3) Identify which land use classification datasets are best to use to assess how and where to transition agricultural land and quantify the crop revenue, crop water requirement, and GHG emission discrepancies due to misclassifications.

CHAPTER 1. INTRODUCTION

1. Global Water Crisis

Water is the center of economic, social, and ecosystem functions worldwide. Maintaining human livelihood, food production, energy security, and economic development is imperative. Global water issues are often highlighted as an issue of water availability, but water access inequality stemming from poor water governance and management is often overlooked (United Nations Development Programme, 2006; Calow and Mason, 2014). Despite water being a crucial resource, millions of people worldwide still do not have access to safe, clean water supplies due to uneven and variable distributions of global water supplies and climate change. About half a billion people face severe water scarcity year-round (Mekonnen & Hoekstra, 2016), a number projected to increase to three billion by 2025 (Hanjra & Qureshi, 2010). Global population totals could reach 9 billion by 2050 (Alexandratos & Bruinsma, 2012), increasing water demand by 30-50% (Damania et al., 2017). Naturally, the conversation of sustaining global food security follows water scarcity. In addition to increasing food production by 60% to feed more than 9 billion people by 2050 (Alexandratos & Bruinsma, 2012; Wise, 2013), increasing per capita income around the world is adding stress on the agricultural sector to meet diverse and nutritious diets (Rosegrant, 2019).

Freshwater being central to the function of many other critical societal sectors, like food, energy, and the environment, make it more critical to rebalance water distribution and address water access inequity. Globally, agriculture has an opportunity to play a role in helping address global water issues and climate change. Agriculture makes up 38% of the global land surface (FAO, 2020), uses about 70% of freshwater resources (FAO, 2017b), and makes up the majority of the 23% of the greenhouse gas (GHG) emissions from agriculture, forestry, and other land use sector (IPCC, 2019). The interrelation between water and agricultural production has fed the cycle of stresses of one on the other, especially in groundwater supplies. Groundwater is a critical resource to meet the drinking water needs of millions of people and irrigate about one-third of the 301 million hectares of irrigated land worldwide (Siebert et al., 2010). Globally, there is an opportunity to address water scarcity and climate change conditions through climate-smart agricultural practices. The high reliance on groundwater for irrigation in many agricultural regions around the world has led to groundwater overdraft at rates higher than is being recharged. The United States, for example, relies on 71% of total groundwater use (Rosegrant, 2019) to irrigate about 17 million hectares of land (Siebert et al., 2010). Globally, there is a need to address water availability and water access inequities to prevent detrimental impacts on natural resources that underserved populations rely on to survive.

2. California: A Mesocosm of Global Water Issues and Poverty Paradox

As a mesocosm of global water issues, California is an exemplary case study for solving global water issues and associated overdemands from water-dependent sectors (e.g., food and energy). Agriculture in California generates more than $50 million in farmgate revenue annually (California Department of Food and Agriculture, 2019) and provides 405,800 agricultural jobs (California Employment Development Department, 2022). The state's central agricultural regions, the San Joaquin Valley, generates more than 400 different commodities and produces one-third of the nation's vegetables and two-thirds of its fruit and nuts (Pathak et al., 2018). A thriving agricultural region—but at what cost? The largesse of California's agriculture is under strain due to water scarcity, increasing drought, and population growth. The San Joaquin Valley is a drought-prone, water-scarce, and water-stressed region. On average, 40% of all freshwater is used for irrigated agriculture, representing 80% of all beneficial water use in the state (Hanak et al., 2017). Surface water supplies are variable, and groundwater is over-pumped, especially during drought. As is the case in many places around the world, groundwater in California plays an important role in supplying ~30-60% of water in a given year. Agricultural water use exceeds sustainable supplies by ~2 million acre-feet per year (Hanak et al., 2017). Although groundwater has been used conjunctively with surface water in the Central Valley to meet water demands (Faunt et al., 2016), the most recent drought (2012-2015) led to an additional overdraft of about 5 million acre-feet of groundwater (Howitt et al., 2015). Exacerbating groundwater has a plethora of consequences like land subsidence and damage to infrastructure (Faunt et al., 2016), drying of domestic wells, lowering of water tables, increased energy from pumping at greater depth (House et al., 2018), reduced water quality (Smith et al., 2018), reduction or elimination of baseflow to streams and rivers, and loss of groundwater dependent ecosystems. The stress on water resources to produce food to feed the state, the nation, and many parts of the world will increase with increasing population growth. Population in the Central Valley is expected to grow faster than the statewide average, contributing to an increase in the state's population by one to two percentage points (Palmer, 2017).

The largesse of California's agriculture is under strain due to water scarcity, increasing drought frequency, and population growth. California's agricultural regions are a poverty paradox. Nestled among the state's multi-billion agricultural landscape, marginalized populations live in poverty and are exposed to poor air and water quality. Socioeconomic, health, and environmental disparities are most acute in the San Joaquin Valley. The San Joaquin Valley is one of the most persistently poor and polluted regions in the United States (California Office of Environmental Health Hazard Assessment 2021). About 31% of children living in the region live in poverty compared to the 19% nationally (U.S. Census Bureau, 2019a). About 165% of San Joaquin Valley residents are exposed to polluted drinking water sources (American Lung Association, 2021). There are more than 500 disadvantaged communities (DACs) in California, predominantly of Latino/Hispanic populations, are disproportionately impacted by unrelenting environmental and socioeconomic conditions and are primarily underrepresented in political settings that affect their well-being (Balazs et al., 2012; Bernacchi et al., 2020; Fernandez-Bou et al., 2021; Flegal et al., 2013; London et al., 2018; Mayzelle et al., 2015; E. Moore et al., 2011). About 87% of DACs in the San Joaquin Valley rely on a community water system that is groundwater-dependent (London et al., 2018), drinking water sources that are contaminated by arsenic, nitrates, and other chemicals (Balazs et al., 2012; Balazs, Morello-Frosch, and Ray 2011; Blake 2014; Harter et al. 2017).

3. The Challenges and Opportunities Under SGMA

California's 2014 Sustainable Groundwater Management Act, commonly referred to as SGMA, aims to stabilize groundwater conditions in critically overdrafted basins, most located in the San Joaquin Valley and Tulare Lake Basin, by 2040. Under SGMA, local control is promoted by enabling self-organized local water agencies known as Groundwater Sustainability Agencies (GSAs) to facilitate the planning and implementation of groundwater sustainability plans. The GSAs consist of irrigation districts, water districts, and county and city agencies. Under SGMA, GSAs must engage with DACs within their basin to ensure sustainability plans that simultaneously address community needs. To date, there has been minimal formal input from DACs to groundwater sustainability plans (Dobbin & Lubell, 2021), and news representation of SGMA has been dominated by agriculture (Bernacchi et al., 2020; Fernandez-Bou et al., 2021). Although the implications of SGMA remain unknown, studies have projected that more than 10-15% (more than 202,342 hectares) of agricultural land in the San Joaquin Valley may have to go out of production to meet groundwater targets under SGMA by 2040 (Hanak et al., 2019). Anticipated land use transitions under SGMA are another incentive for California to rethink water and land use management strategies that rebalance freshwater resources while simultaneously addressing socioeconomic and environmental inequity among DACs. Leaving land out of production or fallow (e.g., without use or not irrigated) could have environmental (e.g., increased dust generation), human health (e.g., asthma and exposure to Valley Fever), and socioeconomic consequences (e.g., local economy, agricultural jobs), especially for agriculturally dependent DACs in the San Joaquin Valley.

Although there are challenges associated with addressing groundwater overdraft under SGMA, there are opportunities to address socioeconomic and environmental inequities that disproportionately impact rural agricultural communities and DACs. In 2021, California created the Multibenefit Land Repurposing Program (MLRP), which provides regional block grants (e.g., GSA, Resource Conservation District, Tribes, public agencies, and local NGOs) that support multibenefit land repurposing projects to reduce groundwater reliance and climate change conditions, while also benefitting communities, ecosystems, and the local economy (Department of Conservation: Multibenefit Land Repurposing Program, 2021). Recent legislation to sustain groundwater supplies will likely reduce the agricultural footprint, but future land use transitions could help address the water access and environmental inequities among DACs in the San Joaquin Valley. Some multi-benefit land repurposing options considered for implementation to address SGMA include 1) habitat restoration (Bourque et al., 2019; Butterfield et al., 2017; Cypher et al., 2013; Lortie et al., 2018; Stewart et al., 2019; Tennant et al., 2013), 2) renewable energy (e.g., solar) (Butterfield et al., 2013; Pearce et al., 2016), 3) carbon sequestration, 4) groundwater recharge (Ghasemizade et al., 2019; Mayzelle et al., 2015; O'Geen et al., 2015), and 5) parks and green space (Jennings et al., 2012). These multi-benefit land repurposing options have the potential to address groundwater overdraft under SGMA while simultaneously addressing the social disparities among San Joaquin Valley DACs. For example, parks, green spaces, and wildlife habitat areas near DACs could provide spaces that are currently lacking in DACs that facilitate healthier activities, like walking, and alleviate mental health issues that are persistent among low-income Latino communities (Galea et al., 2020; Grassi et al., 1999; Lama et al., 2018; Lee, 2020). Implementing groundwater recharge in and around DACs could help replenish the groundwater resources these communities depend on to meet basic human needs.

4. Dissertation Objectives and Broader Impacts

When SGMA was passed, a key question was—how will agricultural land be transitioned to address groundwater overdraft (PPIC, 2019)? Given the severe socioeconomic and environmental implications of taking agricultural land out of production or transitioning to alternative uses, especially for DACs, three key questions must be understood before deciding how and where land should be transitioned to address SGMA. The three critical questions that this dissertation answers to better inform strategic, equitable, and locally representative land use transitions to address groundwater overdraft under SGMA are:

Chapter 2. What alternative land uses meet disadvantaged community needs?

Chapter 3. Where should land transition efforts be focused?

Chapter 4. Are land use classification datasets used to inform water and land use decisions accurately representing what is currently on the ground?

This doctoral work is founded on the principle that water and land use decisions are best made when co-developed with the people most underrepresented in and impacted by these decisions—underserved communities and small-scale farmers. The qualitative and quantitative approaches to answering the key critical questions to strategic and equitable agricultural land transitions under SGMA are multidisciplinary and interdisciplinary, using diverse datasets, statistical and geospatial analysis, and community engagement. To answer what alternative land uses meet disadvantaged community needs (Chapter 2), I, along with a diverse team of social scientists, ecohydrologist, and engineers, developed a short message service (SMS) distributed web-based survey to understand the land use preferences of 32 DACs in the San Joaquin Valley. Chapter 1 is a preliminary attempt at addressing the decision-making gap that has been documented among DACs by GSAs (Bernacchi et al., 2020; Dobbin & Lubell, 2021; Fernandez-Bou et al., 2021), and the dominant focus on agriculture in GSA sustainability plan developments. To identify where land transition efforts should be focused (Chapter 3), I consolidated disaggregate irrigation district variables (e.g., date of formation, surface water allocation, surface water delivery) and derived variables (e.g., crop water requirement, groundwater dependence to conduct a cluster analysis and develop and irrigation district sociohydrologic vulnerability index. This chapter also compared DACs within irrigation districts and groundwater-dependent communities (also known as white areas) to understand how the historical contexts in which irrigation districts were formed shape local water governance structures and impact local communities within their jurisdiction. Finally, to understand whether commonly used land use classification datasets in California accurately represent the state's complex agricultural landscape (Chapter 4), I conducted a geospatial analysis focused on Kern County and compared the Kern County dataset (locally funded), Land IQ (state-funded), and USDA CropScape (nationally funded). I quantified the revenue, crop water demand, and GHG emission discrepancies from land use misclassifications.

Throughout my doctoral journey, I also addressed an information equity gap that persists among marginalized communities and farmers in California. I had the opportunity to engage with underserved community members and farmers, which led me to identify the need for multilingual and multimedia resources on SGMA and other water and land use managements and policies that impact their livelihood. I held bilingual workshops for Latino communities and farmers on SGMA and created CaliWaterAg, a trilingual (Spanish, Hmong, and English) YouTube channel to make the science and policy behind California water and land use management accessible to Californians (Appendix C). Insights from my extension efforts and community land use survey (Chapter 2) resulted in collaboration with the Environmental Defense Fund to develop a guide for effective community and farmer engagement to help guide applicants of California's Multibenefit Land Repurposing Program, including NGOs, academic institutions, tribal groups, and GSAs (Appendix B). I have also had the opportunity to bring forward the importance of involving underserved communities and small-scale farmers in future water and land use decisions through conversations with policymakers at the local, state, and federal levels. This research embraces understanding the relationships between food-energy-water systems (Appendix G) with policy, people, and climate change. This dissertation aims to ameliorate water injustice through qualitative, quantitative, and extension approaches with multistakeholders.

CHAPTER 2. WHAT ALTERNATIVE LAND USES?

1. Introduction

The San Joaquin Valley of California is paradoxical. It is one of the most productive agricultural landscapes on Earth, yet it remains one of the most persistently poor and polluted places in the United States. And the representation of its denizens and community needs in water management and land use planning may be limited, but a 2014 groundwater law provides the impetus for inclusive engagement and planning. In five of the San Joaquin Valley counties of Fresno, Kings, Madera, Merced, and Tulare, 31.1% of children live in poverty compared to 18.5% nationally, and the unemployment rate is 9.2% compared to 4.5% nationally (U.S. Census Bureau, 2019a). The San Joaquin Valley metropolitan areas of Fresno-Madera-Hanford, Bakersfield, and Visalia are three of the nation's most polluted cities for ozone and year-round particle pollution (American Lung Association, 2021). Residents of San Joaquin Valley counties are 165% more likely than in the rest of California to be exposed to the state's most polluted drinking water (California Office of Environmental Health Hazard Assessment 2021). Nitrates, arsenci, and hexavalent chromium (Cr[VI]) have been dectected in higher concentrations in areas of domestic well use (Pace et al., 2022).

The low-income, predominantly Latino population in the San Joaquin Valley's 225 designated disadvantaged communities (DACs), take the brunt of the socioeconomic and environmental impacts. Historical land use, zoning practices, and racial discrimination have led to the concentration of poverty in these communities (Flegal et al., 2013). California defines DACs as communities with a median household income of less than 80% of the statewide annual median household income (California Department of Water Resources, 2018) USD 60,188 in 2019; U.S. Census Bureau, 2019). While many of these communities are highly dependent on agriculture for the well-being of their local economy and livelihood; proximity to agricultural production results in high rates of exposure to pesticides, air pollution, water contamination, and dangerous chemicals (California Office of Environmental Health Hazard Assessment, 2021; Balazs et al., 2011, 2012; Nunez Flores, 2013).

Furthermore, the largesse of its agriculture – over 5 million acres of diverse agriculture producing 400 commodities annually worth USD 25 billion, including 60% of the nation's fruits and nuts and 30% of its vegetables (California Department of Food and Agriculture, 2019) – is under strain as it confronts widespread drought and groundwater overdraft. The increasing magnitude and intensification of extreme precipitation events (Espinoza et al., 2018), like droughts, will exacerbate already critically overdrafted groundwater basins in the region (Hanak et al., 2019). For the San Joaquin Valley, groundwater is the reserve necessary to keep agriculture booming during drought years (Howitt et al., 2015) and meet the drinking water needs of 87% of local community water systems (London et al., 2018). As such, there is a need for water governance agencies to develop climate change adaptation strategies that simultaneously reduce and balance freshwater demands while also addressing the water access inequities (Espinoza & Viers, n.d.). California's sociohydrologic dynamics driven by complex historical water and land use management have led it to become a bellwether of the global climate crisis—competing freshwater demands, agriculturally driven economy, groundwater overdependence, and socioeconomic and environmental disparities.

California instituted the Sustainable Groundwater Management Act (or SGMA) to mitigate groundwater overdraft in 2014. The SGMA legislation aimed to stabilize groundwater conditions in critically overdrafted basins by 2040 by enabling self-organized local water agencies to facilitate the planning and implementation of groundwater sustainability plans. Although the implications of SGMA remain unknown, studies have projected that more than 10% or 1 million acres of agricultural land may not continue as irrigated agriculture to meet groundwater targets by 2040 (Hanak et al., 2019). Anticipated land use transitions under SGMA are another incentive for California to rethink water and land use management that rebalance freshwater resources while simultaneously addressing socioeconomic and environmental inequity among DACs. Legislature passed AB-252, the Multibenefit Land Repurposing Program (MLRP), to transition agricultural land to other uses that reduce groundwater use while also providing community health, especially DACs, economic well-being, habitat, water supply, and climate benefits (Department of Conservation, 2021). Recent legislation to sustain groundwater supplies will likely reduce the agricultural footprint, but future land use transitions could help address the water access and environmental inequities among DACs in the San Joaquin Valley. Some multi-benefit land repurposing options considered for implementation to address SGMA include 1) habitat restoration (Bourque et al., 2019; Butterfield et al., 2017; Cypher et al., 2013; Lortie et al., 2018; Stewart et al., 2019; Tennant et al., 2013), 2) renewable energy (e.g., solar)

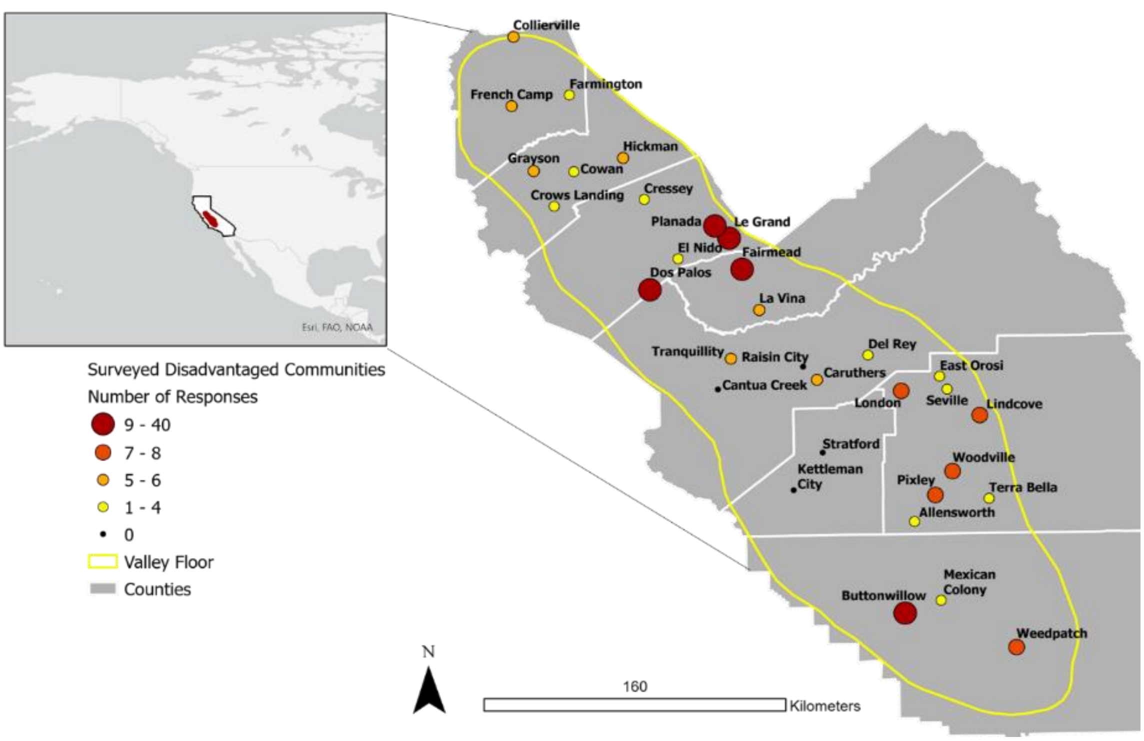


Figure 1. The 32 disadvantaged in the San Joaquin Valley, California surveyed in this study.

(Butterfield et al., 2013; Pearce et al., 2016), 3) carbon sequestration, 4) groundwater recharge (Ghasemizade et al., 2019; Mayzelle et al., 2015; O'Geen et al., 2015), and 5) parks and green space (Jennings et al., 2012).

These multi-benefit land repurposing options have the potential to address groundwater overdraft under SGMA while simultaneously addressing the social disparities among San Joaquin Valley DACs. For example, parks, green spaces, and wildlife habitat areas near DACs could provide spaces that are currently lacking in DACs that facilitate healthier activities, like walking, and alleviate mental health issues that are persistent among low-income Latino communities (Galea et al., 2020; Grassi et al., 1999; Lama et al., 2018; Lee, 2020). Implementing groundwater recharge in and around DACs could help replenish the groundwater resources these communities depend on to meet basic human needs (Mayzelle et al., 2015). Although under SGMA, local water agencies are required to engage community members so that groundwater sustainability plans address DAC water issues, formal input from DACs has been minimal (Dobbin & Lubell, 2021), and news representation of SGMA has been dominated by agricultural needs (Bernacchi et al., 2020; Fernandez-Bou et al., 2021).

Due to the complex interplay between water, land use, and societal well-being under climate change in the San Joaquin Valley, people need to understand how they relate to, value, and depend on the land in their community. This survey asked participants about five land use repurposing options with the community and economic value factors to understand complex water-land-social dynamics. Participants were also asked to identify their most and least important land use priorities to understand community members' relationship to and value for nearby lands and alternative land use options. Questions on agriculture helped identify the value and importance of agriculture to participants' livelihood. Climate change statements to analyze correlations between their land use preferences and their perspectives on climate change. This study addresses the current lack of understanding of how local communities, specifically socially, politically, and economically vulnerable communities in the San Joaquin Valley, value alternative land uses. Further, this study examines perceptions and preferences around climate change resilience and socioeconomic and environmental inequities across rural agricultural communities where future agricultural land use transitions are likely. Understanding individuals' reported values for nearby land use may help identify preferences and values around likely land use transitions and provide insights into our public perception of emergent land uses, including green technologies and sustainable infrastructure. Overall, this study is the first to assess community land use preferences and land use values to inform equitable future land use transitions in the San Joaquin Valley under SGMA and MLRP implementations.

2. Methods

2.1 Sampling and Data Collection

Our multi-disciplinary research team developed an online survey focused on alternative land uses that could address groundwater overdraft by 2040 under SGMA and distributed via short message service (SMS text) from March to June 2021.

Sampling was focused on 32 DACs in the San Joaquin Valley (Figure 1). The sampling frame was based on cell phone numbers purchased from Marketing Systems Group (MSG), which provides samples linked to geographic and demographic information (Marketing Systems Group, 2021), allowing us to capture potential spatial gradients of community land use perspectives across the study region. The number of samples was initially determined by DAC population size and sent to MSG to estimate sample availability within DAC boundaries. Given the limitation of MSG's cell samples within DAC boundaries, the following sampling rules were provided to MSG to increase the number of cell samples per DAC: 5,000 > MSG Record Count > 1,000 = initial MSG DAC count, 1000> MSG Record Count <100 = 100% increase in initial MSG DAC count, and 100> MSG Record Count = 200% increase in initial MSG DAC count. Three thresholds were used until the sample size was met (ordered from highest to lowest sampling priority): within the DAC boundary, 3-mile radius, and 5-mile radius. Small populations were oversampled. (See Appendix A, SI Table 2 for the number of samples per DAC and the geographic limit used to obtain the sample size).

The sampled DACs were selected for variation in terms of population size, environmental risk exposure, and geographic location across the San Joaquin Valley. To be included, a DAC also needed to fulfill the following criteria: 1) not embedded within a major city, 2) diverse levels of CalEnviroScreen 4.0 Scores (i.e., pollution burden and population characteristics variables; SI Table 8) ranging from 40-100th percentile), and 3) having populations less than 5,000 based on the 2018 population (California Office of Environmental Health Hazard Assessment, 2018).

The survey was administered using Qualtrics (Qualtrics, 2021) and distributed via SMS text services by a Qualtrics third-party partner, Twilio (San Francisco, CA). Surveys were distributed across weekdays and non-holiday weekends. Time of survey distribution varied (morning and noon) to avoid structural bias in the resulting data. The survey was offered in English and Spanish to promote inclusion, relying on metadata from MSG to indicate the preferred language.

2.2 Survey Instrument Measurement

The survey consisted of three sections focused on questions related to land use, agriculture, and climate change (See the survey instrument in Appendix A).

The first section of the survey contained questions related to employment (e.g., current job and residential postal code) and familiarity with SGMA. The second section contained questions related to community vision, in which respondents were asked to what extent they agreed or disagreed with how the following five agricultural land repurposing options benefitted their community and local economy: 1) renewable energy (e.g., solar and wind), 2) habitat restoration (e.g., places to see wildlife), 3) groundwater recharge, 4) carbon sequestration (e.g., storing carbon on farmland, getting carbon credits), and 5) parks and green space (e.g., parks, trails, bike paths, and playgrounds). Additionally, respondents were asked to identify their most and least important land use repurposing option out of seven options: 1) wildlife, 2) recreation, 3) clean energy, 4) secure water supplies, 5) reduce GHG and climate change, 6) schools, grocery stores, and housing, and 7) less water-intensive agriculture. Participants were asked statements related to agriculture: 1) they live in the valley because of agriculture, 2) their job depends on agriculture, 3) agriculture is the core of the economy in their community, 4) there needs to be space between agriculture and where people live for health reasons, and 5) agricultural practices contribute to air and water pollution in their community. The third section of the survey was related to demographics: Participants were asked questions related to ethnic background, preferred gender pronouns, total household income, as well as three statements on climate change in their region: 1) climate change is happening, 2) climate change impacts water quantity, and 3) climate change impacts water quality. Participants were also allowed to share anything else they would like at the end of the survey.

Statements were measured on a four-degree Likert scale with levels of agreement from Strongly Agree, Somewhat Agree, Somewhat Disagree, and Strongly Disagree. Respondents answered statements in random order to avoid priming effects, and some statements were reverse coded.

2.3 Survey SMS Dissemination Approach

Before disseminating the survey via SMS-text, the survey instrument was reviewed by bilingual colleagues to assess the clarity of terminology and questions, the accuracy of translation between English and Spanish, and the amount of time needed to complete the survey. Preliminary test runs resulted in a survey completion time of less than 10 minutes. Four SMS distributions were planned for data collection, including the first survey distribution and three reminders spaced by four days from the last reminder. The SMS text messages used to disseminate the web survey for the English and Spanish subsets, along with the planned schedule, are shown in Table 1. The survey was distributed in two phases between March and June of 2021: 1) March 29th – April 9th and 2) May 15th – May 25th. The first phase of the survey was not completed successfully due to internal errors on behalf of Qualtrics' third-party SMS distributor, Twilio, in which the first SMS survey reminder was not delivered successfully. To proceed with this distribution and use the remaining SMS distribution credits, the sample that did not receive a reminder, had not yet completed the survey, and had not opted out of receiving survey messages, were extracted to create an English and Spanish subset consisting of 2,500 cell samples. Due to limited SMS credits, additional credits were purchased to be used in the second phase of the survey, which utilized the extracted phone samples from the first distribution that had not completed the survey, not opted out, and had deliverable cell numbers from the Spanish subset of phase 1.

	Audience	English and non-available	Spanish
ROUND 1	Date	March 29, 2021	March 29, 2021
	Time	2 PM	2 PM
	Survey Version	English	Spanish
	Text message	UC Merced research: what do you want to see in your community? 10-minute survey. Text STOP to opt-out. (Standard messaging rates apply.)	UC Merced investigación: Que quisiera ver en su communidad? Encuesta de 10-minutos. Text STOP to opt-out. (Standard messaging rates apply.)
ROUND 2	Date	April 1, 2021	April 1, 2021
	Time	7 AM	7 AM
	Qualtrics Used	English	Spanish
	Text message	What's the future for your community? 10-minute survey by UC Merced. En Español. Text STOP to opt-out. (Standard messaging rates apply.)	What's the future for your community? 10-minute survey by UC Merced. En Español. Text STOP to opt-out. (Standard messaging rates apply.)
ROUND 3	Date	April 5, 2021	April 5, 2021
	Time	4 PM	4 PM
	Qualtrics used	English	Spanish
	Text message	Elevate your community's voice! Eleve la voz de su comunidad! 10-minute survey. STOP to opt-out. (Standard messaging rates apply.)	Elevate your community's voice! Eleve la voz de su comunidad! 10-minute survey. STOP to opt-out. (Standard messaging rates apply.)
ROUND 4	Date	April 11, 2022	April 11, 2022
	time	2 PM	2 PM
	Qualtrics used	English	Spanish
	Text message	Last chance: Have your voice heard! English/Español. 10-minute survey. Text STOP to opt-out. (Standard messaging rates apply.)	Última oportunidad: Que se escuche su voz! Encuesta de 10-minutos. Text STOP to opt-out. (Standard messaging rates apply.)

Table 1. Schedule and associated text messages for the dissemination of the English and Spanish subsets of the survey.

2.4 Challenges of Working with DACs

The challenges of reaching a socio-economically disadvantaged population likely lowered the response rate of this survey due to factors such as limited access to data and the internet (Bonevski et al., 2014); the participant fatigue and distrust of surveys; and the general disposition of the population living during the COVID-19 pandemic. Our sample included agricultural workers (Pennings et al., 2002) and Latinos (Bonevski et al., 2014; Evans et al., 2008), who are less likely to respond to surveys because of the timing of the survey, difficulty in dealing with survey materials, mistrust in the government, research topic, form or amount of compensation or benefit to be received, length of the survey, and the tendency for a low level of self-disclosure. Socially disadvantaged rural communities in the San Joaquin Valley have limited access to the internet (Balabanis et al., 2007; Reddick et al., 2020). There is also low ownership of smartphones and computers among older, Spanish-speaking dominant and Latinos with no high school diploma (Pew Research Center, 2013). Other factors contributing to the low survey response rate could have been high participant fatigue amongst socially disadvantaged communities as efforts to increase diversity, equity, and inclusion in developing water management strategies under SGMA during a pandemic and fatigue in adapting to new technologies (e.g., video conference software) (Sevelius et al., 2020). Survey reminder texts in this study were interrupted due to technical errors on behalf of the SMS survey distributor, which could have negatively affected a well-documented method of multiple requests to participate in surveys regardless of format (Dillman, 2000). To overcome traditional barriers and the pandemic, the best alternative at a reasonable cost was to conduct an SMS text-distributed link to a web-based survey.

2.4 Survey Data Processing and Analysis

This study's total number of cell phone samples was 27,572 mobile phone numbers, of which 25% (n=6,794) were undeliverable devices resulting in 20,778 deliverable phone samples. Out of the deliverable phone samples, about 7% (n=1,360) of participants opted out of receiving SMS messages, and about 12% (n=2,510) of participants started the survey but did not complete it. A workflow of the analysis is outlined below and shown in Figure 2.

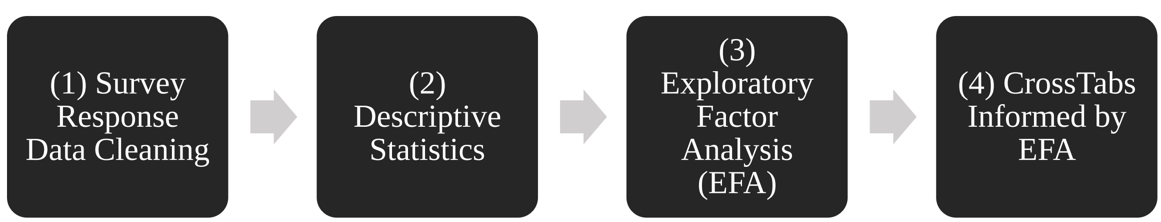


Figure 2. Workflow of survey response data analysis.

(1) The English and Spanish subsets of the surveys were downloaded from the Qualtrics online interface and combined into a single spreadsheet in Excel, resulting in 324 submitted surveys. Qualtrics survey output includes a variable that indicates the completion percentage of the survey. The surveys that were 0-5% complete

(60% of surveys, n=127) were filtered out, resulting in 60% of surveys (n=197) that were more than 5% complete and used for analysis.

(2) Descriptive statistics on survey responses to questions and statements on demographics, familiarity with SGMA, ten land use statements, most and least prioritized land uses, relationship to agriculture, and climate change perception was conducted using R software (version 2.1).

(3) After an initial exploratory analysis, exploratory factor analysis (EFA) was used to identify underlying structures in the data, clarifying the relationships between land use values and identity factors (i.e., climate change and relationship with agriculture). An EFA is a statistical method used to reduce the dimensionality of data and explore underlying theoretical structures within the reduced dataset. All analysis was conducted using R-statistics (version 2.1), and the factor analysis was done using the 'fa' function in the 'psych' package (Revelle, 2015). Three EFAs were conducted for three subsets of the survey data (Figure 3) to identify and compare underlying differences in land use preferences, relationship to agriculture, and climate change perception between all survey respondents (excludes income NAs), DACs (total household income ≤ \$60K and non-declared white), and non-DACs (all respondents excluding DACs). This study uses the state's definition of DACs: communities with a median household annual income (MHI) that is less than 80% the statewide MHI (2021 DAC MHI is \$62,937) and predominantly Latino/Hispanic populations. Given that various studies have identified the underrepresentation of DACs in SGMA and other water and land use decisions in the state that impact their livelihood (Bernacchi et al., 2020; Dobbin & Lubell, 2021; Fernandez-Bou et al., 2021), it is important to identify how land use preferences and values may differ among DAC and non-DAC populations in California.

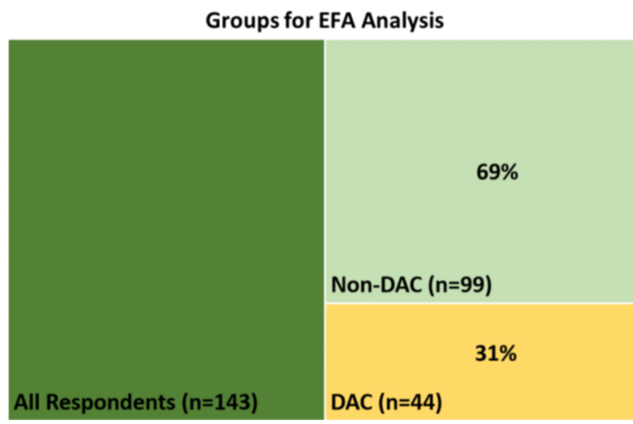


Figure 3. Subset data consisting of all (excluding income NAs), DAC (total household income ≤ \$60K and non-declared white), and non-DAC (total household income > \$60K) respondents for the EFA analysis.

(4) Underlying relationships highlighted from the EFA on all three subsets of the data were used to inform cross-tabulation analysis conducted in R to help further identify compelling insights on participant priorities of land use in their community, familiarity with SGMA, relationship to agriculture, and climate change perceptions based on THI and ethnic background.

The San Joaquin Valley comparative statistics—population, median household income (estimated July 2019), persons in poverty (%), and population ethnicities and race (%)—were obtained from the U.S. Census Bureau for each of the eight San Joaquin Valley counties—Stanislaus, San Joaquin, Merced, Tulare, Fresno, Madera, Kings, and Kern. The population per county was summed to obtain the San Joaquin Valley population estimate, median household income, poverty percentage, and percent of race per county were averaged to obtain an average for the San Joaquin Valley.

3. Results and Discussion

3.1 Demographics and Baseline Groundwater Knowledge

Of the 324 surveys submitted, 60% of surveys (n=197) were more than 5% complete. About 93% (n=183) of the surveys were completed in English, while 7% (n=14) were completed in Spanish. This survey resulted in a response rate of about 1.5%. The demographic information of the sample was compared with the population of the San Joaquin Valley (Table 2). Participant total household incomes were distributed as follows: 42% (n=59) low-income (as defined for disadvantaged communities by California) and 58% (n=83) as high-income. Participants ethnically identified as 25% (n=49) Latino/Spanish Origin, 26% (n= 52) White, and 49% (n= 96) were multi-ethnic or preferred not to answer. The preferred gender pronouns of survey participants were 35% (n=68) she/her/hers, 22% (n=43) he/him/his, and 2% (n=3) they/them/theirs, and 42% (n=83) preferred not to answer. Participants stated their work as retired (21%, n=41), in agriculture (13%, n=25), and as unemployed (9%, n=18). Respondents had higher incomes than the region's general population, were less likely to be Latino, and were more likely not to be part of the workforce.

Participants were asked about their familiarity with SGMA with levels of familiarity, *not at all familiar*, *somewhat familiar*, and *very familiar*. The highest percentage of respondents 54% (n= 105) were not at all familiar, 33% (n=64) were somewhat familiar, and 13% (n= 26) were very familiar (Table 2). Most respondents are not familiar with SGMA, which indicates representation, translation, and education and outreach issues to agricultural communities in the Valley. Understanding SGMA is important given that 87% of community water systems within disadvantaged communities in the San Joaquin Valley are sourced from groundwater (London et al., 2018). Although the implications of SGMA remain unknown, studies have projected that agricultural land may need to go out of production or transition to alternative multibenefit land uses to address groundwater overdraft (Hanak et al., 2019), which could have socioeconomic and environmental impacts on DACs. Given that water strategies under SGMA have implications on agriculture, farmers and agricultural professionals need to understand SGMA to implement effective water management strategies for the next 20 years. Respondents that self-identified as farmers (n=10) were the most familiar (26%, n=6) or somewhat familiar (13%, n=3) with SGMA compared to other agricultural professionals who were primarily not familiar with SGMA (30%, n=7).

3.2 Relationship to Ag

Given that agriculture is the current most extensive land use in California, about 26 million acres classified as farming and ranching out of 101.5 million acres of land (Novan, 2018), we sought to understand participant relationships with agriculture in terms of economics, aesthetics, and exposure to agricultural externalities. The relationship between the status quo and existing land uses may impact what Central Valley residents are interested in converting land under SGMA. We asked five agreement statements about agriculture to develop an index on agricultural relationships and understand the relationship of agriculture to other land use lenses (Table 2). Respondents largely agreed (cumulative agreement of 94% (n=143) that agriculture is the core of the economy in their community, while 6% (n=8) cumulatively disagreed. This response distribution is interesting given that the largest land use in the region is agriculture, but the economic contribution to the region (San Joaquin and Tulare Basin) is 29% (University of California Issues Center, 2009; based on 2002 dataset) and to the state is 2% gross domestic product. Most respondents live in the San Joaquin Valley because of agriculture (38% strongly agreed, n=57). In contrast, even distribution with a third of respondents stated *strongly agree*, *somewhat agree,* and summative disagreed to living the Valley because of agriculture. Despite living here for agriculture, the same proportion of respondents *strongly disagree* that their *job depends on ag*. The adage adorns bumper stickers, and half of the respondents' jobs depend on agriculture. The nuance of the *strongly agree* (29%) and *somewhat agree* (21%) is helpful, illustrating the difference between direct agricultural employment and indirect agriculturally related employment or work.

Low-income agricultural communities are often the most impacted by agricultural practices that contribute to poor air quality and groundwater contamination from fertilizers and pesticide runoff. Buffers or spaces dedicated to non-agricultural practices could provide multibenefit land uses (e.g., groundwater recharge or recreation). Responses on whether *there should be space between farmland and where people live for health reasons* were mixed between summative agreement (55%) and summative disagreement (45%). Analyzing the relationship between *my job depends on ag* with the need for an agricultural buffer in communities shows that people who work in agriculture are more likely to disagree with agricultural buffers (52%, n=39 out of 75) than people who do not work in agriculture (37%, n=28 out of 75). There was an even distribution between *strongly agree* (20%), *somewhat disagree* (24%), and *strongly disagree* (21%). The largest response was 35% for *somewhat agree*.

By definition, DACs are lower-income and, based on CalEnviroScreen, have higher pollution rates. We asked about the level of agreement for *farming contributes to air and water pollution in my community* (Table 2). There was a nearly even distribution between *strongly agree* (19%), *somewhat agree* (23%), and *somewhat disagree* (23%), and a higher rate of respondents *strongly disagree* (36%), perhaps due to the implication that agriculture is at fault. Given that 46% of respondents selected *somewhat agree or somewhat disagree* may indicate respondent unawareness of the impacts of agricultural communities on environmental and human health.

3.3 Stance on Climate Change

Based on prior research, Californians tended to have higher percentages of people believing that climate change was happening (70%), believe that global warming is human-caused (~3%), are worried about climate change (61%), think climate change will moderately or a greatly harm people in the United States; support the regulation of carbon dioxide (CO_2) as a pollutant (71%), and support for a utility renewable energy standard (60%) (Howe et al., 2015). By comparison, averages are lower for the San Joaquin Valley, where 66% of people believe that climate change is happening, 50% believe that global warming is human-caused, 58% are worried about climate change, 58% believe that climate change will moderately or greatly harm people in the United States, 68% strongly support the regulation of CO_2, and 56% somewhat or strongly support for a utility of renewable energy standard (Howe et al., 2015).

Respondents represented the regional bias for climate change impacts on water and quality: 70% agreed that climate change is happening in their region. Regarding climate change impacts local water quantity and quality, 63% of participants agreed that climate change threatens water quantity locally, and 60% agreed that climate change threatens local water quality. A study by Niles, Lubell, and Haden (2013) conducted a study on California farmers' perception of climate change and found that farmers that expressed that water availability had decreased over time were more likely to believe in climate change, which was similar to the case for people who work in agriculture surveyed in this study. People who work in agriculture in this study were more likely to disagree that climate change is happening (30%, n=6 out of 10), that climate change impacts local water quantity (35%, n=7 out of 10), and quality (30%, n=6 out of 10). Generally, public understanding of climate change is not a problem of deficit of knowledge but rather a different understanding of the concept (Weber & Stern, 2011). There is a need to find ways to increase understanding of climate and science, in general, by increasing scientific literacy and two-way communication, and community engagement to address the epistemic trust in science that is especially problematic among marginalized communities (Grasswick, 2010; Sinatra & Hofer, 2016; Weber & Stern, 2011).

Median Household Incomes (National, State, and DAC)	
National MHI (2021 USD)	$67,521
California MHI (2021 USD)	$78,672
DAC MHI (2021 USD)	$62,937
San Joaquin Valley Demographics (US Census Bureau, 2021)	
Population (2021)—	4,350,031
Median Household Income (in 2020 dollars)	$59,476
Persons in poverty (%)	13.52%
Ethnicity (%)	White alone—81%
	White alone, not Hispanic or Latino—31.38%
	Hispanic or Latino— 55%
	Black or African American alone—5%
	American Indian and Alaska Native alone (%)—3%
	Asian alone—7%
	Native Hawaiian and Other Pacific Islander alone— 0.45%
	Two or more races—4%
Survey Respondent Demographics	
Total household Income (N=143)	Low (≤ $60K)—42% (N=59)

	High (> $60K) —58% (N= 83)
Ethnicity (n=197)	Latino/Spanish Origin—25% (n=49) White—26% (n=52) Multi-ethnic/Prefer not to answer—49% (n=96)
Gender (n=197)	She/her/hers—35% (n=68) He/him/his—22% (n=43) They/them/theirs—2% (n=3) Prefer not to respond—42% (n=83)
Occupation	Administration—3% (n=5) Agriculture—13% (n=25) Construction/Heavy Equipment Operator/Mechanic—8% (n=15) Delivery/Transportation—2% (n=4) Education—8% (n=15) Engineering/IT—2% (n=4) Homemaker/Personal Care—7% (n=13) Medical/Dental Health—6% (n=11) Public Service—5% (n=10) Retired—21% (n=41) Self-employed—3% (n=6) Unemployed—9% (n=18) Other—11% (n=22) No Response—4% (n=7)
Familiarity with SGMA *How familiar are you with SGMA? (n=195)*	Not At All Familiar—54% (n=106) Somewhat Familiar—33% (n=64) Very Familiar—13% (n=25)
Relationship to agriculture *Agriculture is the core of the economy in my community (n=151)*	Strongly Agree—81% (n=123) Somewhat Agree—13% (n=20) Somewhat Disagree—3% (n=4) Strongly Disagree—3% (n=4)
I live here because of agriculture (n=151)	Strongly Agree—38% (n=57) Somewhat Agree—30% (n=45) Somewhat Disagree—12% (n=18) Strongly Disagree—21% (n=31)
My job depends on agriculture (n=150)	Strongly Agree—29% (n=44) Somewhat Agree—21% (n=31) Somewhat Disagree—11% (n=17)

	Strongly Disagree—39% (n=58)
Farming contributes to air and water pollution in my community (n=151)	Strongly Agree—19% (n=28) Somewhat Agree—23% (n=34) Somewhat Disagree—23% (n=35) Strongly Agree—36% (n=54)
There should be space between farmland and where people live for health reasons (n=151)	Strongly Agree—20% (n=30) Somewhat Agree—35% (n=53) Somewhat Disagree—24% (n=36) Strongly Disagree—21% (n=32)
Stance on climate change *In my region, climate change is happening (n=147)*	Strongly Agree—38% (n=56) Somewhat Agree—31% (n=46) Somewhat Disagree—14% (n=21) Strongly Agree—16% (n=24)
Climate change threatens water quantity locally (n=148)	Strongly Agree—45% (n=66) Somewhat Agree—18% (n=27) Somewhat Disagree—18% (n=27) Strongly Disagree—19% (n=28)
Climate change threatens local water quality (n=148)	Strongly Agree—39% (n=58) Somewhat Agree—21% (n=31) Somewhat Disagree—18% (n=27) Strongly Disagree—22% (n=32)

Table 2. Survey respondent demographic statistics. National, state, and DAC median household incomes (MHI; 2021 USD). San Joaquin Valley demographic statistics from US Census Bureau (2021) are included for reference to survey respondent demographic statistics.

3.4 Community Land Use Values

Understanding community member relationship to and values for nearby lands and alternative land use options could better inform land use transitions that help address groundwater overdraft and community needs. Participants were asked to state their level of agreement to gain insight into the value that parks and green space, habitat restoration, groundwater recharge, renewable energy, and carbon sequestration could have economic and overall well-being of their community (Table 3, Figure 4). There is a large consensus (93%) of respondents that think groundwater recharge is essential for promoting healthy communities, and 95% summative agreed that it could improve the economy in their community. Many respondents value having more parks and green space in their community (79%) and believe it is not a waste of financial investment for their community (80%). Three-quarters of respondents value wildlife and would like more nearby places to watch wildlife, and 66% of respondents do not think that more wildlife contributes to damage to crops or reduced land values for their community. The nuance in habitat restoration between *strongly agree* (39%) and *somewhat agree* (36%) may indicate that some factors may contribute to respondents valuing wildlife or having nearby places to watch wildlife. Most respondents do not think that land used for renewable energy is a waste of space in their community but could see it helping the economy. Close responses among levels of agreement for carbon sequestration statements could indicate that storing

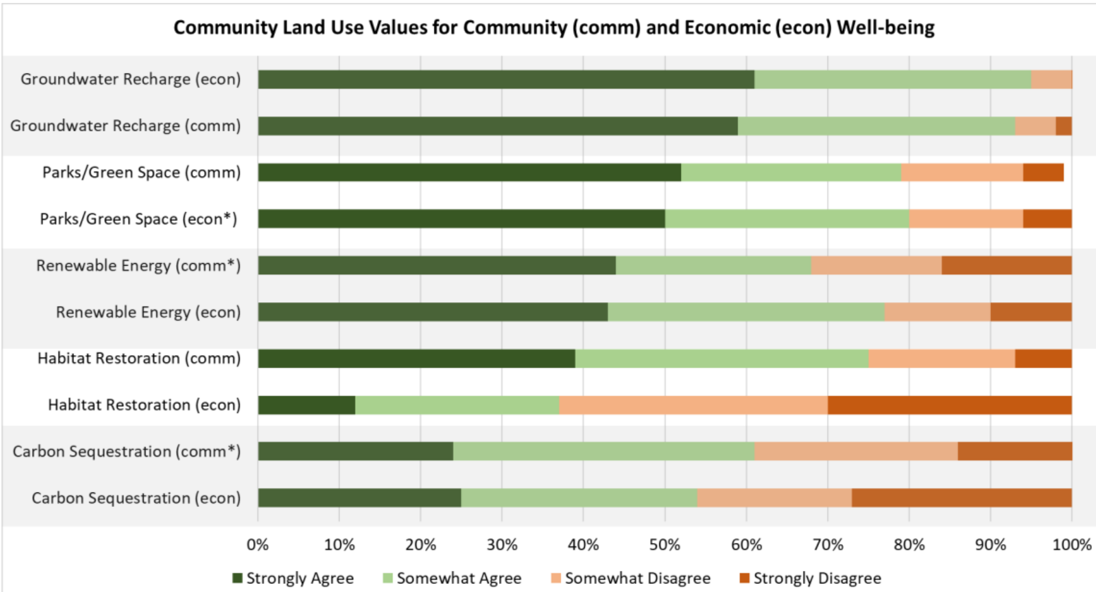


Figure 4. Community land use values in terms of community (comm) and economic (econ) well-being. Values with an asterisk were originally a negative statement in the survey questionnaire, but was flipped to a positive statement for comparison feasibility.

carbon on land and receiving carbon credits is not a well-understood topic among respondents and that these topics are difficult to communicate succinctly and gather perspectives.

	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree
Community				
community value	52% (n=86)	27% (n=45)	15% (n=24)	5% (n=9)
economic value (negative)	6% (n=10)	14% (n=23)	30% (n=49)	50% (n=83)
Habitat Restoration				
community value	39% (n=64)	36% (n=59)	18% (n=30)	7% (n=12)
economic value	12% (n=19)	25% (n=42)	33% (n=54)	30% (n=50)
Groundwater Recharge				
community value	59% (n=97)	34% (n=55)	5% (n=9)	2% (n=3)
economic value	61% (n=100)	34% (n=55)	5% (8)	1% (n=1)
Renewable Energy				
community value (negative)	16% (n=26)	16% (n=27)	24% (n=40)	44% (n=72)

economic value	43% (n=71)	34% (n=55)	13% (21)	10% (n=17)
Carbon Sequestration *community value (negative)*	15% (n=24)	25% (n=40)	37% (n=59)	24% (n=40)
economic value	25% (n=40)	29% (n=48)	19% (n=31)	27% (n=44)
Top and Lowest Land Use Priorities				
Top Land Use Priorities (n=144)	Secure Water Supplies 35% (n=50)	Less Water-Intensive Agriculture 27% (n=39	Reduce GHG and Climate Change 11% (n=16)	
Low Land Use Priorities (n=147)	Schools, Grocery Stores, & Housing 33% (n=48)	Reduce GHG and Climate Change 26% (n=38)	Less Water-Intensive Agriculture 13% (n=19)	

Table 3. Survey participant responses to alternative land use statements in the context of land use benefits for the community (community value) and community economy (economic value) and their top and lowest priority alternative land uses to address groundwater overdraft through land transitions under SGMA and the MLRP.

3.5 Land Use Priorities for Land Use Transitions

To gain insights into what community members envision for a healthy, economically stable, and just environment, we asked respondents to identify their highest and lowest land use priority should agricultural land be transitioned in and around their community to address groundwater overdraft as per SGMA (Figure 5). Most (35%) respondents identified *secure water supplie*s (e.g., groundwater recharge) as the first top land use priority and the second-highest *less water-intensive ag* selected by 27%. The lowest land use priority (33%) was *schools, grocery stores, and housing*, and respondents' second lowest land use priority was *reduced GHG and climate change* at 26% of respondents' selection (Table 3). Participants who value renewable energy for community economic and overall well-being prioritize secure water supplies (35%, 32%) and less water-intensive agriculture (23%, 24%) (SI Figure 9, 10). Respondents who value renewable energy for community well-being do not prioritize schools (41%), reduce GHG and climate change (17%), recreation (17%), and less water-intensive agriculture (17%) (SI Figure 11). In comparison, respondents that support renewable energy for the economic well-being of their community do not prioritize schools (30%), reduce GHG and climate change (20%), and less water-intensive agriculture (15%) (SI Figure 12).

Participants that agreed with the implementation of agricultural buffers around communities (39%, n=32 out of 82), do not live in the Valley because of agriculture (45%, n=22 out of 49), and agreed that agriculture contributes to pollution in their community (36%, n=22 out of 61) ranked *schools, grocery stores, and housing* as their lowest land use priority. Less water-intensive agriculture is among the lowest land use priorities for people that do not live in the Valley because of agriculture (14%, n=7 out of 49) and agree that agriculture contributes to air and water pollution in their community (20%, n=12 out of 61). Participants whose job depends on agriculture had a low priority for land that reduces GHG and climate change (37%, n=26 out of 71) and schools, grocery stores, and housing

(23%, n=16 out of 71), which could be due to the permanence of urban infrastructure and high propensity of people who work in agriculture not to believe that climate change is happening. Those who agreed on implementing agricultural buffers near communities (16%, n=13 out of 82) and do not live in the Valley because agriculture had a low priority for recreation (14%, n=7 out of 49). Participants that disagreed that groundwater recharge is suitable for promoting healthy communities had low land use priorities for secure water supplies (2-%, n=2 out of 10), recreation (20%, n=2 out of 10), and less water-intensive agriculture (20%, n=2 out of 10).

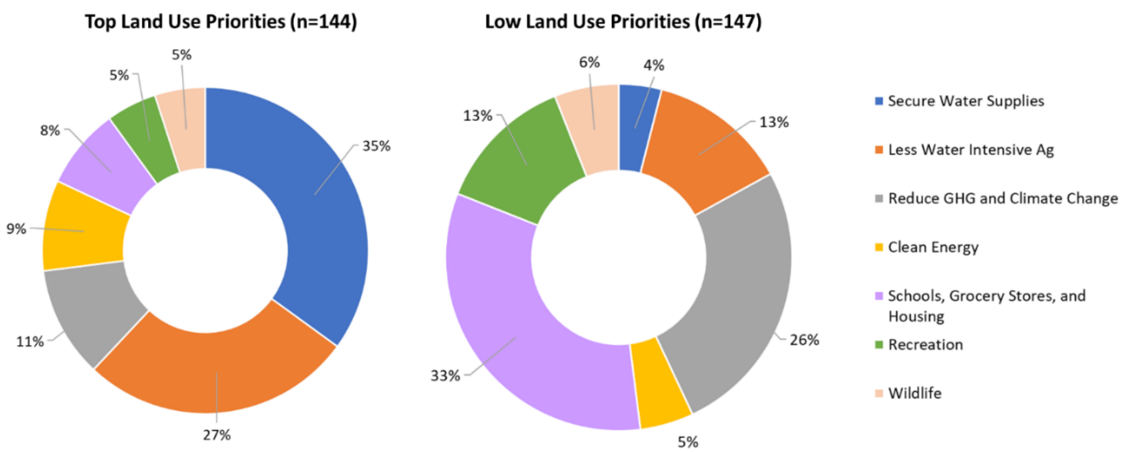


Figure 5. Survey participants' top and lowest land use priorities to address groundwater overdraft in their community.

3.6 Underlying Dimensions

The EFA allowed us to identify underlying dimensions between respondents and their land use preferences, relationship to agriculture, and climate change perceptions and compare perceptions among all, DAC, and non-DAC respondents. Table 4 lists each of the variables with factor loadings greater than 0.4 that explain the key perceptions of each group. The statement associated with each variable is also included in Table 4 to facilitate the interpretation of variables and factor loadings.

3.6.1 Perceptions Across All Survey Respondents

The five main perceptions of all survey respondents (n=143) on land use, agriculture, and climate change are: <u>Agricultural Practice Risk Awareness and Climate Change Consciousness,</u> <u>Ag-centric</u>, <u>More Recreational Spaces</u>, and <u>Cautious Against Habitat and Support Carbon Sequestration</u>, and <u>Support Renewable, Recharge, and Carbon Sequestration</u>. The <u>Agricultural Practice Risk Awareness and Climate Change Consciousness</u> perception is strongly defined by the support for space between agricultural practices and where people live for health reasons, and farming contributes to air and water pollution. This perception also consists of the stance that climate change is happening and impacts water quantity and quality. The <u>Ag-centric</u> perception is defined by the importance of living the San Joaquin Valley because of agriculture, having a job that depends on ag, and believing that agriculture is the core of the community economy. The <u>More Recreational Spaces</u> perception is defined by interest and financial investment in parks and green spaces. Note that the negative factor loading associated with “Q10COMMecon_O” is due to the negative response to the statement that is "My community should NOT spend money on open spaces, like parks, trails, bike paths, and playgrounds," and is interpreted as participants do want to see money spent on open spaces in their community. The Cautious Against Habitat and Carbon Sequestration perception is defined by the belief that wildlife could damage crops and affect land values and that using farmland to store carbon is a waste of space. The Support Renewable, Recharge, and Carbon Sequestration perception is strongly defined by support for groundwater recharge for economic and community benefits, renewable energy for the community and economic well-being, and carbon sequestration to benefit the community economy through carbon credits.

3.6.2 Perception Among DAC Survey Respondents

The four key perceptions resulting for DAC respondents (n=44) are Address Agricultural and Climate Change Risks, Ag Status Quo, More Recreation and Wildlife Habitat, and Ag Against Land for Habitat and Renewable Energy. The Address Agriculture and Climate Change Risk perception among DAC respondents acknowledge that there should be space between farmland and where people live for health reasons (factor loading of 0.8) and that climate change is happening and impacting regional water quality and quantity. This perception also consists of an understanding of the local community's economic benefits from implementing renewable energy and carbon sequestration practices. The Ag Status Quo perception consists of the disagreement that farming contributes to air and water pollution in San Joaquin Valley communities and support for groundwater recharge for community and local economic benefits. The More Recreation and Wildlife perception consists of an interest in the implementation and investment of parks and green spaces and places to watch wildlife. The Ag Against Land for Habitat and Renewable Energy consists of an ag-centric lifestyle, living in the Valley because of agriculture or having a job that depends on ag, and the belief that land uses for renewable energy is a waste of space in the community, and more nearby wildlife could damage crops and reduce land values.

3.6.3 Perception Among non-DAC Survey Respondents

The three key perceptions of the non-DAC respondents are: Support for Alternative Land Uses to Address Climate Change and Agricultural Risks, Non-Ag Relationship, and Opposed to Recreational Spaces. The Support of Alternative Land Uses to Address Climate Change and Agricultural Risks perception consists of the support for renewable energy, groundwater recharge, and carbon sequestration for community and economic benefits. This perception also includes an awareness that climate change is happening and impacting local water quality and quantity and that agricultural practices contribute to air and water pollution. Under this perception, there is a need to implement agricultural buffers around residential communities for health reasons. Among the non-DAC respondents, there is a Non-Ag Relationship perception, which consists of the stance that agriculture is not the core of the local economy, do not live in the Valley because of agriculture, and do not have a job that depends on ag. The Non-Ag Relationship perception also supports places to watch wildlife. The Opposed to Recreational Spaces perception consists of the opposition to more parks, trails, bike paths, and playgrounds and that there should not be more investment in recreational spaces. This perception takes on a "not in my backyard" or NIMBY stance on the implementation of parks and green spaces, which may be attributed to the higher social access to parks (e.g., safety, traffic, and walkability) in higher-income communities and the lack of green spaces in low income, disenfranchised communities

(Wen et al., 2013). The breakdown of respondents between DAC and non-DAC highlights that respondents from DACs are more likely to support the implementation of parks and green spaces than non-DAC because of the lack of spaces that facilitate healthier activities, like walking, and alleviate mental health issues that are persistent among low-income Latino communities (Galea et al., 2020; Grassi et al., 1999; Lama et al., 2018; Lee, 2020). The climate change and agricultural risk consciousness perception persist across all three groups regardless of race and income. The finding that the climate change and agricultural risk perception exist across all three groups highlights an opportunity to focus land transition and climate-smart management strategies on this group (Carvalho & Peterson, 2009). Different strategies need to be developed to engage people with perceptions outside this group, and topics for building common ground need to be further explored for these potentially later adopters of climate change.

Survey Question Variable	All (Percep.)	All Loading	DAC (Percep.)	DAC Loading	non-DAC (Percep.)	non-DAC Loading
Q5COMMcomm_O	PA3	1.2	PA3	0.9	PA3	-0.7
Q6HABTecon_O	PA4	0.6	PA4	0.6		
Q7RECHcomm_O	PA5	0.8	PA2	0.8	PA1	0.7
Q8CARBcomm_O	PA4	0.5				
Q9RENEecon_O	PA5	0.6	PA1	0.4	PA1	0.7
Q10COMMecon_O	PA3	-0.7	PA3	-0.8	PA3	0.9
Q11CARBecon_O	PA5	0.4	PA1	0.6	PA1	0.6
Q12RENEcomm_O	PA5	-0.5	PA4	0.5	PA1	-0.7
Q13HABTcomm_O			PA3	0.5	PA2	0.3
Q14RECHecon_O	PA5	0.6	PA2	0.5	PA1	0.7
Q17AgEcon_O	PA2	0.5			PA2	-0.6
Q18AgLive_O	PA2	1	PA4	0.8	PA2	-0.9
Q19AgJob_O	PA2	0.7	PA4	0.6	PA2	-0.7
Q20AgSpace_O	PA1	0.9	PA1	0.8	PA1	0.4
Q21AgPollution_O	PA1	0.8	PA2	-0.7	PA1	0.5
Q26CC_Happening_O	PA1	0.5	PA1	0.9	PA1	0.6
Q27CC_WaterQuantity_O	PA1	0.7	PA1	0.9	PA1	0.5
Q28CC_WaterQuality_O	PA1	0.6	PA1	0.9	PA1	0.6

Survey Questions:
Q5COMMcomm_O. My community should have more parks, trails, bike paths, and playgrounds.
Q6HABTecon_O. More wildlife habitat means more wildlife will damage crops and reduce land values.
Q7RECHcomm_O. Using wetlands, recharge ponds, and wells to help store water underground is important for healthy communities.
Q8CARBcomm_O. Using farmland to store carbon in soil is a waste of space in my community.

Q9RENEecon_O. Land that generates electricity from the sun and wind could help the economy in my community.
Q10COMMecon_O. My community should NOT spend money on open spaces, like parks, trails, bike paths, and playgrounds.
Q11CARBecon_O. I think our community should use land to reduce climate change impacts and get paid with carbon credits.
Q12RENEcomm_O. Land used to create clean energy, from the sun and wind, is a waste of space in my community.
Q13HABTcomm_O. I value wildlife and would like more nearby places to watch wildlife.
Q14RECHecon_O. Replenishing groundwater in natural underground storage and wells could improve the economy in my community.
Q17AgEcon_O. Agriculture is the core of the economy in my community.
Q18AgLive_O. I live here because of agriculture.
Q19AgJob_O. My job depends on ag.
Q20AgSpace_O. There should be space between farmland and where people live for health reasons.
Q21AgPollution_O. Farming contributes to air and water pollution in my community.
Q26CC_Happening_O. In my region, climate change is happening.
Q27CC_WaterQuantity_O. Climate change threatens water quantity locally.
Q28CC_WaterQuality_O. Climate change threatens local water quality.

Table 4. The survey questions and the perception group and factor loading value resulting from the factor analysis of all (5 factors), DAC (4 factors), and non-DAC (3 factors) survey respondents. See Appendix A for a more detailed factor analysis output. The survey questions are included in this table for reference and to facilitate interpretation of the factor loadings.

4. Study Limitations and Future Work

Although this study had 197 survey respondents, it reached a novel group of residents in the San Joaquin Valley about a novel issue related to agricultural land use transitions in a region that is defined by a predominantly agricultural culture. This exploratory research will drive future questions and multimodal outreach in rural agricultural regions of California's San Joaquin Valley. To overcome traditional barriers to working with marginalized, underserved populations and the pandemic, this study implemented the best survey alternative at a reasonable cost: to conduct an SMS text-distributed link to a web-based survey. Given that 42% of survey participants were considered DAC members and the 1.5% response rate to the SMS text-distributed web survey, future work is needed to ensure that the needs of community members are represented in future water and land use decisions in and around SGMA and the MLRP in the San Joaquin Valley. Financial investment is critical to effectively implement survey methods to engage hard-to-reach marginalized and disenfranchised populations. Given non-pandemic circumstances and unrestricted funding, the following approach would be the alternative approach to conducting this survey study on San Joaquin Valley community land use preferences:

1) **Introductory workshop and Preliminary Survey.** Introduce the research team, provide a brief overview of SGMA and MLRP objectives, and state project objectives. Gauge community interest in engagement and informing strategic agricultural transitions. Conduct a preliminary survey to gauge information and knowledge gap on SGMA, MLRP, and the benefit of implementing alternative land

uses to potentially retired agricultural land under SGMA. The preliminary survey will inform which topics to focus detail on for the second interactive workshop

2) **Informational workshop and collect most and least preferred alternative land uses**. Provide information on the costs and benefits of alternative land uses that have been considered in place of potentially retired agricultural land to address groundwater overdraft under SGMA (e.g., parks and green space, habitat restoration, renewable energy, carbon sequestration, groundwater recharge).
3) **Participatory GIS.** Provide individual maps to each workshop participant depicting the location where each land use is optimal for implementation. Some land parcels will have more than one alternative land use suitable for implementation. Participants can identify where they want to see specific suitable land uses implemented and rank their land use preference for specific parcels or regions of interest. This Participatory GIS method allows community members to identify land uses they would like to see in their community and where and reconcile any conflicting land uses that may not work well together. It is also suggested to allow participants to identify alternative land use options that have not been provided to them. Community members have community knowledge and lived experiences to inform alternative land uses that may not have been considered more representative of their community needs, values, and culture.

The following recommendations can be made given non-pandemic circumstances to increase the reach and decision-making involvement of over-looked communities in the state:

(1) Use a combination of different platforms to conduct surveys that encompass diverse community needs and circumstances (e.g., access to technology, language barriers, broadband limitations). Ensure that survey questions across the different platforms contain the same questions and wording to facilitate consolidation and analysis of survey responses. Different platforms include mail, text message, email, web, and in-person.

(2) Provide clear and concise definitions of new or complicated concepts and terminology. Findings from this survey suggest that concepts such as carbon credits and carbon sequestration were difficult to grasp within a limited survey context. There is a need for state and local water and land use agencies in California to develop standard terminology to prevent confusion of concepts related to SGMA and the MLRP.

(3) There is a need for multilingual and multi-modal information dissemination (e.g., mail, in-person, workshops, videos, web, flyers, email) that provide insights on the costs and benefits of different land repurposing projects in and around their communities. There is a need to provide examples, including visuals, of what land repurposing options could look like to help stakeholders better envision what they would like to see in their community.

More recommendations on effective community engagement on land repurposing can be found in Appendix B.

5. Conclusions

California's San Joaquin Valley is paradoxical. Nestled among the multi-billion-dollar agricultural landscape, more than 200 DACs are faced with the highest poverty and pollution rates in the United States. Increasing drought conditions and groundwater overdraft is straining agriculture, leading to 10-15% of agricultural land going out of production to address groundwater overdraft under SGMA. A combination of SGMA and MLRP could lead to transitions in agricultural land that address groundwater overdraft and address the needs of communities, especially DACs and ecosystems. Incorporation of San Joaquin Valley community needs into water management and land use planning has been limited to date, but SGMA and MLRP provide the impetus for inclusive engagement and planning. This survey study addressed the current lack of understanding of how local communities, specifically DACs in the San Joaquin Valley, value alternative land uses by focusing on surveying 32 disadvantaged communities in the region through a novel text message delivery of a web survey.

This study found that most respondents were largely unfamiliar with the 2014 California SGMA, highlighting the need for increased outreach efforts to explain SGMA and groundwater overdraft implications on agriculture among rural agricultural communities. Given that formal input from DACs on groundwater sustainability plans under SGMA has been minimal and the news representation of SGMA has been dominated by agriculture, there is a need to dedicate outreach efforts to overcome barriers to representation, translation, and education to develop land use transition strategies that are equitable, inclusive, and representative of community needs. Results of this survey also highlight the need for clear, concise definitions of new terminology or complicated concepts (e.g., carbon sequestration and carbon credits). Insights on complicated terminology and the need for increased outreach efforts helped develop a guide for MLRP applicants on community and grower engagement in multibenefit land repurposing[1].

Supporting current status quo land uses was preferred among survey participants to alternative future land uses. In other words, respondents were likely to select secure water supplies (e.g., groundwater recharge) and less water-intensive agriculture as the most preferred land uses. Strong agricultural identity and lack of interest in community or global benefits, such as schools and climate change mitigation, point to high values for agriculture to remain a primary land use among survey participants. Regarding non-agricultural land use transitions to address groundwater overdraft under SGMA, participants supported parks, green space, and renewable energy. Three-quarters of respondents value wildlife and would like more nearby places to watch wildlife, and 66% of respondents do not think that more wildlife contributes to damage to crops or reduced land values for their community. While this study provides a broad snapshot of San Joaquin Valley community land use preferences, targeted surveys should be conducted to understand better the unique preferences and priorities of local and regional land repurposing, particularly when developing regional land repurposing plans with MLRP funding. Further exploration of key perceptions among various dataset subsets (i.e., all, DAC, and non-DAC respondents) highlighted that non-DAC participants oppose recreational spaces. An opposition to parks

[1] Environmental Defense Fund and UC Merced Land Repurposing Engagement Guide (2022): https://www.edf.org/sites/default/files/documents/CA%20Land%20Repurposing%20Engagement%20Guide.pdf

and green spaces among non-DAC (i.e., income ≥ $60K, regardless of race) brings forward a "not in my backyard" or NIMBY stance on the implementation of parks and green spaces, which may be attributed to the higher social access of parks (e.g., safety, traffic, and walkability) in higher-income communities and the lack of green spaces in low income, disenfranchised communities (Wen et al., 2013). The support for parks, green spaces, and places to see wildlife among DAC respondents may be attributed to the current lack of spaces that facilitate healthier activities, like walking, and alleviate mental health issues that are persistent among low-income Latino communities (Galea et al., 2020; Grassi et al., 1999; Lama et al., 2018; Lee, 2020). An awareness of climate change and agricultural risks is present across all three participant groups regardless of race and income. Finding that climate change and agricultural risk perception exists across all three participant groups highlights an opportunity to focus land transition and climate-smart management strategies on people that already acknowledge climate change and agricultural risks in the San Joaquin Valley (Carvalho & Peterson, 2009). Different strategies need to be developed to engage people with perceptions that do not acknowledge climate change and agricultural risks, and topics for building common ground need to be further explored for certain stakeholders that will potentially adopt climate change later.

CHAPTER 3. WHERE TO FOCUS LAND TRANSITION EFFORTS?

1. Introduction

The global water crisis is often highlighted as an issue of water availability (Gleick & Cooley, 2021). However, water access inequality stemming from poor governance and mismanagement is often overlooked (United Nations Development Programme, 2006; Calow & Mason, 2014). Surging human population and climate-change-induced, extreme hydrological events (Bates et al., 2008; Vörösmarty et al., 2000), like meteorological droughts, have increased the use of and reliance on groundwater for irrigated agriculture (Siebert et al., 2010; Wada et al., 2012). Wada Further, groundwater exploitation is projected to increase to counteract the impacts of climate change on surface water supplies (e.g., increased precipitation variability and reduced snowpack) and increasing human population (Green et al., 2011). Water management and water governance agencies worldwide are already dealing with the repercussions of suboptimal water resource management practices and non-existent or decaying infrastructure (Ehrlich & Landy, 2005) and are not well-equipped to deal with additional stresses of non-stationary hydroclimate and projected population growth (Overseas Development Institute et al., 2012; Milly et al., 2008).

Recent approaches to water governance in coupled human-natural systems point to sociohydrology as a means to address the twin challenges of climate change adaptation and equitable water management (Sivapalan et al., 2014; Sivapalan et al., 2012). Researchers on common property resource management identified the need to distinguish between the characteristics of the natural resource and the managing governance system given the complexity in human motivation to control resources, governance structures that do not always facilitate free and equal access to all, and the changing dynamics of the resource itself (National Research Council, 2002). Sociohydrology aims to evaluate the impacts of human values and norms on water structures and dynamics and the impacts of water systems on societal well-being at various spatio-temporal scales to develop water management solutions that account for human behavior impacts on water systems. Embedded within sociohydrological systems are differing forms of governance, at times contradictory but bound to historical precedent, most evident in the idea of water as property (Roth et al., 2015). Jurist Franz von Benda-Beckmann explored water as property, established relationships between water, legal systems, and human behavior, and concluded that regional historical and cultural contexts are embedded in water rights and the role of human agency in reinterpreting and translating water laws and management (von Benda-Beckmann, 2006). By integrating multi-stakeholder perspectives, von Benda-Beckmann linked system management to water rights and water, which has led to understanding water rights, irrigation infrastructure, and human decision-making as constructs of sociohydrological governance systems (Roth et al., 2015). By extension, humans establish, arrange, and enact the rules, responsibilities, and rights to control water to facilitate financial and human capital investments in water for human benefit via irrigation and conveyance (Coward, 1980). Thus, the control of water is the control of society, much as it has been since the dawn of human civilization (Berking & Schütt, 2021; Hundley, 2002). Thus, a more fundamental understanding of water governance and management concepts specific to a given geography – and that account for the inherent dynamics between water, people, and governance – could provide insight into developing resilient climate change management in drought-prone agricultural regions, like California (Figure 6). This work analyzes the complex sociohydrologic dynamics and history in California water to inform the development of climate change adaptation strategies that account for the human and governance structures that have influenced water in the region.

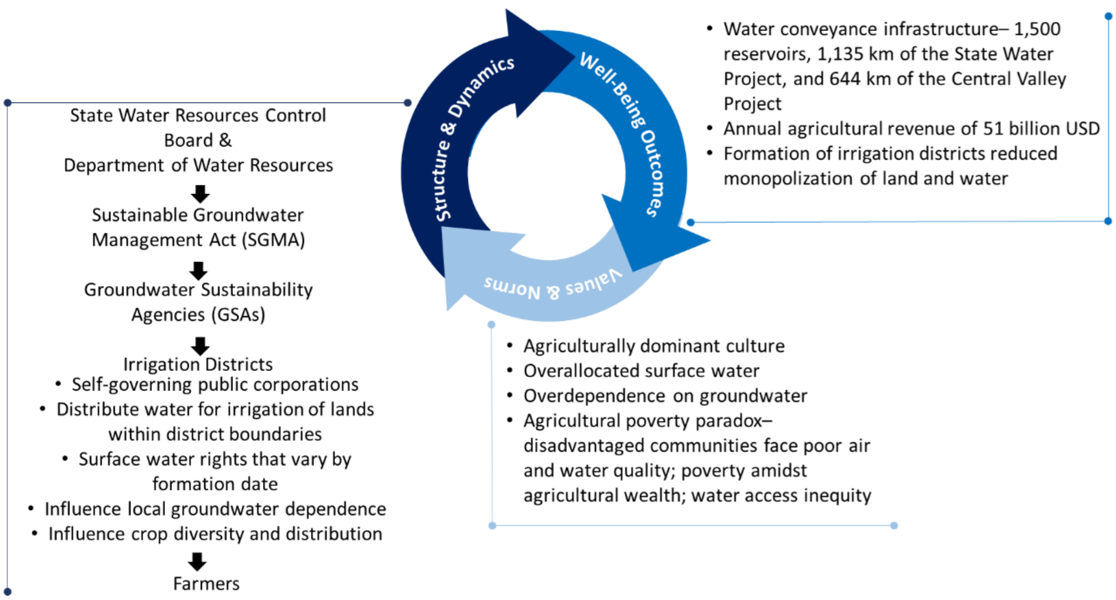


Figure 6. The sociohydrology framework adapted from Sivapalan et al. (2014) applied *to the San Joaquin Valley's local water governance, specifically irrigation districts.*

California is a bellwether of attributes encompassing the global water crisis and sociohydrology (*sensu* Sivapalan et al., 2014)—competing demands for surface water, groundwater overdraft, complex surface water rights, water access inequity, poverty, food insecurity, increasing population, and climate change. One might think that California is a water-rich region, given that it reaps 50.1 billion USD in cash receipts from agricultural and livestock production (California Department of Food and Agriculture, 2019) and is the most populous state in the United States. However, the agricultural productivity and high-density populations in water-scarce regions exist because of the alteration of California's natural water systems. California's water conveyance system as it is known today—1,500 reservoirs, 1,135 km of the State Water Project, and 644 km of the Central Valley Project (Hanak et al., 2011)—nourishes the state's agricultural economy and redistributes water to the water-scarce south, but is facilitated by an arcane and contradictory patchwork of water rights and regulatory jurisdictions (Grantham & Viers, 2014; Owen et al., 2019). Despite the urban and agricultural prosperity that flourished from redistributing water through expansive water conveyance networks, water access inequity persists. Under current management practices, the western United States is at its water capacity limit for sustaining cities, agriculture, and ecosystems (Sabo et al., 2010) with missed opportunities to reduce water waste and make use of new water supplies (e.g., recycled water, desalinated brackish water, stormwater). While agriculture in California uses 40% of available water compared to 10% used by cities (Hanak et al., 2019), about one million people in California live in underserved, unincorporated communities without access to safe, clean drinking water (London et al., 2018). Disadvantaged communities (DACs)[2] in the San Joaquin Valley represent the region's poverty paradox—communities surrounded by the productive agricultural fields that drive local economies, and yet are disproportionately burdened with poor air and water quality, poverty, food insecurity, and political underrepresentation (Balazs et al., 2011; Dobbin & Lubell, 2021; Fernandez-Bou et al., 2021; London et al., 2018; Pannu, 2012). California's conflicting water demands between agriculture and booming cities stem from the poor management practices based on optimistic estimates of available surface water (Sabo et al., 2010). Much of California's surface water has been claimed several times more than the amount available since the 1890's through surface water rights allocations (Grantham & Viers, 2014; Hundley, 2002). California's tortuous water management, tortuous infrastructure, and the role of water in shaping California's history have been recounted by many, including both popular (Arax, 2019; Arax & Wartzman, 2003; Reisner, 1993) and scientific (Pinter et al., 2019; Sabo et al., 2010) accounts.

For California, a step toward building climate change resilience and addressing water access inequity starts with local water governance in the San Joaquin Valley, specifically irrigation districts, which are at the forefront of redeveloping water management strategies under the 2014 Sustainable Groundwater Management Act (SGMA). Before SGMA, groundwater in California was rarely monitored and regulated (Sax, 2002), which led to 1.7 billion cubic meters (m^3) per year of overdraft and about 6.2 billion m^3 of overdraft during the 2012-2016 drought (Howitt et al., 2015). The SGMA aims to balance the surface water and groundwater portfolio to bring the state's overdrafted groundwater basins to sustainable levels by 2040. California's most critically overdrafted groundwater basins are in the San Joaquin Valley (Hanak et al., 2019). SGMA places authority and responsibility on local water agencies (e.g., irrigation districts, water districts, and city and county water agencies), which have formed Groundwater Sustainability Agencies (GSAs) (Green, 2014). GSAs are tasked with developing and implementing strategies to address groundwater overdraft in the next two decades. California irrigation districts exemplify the sociohydrological construct that historical and cultural context underpin surface water rights. Thus, financial and human capital investments needed for irrigation infrastructure are used to support self-maintaining water governance structures.

[2] Disadvantaged Communities are defined by the State of California as a community with an annual median household income of less than 80% of the statewide annual median household income.

There remains a need to evaluate the impact of the human values and norms on governance structures and dynamics, and in turn, societal well-being in the San Joaquin Valley if California is to develop successful water management plans that address the imbalance of surface water and groundwater in a changing climate.

Water development in California initiated to power gold mining operations in the mid-1800s, which later catalyzed urban and agricultural prosperity. The late 1800s was a formative period for this economic growth as water rights were formalized, and the land was converted to agriculture. Water utilization during this period favored wealthy landowners, and riparian surface water rights[3] were prioritized over appropriative water rights[4] (*Lux v Haggin*, 1886). The Wright Act of 1887 was passed to break the monopolization of the land and water spell by forming irrigation districts. Under this act, residents and farmers formed irrigation districts to represent the best interests of family farms and keep water rights in the irrigation district instead of private corporations or individuals (Hundley, 2002). The early formation of irrigation districts in 1887 also catalyzed the creation and transformation of agricultural communities throughout California, especially the San Joaquin Valley, by governing water resources in the interest of local water users (Henley, 1968; Teilmann, 1963).

In California, water rights allocations with the most water by volume are allocated to public entities (78%), and agriculture has the highest count of designated water rights (70%) (Grantham & Viers, 2014). For irrigation districts, the date of formation is critical in determining the type of surface water right (pre-1914 or post-1914 appropriative rights), which dictates whether an entity's rights are regulated by the State Water Resources Control Board (SWRCB) or not. The lack of a surface water rights permitting system before 1914 allowed water users to claim a surface water right to be used for beneficial and reasonable use without the approval of a governing agency. When the Water Commission Act of 1914 was established to regulate the surface water rights permitting system, claims before 1914 were grandfathered into the water rights system as existing and senior. These senior pre-1914 water rights remain unmanaged by the SWRCB (State Water Resources Control Board, 2020), and their allocations are prioritized over post-1914 water rights, considered junior appropriations. Irrigation districts and water users that do not receive surface water allocations, either due to junior or non-existent rights, turn to groundwater to meet irrigation demands (Medellín-Azuara et al., 2016).

Given that surface water rights have been claimed several times more than the available supply since the 1890s (Hundley, 2002), contemporary water rights exceed the state's actual water supply by five times the average annual runoff and eight times the actual surface water supply in some river basins (Grantham & Viers, 2014). While all rights holders, riparian and appropriated, may get their share of surface water supplies during wet years, California's frequent droughts create access disparities and generate conflicts among

[3] Water rights for landowners adjacent to a natural body of water (Attwater & Markle, 1988)

[4] Right to water for "beneficial use" regardless of relationship between land and water (Attwater & Markle, 1988)

water users. In September of 2021, climate change-induced drought conditions halted water rights diversions for all pre-1914 and post-1914 water rights holders in the Sacramento-San Joaquin watersheds (State Water Resources Control Board, 2021a).

In this paper, we use geospatial analysis to identify and assess the sociohydrologic vulnerabilities of irrigation districts in California's San Joaquin Valley, the state's agricultural core (Figure 7). By assessing how various interconnected factors, like location, formation date, and surface water rights (see Appendix D, SI Table 10 for a complete list of variables), a sociohydrologic vulnerability index was developed and applied to 102 irrigation districts to better understand freshwater and DAC stress within irrigation district boundaries. This approach to sociohydrology facilitates the assessment of socioeconomic equity and freshwater reliability, important considerations for climate change adaptation. Further, this assessment uses cluster analysis to distinguish similarities and differences among irrigation districts to determine how decreasing groundwater availability due to physical constraints and policy restrictions on new or deeper groundwater wells may affect DACs. This paper is the first to identify DACs within irrigation district boundaries and highlight the poverty paradox and environmental inequities that persist among DACs within irrigation districts compared to areas without dedicated surface water supplies despite being within the jurisdiction of local groundwater sustainability agencies.

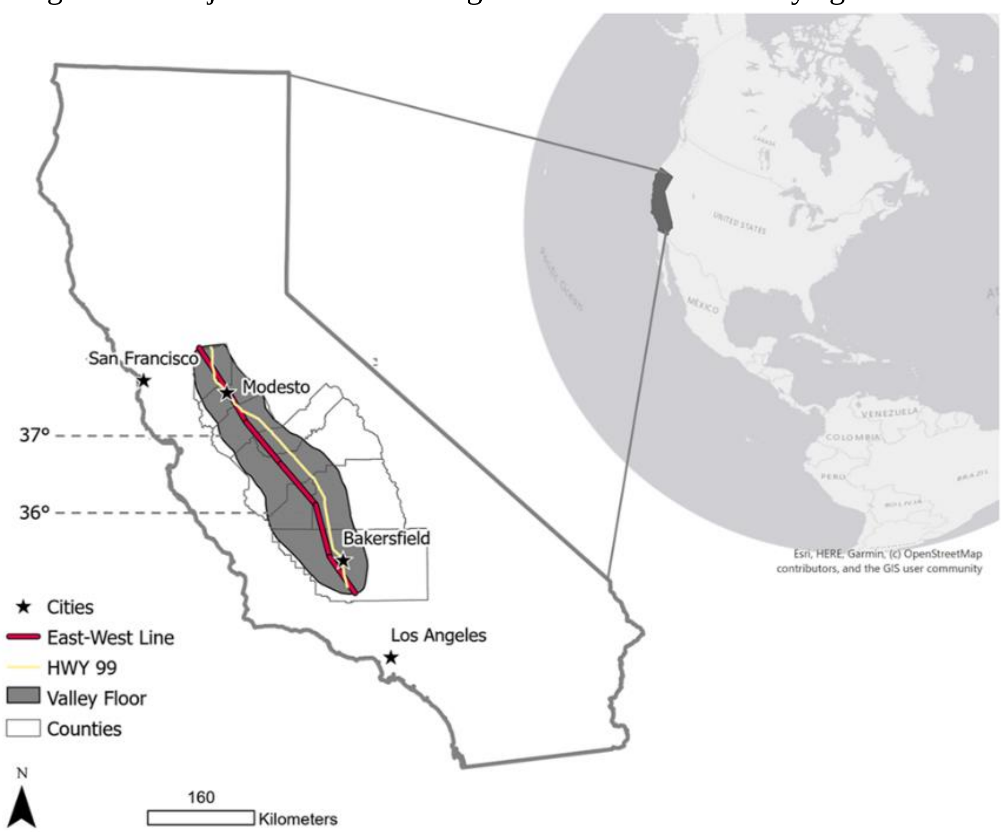


Figure 7. Map of the study region for this analysis is the San Joaquin Valley floor (shaded grey) in California, located in the western United States.

2. Materials and Methods

2.1 Data Availability & Software

This study reconciles various disaggregated irrigation district information from various local and state resources and databases. This work derives the variables necessary to understand how irrigation districts' historical, political, environmental, and cultural characteristics could drive surface water scarcity and groundwater reliance in the state's agricultural region. SI Table 9 in Appendix D lists the datasets and the source from which they were obtained. SI Table 10 documents the variables derived from the primary datasets highlighted in SI Table 9 used in this analysis, their units, and a description of how they were derived. The major variables used in this analysis encompass an irrigation district's history (i.e., age, dedicated water), surface water allocation and delivery, and crop composition within the district's boundaries (e.g., total, perennial, annual crop fractions, and revenue). Data on the variable values per irrigation district (freshwater variable normalized values reported), the surface water allocation amounts for irrigation districts in this study, and the source of information, Land IQ crop types that make up the annual, perennial, and irrigated forage categories, and lists of the crop revenue values and the associated crop type used in the analysis for irrigation districts within the eight San Joaquin Valley counties can be found in Appendix D. County Crop Report 2016 for each county was used to derive crop revenue values (County of Fresno Department of Agriculture, 2016; County of Stanislaus Agricultural Commissioner, 2016; Kern County Department of Agriculture and Measurement Standards, 2016; Kings County Department of Agriculture, 2016; Madera County Department of Agriculture, 2016; Merced County Department of Agriculture, 2016; San Joaquin County Agricultural Commissioner's Office, 2016; Tulare County Economic Development Office, 2016). The primary software used to facilitate this analysis was ESRI ArcPro GIS (ESRI, 2011) and R software (R Core Team, 2021).

2.2 Irrigation District Boundaries

The most up-to-date irrigation district boundaries were obtained directly from the Local Agency Formation Commission (LAFCO) for seven counties in the San Joaquin Valley—San Joaquin, Stanislaus, Merced, Fresno, Madera, Tulare, and Kern. Kings County LAFCO could not provide updated boundaries, and the Department of Water Resources 2015 water agency boundaries were used for irrigation districts in this county. This study focuses solely on water agencies in the San Joaquin Valley floor that distribute water for irrigation and exclude water conservation, domestic, and municipal water agencies. The irrigation district boundaries from these various sources were digitally reconciled to create a single geospatial data file for irrigation districts on the San Joaquin Valley floor.

2.3 Era Analysis

Statistical analysis of the variables outlined in SI Table 10 in Appendix D was conducted for irrigation districts within four major eras to shed light on how key water management events may have shaped irrigation districts during their formation. Irrigation district formation dates were categorized into major water management periods for infrastructure investments and economic development as outlined by Hanak et al. (2011). The four major eras considered in this study are the Era of Local Organization (1887-1913), Hydraulic Era

(1914-1968), Era of Conflict (1969-2000), and Era of Reconciliation (2001-2020), mainly following Hanak et al. (2011) (Hanak et al., 2011). The statistical analysis was conducted in R 4.0.5.

2.4 Groundwater Reliance Calculation

Actual groundwater use in the San Joaquin Valley is largely unknown, and estimates have relied on coarse data such as Gravity Recovery and Climate Experiment satellites (GRACE) (36). Hence, resolving such data unknowns is a focus of SGMA legislation. Key datasets used to quantify the estimates of groundwater reliance per irrigation district in this study were Land IQ 2016 for California (Land IQ & California Department of Water Resources, 2016), electronic Water Rights Information Management System (eWRIMS) (State Water Resources Control Board, 2020), U.S. Bureau of Reclamation agricultural contractors list, and a water footprint model, Water Footprint Analysis in R (WAFR) (Booth, 2018). The Land IQ 2016 dataset represents primary agricultural land use, wetlands, and urban boundaries for 58 counties in California that are derived from the 2016 National Agriculture Imagery Program imagery and commissioned by the California Department of Water Resources. This study uses only agricultural land use classifications from the Land IQ 2016 dataset to calculate crop composition within irrigation district boundaries. Crop composition within irrigation districts also served as an input to the WAFR model to calculate crop water requirements for each district. Surface water allocation amounts are obtained from various sources—eWRIMS, USBR agricultural contract amount lists, reports, Groundwater Sustainability Plans (GSP), Agricultural Water Management Plans (AWMP), and irrigation district web pages. Surface water delivery averages from 2001 to 2015 were obtained from (Jezdimirovic et al., 2020a) except for Banta Carbona Irrigation Districts, Byron-Bethany Irrigation District, and South San Joaquin Irrigation District. Average 2008-2019 surface water deliveries 2008-2019 for Banta-Carbona and Byron-Bethany irrigation districts were obtained from Tracy Subbasin GSP and South San Joaquin Irrigation District 2005-2019 average surface water deliveries were obtained from their 2020 AWMP.

The water budget equation (Eqn. 1) is used to derive estimates of groundwater reliance per irrigation district, meaning the amount of groundwater needed to make up for irrigation demand unmet by surface water. The water budget describes water flow in and out of a system and can quantify water uses within a region. The water budget equation is defined as:

$$\Delta S + P + Q_{GW} + Q_{SW} - ET = 0 \ (Eqn. 1)$$

Where ΔS is the change in storage, P is precipitation, Q_{GW} is groundwater runoff, Q_{SW} is surface water runoff, and ET is evapotranspiration. For this project, a series of assumptions were made to quantify the reliance on groundwater for each irrigation district in the San Joaquin Valley using the water budget equation. These are:

- Precipitation, P, varies by irrigation district. Precipitation observations from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) were used in the WAFR model to obtain the proportion of crop water requirements for irrigation districts. For more information on the data processing and WAFR model, refer to Booth (2018) and Appendix E for WAFR CWR calculations.

- Q_{SW} varies across irrigation districts, and values are based on the amount of surface water allocations determined by each irrigation district's surface water. This study assumes that irrigation districts have 100% allocation to meet irrigation demands (i.e., crop water requirements). Refer to SI Tables 9 and 10 in Appendix D for more details on surface water allocation sources.
- Within WAFR, crop water requirements (CWR) are calculated by accumulating daily crop evapotranspiration in the growing period for 2016 within irrigation districts. In this study, Evapotranspiration, ET, represents the irrigated, freshwater component of crop evapotranspiration, $ET_{c,\ blue}$, and is used in the WAFR model to derive CWR. For more information on the data processing and WAFR model, refer to Booth (2018). The WAFR model compared well with DWR's Cal-SIMETAW and OpenET model ET estimates (refer to model comparisons in Appendix E).

Being cognizant of the inaccuracy in solely calculating irrigation district groundwater dependence based on surface water allocations, which for this study are assumed to be 100% allocation available to meet irrigation demands, this analysis quantifies irrigation district groundwater runoff, Q_{GW}, based on surface water allocation amounts (Eqn. 2) and average surface water delivery for irrigation districts (Eqn. 3).

$$SW_{allocation} - CWR = \pm SW \text{ (Eqn. 2) and}$$
$$SW_{delivery} - CWR = \pm SW \text{ (Eqn. 3),}$$

$SW_{allocation}$ is an irrigation district's surface water allocation, $SW_{delivery}$ is an irrigation district's surface water delivery, and CWR is an irrigation district's crop water requirement. If Equation 2 or 3 results in surface water surplus, +SW, it is assumed that an irrigation district does not rely on groundwater to meet irrigation demands or CWR. Whereas, if Equation 2 or 3 results in surface water deficit, -SW, it is assumed that an irrigation district does not have enough surface water allocations or average surface water deliveries to meet irrigation demands and relies on groundwater to meet CWR amounts. Irrigation districts with surface water delivery of "no record" are assumed to receive no surface water delivery to facilitate calculating the surface water delivery surplus/deficit.

2.5 Cluster Analysis

Irrigation district attributes with an asterisk in SI Table 10 (Appendix D) were used for the cluster analysis. A two-step clustering analysis was conducted. First, a Principal Components Analysis (PCA) was run on the variables and the rotated components were used as input for the cluster analysis. The 'ConsensusClusterPlus' package in R was used to conduct an unsupervised, k-means cluster analysis (Monti et al., 2003). The silhouette method function was applied to the cluster dataset using 'fviz_nbclust' from the 'factoextra' package in R (Kassambara & Mundt, 2020), which resulted in five optimal clusters. The Silhouette Method finds the optimal number of clusters by measuring how close observations in its assigned cluster are relative to neighboring cluster. Measurement known as the silhouette coefficients ranging from [-1, +1] determine valid clusters, where values of +1 indicate samples that are far from neighboring clusters, values of zero samples are on or close to neighboring cluster boundaries, and negative values indicate samples that may have been assigned to the wrong cluster.

2.6 Irrigation District Sociohydrologic Vulnerability

A sociohydrologic vulnerability index was derived by calculating each irrigation district's freshwater and DAC status. Figure 8 provides an overview of the derivation process adopted from Huggins et al. (2022) and (See SI Figure 44, Appendix D for results for individual results of the DAC status, freshwater status, and sociohydrologic vulnerability).

Given the importance of GSAs engaging over-looked, underserved communities under California's SGMA to ensure that groundwater sustainability plans address community water needs, the sociohydrologic vulnerability index incorporates the socioeconomic and environmental status of DACs within irrigation districts. The freshwater status of irrigation districts to identify which irrigation districts have a high tendency for groundwater overdependence and DACs disproportionately impacted by environmental impacts and rely on groundwater to meet drinking water and other basic human needs.

The freshwater status is representative of the groundwater dependence as a function of surface water delivery. Raw data inputs for calculation of the freshwater status include CWR and $SW_{delivery}$, to derive the groundwater dependence per irrigation district. The CWR was derived using WAFR, a crop evapotranspiration estimate model, on Land IQ land use classification data for 2016. The CWR was normalized by irrigation district crop area (units of ML/Ha). The $SW_{delivery}$ data were obtained from Jezdimirovic et al. (2020), which calculated $SW_{delivery}$ averages per irrigation district from 2001 to 2015. $SW_{delivery}$ values were normalized by irrigation district crop area (units of ML/Ha). The groundwater dependence ($GD_{sw\ delivery}$) amount was calculated by taking the difference between $SW_{delivery}$ and CWR. Irrigation districts with surface water surplus were given zeros for groundwater dependence due to sufficient surface water to meet crop water requirements and irrigation districts with surface water deficit were given the deficit amount reported as positive values. The freshwater status was normalized using minimum-maximum scaling. The freshwater status, used in the final calculation of the sociohydrologic vulnerability index per irrigation district, was calculated as:

$$\textit{Freshwater Status} = \frac{GD_{SW\ delivery} - \min(GD_{SW\ delivery})}{\max(GD_{SW\ delivery}) - \min(GD_{SW\ delivery})} \text{ (Eqn. 4)}$$

The raw data inputs used to calculate each irrigation district's DAC status consists of the overall CalEnviroScreen 4.0 score percentile value (DAC CES Score), calculated from the scores for two indicators—pollution burden and population characteristics (California Office of Environmental Health Hazard Assessment, 2021). The CalEnviroScreen 4.0 pollution burden indicator consists of pollution exposures and environmental effects (See SI Table 8 for a list of pollution exposures and environmental effects). CalEnviroScreen 4.0 dataset is derived for larger Census Tracts than the smaller Census Places that define DACs. The DAC CES Score per DAC within irrigation districts was obtained using geospatial procedures of spatially joining the centroid of the DAC to the CalEnviroScreen 4.0 polygon feature dataset (California Office of Environmental Health Hazard Assessment, 2018) (Figure 9). The DAC CES Score were converted from percentiles into fractions by dividing by 100 and all the DACs within each irrigation district were averaged. Irrigation districts without DACs within their boundaries were given a DAC status value of zero. The DAC status has the following equation:

$$DAC\ Status = \sum \frac{\frac{DAC\ CES\ Score}{100}}{n\ DACs} \text{ (Eqn. 5)}$$

The sociohydrologic vulnerability index is calculated as follows:

$$Sociohydrologic\ Vulnerability = (Freshwater\ Status) * (DAC\ Status) \text{ (Eqn. 6)}$$

The mode of the sociohydrologic vulnerability index was used to represent the final irrigation district vulnerability index and were classified into three categories (i.e., low, moderate, and high vulnerability) based on quantiles. The ‘classIntervals’ function from the ‘classInt’ package in R (Bivand et al., 2022). The ‘classIntervals’ function provides finds class intervals for continuous numerical variables by specifying from a variety of styles (e.g., quantiles, head/tails, k-means). This analysis used the quantiles style with specification of three classes.

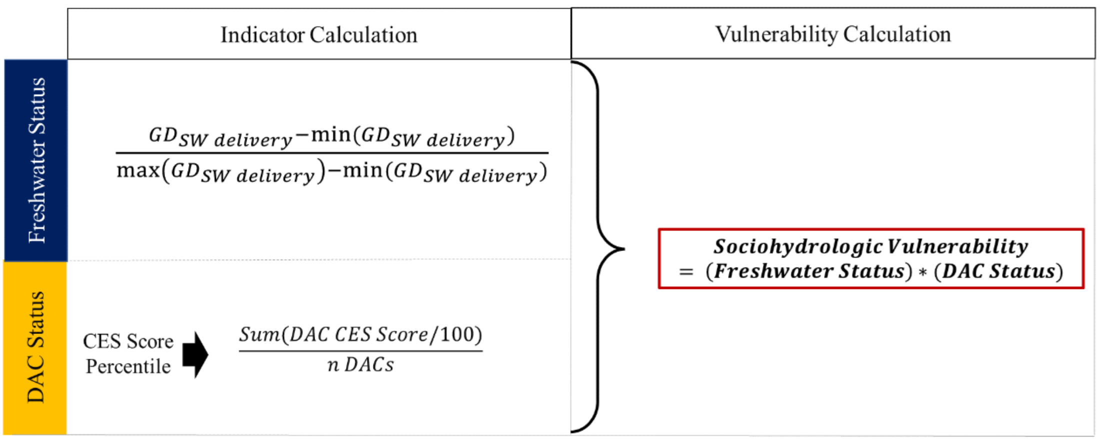


Figure 8. Overview of the sociohydrologic vulnerability derivation process (method adapted from Huggins et al., 2022).

2.7 Irrigation District and GDC Disadvantaged Community Comparison

The CalEnviroScreen 4.0 dataset was obtained for the most recent environmental health hazard assessment (2018) from the California Office of Environmental Health Hazard Assessment (OEHHA) (California Office of Environmental Health Hazard Assessment, 2018). The most up-to-date (2018) disadvantaged community (DAC) census places boundaries were obtained from the Department of Water Resources (DWR) DAC Mapping Tool (California Department of Water Resources, 2018). The CalEnviroScreen 4.0 dataset provides several indicators that reflect environmental conditions or poverty vulnerability for populations at the census tract level. The DAC census place boundaries provide the area, name, and location of DACs in California, reduced to the San Joaquin Valley floor for this analysis. The following workflow was used to preprocess the data and conduct the comparison analysis using ArcGIS Pro and R (Figure 9):

(1) To obtain environmental and poverty conditions for DACs within San Joaquin Valley floor irrigation districts and GDCs, the CalEnviroScreen 4.0 spatial vector dataset was spatially joined with the centroids of DAC census places within ESRI ArcGIS software.

(2) Irrigation district boundaries were used to derive a dataset that includes county valley floor GDCs, the regions within the San Joaquin Valley floor void of an

irrigation district service area. The DACs within irrigation districts and groundwater-dependent communities were derived by spatially joining DAC census place centroids with irrigation district and white area names.

(3) Descriptive statistics (e.g., mean, median) were used to compare the traits between DACS with GDCs and irrigation districts, and an unpaired two-sample Wilcoxon test comparing the mean of the variables between the two groups was used to derive the p-value (α=0.05).

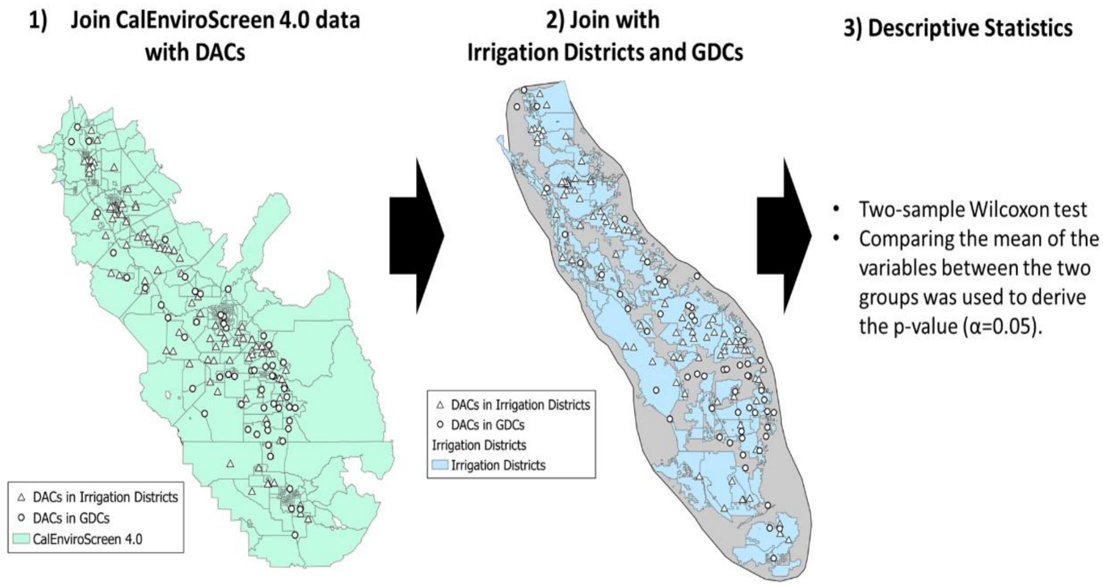


Figure 9. Workflow of the comparison between DACs in white areas and GDCs.

3. Results and Discussion

3.1 Era Analysis: Age Driven Water and Land Ownership Wealth

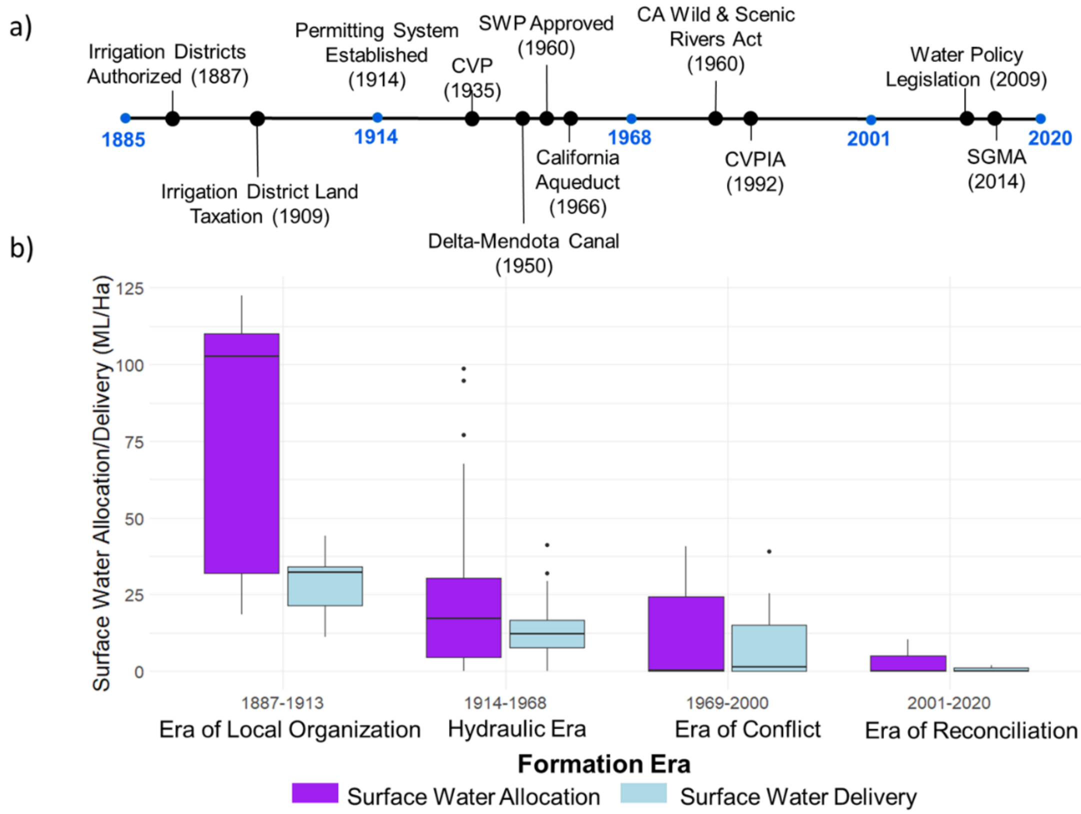


Figure 10. a) Timeline of major California water development events from 1885 to 2020 per era (intervals in blue) to compare with b) irrigation district surface water allocation (purple) and average surface delivered from 2001-2015 (light blue) per era.

California irrigation district's physical and water governance culture reflects the historical water development contexts and the sociohydrological and land-use dynamics in which they were formed (Figure 10 a, b). This study categorized districts into four primary eras of change to determine how age drives surface water allocation and priority, therefore, groundwater reliance for most districts. California's transformative water management eras of change, adopted from Hanak et al. (Hanak et al., 2011), are the Era of Local Organization (1887-1913), Hydraulic Era (1914-1968), Era of Conflict (1969-2000), and Era of Reconciliation (2001-2020). This study reveals that age influences irrigation districts' surface water allocations, deliveries, and service areas. Older irrigation districts, formed in the Era of Local Organization, have the most annual surface water allocation and deliveries (Figure 10 b) and larger service areas than younger districts. The trend in older irrigation districts having higher surface water allocation and deliveries is due to the surface water rights claimed during the Era of Local Organization before the formation of the surface water right permitting system (Figure 10 a). Irrigation districts with pre-1914 water rights remain unmanaged by the SWRCB.

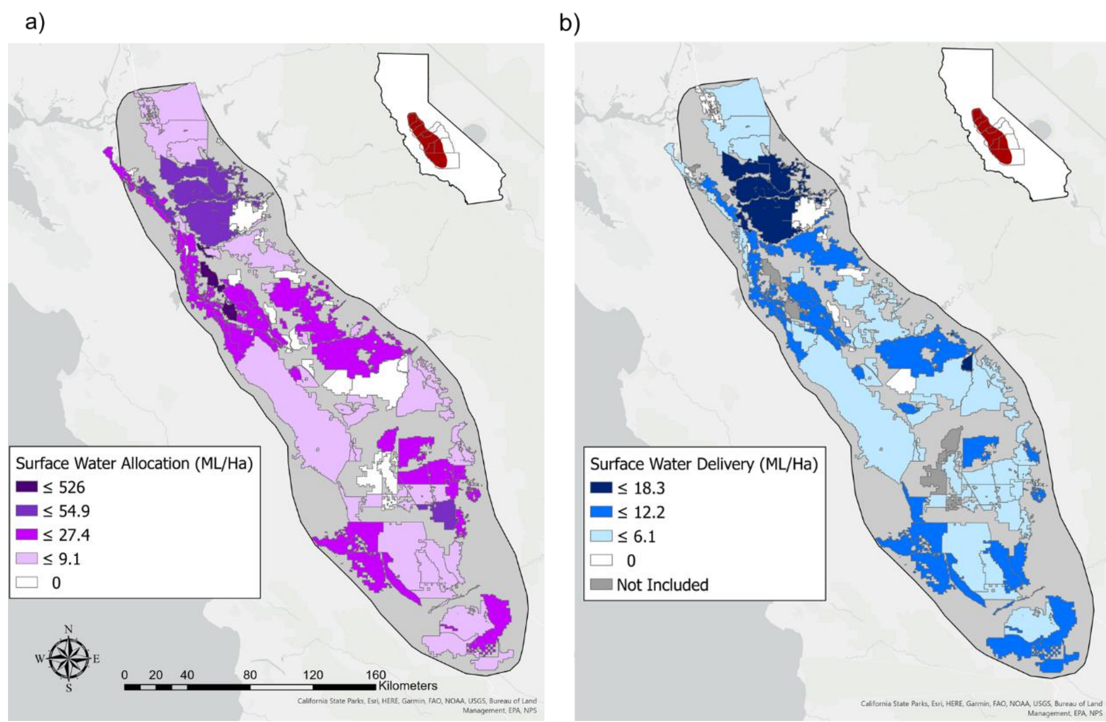
Some surface water allocations within the SWRCB's Electronic Water Rights Information Management System (eWRIMS) database are pending approval for allocation, primarily for irrigation districts formed during the Hydraulic Era (1914-1968) and an irrigation district recently formed during the Era of Reconciliation (2001-2020) with none for pre-1914 irrigation districts nor districts formed during the Era of Conflict (1969-2000). Most of the pending water rights are recently submitted (2014-2017), reflecting irrigation districts' anticipation of the need for additional surface water supplies to comply with SGMA through groundwater recharge methods or reducing reliance on groundwater pumping to meet irrigation demands. Another potential outcome of SGMA is the recent formation of a few irrigation districts that fall under the Era of Reconciliation (2001-2020). Under SGMA, water governance uncertainty may have led agricultural landowners to form districts after SGMA was passed to maintain greater control of water and land use management planning and implementation to address groundwater overdraft.

The decrease in irrigation district service areas with decreasing age reflects how California's land taxation laws transformed agricultural land ownership in the San Joaquin Valley and led to smaller farms. Land taxation amendments in 1909 exempted all improvements within an irrigation district from district tax, meaning that the levy for large landholders with unimproved or underutilized land would go up (Henley, 1968; Teilmann, 1963). These tax changes were an incentive for landholders with large, underutilized land tracts to sell to avoid paying high taxes and resulted in the dissolution of many large ranches into smaller land tracts bringing more crop diversity and prosperity to the region. Although older districts have larger service areas and more surface water availability on average, they are less agriculturally productive, based on their crop area fraction, than younger irrigation districts. Districts formed in the Era of Local Organization have larger service areas but have, on average, 69% crop area, while districts formed in the Hydraulic Era have 67% crop area compared to smaller, younger districts formed in the Era of Conflict and Era of Reconciliation with crop areas 81% and 71%, respectively.

Older districts formed in the Era of Local Organization and Hydraulic Era have less crop area fraction dedicated to perennial crops (53% and 59%, respectively). Older irrigation districts' focus on water-thirsty and lucrative crops reflects the higher ability of landowners contracted within these districts to obtain water supplies for irrigation than districts formed in other eras. Less agriculturally productive older irrigation districts may result from higher surface water rights allocations and access to water conveyance infrastructure (i.e., local canals and aqueducts, SWP, and CVP). Some older irrigation districts may be opting to sell surplus surface water allocations to other irrigation districts or allocate it to other beneficial uses. An example of the flexibility and control over water mobility that pre-1914 surface water rights holders have that allows them to control their surface water to meet irrigation demands and comply with new laws, especially during drought, is the Modesto Irrigation District. Modesto Irrigation District, located in Stanislaus County and formed in 1887 under the Wright Act, opted to deliver surplus water supplies, when available, to actively farmed agricultural lands outside the district's service area but within their sphere of influence to help comply with SGMA (Modesto Irrigation

District, 2020). However, in the early implementation of SGMA and during the 2012-2016 California drought, Modesto Irrigation District shifted to securing surplus surface water contracts with the county to ensure that surplus water supplies stayed within the county (Modesto Irrigation District, 2015). Younger irrigation districts formed in the Era of Conflict and the Era of Reconciliation have the highest crop area fraction dedicated to perennial crops (69% and 92%, respectively). Although perennial crops are often water-intensive, most growers may default to them due to their high crop revenue to help relieve higher surface water prices for irrigation districts without senior pre-1914 surface water rights. Generally, irrigation districts across water management eras have high crop area fractions dedicated to perennial crops. Overall, there is a strong trend between age and surface water and land use affluence among the irrigation districts in the San Joaquin Valley that reflect the transformation of water and land use developments in the state.

3.2 Groundwater Reliance Calculation: Addressing Groundwater Overdependence Through SGMA and Water and Land Use Management



c)

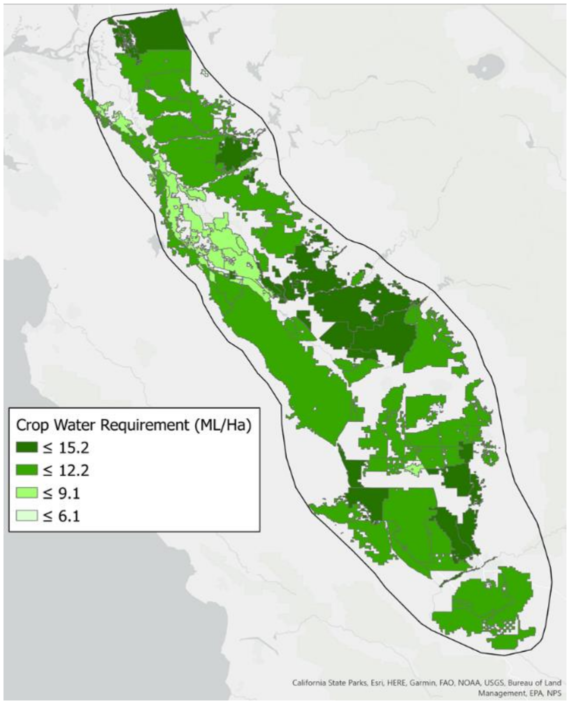


Figure 11. Irrigation district a) surface water allocation, b) surface water delivery (average 2001-2015), and c) crop water requirement values used to calculate irrigation district surface water surplus and deficit (refer to Figure 12).

This analysis shows that irrigation districts have been and will most likely become more groundwater-dependent as climate change, drought conditions, and water access inequity persists due to high crop water requirements and low surface water security (Figure 11 a-c). About 60% of irrigation districts with pre-1914 water rights have two times the crop water demand in surface water allocations. In contrast, 86% of San Joaquin Valley irrigation districts depend on groundwater to meet agricultural irrigation demands, of which 12% rely exclusively on groundwater. When assessing irrigation districts' groundwater overdependence based on surface water allocations, irrigation districts with high surface water rights do not classify as groundwater reliant (Figure 12a). Identifying irrigation districts' groundwater overdependence based on average surface water deliveries (2001-2015[5]) leads to a 32% increase in the number of irrigation districts classified as over-dependent on groundwater to meet crop water demands (Figure 12b). Generally, irrigation districts with higher crop water requirements are located on the eastern side of the San Joaquin Valley, where citrus production is highest. Irrigation districts with pre-1914 water rights do not identify as groundwater overdependent on surface water allocations and have up to three times more in surface water amounts claimed than needed to meet crop water demand. The irrigation districts lacking or having minimal surface water allocations become severely vulnerable to groundwater dependence during drought. During drought, irrigation districts with minimal surface water allocations receive their surface water deliveries after their senior counterparts. Regardless of their age or formation era, irrigation districts throughout the San Joaquin Valley are at risk of groundwater dependence in a changing climate. However, the water access inequity present across local water management better positions irrigation districts with higher surface-water allocations to be equipped to deal with surface water scarcity than irrigation districts that do not have surface water allocations and are dependent on groundwater to meet irrigation demands, especially under SGMA.

[5] Most irrigation districts have an average surface water delivery based on 2001-2015 deliveries, but there are a few exceptions due to data availability refer to Appendix D SI Table 9 for more details.

For irrigation districts to achieve SGMA targets by 2040, GSAs need to have a realistic approach to water management, which has not been the case based on SGMA implementation plans submitted in 2017 in many critically overdrafted basins (Jezdimirovic et al., 2020b). Most plans for addressing groundwater overdraft under SGMA focus on supply expansion (e.g., recharge, conveyance, and recycled water), which relies on the hope that sufficient surface water supplies will be distributed among competing supply expansion methods, including groundwater recharge. Some GSAs have relied on the surface water allocation defined by their water rights to address groundwater overdraft under SGMA in the next 20 years, which is unreasonable given increased water scarcity and severe drought conditions. Surface water scarcity is becoming more frequent—take the 2014-2016 drought and the severe introduction to the 2021 drought. California water rights account for 861% of natural surface water supplies and about five times the state's mean annual runoff (Grantham & Viers, 2014). As observed in the 2012-2016 drought, lucrative and water-intensive crops grown in the Central Valley did not experience a loss in production or revenue due to groundwater's critical role in meeting crop water demands during the drought (Howitt et al., 2015). Studies have projected that to address groundwater overdraft as per SGMA and under a more water-scarce future, more than 10% of agricultural land may have to go out of production (Hanak et al., 2019). To emphasize, 10% of agricultural land in addition to already idle land (e.g., previously irrigated land currently not in use) in the San Joaquin Valley. The loss of agricultural land could affect vulnerable DACs within highly groundwater-dependent, agriculturally productive irrigation districts.

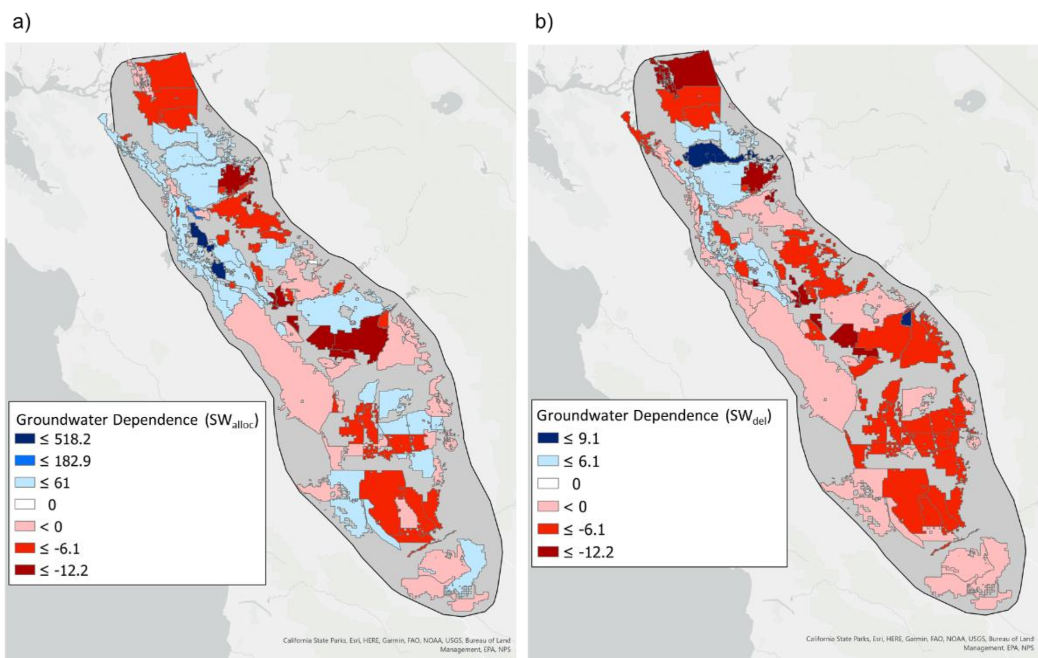


Figure 12. Groundwater dependence calculated by taking the difference between a) surface water allocation (SW_{alloc}) and crop water requirement and b) surface water delivery (SW_{del}) and crop water requirement.

3.3 DAC Comparison: Poverty Paradox Among Disadvantaged Communities in Irrigation Districts and Groundwater-Dependent Communities

Water access inequity is prevalent across irrigation districts and groundwater-dependent communities (GDCs), which rely solely on groundwater supplies to meet water demands. It was hypothesized that DACs within irrigation district jurisdictional boundaries would have better socioeconomic and environmental conditions than DACs in GDCs due to the controlled governance of surface water distribution within the district. To understand the dynamics of irrigation districts, their constituents, and the complexities of water accessibility, DACs within irrigation district boundaries (n=97), hereafter ID DACs, and DACs in GDCs (n=56), hereafter GDC-DACs were compared. See Table 5 for a summary of comparison statistics. The median household income is slightly lower for ID DACs (on average USD 34,276) than GDC-DACs (on average USD 36,450) and has similar poverty burden percentiles of about 83%. ID DACs face higher pollution burden exposure (average 81%) than GDC-DACs (average 74%). Both ID DACs and GDC-DACs have high particulate matter 2.5 microns in size ($PM_{2.5}$) burden exposures that average 92% and high exposure to asthma on average, about 60%. Pesticide burden exposures are higher in ID DACs (average of 83%) than GDC-DACs (average of 77%), which may contribute to a similar proportion of drinking water issues in ID DACS (average of 83%) and GDC-DACs (average of 79%). Groundwater threat exposure percentiles do not differ between ID DACs and GDC-DACs (averaging 55%).

The comparison highlights that ID DACs, on average, face higher poor air quality burdens and pesticide exposures than GDC-DACs. Both ID DACs and GDC-DACs face high poverty, poor drinking water issues, and high socioeconomic and environmental burdens. Overall, this comparison found that DACs under local government jurisdiction do not have better socioeconomic and environmental conditions than those in GDCs, underscoring how historical and cultural irrigation district contexts define agricultural regions' sociohydrological dynamics. Irrigation districts were initially designed to protect and ensure water for agriculture in the San Joaquin Valley and not necessarily govern water and agricultural practices to ensure safe drinking water or good air quality. The findings in this study highlight how farmers historically and culturally developed irrigation districts in the late 1880s to facilitate rights and regulations that promoted irrigation and water conveyance infrastructure that would catalyze the region as the world's multi-billion-dollar fruit basket. The socioeconomic comparison highlights that local water agencies in the San Joaquin Valley are not well-equipped to address the water access inequities among DACs within their boundaries. Before SGMA, irrigation districts were not required to engage DACs to understand and incorporate community members' concerns on water. For SGMA to result in effective, locally representative, and equitable climate change adaptation strategies, future policies need to work with current policies to facilitate meaningful engagement in current governance structures. Agriculture and agricultural communities in the San Joaquin Valley most threatened by increasing drought conditions could be determined by an irrigation district's sociohydrologic vulnerability index.

Socioeconomic Variable (mean)	Irrigation District (n=97)	White Area (n=56)	P-Value (α=0.05)
Population (2018)	9,899	20,515	0.003456
Pollution Exposure (%)	81	74	0.005413
Pesticide Exposure (%)	83	77	0.00965
$PM_{2.5}$ Exposure (%)	92	92	0.03291
Poverty (%)	83	84	0.1166
Poor Drinking Water Exposure (%)	83	79	0.1363
Overall DAC Vulnerability (%)	83	81	0.3147
Asthma Exposure (%)	63	64	0.7006
Median Household Income (2018)	$34,276	$36,450	0.7893
Threats to Groundwater (%)	56	55	0.829

Table 5. Irrigation District and White Area disadvantaged communities (DACs) socioeconomic and environmental burden variable means comparison ordered from most to least significant p-value (α=0.05) (OEHHA, 2018). The p-value is derived using the unpaired two-sample Wilcoxon test.

3.4 Irrigation District Sociohydrologic Vulnerability

Determining the DAC and freshwater status (herein sociohydrologic vulnerability) of the San Joaquin Valley irrigation districts is critical for identifying which local governance structures are the least well-equipped to deal with the increasing population, climate change, and limitations on freshwater resources under laws like SGMA. Freshwater and DAC status comprise the sociohydrologic vulnerability index developed in this study (methods adopted from Huggins et al., 2022). The freshwater status per irrigation district is representative of the groundwater dependence as a function of suface water delivery (Figure 8). The CalEnviroScreen 4.0 percentile score consisting of pollution burden and population characteristics (SI Table 8) (California Office of Environmental Health Hazard Assessment, 2018) for DACs within irrigation districts determines its DAC status. About 15% (n=15) of irrigation districts have high sociohydrologic vulnerability, 14% (n=14) moderate vulnerability, and 84% (n=73) low vulnerability (based on classes defined by dataset quantiles) (Figure 13).

The irrigation districts with high sociohydrologic vulnerability are characterized by lower suface water delivery (average 3.8 ML/Ha) compared to irrigation districts that fall in the moderate (average 7.9 ML/Ha) and low (average 7 ML/Ha) vulnerability classes. The high vulnerability irrigation districts also have the highest CWR (~ 12.1 ML/Ha) compared to those in the moderate and low vulnerability classes (~10.7 ML/Ha). Although the low vulnerability class has more DACs (n=87) than moderate (n=35) and high (n=41) vulnerability classes, the DACs within irrigation districts that classify as low vulnerability have lower, on average, DAC status score (~0.20) compared to DACs in the moderate (~0.79) and high (~0.84) vulnerability classes. The average freshwater score for each sociohydrologic vulnerability class is as follows: high with 0.89, moderate with 0.58, and low with 1. The average sociohydrologic vulnerability index score for irrigation districts in each class are 0.46 for high, 0.13 for moderate, and 0 for low vulnerability. Irrigation districts with high sociohydrologic vulnerabilty are likely to be more groundwater dependendent and have DACs with higher CES 4.0 scores than those in the moderate and low sociohydrologic vulnerability classes.

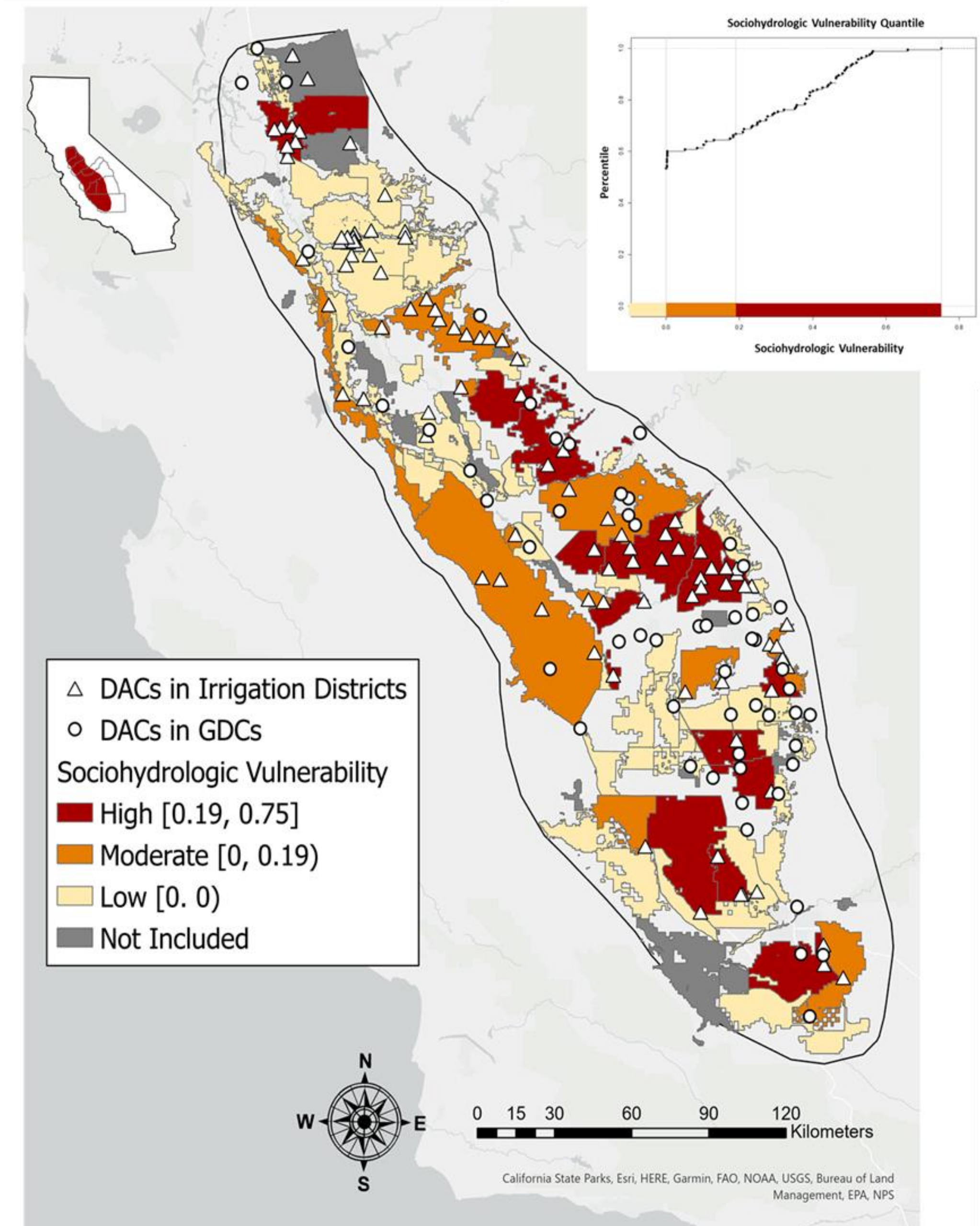


Figure 13. Irrigation district sociohydrologic vulnerability (methods adapted from Huggins et al.,2022) is defined by irrigation district freshwater status and DAC statusThe graph depicts the quantiles used to classify the index into low (beige), moderate (orange), and high (red) vulnerability classes.

3.5 Cluster Analysis: Differing Water Governance Features and Their Role in Driving Sociohydrologic Vulnerability

Water scarcity and droughts do not discriminate by the seniority of the irrigation district. However, water governance structures reflect the sociohydrological and historical contexts in which irrigation districts were established—to protect surface water dedicated to irrigated agriculture. Irrigation district history, location, water right seniority, and irrigation demands define differences in districts that struggle most or least during drought events. Irrigation district features were clustered to identify how historical and cultural contexts shape differing water governance structures and practices and drive sociohydrologic vulnerability. This analysis resulted in five irrigation district group types (Figure 14) ordered from most to least groundwater-dependent: 1) Groundwater Dependent Vineyards (GDV), 2) California Citrus Belt (CCB), 3) Sizeable Crop Generalists (SCG), 4) Forage and Cotton Corridor (FCC), and 5) Senior, Secure Nut Growers (SSN). Overall, the differences in irrigation district water governance and sociohydrologic vulnerabilities are driven by surface water delivery amounts influenced by formation era and crop water requirements influenced by crop type. These groups also have many irrigation districts with high CalEnviroScreen vulnerability score percentiles. See Appendix D SI Table 11 for a summary of irrigation district group features.

The irrigation districts within the GDV group are the most groundwater-dependent out of all the other groups and are mainly located in the eastern San Joaquin Valley (Figure 14, brown). The GDV group comprises irrigation districts formed in all formation eras except the era of Local Organization (pre-1914), the oldest irrigation districts. All districts in this group are groundwater-dependent based on surface water deliveries (surface water deficit ranges from -5 to -15 ML/Ha). The GDV has the lowest surface water delivery and allocations compared to the other groups, with 43% of districts receiving zero surface water delivery on average from 2001 to 2015 and 48% having zero surface water allocation. In anticipation of reduced groundwater use under SGMA and lack of claims to surface water, irrigation districts in this group have the most pending requests for surface water rights allocations (n=5) in the SWRCB eWRIMS database ranging from 0.6 to 27 ML/Ha. The need for more surface water and high dependence on groundwater is reflected in the high crop water demands and primary focus of crop area on grape production (average 23%) among irrigations districts in this group.

The CCB consists of irrigation districts mainly in the Central Eastern and Southern San Joaquin Valley (Figure 14, dark orange) and contains irrigation districts formed mainly in the Hydraulic Era (1914-1968) (82%, n=19 out of 23), a few from the Era of Conflict (1969-2000) (13%, n=3 out of 23), one from the Era of Reconciliation (2001-2020), and none formed pre-1914. These smaller service area districts, ranging from 300 to 52,000 Ha, have the highest perennial fraction (average 92% of crop area) and make the highest perennial average revenue (USD2,300 to 3,570). Citrus is the most prominent perennial crop within irrigation districts in this group, making up 44% of the crop area on average. About 91% of districts in the CCB have surface water allocations, and 96% receive surface water deliveries, yet 96% of the CCB districts are groundwater dependent. The surface water deficit/surplus for irrigation districts in this group range from -11 to 4 ML/Ha.

The SCG group consists of 13 irrigation districts formed during the Hydraulic Era (1914-1968) and one formed pre-1914 (Figure 14, light orange). This group's surface water availability is moderate compared to irrigation districts in other groups. In other words, all SCG districts have, on average moderate amounts of surface water allocations (average 7 ML/Ha) and deliveries (average 6 ML/Ha). However, all have surface water allocations, with some districts pending additional surface water allocations from the SWRCB ranging from 0.02 to 59 ML/Ha. Compared to other groups, SCG districts have moderate crop water requirements, ranging from 9 to 13 ML/Ha. The irrigation districts in this group have the most extensive service areas, ranging from 6,440 to 247,000 Ha. This group comprises crop generalists meaning that there are crop fractions dedicated to irrigated forage, perennials, and annuals, with no specific crop being the standout crop for the group as with other groups. These irrigation districts may seem to be doing well, given the moderate levels of crop water requirement, surface water supplies, and crop diversity compared to other groups. However, on the contrary, 93% of SCG districts are groundwater dependent. The groundwater dependence brings to light the mismanagement of surface water supplies by exceeding surface water supply to meet irrigation demands.

The FCC group comprises 27 irrigation districts located down the western side of the San Joaquin Valley from north to south (Figure 14, yellow). Irrigation districts formed in this group mainly formed during the Hydraulic Era (1914-1968) (n=23), with two formed pre-1914 and two others formed in the Era of Conflict (1969-2000). These irrigation districts are generally moderately older (average age 70) and have the smallest service areas compared to other groups, ranging from 347 to 41,250 Ha. About 17% of FCC districts do not have surface water allocations, and one district received zero surface water deliveries on average from 2001 to 2015. The most prominent crops within FCC districts are cotton (11% of the crop area on average) and irrigated forage (27% of the crop area on average) compared to other districts. This group's low crop water requirement may reflect more crop area dedicated to annual crops, which are more drought flexible than perennial crops. Although this group has the lowest crop water requirement averaging 9 ML/Ha, about 81% of FCC irrigation districts are dependent on groundwater to meet irrigation demands.

The SSN group comprises seven older and water-secure irrigation districts in the northern San Joaquin Valley (Figure 14, beige). Irrigation districts in this group have large service areas, ranging from 6,700 to 77,300 Ha, compared to other groups but not as large as districts in the SCG group. The SSN districts have the highest surface water allocation, ranging from 31 to 50 ML/Ha, and surface water delivery, ranging from 0.09 to 10 ML/Ha, compared to districts in other groups. The service areas are large, but the crop water requirements are relatively moderate due to a low crop area fraction. Although there is a high fraction of crop area dedicated to almonds (41% of the crop area on average) and walnuts (8% of the crop area on average), the perennial crop revenue is low (on average USD2,200) compared to other groups. This trend could indicate these districts' lessened pressure to sell water-intensive and lucrative crops at top dollar to make up for the additional purchase of surface water, cover high groundwater pumping costs, or make a higher profit from selling surplus irrigation water to other districts. The SSN districts are the least groundwater-dependent of the groups, with 30% of this group dependent on groundwater to meet irrigation demand but not as severely overdependent as districts in other groups.

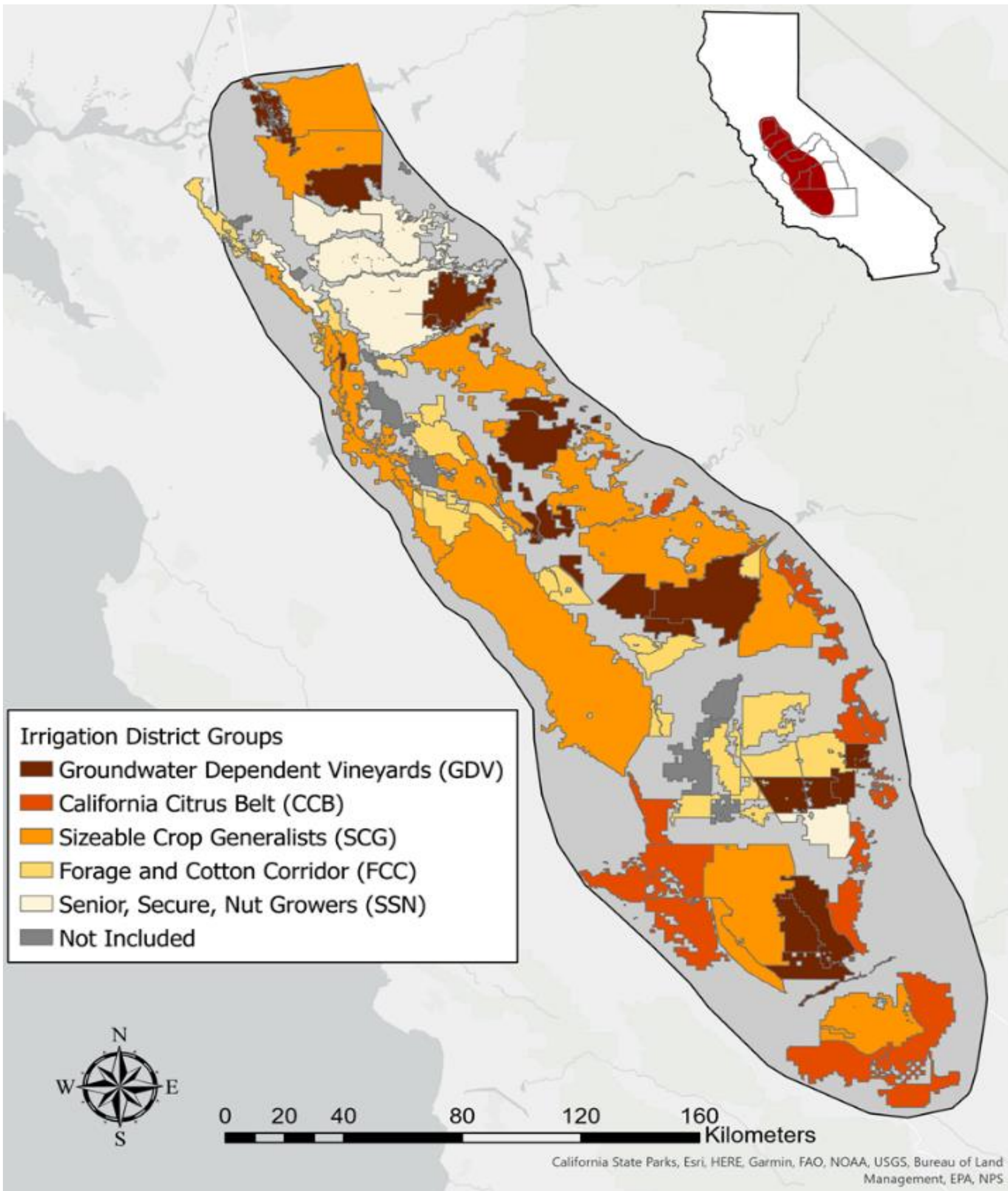


Figure 14. Irrigation District trait groupings based on a cluster analysis on irrigation district age, surface water allocation, water conveyance, and crop variables. For a list of variables used for this analysis, refer to SI Table 10 (Appendix D).

4. Study Limitations and Future Work

The disaggregated information of California irrigation districts may result in dated and missing information. To ensure the accuracy of the data used for this study, data were obtained and cross-validated across various web-based sources (e.g., irrigation district websites, Agricultural Water Management Plans, Groundwater Sustainability Plans, eWRIMS), multi-agency sources (e.g., U.S. Bureau of Reclamation, State Water Resources Control Board, Department of Water Resources, county, and districts), and verification of information by speaking with irrigation district general managers. It is also important to consider how the misclassification of land cover data plays a role in crop water requirement inaccuracies. To address this concern, this study used the best thematic dataset available to represent the San Joaquin Valley's complex agricultural landscape, Land IQ (See Chapter 4 for land cover dataset comparisons for California). Future would include incorporating the price of surface water and estimated costs of groundwater pumping within irrigation districts to analyze how an irrigation district's historical context plays a role in determining surface water pricing and how water price defines water access inequities across San Joaquin Valley irrigation districts, especially under the SGMA. A comparison between surface water pricing and groundwater pumping between irrigation districts and GDC would be interesting and could provide insight into how water is valued across different water governance structures. Another future application of this work is to develop a statewide, standardized sociohydrologic vulnerability index that GSAs and other statewide entities could use to inform where to focus water and land use management.

5. Conclusions

This geospatial study provides a fundamental understanding of local water governance and management, specifically of irrigation districts in the San Joaquin Valley, California. Analyzing the historical and cultural contexts embedded in irrigation district features and water management practices provides insights into the inherent dynamics between water, people, and the legal system that must be accounted for in climate change resilient water management plans. Very early in California's water development, water is the property, and the control of water is the control of society mantras played a role in shaping California water as it is known today. Irrigation districts and surface water rights in the state represent historical and cultural contexts embedded within their governance structures. These surface water laws and governance entities represent the role of human agency in shaping water control for irrigation and the mobilization of surface water supplies as it is known across California's agricultural regions, as theorized by Jurist Franz von Benda-Beckmann.

The irrigation district formation period has defined the laws that better position some irrigation districts to deal with climate change and shifts in water laws, like SGMA. For instance, older irrigation districts formed pre-1914 are less groundwater-dependent than irrigation districts formed in other eras. Large claims to surface water supplies allow older irrigation districts to control water in the state and inherently grant them the capacity and flexibility to cope with climate change than younger districts. This work found that 86% of San Joaquin Valley irrigation districts depend on groundwater to meet agricultural irrigation demands, of which 12% rely exclusively on groundwater. Regardless of their water age or formation era, irrigation districts throughout the San Joaquin Valley are at risk of groundwater dependence in a changing climate and surging population growth. However, the water access inequity in water governance puts older districts with higher claims to surface water at an advantage, given their higher surface water capacity and ability to control water without SWRCB interference.

For SGMA and climate change adaptation strategies to result in effective, locally representative, and equitable climate change adaptation strategies, policies need to work with current policies to facilitate meaningful engagement to close the water access inequity gap in current governance structures. This study found that DACs within local government jurisdiction are not socioeconomically nor environmentally better off than DACs in GDCs, which is attributed to the historical and cultural context for which irrigation districts were formed—to secure water for irrigated agriculture. To develop water management that balances competing freshwater demands and addresses water access inequities across marginalized communities, it will be necessary to guide water governance entities in conducting inclusive and meaningful engagement.

To ensure a food and water-secure future for the state and the world, California needs to implement local, regional, and state climate change adaptation strategies that address the water access inequity faced by marginalized groups. SGMA is an opportunity to rethink surface water and groundwater management to develop climate change and drought resilience. For the state to address many of its water woes, it will need to prevent excessive water allocation, primarily through the surface water rights system, which represents 861% of the San Joaquin River's natural surface water supplies (Grantham & Viers, 2014). The beginning of California's 2021 drought has demonstrated that current surface water allocations through the current water rights system are unsustainable for drought-prone regions. In August 2021, the SWRCB curtailed water claims for all principal water rights (i.e., pre-and post-1914 and riparian rights) for the Sacramento River, San Joaquin River, and the legal Delta (the waterwheel of California water supplies) ([SWRCB] State Water Resources Control Board, 2021b). As has been the case in managing water in Australia's Murray-Darling Basin, California also needs to overcome the legacy of its sociohydrological past, particularly its deeply rooted cultural and management customs such as excessive allocation of surface water and conflicting water management targets (Pittock & Connell, 2010). The Mediterranean biome reflects challenges in sustaining water for humans and the environment (Underwood et al., 2009).

Thus, it is not unreasonable to think that California may follow its counterparts in Australia and South Africa, which reformed their water rights to promote natural resource sustainability, management efficiency, and social justice because their regulatory frameworks failed to effectively and equitably manage water allocation and distribution (Godden, 2005). In many ways, Australia's Murray-Darling Basin and South Africa's water woes parallel those in California, especially those of the San Joaquin Valley, because of the prolonged mismanagement of natural water resources that stems from market-driven decision-making and governance that bends toward vested interests. Moving forward, California needs to develop climate change adaptation for water management by understanding why Australia's 2012 Murray-Darling Basin Plan is falling short of expectations (H. E. Moore et al., 2020; The Wentworth Group of Concerned Scientists, 2017) if California is to avoid a similar fate under SGMA and its climate adaptation strategies. For California to maintain a thriving agricultural economy and climate-smart water management, it needs to develop policy and governance structures that reduce favoring and bending toward vested interests, balance freshwater demands, and ensure that water access inequity is addressed in the future water and land use management decisions.

CHAPTER 4. WHICH DATA TO USE?

1. Introduction

Regions worldwide face the repercussions of the decadal accumulation of anthropogenic contributions to climate change as more intensified precipitation events, like droughts and floods (Espinoza et al., 2018). Climate change challenges are beyond mitigation, and countries worldwide need to develop resilient adaptation strategies that balance surface water and groundwater supplies among competing demands to prevent further overexploitation of freshwater resources (Taylor et al., 2013) and address water access inequities. Globally, the agricultural sector is currently positioned to better climate change conditions given that irrigated agricultural land use makes up 300 million hectares globally, uses ~70% of freshwater withdrawals, and accounts for a majority of the 23% of GHG emissions from agriculture, forestry and other land use (FAO, 2017b, 2020; IPCC, 2020). The interrelationship between water and land use leads to management decisions with tradeoffs for each sector, especially in agricultural landscapes. The expansive presence of agriculture worldwide and its high dependence on freshwater resources allow the development of climate-smart agricultural practices that help address global water scarcity and water access inequities and reduce greenhouse gas (GHG) emissions.

Land use classification datasets have provided insights into global, national, and regional inventories of agricultural water footprints, virtual water trading, food production, and many environmental applications (Han et al., 2012; Konar et al., 2011, 2013; Konar & Marston, 2020; Ruddell et al., 2017). Given the regional need to address water scarcity while maintaining food production to feed an increasing population (Vörösmarty et al., 2000), there is a need for high thematic data. Accurately quantifying the current state of climate change is critically dependent on reliable land use classification data representing complex agricultural landscapes. Although there is a common belief that higher resolution data leads to better quality data, the thematic resolution of the land cover classes is the more important feature for determining land use classification data quality (Verburg et al., 2011). A commonly used dataset across the United States is the U.S. Department of Agriculture's (USDA) Crop Data Layer (CropScape) (Han et al., 2012). It is one of the most highly reported datasets used in California, Illinois, Minnesota, Virginia, and Iowa (Mueller & Harris, 2013). The CropScape dataset has been known to have higher accuracy in regions with a single dominant crop (Reitsma et al., 2016), limiting agricultural policy development in highly agriculturally diversified landscapes like California. Although there are increasing investments in acquiring and classifying remotely sensed data to produce land use datasets, there is a need for improved regional crop representation in satellite-based remote sensing data so that it continues to provide unbiased information for effective agricultural policy and management (Atzberger, 2013).

California's San Joaquin Valley is an excellent example of a complex agricultural region needing highly representative crop classification datasets. This drought-prone state is currently faced with developing climate change adaptation strategies that address groundwater overdraft, surface water access inequities, and changes in agricultural land use. Land use in many parts of the Valley leads to competing water demands, especially between agricultural and municipal land uses, and strongly governs annual surface water diversions (Goodrich et al., 2020) and groundwater overdependence. California's 2014

Sustainable Groundwater Management Act (SGMA) (University of California, 2016) aims to address groundwater overdraft by 2040. Some studies have projected that more than 202,350 hectares of agricultural land may go out of production to address groundwater overdraft (Hanak et al., 2019), which could have detrimental socioeconomic and environmental impacts on rural agricultural communities (Howitt et al., 2015). The extensive impact of land use transitions makes it more critical to utilize regionally representative land use classification datasets. For California, this means using land-use classification datasets designed to capture its agricultural complexity— 400 diverse commodities generating more than 25 billion USD annually (California Department of Food and Agriculture, 2019).

To date, no paper has quantified the revenue, crop water requirement, and GHG

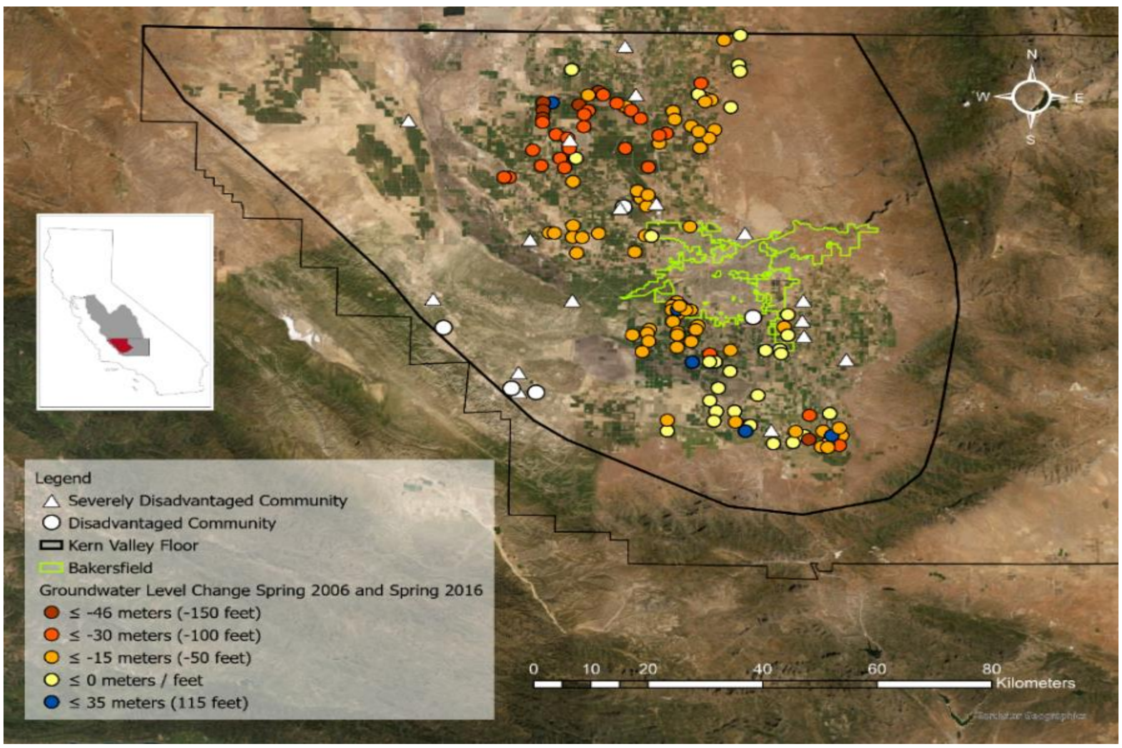


Figure 15. Kern County's predominantly agricultural region (Kern Valley floor) faces declining groundwater levels (dark orange to yellow), which has detrimental impacts to groundwater dependent agricultural disadvantaged communities (white triangles and circles).

emission discrepancies of land use misclassifications in a highly diversified agricultural landscape like the San Joaquin Valley. This study focuses on Kern County due to the limited availability of county-level geospatial crop classification datasets in California, except for Kern County, one of the eight counties in the San Joaquin Valley (Figure 15). Land use classification datasets were compared for 2014 and 2016, the beginning and end of California's 2014-2016 drought, to facilitate insights into misclassification discrepancies during the worst-case scenario in California— drought and water scarcity— and in part due to LIQ data limitations during the time of this analysis. This study focuses on identifying common crop misclassifications and their implications on revenue, crop water requirement, and GHG emission estimates for three commonly used datasets in California—1) Kern County Department of Agriculture's geospatial dataset (herein, Kern Ag), 2) Land IQ (LIQ), and 3) USDA's CropScape (CropScape). Quantifying land use misclassifications in these datasets is critical if they inform future water and land-use decisions that have implications on marginalized rural agricultural communities. This paper will highlight common misclassifications to help inform future improvements in land use classification datasets, especially in diversified crop landscapes, and provide misclassification estimates that can help improve land use, crop water requirement, and GHG emission inventories.

2. Methodology

2.1 Datasets

The three datasets used in this analysis encompass a gradient of sponsor government agencies from countywide (i.e., Kern Ag), statewide (i.e., LIQ), and nationwide (i.e., CropScape). Table 6 provides a summary of dataset details.

The Kern County Department of Agriculture had the longest record of geospatial data integrated with tabular permit information publicly available with records from 1997 to 2021. Although recent guidelines have led to data availability in 2016 only available to the public, it is still the only crop classification dataset available at the county level in the San Joaquin Valley. The dataset comprises geospatial permitted county crop boundaries and pesticide use and permit reports (Kern County Department of Agriculture, 2020). Local growers and inspectors collaborate to digitize permitted sites. The vector format dataset contains 115 crop classes. For comparison purposes in this analysis, the Kern Ag classification dataset is assumed to be ground truth.

Land IQ, LLC is a private remote sensing analytics and consulting organization based in California that provides a full suite of data, analytics, image, and mapping services for diverse clients. Specific to California's land use datasets, LIQ land use classification datasets are derived from remote sensing (i.e., LandSat 8 OLI/TIRS, DEIMOS-1 DMC2, and UK2 DMC-2). Agricultural training and validation data are derived from the Farm Service Agency (FSA) Common Land Unit (CLU) data, US Bureau of Reclamation Lower Colorado River Accounting System crop classifications, and vineyard locations as identified by E & J Gallo Winery (2013 data). Generally, LIQ datasets are available for purchase based on the size of the area of interest. Although Land IQ, LLC recently partnered with DWR to classify more than 14 million acres of statewide land use with 97.6% accuracy (Land IQ & California Department of Water Resources, 2016), open-access data through this partnership is currently limited for 2014, 2016, and 2018 via the California Department of Water Resources Land Use Viewer (DWR, 2014). The vector format dataset contains 38 crop classes.

The United States Department of Agriculture (USDA) CropScape is an interactive digital resource that allows users to query, visualize, download, and develop statistics from Cropland Data Layer (CDL) throughout the United States (Han et al., 2012). CDL is a crop and land cover classification dataset in georeferenced raster format obtained from medium resolution satellite imagery (e.g., MODIS, NASA Terra, and Disaster Monitoring Constellation satellites, Landsat 8, ESA SENTINEL-2 sensors). The data are classified using supervised classification methods (e.g., maximum likelihood and decision tree analysis) and validated with ground truth verification (i.e., Farm Service Agency Common

Land Unit). The advantage of using the Farm Service Agency Common Land Unit is that it contains field-level information in GIS format, while disadvantages include that it may be biased toward subsidized program crops and is not truly a probability sample of land cover (USDA NASS, 2020). Another limitation of using land use classification datasets tailored to capture national agricultural crop trends is that it does not capture the diversity in crops that define highly diversified and complex agricultural landscapes (Reitsma et al., 2016). The raster format dataset contains 54 crop classes.

Dataset Specifications			
Specifics	Kern County (Kern Ag)	Land IQ (LIQ)	USDA NASS CDL (CropScape)
Data Funder/ Sponsor	Kern County Department of Agriculture (County)	DWR (State)	USDA (Federal)
Spatial Extent	County	State	National
Temporal Extent	1997-2018[1]	2014, 2016, 2018	2007-present
Num. of Crop Classes[2]	115	38	54
Data Source & Methodology	• Permitted county crop boundaries • Pesticide use and permit reports • Inspectors and local growers collaborate to digitize permitted sites	• Initial crop classification with multiple LandSat8 images • Fields delineated from the USDA NAIP • Central Valley ground truth data points are distributed among crop types	• Classification datasets: Landsat8 OLI/TIRS, DEIMOS-1 DMC2, and UK2 DMC-2 • Agricultural training and validation data are derived from the FSA CLU, USBR Lower Colorado River Accounting System crop classifications, and E & J Gallo Winery (2013 data)

Table 6. Kern County Ag. Commission, Land IQ, and Cropscape (USDA NASS CDL) specification table.

[1] Due to recent changes in guidelines, the Kern County Agricultural Commission will no longer make data past 2016 publicly available.

[2] Some datasets have non-agricultural land uses, but only crop classes are considered unless crops are misclassified for non-agricultural land cover.

2.2 Data Processing

All geospatial land classification datasets were processed in ArcGIS Pro 2.7.0 (ESRI, Redlands, CA) with a common coordinate projection (NAD 1983 California Teale Albers), origin, and extent. Data were cropped to restrict the analysis to the agricultural lands within

Kern County (Figure 15). The LIQ and Kern Ag vector data were converted to 30-meter by 30-meter rasters to match the resolution of CropScape. Conversion from vector to raster was appropriate given the large agricultural polygons (mean area), facilitation of raster comparison tools, and reduced production of slivers and gaps in spatial coverage if converting from raster to vector format. This analysis focused on non-rangeland crops. Thus, non-agricultural land uses were only considered when a crop was misclassified as non-agricultural land use (e.g., cotton labeled as grasses). Since the three datasets have different crop classes and levels of specificity, this study reconciled crop categories to facilitate comparisons (see SI Table 21 in Appendix F for general crop categories and specific crop components). For example, sweet potato within LIQ and Kern Ag was made potatoes. Using combinatorial tools, unique class combinations across datasets were identified and coded—Kern Ag and Cropscape, Kern Ag and LIQ, and LIQ and Cropscape—which provided the count of matched and mismatched classes between datasets. Land use comparison results were used to create confusion matrices and perform statistical tests (i.e., overall, producer's, and user's accuracy and Cohen's Kappa Coefficient of Accuracy).

Equation 1. $Overall\ Accuracy = \frac{Correctly\ Classified}{Total\ Number\ of\ Values}$

Equation 2. Producer's Accuracy= 100% - Omission Error

Equation 3. Users Accuracy= 100% - Commission Error

Equation 4. $Kappa = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(T_i P_i)}{N^2 - \sum_{i=1}^{n}(T_i P)}$,

In equation 4, i is the class number, N is the total number of classified values compared to truth values, $m_{i,i}$ is the number of values belonging to the truth class i that have also been classified as class i (i.e., along the diagonal), P_i= is the total number of predicted values belonging to class i, and T_i= is the total number of truth values belonging to class i.

2. 3 Land Use Misclassification Discrepancies on the User's End

Given the focus of this study on understanding the discrepancies that result from land use classification inaccuracies on the user's end, the discrepancy calculations and results will reflect only the discrepancies from the user's error in the sections below for revenue (Section 3.3.1), crop water requirements (Section 3.3.2), and GHG emissions (Section 3.3.3).

2.3.1 Deriving Revenue Discrepancies

The crop revenues were obtained individually for 2014 and 2016 from Kern County Crop Reports. The USDA California National Agricultural Statistics Survey (NASS) provided crop revenues not available in the Kern County Crop Reports mainly due to crops aggregated into broader crop categories. For some crops, the crop reports have more specific crop categories (e.g., Navel orange and Valencia orange), and the crop with the highest harvested acreage was selected to represent the reconciled crop categories developed for this study. The crop revenue table was joined with the actual and misclassified crop from the per-pixel comparison disagreement output. The crop revenue table was joined with the actual and misclassified crop from the per-pixel comparison disagreement output. The revenue was calculated for the misclassified crop (equation 5) and actual crop (equation 6) and then used to calculate the net and gross revenue discrepancies (equation 7 and 8, respectively).

Equation 5. $Revenue_{misclassified\ crop} = misclassified\ area * production\ per\ hectare_{misclassified\ crop} * unit\ value\ USD_{misclassified\ crop}$

Equation 6. $Revenue_{actual\ crop} = misclassified\ area * production\ per\ hectare_{actual\ crop} * unit\ value\ USD_{actual\ crop}$

Equation 7. $\mathrm{N}et\ Revenue\ Discrepancy = Revenue_{misclassified\ crop} - Revenue_{actual\ crop}$

Equation 8. $Gross\ Revenue\ Discrepancy = \left|\sum Revenue_{misclassified\ crop} - \sum Revenue_{actual\ crop}\right|$

SI Tables 22 and 23 (Appendix F) provide the crop revenue values used for this analysis with specifics on the report crop type used, production per acres, product units, price per unit, data source, and notes for 2014 and 2016, respectively, and the USD for total acres were converted to USD for total hectares.

2.3.2 Deriving Crop Water Requirement Discrepancies

The crop water requirement (CWR) values were calculated by accumulating the daily crop evapotranspiration in the growing period for each crop class in each dataset for 2014 and 2016. The evapotranspiration is represented by the irrigated, freshwater component of crop evapotranspiration, $ET_{c,\ blue}$, and is used in the WAFR model to derive crop water requirement. For more information on the data processing and WAFR model, refer to (Booth, 2018).

The CWR for each crop misclassification in all datasets for 2014 and 2016 was derived by taking the sum of the crop area and dividing it by the CWR for the misclassified crop (equation 9) and the actual crop (equation 10), and the net and gross crop water requirement discrepancy were calculated by using equations 10 and 11, respectively.

Equation 9. $CWR_{misclassified\ crop} = \frac{\sum crop\ water\ requirement_{misclassified\ crop}}{\sum crop\ area_{misclassified}}$

Equation 10. $CWR_{actual\ crop} = \frac{\sum crop\ water\ requirement_{actual\ crop}}{\sum crop\ area_{misclassified}}$

Equation 11. $Net\ CWR\ discprepancy = CWR_{misclassified\ crop} - CWR_{actual\ crop}$

Equation 12. $Gross\ CWR\ discrepancy = \left|\sum CWR_{misclassified\ crop} - \sum CWR_{actual\ crop}\right|$

The crop water requirement for broader crop categories (e.g., other crops, other fruits, and other vegetables) was derived by taking the averages of the crop water requirements for crop types that comprise the broad categories for the 2014 and 2016 datasets. (See SI Tables 25 and 27, Appendix F). A list of crop water requirement values per crop type per dataset for 2014 and 2016 is outlined in SI Tables 24 and 26 (Appendix F).

2.3.3 Deriving GHG emission Discrepancies

The GHG emissions per crop type were the same across all datasets for 2014 and 2016 and were obtained from (Carlson et al., 2017). A reconciled table of GHG emission values from Carlson et al. (2017) was created to join with the actual and misclassified crops (SI Table 28, Appendix F). Equations 13 and 14 were used to calculate the GHG emission value for the misclassified crop and the actual crop, respectively, which are used to calculate the net and gross GHG emission discrepancies in Equations 15 and 16.

Equation 13. $GHG_{misclassified\ crop} = misclassified\ area * GHGemission_{misclassified\ crop}$

Equation 14. $GHG_{actual\ crop} = misclassified\ area * GHGemission_{actual\ crop}$

Equation 15. $Net\ GHG\ emission\ discrepancy = GHG_{\ misclassified\ crop} - GHG_{\ actual\ crop}$

Equation 16. $Gross\ GHG\ emission\ discrepancy =$

$$\left|\sum GHG_{\ misclassified\ crop} - \sum GHG_{\ actual\ crop}\right|$$

3. Results and Discussion

3.1 Crop Misclassification Trends by Area

Technological advancements and increased investment in satellite and remote sensing have led to increased accessibility of land use and increasingly accurate maps specifying crops planted. Nevertheless, there is still a need to address the inaccuracies in land use classification algorithms for complex agricultural landscapes. Crop misclassification trends based on misclassified hectares show that from 2014 to 2016, CropScape users' accuracy improved by about 9%. In contrast, LIQ users' inaccuracy compared to Kern Ag seems to have worsened by 458% (Tables 7-9 includes a breakdown of misclassified hectares per crop). It is important to highlight that although there seems to be an improvement in the user's accuracy in the CropScape dataset between 2014 and 2016 than LIQ, the number of misclassified hectares in CropScape range between 100,000 – 114,000 hectares compared to the misclassified hectares in the LIQ datasets of 7,200 – 40,000 hectares. In other words, LIQ is still the highest thematic dataset that best represents the diversity and complexity of California's agricultural landscape. Crop misclassification comparison by area, in hectares, highlights that the top misclassified crops in CropScape from 2014 and 2016 were pistachios, grapes, citrus, and almonds (Figure 16-17, yellow and blue; Table 7-9), while LIQ had lower misclassifications for these lucrative and water-intensive crops (Figure 16-17, green; Table 7-9). LIQ demonstrated higher misclassifications in 2016 than in 2014. The most misclassified water-intensive, lucrative crop across all datasets was pistachios and was misclassified for fallowed land (~6,500 hectares) and almonds (~6,000 hectares) (Figure 16, 17). The importance of accurately classifying fallowed land is magnified in California, given the detrimental social, economic, and environmental impacts of potentially transitioning more than 202,342 hectares of agricultural land to address groundwater overdraft under SGMA. Fallowed land was mainly misclassified for almonds by the LIQ 2016 dataset (~5,000 hectares), followed by grains (~1,500 hectares) and cotton (~1,000 hectares), which results in unaccounted hectares of fallowed land and an overestimation of crop revenue, crop water requirement, and GHG emissions (Figure 17).

	Kern Ag and CropScape				
	2014 Misclassified		2016 Misclassified		2016-2014
Total	113,831 Ha		103,903 Ha		-9%
Crop Category	Hectares	Percent	Hectares	Percent	Percent +/-
Alfalfa	2,957	30	3,812	26	29
Almonds	12,276	19	12,105	23	-1
Apples	221	71	168	28	-24
Bushberries	260	98	264	61	1
Carrots	6,248	38	6,015	31	-4
Cherries	1,695	80	2,094	84	24
Citrus	14,305	31	13,853	22	-3
Corn	3,405	46	3,458	32	2
Cotton	2,875	22	2,404	25	-16
Fallow	8,340	69	7,762	68	-7
Garlic Onion	1,629	38	1,583	26	-3
Grains	6,460	43	8,188	38	27
Grapes	17,476	20	13,926	17	-20
Lettuce Greens	197	46	544	93	176
Other Crops	1,506	90	1,513	93	0
Other Fruit	1,483	72	1,053	80	-29
Other Vegetables	1,809	63	1,851	70	2
Peppers	623	61	523	78	-16
Pistachios	20,684	22	17,361	21	-16
Plums	1	100	1	100	-7
Pomegranate	5,040	46	1,507	22	-70
Potato	2,999	55	2,502	61	-17
Safflower	333	97	321	72	-3
Strawberries	5	100	1	100	-80
Tomatoes	722	50	717	59	-1
Walnuts	281	94	374	81	33

Table 7. The percent increase or decrease in crop misclassifications between 2014 and 2016 for Cropscape compared with Kern Ag.

	Kern Ag and LIQ				
	2014 Misclassified		2016 Misclassified		2016-2014
Total	7,182 Ha		40,075 Ha		458%
Crop Category	Hectares	Percent	Hectares	Percent	Percent +/-
Alfalfa	153	1	521	3	239
Almonds	106	0	264	0	149
Apples	0	0	5	2	1,600
Bushberries	9	4	4	2	-59
Carrots	100	1	1,170	19	1,069
Cherries	34	1	24	1	-30
Citrus	25	0	36	0	42
Corn	3,256	36	12,586	74	287
Cotton	31	0	587	7	1,818
Fallow	676	4	13,775	50	1,938
Garlic Onion	136	4	403	16	197
Grains	185	1	1,780	16	861
Grapes	37	0	169	1	350
Lettuce Greens	1,131	85	1,497	81	32
Other Crops	993	43	1,101	59	11
Other Fruit	111	6	261	19	135
Other Vegetables	4	1	220	48	5,866
Peppers	14	2	133	20	872
Pistachios	37	0	1,154	2	3,020
Plums	50	98	53	99	6
Pomegranate	5	0	3	0	-50
Potato	58	1	1,361	40	2,248
Safflower	2	0	1,260	65	82,271
Strawberries	0	2	-	0	-100
Tomatoes	28	1	1,710	35	6,028
Walnuts	1	0	1	0	0

Table 8. Compared with Kern Ag, the percent increase or decrease in crop misclassifications between 2014 and 2016 for Land IQ.

	LIQ and CropScape				
	2014 Misclassified		2016 Misclassified		2016-2014
Total	117,321 Ha		107,059 Ha		-9%
Crop Category	Hectares	Percent	Hectares	Percent	Percent +/-
Alfalfa	2,977	30	2,558	27	-14
Almonds	12,291	19	11,357	28	-8
Apples	221	71	173	28	-22
Bushberries	247	98	214	61	-13
Carrots	6,266	38	4,398	31	-30
Cherries	1,684	81	1,875	84	11
Citrus	14,302	31	13,458	22	-6
Corn	6,523	45	14,146	8	117
Cotton	2,835	22	956	24	-66
Fallow	8,572	69	12,672	55	48
Garlic Onion	1,710	38	1,044	21	-39
Grains	6,268	44	4,461	66	-29
Grapes	17,256	20	13,103	18	-24
Lettuce Greens	1,328	46	1,815	75	37
Other Crops	2,290	90	1,750	83	-24
Other Fruit	1,526	72	1,093	76	-28
Other Vegetables	419	69	168	49	-60
Peppers	593	62	526	75	-11
Pistachios	20,618	22	17,249	18	-16
Plums	51	100	54	100	5
Pomegranate	5,026	46	723	22	-86
Potato	2,979	55	1,806	60	-39
Safflower	334	97	440	7	32
Strawberries	5	100	1	100	-82
Tomatoes	717	50	671	36	-6
Walnuts	281	94	348	81	24

Table 9. The percent increase or decrease in crop misclassifications between 2014 and 2016 for CropScape compared with LIQ.

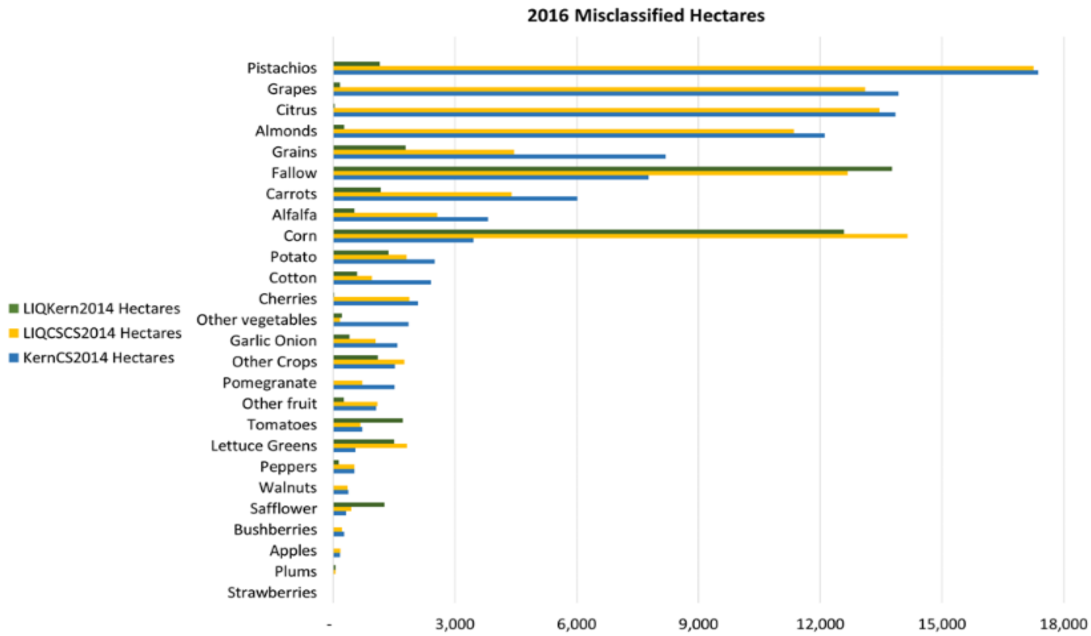


Figure 16. The total area misclassified (hectares) per crop for 2016 data comparisons.

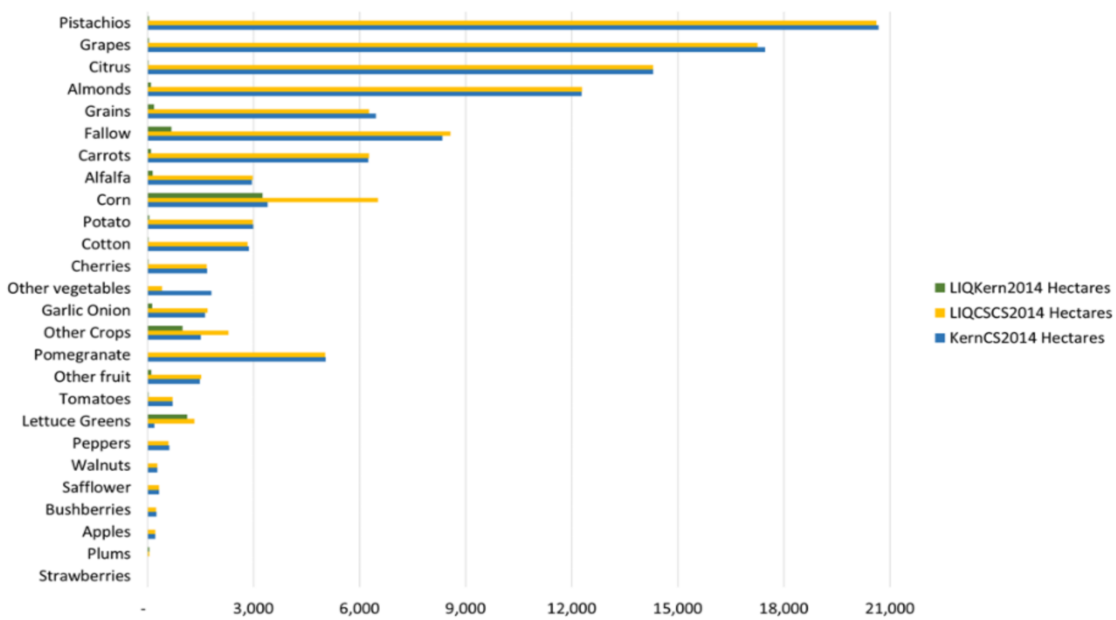


Figure 17. The total area misclassified (hectares) per crop for 2014 data comparisons.

3.2 Crop Classification StatisticsI

The authors assumed Kern Ag to be the ground truth dataset for this study. Comparison across these most-used datasets in California shows better land use classification agreements between LIQ and Kern Ag for 2014 with 98% overall accuracy and 2016 with 87% overall accuracy than with either dataset compared with CropScape (Table 10). The high agreement between Kern Ag and LIQ is no surprise since the Kern Ag data is based on local information (i.e., county permit data and grower land use reports) for local decision-making and land use classifications deduced from high-resolution satellite imagery with in-situ ground-truthing. Land use classification agreements between LIQ and CropScape are not as high, with values for 2014 land use classifications of 61% overall accuracy and 2016 overall accuracy of 64% (Table 10). A similar high disagreement exists between the Kern Ag dataset and CropScape with land use classification for 2014 with 61% overall accuracy and 2016 classifications with 65% overall accuracy.

2014 Datasets Compared	**Overall Accuracy (%)**	**Kappa Coefficient of Agreement**
Kern Ag and CropScape	61	0.55 (moderate)
LIQ and CropScape	61	0.55 (moderate)
Kern Ag and LIQ	98	0.97 (very good)
2016 Datasets Compared	**Overall Accuracy (%)**	**Kappa Coefficient of Agreement**
Kern Ag and CropScape	65	0.59 (moderate)
LIQ and CropScape	64	0.59 (moderate)
Kern Ag and LIQ	87	0.84 (very good)

Table 10. Overall accuracy and kappa coefficients between datasets were compared (i.e., Kern and CropScape, Kern and Land IQ, and Land IQ and CropScape) for the years 2014 and 2016.

Cohen's kappa coefficient of accuracy, κ, is a statistic that measures inter-rater reliability, though caution should be used in its interpretation (Delgado & Tibau, 2019). The κ accuracy was also calculated for the dataset comparisons since it is thought to be more robust than the percent agreement calculations because it accounts for the possibility of agreement occurring by chance (Table 10). The κ for Kern Ag and LIQ 2014 and 2016 is 0.97 (very good) and 0.84 (very good). The κ values CropScape compared with LIQ and Kern Ag 2014 and 2016 are 0.55 (moderate) and 0.59 (moderate). Overall, the κ with the percent agreements between the land use classification datasets illustrate that the LIQ and Kern Ag datasets are in better agreement with each other than either of these datasets with CropScape. The percent decrease in overall accuracy and κ for datasets compared with CropScape may be attributed to the CropScape dataset having a national spatial focus than the state and locally tailored focus of Kern Ag and LIQ datasets, respectively. Overall results highlight the need for increased datasets across other natural resources, like water, to be tailored at the regional and local spatial scales to represent geographic differences across various study regions (Rallings et al., 2021). Although the investment in global or national datasets increases the ability to understand natural resources systems, these datasets may not fully represent the geographic characteristics and differences across regions, even adjacently located, to infer well-informed and robust climate change adaptation and management plans.

Crop-specific producer’s and user’s accuracy (Tables 11-13) provide insight into the crops contributing to misclassification errors on the producer’s and user’s end. This study calculated producer’s accuracy to inform future improvement in land use classification datasets, especially for regions that have complex landscapes like the San Joaquin Valley. The producer’s accuracy for CropScape 2014 compared to both Kern Ag and LIQ 2014 resulted in low inaccuracy for the following crops (less than 20% accuracy) (Tables 11-12): Grasses, Plums, Pomegranates, Other Crops, Bushberries, Lettuce Greens, Other Fruit, Other Vegetables, Peppers, Safflower, Strawberries, and Walnuts. The producer’s accuracy for CropScape 2016 compared to both Kern Ag and LIQ result in low accuracy for the following crops: Apples, Bushberries, Cherries, Grasses, Lettuce Greens, Other Crops, Other Fruit, Other Vegetables, Plums, Strawberries, Corn, and Walnuts. The low accuracy in classification could be attributed to the difficulty in correctly representing what is one the ground for crops that could be misclassified as fallowed ground, grains, corn, or other crops by classification algorithms. The reduced greenness of crops during dry periods may be causing the algorithm to result in incorrect crop signatures.

CropScape has been known to be best at classifying single, expansive crop landscapes (Reitsma et al., 2016). The decreased producer’s accuracy may result from crops that blend in with surrounding bare ground. Producers' accuracy for water-intensive, lucrative crops (e.g., almonds and pistachios) and fallowed land remain above 50% of producer’s accuracy. The error for the common, lucrative crops and fallowed land slightly decreased from 2014 to 2016, which could be due to the increase in the land cover area of these crops during the drought period. The producer’s accuracy for LIQ 2014 and 2016 is lowest for Grasses and, in the case of the 2016 dataset, Other Vegetables. The user’s accuracy for CropScape 2014 and 2016 are lowest for the following crops: Bushberries, Cherries, Grasses, Other Crops, Other Fruit, Plums, Safflower, Strawberries, and Walnuts. Like the producer’s accuracy, the user’s accuracy is high for the water-intensive, expansive crops in the San Joaquin Valley (e.g., almonds, grapes, pistachios). LIQ 2014 and 2016 have the lowest user accuracy among lettuce greens and plums. Given that the reviewed misclassifications are lower for LIQ than CropScape, this study finds LIQ to be the most suitable dataset to represent agriculture in California.

Kern Ag and CropScape Producer’s and User’s Accuracy				
	2014		2016	
	Producer’s Accuracy	User’s Accuracy	Producer’s Accuracy	User’s Accuracy
Alfalfa	89%	70%	83%	74%
Almonds	84%	81%	86%	77%
Apples	56%	29%	10%	72%
Bushberries	4%	2%	0%	39%
Carrots	22%	62%	21%	69%
Cherries	31%	20%	4%	16%
Citrus	40%	69%	43%	78%
Corn	41%	54%	39%	68%
Cotton	80%	78%	77%	75%
Fallow	53%	31%	58%	32%

Garlic Onion	47%	62%	47%	74%
Grains	67%	57%	61%	62%
Grapes	50%	80%	59%	83%
Grasses	0%	3%	2%	3%
Lettuce Greens	5%	54%	2%	7%
Non-Ag	1%	0%	50%	0%
Other Crops	2%	10%	3%	7%
Other Fruit	18%	28%	18%	20%
Other Vegetables	13%	37%	9%	30%
Peppers	14%	39%	20%	22%
Pistachios	48%	78%	62%	79%
Plums	0%	0%	0%	0%
Pomegranate	0%	54%	63%	78%
Potato	31%	45%	38%	39%
Safflower	0%	3%	59%	28%
Strawberries	0%	0%	0%	-
Tomatoes	74%	50%	79%	41%
Walnuts	15%	6%	0%	0%

Table 11. Results of producer's and user's accuracy of CropScape compared with Kern Ag for the 2014 and 2016 datasets.

LIQ and CropScape Producer's and User's Accuracy				
	2014		2016	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Alfalfa	89%	70%	87%	73%
Almonds	84%	81%	85%	72%
Apples	56%	29%	10%	72%
Bushberries	4%	2%	0%	39%
Carrots	22%	62%	27%	69%
Cherries	29%	19%	4%	16%
Citrus	39%	69%	43%	78%
Corn	27%	55%	17%	92%
Cotton	81%	78%	89%	76%
Fallow	53%	31%	54%	45%
Garlic Onion	46%	62%	59%	79%
Grains	68%	56%	61%	34%
Grapes	50%	80%	61%	82%
Grasses	-	0%	-	0%
Lettuce Greens	1%	54%	2%	25%
Non-Ag	-	0%	-	0%

Other Crops	1%	10%	7%	17%
Other Fruit	18%	28%	21%	24%
Other Vegetables	36%	31%	64%	51%
Peppers	14%	38%	22%	25%
Pistachios	48%	78%	63%	82%
Plums	0%	0%	0%	0%
Pomegranate	0%	54%	78%	78%
Potato	32%	45%	47%	40%
Safflower	0%	3%	77%	93%
Strawberries	0%	0%	0%	-
Tomatoes	74%	50%	86%	64%
Walnuts	15%	6%	36%	19%

Table 12. Results of producer's and user's accuracy of CropScape compared with LIQ for the 2014 and 2016 datasets

Kern Ag and LIQ Producer's and User's Accuracy				
	2014		2016	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Alfalfa	100%	99%	91%	97%
Almonds	100%	100%	93%	100%
Apples	100%	100%	100%	98%
Bushberries	92%	96%	80%	98%
Carrots	99%	99%	64%	81%
Cherries	96%	99%	89%	99%
Citrus	100%	100%	98%	100%
Corn	99%	64%	80%	26%
Cotton	99%	100%	81%	93%
Fallow	99%	96%	75%	50%
Garlic Onion	98%	96%	71%	84%
Grains	97%	99%	46%	84%
Grapes	99%	100%	97%	99%
Grasses	0%	-	0%	-
Lettuce Greens	100%	15%	63%	19%
Non-Ag	0%	-	0%	-
Other Crops	86%	57%	50%	41%
Other Fruit	96%	94%	87%	81%
Other Vegetables	31%	99%	12%	52%
Peppers	93%	98%	83%	80%
Pistachios	100%	100%	99%	98%
Plums	100%	2%	54%	1%
Pomegranate	100%	100%	81%	100%
Potato	98%	99%	50%	60%
Safflower	100%	100%	89%	35%
Strawberries	98%	98%	91%	100%
Tomatoes	99%	99%	93%	65%
Walnuts	100%	100%	95%	100%

Table 13. Results of producer's and user's accuracy of LIQ compared with Kern Ag for the 2014 and 2016 datasets.

3.3 Overall Revenue, Crop Water Requirement, and GHG Emission Discrepancies

The normalization of revenue, CWR, and GHG emission discrepancies by Kern Ag datasets totals provided a sense of the magnitude of the impacts of user's inaccuracy of the land use classification datasets in this study and are outlined in sections 3.3.1-3.3.3. Quantifying the misclassifications in land use datasets is essential since a comparison of cumulative total revenue, crop water requirement, and GHG emission across all 2014 and 2016 datasets result in values like each other (Table 15). Therefore, overlooking the misclassifications within each dataset and which crop misclassifications result in considerable inaccuracies. Overall, the CropScape misclassifications resulted in underestimates of user's accuracy revenue and crop water requirement discrepancies, while LIQ misclassifications led to overestimates of user's accuracy discrepancies for revenue and crop water requirement (Table 16). The sections below provide an overview of the overall dataset misclassification of crop revenue, crop water requirement, and GHG emission discrepancies (Tables 17-22). Crop-specific contributions to considerable implications are also covered since identifying crop-specific misclassification implications could help target improvements in crop-specific land use classification methods and quantify the crop-specific crop revenue, crop water requirement, and GHG emission discrepancies.

Revenue, CWR, and GHG Emission Discrepancies Proportion by the Kern Ag Total				
Discrepancy (Units)	**Year**	**Dataset**	**Proportion of User's Accuracy Discrepancy (%)**	**Proportion of Gross Discrepancy (%)**
Revenue (Million USD)[1]	2014	Kern Ag and CropScape	25%	40%
		LIQ and CropScape	25%	40%
		Kern Ag and LIQ	1%	1%
	2016	Kern Ag and CropScape	22%	35%
		LIQ and CropScape	19%	34%
		Kern Ag and LIQ	4%	8%
Crop water requirement (ML)[2]	2014	Kern Ag and CropScape	15%	26%
		LIQ and CropScape	14%	25%
		Kern Ag and LIQ	1%	1%
	2016	Kern Ag and CropScape	12%	20%
		LIQ and CropScape	7%	20%
		Kern Ag and LIQ	5%	8%
GHG Emissions (Mg CO_{2e})[3]	2014	Kern Ag and CropScape	18%	43%
		LIQ and CropScape	20%	44%
		Kern Ag and LIQ	2%	3%
	2016	Kern Ag and CropScape	20%	10%

		LIQ and CropScape	22%	41%
		Kern Ag and LIQ	3%	14%

Table 14. The proportion of revenue, CWR, and GHG emission discrepancy (untis %). Calculated by normalizing the user's discrepancy and gross discprepancy by the Kern Ag dataset (assumed ground truth) totals for 2014 and 2016.

Total Area, Revenue, Crop Water Requirement, and GHG Emissions			
Year	Dataset	Multiplier	Total
2014	LIQ	Hectares	298,266
		Revenue (Million USD)	5,578
		Crop Water Requirement (ML)	3,199,671
		GHG emissions (Mg CO_2e)	237,437
	Kern Ag	Hectares	298,266
		Revenue (Million USD)	5,608
		Crop Water Requirement (ML)	3,242,377
		GHG emissions (Mg CO_2e)	233,994
	CropScape	Hectares	298,266
		Revenue (Million USD)	4,180
		Crop Water Requirement (ML)	2,749,087
		GHG emissions (Mg CO_2e)	194,504
2016	LIQ	Hectares	298,266
		Revenue (Million USD)	5,506
		Crop Water Requirement (ML)	3,057,483
		GHG emissions (Mg CO_2e)	237,795
	Kern Ag	Hectares	298,266
		Revenue (Million USD)	5,735
		Crop Water Requirement (ML)	3,456,895
		GHG emissions (Mg CO_2e)	231,252
	CropScape	Hectares	298,266
		Revenue (Million USD)	4,445
		Crop Water Requirement (ML)	3,100,156
		GHG emissions (Mg CO_2e)	186,102

Table 15. Total for each multiplier (i.e., revenue, crop water requirement, and GHG emissions) for each dataset for 2014 and 2016.

Discrepancy (Units)	Year	Dataset	Misclassified Hectares	Difference Discrepancy	Gross Discrepancy
Revenue (Million USD)[1]	2014	Kern Ag and CropScape	117,153	(1,428)	2,238
		LIQ and CropScape	117,321	(1,398)	2,230
		LIQ and Kern Ag	7,181	29	62
	2016	Kern Ag and CropScape	105,357	(1,290)	2,006
		LIQ and CropScape	107,058	(1,061)	1,933
		LIQ and Kern Ag	40,070	229	436
Crop water requirement (ML)[2]	2014	Kern Ag and CropScape	117,153	(482,322)	834,141
		LIQ and CropScape	117,074	(446,254.82)	823,670
		LIQ and Kern Ag	7,172	26,078	37,440
	2016	Kern Ag and CropScape	105,357	(416,891)	694,561
		LIQ and CropScape	107,058	(247,601)	676,846
		LIQ and Kern Ag	40,070	179,011	285,268
GHG Emissions (Mg CO_{2e})[3]	2014	Kern Ag and CropScape	110,354	(41,844)	100,769
		LIQ and CropScape	109,751	(45,905.03)	102,727
		LIQ and Kern Ag	5,956	(3,859)	6,606
	2016	Kern Ag and CropScape	100,892	(45,190)	23,287
		LIQ and CropScape	103,219.53	(51,858)	95,127
		LIQ and Kern Ag	37,394	(7,370)	33,514

Note: The misclassified hectares for the GHG emission multiplier differ from other multipliers due to the limited availability of GHG emission data for some crops. The misclassified hectares for LIQ 2014 crop water requirement multiplier do not include bush berries due to no WAFR output for that crop.

[1] Revenue perspective: One million USD is equivalent to the annual income for 42 people in Kern County (per capita income in the past 12 months, in 2020 dollars in Kern County is USD 23,855; U.S. Census Bureau, 2019)

[2] Crop water requirement perspective: A standard Olympic-sized swimming pool measuring 50m x 25m holds 2.5 ML of water

[3] GHG emission perspective: 1,000 Mg of CO_{2e} is equivalent to the GHG emission of 215 gasoline-power passenger vehicles driven for one year (U.S. Environmental Protection Agency, 2019)

Table 16. The user's net and gross discrepancies of study multipliers (i.e., revenue, crop water requirement, and GHG emissions) resulted from crop misclassifications between datasets—CropScape, LIQ and Cropscape, and LIQ and Kern Ag for 2014 and 2016. Value in parenthesis represents an underestimation of discrepancy.

3.3.1 Revenue User's Accuracy Discrepancies

Quantifying revenue discrepancies on the user's end can help understand the magnitude of the impact of crop misclassification, especially for a state that generates 50.1 billion USD in annual agricultural revenue. The gross revenue discrepancy of CropScape is about 2 billion USD (Table 16), which is equivalent to the annual income for 84,000 Kern County residents (per capita income in the past 12 months, in 2020 dollars in Kern County is 23,855 USD; U.S. Census Bureau, 2019). The gross revenue discrepancy in high thematic datasets, like LIQ, is less than that of using CropScape with 446 million USD, which is equivalent to the annual income for 18,277 Kern County residents. The crop revenue discrepancies of crops by area (in hectares) for the 2014 CropScape dataset resulted in revenue discrepancies on the user's end, underestimating 1.3 to 1.4 billion USD, and LIQ datasets overestimating by 29 million USD (Table 16). Increased misclassifications on the user's end in the LIQ 2016 datasets were reflected in higher revenue overestimations of 229 million USD. Whereas, decreased misclassification of CropScape in 2016 led to decreased revenue discrepancies compared to 2014, ranging in underestimations from 1 to 1.2 billion USD. Over and underestimating crop revenue results in inaccuracies in the user's calculations of agricultural revenue contributions to the local, state, and national economy, which could be improved, but a comparison with the total Kern County revenue total shows that LIQ is better suited to represent California's agricultural regions than CropScape. More specifically, if a user derives revenue for Kern County using CropScape land use classification datasets, there is a 20-25% user error and a 35-40% gross user error. Using the LIQ dataset results in a 1-4% user revenue discrepancy and a 1-8% gross revenue discrepancy (Table 14).

Crop-specific user discrepancies across datasets could help highlight which specific crop misclassifications result in higher crop revenue user discrepancies, both over and underestimations of revenue. In the CropScape datasets, the high revenue implications result from the misclassification of water-intensive, lucrative orchard and vineyard crops (e.g., pistachios, almonds, citrus, and grapes) for other orchard and vineyard crops. Fallowed land contributed to the highest overestimation of revenue discrepancy for the CropScape 2014 and 2016 datasets on the user's end, resulting in an underestimation (Tables 17, 18, 21, 22). Grasses contributed to the highest overestimation of revenue discrepancy on the user's end in the LIQ 2014 dataset and fallowed land in the 2016 dataset, while grapes contributed to the highest underestimation in revenue discrepancy on the user's end for the 2014 dataset and almonds for the 2016 dataset (Tables 19-20). For specifics on crop-specific misclassifications, refer to each dataset's SI Tables 29-84.

3.3.2 Crop Water Requirement User's Accuracy Discrepancies

Given the worsening drought and water scarcity conditions under climate change, quantifying water use discrepancies on the user's end due to crop misclassifications could help improve water budgeting and future water management. For California, accurate crop water requirements within each basin are needed to effectively develop groundwater sustainability plans informed by accurate water budgets, especially given the socioeconomic and environmental implications of water management strategies being considered to address SGMA (e.g., agricultural land use transitions and water markets). The gross water requirement discrepancy of ~700,000 ML (567,500 AF) in CropScape is equivalent to the amount needed to water ~10% of almond acres in the state for a year.

While the gross crop water requirement discrepancy of ~285,000 ML (231,054 AF) in LIQ is equivalent to the amount of water needed to water ~4% of almond acres in California for a year. Overall, the net crop water requirement discrepancies in CropScape are underestimated by 446,255 to 482,322 ML of water in 2014 and 247,601 to 416,891 ML in 2016 (Table 16). The LIQ datasets overestimate crop water requirement by 26,078 ML and 179,011 ML of water for 2014 and 2016, respectively (Table 16).

Crop-specific contributions of crop water requirement user end discrepancies for CropScape are generally due to the misclassification of orchards, vineyards, grains, and fallowed land. The highest overestimation of crop water requirement for the CropScape 2014 and 2016 dataset compared with Kern Ag and LIQ is due to the misclassification of fallowed land, while pistachios contribute to underestimating CWR estimates on the user end (Tables 17, 18, 21, 22). The overestimation in CWR discrepancy for users that use LIQ 2014 and 2016 is attributed most by fallowed land, while grasses and grains contribute to the underestimation of CWR for the 2014 and 2016 LIQ datasets, respectively (Tables 19-20). Although the land use classification dataset could be improved to better water budget estimates, this study shows that the CWR user and gross discrepancy are below 30% for CropScape and below 10% for LIQ (Table 14). The CWR user's accuracy discrepancy using CropScape ranges from 12-15% and 20-26% for the gross discrepancy, while the user's accuracy CWR discrepancy ranges from 1-5% with a gross discrepancy of 1-8% for LIQ. It is recommended that users utilize LIQ datasets for higher accuracy in water budgets informing future water management strategies in the state. For specifics on crop-specific misclassifications, refer to each dataset's SI Tables 29-84.

3.3.3 GHG Emission User's Accuracy Discrepancies

Quantifying discrepancies in GHG emissions can help better understand where California stands in achieving its carbon-neutral goals by 2045. Overall, all datasets underestimate net GHG emissions. The gross GHG emission discrepancies of 23,300 – 95,000 MgCO2e for CropScape 2016 (Table 16) are equivalent to 5,020 to 20,500 gasoline-powered vehicles driven for a year (U.S. Environmental Protection Agency, 2019). CropScape underestimates GHG emissions by 41,844 to 45,905 MG CO2e and 45,190 to 51,858 MG CO2e of GHG emissions for 2014 and 2016 respectively (Table 16). The gross GHG emission discrepancy of ~33,600 Mg CO2e for LIQ in 2016 is equivalent to the emission from 7,240 gasoline-powered vehicles driven for a year (U.S. Environmental Protection Agency, 2019). The LIQ 2014 and 2016 datasets underestimate GHG emissions by 3,859 Mg CO2e and 7,370 Mg CO2e (Table 16).

Crop-specific misclassification contributing to the most considerable GHG emission discrepancies for CropScape were nuts, grapes, fallow land, and alfalfa. Fallowed land contributes most to the overestimation of GHG emissions, and citrus to the underestimation of GHG emissions in the CropScape 2014 and 2016 datasets compared with Kern Ag and LIQ (Tables 17, 18, 21, 22). For LIQ 2016, considerable GHG emission discrepancies were mainly attributed to the misclassification of fallowed land and grains as nuts, alfalfa, annual crops (e.g., carrots, lettuce greens), and corn. Grasses and fallowed land contributed to the overestimation of GHG emissions for LIQ 2014 and 2016, respectively, while grains and corn contributed to the highest underestimation of GHG emissions on the user end for 2014 and 2016, respectively (Tables 19-20). Observing that all three datasets are underestimating GHG emissions brings to light the importance of improving crop classification datasets and the quantification of misclassification discrepancies so that future GHG emission plans effectively push California toward climate-smart agricultural practices to help achieve carbon neutrality. Given that the GHG emission user's discrepancy using CropScape is ~18-22% and gross discrepancy of ~40% compared to the user's GHG emission discrepancy for LIQ of ~2-3% and gross discrepancy of 3-14% (Table 14), it is recommended that LIQ land use classification datasets be used for best estimates of GHG emissions for California. For specifics on crop-specific misclassifications, refer to each dataset's SI Tables 29-84.

Discrepancy of User's Accuracy of CropScape 2014 Against Kern Ag 2014				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	115,257	(26,400)	641	2,957
Almonds	(135,533,718)	(55,764)	2,490	12,276
Apples	(3,803,173)	(1,933)	(194)	221
Bushberries	(21,582,538)	573	(640)	260
Carrots	(107,089,680)	1,166	(4,300)	6,248
Cherries	7,552,487	(2,121)	(348)	1,695
Citrus	(152,922,077)	(122,754)	(24,655)	14,305
Corn	(657,295)	(8,990)	(4,965)	3,405
Cotton	(5,218,297)	(6,188)	216	2,875
Fallow	67,803,242	43,045	7,899	8,340
Garlic Onion	(7,036,033)	(1,295)	77	1,629
Grains	13,684,391	2,047	(9,343)	6,460
Grapes	(939,492,485)	(44,992)	5,918	17,476
Grasses	12,685,579	(14,892)	(90)	3,211
Lettuce Greens	(4,694,010)	(782)	(125)	197
Non-Ag	256,883	354	75	110
Other Crops	19,601,423	(1,052)		1,506
Other Fruit	(11,410,430)	(9,913)	(128)	1,483
Other Vegetables	(41,305,360)	(4,949)	(417)	1,809
Peppers	(40,347,617)	(650)	(1,537)	623
Pistachios	(55,126,109)	(141,962)	(10,535)	20,684
Plums	(19,586)	(5)	0	1
Pomegranate	6,253,520	12,934		5,040
Potato	(28,549,074)	(5,890)	(1,730)	2,999
Safflower	1,172,951	321	396	333
Strawberries	(770,240)	(16)	(7)	5

Tomatoes	(2,415,001)	(752)	(519)	722
Walnuts	1,186,022	(313)	(24)	281
Total	**(1,427,660,970)**	**(391,170)**	**(41,843)**	**117,152**

Table 17. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions (MgCO2e) discrepancies per crop reflecting the user's accuracy of CropScape 2014 compared with Kern Ag 2014.

Discrepancy of User's Accuracy of CropScape 2016 Against Kern Ag 2016				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	9,625,510	(32,230)	376	3,812
Almonds	(59,839,681)	(50,095)	2,972	12,105
Apples	1,241,422	(495)	(103)	168
Bushberries	(20,203,447)	565	(646)	264
Carrots	(117,278,909)	4,648	(2,179)	6,015
Cherries	(66,113,648)	(158)	(219)	2,094
Citrus	(121,490,078)	(97,887)	(24,422)	13,853
Corn	2,675,494	(12,990)	(6,145)	3,458
Cotton	4,865,112	(4,925)	42	2,404
Fallow	91,356,450	56,616	6,265	7,762
Garlic Onion	(29,372,613)	(1,900)	18	1,583
Grains	19,083,303	(39,855)	(12,309)	8,188
Grapes	(750,086,465)	(34,080)	2,795	13,926
Grasses	2,393,122	(9,171)	(210)	1,454
Lettuce Greens	(7,665,625)	189	(101)	544
Non-Ag	123	0	0	0
Other Crops	15,613,721	2,916		1,513
Other Vruit	(13,808,897)	(3,711)	223	1,053
Other Vegetables	(40,323,689)	(2,640)	(261)	1,851
Peppers	(18,537,118)	(930)	(1,149)	523
Pistachios	(158,606,692)	(105,228)	(8,449)	17,361
Plums	(3,525)	(5)	0	1
Pomegranate	(22,659,294)	(1,403)		1,507
Potato	(12,225,176)	(2,355)	(1,005)	2,502
Safflower	1,632,124	(188)	58	321
Strawberries	(172,719)	(3)	(1)	1
Tomatoes	(2,194,816)	(2,156)	(738)	717
Walnuts	2,419,375	(641)	(2)	374

Total	**(1,289,676,637)**	**(338,111)**	**(45,190)**	**105,357**

Table 18. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions (MgCO2e) discrepancies per crop reflecting the user's accuracy of CropScape 2016 compared with Kern Ag 2016.

Discrepancy of User's Accuracy of LIQ 2014 Against Kern Ag 2014				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	505,513	(729)	49	108
Almonds	(2,928,584)	(607)	60	224
Apples	679	(0)	(0)	0
Bushberries	(1,678,524)	99	(48)	22
Carrots	(698,901)	353	(35)	78
Cherries	103,593	(86)	(0)	90
Citrus	(194,353)	(296)	(60)	45
Corn	329,836	(33)	(73)	55
Cotton	(300,152)	(356)	(28)	86
Fallow	2,132,193	1,696	167	206
Garlic Onion	(42,525)	(19)	27	57
Grains	10,780	(1,044)	(838)	558
Grapes	(20,894,847)	(764)	46	345
Grasses	5,052,029	(17,681)	4,463	3,214
Lettuce Greens	(311)	(0)	0	0
Non-Ag	-	-	-	111
Other Crops	3,603,287	197		209
Other Fruit	(41,092)	(211)	4	66
Other Vegetables	(10,442,097)	(1,331)	239	1,440
Peppers	(3,187,836)	(151)	(95)	49
Pistachios	(313,616)	(320)	(7)	104
Pomegranate	(37,066)	(16)		19
Potato	(622,213)	77	(0)	77
Strawberries	(5,709)		0	0
Tomatoes	130,874	72	(11)	20
Walnuts	28,844	(0)	0	1
Total	**(29,490,198)**	**(21,150)**	**3,859**	**7,182**

Table 19. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions (MgCO2e) discrepancies per crop reflecting the user's accuracy of LIQ 2014 compared with Kern Ag 2014.

Discrepancy of User's Accuracy of LIQ 2016 Against Kern Ag 2016				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	4,694,522	(18,259)	2,008	2,077
Almonds	(75,909,339)	(49,968)	(1,012)	5,602
Apples	2,497	(0)	(0)	0
Bushberries	(4,020,237)	(5)	(140)	53
Carrots	(50,062,285)	978	(550)	2,771
Cherries	(12,802,632)	(2,065)	(174)	243
Citrus	(10,375,588)	(3,929)	(414)	476
Corn	1,148,671	(6,900)	(2,558)	1,113
Cotton	(4,465,861)	(7,206)	992	1,928
Fallow	46,106,198	32,579	4,302	4,619
Garlic Onion	(12,242,032)	(509)	211	860
Grains	16,744,368	(55,688)	4,007	11,162
Grapes	(74,235,309)	(9,887)	(243)	1,176
Grasses	544,413	(10,290)	2,016	1,483
Lettuce Greens	(1,850,800)	308	6	203
Non-Ag	-	-	-	0
Other Crops	8,345,170	656		788
Other Fruit	(2,860,147)	(692)	(13)	171
Other Vegetables	(21,217,002)	(1,925)	421	1,783
Peppers	(5,070,480)	(348)	(157)	114
Pistachios	(3,916,686)	(1,683)	(99)	285
Plums	(15,768)	(1)		1
Pomegranate	(15,374,078)	(2,674)		786
Potato	(10,431,505)	(5,873)	(935)	2,033
Safflower	(61,607)	(310)	19	84
Strawberries	(7,530)	(0)	0	0
Tomatoes	(1,410,712)	(1,313)	(307)	236
Walnuts	(88,181)	(207)	(6)	26
Total	**(228,831,939)**	**(145,212)**	**7,373**	**40,075**

Table 20. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions (MgCO2e) discrepancies per crop reflecting the user's accuracy of LIQ 2016 compared with Kern Ag 2016.

Discrepancy of User's Accuracy of CropScape 2014 Against LIQ 2014				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	335,524	(27,359)	674	2,977
Almonds	(135,533,779)	(55,665)	2,546	12,291
Apples	(3,808,462)	(1,944)	(194)	221
Bushberries	(20,500,936)		(611)	247
Carrots	(106,719,994)	7,287	(4,273)	6,266
Cherries	7,347,342	(2,121)	(342)	1,684
Citrus	(152,263,993)	(122,186)	(24,655)	14,302
Corn	7,646,044	4,834	(9,521)	6,523
Cotton	(4,998,287)	(6,153)	222	2,835
Fallow	68,738,205	44,270	8,264	8,572
Garlic Onion	(7,466,879)	(10,102)	48	1,710
Grains	13,475,894	6,919	(8,974)	6,268
Grapes	(927,535,199)	(43,860)	5,819	17,256
Lettuce Greens	(29,103,795)	(2,114)	(777)	1,328
Other Crops	29,405,082	(3,076)		2,290
Other Fruit	(12,431,193)	(11,346)	(158)	1,526
Other Vegetables	(9,697,946)	(825)	(127)	419
Peppers	(37,899,670)	(745)	(1,471)	593
Pistachios	(54,294,169)	(141,315)	(10,493)	20,618
Plums	(643,456)	(120)	10	51
Pomegranate	6,395,211	12,969		5,026
Potato	(27,832,215)	(8,619)	(1,742)	2,979
Safflower	1,174,607	322	398	334
Strawberries	(768,619)	(16)	(7)	5
Tomatoes	(2,371,407)	(647)	(517)	717
Walnuts	1,181,318	(315)	(24)	281
Total	**(1,398,170,772)**	**(361,926)**	**(45,905)**	**117,321**

Table 21. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions (MgCO2e) discrepancies per crop reflecting the user's accuracy of CropScape 2014 compared with LIQ 2014.

Discrepancy of User's Accuracy of CropScape 2016 Against LIQ 2016				
Crop	Revenue (USD)	CWR (AF)	GHG Emission ($MgCO_2e$)	Total Hectares
Alfalfa	6,987,213	(22,818)	(183)	2,558
Almonds	(56,122,739)	(46,015)	2,914	11,357
Apples	1,309,946	(497)	(106)	173
Bushberries	(16,190,690)	1,286	(528)	214
Carrots	(86,161,263)	9,889	(1,909)	4,398
Cherries	(56,934,743)	(395)	(107)	1,875
Citrus	(113,144,068)	(92,257)	(23,676)	13,458
Corn	5,508,976	10,047	(19,988)	14,146
Cotton	2,381,874	(1,464)	31	956
Fallow	186,149,046	100,402	7,717	12,672
Garlic Onion	(23,715,481)	(6,149)	(189)	1,044
Grains	13,865,115	(2,178)	(7,710)	4,461
Grapes	(701,334,011)	(28,514)	2,843	13,103
Lettuce Greens	(31,216,594)	(734)	(549)	1,815
Other Crops	17,065,481	(4,585)		1,750
Other Fruit	(14,834,484)	(4,915)	352	1,093
Other Vegetables	(3,519,470)	(61)	(43)	168
Peppers	(19,053,130)	(894)	(1,148)	526
Pistachios	(158,162,465)	(105,261)	(8,397)	17,249
Plums	(440,748)	(80)	(0)	54
Pomegranate	(7,410,838)	1,232		723
Potato	(8,959,133)	(4,577)	(635)	1,806
Safflower	1,829,049	(199)	73	440
Strawberries	(156,769)	(2)	(1)	1
Tomatoes	(850,629)	(1,446)	(619)	671
Walnuts	2,265,859	(625)	0	348
Total	**(1,060,844,697)**	**(200,812)**	**(51,858)**	**107,059**

Table 22. The revenue (USD), crop water requirement (CWR; acre-feet), and GHG emissions ($MgCO2e$) discrepancies per crop reflecting the user's accuracy of CropScape 2016compared with LIQ 2016.

4. Study Limitations and Future Work

A limitation to comparing datasets from diverse funding sources and sponsors, in the case of this study, county, state, and federal, is that the granularity and number of crop categories differ, as well as the land use classification algorithm thresholds used to classify different crop types. For example, the federally sponsored and funded USDA CDL (CropScape) land cover dataset tends to be biased toward subsidized program crops and is not truly a probability sample of land cover stemming from the use of the Farm Service Agency Common Land Unit as ground truth verification (USDA NASS, 2020). For this study, crops that were not common across all three datasets were combined into general categories (e.g., other vegetables and other fruits), leading to differences in the crop components for the general crop categories and resulting in inaccuracy for crop water requirement, revenue, and GHG emissions estimates. To ensure reproducibility in terms of crop type and the crop revenue, crop water requirement, and GHG emission values from the specified sources used in this study, tables were provided in the Appendix with details on the data source, data source crop type, and value for each crop category across all datasets for the 2014 and 2016 study years. Future work could include running a similar analysis at the statewide level to quantify the revenue, crop water requirement, and GHG emission discrepancies resulting from user and producer errors.

5. Conclusions

In many drought-prone and water-scarce regions worldwide, agriculture is a major source of freshwater use and contributes to the local and national economy, like California's San Joaquin Valley. If water-scarce agriculturally dependent regions effectively develop climate change adaptation strategies while maintaining agriculture, reliable land use classification data with a high thematic resolution of land cover classes will be critical. Without land use classification datasets with a high thematic resolution, irrigation, GHG emission, and revenue inventories are not providing an accurate baseline to inform future strategies for meeting goals to adapt to climate change and reduce drivers of climate change conditions. A comparison of both producer’s and user’s accuracy between CropScape and LIQ show that increased investments in high thematic and spatial resolution datasets, like LIQ, represent highly diverse and complex landscapes in California.

This study quantified the revenue, crop water requirement, and GHG emission discrepancies on the user’s end resulting from land use misclassification in the United States' most complex agricultural region, California's San Joaquin Valley. By comparing three commonly used land use datasets, Kern Ag, LIQ, and CropScape, this study found that the CropScape datasets did not capture the agricultural diversity (61 - 65% overall accuracy) as well as the statewide focused dataset, LIQ (87 - 98% overall accuracy). A further look at the most misclassified crop trends by area in hectares across all 2014 and 2016 datasets showed that CropScape had higher misclassifications of pistachios, grapes, citrus, and almonds, while LIQ had lower misclassifications for these popular, lucrative, and water-intensive crops. Misclassification of California's most popular, water-intensive, and lucrative crops is a limitation when managing water and land use because of the magnitude of their presence, contribution to the economy, and intense water demand, especially in drought, magnify the repercussion of misclassification. Reliable and high thematic resolution data are necessary for drought-prone and water-scarce regions because of the need to represent the current state to address climate change accurately, and LIQ is best suited to meet these needs for California.

This study also highlights the need for classification algorithms encompassing dynamic landscape changes and capturing seasonal shifts in climate conditions. The crop-specific producer’s and user’s error provides insight into which crop types could be improved in classifying both on the producer’s and user’s end. By quantifying crop misclassification's revenue, crop water requirement, and GHG emission discrepancies on the user end, it was found that the CropScape dataset misclassifications underestimated user revenue and crop water requirement discrepancies. In contrast, LIQ misclassifications resulted in overestimating user discrepancies. Crop misclassification across all datasets resulted in the underestimation of GHG emissions impacts. Understanding crop-specific misclassifications and quantifying crop revenue, water requirement, and GHG emission discrepancies are vital in accounting for the tradeoffs in budgeting reports that inform effective climate change adaptation strategies. Overall, the lower producer and user errors resulting from LIQ compared to CropScape provide insight that LIQ is better suited to inform California’s water and land use management strategies to address climate change.

CHAPTER 5. SUMMARY AND OUTLOOK

This dissertation, titled "A Framework for Strategic and Equitable Multibenefit Land Repurposing to Sustain Food-Energy-Water Systems and Address Water Injustice in the San Joaquin Valley, California," discussed the findings of three key questions explored to inform strategic and equitable agricultural land use transitions in California's San Joaquin Valley under the Sustainable Groundwater Management Act (SGMA) and the Multibenefit Land Repurposing Program (MLRP):

1) What alternative land uses meet disadvantaged community needs?
2) Where should land transition efforts be focused?
3) Are land use classification datasets used to inform water and land use decisions accurately representing what is currently on the ground?

The first question of this dissertation, "what alternative land uses meet disadvantaged community needs," was motivated by several studies highlighting the lack of engagement and involvement of disadvantaged communities in strategies to address SGMA targets (Bernacchi et al., 2020; Dobbin, 2020; Dobbin & Lubell, 2021; Fernandez-Bou et al., 2021). Given the potential for agricultural land use transitions to reduce water demand under SGMA and associated socioeconomic and environmental implications of taking land out of production in and around predominantly agriculturally dependent communities, I found the need to learn from San Joaquin Valley community members what their preferred land use alternative is to reduce water demand. The timing of this work has been optimal in not only informing agricultural land use transitions to meet SGMA goals but also informing agricultural land transitions under the Department of Conservation's Multibenefit Land Repurposing Program (MLRP). This work also leveraged potential alternative land use solutions explored for implementation in previous studies and used these land use types to gauge community preference in the survey: 1) habitat restoration (Bourque et al., 2019; Butterfield et al., 2017; Cypher et al., 2013; Lortie et al., 2018; Stewart et al., 2019; Tennant et al., 2013), 2) renewable energy (e.g., solar) (Butterfield et al., 2013; Pearce et al., 2016), 3) carbon sequestration, 4) groundwater recharge (Ghasemizade et al., 2019; Mayzelle et al., 2015; O'Geen et al., 2015), and 5) parks and green space (Jennings et al., 2012): Through an SMS distributed web survey this dissertation obtained insights on community land use preferences with a focus to sample in 32 underserved communities in the region despite the challenges of engaging communities during a pandemic and implementing best practices among marginalized populations given restrictions to in-person engagement. The findings of this work led to the development of a guide for community and farmer engagement of multibenefit land repurposing efforts to ensure inclusive engagement approaches are implemented in the newest land management program, MLRP. Major insights of this work include:

- Learning that most survey participants were not at all or only somewhat familiar with SGMA highlighted the need to conduct effective outreach efforts on SGMA and MLRP that implement the use of multilingual and multimodal educational resources and tools

- Based on some survey questions, specifically those related to carbon sequestration and carbon credits, I learned that there is a need to develop standardized terminology and definitions for complicated land repurposing concepts across all languages to ensure that farmers and community members understand what the implementation of each land use entails for their community.
- Based on survey participants, I found that maintaining agriculture in the region is important, and land uses alternative that helps maintain that agricultural status quo are prioritized, like groundwater recharge.
- This survey study also helped identify key perceptions of alternative land uses, climate change, and agriculture. By conducting a factor analysis on three data subsets – all, DAC, and non-DAC participants—this work found that climate change and agricultural risk awareness is a perception that exists across all three groups. This finding helps inform that targeted outreach efforts are dedicated to early climate change adopters and that different approaches and topics for building common ground with potentially late climate change adapters are needed. The development of educational resources tailored to perceptions across California's agricultural regions could help address climate change, agriculture, and land use transition misconceptions.

The second question, "where should land transition efforts be focused," incorporates a body of work related to sociohydrology—analysis and quantification of the dynamics between people and water at multiple scales to facilitate effective approaches to water scarcity (Kumar et al., 2020; Sivapalan et al., 2014; Sivapalan et al., 2012; Wens et al., 2019). This dissertation applies the concept of sociohydrology by analyzing how the historical context in which irrigation districts in the San Joaquin Valley were formed and how irrigation district traits influenced the agricultural norms and water dynamics in the region. By consolidating disaggregated irrigation district attributes (e.g., formation date, surface water allocation/delivery, crop composition, service area, number of DACs within the boundary), this work was able to quantify groundwater dependence, identify five key irrigation district governance groups, and determine sociohydrologic vulnerability based on DAC status and freshwater status for 102 irrigation districts. Overall, this dissertation chapter provides insight into which irrigation districts and their associated GSA under SGMA are more likely to be most vulnerable to water scarcity and groundwater limitations under SGMA based on their groundwater overdependence.

The final question of this dissertation, "are land use classification datasets used to inform water and land use decisions accurately representing what is currently on the ground," was motivated by an understanding that high user errors in land use classification datasets used to make critical water and land use management strategies in California could have further implications on already disproportionately impacted populations if discrepancies are not accounted for in decision making. Previous studies have shown that datasets like the USDA CDL (CropScape), a commonly used dataset across the United States, including California (Mueller & Harris, 2013), have higher accuracy in regions with a single dominant crop (Reitsma et al., 2016). This dissertation quantified the crop revenue, crop water requirement, and GHG emission discrepancies to understand the implications of user error when land use classification datasets are used to provide baselines and budget estimates to inform future water, land use, and climate change management strategies. By comparing the three most used and available land cover datasets for California—CropScape, Land IQ (assumed most accurate California dataset), and Kern County geospatial dataset (assumed ground truth)—I found that the dataset that is most suitable to represent California's agriculturally complex landscape is Land IQ. Compared to CropScape, Land IQ has higher producer and user accuracies. Although the discrepancies for this study focused on discrepancies due to user's error, calculation of the producer's error provided insights into which specific crops could benefit from improvement in representing what is actually grown. This dissertation also provided detailed crop misclassifications to inform users of the potential discrepancies they may encounter when using CropScape and Land IQ to make water, land use, economic, and GHG emission estimates and management decisions.

The outcomes and findings from this dissertation have resulted in a framework for community and farmer engagement, approaches, and lessons learned to obtain community land use preferences and inform strategic and equitable agricultural land use transitions to reduce water demand in California. Potential next steps regarding the community and farmer engagement and survey approach developed from this doctoral work could be to implement a similar engagement and community input framework to guide GSAs and other statewide entities on how to implement strategic and equitable land use transition plans under SGMA and the MLRP. The analysis of irrigation district groundwater overdependence could motivate other studies to develop a standardized sociohydrologic vulnerability index that could inform stakeholders (e.g., water agencies, conservation groups, environmental justice groups, policymakers, and land use planners) on where to focus land and water management efforts to ensure timely adaptation to climate change and a water-scarce future. Another potential next step~~,~~ could be to conduct a GSA-level analysis of groundwater dependence which could provide insight on the regions that are highly prone to groundwater dependence. The irrigation districts analysis of this dissertation would complement the GSA-level analysis by providing insights of individual irrigation district groundwater dependence that comprise the GSAs under SGMA. The findings of the comparison of the land cover dataset could inform users on accounting for discrepancies resulting from using a specified dataset and ensuring that estimated budgets and baseline values are accounting for discrepancies on the user end. The land use cover dataset comparison could inform approaches to conducting a statewide approach to quantifying the revenue, crop water requirement, and GHG emission discrepancies that results from user and producer errors. Overall, this doctoral work and associated community and farmer could contribute to elevating the importance of developing future strategies for California that are inclusive, equitable, and locally representative to build a climate-change resilient state—together.

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APPENDIX A. CHAPTER 1 SUPPLEMENTARY INFO

Survey Instrument

Welcome to the Land Use Community Survey!
To complete the survey in English please continue.

¡Bienvenido a la encuesta comunitaria sobre el uso del la tierra!
Para completar la encuesta en Español, seleccione el botón en la esquina superior derecha de la pantalla que actualmente dice "English". Haga clic en él y seleccione Español para continuar en Español.

The Viers Lab at University of California, Merced is conducting a community survey of the Central Valley of California. This research is part of CaliWaterAg and Vicky Espinoza's doctoral research. The results will be shared in a report that will be published on our lab website in June 2021. The results will contribute to land use planning in the Central Valley. Your responses are very helpful!

You are being asked to participate in a research study. If you decide to volunteer, it will take approximately 10 minutes to complete the web survey. If you are unable to access the webform or you'd like to conduct the survey via phone call Vicky Espinoza at (323) 547-5506. Habla Español.
Thank you for taking the time to participate.

There are no risks to you for your participation in this study. It is possible that you will not benefit directly by participating in this study. The survey is confidential. Absolute confidentiality cannot be guaranteed, since research documents are not protected from subpoena. There is no cost to you beyond the time and effort required to complete the online survey described above.
Contact the research team via this survey or email water@ucmerced.edu about this study with any questions. More information about the study can be found on http://vicelab.ucmerced.edu/communitysurvey/.

By continuing with the survey, you are consenting to participation in the study. You can discontinue this study at any time. You can skip any question.
Thank you for your time!

I. About You

1. What is your current job? [open text box]
2. Where do you work most of the time? Provide 5-digit ZIP code. [open text box]
3. Where do you live currently? Provide 5-digit ZIP code [open text box]
4. How familiar are you with the ***Sustainable Groundwater Management Act***? It is also known as ***SGMA*** and pronounced as ***sigma***.
   - Select from the following: (1) Not at all familiar, (2) Somewhat familiar, (3) Very familiar

II. Community Vision

This survey is about land in your community. Different land uses consume different amounts of water.
We are interested in your values and vision for your community. Please answer each question to the best of your ability.
Please the level of agreement with the following statements regarding your community:
Strongly Agree, Somewhat Agree, Somewhat Disagree, Strongly Disagree.

5. My community should have more parks, trails, bike paths, and playgrounds.
6. More wildlife habitat means more wildlife will damage crops and reduce land values.

7. Using wetlands, recharge ponds, and wells to help store water underground is important for healthy communities.
8. Using farmland to store carbon in soil is a waste of space in my community.
9. Land that generates electricity from the sun and wind could help the economy in my community.
10. My community should NOT spend money on open spaces, like parks, trails, bike paths, and playgrounds.
11. I think our community should use land to reduce climate change impacts and get paid with carbon credits.
12. Land used to create clean energy, from the sun and wind, is a waste of space in my community.
13. I value wildlife and would like more nearby places to watch wildlife.
14. Replenishing groundwater in natural underground storage and wells could improve the economy in my community.
15. In order to reduce groundwater overdraft, agricultural land could be used for another purpose. What land use is your ***TOP*** priority?
    - Select from the following: (1) Wildlife, (2) Recreation, (3) Clean energy, (4) Secure water supplies, (5) Reduce greenhouse gases and climate change, (6) Schools, grocery stores, and housing, (7) Less-water intensive agriculture, like different crops or fallowing
16. In order to reduce groundwater overdraft, agricultural land could be used for another purpose. What land use is your LOWEST priority?
    - Select from the following: (1) Wildlife, (2) Recreation, (3) Clean energy, (4) Secure water supplies, (5) Reduce greenhouse gases and climate change, (6) Schools, grocery stores, and housing, (7) Less-water intensive agriculture, like different crops or fallowing

Please state the level of agreement with the following statements regarding agriculture: Strongly Agree, Somewhat Agree, Somewhat Disagree, Strongly Disagree.

17. Agriculture is the core of the economy in my community.
18. I live here because of agriculture
19. My job depends on ag.
20. There should be space between farmland and where people live for health reasons.
21. Farming contributes to air and water pollution in my community.

Demographics

The following questions are used only for demographics purposes.

22. Which categories describe you? Please check all that apply.
    - Select from the following: (1) American Indian or Alaska Native, (2) Asian, (3) Black or African American, (4) Latino or Hispanic or Spanish Origin, (5) Native Hawaiian or Other Pacific Islander, (6) White, (7) Prefer not to answer
23. In your own words, how would you describe your racial and ethnic identity? [open text box]
24. What are your preferred gender pronouns?
    - Select from the following: (1) She/her/hers, (2) He/him/his, (3) They/them/theirs, (4) Prefer not to respond
25. What is your total household income?
    - Select from the following: (1) Under $20,000, (2) $20,001 - $40,000, (3) $40,001 - $60,000, (4) $60,001 - $80,000, (5) $80,001 - $100,000, (6) $100,000 or over

Please state the degree to which you agree or disagree with the following statements on climate change: Strongly Agree, Somewhat Agree, Somewhat Disagree, Strongly Disagree

26. In my region, climate change is happening.
27. Climate change threatens water quantity locally.
28. Climate change threatens local water quality.

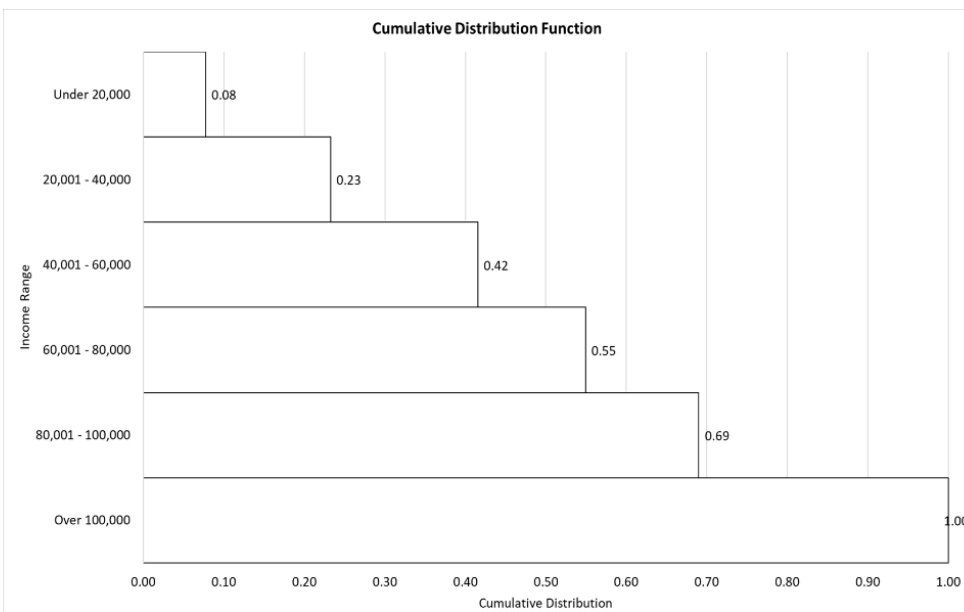
29. How did you find out about this survey? Select from the following: (1) Text, (2) Web, (3) Friend, (4) Other [Open text]
30. Is there anything else you would like to share with us? [Open text box]

2. Cumulative Distribution Function to Data Subsets for EFA

A cumulative distribution function (CDF) was conducted on the total household income of survey respondent data (NAs were excluded) to determine the subsets based on income and ethnicity for the EFA. The total responses per income bracket (Under $20,000, $20,001 - $40,000, $40,001 - $60,000, $60,001 - $80,000, $80,001 - $100,000, and $100,000 or over) were tallied in R. The income categories were then ranked from least to most and the CDF was calcualted by adding each new category count and dividing by the total count to get percentage responses (results in SI Table 1). The threshold for the low-income bracket was determined to be less than equal to $60K USD given that 42% of the resulting responses were below this income bracket (SI Figure 1).

SI Table 1. Results of the CDF on income.

	Income	n	pct	CDF (n)	CDF (n/total n)
1	Under 20,000	11	8%	11	0.08
2	20,001 - 40,000	22	15%	33	0.23
3	40,001 - 60,000	26	18%	59	0.42
4	60,001 - 80,000	19	13%	78	0.55
5	80,001 - 100,000	20	14%	98	0.69
6	Over 100,000	44	31%	142	1.00



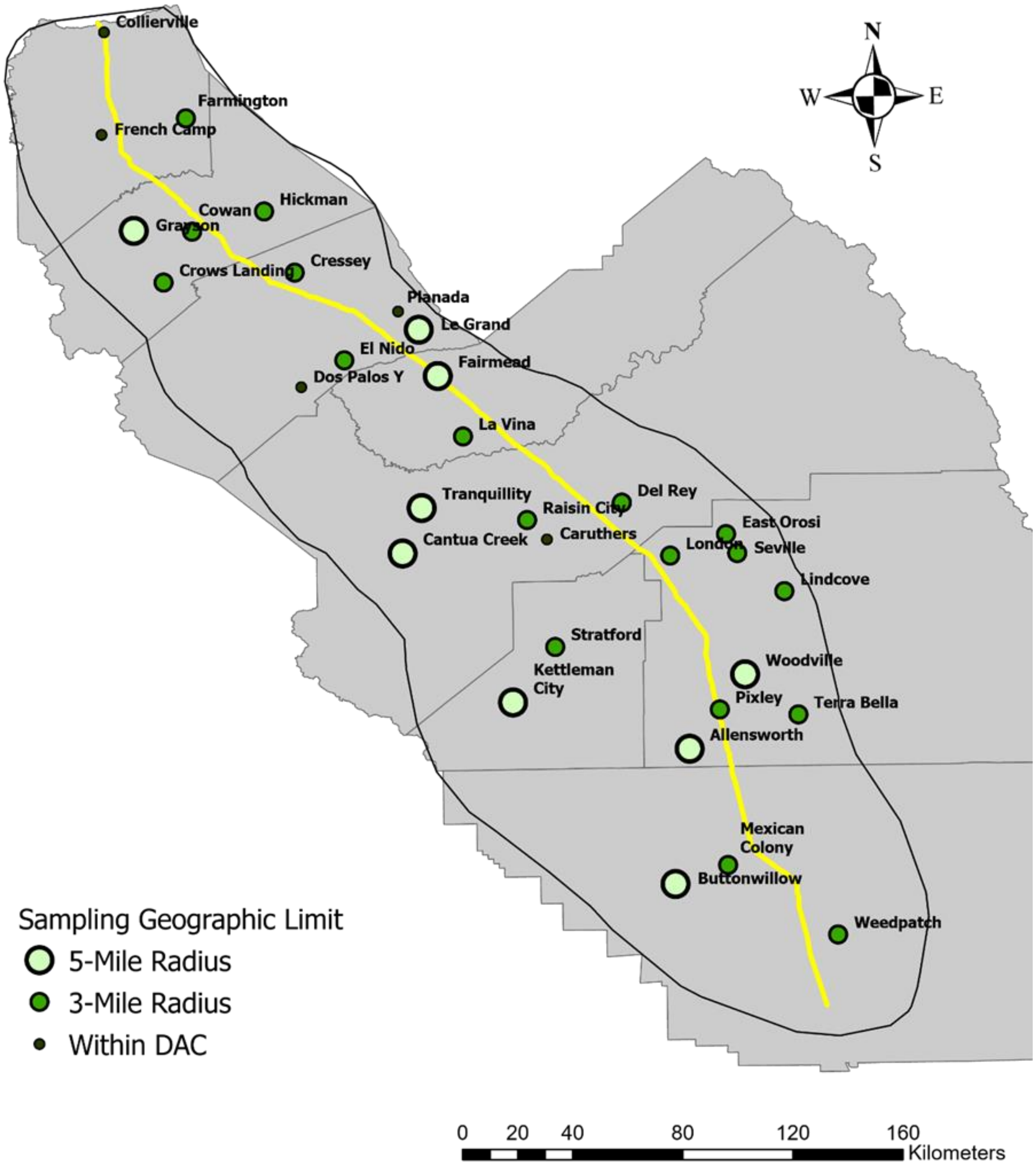
SI Figure 1. Resulting distribution of the CDF on income.

3. Supplementary Figures and Tables

SI Table 2 The population (2018), MSG Record Count, News Sample Size (based on the rule applied), the Sample Fraction of Total used to determine how many samples to remove from each DAC to meet the reduction of 405 samples to stay within funding limits, and the Final Sample Size for each DAC. Note: the DACs with an asterisk did not have any sample removed to meet the 405 reduction.

DAC Name	Population (2018)	MSG Record Count	New Sample Size (rule applied)	Geographic Limit	Sample Fraction	Sample Reduction	Final Sample Size
Dos Palos Y	242	4,156	4156	Within	0.16	67	4089
Collierville	2642	2,069	2069	Within	0.08	33	2036
Weedpatch	2238	991	1982	3-Mile	0.08	32	1950
Pixley	3796	855	1710	3-Mile	0.07	27	1683
Fairmead	1876	805	1610	5-Mile	0.06	26	1584
Planada	4418	1,361	1361	Within	0.05	22	1339
Del Rey	1498	654	1308	3-Mile	0.05	21	1287
London	1854	554	1108	3-Mile	0.04	18	1090
Grayson	1224	544	1088	5-Mile	0.04	17	1071
Caruthers	2773	1,018	1018	Within	0.04	16	1002
French Camp	3857	1,007	1007	Within	0.04	16	991
Woodville	1852	499	998	5-Mile	0.04	16	982
Terra Bella	3304	475	950	3-Mile	0.04	15	935
Tranquillity	839	356	712	5-Mile	0.03	11	701
Hickman	566	352	704	3-Mile	0.03	11	693
La Vina	239	297	594	3-Mile	0.02	10	584
Lindcove	438	247	494	3-Mile	0.02	8	486
Cowan	570	192	384	3-Mile	0.02	6	378
East Orosi	955	183	366	3-Mile	0.01	6	360
Seville	691	163	326	3-Mile	0.01	5	321
Farmington	89	83	249	3-Mile	0.01	4	245
Mexican Colony	363	118	236	3-Mile	0.01	4	232
Cressey	356	76	228	3-Mile	0.01	4	224
Crows Landing	278	62	186	3-Mile	0.01	3	183
El Nido	328	58	174	3-Mile	0.01	3	171
Stratford	878	50	150	3-Mile	0.01	2	148
Raisin City	389	40	120	3-Mile	0.00	2	118
Cantua Creek*	273	286	286	5-Mile			286
Buttonwillow *	1591	685	1370	5-Mile			941
Kettleman City*	1395	19	57	5-Mile			57
Le Grand*	1726	661	1322	5-Mile			1258

Allensworth*	527	196	196	5-Mile			196

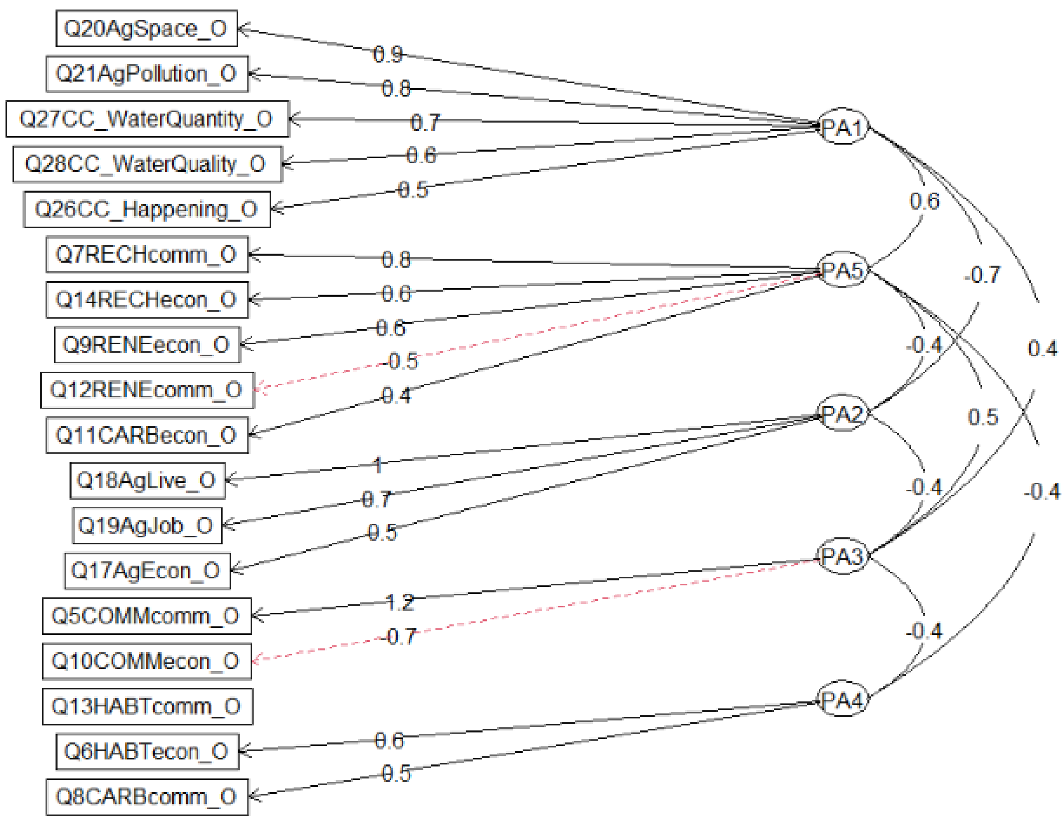


SI Figure 2. The geographic limit used to obtain cell samples for each DAC.

Factor Analysis (5 Factors) All Survey Respondents								
Survey Questions	PA1	PA5	PA2	PA3	PA4	h2	u2	com
Q5COMMcomm_O	0.22	-0.27	0.13	1.16	0.19	1.09	-0.09	1.3
Q6HABTecon_O	-0.1	0.05	0.03	0.1	0.63	0.37	0.63	1.1
Q7RECHcomm_O	-0.19	0.79	0.21	-0.02	0.14	0.39	0.61	1.3
Q8CARBcomm_O	0.04	0.15	-0.11	-0.03	0.51	0.24	0.76	1.3
Q9RENEecon_O	0.11	0.6	-0.2	0	0.08	0.59	0.41	1.3
Q10COMMecon_O	0.15	-0.18	0.06	-0.72	0.07	0.66	0.34	1.2
Q11CARBecon_O	0.31	0.41	-0.17	-0.07	0.04	0.66	0.34	2.3
Q12RENEcomm_O	-0.06	-0.48	0.27	0.11	0.19	0.53	0.47	2.1
Q13HABTcomm_O	0	0.18	-0.22	-0.27	0.12	0.36	0.64	3.2
Q14RECHecon_O	0.09	0.62	0.3	-0.02	0.07	0.32	0.68	1.5
Q17AgEcon_O	-0.05	0.14	0.45	0.04	-0.22	0.21	0.79	1.7
Q18AgLive_O	0.07	0.25	1	0.03	0	0.75	0.25	1.1
Q19AgJob_O	0.11	0.09	0.74	-0.04	0.05	0.46	0.54	1.1
Q20AgSpace_O	0.91	-0.07	0.27	-0.01	0.02	0.51	0.49	1.2
Q21AgPollution_O	0.82	-0.25	0	-0.03	0.02	0.51	0.49	1.2
Q26CC_Happening_O	0.55	0.32	-0.13	0.01	0.02	0.76	0.24	1.8
Q27CC_WaterQuantity_O	0.66	0.2	-0.15	-0.01	0	0.81	0.19	1.3
Q28CC_WaterQuality_O	0.59	0.24	-0.15	0.02	0	0.76	0.24	1.5
				PA1	PA5	PA2	PA3	PA4
SS loadings				3.03	2.22	2.12	1.85	0.74
Proportion Var				0.17	0.12	0.12	0.1	0.04
Cumulative Var				0.17	0.29	0.41	0.51	0.55
Proportion Explained				0.3	0.22	0.21	0.19	0.07
Cumulative Proportion				0.3	0.53	0.74	0.93	1
With factor correlations of:				PA1	PA5	PA2	PA3	PA4
			PA1	1	0.59	-0.69	0.44	-0.22
			PA5	0.59	1	-0.45	0.48	-0.38
			PA2	-0.69	-0.45	1	-0.44	0.25
			PA3	0.44	0.48	-0.44	1	-0.39
			PA4	-0.22	-0.38	0.25	-0.39	1
Mean item complexity = 1.5								
Test of the hypothesis that 5 factors are sufficient.								
The degrees of freedom for the model are 73 and the objective function was 1.39								
The root mean square of the residuals (RMSR) is 0.04								
The df corrected root mean square of the residuals is 0.06								

Tucker Lewis Index of factoring reliability = 0.795
RMSEA index = 0.103 and the 90 % confidence intervals are 0.085 0.122
BIC = -178.55
Fit based upon off diagonal values = 0.99

SI Table 3. Exploratory Factor Analysis (EFA) for all survey respondents (excluding participants with NA for the income variable) with five factors. Note: this 5 factor anlysis was compared with EFAs on all survey respondents for 3 and 4 factors to understand factor analysis structure, and was chosen given that there was no stark difference among the compared models and the model with five factors provided more nuance between clusters.



SI Figure 3. Resulting Exploratory Factor Analysis (EFA) of five underlying perceptions between land use, relationship to agriculture, and climate change statements for ***all survey respondents*** *(n=143). The numbers indicate factor loadings and the dashed red lines represent a negative loading.*

Factor Analysis (4 Factors) for DAC Survey Respondents							
Survey Questions	PA1	PA4	PA3	PA2	h2	u2	com
Q5COMMcomm_O	-0.01	0.12	0.94	-0.46	0.967	0.033	1.5
Q6HABTecon_O	-0.12	0.57	0.04	0.06	0.365	0.635	1.1
Q7RECHcomm_O	0.1	0.2	0	0.75	0.629	0.371	1.2
Q8CARBcomm_O	0.16	0.23	0	0.02	0.068	0.932	1.8

Q9RENEecon_O	0.45	-0.23	0.11	0.22	0.413	0.587	2.2
Q10COMMecon_O	0.1	0.21	-0.75	0.11	0.591	0.409	1.2
Q11CARBecon_O	0.62	-0.01	0.24	0.13	0.592	0.408	1.4
Q12RENEcomm_O	-0.24	0.5	-0.07	-0.16	0.407	0.593	1.7
Q13HABTcomm_O	-0.09	0.02	0.47	0.12	0.221	0.779	1.2
Q14RECHecon_O	0.17	0.19	0.19	0.49	0.381	0.619	1.9
Q17AgEcon_O	-0.03	-0.02	-0.09	0.21	0.051	0.949	1.4
Q18AgLive_O	-0.05	0.79	-0.1	0.2	0.709	0.291	1.2
Q19AgJob_O	-0.13	0.6	0	-0.01	0.402	0.598	1.1
Q20AgSpace_O	0.83	0.08	-0.16	-0.24	0.637	0.363	1.3
Q21AgPollution_O	0.43	0.14	0.01	-0.67	0.583	0.417	1.8
Q26CC_Happening_O	0.89	-0.01	-0.11	-0.05	0.738	0.262	1
Q27CC_WaterQuantity_O	0.94	-0.14	-0.13	-0.01	0.858	0.142	1.1
Q28CC_WaterQuality_O	0.86	-0.14	-0.07	-0.08	0.754	0.246	1.1

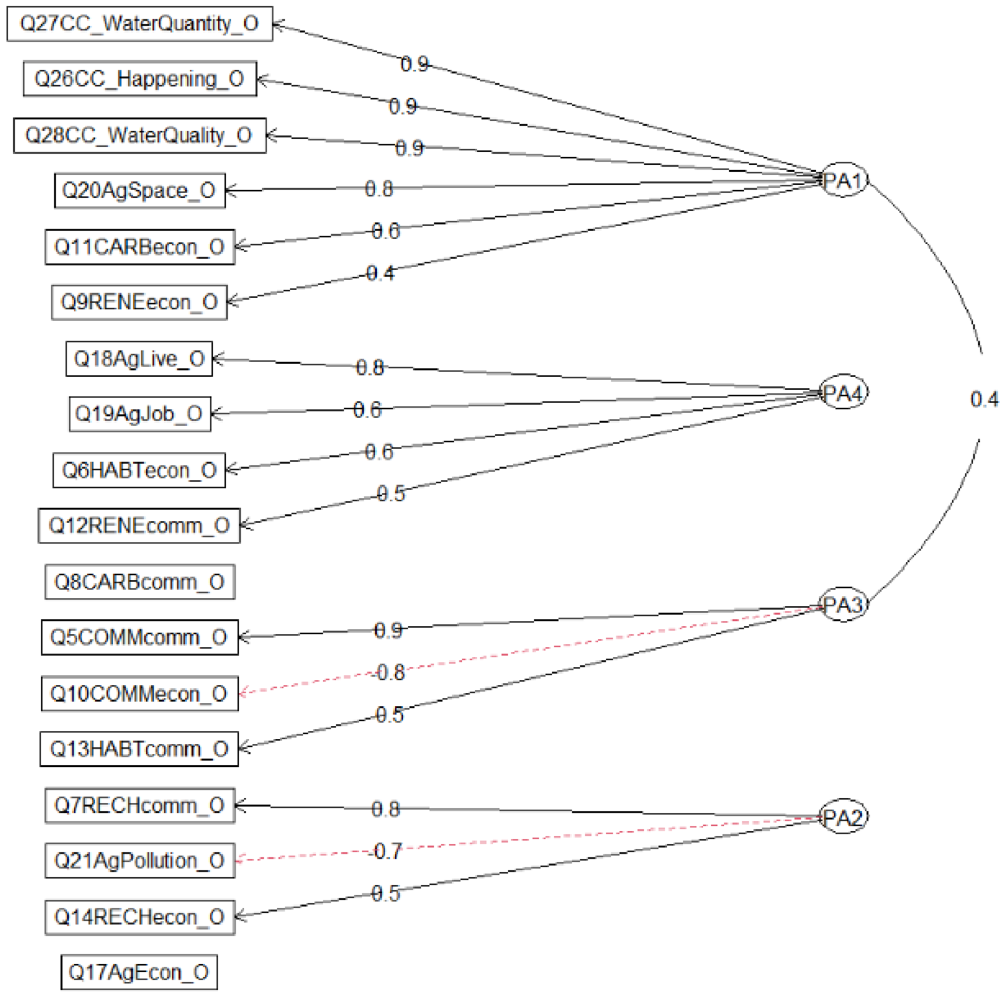
	PA1	PA4	PA3	PA2
SS loadings	4.00	1.96	1.72	1.69
Proportion Var	0.22	0.11	0.10	0.09
Cumulative Var	0.22	0.33	0.43	0.52
Proportion Explained	0.43	0.21	0.18	0.18
Cumulative Proportion	0.43	0.64	0.82	1.00

With factor correlations of		PA1	PA4	PA3	PA2
	PA1	1.00	-0.17	0.38	0.09
	PA4	-0.17	1.00	-0.12	0.03
	PA3	0.38	-0.12	1.00	0.11
	PA2	0.09	0.03	0.11	1.00

Mean item complexity = 1.4 Test of the hypothesis that 4 factors are sufficient.
The degrees of freedom for the null model are 153 and the objective function was 10.46 with Chi Square of 378.4
The degrees of freedom for the model are 87 and the objective function was 2.81

The root mean square of the residuals (RMSR) is 0.06 The df corrected root mean square of the residuals is 0.08				
The harmonic number of observations is 44 with the empirical chi square 52.06 with prob < 1				
The total number of observations was 44 with Likelihood Chi Square = 94.22 with prob < 0.28				
Tucker Lewis Index of factoring reliability = 0.936 RMSEA index = 0.037 and the 90 % confidence intervals are 0 0.097				
BIC = -235.01				
Fit based upon off diagonal values = 0.95				
Measures of factor score adequacy	PA1	PA4	PA3	PA2
Correlation of (regression) scores with factors	0.97	0.91	0.99	0.90
Multiple R square of scores with factors	0.94	0.83	0.98	0.81
Minimum correlation of possible factor scores	0.88	0.67	0.96	0.62

SI Table 4. Exploratory Factor Analysis (EFA) for DAC survey respondents (income ≤ $60K and non-declared white) with four factors.



SI Figure 4. Resulting Exploratory Factor Analysis (EFA)of four underlying perceptions between land use, relationship to agriculture, and climate change statements among ***DAC survey respondents*** *(n=44). The numbers indicate factor loadings and the dashed red lines represent a negative loading. Acronyms: PA1= Address Agricultural and Climate Change Risks, PA2=Agricultural is Not the Problem & Focus on Groundwater Recharge, PA3=More Recreation and Wildlife Habitat, and PA4=Ag Against Land for Habitat & Renewable Energy.*

Factor Analysis (3 Factors) for non-DAC Survey Respondents						
Survey Questions	PA1	PA2	PA3	h2	u2	com
Q5COMMcomm_O	0	0.22	-0.72	0.636	0.36	1.2
Q6HABTecon_O	-0.26	0.09	0.11	0.088	0.91	1.6
Q7RECHcomm_O	0.67	-0.32	0.01	0.341	0.66	1.4
Q8CARBcomm_O	0.05	0.18	0.28	0.087	0.91	1.8
Q9RENEecon_O	0.69	0.14	0.02	0.576	0.42	1.1
Q10COMMecon_O	-0.13	0.05	0.88	0.883	0.12	1
Q11CARBecon_O	0.6	0.27	-0.12	0.692	0.31	1.5
Q12RENEcomm_O	-0.73	-0.06	-0.01	0.575	0.43	1
Q13HABTcomm_O	0.28	0.3	-0.29	0.46	0.54	3
Q14RECHecon_O	0.71	-0.33	0.13	0.335	0.66	1.5
Q17AgEcon_O	0.06	-0.57	-0.19	0.288	0.71	1.2
Q18AgLive_O	0.15	-0.91	-0.02	0.711	0.29	1.1
Q19AgJob_O	0.16	-0.73	0.2	0.527	0.47	1.3
Q20AgSpace_O	0.43	0.16	0.03	0.268	0.73	1.3
Q21AgPollution_O	0.49	0.4	0.16	0.498	0.5	2.2
Q26CC_Happening_O	0.64	0.32	-0.12	0.816	0.18	1.6
Q27CC_WaterQuantity_O	0.55	0.43	-0.07	0.771	0.23	1.9
Q28CC_WaterQuality_O	0.58	0.35	-0.11	0.748	0.25	1.7

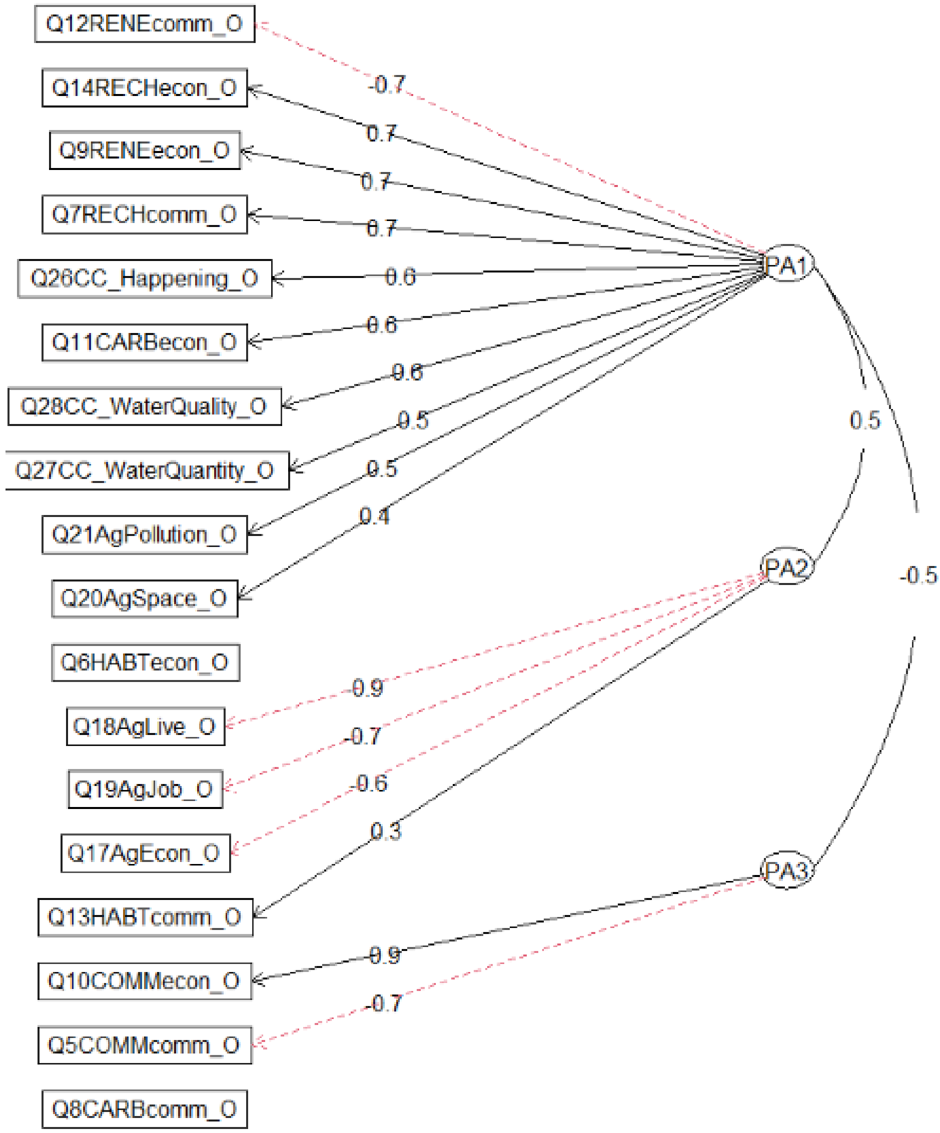
	PA1	PA2	PA3
SS loadings	4.39	3.09	1.82
Proportion Var	0.24	0.17	0.10
Cumulative Var	0.24	0.42	0.52
Proportion Explained	0.47	0.33	0.20
Cumulative Proportion	0.47	0.80	1.00

With factor correlations of:		PA1	PA2	PA3
	PA1	1.00	0.47	-0.49
	PA2	0.47	1.00	-0.23
	PA3	-0.49	-0.23	1.00

Mean item complexity = 1.5
Test of the hypothesis that 3 factors are sufficient.
The degrees of freedom for the null model are 153 and the objective function was 12.09 with Chi Square of 1101.81
The degrees of freedom for the model are 102 and the objective function was 2.85
The root mean square of the residuals (RMSR) is 0.06
The df corrected root mean square of the residuals is 0.07

The harmonic number of observations is 98 with the empirical chi square 103.06 with prob < 0.45			
The total number of observations was 99 with Likelihood Chi Square = 253.72 with prob < 6.3e-15			
Tucker Lewis Index of factoring reliability = 0.754			
RMSEA index = 0.122 and the 90 % confidence intervals are 0.104 0.142			
BIC = -214.98			
Fit based upon off diagonal values = 0.98			
Measures of factor score adequacy			
	PA1	PA2	PA3
Correlation of (regression) scores with factors	0.96	0.94	0.96
Multiple R square of scores with factors	0.91	0.89	0.92
Minimum correlation of possible factor scores	0.83	0.78	0.83

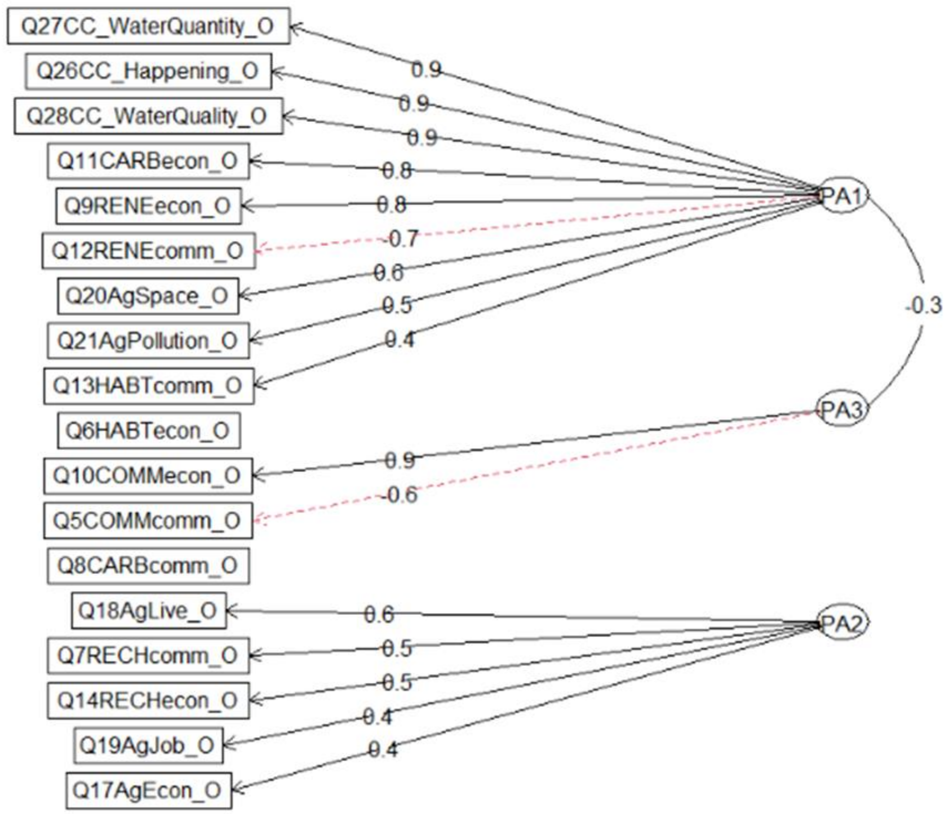
SI Table 5. Exploratory Factor Analysis (EFA) for non-DAC survey respondents (excludes DAC survey respondents) with three factors.



*SI Figure 5. Resulting Exploratory Factor Analysis (EFA) of three underlying perceptions between land use, relationship to agriculture, and climate change statements among **non-DAC survey respondents** (n=99). The numbers indicate factor loadings and the dashed red lines represent a negative loading. Acronyms: PA1= Address Agricultural and Climate Change Risks, PA2=Non-Ag for Habitat, PA3=Opposed to Recreational Spaces.*

Factor Analysis (3 Factors) for All Survey Respondents						
Survey Questions	PA1	PA3	PA2	h2	u2	com
Q5COMMcomm_O	0.21	-0.6	-0.14	0.525	0.4746	1.3
Q6HABTecon_O	-0.18	0.12	0	0.061	0.9393	1.7
Q7RECHcomm_O	0.38	0.01	0.52	0.326	0.6745	1.8
Q8CARBcomm_O	0.11	0.19	-0.04	0.037	0.9628	1.7
Q9RENEecon_O	0.75	-0.01	0.14	0.539	0.4608	1.1
Q10COMMecon_O	-0.16	0.93	-0.05	0.991	0.0091	1.1
Q11CARBecon_O	0.79	-0.08	0.04	0.656	0.3436	1
Q12RENEcomm_O	-0.66	0.03	-0.08	0.437	0.5629	1
Q13HABTcomm_O	0.39	-0.3	-0.05	0.34	0.6598	1.9
Q14RECHecon_O	0.46	0.03	0.48	0.335	0.665	2
Q17AgEcon_O	-0.13	-0.09	0.36	0.165	0.835	1.4
Q18AgLive_O	-0.29	0.06	0.64	0.595	0.4046	1.4
Q19AgJob_O	-0.28	0.12	0.45	0.379	0.6208	1.9
Q20AgSpace_O	0.59	0.1	-0.04	0.332	0.6681	1.1
Q21AgPollution_O	0.52	0.06	-0.25	0.378	0.6216	1.5
Q26CC_Happening_O	0.88	0.03	-0.02	0.761	0.2387	1
Q27CC_WaterQuantity_O	0.88	0.06	-0.11	0.803	0.197	1
Q28CC_WaterQuality_O	0.85	0.02	-0.08	0.756	0.2443	1
	PA1	PA3	PA2			
SS loadings	5.47	1.54	1.41			
Proportion Var	0.3	0.09	0.08			
Cumulative Var	0.3	0.39	0.47			
Proportion Explained	0.65	0.18	0.17			
Cumulative Proportion	0.65	0.83	1			
				PA1	PA3	PA2
With factor correlations of:			PA1	1	-0.34	-0.23
			PA3	-0.34	1	0.02
			PA2	-0.23	0.02	1
Mean item complexity = 1.4						
Test of the hypothesis that 3 factors are sufficient.						
The root mean square of the residuals (RMSR) is 0.06						
The df corrected root mean square of the residuals is 0.07						
Tucker Lewis Index of factoring reliability = 0.775						
BIC = -232.96						
Fit based upon off diagonal values = 0.97						

SI Table 6. Exploratory Factor Analysis (EFA) for all survey respondents (excluding participants with NA for the income variable) with three factors. Note: this factor anlysis was used for comparative purposes with EFAs for all survey respondents across 3-5 factors.

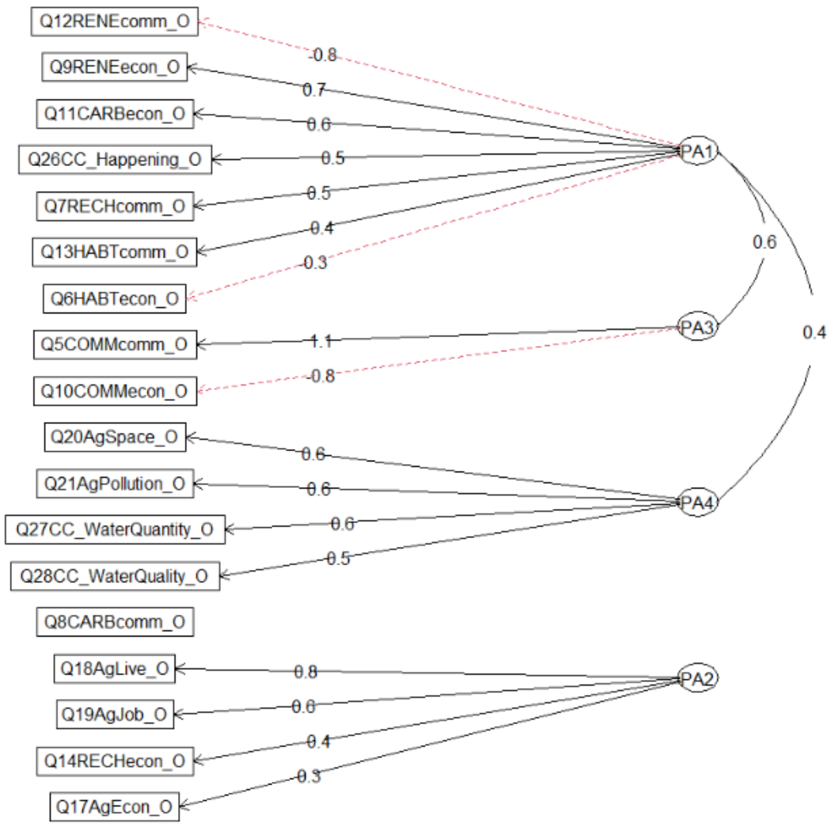


*SI Figure 6. Resulting Exploratory Factor Analysis (EFA) of three underlying perceptions between land use, relationship to agriculture, and climate change statements for **all survey respondents** (n=143). The numbers indicate factor loadings and the dashed red lines represent a negative loading. Note: this factor anlysis was used for comparative purposes with EFAs for all survey respondents across 3-5 factors.*

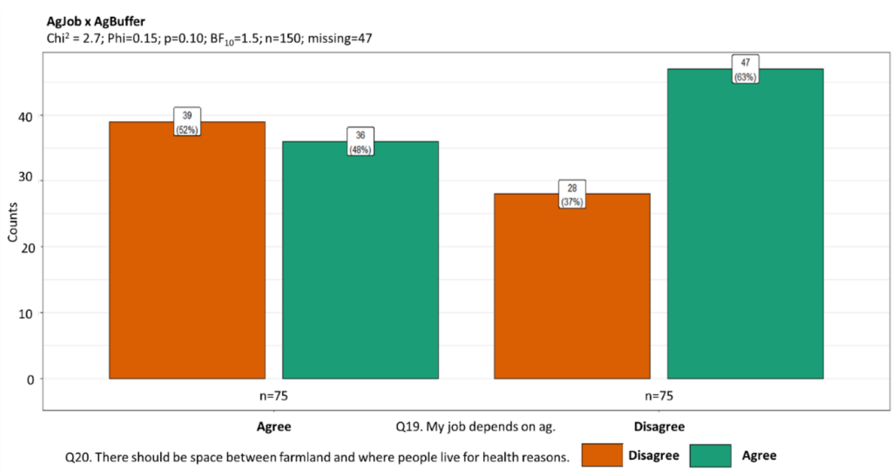
Factor Analysis (4 Factors) for All Survey Respondents							
Survey Question	PA1	PA3	PA4	PA2	h2	u2	com
Q5COMMcomm_O	-0.34	1.09	0.23	0.07	0.918	0.082	1.3
Q6HABTecon_O	-0.34	0.01	0.13	0.08	0.102	0.898	1.4
Q7RECHcomm_O	0.47	-0.07	-0.02	0.41	0.317	0.683	2
Q8CARBcomm_O	-0.08	-0.09	0.23	-0.01	0.052	0.948	1.6
Q9RENEecon_O	0.71	-0.06	0.16	0.02	0.571	0.429	1.1
Q10COMMecon_O	-0.17	-0.78	0.11	-0.1	0.728	0.272	1.2
Q11CARBecon_O	0.62	0.07	0.26	-0.03	0.661	0.339	1.4
Q12RENEcomm_O	-0.82	0.15	0.01	0.09	0.561	0.439	1.1
Q13HABTcomm_O	0.39	0.27	-0.02	-0.1	0.369	0.631	1.9
Q14RECHecon_O	0.4	-0.03	0.13	0.41	0.313	0.687	2.2
Q17AgEcon_O	0.01	0.07	-0.17	0.35	0.164	0.836	1.6

Q18AgLive_O	-0.28	0.06	-0.04	0.77	0.712	0.288	1.3
Q19AgJob_O	-0.34	-0.01	0.04	0.56	0.458	0.542	1.7
Q20AgSpace_O	0.07	0.12	0.61	0.06	0.446	0.554	1.1
Q21AgPollution_O	-0.01	0.14	0.59	-0.16	0.478	0.522	1.3
Q26CC_Happening_O	0.52	0.05	0.48	-0.04	0.761	0.239	2
Q27CC_WaterQuantity_O	0.44	0.05	0.56	-0.11	0.816	0.184	2
Q28CC_WaterQuality_O	0.46	0.08	0.5	-0.09	0.762	0.238	2.1
				PA1	PA3	PA4	PA2
SS loadings				3.52	1.88	2.29	1.50
Proportion Var				0.20	0.10	0.13	0.08
Cumulative Var				0.20	0.30	0.43	0.51
Proportion Explained				0.38	0.20	0.25	0.16
Cumulative Proportion				0.38	0.59	0.84	1.00
With factor correlations of				PA1	PA3	PA4	PA2
			PA1	1.00	0.58	0.42	-0.14
			PA3	0.58	1.00	0.19	-0.25
			PA4	0.42	0.19	1.00	-0.23
Mean item complexity = 1.6 Test of the hypothesis that 4 factors are sufficient.							
The degrees of freedom for the null model are 153 and the objective function was 9.73 with Chi Square of 1315.33							
The degrees of freedom for the model are 87 and the objective function was 1.56							
The root mean square of the residuals (RMSR) is 0.05 The df corrected root mean square of the residuals is 0.06							
The harmonic number of observations is 142 with the empirical chi square 104.02 with prob < 0.1							
The total number of observations was 143 with Likelihood Chi Square = 206.58 with prob < 1e-11							
Tucker Lewis Index of factoring reliability = 0.815							
RMSEA index = 0.098 and the 90 % confidence intervals are 0.081 0.116							
BIC = -225.19							
Fit based upon off diagonal values = 0.98							
Measures of factor score adequacy				PA1	PA3	PA4	PA2
Correlation of (regression) scores with factors				0.94	0.96	0.90	0.88
Multiple R square of scores with factors				0.88	0.93	0.82	0.78
Minimum correlation of possible factor scores				0.76	0.85	0.63	0.55

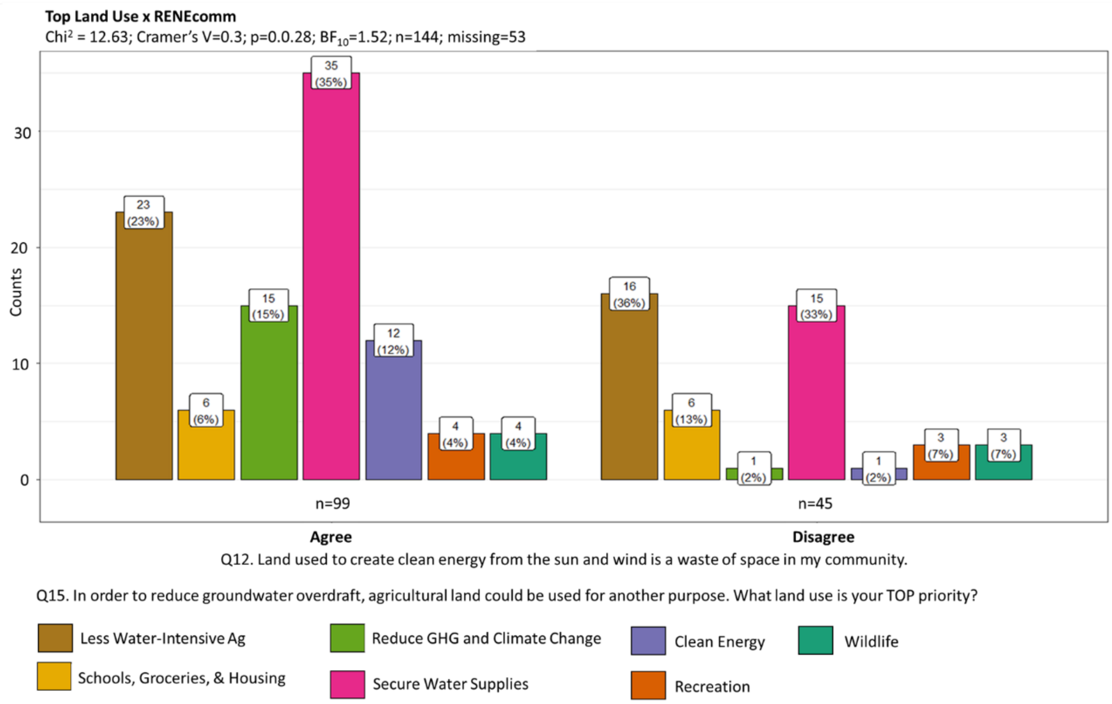
SI Table 7. Exploratory Factor Analysis (EFA) for all survey respondents (excluding participants with NA for the income variable) with four factors. Note: this factor anlysis was used for comparative purposes with EFAs for all survey respondents across 3-5 factors.



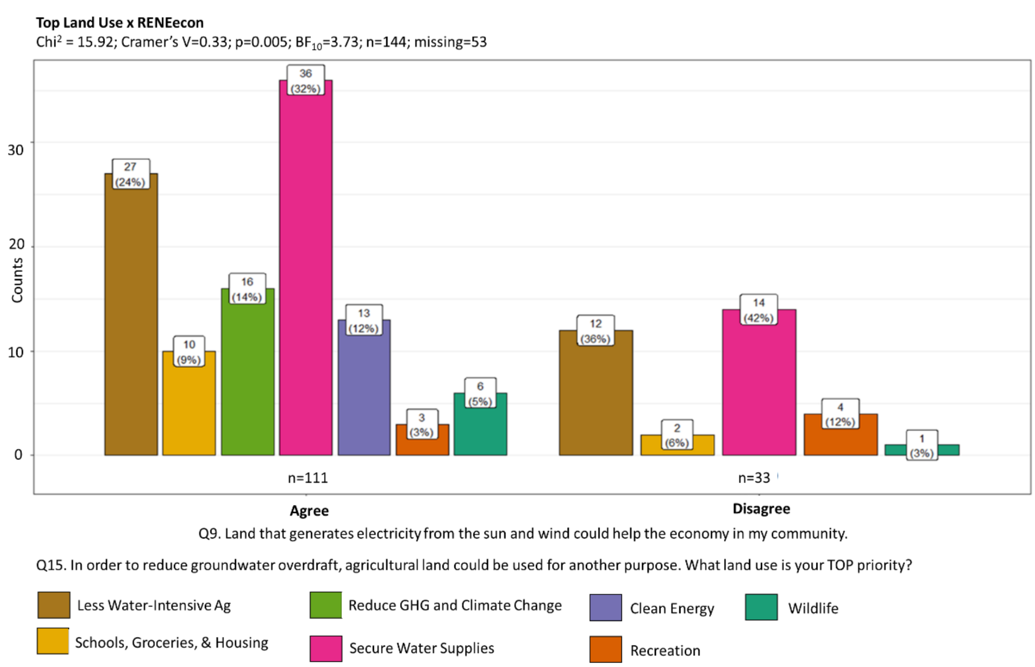
*SI Figure 7. Resulting Exploratory Factor Analysis (EFA) of four underlying perceptions between land use, relationship to agriculture, and climate change statements for **all survey respondents** (n=143). The numbers indicate factor loadings and the dashed red lines represent a negative loading. Note: this factor anlysis was used for comparative purposes with EFAs for all survey respondents across 3-5 factors.*



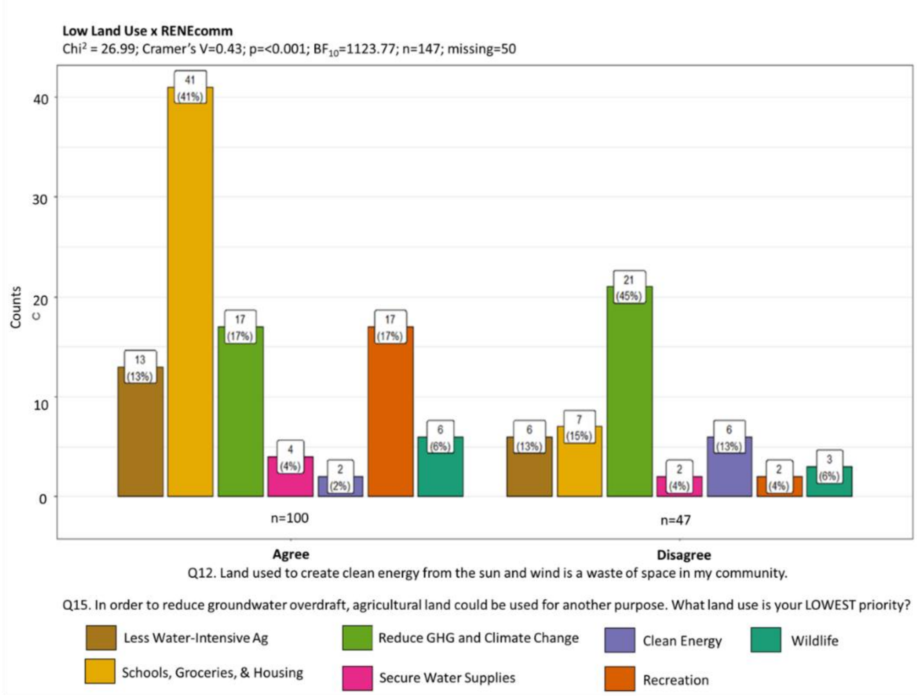
SI Figure 8. Cross tabulation of participant responses as cumulative agree and disagree for "my job depends on ag" with "there should be space between farmland and where people live for health reasons"



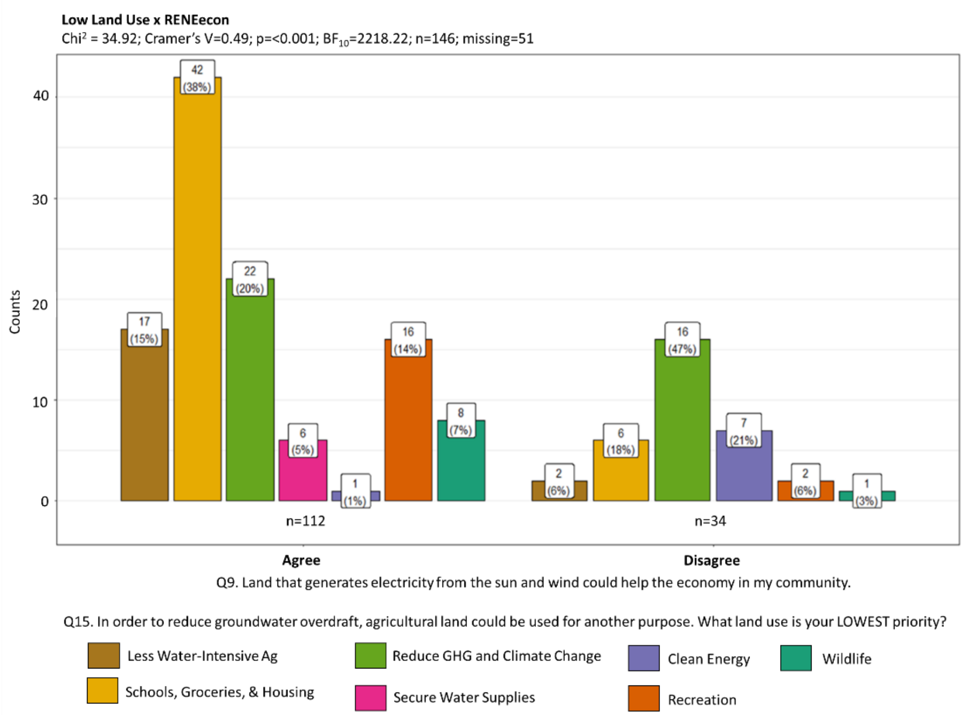
SI Figure 10. Cross tabulation *of participant responses as cumulative agree and disagree for renewable energy for community* factor (x-axis) *with TOP land use priority to address groundwater overdraft.*



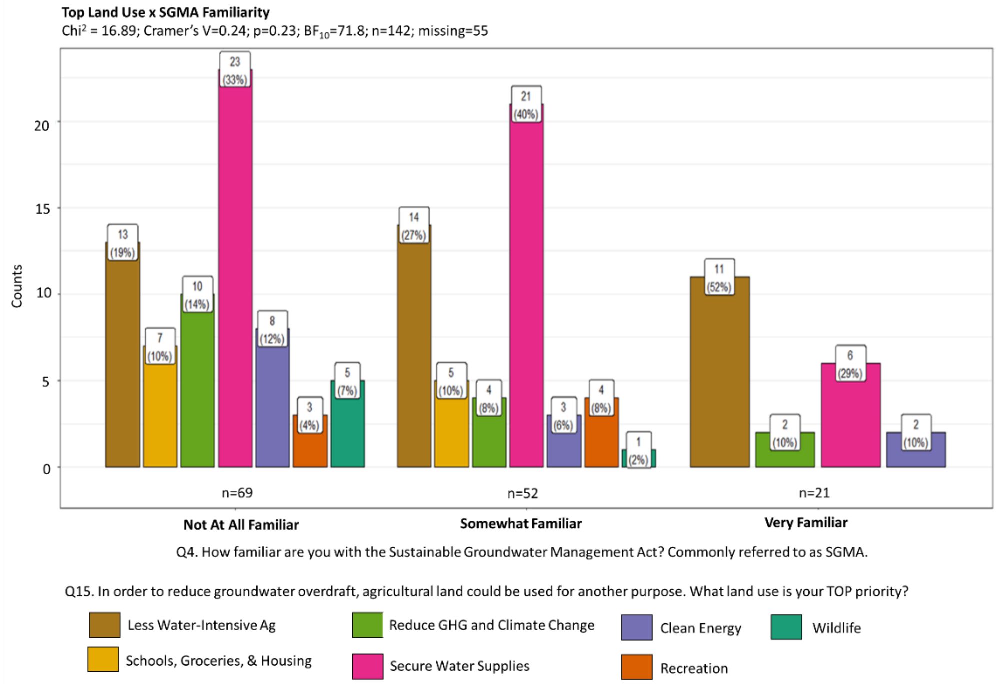
SI Figure 9. Cross tabulation of participant responses as cumulative agree and disagree for renewable energy for the economic factor (x-axis) with TOP land use priority to address groundwater overdraft.



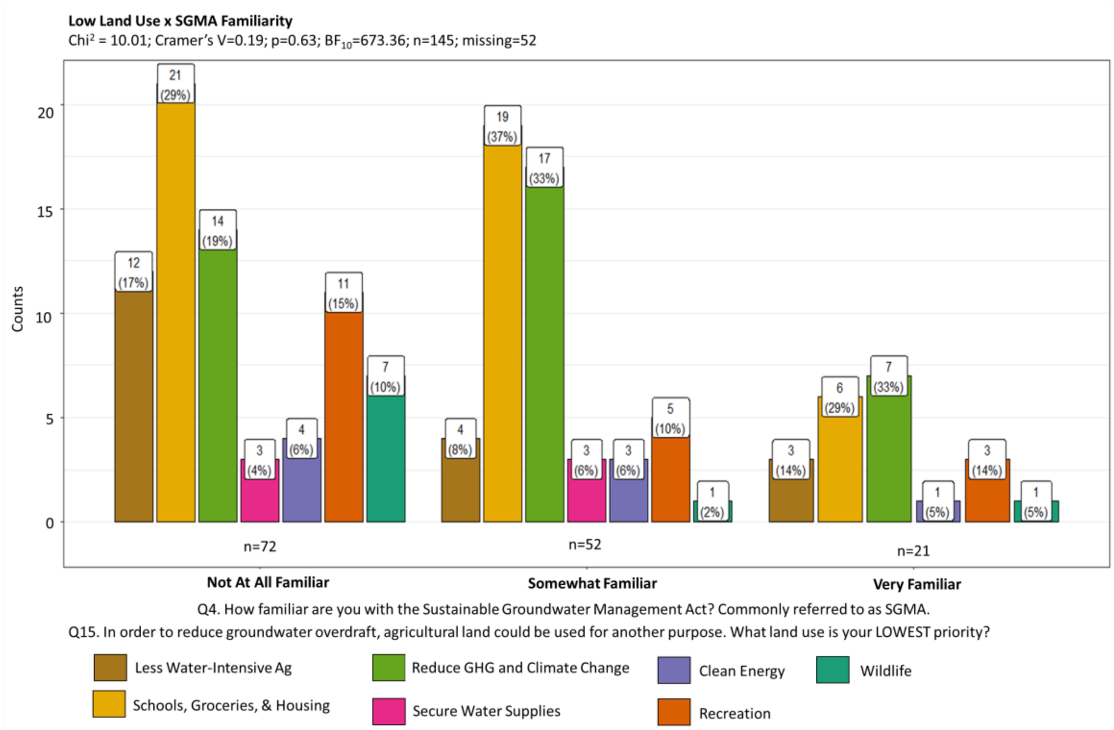
SI Figure 11. Cross tabulation of participant responses as cumulative agree and disagree for renewable energy for community factor (x-axis) with lowest land use priority to address groundwater overdraft.



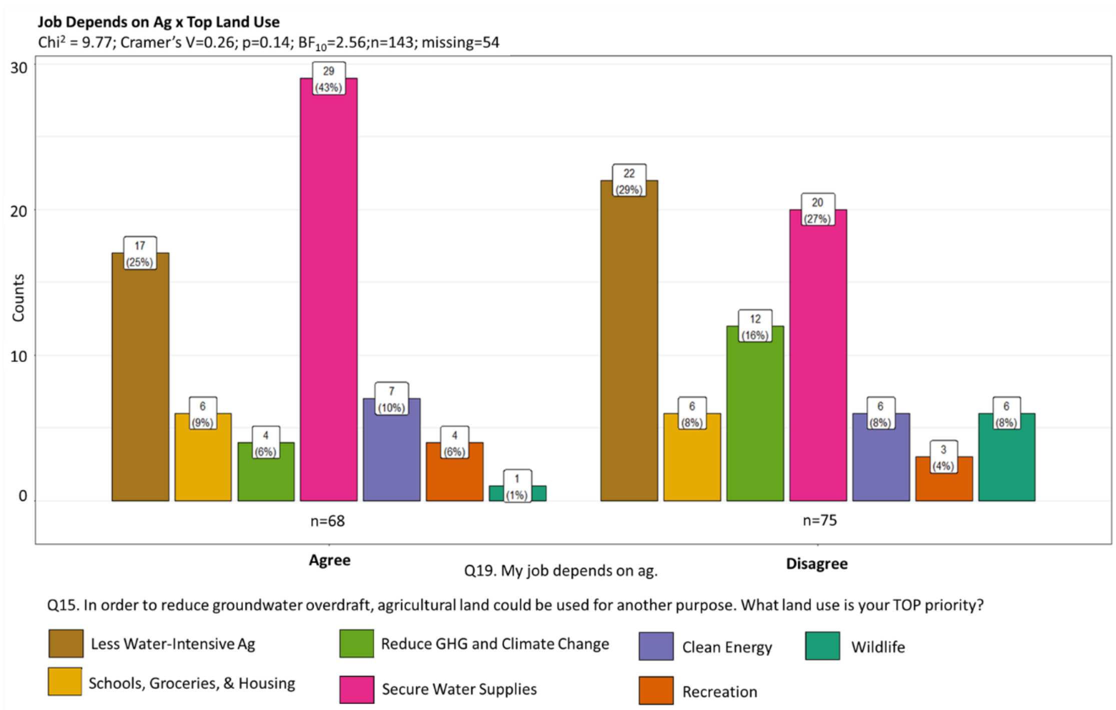
SI Figure 12. Cross tabulation of participant responses as cumulative agree and disagree for renewable energy for economic factor (x-axis) with lowest land use priority to address groundwater overdraft.



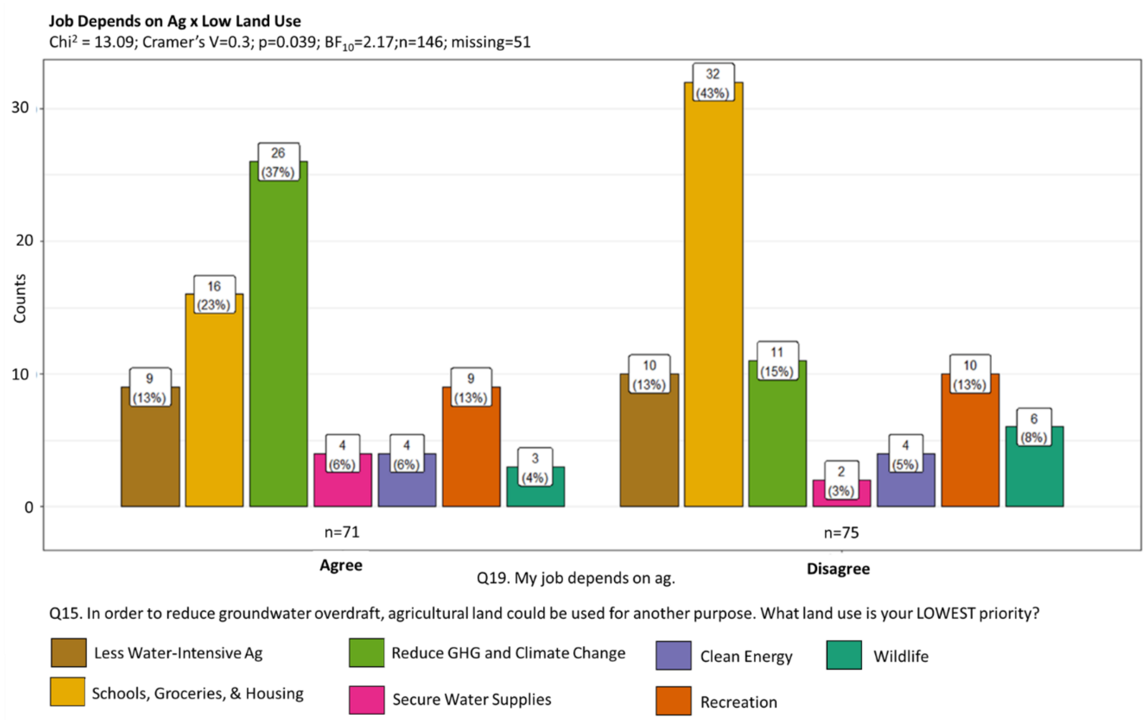
SI Figure 13. Cross tabulation of TOP land use priority to address groundwater overdraft and familiarity to SGMA (x-axis).



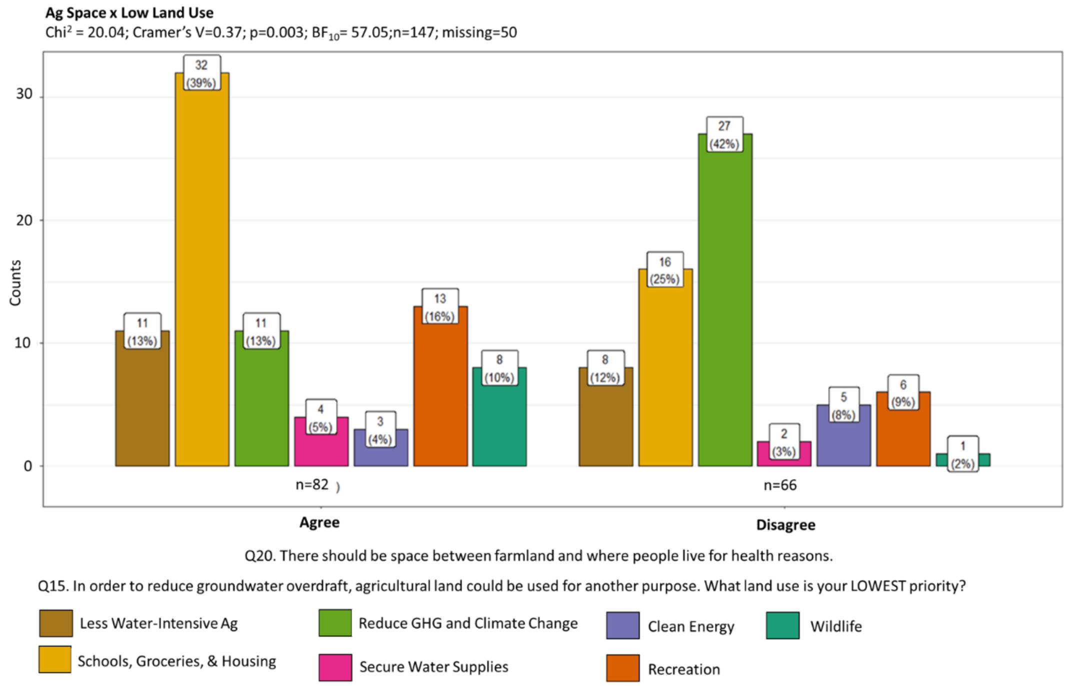
SI Figure 14. Cross tabulation of LOWEST land use priority to address groundwater overdraft and familiarity to SGMA (x-axis).



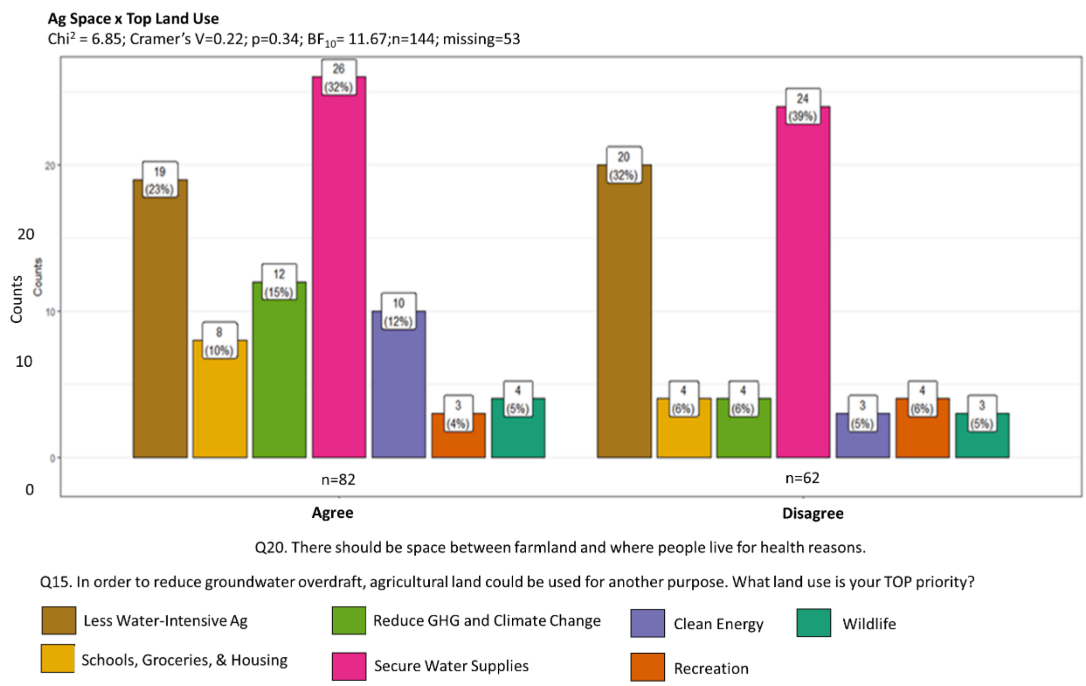
SI Figure 15. Cross tabulation of "my job depends on ag"(x-axis) and TOP land use priority to address groundwater overdraft.



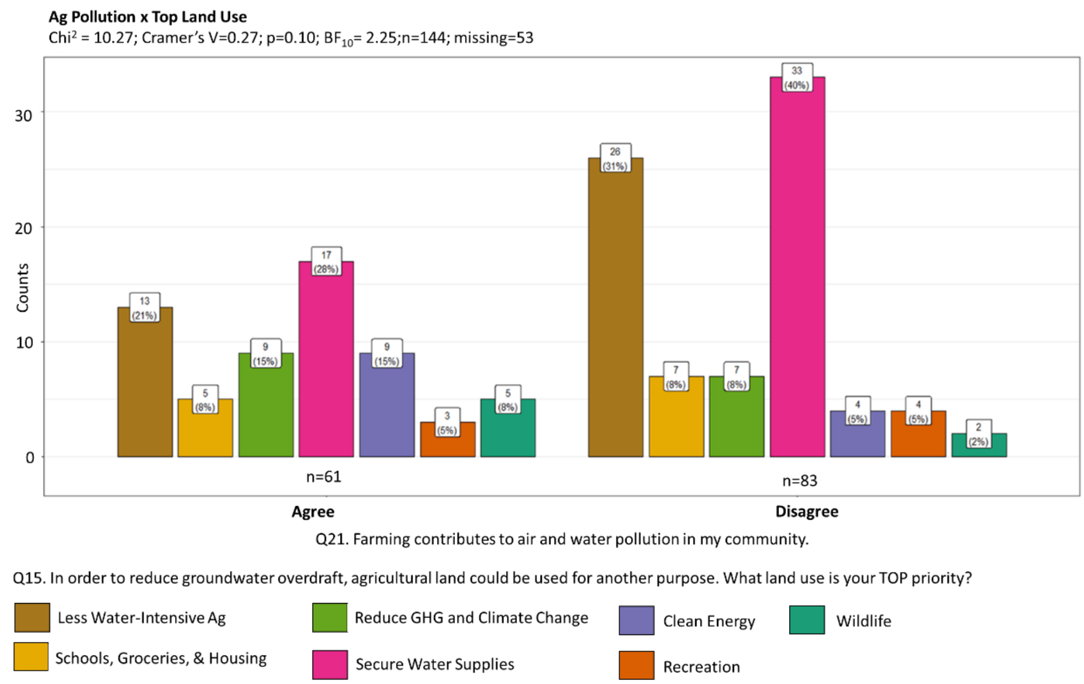
SI Figure 16. Cross tabulation of "my job depends on ag"(x-axis) and LOWEST land use priority to address groundwater overdraft.



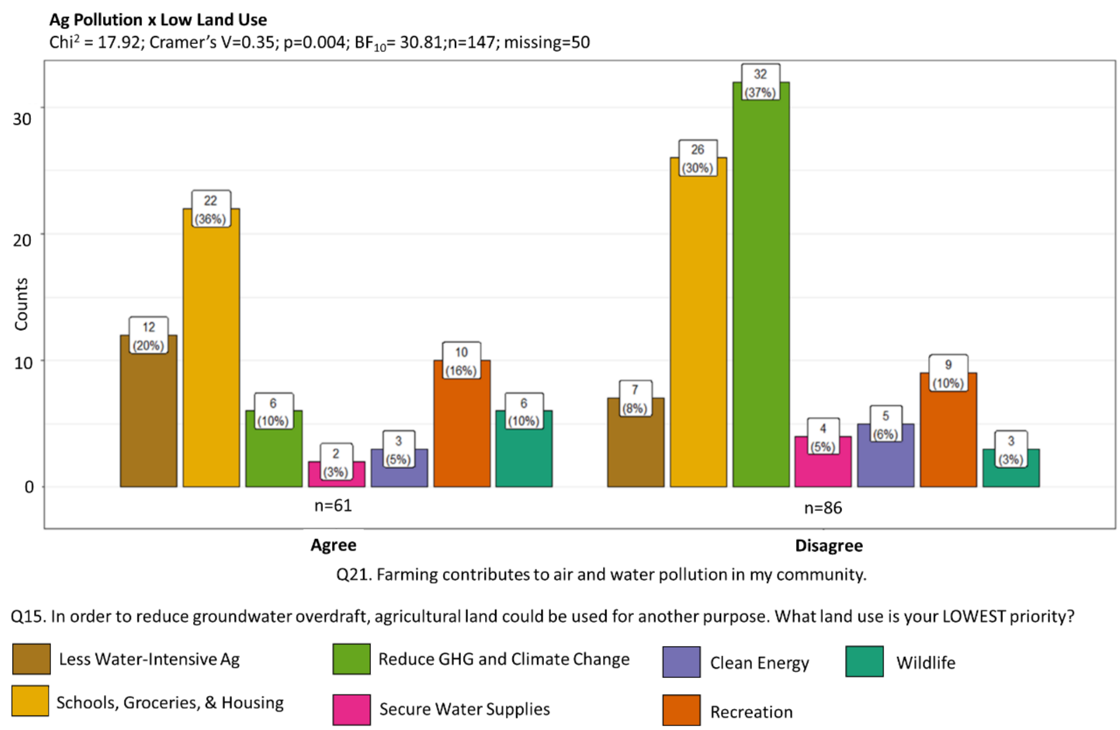
SI Figure 17. Cross tabulation of "there should be more space between agriculture and where people live for health reasons"(x-axis) and LOWEST land use priority to address groundwater overdraft.



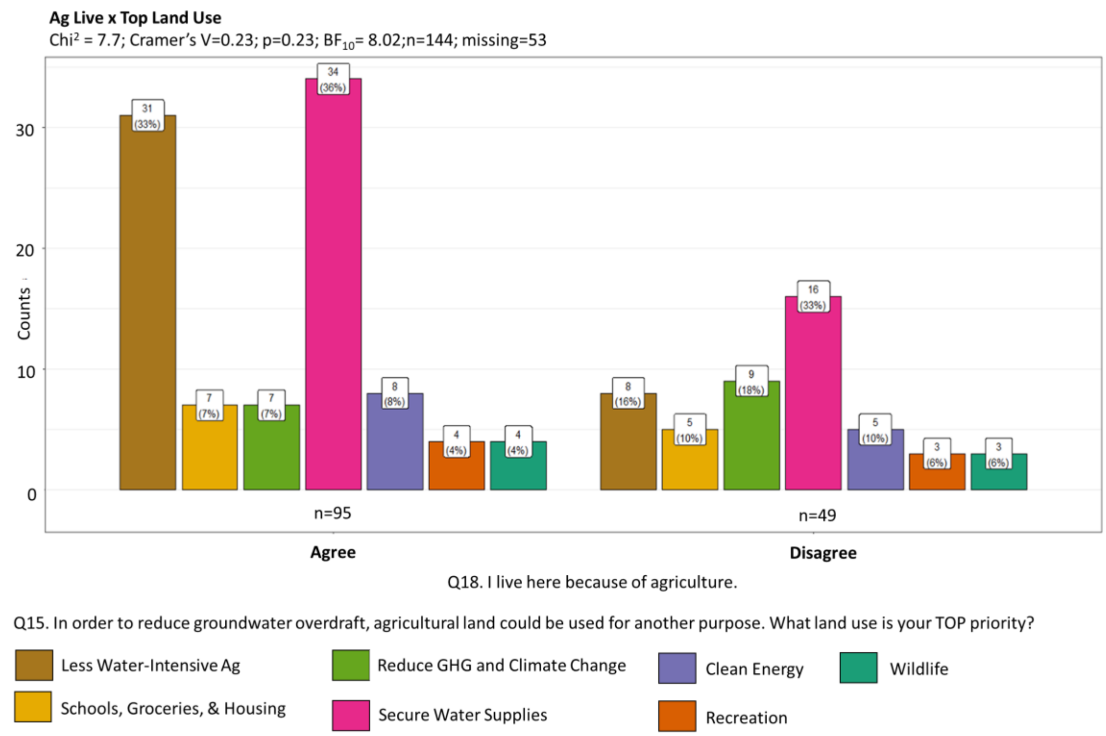
SI Figure 18. Cross tabulation of "there should be more space between agriculture and where people live for health reasons"(x-axis) and TOP land use priority to address groundwater overdraft



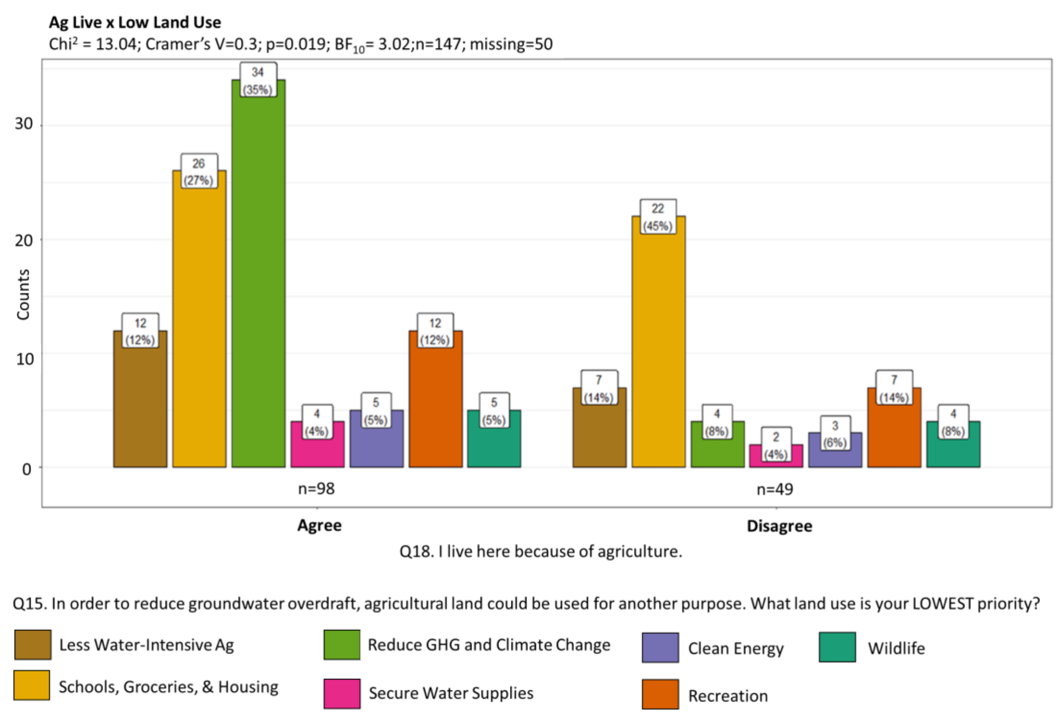
SI Figure 19. Cross tabulation of "farming contributes to air and water pollution in my community" (x-axis) and TOP land use priority to address groundwater overdraft.



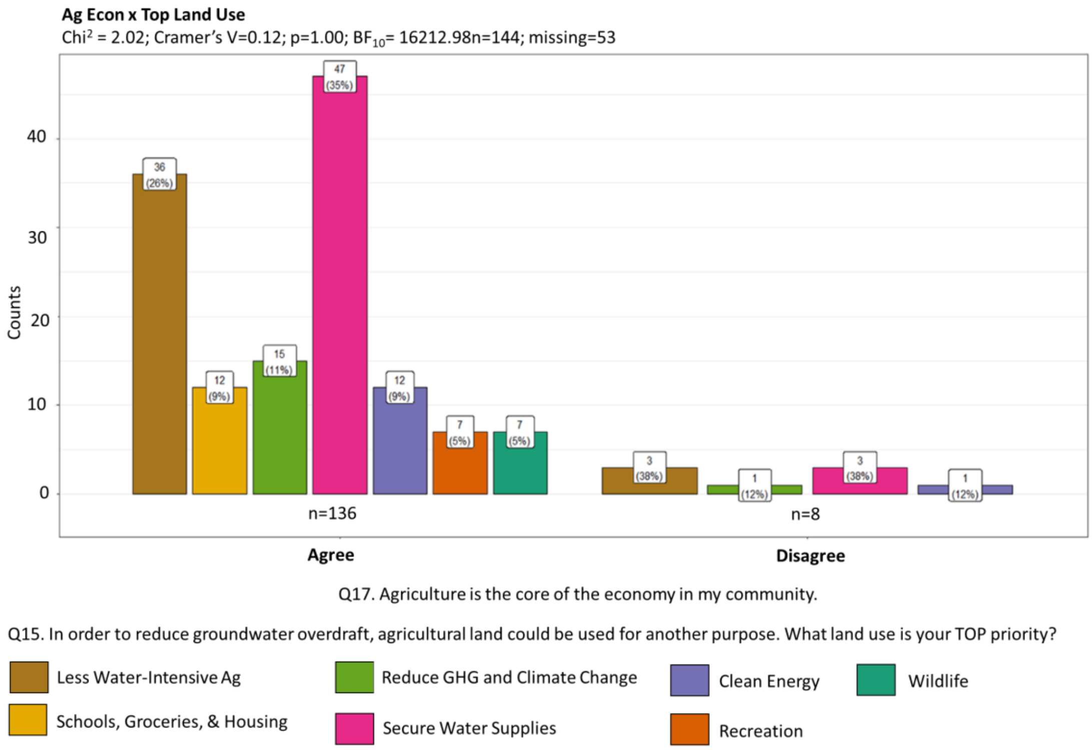
SI Figure 20. Cross tabulation of "farming contributes to air and water pollution in my community"(x-axis) and LOWEST land use priority to address groundwater overdraft.



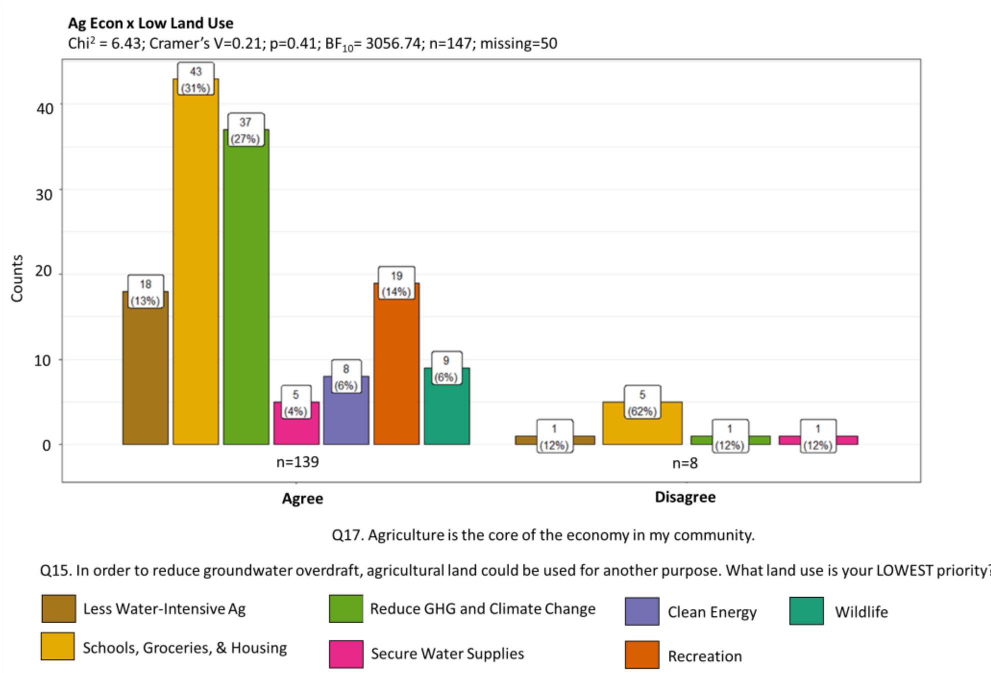
SI Figure 21. Cross tabulation of "I live here because of agriculture"(x-axis) and TOP land use priority to address groundwater overdraft.



SI Figure 22. Cross tabulation of "I live here because of agriculture" (x-axis) and LOWEST land use priority to address groundwater overdraft.



SI Figure 23. Cross tabulation of "agriculture is the core of the economy in my community" (x-axis) and TOP land use priority to address groundwater overdraft.



SI Figure 24. Cross tabulation of "agriculture is the core of the economy in my community" (x-axis) and LOWEST land use priority to address groundwater overdraft.

Community Statement. My community should have more parks, trails, bike paths, and playgrounds.

Economic Statement. My community should NOT spend money on open spaces, like parks, trails, bike paths, and playgrounds.

	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree	Did Not Respond	Total
Strongly Disagree	41% (68)	7% (12)	2% (3)			50% (83)
Somewhat Disagree	9% (16)	13% (22)	5% (9)	1% (2)		28% (49)
Somewhat Agree	1% (1)	6% (9)	7% (11)	1% (1)	1% (1)	16% (23)
Strongly Agree	1% (1)	1% (2)	1% (1)	3% (6)		6% (10)
Total	52% (86)	27% (45)	15% (24)	5% (9)	1% (1)	**165**

SI Figure 25. Cross tabulation between the parks and green space community and economic statements to understand fidelity in participant value on land use in their community. Generally, respondents would like economic investments for more parks and green space in their community.

Community Statement. I value wildlife and would like more nearby places to watch wildlife.

Economic Statement. More wildlife habitat means more wildlife will damage crops and reduce land values.

	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree	Total
Strongly Disagree	20% (32)	7% (12)	2% (4)	1% (2)	30% (50)
Somewhat Disagree	8% (13)	14% (22)	10% (17)	1% (2)	33% (54)
Somewhat Agree	5% (9)	14% (23)	4% (6)	2% (4)	25% (42)
Strongly Agree	6% (10)	1% (2)	2% (3)	2% (4)	12% (19)
Total	39% (64)	36% (59)	18% (30)	7% (12)	**165**

SI Figure 26. Cross tabulation between habitat restoration community and economic statements to understand fidelity in participant value on land use in their community. Some respondents value wildlife and don't think they damage crops nor reduce land values, while others somewhat value places to watch wildlife in their community and somewhat disagree or somewhat agree that this would lead to reduction in land values.Generally, respondents would like economic investments for more parks and green space in their community.

Community Statement. Using farmland to store carbon is a waste of space in my community.

Economic Statement. I think my community should use land to reduce climate change impacts and get paid with carbon credits.

	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree	Did Not Respond	Total
Strongly Agree	7% (11)	8% (13)	5% (8)	5% (8)		24% (40)
Somewhat Agree	8% (14)	10% (17)	8% (13)	2% (3)	1% (1)	29% (48)
Somewhat Disagree	2% (3)	9% (15)	5% (9)	2% (4)		19% (31)
Strongly Disagree	6% (10)	8% (13)	6% (10)	5% (8)	2% (3)	27% (44)
Did Not Respond		1% (1)		1% (1)		1% (2)
Total	23% (38)	36% (59)	24% (40)	15% (24)	2% (4)	**165**

SI Figure 27. Cross tabulation between carbon sequestration community and economic statements to understand fidelity in participant value on land use in their community. There's a support and interest for carbon credits, but moreso with economic incentives. More outreach on carbon sequestration and impacts would be helpful.

Community Statement. Using wetlands, recharge ponds, and wells to help store water underground is important for healthy communities.

Economic Statement. Replenishing groundwater in natural underground storage and wells could improve the economy in my community.

	Strongly Agree	Somewhat Agree	Somewhat Disagree	Strongly Disagree	Did Not Respond	Total
Strongly Agree	47% (79)	10% (16)	2% (3)	1% (2)		61% (100)
Somewhat Agree	10% (17)	21% (34)	2% (3)	1% (1)		33% (55)
Somewhat Disagree	1% (1)	2% (4)	2% (3)			5% (8)
Strongly Disagree					1% (1)	1% (1)
Did Not Respond		1% (1)				1% (1)
Total	58% (97)	33% (55)	5% (9)	2% (3)	1% (1)	**165**

SI Figure 28. Cross tabulation between groundwater recharge community and economic statements to understand fidelity in participant value on land use in their community. Most respondents value groundwater recharge for the well-being, both health and economic, of their community.

Community Statement. Land used to create clean energy, from the sun and wind, is a waste of space in my community.

Economic Statement. Land that generates electricity from the sun and wind could help the economy in my community.

	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree	Total
Strongly Agree	32% (52)	6% (10)	2% (3)	4% (6)	43% (71)
Somewhat Agree	10% (17)	15% (24)	6% (10)	2% (4)	33% (55)
Somewhat Disagree	1% (2)	3% (5)	7% (11)	2% (3)	13% (21)
Strongly Disagree	1% (1)	1% (1)	2% (3)	7% (12)	10% (17)
Did Not Respond				1% (1)	1% (1)
Total	44% (72)	24% (40)	16% (27)	16% (26)	165

SI Figure 29. Cross tabulation between groundwater recharge community and economic statements to understand fidelity in participant value on land use in their community. Most respondents strongly disagree that clean energy is a waste of space and believe that it could improve the economy in their community.

Ag Space. There should be space between farmland and where people live due to health concerns.

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td>10% (2)</td><td rowspan="2">15% (3)</td><td>20% (4)</td><td rowspan="2">35% (7)</td></tr>
<tr><td>Somewhat Agree</td><td>5% (1)</td><td>15% (3)</td></tr>
<tr><td>Somewhat Disagree</td><td>25% (5)</td><td rowspan="2">35% (7)</td><td>10% (2)</td><td rowspan="2">15% (3)</td></tr>
<tr><td>Strongly Disagree</td><td>10% (2)</td><td>5% (1)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

SI Figure 30. Breakdown of farmers and other agricultural professionals pespective on the implementation of space between agriculture and communities for health reasons. Farms are more likely to disagree with the implementation of space between farmland and communities, while other ag professional agree.

Ag pollution. Ag contributed to air and water quality in my community

	Farmer	Farmer Agree/Disagree	Other Ag	Other Ag Agree/Disagree
Strongly Agree		5% (1)	10% (2)	20% (4)
Somewhat Agree	5% (1)		10% (2)	
Somewhat Disagree	15% (3)	45% (9)	5% (1)	30% (6)
Strongly Disagree	30% (6)		25% (5)	
Grand Total	10	50% (10)	10	50% (10)

SI Figure 31. Breakdown of farmers and other agricultural professionals pespective on agriculture contributes to air and water pollution their community. Both farmers and other ag professionals disagree that agriculture contributes to air and water pollution in their community.

Climate Change is happening in my community.

	Farmer	Farmer Agree/Disagree	Other Ag	Other Ag Agree/Disagree
Strongly Agree	15% (3)	20% (4)	20% (4)	25% (5)
Somewhat Agree	5% (1)		5% (1)	
Somewhat Disagree	25% (5)	30% (6)	5% (1)	25% (5)
Strongly Disagree	5% (1)		20% (4)	
Grand Total	10	50% (10)	10	50% (10)

SI Figure 32. Breakdown of farmers and other agricultural professionals stance on climate change is happening. Farmers are more likely to disagree that climate change is happening. There is an even split among other ag professionals that strongly disagree and strongly agree that climate change is happening.

Climate change is impacting water quantity in my region.

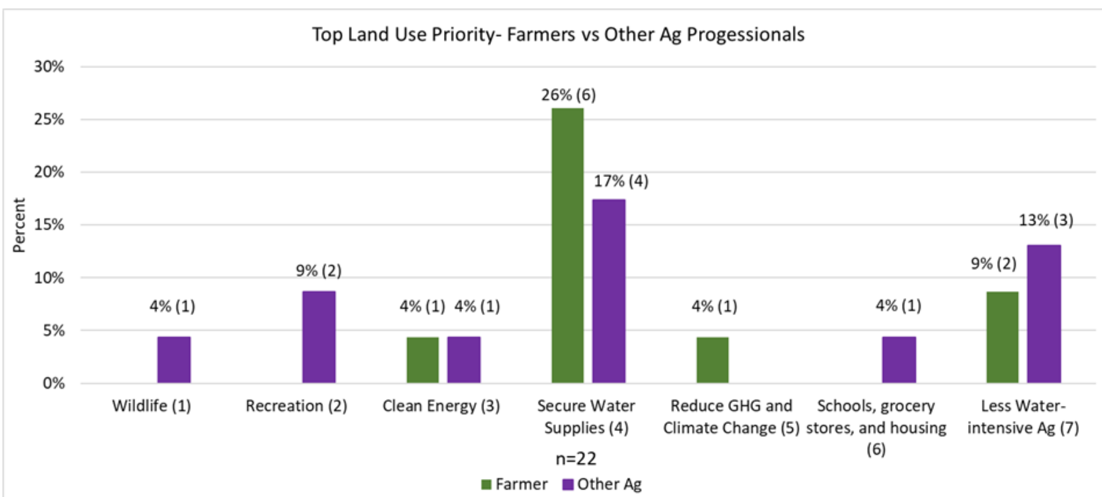
	Farmer	Farmer Agree/Disagree	Other Ag	Other Ag Agree/Disagree
Strongly Agree	15% (3)	15% (3)	15% (3)	25% (5)
Somewhat Agree			10% (2)	
Somewhat Disagree	15% (3)	35% (7)	5% (1)	25% (5)
Strongly Disagree	20% (4)		20% (4)	
Grand Total	10	50% (10)	10	50% (10)

SI Figure 33. Breakdown of farmers and other agricultural professionals stance on climate change is impacting water quantity in the region. Farmers are more likely to disagree that *climate change impacts water quantity in their region, while other ag professional are evenly split between agree and disagree.*

Climate change is impacting water quality in my region.

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td>15% (3)</td><td rowspan="2">20% (4)</td><td>15% (3)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Somewhat Agree</td><td></td><td>10% (2)</td></tr>
<tr><td>Somewhat Disagree</td><td>15% (3)</td><td rowspan="2">30% (6)</td><td>5% (1)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Strongly Disagree</td><td>20% (4)</td><td>20% (4)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

SI Figure 34. Breakdown of farmers and other agricultural professionals stance on climate change is impacting water quality in the region. Farmers are more likely to disagree that climate change impacts water quality in their region, while other ag professional are evenly split between agree and disagree.



SI Figure 35. Breakdown of top land use priority should agricultural land transition to address groundwater overdraft between farmers and other agricultural professionals. The top land use priority is secure water supplies for farmers and other ag professionals, but between the two most farmers selected secure water supplies. The second preferred top land use is less water-intensive ag.

Geographic distribution of farmers and other ag professionals (County)								
	Fresno	Kern	Madera	Merced	San Joaquin	Stanislaus	Tulare	Grand Total
Farmer	5% (1)	10% (2)		10% (2)		10% (2)	15% (3)	50% (10)
Other Ag		5% (1)	5% (1)	20% (4)	10% (2)		10% (2)	50% (10)
Grand Total	5% (1)	15% (3)	5% (1)	30% (6)	10% (2)	10% (2)	25% (5)	20

SI Figure 36. Geographic distribution of farmer and other agricultural professionals that responded to the survey by county.

	Farmer	Other Ag
She/her/hers	15% (3)	20% (4)
He/him/his	20% (4)	20% (4)
They/them/theirs	15% (3)	10% (2)
Grand Total	10	10

SI Figure 37. Preferred gender pronouns of respondents that have jobs that depend on agriculture.

Income Level	Farmer	Other Ag
Low (<$40K)		15% (3)
Medium (>$40K & <$80K)	20% (4)	10% (2)
High (>$80K)	30% (6)	25% (5)
Grand Total	10	10

SI Figure 38. The income distribution of respondents that stated that their job depends on agriculture.

Ethnicity	Farmer	Other Ag
Latino /Spanish Origin	0% (0)	16% (7)
White	31% (14)	13% (6)
Multi-Ethnic/Prefer Not To Answer	20% (9)	20% (9)
Grand Total	51% (23)	49% (22)

SI Figure 39. Ethnicity distribution of respondents that identified as farmers and other agricultural professionals.

Familiarity with SGMA	Farmer	Other Ag	Grand Total
Not at all familiar (1)	5% (1)	20% (4)	25% (5)
Somewhat familiar (2)	15% (3)	15% (3)	30% (6)
Very familiar (3)	30% (6)	15% (3)	45% (9)
Grand Total	10	10	20

SI Figure 40. Respondents that identify as farmers are somewhat (15%) to very (30%) familiar with SGMA, while other agricultural professionals are mostly not at all familiar with SGMA (20%).

My job depends on ag.

	Farmer	Other Ag	Grand Total
Strongly Agree	48% (10)	43% (9)	90% (19)
Somewhat Agree		10% (2)	10% (2)
Grand Total	48% (10)	52% (11)	21

I live here because of agriculture.

	Farmer	Other Ag	Grand Total
Strongly Agree	50% (10)	35% (7)	85% (17)
Somewhat Agree		15% (3)	15% (3)
Grand Total	50% (10)	50% (11)	20

Agriculture is the core of the economy in my community.

	Farmer	Other Ag	Grand Total
Strongly Agree	45% (9)	35% (7)	80% (16)
Somewhat Agree	5% (1)	10% (2)	15% (3)
Somewhat Disagree		5% (1)	5% (1)
Grand Total	50% (10)	50% (11)	20

SI Figure 41. Respondents whose job depends on agriculture and their responses to agriculture statements.

Ag Space. There should be space between farmland and where people live due to health concerns.

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td>10% (2)</td><td rowspan="2">15% (3)</td><td>20% (4)</td><td rowspan="2">35% (7)</td></tr>
<tr><td>Somewhat Agree</td><td>5% (1)</td><td>15% (3)</td></tr>
<tr><td>Somewhat Disagree</td><td>25% (5)</td><td rowspan="2">35% (7)</td><td>10% (2)</td><td rowspan="2">15% (3)</td></tr>
<tr><td>Strongly Disagree</td><td>10% (2)</td><td>5% (1)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

Ag pollution. Ag contributed to air and water quality in my community

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td></td><td rowspan="2">5% (1)</td><td>10% (2)</td><td rowspan="2">20% (4)</td></tr>
<tr><td>Somewhat Agree</td><td>5% (1)</td><td>10% (2)</td></tr>
<tr><td>Somewhat Disagree</td><td>15% (3)</td><td rowspan="2">45% (9)</td><td>5% (1)</td><td rowspan="2">30% (6)</td></tr>
<tr><td>Strongly Disagree</td><td>30% (6)</td><td>25% (5)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

SI Figure 42. Respondents who identify as farmers or other agricultural professionals and their levels of agreement to statements on agricultural buffers/space between farmland and where people live and agriculture's contribution to pollution.

Climate Change is happening in my community.

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td>15% (3)</td><td rowspan="2">20% (4)</td><td>20% (4)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Somewhat Agree</td><td>5% (1)</td><td>5% (1)</td></tr>
<tr><td>Somewhat Disagree</td><td>25% (5)</td><td rowspan="2">30% (6)</td><td>5% (1)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Strongly Disagree</td><td>5% (1)</td><td>20% (4)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

Climate change is impacting water quantity in my region.

<table>
<tr><th></th><th>Farmer</th><th>Farmer Agree/Disagree</th><th>Other Ag</th><th>Other Ag Agree/Disagree</th></tr>
<tr><td>Strongly Agree</td><td>15% (3)</td><td rowspan="2">15% (3)</td><td>15% (3)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Somewhat Agree</td><td></td><td>10% (2)</td></tr>
<tr><td>Somewhat Disagree</td><td>15% (3)</td><td rowspan="2">35% (7)</td><td>5% (1)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Strongly Disagree</td><td>20% (4)</td><td>20% (4)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

Climate Change is happening in my community.

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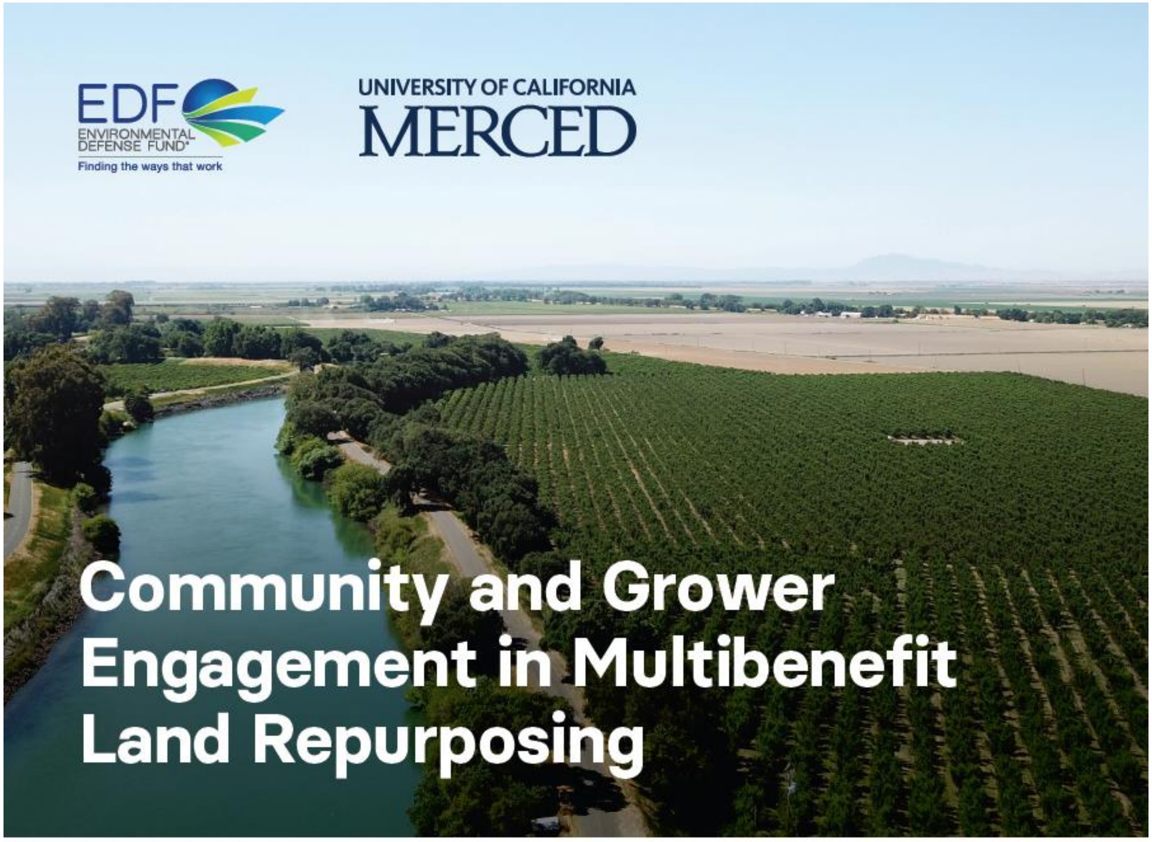
<tr><td>Strongly Agree</td><td>15% (3)</td><td rowspan="2">20% (4)</td><td>15% (3)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Somewhat Agree</td><td></td><td>10% (2)</td></tr>
<tr><td>Somewhat Disagree</td><td>15% (3)</td><td rowspan="2">30% (6)</td><td>5% (1)</td><td rowspan="2">25% (5)</td></tr>
<tr><td>Strongly Disagree</td><td>20% (4)</td><td>20% (4)</td></tr>
<tr><td>Grand Total</td><td>10</td><td>50% (10)</td><td>10</td><td>50% (10)</td></tr>
</table>

SI Figure 43. Responses of respondents that identify as farmers or other agricultural professionals to climate change statements.

APPENDIX B. GUIDE TO COMMUNITY ENGAGEMENT



Multibenefit land repurposing is the practice of transitioning irrigated land to new uses that conserve water and deliver new benefits to communities or ecosystems.

Over the next two decades, major agricultural regions in California will transition to sustainable groundwater use, as mandated by the 2014 Sustainable Groundwater Management Act (SGMA). As much as 750,000 acres of farmland in the San Joaquin Valley may need to be taken out of production by 2040 to balance groundwater supply and demand and address climate change-driven water scarcity and water access inequities.

If unmanaged, fallowed fields can emit dust and worsen air quality, host weeds and pests, and pose an economic threat to agricultural regions. Low-income and other marginalized communities will likely be affected most severely by these impacts.

However, there is an alternative to land fallowing: **multibenefit land repurposing**. Potential new uses of agricultural lands include restored habitat corridors, community recreational spaces, low-impact solar and groundwater recharge basins, all of which can help improve air quality and soil health.

New California Multibenefit Land Repurposing Program

In 2021 California established and funded the Multibenefit Land Repurposing Program with an initial $50 million to reduce reliance on groundwater while providing community health, economic well-being, water supply, habitat, renewable energy and climate benefits.

California's Department of Conservation will administer this new program and provide block grants to local agencies, tribes and nonprofits[1]. These block grants can in turn be used to develop regional agricultural land repurposing plans and provide payments to landowners for voluntarily participating in land repurposing projects, such as habitat restoration, cover cropping, multibenefit groundwater recharge, community park creation and renewable energy production.

This new program recognizes the importance of engaging disadvantaged communities and requires block grant recipients to actively engage stakeholders, including rural community residents and small-scale growers, in the development of local agricultural land repurposing plans. The program also requires prioritizing projects that benefit disadvantaged communities and socially disadvantaged farmers and ranchers for funding.

Block grant applicants

who demonstrate expertise and develop plans to engage with and meaningfully include the feedback of farmers, ranchers, disadvantaged community members and tribes in the development and implementation of land repurposing will be ranked more competitively and be more likely to receive funding from the Multibenefit Land Repurposing Program.

Block grant recipients can use funding from the program for outreach-related expenses such as translation services, stipends to compensate participants for their time and input, and other services to alleviate barriers to participation such as transportation and child care.

For more information on eligible outreach, education and training costs, please see Section 5 of the Multibenefit Land Repurposing Guidelines.

UC Merced Lessons Learned

Recognizing the importance of involving often over-looked communities, University of California, Merced, researchers launched a project in 2021 to identify the priorities of underserved populations who may not otherwise be participating in SGMA and land use discussions, and determine the best strategies to engage them.

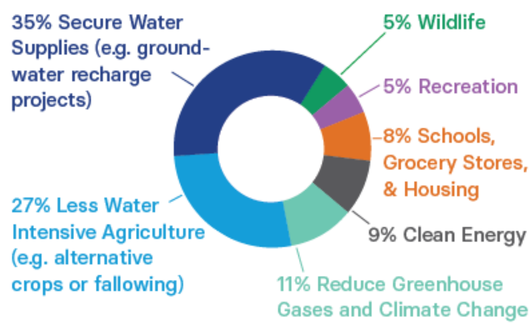
Videos open the door to conversation

UC Merced Ph.D. student Vicky Espinoza developed a trilingual (Spanish, Hmong and English) YouTube channel, CaliWaterAg, to address a knowledge equity gap by providing digestible information on the science and policy of water and land use management in California. The channel covers water management challenges and opportunities under SGMA, potential land use options to conserve water, and ways that community members can actively inform local water and land use solutions. These videos provide a common foundation of knowledge for community members, who could then choose to participate in workshops that explored SGMA and approaches to addressing groundwater overdraft, including multibenefit land repurposing options.

UC Merced hosted workshops and conducted a bilingual survey in 2021 to hear directly from impacted stakeholders and community members about their preferences for land repurposing.

The following pie chart shows the priorities of the survey's 149 respondents. While these results provide one snapshot of broad preferences for land uses among San Joaquin Valley residents, more targeted surveys are recommended to best understand the unique preferences and priorities for local and regional land repurposing.

Land Use Priorities



1 Eligible Block Grant Applicants include: (1) Groundwater Sustainability Agencies ("GSAs"), (2) federally recognized California Native American tribes, (3) non-federally recognized California Native American tribes on the contact list maintained by the Native American Heritage Commission; (4) public agencies; (5) nonprofit groups with 501(c) status; and (7) watermasters implementing an approved groundwater sustainability plan or approved alternate plan.

Recommendations for effective community engagement on land repurposing

1. INCREASE INFORMATION ACCESSIBILITY

- **Recorded videos can provide digestible information** and be watched when convenient. Short videos (aim for less than 15 minutes) help maintain audience interest and attention.
- **Offer multilingual materials** (e.g., brochures, videos, meetings, meeting announcements, social media postings). Find subject experts that speak constituents' preferred language (Spanish, Hmong, etc.) to present material or use a translator well-versed in the terminology.
- **Distribute materials across multiple channels** to be more inclusive and reach a broader audience. This could include mail, text message, email, websites, and informational flyers at schools, grocery stores, post offices, community centers and fire stations.
- **Consider using surveys to learn about constituents' knowledge, values and preferences on land uses.** Using different platforms to conduct surveys (e.g. mail, in-person, web, email, or text) is highly recommended. Ensure survey questions across the different platforms include the same questions to allow for consolidation of survey responses. Allow ample time for completing the survey, send repeated requests, and provide reminders of the survey deadline.
- **If hosting a workshop or webinar, use interactive presentations** to engage the audience, maintain interest and attention, and spark discussion. Consider using software that implements interactive polls remotely (e.g., Zoom) or both remotely and in-person (e.g., Mentimeter). Some community members may not have access to reliable broadband, so keep in mind that online forums exclude a large portion of community members in the Valley, and consider providing a call-in option.
- **Hold meetings or workshops at times and locations that are feasible** for most participants to attend, or offer multiple meetings or workshops on different days/times with transportation and child care provided.

2. PROVIDE CLEAR DEFINITIONS

- **Provide clear, concise definitions** to new terminology or complicated concepts (e.g., carbon credits, carbon sequestration, aquifers, groundwater recharge).
- **Review different land repurposing options** with participants in terms of costs and benefits to their community.
- **Provide examples**, including visuals, of what land repurposing options could look like to help stakeholders better envision what they would like to see in their community.

3. LEARN FROM YOUR COMMUNITY

- **Diverse perspectives** help create equitable, locally representative and resilient climate change solutions. Think about underrepresented groups in your groundwater basin and ensure that they are included in the conversation. These groups often include but are not limited to communities of color, those for whom English is a second language, state-defined "disadvantaged communities"[2], native/tribal groups, small-scale farmers and refugee farmers.
- **Actively learn and listen** to stakeholders as they face environmental and water challenges and share insights about their community needs.
- **Use a combination of methods to obtain community input** to broaden reach and increase diversity, equity and inclusion in community land repurposing plans. These methods could include surveys, workshops and webinars.
- **Create an advisory committee that represents diverse stakeholder groups** to guide the creation of agricultural land repurposing plans. Advisory committees are also a powerful way to ensure priorities of low-income communities and small-scale growers and ranchers are reflected in planning and repurposing projects.

2 For the purposes of the Multibenefit Land Repurposing Program, the Department of Conservation defines a disadvantaged community as a community with a median household income less than 80 percent of the statewide average.

Restoring habitat for species like this San Joaquin kit fox is one land repurposing option growers can use to conserve groundwater.

Guiding Principles for Equitable Engagement in Coordinated Planning

Recognizing the pressing need to include historically underrepresented voices (often predominantly Black, Brown and Indigenous communities of color) in local planning efforts, CivicWell developed the following seven principles to guide equitable collaborative planning:

1. **Acknowledge and re-evaluate** previous histories of inequitable decision-making.
2. **Require** all planning processes, projects and/or grantees to develop a plan for building authentic community relationships.
3. **Increase and promote accessibility** to public meetings, whether online or in person.
4. **Foster two-way communication** and reciprocity with your community.
5. **Focus on building relationships** with local organizations or informal groups that are already engaging with marginalized communities.
6. **Coordinate** with partner agencies and across internal departments to leverage resources, staff and data to address participant fatigue.
7. **Be responsive** to the interconnectedness of community concerns.

Case Study: Fairmead Groundwater Resilience Project

The Fairmead Groundwater Resilience Project is one emerging example of a land repurposing project with strong community benefits. The project will evaluate land repurposing opportunities and assess groundwater recharge potential that can improve community well reliability. Implementation of the project will enhance Fairmead's drinking water supply and stabilize groundwater levels in the surrounding area. The project is a collaborative effort led by Madera County in partnership with Leadership Counsel for Justice and Accountability, Sustainable Conservation and CivicWell. It is supported by Fairmead Community & Friends, a local organization with strong interest in drinking water and other issues in the Fairmead area.

More resources

Advancing Strategic Land Repurposing and Groundwater Sustainability in California, Environmental Defense Fund

Climate Change in the San Joaquin Valley: A Household and Community Guide to Taking Action, Union of Concerned Scientists

Collaborating for Success: Stakeholder Engagement for Sustainable Groundwater Management Act Implementation, Community Water Center, Clean Water Fund, Union of Concerned Scientists

Guiding Principles for Equitable Engagement in Coordinated Planning, CivicWell

Multibenefit Land Repurposing Guidelines, Appendix E: Best Practices for Disadvantaged Community Engagement, California Department of Conservation

Multibenefit Land Repurposing Program, California Department of Conservation

Contacts:

Anna Schiller, Environmental Defense Fund, aschiller@edf.org

Vicky Espinoza, UC Merced, caliwaterag@gmail.com

APPENDIX C. CALIWATERAG YOUTUBE CHANNEL

Trilingual YouTube Channel

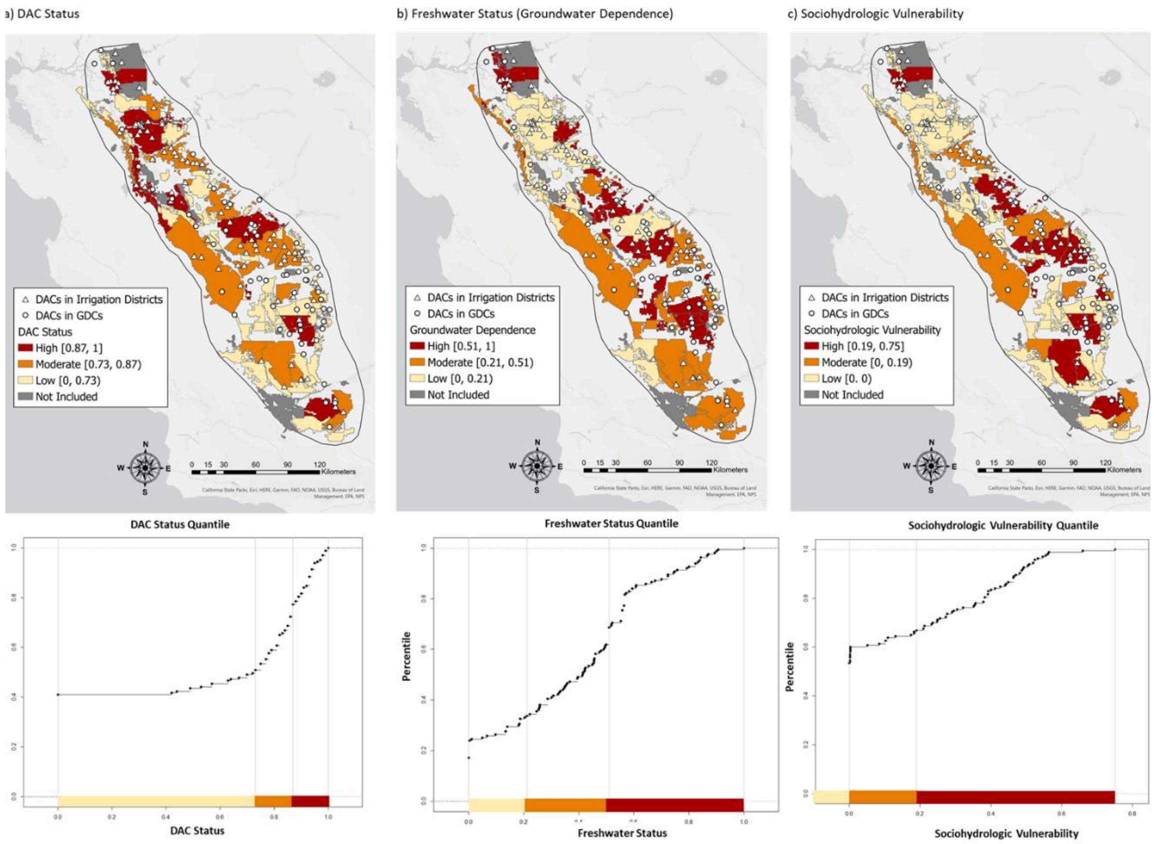
Fostering a better understanding of the science and policy behind California water and land use management.

* Videos available in Spanish, Hmong, and English
* San Joaquin Valley & Water Land Use series: Learn more about the Sustainable Groundwater Management Act (SGMA) & its implications on agriculture
* Drinking Water Issues in Underserved Communities in the San Joaquin Valley series

Visit CaliWaterAg at www.tinyurl.com/caliwaterag or scan the QR code with your phone

For questions contact CaliWaterAg creator:
Vicky Espinoza
PhD Candidate at UC Merced
(323) 547-5506
caliwaterag@gmail.com

APPENDIX D. CHAPTER 3 SUPPLEMENTARY INFO



SI Figure 44. Irrigation district a) DAC status (California Office of Environmental Health Hazard Assessment, 2018), b) freshwater status, and c) sociohydrologic vulnerability. Freshwater status is defined by groundwater dependence as a function of an irrigation district's surface water delivery. The DAC status is defined by the socioeconomic and environmental burden conditions for disadvantaged communities (DACs) within irrigation districts (triangles) and within groundwater-dependent communities (GDCs) (circles). Calculation of the high, moderate, and low classes are defined by DAC status, freshwater status, and sociohydrologic vulnerability quantiles shown below the maps.

Pollution Burden	Population Characteristics
Exposures	***Exposures***
• Ozone Concentrations • PM2.5 Concentrations • Children's Lead Risk from Housing • Diesel PM Emissions • Drinking Water Contaminants • Pesticide Use • Toxic Releases from Facilities • Traffic Density	• Asthma • Cardiovascular Disease • Low Birth Weight Infants
Environmental Effects	***Socioeconomic Factors***
• Solid Waste Sites and Facilities • Groundwater Threats • Hazardous Waste • Impaired Water Bodies • Cleanup Sites	• Educational Attainment • Housing Burdened Low Income Households • Linguistic Isolation • Poverty • Unemployment

SI Table 8. Components that make up the pollution burden and population characteristics of the overall CalEnviroScreen4.0 score obtained to represent the socioeconomic and environmental status of DACs within irrigation districts. The DAC status is one component of the sociohydrologic vulnerability index for this study.

Major Datasets	Source
Irrigation District Boundaries	Most updated irrigation district boundaries were obtained mainly from county LAFCOs in 2019. • San Joaquin Local Agency Formation Commission (LAFCO)- www.sjgov.org/commission/lafco/ • Stanislaus LAFCO- www.stanislauslafco.org/ • Merced LAFCO- www.lafcomerced.org/ • Fresno LAFCO- www.fresnolafco.org/ • Madera LAFCO- www.maderacounty.com/government/madera-lafco • Tulare LAFCO- lafco.co.tulare.ca.us/lafco/ • Kern LAFCO- www.kerncounty.com/government/other-agencies/local-agency-formation-commission-lafco • Kings County and Irrigation Districts not included in the LAFCO boundaries from the Department of Water Resources (DWR) Atlas Database (decommissioned webpage): Irrigation and Water District Boundaries (accessed in September 2019)- data now available via gis.data.cnra.ca.gov/datasets/

Surface Water Allocations	• State Water Resources Control Board (SWRCB) eWRIMS – Electronic Water Rights Information Management System; accessed November 2020- https://www.waterboards.ca.gov/waterrights/water_issues/programs/ewrims/ • DWR State Water Project Contractor lists (Averages 1962-2017); Dataset obtained from Alvar Escriva-Bou (Public Policy Institute of California); data originally accessed from- https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/State-Water-Project/Management/Bulletin-132/Bulletin-132/Files/B132-18-Appendix_B.pdf • U.S. Bureau of Reclamation (USBR) CVP Agricultural Contractors list; accessed in 2020- https://www.usbr.gov/mp/cvp-water/water-contractors.html • Other sources obtained from individual irrigation districts – Agricultural Water Management Plans; Groundwater Sustainability Plans; USBR reports
Surface Water Delivery (Average)	• Irrigation District surface water delivery 2001-2015 average. Data from J. Jezdimirovic, E. Hanak, A. Escriva-Bou. 2020. PPIC San Joaquin Valley Surface Water Availability. Public Policy Institute of California. • Banta-Carbona Irrigation District and Byron-Bethany Irrigation District surface water delivery average 2008-2019. Data from Tracy Subbasin GSP, Table 7.3: https://tracysubbasin.org/gsp-chapters/ • South San Joaquin Irrigation District (SSJID) surface water delivery average 2005-2019. Data from SSJID 2020 Agricultural Water Management Plan, Table 4-1: https://www.ssjid.com/wp-content/uploads/2020-Ag-Water-Management-Plan.pdf
Land Use Classification	• DWR 2016 Statewide Crop Mapping dataset; accessed from CNRA in December 2020- https://data.cnra.ca.gov/dataset/statewide-crop-mapping
2016 Crop Revenue Values	• San Joaquin County 2016 Crop Report- https://www.sjgov.org/department/agcomm/crop_reports • Stanislaus County 2016 Crop Report- http://www.stanag.org/agricultural-statistics.shtm • Merced County 2016 Crop Report- https://www.co.merced.ca.us/151/Crop-Statistics-Reports • Fresno County 2016 Crop Report- https://www.co.fresno.ca.us/departments/agricultural-commissioner/fresno-county-crop-report-dmi • Madera County 2016 Crop Report- https://www.maderacounty.com/government/agricultural-commissioner-weights-and-measures/annual-crop-reports • Kings County 2016 Crop Report- https://www.countyofkings.com/departments/general-services/crop-reports • Tulare County 2016 Crop Report- https://agcomm.co.tulare.ca.us/ag/index.cfm/standards-and-quarantine/crop-reports1/crop-reports-2011-2020/ • Kern County 2016 Crop Report- http://www.kernag.com/caap/crop-reports/crop-reports.asp
Disadvantaged Community Environmental and Poverty Percentiles	• CalEnviroScreen 4.0 (2018) results by census tract; accessed from OEHHA in October 2021: https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40 • DWR 2018 census places shapefile (2018): https://gis.water.ca.gov/app/dacs/ • DWR census places and CalEnviroScreen Census tract shapefiles were joined in ArcPro

SI Table 9. List of major datasets and their sources used to derive variables used in this analysis.

Variable	Acronym	Unit	Description
Irrigation District Traits			
Irrigation District Unique Identification	UID	NA	Unique identification created for each irrigation district (ID)
Irrigation District Short Name	IDShortName	NA	Shortened version of the ID name
Formation	Formation	Year	ID websites, Agricultural Water Management Plans (AWMPs), Groundwater Sustainability Plans (GSPs)
Age*	Age	Years (Yrs.)	Deduced from 'Formation' year (2021 – Year Formed)
Formation Era	Era	Year Range	There are four formation eras reflective of major water management events in California: 1887-1913, 1914-1968, 1969-2000, 2001-2020 based on Hanak et al, 2011
Era Name	EraLabel	Name	Era names are as following in chronological order based on Formation Era description: Era of Local Organization, Hydraulic Era, Era of Conflict, Era of Reconciliation based on Hanak et al, 2011
Service Area	ServArea_Ha	Hectares (Ha)	Based off the LAFCO irrigation district boundaries; calculate the area in ArcGIS in Acres and Hectares; validated using ID websites and other resources
Latitude	LAT	Decimal degrees	y-coordinate of the centroid of ID boundaries; for ID with multiple polygons the polygon with the larger area was selected
Longitude	LON	Decimal degrees	x-coordinate of the centroid of ID boundaries; for ID with multiple polygons the polygon with the larger areas was selected
Group Name	GroupName	NA	The group named reflects the irrigation district's cluster group
Surface Water Allocation Variables			
Surface Water Allocation	SWAlloc	Megaliter (ML)	The amount of 100% surface water allocation in a year (i.e., total surface water rights); Amounts obtained from SWRCB eWRIMS database, USBR contract lists, Agricultural Water Management Plans, and Groundwater Sustainability Plans; sum of all surface water allocation sources (e.g., CVP, SWP, other)
Normalized Surface Water Allocation*	SWAlloc_MLHa	Megaliter per Hectare (ML/Ha)	Derived by dividing the surface water allocation by the ID crop area (Ha)

Pending Surface Water Allocations	PendingSW	ML	The amount of surface water allocation pending approval by the State Water Resource Control Board (SWRCB); data from SWRCB electronic Water Rights Information Management System (eWRIMS)
Normalized Pending Surface Water Allocations*	PendingSW_MLHa	ML/HA	Derived by dividing the pending surface water allocation amounts by irrigation district crop areas (Ha)
Surface Water Delivery (Average)	SWDelivery	ML	Based on average surface water deliveries from 2001-2015 as reported by (Jezdimirovic *et al.*, 2020b) for available irrigation districts. Banta-Carbona ID and Byron-Bethany ID surface water delivery average from 2008-2019; data from Tracy Subbasin GSP. South San Joaquin ID surface water delivery average from 2005-2019; Data from SSJID 2020 Agricultural Water Management Plan
Normalized Surface Water Delivery*	SWDelivery_MLHa	ML/Ha	Derived from dividing the Surface Water Delivery by the ID crop area
Central Valley Project Water (CVP) Allocation	TheoCVP	ML	Values obtained from USBR contract water allocation reports, Agricultural Water Management Plans, and Groundwater Sustainability Plans
Normalized Central Valley Project Water Allocation*	TheoCVP_MLHa	ML/Ha	Derived from dividing the CVP allocation by the ID crop area
State Water Project (SWP) Allocation	TheoSWP	ML	Values obtained from DWR contract water allocation reports, Agricultural Water Management Plans, and Groundwater Sustainability Plans
Normalized State Water Project Allocation*	TheoSWP_MLHa	ML/Ha	Derived from dividing the SWP by the ID crop area
Difference in Surface Water Allocation vs Delivery*	DiffThRel_MLHa	AF/Ha	The difference between surface water allocation and actual average amount of surface water delivered
Crop Water Requirement	CWR	ML	Deduced from WAFR model (Booth et al., 2018) CWR output on Land IQ 2016 data for San JoaquinValley applied to Land IQ 2016 land uses; Sum of the CWR of all crops within the IDs; CWR is derived by the evapotranspiration of blue water (surface water/groundwater) divided by the harvested acres within an irrigation district, which results in the depth of water multiplied by the ID crop area
Normalized Crop Water Requirement*	NCWR16_AFHa	ML/Ha	Derived by dividing the CWR for Land IQ 2016 by the IDcrop area

Surface Water Allocation Surplus/Deficit	SWAllocSurDef	ML	Difference between Surface Water Allocation and CWR
Normalized Surface Water Allocation Surplus/Deficit *	SWAllocSurDef_ MLHa	ML/Ha	Derived by dividing the surplus/deficit amounts resulting after meeting CWR based on surface water allocation by ID crop area
Surface Water Delivery Surplus/Deficit	SWDelSurDef	ML	Difference between Surface Water Delivery and CWR
Normalized Surface Water Delivery Surplus/Deficit *	SWDelSurDef_M LHa	ML/Ha	Derived by dividing the surplus/deficit amounts resulting after meeting CWR based on surface water delivery by ID crop area
Crop Variables			
Total Irrigated Crop Area	CropFct	Ha	Obtained from Land IQ 2016 data for crops within IDs; includes Mixed Pasture & Miscellaneous Grasses
Fraction of Total Irrigated Crop Area*	CropFct	Fraction	Divided the Total Irrigated Crop Area by the ID Service Area
Perennial Crop Area	PerennialCropAre a	Ha	Obtained from Land IQ 2016 data for crops within IDs; Categorized Land IQ perennial crops as perennial to create this variable
Fraction of Perennial Crops *	PerenFct	Fraction	Deduced dividing by ID perennial area by the ID total crop area
Annual Crop Area	AnnCrpArea	Ha	Obtained from Land IQ 2016 data for crops within IDs; Categorized Land IQ annual crops as annual to create this variable
Fraction Annual Crop Area*	AnnualFct	Fraction	Deduced by dividing each ID annual crop area by ID crop area
Irrigated Forage Crop Area	IrrigPastCropArea	Ha	Obtained from Land IQ 2016 data for crops within IDs; Categorized pasture, Miscellaneous Grain and Hay, Miscellaneous Grasses, and Alfalfa as irrigated forage
Fraction Irrigated Forage Area*	IrrigPastFct	Fraction	Deduced by dividing each ID irrigated forage area by ID crop area
Fraction for Top Crops in the San Joaquin Valley*	Fct_[Crop Name]	Fraction	Obtained the areas for the top crops in the San Joaquin Valley from Land IQ 2016 data for crops within IDs; The top crops in the San Joaquin Valley are Almond, Walnuts, Grapes, Cotton, and Citrus.
Crop Economic Variables			
Total Crop Revenue	TotCropRev	USD	Land IQ 2016 data was used to calculate the sum of acres across all crop types within each ID. County Crop Reports 2016 were used to assign crop revenues to associated crops (for more details on Crop Report values used per crop type see Excel Sheet 2). The final total crop revenue is the sum of revenue for all crop types per ID

Normalized Total Crop Revenue *	TotCropRev_USDHA	USD/Ha	Derived by dividing the total crop revenue by ID crop area
Annual Crop Revenue	AnnualRev	USD	Land IQ 2016 data was used to calculate the sum of acres across all crop types within each ID. County Crop Reports 2016 were used to assign crop revenues to associated crops (for more details on Crop Report values used per crop type see Excel Sheet 2). The final annual crop revenue is the sum revenue for all annual crop types per ID
Normalized Annual Crop Revenue *	AnnualRev_USDHA	USD/Ha	Derived by dividing the annual crop revenue by ID annual crop area
Perennial Crop Revenue	PerennCropRev	USD	Land IQ 2016 data was used to calculate the sum of acres across all crop types within each ID. County Crop Reports 2016 were used to assign crop revenues to associated crops (for more details on Crop Report values used per crop type see Excel Sheet 2). The final perennial crop revenue is the sum revenue for all perennial crop types per ID
Normalized Perennial Crop Revenue *	PerennRev_USDHa	USD/Ha	Derived by dividing the perennial crop revenue by ID perennial crop area
Disadvantaged Community Variables			
DAC Name	DACName	NA	Identifier of disadvantaged communities
Associated Irrigation District or White Area	ID_WA	NA	Derived by joining DAC centroids to irrigation district and white area vector shapefile
DAC Population (2018)	Pop18	NA	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset
Median Household Income (2018)	MHI18	USD	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset
DAC Severity Status	Status	NA	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset
DAC Longitude	Longitude	Decimal degrees	Derived by finding the coordinate of each DAC polygon centroid in ESRI ArcPro software
DAC Latitude	Latitude	Decimal degrees	Derived by finding the coordinate of each DAC polygon centroid in ESRI ArcPro software
CalEnviroScreen 4.0 Score Percentile	CIScoreP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen4.0 states that derived from CalEnviroScreen Score which is the Pollution Score multiplied by Population Characteristics Score; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
PM2.5 Percentile	pmP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen4.0 states that derived from

			PM2.5 Score which is the annual mean PM2.5 concentrations; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
Drinking Water Score Percentile	drinkP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 states that it is the drinking water contaminant index for selected contaminants; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
Groundwater Threats Score Percentile	gwthreatsP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 states that it is the percentile of the sum of weighted GeoTracker leaking underground storage tank sites within buffered distances to populated blocks of census tracts; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
Pollution Score Percentile	PollutionP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen states that the Pollution Burden is the average of percentiles from the Pollution Burden indicators (with a half weighting for the Environmental Effects indicators) and the Pollution Burden Score is the Pollution Burden variable scaled with a range of 0-10. (Used to calculate CES 4.0 score) which is used for the pollution burden percentile; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
Asthma Percentile	asthmaP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; is the percentile of the age-adjusted rate of emergency department visits for asthma; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
Poverty Percentile	povP	Percentile	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen states that it is the percentile of the percent of the population living below two times the federal poverty level; See CalEnviroScreen Data Dictionary for more details https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40

Hispanic Population Percentage	Hispanic_pct	Percent	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 derives this from 2019 ACS population estimates of the percent per census tract of those who identify as Hispanic or Latino
White Population Percentage	White_pct	Percent	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 derives this from 2019 ACS population estimates of the percent per census tract of those who identify as non-Hispanic white
African American Population Percentage	African_American_pct	Percent	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 derives this from 2019 ACS population estimates of the percent per census tract of those who identify as non-Hispanic African American or black
Native American Population Percentage	Native_American_pct	Percent	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 derives this from 2019 ACS population estimates of the percent per census tract of those who identify as non-Hispanic Native American
Asian American Population Percentage	Asian_American_pct	Percent	Derived by joining DAC census place centroids to the CalEnviroScreen vector dataset; CalEnviroScreen 4.0 derives this from 2019 ACS population estimates of the percent per census tract of those who identify as non-Hispanic Asian or Pacific Islander

SI Table 10. Irrigation district variables and their associated acronyms, units, and descriptions categorized by irrigation district traits, surface water variables, crop variables, crop economic variables, and DAC variables. Variables with an asterisk were used for the cluster analysis.

District/White Area	**DACName**	**Pop18**	**CI (%)**	**$PM_{2.5}$ (%)**	**Poor Drinking Water (%)**	**GW Threats (%)**	**Pollution (%)**	**Asthma (%)**
003AID	Traver	740	91	98	95	66	89	40
	London	1854	91	98	95	66	89	40
	Seville	691	70	95	97	39	64	41
	Yettem	441	77	95	96	61	75	19
	Monson	380	75	97	99	57	96	43
	Delft Colony	653	75	97	99	57	96	43
	Cutler	5774	77	95	96	61	75	19
	Orosi	7441	88	95	74	43	81	57
	Dinuba City	23871	87	97	80	77	84	46

	Sultana	1030	75	97	99	57	96	43
	Reedley City	25493	91	98	51	91	81	73
006AEWSD	Arvin city	21005	79	94	99	84	91	39
017CCID	South Dos Palos	1682	89	93	45	87	60	95
	Volta	216	93	69	89	88	86	84
019CWD	Chowchilla City	18533	72	82	32	90	63	65
020CID	Caruthers	2773	87	97	94	0	65	89
	Monmouth	103	86	97	93	39	91	83
	Selma City	24598	86	98	42	52	86	93
	Parlier City	15120	99	98	82	32	93	93
	Bowles	194	98	97	98	32	97	85
	Del Rey	1498	94	97	90	50	86	68
	Sanger City	24978	83	97	74	0	69	79
022DPWD	Crows Landing	278	82	66	93	83	92	55
023DEID	Rodriguez Camp	87	89	98	88	14	78	55
032EID	Tooleville CD	309	49	94	97	53	60	32
	Exeter City	10505	57	97	56	34	50	37
	Lindcove	438	49	94	97	53	60	32
036FID	Easton	2206	98	97	99	59	98	95
	West Park	1035	93	97	91	14	89	98
	Biola CDP	1451	70	95	97	14	71	36
047KDWD	Weedpatch	2238	63	99	98	0	54	28
	Fuller Acres	841	96	99	100	86	90	83
050LID	Laton	2166	77	98	91	9	64	59
058LID	Plainview	863	86	95	95	89	76	71
059LSID	El Rancho	65	73	95	96	81	77	48
	Tonyville	881	73	95	96	81	77	48
060LHWD	Lost Hills	1943	87	84	91	98	95	39
062MID	La Vina	239	85	95	100	83	98	68
	Parkwood	1853	95	82	92	76	94	90
066MID	El Nido	328	81	93	93	93	94	63
	Le Grand	1726	75	84	87	36	71	37
	Planada	4418	87	93	63	50	63	99
	Tuttle	63	87	93	63	50	63	99
	Bear Creek	157	78	93	74	67	82	98
	Merced City	82289	94	93	42	95	73	99
	Franklin	7314	93	93	84	78	91	87
	Atwater City	29197	64	93	52	9	41	77
	Winton	11761	90	93	71	81	83	72

	Livingston City	13997	82	93	84	0	75	47
	Cressey	356	78	93	71	98	92	52
068MCWD	Stevinson	331	78	93	54	55	66	44
070MID	West Modesto	5911	93	93	92	4	80	88
	Rouse	2420	99	93	92	57	90	90
	Airport	1222	100	93	92	47	99	91
	Waterford City	8823	67	93	65	36	66	37
	Empire	3667	94	93	96	0	93	55
073NKWSD	Shafter City	18923		100	97	80	96	78
076OID	Oakdale City	22599	78	93	65	36	94	62
083PID	Pixley	3796	91	99	94	62	84	58
086RCWD	Raisin City	389	84	97	95	71	78	91
087RID	Riverdale CDP	3625	82	97	87	0	64	72
	Lanare	234	82	97	87	0	64	72
093SLWD	Santa Nella	2508	93	69	89	88	86	84
095SWSD	Buttonwillow	1591	84	99	87	46	91	25
096SWID	Mexican Colony	363	85	100	94	51	88	44
	Cherokee Strip	191	85	100	94	51	88	44
	Wasco City	26708	87	100	88	72	86	38
102SEWD	French Camp	3857	94	82	100	98	100	32
	Taft Mosswood	951	98	82	29	75	90	97
	Kennedy	3665	93	93	54	58	81	83
	Garden Acres	10701	88	94	87	41	79	61
	Country Club	9846	79	94	54	84	79	77
	Stockton City	306283	53	94	29	92	67	60
	August	8774	94	94	29	66	78	91
104SID	Stratford	878	89	95	74	69	81	73
107TID	Tranquillity	839	87	95	81	74	79	54
110TID	Waukena	215	86	99	94	47	85	79
	Matheny	1134	86	99	94	47	85	79
111TID	Turlock City	72335	81	93	85	64	71	59
	Monterey Park Tract	291	95	93	100	85	97	70
	Cowan	570	82	93	100	58	84	46
	Keyes	6185	82	93	100	58	84	46
	Ceres City	47975	90	93	95	22	94	50
	Bret Harte	5319	99	93	92	0	89	87
	Riverdale Park	1301	95	93	100	85	97	70
	Parklawn	1082	97	93	100	61	98	59

	Bystrom	4099	100	93	91	42	97	91
	Hickman	566	63	93	96	65	86	26
116WSID	Westley	838	86	66	95	92	95	47
118WWD	Lemoore Station	7063	82	98	42	71	77	84
	Westside	182	81	95	64	77	61	70
	Cantua Creek	273	87	95	81	74	79	54
	Three Rocks	210	95	84	61	76	73	88
122CSJWCD	Farmington	89	44	66	79	69	71	23
124NSJWCD	Victor	444	42	55	99	54	68	22
	Collierville	2642	57	54	96	89	90	16
125SLCC	Dos Palos Y	242	92	93	65	14	73	95
123WA02Kern	Mettler	138	78	93	49	99	97	15
	Lamont	15222	59	100	99	0	52	32
	Greenfield	3534	87	100	100	14	73	89
	Oildale	34723	86	100	52	96	96	86
	McFarland City	14456	78	100	52	0	56	67
	Delano City	52713	96	99	90	58	92	60
129WA07Tula 129WA07Tula	Richgrove	2611	89	98	88	14	78	55
	Allensworth	527	89	98	88	14	78	55
	Earlimart	8790	72	99	79	14	48	60
	Alpaugh	1074	89	98	88	14	78	55
	Ducor	651	81	95	88	94	76	53
	Teviston	1027	91	99	94	62	84	58
	Terra Bella	3304	81	95	88	94	76	53
122WA01King	Kettleman City	1395	89	95	74	69	81	73
129WA07Tula	Poplar-Cotton Center	2436	95	95	98	99	95	64
	Tipton	3218	83	98	91	27	81	53
	East Porterville	6679	81	93	99	51	58	59
	Porterville City	59797	82	99	70	9	57	67
122WA01King	Corcoran city	22301	67	99	44	4	32	86
129WA07Tula	Woodville	1852	83	98	91	27	81	53
	Strathmore	2915	86	95	95	89	76	71
	Tulare City	62838	95	99	56	78	85	84
124WA03Fres	Huron City	7019	70	95	58	37	68	70
129WA07Tula	Lindsay City	13232	73	95	91	73	57	63
122WA01King	Lemoore City	25791	63	99	53	59	62	84
	Home Garden	1643	97	99	57	98	88	98
129WA07Tula	Farmersville City	10742	81	98	92	24	77	47
	Linnell Camp	686	81	98	92	24	77	47

122WA01King	Armona	3795	77	98	61	74	61	95
129WA07Tula	West Goshen	567	90	97	100	93	96	44
	Goshen	3316	90	97	100	93	96	44
	Patterson Tract	2351	90	97	100	93	96	44
	Ivanhoe	4198	70	95	97	39	64	41
	Woodlake City	7636	73	82	55	52	52	60
	East Orosi	955	85	93	91	14	72	55
124WA03Fres	San Joaquin City	4021	87	95	81	74	79	54
	Orange Cove City	9564	90	95	79	59	69	80
	Malaga	1337	100	97	99	92	100	90
	Calwa	1974	100	97	81	95	99	89
	Kerman City	14649	75	95	36	41	73	64
	Mendota City	11393	95	84	61	76	73	88
	Mayfair	5091	85	97	81	0	60	97
	Fresno City	522277	72	97	81	0	56	83
	Firebaugh City	8295	84	69	41	91	82	66
125WA04Made	Parksdale	2493	75	93	94	6	60	87
	Madera city	64362	67	82	56	58	64	90
124WA03Fres	Friant	548	32	97	99	70	91	32
127WA06Merc	Dos Palos City	5272	89	93	45	87	60	95
	Los Banos City	38119	96	93	57	95	76	96
125WA04Made	Fairmead	1876	90	84	91	23	78	64
127WA06Merc	Gustine city	5774	91	94	85	81	85	72
	UC Merced	0	87	93	63	50	63	99
130WA08Stani	Grayson	1224	86	66	95	92	95	47
126WA05SJoa	Terminous	411	65	43	96	76	76	12
	Lodi City	65006	24	55	65	16	27	21
	Thornton	1038	65	43	96	76	76	12

SI Table 11. Irrigation District and White Area DAC list and statistics

		High [0.19, 0.75]	***Moderate [0, 0.19)***	***Low [0, 0)***
Number Of Irrigation Districts		*15*	*14*	*73*
Number Of Disadvantaged Communities		*41*	*35*	*87*
Freshwater Status (Groundwater Dependence)				
	Maximum	*0.89*	*0.58*	*1.00*
	Average	*0.55*	*0.19*	*0.35*
	Minimum	*0.40*	*0.00*	*0.00*
DAC Status				
	Maximum	*0.99*	*0.98*	*1.00*
	Average	*0.84*	*0.79*	*0.20*
	Minimum	*0.42*	*0.44*	*0.00*
Sociohydrologic Vulnerability Index				
	Maximum	0.75	0.30	0
	Average	0.46	0.13	0
	Minimum	0.31	0.00	0

SI Table 12. Summary of total number of irrigation districts and disadvantaged community counts, irrigation district age, freshwater status, DAC Status, and Sociohydrologic Vulnerability Index values for High, Moderate, and Low classes defined by quantiles.

		High	Moderate	Low
Era of Conflict				
	DAC Count		1	12
	Freshwater Status		0.07	0.55
	DAC Status		0.78	0
	Sociohydrologic Vulnerability Index		0.05	0
Era of Local Organization				
	DAC Count	11	2	18
	Freshwater Status	0.5	0.2	0
	DAC Status	0.8	0.9	0.8
	Sociohydrologic Vulnerability Index	0.4	0.2	0
Era of Reconciliation				
	DAC Count			3
	Freshwater Status			0.8
	DAC Status			0
	Sociohydrologic Vulnerability Index			0
Hydraulic Era				
	DAC Count	30	32	54
	Freshwater Status	0.6	0.2	0.4
	DAC Status	0.8	0.8	0.05
	Sociohydrologic Vulnerability Index	0.5	0.1	0

SI Table 13. Summary of sociohydrologic vulernability, freshwater status, DAC status, and DAC count for irrigation districts in their respective formation periods or eras..

IDShortName	UID	Cluster	GroupName	Era	EraLabel
AlisoAWD	001AWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
AlpaughAID	002AID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
AltaAID	003AID	3	Sizeable Crop Generalists	1887-1913	Era of Local Organization
AmsterdamAWD	004AWD	1	Groundwater Dependent Vineyards	2001-2020	Era of Reconciliation
AngiolaAWD	005AWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
ArvinAEWSD	006AEWSD	4	California Citrus Belt	1914-1968	Hydraulic Era
BallicoBCWD	008BCWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
BantaBCID	009BCID	5	Senior, Secure Nut Growers	1914-1968	Hydraulic Era
BelridgeBWSD	010BWSD	4	California Citrus Belt	1914-1968	Hydraulic Era
BerrendaBMWD	011BMWD	4	California Citrus Belt	1914-1968	Hydraulic Era
BuenaBVWSD	012BVWSD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
ByronBBID	013BBID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
CaweloCWD	015CWD	4	California Citrus Belt	1914-1968	Hydraulic Era
CentralCalCCID	017CCID	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
ChowchillaCWD	019CWD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
ConsolidatedCID	020CID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era

CorcoranCID	021CID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
DelPuertoDPWD	022DPWD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
DelanoDEID	023DEID	5	Senior, Secure Nut Growers	1914-1968	Hydraulic Era
DudleyDRWD	026DRWD	4	California Citrus Belt	1914-1968	Hydraulic Era
EaglefieldEWD	027EWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
EastinEWD	028EWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
EastsideEWD	029EWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
ElSolyoESWD	030ESWD	Not Included	Not Included	1914-1968	Hydraulic Era
EmpireEWSID	031EWSID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
ExeterEID	032EID	4	California Citrus Belt	1914-1968	Hydraulic Era
FarmersFWD	033FWD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
FirebaughCWD	034FCC	2	Forage and Corron Corridor	1969-2000	Era of Conflict
FreeFWC	035FWC	4	California Citrus Belt	1914-1968	Hydraulic Era
FresnoFID	036FID	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
FresnoSloFSWD	037FSWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
GarfieldGWD	038GWD	4	California Citrus Belt	1914-1968	Hydraulic Era
GravellyGFWD	040GFWD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
HillsHVID	042HVID	4	California Citrus Belt	1914-1968	Hydraulic Era

InternationalIWD	044IWD	4	California Citrus Belt	1969-2000	Era of Conflict
IvanhoeIID	045IID	4	California Citrus Belt	1914-1968	Hydraulic Era
JamesJID	046JID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
KernDeltaKDWD	047KDWD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
KernTulKTWD	048KTWD	4	California Citrus Belt	1969-2000	Era of Conflict
KingsKRWD	049KRWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
LagunaLID	050LID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
LagunaLWD	051LWD	Not Included	Not Included	1969-2000	Era of Conflict
LakesideLID	052LID	Not Included	Not Included	1914-1968	Hydraulic Era
LeGrandLGAWD	055LGAWD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
LibertyLWD	057LWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
LindmoreLID	058LID	4	California Citrus Belt	1914-1968	Hydraulic Era
LindsayLSID	059LSID	4	California Citrus Belt	1914-1968	Hydraulic Era
LostLHWD	060LHWD	4	California Citrus Belt	1914-1968	Hydraulic Era
LowerTulLTID	061LTID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
MaderaMID	062MID	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
MaderaMWD	063MWD	4	California Citrus Belt	1969-2000	Era of Conflict
MelgaMWD	065MWD	Not Included	Not Included	1914-1968	Hydraulic Era
MercedMID	066MID	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era

MercyMSWD	067MSWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
MerquinMCWD	068MCWD	2	Forage and Corron Corridor	1969-2000	Era of Conflict
MidvalleyMWD	069MWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
ModestoMID	070MID	5	Senior, Secure Nut Growers	1887-1913	Era of Local Organization
NagleeBurkNBID	071NBID	Not Included	Not Included	1914-1968	Hydraulic Era
NewStoneNSWD	072NSWD	1	Groundwater Dependent Vineyards	1969-2000	Era of Conflict
NKernNKWSD	073NKWSD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
OakOFWD	075OFWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
OakdaleOID	076OID	5	Senior, Secure Nut Growers	1887-1913	Era of Local Organization
OraOLWD	078OLWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
OrangeOCID	079OCID	4	California Citrus Belt	1914-1968	Hydraulic Era
PachecoPWD	080PWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
PanochePWD	081PWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
PattersonPID	082PID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
PixleyPID	083PID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
PortervillePID	085PID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
RaisinRCWD	086RCWD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era

RiverdaleRID	087RID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
RootRCWD	089RCWD	4	California Citrus Belt	2001-2020	Era of Reconciliation
RosedaleRRBWSD	090RRBWSD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
SalyerSWD	091SWD	Not Included	Not Included	1914-1968	Hydraulic Era
ColumbiaCCC	092CCC	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
SanLuisSLWD	093SLWD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
SaucilitoSID	094SID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
SemitropicSWSD	095SWSD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
ShafterSWID	096SWID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
SSanJoaqSSJID	098SSJID	5	Senior, Secure Nut Growers	1887-1913	Era of Local Organization
StevinsonSWD	099SWD	Not Included	Not Included	1914-1968	Hydraulic Era
StocktonSEWD	102SEWD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
StoneSCID	103SCID	4	California Citrus Belt	1914-1968	Hydraulic Era
StratfordSID	104SID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
TeapotTDWD	105TDWD	4	California Citrus Belt	1914-1968	Hydraulic Era
TerrabellaTID	106TID	4	California Citrus Belt	1914-1968	Hydraulic Era
TranquillityTID	107TID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
TriangleTTTWD	108TTWD	1	Groundwater Dependent Vineyards	2001-2020	Era of Reconciliation

TrivalleyTWD	109TWD	4	California Citrus Belt	1914-1968	Hydraulic Era
TulareTID	110TID	2	Forage and Corron Corridor	1887-1913	Era of Local Organization
TurlockTID	111TID	5	Senior, Secure Nut Growers	1887-1913	Era of Local Organization
TurnerTIWD	112TIWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
WestSideWSID	115WSID	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
WestStanWSID	116WSID	5	Senior, Secure Nut Growers	1914-1968	Hydraulic Era
WestlandsWWD	118WWD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
WheelerWRMWSD	119WRMWSD	4	California Citrus Belt	1914-1968	Hydraulic Era
WidrenWWD	120WWD	2	Forage and Corron Corridor	1914-1968	Hydraulic Era
WoodbridgeWID	121WID	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
CSJWCD	122CSJWCD	1	Groundwater Dependent Vineyards	1914-1968	Hydraulic Era
Rock Creek WD	123RCWD	Not Included	Not Included	1914-1968	Hydraulic Era
NSJWCD	124NSJWCD	3	Sizeable Crop Generalists	1914-1968	Hydraulic Era
San Luis Canal Co	125SLCC	2	Forage and Corron Corridor	1887-1913	Era of Local Organization

SI Table 14. Table of irrigation districts and their associated variables. Note: Table broken up into five parts. This is Part 1/5

ID ShortName	Formation	ServArea_HA	LONG	LAT	Age_Diff 2021	SWDelivery_MLHa	SWAlloc_MLHA
AlisoAWD	1978	10720	-120.282	36.82289	43	0.25	0.00
AlpaughAID	1915	5047	-119.47	35.89505	106	2.65	0.06
AltaAID	1888	53562	-119.401	36.52797	133	4.45	7.47
AmsterdamAWD	2018	2775	-120.53	37.42068	3	0.00	0.00
AngiolaAWD	1957	14810	-119.641	35.92696	64	2.84	6.29
ArvinAEWSD	1942	45554	-118.864	35.20697	79	6.19	13.56
BallicoBCWD	1970	2853	-120.706	37.46506	51	0.00	0.00
BantaBCID	1921	6735	-121.353	37.68297	100	8.22	31.15
BelridgeBWSD	1962	37974	-119.727	35.51648	59	11.89	12.46
BerrendaBMWD	1963	22401	-119.95	35.66188	58	9.47	10.90
BuenaBVWSD	1924	20311	-119.498	35.43105	97	6.71	14.34
ByronBBID	1919	11453	-121.556	37.78543	102	1.71	22.49
CaweloCWD	1965	18778	-119.134	35.56817	56	6.55	6.31
CentralCalCCID	1951	60984	-120.775	37.08014	70	10.27	13.24
ChowchillaCWD	1949	34900	-120.316	37.09229	72	5.09	14.54

ConsolidatedCID	1921	64299	-119.648	36.58473	100	5.39	0.00
CorcoranCID	1919	18857	-119.593	36.07162	102	3.11	0.00
DelPuertoDPWD	1947	21521	-121.164	37.40205	74	6.07	12.95
DelanoDEID	1938	25900	-119.214	35.84225	83	5.94	39.97
DudleyDRWD	1963	15382	-119.86	35.88409	58	6.30	7.79
EaglefieldEWD	1957	573	-120.709	36.91077	64	5.06	13.01
EastinEWD	2000	1434	-121.063	37.33639	21	0.00	0.00
EastsideEWD	1985	28437	-120.636	37.54423	36	0.00	0.00
ElSolyoESWD	1959	1645	-121.237	37.61489	62	0.00	22.02
EmpireEWSID	1930	3127	-119.859	36.18072	91	4.18	1.30
ExeterEID	1937	6068	-119.116	36.30416	84	3.11	8.88
FarmersFWD	1949	896	-120.317	36.76762	72	0.00	0.00
FirebaughCWD	1988	9510	-120.5	36.83756	33	10.27	13.11
FreeFWC	1955	803	-119.494	36.74414	66	0.00	0.00
FresnoFID	1920	98778	-119.825	36.75393	101	9.90	22.31
FresnoSloFSWD	1955	533	-120.295	36.65858	66	11.66	26.16

GarfieldGWD	1956	729	-119.712	36.89698	65	6.42	11.23
GravellyGFWD	1962	3389	-120.207	36.84283	59	3.35	5.76
HillsHVID	1948	1750	-119.304	36.67224	73	5.84	5.65
InternationalIWD	1970	296	-119.609	36.86068	51	15.81	16.44
IvanhoeIID	1948	4451	-119.189	36.40884	73	5.09	6.47
JamesJID	1920	10667	-120.19	36.60779	101	3.81	6.12
KernDeltaKDWD	1965	51537	-119.046	35.21856	56	4.78	7.18
KernTulKTWD	1974	8682	-119.091	35.78066	47	5.97	9.83
KingsKRWD	1952	5636	-119.498	36.69389	69	16.69	0.00
LagunaLID	1920	14704	-119.814	36.40465	101	4.29	6.03
LagunaLWD	1997	174	-120.666	36.98245	24	0.00	6.40
LakesideLID	1962	13058	-119.606	36.25759	59	0.00	27.36
LeGrandLGAWD	1964	9902	-120.315	37.19956	57	0.00	0.00
LibertyLWD	1970	8609	-119.806	36.49078	51	0.76	0.07
LindmoreLID	1937	10992	-119.113	36.16312	84	4.41	7.74
LindsayLSID	1915	6456	-119.045	36.18655	106	9.59	8.60

LostLHWD	1963	31624	-119.759	35.71977	58	9.17	14.04
LowerTulLTID	1950	41250	-119.317	36.06621	71	3.50	15.42
MaderaMID	1920	54257	-120.103	36.94333	101	4.35	9.16
MaderaMWD	1987	1511	-120.037	37.04531	34	2.32	0.00
MelgaMWD	1953	29069	-119.689	36.01884	68	0.00	0.00
MercedMID	1919	66945	-120.533	37.31672	102	10.48	1.79
MercyMSWD	1950	1458	-120.635	36.89949	71	1.70	2.90
MerquinMCWD	1973	4550	-120.869	37.3238	48	6.49	5.94
MidvalleyMWD	1970	5164	-120.175	36.6822	51	0.21	0.00
ModestoMID	1887	41084	-120.976	37.6653	134	17.85	46.33
NagleeBurkNBID	1921	1909	-121.465	37.77866	100	0.00	0.00
NewStoneNSWD	1983	1692	-120.357	36.92177	38	0.00	12.02
NKernNKWSD	1935	32146	-119.234	35.53279	86	6.77	1.41
OakOFWD	1964	1908	-121.154	37.39885	57	4.60	4.86
OakdaleOID	1909	33116	-120.839	37.7647	112	13.05	41.58
OraOLWD	1953	467	-120.672	36.89987	68	2.40	2.04

OrangeOCID	1937	11857	-119.305	36.6177	84	3.75	5.51
PachecoPWD	1953	1922	-120.764	36.88969	68	4.20	11.15
PanochePWD	1950	16145	-120.661	36.83426	71	4.81	9.98
PattersonPID	1955	5193	-121.105	37.47973	66	12.88	6.76
PixleyPID	1958	27341	-119.321	35.95611	63	0.83	1.88
PortervillePID	1949	6903	-119.099	36.07587	72	5.97	14.50
RaisinRCWD	1962	20913	-119.955	36.58656	59	0.00	0.00
RiverdaleRID	1920	6163	-119.914	36.43633	101	7.80	6.84
RootRCWD	2016	3751	-119.84	36.8909	25	0.79	4.12
RosedaleRRBWSD	1959	17501	-119.278	35.38963	62	6.03	3.36
SalyerSWD	1926	1687	-119.626	36.17405	95	0.00	0.00
ColumbiaCCC	1926	6440	-120.404	36.86093	95	10.27	13.50
SanLuisSLWD	1951	26824	-120.838	36.91093	70	7.62	11.56
SaucilitoSID	1941	7987	-119.151	35.98103	80	4.60	9.28
SemitropicSWSD	1958	90947	-119.49	35.62571	63	3.93	1.65
ShafterSWID	1937	19783	-119.323	35.52185	84	5.18	7.57

SSanJoaqSSJID	1909	29262	-121.125	37.78699	112	14.29	49.55
StevinsonSWD	1928	3040	-120.933	37.33529	93	8.53	174.69
StocktonSEWD	1948	58822	-121.17	37.99876	73	2.00	1.35
StoneSCID	1948	2760	-119.189	36.47945	73	4.14	5.61
StratfordSID	1916	4137	-119.823	36.1924	105	1.64	5.44
TeapotTDWD	1954	1411	-119.016	36.01682	67	5.57	7.33
TerrabellaTID	1915	5636	-119.003	35.95247	106	6.52	10.78
TranquillityTID	1918	4294	-120.265	36.63414	103	8.56	11.44
TriangleTTTWD	2016	5828	-120.449	36.9812	5	0.00	0.00
TrivalleyTWD	1964	804	-119.361	36.71537	57	4.02	6.12
TulareTID	1889	27748	-119.431	36.20807	132	7.00	11.94
TurlockTID	1887	77254	-120.885	37.51248	134	13.34	42.68
TurnerTIWD	1966	5820	-120.712	37.17825	55	4.64	0.00
WestSideWSID	1916	2754	-121.469	37.74627	105	0.00	23.82
WestStanWSID	1920	8808	-121.224	37.56482	101	9.57	38.34
WestlandsWWD	1952	246815	-120.243	36.42031	69	5.51	8.76

WheelerWRMWSD	1959	51925	-119.073	35.05671	62	7.37	8.64
WidrenWWD	1955	347	-120.579	36.86547	66	0.12	0.00
Woodbridge WID	1924	15750	-121.358	38.12794	97	0.00	7.33
CSJWCD	1959	29689.51	-121.069	37.9057	61	2.17	4.35
Rock Creek WD	1941	746.0907	-120.839	37.96184	79	0.00	0.00
NSJWCD	1948	62641.62	-121.147	38.1722	72	0.10	0.91
San Luis Canal Co	1913	19134.23	-120.692	37.08923	107	10.27	13.85

SI Table 15. Table of irrigation districts and their associated variables. Note: Table broken up into five parts. This is Part 2/5.

ID ShortName	CWR_ MLHA	TheoCVP_ MLHA	TheoSWP _MLHA	DiffThRel _MLHA	SWAlloc SurDef_ MLHA	SWDelSur Def_MLH A
AlisoAWD	13.20	0	0	-0.2466	-13.20	-12.96
AlpaughAI D	7.84	0.06165	0	-2.5893	-7.78	-5.19
AltaAID	12.08	0	0	3.02085	-4.60	-7.62
Amsterdam AWD	13.45	0	0	0	-13.45	-13.45
AngiolaAW D	9.15	0	3.11949	3.4524	-2.86	-6.31
ArvinAEW SD	11.69	13.563	0	7.37334	1.87	-5.50
BallicoBC WD	11.96	0	0	0	-11.96	-11.96
BantaBCID	8.96	4.35249	0	22.92147	22.19	-0.74
BelridgeB WSD	12.05	0	12.46563	0.57951	0.42	-0.16
BerrendaB MWD	12.18	0	10.89972	1.43028	-1.28	-2.71
BuenaBVW SD	10.58	0	1.77552	7.63227	3.76	-3.87
ByronBBID	9.19	5.57316	0	20.77605	13.30	-7.48
CaweloCW D	13.33	0	3.52638	-0.23427	-7.01	-6.78
CentralCal CCID	8.78	13.24242	0	2.97153	4.46	1.49
Chowchilla CWD	11.43	10.78875	0	9.44478	3.11	-6.33
Consolidate dCID	13.85	0	0	-5.38821	-13.85	-8.47
CorcoranCI D	10.21	0	0	-3.10716	-10.21	-7.10
DelPuertoD PWD	9.89	12.95883	0	6.89247	3.07	-3.82
DelanoDEI D	14.49	39.96153	0	34.01847	25.47	-8.55
DudleyDR WD	13.01	0	7.79256	1.49193	-5.21	-6.71
EaglefieldE WD	8.91	13.00815	0	7.95285	4.10	-3.85
EastinEWD	9.08	0	0	0	-9.08	-9.08
EastsideEW D	12.31	0	0	0	-12.31	-12.31
ElSolyoES WD	11.33	0	0	22.02138	10.70	-11.33
EmpireEW SID	9.30	0	1.30698	-2.87289	-8.00	-5.12

ExeterEID	11.54	8.8776	0	5.77044	-2.66	-8.43
FarmersFWD	14.94	0	0	0	-14.94	-14.94
FirebaughCWD	8.84	13.11912	0	2.84823	4.28	1.43
FreeFWC	11.13	0	0	0	-11.13	-11.13
FresnoFID	12.71	1.92348	0	12.40398	9.60	-2.80
FresnoSloFSWD	5.70	26.15193	0	14.48775	20.45	5.96
GarfieldGWD	12.35	11.2203	0	4.79637	-1.13	-5.93
GravellyGFWD	13.48	5.75811	0	2.40435	-7.72	-10.13
HillsHVID	10.78	5.64714	0	-0.19728	-5.13	-4.94
InternationalIWD	11.42	16.44822	0	0.64116	5.03	4.39
IvanhoeIID	11.39	5.1786	0	1.38096	-4.92	-6.30
JamesJID	10.32	6.11568	0	2.30571	-4.20	-6.51
KernDeltaKDWD	10.69	0	0.88776	2.39202	-3.51	-5.91
KernTulKTWD	13.69	9.82701	0	3.85929	-3.87	-7.73
KingsKRWD	10.13	0	0	-16.69482	-10.13	6.56
LagunaLID	11.11	0	0	1.73853	-5.08	-6.82
LagunaLWD	5.35	6.39927	0	6.39927	1.05	-5.35
LakesideLID	11.19	0	0	27.36027	16.16	-11.19
LeGrandLGAWD	10.49	0	0	0	-10.49	-10.49
LibertyLWD	13.78	0	0	-0.69048	-13.71	-13.02
LindmoreLID	11.82	7.74324	0	3.3291	-4.08	-7.41
LindsayLSID	11.71	8.59401	0	-0.99873	-3.11	-2.11
LostLHWD	12.33	0	14.04387	4.87035	1.71	-3.16
LowerTulLTID	11.25	11.52855	0	11.92311	4.17	-7.75
MaderaMID	13.24	9.16119	0	4.8087	-4.08	-8.88
MaderaMWD	0.00	0	0	-2.31804	0.00	2.32
MelgaMWD	10.81	0	0	0	-10.81	-10.81

MercedMID	10.53	0	0	-8.69265	-8.74	-0.05
MercyMSWD	14.25	2.89755	0	1.19601	-11.35	-12.55
MerquinMCWD	7.48	0	0	-0.54252	-1.53	-0.99
Midvalley MWD	12.51	0	0	-0.20961	-12.51	-12.30
ModestoMID	11.16	0	0	28.46997	35.16	6.69
NagleeBurkNBID	7.20	0	0	0	-7.20	-7.20
NewStoneNSWD	13.55	0	0	12.02175	-1.54	-13.55
NKernNKWSD	12.98	0	0	-5.36355	-11.57	-6.21
OakOFWD	9.10	0	4.85802	0.25893	-4.24	-4.50
OakdaleOID	9.71	16.22628	0	28.53162	31.87	3.33
OraOLWD	12.02	2.04678	0	-0.35757	-9.98	-9.62
OrangeOCID	11.15	5.51151	0	1.76319	-5.65	-7.40
PachecoPWD	8.02	7.6446	0	6.94179	3.13	-3.82
PanochePWD	9.79	9.97497	0	5.16627	0.19	-4.98
PattersonPID	8.35	6.75684	0	-6.12801	-1.59	4.54
PixleyPID	11.65	1.87416	0	1.04805	-9.78	-10.83
PortervillePID	12.17	14.50008	0	8.53236	2.34	-6.20
RaisinRCWD	13.35	0	0	0	-13.35	-13.35
RiverdaleRID	9.79	0	0	-0.96174	-2.96	-2.00
RootRCWD	11.60	0	0	3.34143	-7.48	-10.81
RosedaleRRBWSD	10.89	0	3.36609	-2.66328	-7.53	-4.86
SalyerSWD	9.93	0	0	0	-9.93	-9.93
ColumbiaCCC	12.38	13.50135	0	3.23046	1.12	-2.11
SanLuisSLWD	10.68	11.56554	0	3.9456	0.88	-3.06
SaucilitoSID	13.70	9.28449	0	4.6854	-4.42	-9.10
Semitropic SWSD	11.26	1.65222	0	-2.28105	-9.60	-7.32

ShafterSWID	12.06	7.57062	0	2.39202	-4.50	-6.89
SSanJoaqSSJID	11.76	19.33344	0	35.25147	37.79	2.53
StevinsonSWD	7.64	0	0	166.15908	167.06	0.89
StocktonSEWD	10.34	1.3563	0	-0.65349	-8.99	-8.34
StoneSCID	10.97	5.61015	0	1.46727	-5.36	-6.83
StratfordSID	9.44	0	0	3.79764	-4.00	-7.80
TeapotTDWD	11.75	7.34868	0	1.76319	-4.41	-6.17
TerrabellaTID	11.76	10.77642	0	4.25385	-0.99	-5.24
TranquillityTID	10.02	11.44224	0	2.88522	1.42	-1.46
TriangleTTTWD	11.85	0	0	0	-11.85	-11.85
TrivalleyTWD	10.82	6.11568	0	2.0961	-4.70	-6.80
TulareTID	10.69	9.23517	0	4.932	1.25	-3.68
TurlockTID	10.93	0	0	29.33307	31.74	2.41
TurnerTIWD	7.39	0	0	-4.63608	-7.39	-2.75
WestSideWSID	8.27	3.71133	0	23.82156	15.55	-8.27
WestStanWSID	9.29	8.07615	0	28.76589	29.05	0.28
Westlands WWD	9.81	8.7543	0	3.24279	-1.05	-4.30
WheelerWRMWSD	11.97	0	8.64333	1.26999	-3.32	-4.60
WidrenWWD	5.41	0	0	-0.1233	-5.41	-5.29
WoodbridgeWID	12.44	0	0	7.32402	-5.11	-12.44
CSJWCD	10.88	4.35249	0	2.17008	-6.53	-8.70
Rock Creek WD	3.31	0	0	0	-3.31	-3.31
NSJWCD	12.72	0	0	0.81378	-11.80	-12.62
San Luis Canal Co	8.34	13.84659	0	3.5757	5.51	1.93

SI Table 16. Table of irrigation districts and their associated variables. Note: Table broken up into five parts. This is Part 3/5

ID ShortName	Crop Fct	PerenFct	AnnualFct	IrrigForageFct	AnnualRev_USDHa	IrrigForageRev_USDHa	PerennRev_USDHa
AlisoAWD	0.90	0.96	0.02	0.02	1663.02	462.97	1926.73
AlpaughAID	0.42	0.39	0.23	0.38	282.99	418.71	406.50
AltaAID	0.70	0.77	0.15	0.07	490.64	310.04	3677.22
AmsterdamAWD	0.43	0.91	0.00	0.09	0.00	191.36	2238.38
AngiolaAWD	0.14	0.00	0.54	0.46	268.83	126.82	0.00
ArvinAEWSD	0.70	0.58	0.41	0.02	1785.17	342.44	6669.52
BallicoBCWD	0.84	0.83	0.15	0.02	555.10	78.92	2148.98
BantaBCID	0.84	0.60	0.31	0.09	1077.75	350.59	1804.87
BelridgeBWSD	0.32	0.92	0.06	0.02	0.00	223.80	2799.02
BerrendaBMWD	0.47	0.86	0.04	0.09	185.21	223.80	2665.13
BuenaBVWSD	0.72	0.48	0.37	0.15	746.43	441.93	4061.11
ByronBBID	0.38	0.43	0.32	0.26	503.71	298.78	1760.05
CaweloCWD	0.71	0.99	0.01	0.01	1454.82	223.80	5190.96
CentralCalCCID	0.81	0.18	0.59	0.23	888.67	428.14	1570.56
ChowchillaCWD	0.78	0.70	0.18	0.12	644.15	445.17	1740.23
ConsolidatedCID	0.71	0.96	0.02	0.02	955.73	219.29	3686.08
CorcoranCID	0.76	0.17	0.70	0.13	616.53	429.99	1600.23
DelPuertoDPWD	0.62	0.71	0.20	0.09	910.90	219.97	1987.20
DelanoDEID	0.81	0.97	0.02	0.01	1084.55	124.76	4662.41
DudleyDRWD	0.46	1.00	0.00	0.00	0.00	0.00	2296.05
EaglefieldEWD	0.75	0.00	1.00	0.00	1021.42	0.00	0.00
EastinEWD	0.83	0.50	0.44	0.07	741.62	410.45	1925.44
EastsideEWD	0.85	0.90	0.07	0.04	550.05	78.16	2080.18
ElSolyoESWD	0.78	0.91	0.04	0.06	985.41	424.12	1655.37
EmpireEWSID	0.56	0.16	0.47	0.36	836.46	76.05	2125.45

ExeterEID	0.69	0.99	0.01	0.00	218.33	8.84	3811.23
FarmersFWD	0.61	1.00	0.00	0.00	0.00	0.00	2266.38
FirebaughCWD	0.84	0.22	0.71	0.07	1301.09	394.11	1367.47
FreeFWC	0.74	0.95	0.00	0.05	0.00	6.88	3143.10
FresnoFID	0.49	0.85	0.08	0.07	693.05	286.40	3054.37
FresnoSloFSWD	0.43	0.00	0.86	0.14	3492.35	511.53	0.00
GarfieldGWD	0.53	0.72	0.14	0.14	101.17	175.23	3136.57
GravellyGFWD	0.88	0.91	0.09	0.00	1797.36	0.00	1608.68
HillsHVID	0.57	0.97	0.00	0.03	101.17	88.04	3462.55
InternationalIWD	0.30	1.00	0.00	0.00	0.00	0.00	2367.29
IvanhoeIID	0.84	1.00	0.00	0.00	0.00	0.00	3893.49
JamesJID	0.85	0.50	0.31	0.20	1812.21	510.90	1786.30
KernDeltaKDWD	0.68	0.31	0.48	0.21	733.66	412.98	4293.42
KernTulKTWD	0.84	0.99	0.01	0.00	206.81	223.80	4859.49
KingsKRWD	0.63	0.63	0.03	0.33	877.29	93.46	3041.89
LagunaLID	0.73	0.42	0.38	0.21	417.33	384.81	1892.89
LagunaLWD	0.89	0.00	0.00	1.00	0.00	500.61	0.00
LakesideLID	0.75	0.21	0.63	0.15	546.17	417.70	1691.19
LeGrandLGAWD	0.71	0.51	0.30	0.19	905.49	435.95	2184.45
LibertyLWD	0.84	0.92	0.05	0.03	1747.98	365.06	3089.39
LindmoreLID	0.80	0.90	0.06	0.04	440.43	375.84	3281.79
LindsayLSID	0.61	1.00	0.00	0.00	0.00	8.36	3567.80
LostLHWD	0.33	0.93	0.02	0.05	191.42	223.80	2397.45
LowerTulLTID	0.78	0.31	0.55	0.15	447.97	463.34	2297.26
MaderaMID	0.73	0.94	0.04	0.02	1142.39	179.87	1711.16
MaderaMWD	0.94	1.00	0.00	0.00	0.00	0.00	2822.34
MelgaMWD	0.86	0.00	0.99	0.01	718.29	203.56	0.00

MercedMID	0.65	0.54	0.34	0.12	533.68	270.38	2081.70
MercyMSWD	0.83	0.23	0.07	0.70	390.53	0.00	1088.22
MerquinMCWD	0.65	0.07	0.57	0.36	398.97	232.23	1678.17
Midvalley MWD	0.91	0.86	0.10	0.04	1189.40	511.53	1901.87
ModestoMID	0.53	0.71	0.18	0.11	596.84	166.46	1693.42
NagleeBurk NBID	0.63	0.02	0.55	0.43	515.46	328.26	1758.27
NewStoneNSWD	0.95	0.77	0.16	0.08	403.89	462.97	1370.70
NKernNKWSD	0.68	0.90	0.08	0.02	1158.01	320.80	3239.99
OakOFWD	0.47	0.31	0.31	0.38	912.89	132.95	1860.78
OakdaleOID	0.69	0.55	0.15	0.31	396.89	29.66	1673.48
OraOLWD	0.78	0.00	0.08	0.92	1440.71	106.23	0.00
OrangeOCID	0.74	0.99	0.00	0.01	50.08	132.48	3339.15
PachecoPWD	0.84	0.35	0.61	0.04	1124.68	500.61	1939.24
PanochePWD	0.72	0.54	0.41	0.05	1569.52	298.73	2009.31
PattersonPID	0.79	0.43	0.32	0.25	1490.22	355.44	1460.97
PixleyPID	0.75	0.37	0.48	0.14	445.60	404.79	2703.24
PortervillePID	0.71	0.75	0.16	0.09	597.92	364.82	2672.21
RaisinRCWD	0.87	0.81	0.12	0.07	692.39	504.76	3215.10
RiverdaleRID	0.76	0.32	0.47	0.21	457.99	479.66	1217.89
RootRCWD	0.78	0.99	0.01	0.00	171.59	0.00	2612.95
RosedaleRRBWSD	0.63	0.58	0.23	0.19	607.78	420.39	2893.37
SalyerSWD	0.91	0.00	0.50	0.50	443.93	298.72	0.00
ColumbiaCCC	0.84	0.94	0.03	0.03	1167.16	276.08	1871.23
SanLuisSLWD	0.49	0.67	0.22	0.11	759.66	236.04	2072.60
SaucilitoSID	0.90	0.86	0.11	0.02	399.79	180.29	3216.79
SemitropicSWSD	0.54	0.68	0.17	0.15	661.07	407.74	3053.71

ShafterSWID	0.74	0.77	0.14	0.09	409.16	414.37	2856.32
SSanJoaqSSJID	0.65	0.83	0.11	0.06	565.57	165.99	1872.21
StevinsonSWD	0.44	0.14	0.29	0.56	625.01	370.92	2260.62
StocktonSEWD	0.45	0.82	0.12	0.06	1532.11	266.80	1515.27
StoneSCID	0.80	0.87	0.09	0.04	220.78	127.21	4092.97
StratfordSID	0.60	0.18	0.59	0.23	758.40	362.11	830.67
TeapotTDWD	0.86	0.95	0.04	0.02	222.18	107.27	3878.10
TerrabellaTID	0.59	0.90	0.03	0.07	217.52	124.22	3250.20
Tranquillity TID	0.85	0.36	0.53	0.11	1738.86	511.53	1751.70
TriangleTTTWD	0.92	0.85	0.08	0.07	393.94	371.04	2258.65
TrivalleyTWD	0.39	0.88	0.03	0.09	101.17	171.43	2915.23
TulareTID	0.82	0.31	0.50	0.18	489.43	479.25	1805.11
TurlockTID	0.67	0.50	0.37	0.12	710.61	284.91	1946.68
TurnerTIWD	0.69	0.00	0.77	0.23	730.95	500.61	0.00
WestSideWSID	0.60	0.41	0.15	0.44	446.67	255.36	1887.57
WestStanWSID	0.87	0.66	0.33	0.01	2020.56	419.51	1806.62
Westlands WWD	0.68	0.44	0.49	0.06	1591.37	237.10	1960.76
WheelerWRMWSD	0.54	0.87	0.09	0.04	1753.58	422.61	5642.80
WidrenWWD	0.95	0.58	0.00	0.42	0.00	275.85	1088.22
WoodbridgeWID	0.73	0.75	0.20	0.05	751.37	311.44	1706.95
CSJWCD	0.76	0.53	0.40	0.07	20.38	7.46	39.56
Rock Creek WD	0.25	0.00	0.25	0.75	39.94	0.29	0.00
NSJWCD	0.43	0.82	0.07	0.11	36.07	10.40	85.20
San Luis Canal Co	0.76	0.02	0.79	0.19	19.27	12.73	36.17

SI Table 17. Table of irrigation districts and their associated variables. Note: Table broken up into five parts. This is Part 4/5

ID ShortName	TotCropRev_USDHa	Fct_Almd	Fct_Citrus	Fct_Cotton	Fct_Grpe	Fct_Walnt
AlisoAWD	1893.19	0.37	0.00	0.00	0.24	0.01
AlpaughAID	383.23	0.00	0.00	0.00	0.00	0.00
AltaAID	2944.62	0.04	0.19	0.01	0.11	0.01
AmsterdamAWD	2055.85	0.23	0.00	0.00	0.47	0.21
AngiolaAWD	203.64	0.00	0.00	0.00	0.00	0.00
ArvinAEWSD	4590.54	0.09	0.18	0.00	0.23	0.00
BallicoBCWD	1866.89	0.66	0.00	0.00	0.00	0.07
BantaBCID	1446.34	0.35	0.00	0.00	0.02	0.16
BelridgeBWSD	2577.68	0.40	0.12	0.00	0.00	0.00
BerrendaBMWD	2330.79	0.28	0.00	0.00	0.00	0.00
BuenaBVWSD	2306.09	0.00	0.00	0.23	0.09	0.02
ByronBBID	987.00	0.22	0.00	0.00	0.07	0.03
CaweloCWD	5129.54	0.18	0.29	0.00	0.25	0.00
CentralCalCCID	907.34	0.09	0.00	0.23	0.00	0.04
ChowchillaCWD	1393.49	0.53	0.00	0.00	0.06	0.01
ConsolidatedCID	3570.28	0.12	0.05	0.00	0.50	0.02
CorcoranCID	756.94	0.00	0.00	0.37	0.00	0.00
DelPuertoDPWD	1612.73	0.47	0.01	0.00	0.02	0.05
DelanoDEID	4563.28	0.24	0.03	0.00	0.47	0.01
DudleyDRWD	2296.05	0.28	0.00	0.00	0.07	0.00
EaglefieldEWD	1021.42	0.00	0.00	0.52	0.00	0.00
EastinEWD	1305.64	0.15	0.00	0.00	0.00	0.20
EastsideEWD	1906.08	0.78	0.00	0.00	0.07	0.01
ElSolyoESWD	1559.67	0.62	0.00	0.00	0.05	0.17

EmpireEWSID	771.11	0.00	0.00	0.36	0.03	0.00
ExeterEID	3760.67	0.00	0.83	0.00	0.02	0.00
FarmersFWD	2266.38	0.00	0.00	0.00	0.44	0.00
FirebaughCWD	1251.75	0.08	0.00	0.28	0.00	0.00
FreeFWC	2981.32	0.01	0.74	0.00	0.00	0.00
FresnoFID	2680.27	0.29	0.08	0.00	0.37	0.01
FresnoSloFSWD	3062.92	0.00	0.00	0.00	0.00	0.00
GarfieldGWD	2301.97	0.28	0.02	0.00	0.24	0.00
GravellyGFWD	1625.36	0.29	0.00	0.00	0.38	0.00
HillsHVID	3347.01	0.02	0.75	0.00	0.00	0.00
InternationalIWD	2367.29	0.24	0.50	0.00	0.00	0.00
IvanhoeIID	3893.49	0.00	0.89	0.00	0.00	0.00
JamesJID	1542.28	0.21	0.00	0.14	0.09	0.01
KernDeltaKDWD	1751.61	0.16	0.00	0.08	0.06	0.00
KernTulKTWD	4801.87	0.06	0.29	0.00	0.31	0.00
KingsKRWD	1985.41	0.09	0.01	0.00	0.12	0.09
LagunaLID	1023.66	0.16	0.00	0.04	0.03	0.11
LagunaLWD	500.61	0.00	0.00	0.00	0.00	0.00
LakesideLID	770.15	0.05	0.00	0.13	0.00	0.06
LeGrandLGAWD	1468.50	0.42	0.00	0.04	0.05	0.00
LibertyLWD	2940.14	0.32	0.00	0.00	0.41	0.05
LindmoreLID	2995.25	0.05	0.48	0.01	0.06	0.06
LindsayLSID	3560.60	0.00	0.79	0.00	0.00	0.00
LostLHWD	2254.50	0.17	0.00	0.00	0.01	0.00
LowerTulLTID	1016.83	0.11	0.00	0.03	0.03	0.04

MaderaMID	1652.41	0.42	0.02	0.00	0.33	0.01
MaderaMWD	2822.34	0.00	0.00	0.00	0.00	0.00
MelgaMWD	712.47	0.00	0.00	0.44	0.00	0.00
MercedMID	1336.66	0.40	0.00	0.04	0.02	0.02
MercyMSWD	277.87	0.00	0.00	0.00	0.00	0.00
MerquinMCWD	431.60	0.04	0.00	0.00	0.01	0.00
MidvalleyMWD	1774.35	0.21	0.00	0.00	0.17	0.00
ModestoMID	1329.02	0.44	0.00	0.00	0.01	0.16
NagleeBurkNBID	466.04	0.02	0.00	0.00	0.00	0.00
NewStoneNSWD	1148.26	0.00	0.00	0.00	0.77	0.00
NKernNKWSD	3023.78	0.72	0.00	0.00	0.09	0.00
OakOFWD	914.17	0.15	0.00	0.00	0.04	0.07
OakdaleOID	983.62	0.38	0.00	0.00	0.02	0.10
OraOLWD	218.00	0.00	0.00	0.00	0.00	0.00
OrangeOCID	3303.46	0.01	0.78	0.00	0.03	0.00
PachecoPWD	1387.18	0.30	0.00	0.03	0.00	0.00
PanochePWD	1743.63	0.15	0.00	0.08	0.12	0.00
PattersonPID	1194.35	0.21	0.00	0.00	0.00	0.08
PixleyPID	1282.07	0.19	0.00	0.00	0.08	0.00
PortervillePID	2134.95	0.13	0.09	0.00	0.09	0.26
RaisinRCWD	2732.27	0.28	0.00	0.00	0.46	0.01
RiverdaleRID	706.42	0.04	0.00	0.05	0.01	0.00
RootRCWD	2578.97	0.19	0.39	0.00	0.03	0.00
RosedaleRRBWSD	1893.72	0.47	0.00	0.03	0.03	0.00
SalyerSWD	370.69	0.00	0.00	0.07	0.00	0.00

ColumbiaCCC	1809.32	0.73	0.00	0.01	0.00	0.00
SanLuisSLWD	1589.99	0.58	0.01	0.03	0.01	0.00
SaucilitoSID	2822.32	0.21	0.05	0.01	0.23	0.11
SemitropicSWSD	2250.23	0.40	0.00	0.01	0.05	0.00
ShafterSWID	2293.03	0.66	0.00	0.02	0.04	0.01
SSanJoaqSSJID	1628.85	0.67	0.00	0.00	0.05	0.05
StevinsonSWD	716.27	0.14	0.00	0.00	0.00	0.00
StocktonSEWD	1436.34	0.00	0.00	0.00	0.08	0.47
StoneSCID	3574.10	0.01	0.70	0.00	0.02	0.00
StratfordSID	679.79	0.03	0.00	0.26	0.00	0.00
TeapotTDWD	3683.01	0.01	0.84	0.00	0.00	0.00
TerrabellaTID	2934.25	0.00	0.57	0.00	0.00	0.00
TranquillityTID	1608.06	0.22	0.00	0.22	0.02	0.00
TriangleTTTWD	1978.97	0.48	0.00	0.00	0.00	0.00
TrivalleyTWD	2574.93	0.00	0.87	0.00	0.00	0.00
TulareTID	900.01	0.06	0.00	0.09	0.01	0.08
TurlockTID	1280.85	0.38	0.00	0.00	0.01	0.04
TurnerTIWD	678.82	0.00	0.00	0.25	0.00	0.00
WestSideWSID	959.98	0.36	0.00	0.00	0.03	0.01
WestStanWSID	1859.50	0.42	0.00	0.00	0.04	0.07
WestlandsWWD	1673.14	0.21	0.01	0.06	0.04	0.00
WheelerWRMWSD	5096.97	0.20	0.30	0.01	0.27	0.00
WidrenWWD	747.00	0.00	0.00	0.00	0.00	0.00
WoodbridgeWID	1443.90	0.01	0.00	0.00	0.62	0.05
CSJWCD	29.68	0.11	0.00	0.00	0.13	0.24

Rock Creek WD	10.28	0.00	0.00	0.00	0.00	0.00
NSJWCD	73.81	0.01	0.00	0.00	0.62	0.10
San Luis Canal Co	18.42	0.00	0.00	0.36	0.00	0.00

SI Table 18. Table of irrigation districts and their associated variables. Note: Table broken up into five parts. This is Part 5/

UID	ShortName	Group Name	TheoSW16_AF	PendingSW_AF	PendingSW_AFAc	PendingSW_AFHa	TheoSW16_AFAc	TheoSW16_AFHA
001AWD	AlisoAWD	Groundwater Dependent Vineyards	0	0	0	0	0	0
002AID	AlpaughAID	Forage and Corron Corridor	100	0	0	0	0.01916198	0.047349253
003AID	AltaAID	Thirsty Crop Generalists	226401.6667	0	0	0	2.452155681	6.059276688
004AWD	AmsterdamAWD	Groundwater Dependent Vineyards			0	0	0	0
005AWD	AngiolaAWD	Forage and Corron Corridor	10670	10000	1.935495774	4.782610058	2.065173991	5.103044932
006AEWSD	ArvinAEWSD	California Citrus Belt	351675	0	0	0	4.45038012	10.99688928
008BCWD	BallicoBCWD	Groundwater Dependent Vineyards			0	0	0	0
009BCID	BantaBCID	Senior, Secure Nut Growers	143102.7	0	0	0	10.22442188	25.26454646
010BWSD	BelridgeBWSD	California Citrus Belt	121508	0	0	0	4.090383605	10.10733789
011BMWD	BerrendaBMWD	California Citrus Belt	92600	0	0	0	3.577475781	8.839942655
012BVWSD	BuenaBVWSD	Thirsty Crop Generalists	171300	700000	19.23893061	47.53939754	4.708041163	11.63356971
013BBID	ByronBBID	Forage and Corron Corridor	79800	0	0	0	7.380834811	18.23804282
015CWD	CaweloCWD	California Citrus Belt	68200	0	0	0	2.072586311	5.121360775
017CCID	CentralCalCCID	Thirsty Crop Generalists	532392	0	0	0	4.347060483	10.74158645
019CWD	ChowchillaCWD	Groundwater Dependent Vineyards	322508.5	0	0	0	4.770972013	11.78907184
092CCC	Columbia Canal C	Thirsty Crop Generalists	58968	0	0	0	4.432396878	10.95245269
020CID	Consolidated CID	Groundwater Dependent Vineyards	0	1000000	8.822039487	21.79925957	0	0

021CID	CorcoranCID	Forage and Corron Corridor			0	0	0	0
122CSJWCD	CSJWCD	Groundwater Dependent Vineyards	80000	0	0	0	1.426979881	3.526067286
023DEID	DelanoDEID	Senior, Secure Nut Growers	683300	0	0	0	13.11739933	32.41309375
022DPWD	DelPuertoDPWD	Thirsty Crop Generalists	140181	0	0	0	4.251329712	10.50503572
026DRWD	DudleyDRWD	California Citrus Belt	44980	0	0	0	2.557334281	6.319173008
027EWD	EaglefieldEWD	Forage and Corron Corridor	4550	0	0	0	4.271148345	10.55400756
028EWD	EastinEWD	Groundwater Dependent Vineyards			0	0	0	0
029EWD	EastsideEWD	Groundwater Dependent Vineyards			0	0	0	0
030ESWD	ElSolyoESWD	Not Included	22806.4	0	0	0	7.228813927	17.86239921
031EWSID	EmpireEWSID	Forage and Corron Corridor	1845	0	0	0	0.427408125	1.056125476
032EID	ExeterEID	California Citrus Belt	30100	0	0	0	2.913612294	7.19953598
033FWD	FarmersFWD	Groundwater Dependent Vineyards			0	0	0	0
034FCC	FirebaughFCC	Forage and Corron Corridor	85008	0	0	0	4.303967138	10.6351028
035FWC	FreeFWC	California Citrus Belt			0	0	0	0
036FID	FresnoFID	Thirsty Crop Generalists	875000	863	0.007221227	0.017843652	7.321638146	18.09176786
037FSWD	FresnoSloFSWD	Forage and Corron Corridor	4866	0	0	0	8.585351392	21.21440329
038GWD	GarfieldGWD	California Citrus Belt	3500	0	0	0	3.684308832	9.103927123
039GWD	GrasslandGWD	Not Included	181536	0	0	0	174.0517737	430.0819329
040GFWD	GravellyGFWD	Groundwater Dependent Vineyards	14000	0	0	0	1.8905076	4.67144428

042HVID	HillsHVID	California Citrus Belt	4597	0	0	0	1.853570038	4.580171563
044IWD	InternationalIWD	California Citrus Belt	1200	0	0	0	5.397341154	13.33682999
045IID	IvanhoeIID	California Citrus Belt	19550	0	0	0	2.124310653	5.249171624
046JID	JamesJID	Forage and Corron Corridor	45200	0	0	0	2.007604447	4.960790588
047KDWD	KernDeltaKDWD	Thirsty Crop Generalists	204883	0	0	0	2.356395112	5.822652322
048KTWD	KernTulKTWD	California Citrus Belt	58300	0	0	0	3.226097739	7.971687513
049KRWD	KingsKRWD	Forage and Corron Corridor			0	0	0	0
050LID	LagunaLID	Forage and Corron Corridor	52481	0	0	0	1.979508824	4.891366304
051LWD	LagunaLWD	Not Included	800	0	0	0	2.100318448	5.189886885
052LID	LakesideLID	Not Included	217914	0	0	0	8.978902448	22.18686795
055LGAWD	LeGrandLGAWD	Groundwater Dependent Vineyards			0	0	0	0
057LWD	LibertyLWD	Groundwater Dependent Vineyards	429	0	0	0	0.024075309	0.059490089
058LID	LindmoreLID	California Citrus Belt	55000	0	0	0	2.541306816	6.279569143
059LSID	LindsayLSID	California Citrus Belt	27500	0	0	0	2.821566094	6.972089817
060LHWD	LostLHWD	California Citrus Belt	119110	0	0	0	4.609480623	11.39002662
061LTID	LowerTulLTID	Forage and Corron Corridor	400302	0	0	0	5.061342169	12.5065765
062MID	MaderaMID	Thirsty Crop Generalists	295000	0	0	0	3.005567153	7.426756434
063MWD	MaderaMWD	California Citrus Belt			0	0	0	0
065MWD	MelgaMWD	Not Included			0	0	0	0
066MID	MercedMID	Thirsty Crop Generalists	63720	0	0	0	0.588095114	1.453183026

067 MS WD	Mercy MSW D	Forage and Corron Corridor	2842	0	0	0	0.951317 993	2.350706 76
068 MC WD	Merqui nMCW D	Forage and Corron Corridor	14211	0	0	0	1.950220 838	4.818995 691
069 MW D	Midval leyM WD	Groundwater Dependent Vineyards			0	0	0	0
070 MID	Modest oMID	Senior, Secure Nut Growers	823432. 5952	0	0	0	15.20548 354	37.57274 983
071N BID	Naglee BurkN BID	Not Included			0	0	0	0
072N SWD	NewSt oneNS WD	Groundwater Dependent Vineyards	15700	0	0	0	3.944520 756	9.746910 788
073N KWS D	NKern NKWS D	Groundwater Dependent Vineyards	25000	500000	9.26257 1893	22.88781 515	0.463128 595	1.144390 757
124N SJW CD	NSanJ oaqNS JWCD	Thirsty Crop Generalists	20000	0	0	0	0.300055 576	0.741437 328
076O ID	Oakdal eOID	Senior, Secure Nut Growers	768848. 25	0	0	0	13.64704 672	33.72185 245
075O FWD	OakOF WD	Forage and Corron Corridor	3506	0	0	0	1.594356 029	3.939653 747
079O CID	Orange OCID	California Citrus Belt	39200	0	0	0	1.807163 64	4.465501 355
078O LW D	OraOL WD	Forage and Corron Corridor	600	0	0	0	0.670303 465	1.656319 862
080P WD	Pachec oPWD	Forage and Corron Corridor	14665	0	0	0	3.659196 333	9.041874 14
081P WD	Panoch ePWD	Forage and Corron Corridor	93922	0	0	0	3.275552 443	8.093890 087
082P ID	Patters onPID	Forage and Corron Corridor	22500	0	0	0	2.218712 032	5.482437 43
083P ID	Pixley PID	Groundwater Dependent Vineyards	31102	10000	0.19798 4188	0.489218 929	0.615770 422	1.521568 712
085P ID	Porterv illePID	Groundwater Dependent Vineyards	57900	0	0	0	4.760278 496	11.76264 816
086R CW D	Raisin RCWD	Groundwater Dependent Vineyards			0	0	0	0

087RID	RiverdaleRID	Forage and Corron Corridor	26000	0	0	0	2.243810537	5.544455838
123RCWD	Rock Creek WD	Not Included	0	0	0	0	0	0
089RCWD	RootRCWD	California Citrus Belt	9840	0	0	0	1.353777536	3.345184292
090RRBWSD	RosedaleRRBWSD	Groundwater Dependent Vineyards	29900	65750	2.427441512	5.998207976	1.10388595	2.727702182
091SWD	SalyerSWD	Not Included			0	0	0	0
125SLCC	SanLuisCC	Forage and Corron Corridor	163632	0	0	0	4.54481584	11.23023994
093SLWD	SanLuisSLWD	Thirsty Crop Generalists	124009	0	0	0	3.794183481	9.375427381
094SID	SauciliitoSID	Groundwater Dependent Vineyards	54300	0	0	0	3.046914033	7.528924576
095SWSD	SemitropicSWSD	Thirsty Crop Generalists	66000	1600000	13.161043	32.52093724	0.542893024	1.341488661
096SWID	ShafterSWID	Groundwater Dependent Vineyards	89600	0	0	0	2.48404138	6.138066249
098SSJID	SSanJoaqSSJID	Senior, Secure Nut Growers	768848.25	0	0	0	16.26261213	40.18491457
099SWD	StevinsonSWD	Not Included	190424	0	0	0	57.33824402	141.682801
102SEWD	StocktonSEWD	Thirsty Crop Generalists	28786	0	0	0	0.444461493	1.09826435
103SCID	StoneSCID	California Citrus Belt	10000	0	0	0	1.84107205	4.549289035
104SID	StratfordSID	Forage and Corron Corridor	11000	0	0	0	1.785154906	4.411117772
105TDWD	Teapot TDWD	California Citrus Belt	7200	0	0	0	2.40642633	5.946279463
106TID	TerrabellaTID	California Citrus Belt	29000	0	0	0	3.53660359	8.738947471
107TID	TranquillityTID	Forage and Corron Corridor	34000	0	0	0	3.756342389	9.281922044

108TTWD	TriangleTTTWD	Groundwater Dependent Vineyards	0	50500	3.793847436	9.374597014	0	0
109TWD	TrivalleyTWD	California Citrus Belt	1542	0	0	0	2.00847865	4.962950744
110TID	Tulare TID	Forage and Corron Corridor	221000	0	0	0	3.918128973	9.681696693
111TID	TurlockTID	Senior, Secure Nut Growers	1798964.205	0	0	0	14.00701138	34.61132512
112TIWD	Turner TIWD	Forage and Corron Corridor	0	0	0	0	0	0
118WWD	WestlandsWWD	Thirsty Crop Generalists	1193000	0	0	0	2.874559469	7.103036449
115WSID	WestSideWSID	Forage and Corron Corridor	32000	0	0	0	7.817051907	19.31593526
116WSID	WestStanWSID	Senior, Secure Nut Growers	237791	0	0	0	12.58324602	31.09320092
119WRMWSD	WheelerWRMWSD	California Citrus Belt	197088	0	0	0	2.837318874	7.011014937
120WWD	Widren WWD	Forage and Corron Corridor			0	0	0	0
121WID	WoodbridgeWID	Groundwater Dependent Vineyards	68622	0	0	0	2.404987306	5.942723633

SI Table 19. Table of surface water allocation amounts for irrigation districts included in this analysis and value sources. Note: This is part 1 of 2.

UID	Sources of Data
001AWD	Based on the GSP AWD does not have SW rights http://www.alisowdgsa.org/assets/aliso-gsp-final_20200117.pdf
002AID	USBR contractor Appendix A https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=24921
003AID	Alta ID Entitlement Estimate: http://www.altaid.org/surface-water-mainmenu-43 ; KRWA Headgate diversion 2017 was 252,506AF, 2011 was 206,715, and 2010 was 219984 AF so took average of these; no documentation on exact entitlement
004AWD	Cannot confirm no surface water rights
005AWD	EWRIMS 5,370 AF irrigation licensed for Deer Creek and 10,000 AF pending for white river; SWP amount source from TriCountyWaterAgencyGSP_ PDF file downloaded states that Mercy Springs and Fresno Slough have requested, pursuant to their respective CVP contracts, approval from Reclamation to annually transfer up to 1,300 AFY of Mercy Springs' CVP water and up to 4,000 AFY of Fresno Slough's CVP water over a nine-year period to Angiola.
006AEWSD	AEWD GSP: AEWSD's only contracted source of surface water supply is its Class 1 and Class 2 contracts for CVP (Friant Division) water, at 40,000 AFY and 311,675 AFY respectively.
008BCWD	Cannot confirm no surface water rights
009BCID	USBR 20,000 AF; EWRIMS 107993.8 AF and 15108.9 AF from San Joaquin River
010BWSD	KWCA Report Josh sent has SWP water to 121,508 Af
011BMWD	KCWA Report Josh sent has SWP as 92,600 AF
012BVWSD	EWRIMS 700,000 AF pending; http://bvh2o.com/; from webpage The District controls an average entitlement of approximately 150,000 AF/yr of surface water from the Kern River along with an additional entitlement of approximately 21,300 AF/yr from the State Water Project
013BBID	USBR 20,600AF total, 800 M&I, and 19800 AF for irrigation; 60,000 AF of pre-1914 watr rights on Italian Slough https://bbid.org/wp-content/uploads/2017/09/BBID_AWMP_Draft_09182017_Compiled.pdf
015CWD	KCWA Report Josh sent 38,200 AF; EWRIMS 30,000 AF for irrigation from Poso Creek
017CCID	CVP Contractors List states that SJRECWA share 840,000 AF; email exchange with Joann White and she gave the following % breakdown for each member district-- Central California Irrigation District: 63.38% San Luis Canal Company: 19.48% Firebaugh Canal Water District: 10.12% Columbia Canal Company: 7.02%
019CWD	USBR 55,000 AF and 160,000 AF class1/2 from friant and 24,000 from Buchanan; EWRIMS 6195.7 AF from Ash Creek and 77312.8 Af from Chowchilla River
092CCC	CVP Contractors List states that SJRECWA share 840,000 AF; email exchange with Joann White and she gave the following % breakdown for each member district-- Central California Irrigation District: 63.38% San Luis Canal Company: 19.48%

	Firebaugh Canal Water District: 10.12% Columbia Canal Company: 7.02%
020CID	EWRIMS; pending irrigation water on Kings River
021CID	Cannot confirm no surface water rights
122CSJWCD	USBR 80,000 AF expires in 2022
023DEID	USBR Report: https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=24921
022DPWD	USBR 140210 AF total, 29 for M&I and 140,181AF for irrigation
026DRWD	SWP water calculated from average of 1962-2017 (document provided by Alvar)
027EWD	USBR CVP 4,550 AF from Delta Mendota Canal expires in 2030
028EWD	Cannot confirm no surface water rights
029EWD	Cannot confirm no surface water rights
030ESWD	EWRIMS
031EWSID	SWP Amount from document sent by Alvar baed on average from 1988-2017
032EID	USBR CVP 11,100 AF and 19,000 AF from Friant indefinite
033FWD	Cannot confirm no surface water rights
034FCC	CVP Contractors List states that SJRECWA share 840,000 AF; email exchange with Joann White and she gave the following % breakdown for each member district-- Central California Irrigation District: 63.38% San Luis Canal Company: 19.48% Firebaugh Canal Water District: 10.12% Columbia Canal Company: 7.02%
035FWC	Cannot confirm no surface water rights
036FID	CVP water 75,000 AF and Kings River Water; EWRIMS 863 AF irrigation water from Pup Creek is pending; document from USBR 800,000 from the Kings River
037FSWD	USBR CVP 4,000 Af expires in 2030 and 866 AF indefinitee from Mendota Pool
038GWD	USBR CVP 3,500 AF indefinite from Friant Kern
039GWD	USBR 180,000AF (Grasslands CVP Document in Other Sources Folder); EWRIMS 1,536 AF from Banos Creek (% distribution for ag and wetlands) ET 6ft/year (4.5 ft/year for Almonds)
040GFWD	USBR CVP 14,000 AF indefinite from Friant Div; EWRIMS 5,000 AF for Domestic water use
042HVID	USBR CVP 3,347 Af expired in 2018 but included in this study conducted for 2016; 250 indefinite, 1,000 AF indefinite
044IWD	USBR CVP 1200 AF expires in 2026 from Friant
045IID	USBR CVP 6,500 and 500 AF of indefinite from Friant; owns 7.9 shares of Watchuma Water stock ~3,950 AF water; USBR 7,700 AF Class 1 and 7,900 AF of class 2 (going to use the numbers for USBR Report) https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=24921
046JID	USBR 35,500 for ag expires in 2030 and 9,700 AF indefinite

047KDWD	SWP Kern County Water Agency Member Unit doc 25,500 AF; AWMP https://www.kerndelta.org/wp-content/uploads/2019/12/KernDelta-WD-2015-AWMP.pdf Table 7. 168,895AF for irrigation within service areas,deliver available water for irriation within district 10,488 AF
048KTWD	USBR 40,000 AF and 13,300 AF that expired in 2018, and 5,000 AF from Friant that is indefinite; keeping the expired water allocation bc analysis is for 2016 crop
049KRWD	Cannot confirm no surface water rights
050LID	Report https://www.kingsbasinauthority.org/wp-content/uploads/2019/01/20181017IRWMP.pdf states that Kings River water rights held in trust by Kings River Water Association = 44,000 AF from Pine Flat and 8,481 AF from upstream storage pts
051LWD	USBR CVP 800 AF expires in 2030 from Mendota Pool
052LID	USBR report states that Lakeside Irrigation WD administers water rights of Lakeside Ditch Company stockholders on the Kaweah River; Historical webpage states The company appropriated three hundred and one cubic feet per second from Cross creek, a branch of Kaweah river. http://genealogytrails.com/cal/kings/books/chapt23.html
055LGAWD	Cannot confirm no surface water rights
057LWD	Liberty is a Liberty Canal Company sharholder for3.3% Kings river storage of 13,000 AF which is 429 AF
058LID	USBR 33,000 AF and 22,000 AF from Friant
059LSID	USBR CVP 27,500 AF indefinite; USBR report it has original imported water supplies through Wutchumna Water Company Stock and 39 deep wells that give range of 5,000 to 14,000 AF of water (I am not going to count this)
060LHWD	KWCA Report Josh sent has SWP 119,110 AF
061LTID	USBR Report https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=6086 Table 3 states the following: Fraint Canal Class 1 61,200 AF, Class 2 238,000AF, Tule River 70,000AF and 31,102 CVP
062MID	USBR CVP contract
063MWD	Cannot confirm no surface water rights
065MWD	Cannot confirm no surface water rights
066MID	EWRIMS 400,000 AF pending for aquaculture; total water rights from ERIMS 4,909,115 AF; 356,757 Af for domestic, 63,719 for irrigation, and 4,488,638 AF for power
067MSWD	USBR CVP 2,842 expires in 2030 from delta mendota canal
068MCWD	https://www.calwaterlaw.com/merquin-county-water-district-stevinson-ca#:~:text=Merquin%20has%20a%20contractual%20water,5%2Dmember%20Board%20of%20Directora states Merquin has a contractual water right to 14,211 acre feet per year serving approximately 6,000 acres of farmland.
069MWD	Cannot confirm no surface water rights
070MID	EWRIMS; based on a phone call with TID Mr Weimer the allocation of 68.6% and 31.4% are used to divvy up a lot of resources between TID and MID; so ewrims allocation was split 68% for TID and 31% for MID
071NBID	Cannot confirm no surface water rights

072NSWD	New Stone GSP: https://57d30904-37e1-4f05-a28b-67136050bc86.filesusr.com/ugd/449124_58a618ab4acb479ab24e9fd193973813.pdf Although the NSWD GSA does have an appropriative water right along the Chowchilla Bypass (referred toas Eastside Bypass/Chowchilla Canal in permit) of 15,700 acre-feet/year (permit number 19615), surfacewater is not consistently used for irrigation
073NKWSD	EWRIMS: 500000 AF pending for irrigation and 25,000 AF permitted for Poso Creek
124NSJWCD	USBR Report https://www.usbr.gov/watersmart/swep/docs/2018/applications/074-SWEP-North-San-Joaquin-WCD-Project1508.pdf NSJWCD has the right to divert 20,000 AF from Mokelumne River (junior water right)
076OID	USBR 600,000 split in half with SSJID (confirmed via phone call with SSJID); EWRIMS total rights 5,142,894.1 AF, 937,696.5 AF irrigation, 184,997.7 AF domestic, and 4,020,199.9 AF for power
075OFWD	SWP Amount from document sent by Alvar baed on average from 1988-2017
079OCID	USBR 39,200 AF indefinite from Friant ;EWRIMS has 23,339.2 AF and 814,474.7 AF for power (not included just a note)
078OLWD	USBR 600 AF expires in 2030 from Delta Mendota Canal
080PWD	USBR CVP 10,080 AF total of which 10,068 Af for ag and 12 AF for M&I; Right to 4,597 AF from CCID contract
081PWD	USBR CVP 94,000 AF total, 78 is M&I and 93,922 AF is irrigation
082PID	USBR CVP 22,500 AF from Delta-Mendota Canal
083PID	USBR CVP 31,102 AF for irrigation from Cross Valley Canal; EWRIMS 10,000 AF pending from Deer Creek
085PID	USBR 15,000 AF and 30,000 AF from Friant; USBR report https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=24921 avg annual entitlement of 12,900 Af from Tule River
086RCWD	Cannot confirm no surface water rights
087RID	Report https://www.kingsbasinauthority.org/wp-content/uploads/2019/01/20181017IRWMP.pdf states that it has 26,000 AF on Kings River of combined storage share
123RCWD	EWRIMS 8,395 AF for power from the rock creek
089RCWD	Madera GSP https://www.maderacountywater.com/wp-content/uploads/2020/02/Madera_GSP_2020_FinalReport.pdf states that RCWD holds a historical right to divert water from the San Joaquin River on average 9840 AFY; MID states that RCWD may purchase water in excess of MID water demands, up to 10,000 AF in any one year (not including the amount that they can purchase)
090RRBWSD	KCWA Report Josh sent has SWP as 29,900AF; EWRIMS 65,570 AF is pending use code is NA
091SWD	Cannot confirm no surface water rights
125SLCC	CVP Contractors List states that SJRECWA share 840,000 AF; email exchange with Joann White and she gave the following % breakdown for each member district-- Central California Irrigation District: 63.38% San Luis Canal Company: 19.48%

	Firebaugh Canal Water District: 10.12% Columbia Canal Company: 7.02%
093SLWD	USBR 125,080 AF total, 1,071 Af M&I, and 124,009 AF for irrigation expired in 2017; keeping the sw allocation value since the analysis was conducted for 2016 crops
094SID	USBR 300 AF, 21,200 AF, and 32,800 AF from the Friant
095SWSD	USBR CVP 66,000 AF and 1,600,000 AF pending in EWRIMS
096SWID	USBR CVP 50,000 AF and 39,600 AF maximum
098SSJID	USBR 600,000 split in half with SSJOD (confirmed via phone call with SSJID); EWRIMS 36,000 AF for incidental power from stanislaus river; Based on AWMP the split is also for pre-1914 water rights to the stanislaus river https://www.ssjid.com/wp-content/uploads/2020-Ag-Water-Management-Plan.pdf
099SWD	EWRIMS irrigation 16,717 AF from Merced river, 79,534.4 AF and 35,619.7 AF from Bear Creek, and 58,552.9 AF Arena Spillway
102SEWD	EWRIMS total rights 1,868,557.3 AF, 16,027 AF domestic, 925,900 AF cancelled irrigation (I think bc irrigation covered by Woodbridge ID), 822,630AF pending for F&W; USBR total 75,000 AF, 46,214 AF M&I and rest is not labelled so assigned to ag expires in 2022
103SCID	USBR CVP 10,000 AF from Friant indefinite
104SID	GSP https://southforkkings.org/wp-content/uploads/2021/04/tulare-lake-subbasin-groundwater-sustainability-plan-january-2020.pdf states that has storage share of Kings River of 11,000 AF
105TDWD	USBR CVP 7,200 AF indefinite from Friant
106TID	USBR CVP 29,000 AF indefinite
107TID	USBR CVP 13,800 AF expires in 2030 and 20,200 AF indefinite from Mendota Pool
108TTWD	EWRIMS 50,500 AF pending from Chowchilla Bypass for irrigation
109TWD	USBR CVP 1142 Af expired inss 2018 included since crops used from 2016 and 400 Af indefinite from Friant Kern
110TID	CVP 30,000AF and 141,000 AF from Friant; USBR report https://www.usbr.gov/mp/nepa/includes/documentShow.php?Doc_ID=24921 Tulare ID has 50,000 AF rights to the Kaweah River
111TID	EWRIMS; based on a phone call with TID Mr Weimer the allocation of 68.6% and 31.4% are used to divvy up a lot of resources between TID and MID; so ewrims allocation was split 68% for TID and 31% for MID
112TIWD	TIWD relies on surface water from SLCC during non-critical years under the Exchange Contract.
118WWD	WestlandsWD webpage matches USBR: https://wwd.ca.gov/water-management/water-supply/annual-water-use-and-supply/
115WSID	EWRIMS 27,000 AF from Old River for irrigation; USBR CVP 5,000 AF expires in 2030
116WSID	CVP 50,000 AF; EWRIMS 187791 AF for irrigation
119WRMWSD	KWCA Report Josh sent has SWP water to 197088 AF
120WWD	Cannot confirm no surface water rights
121WID	*EWRIMS total surface water 219,854.5 AF, 211,232.5 AF Domestic, and 8,622 AF irrigation water; Water rights for WID are included in EBMUD*

	for Mokelumne River for 60,000AF when Pardee reservoir flow are greater than 375 TAF or greater https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnx3b29kYnJpZGdlaXJyaWdhdGlvbmRpc3RyaWN0fGd4OmFlYTZkM2RhZGRlMTdjZg. Do I include the water rights from EBMUD?

SI Table 20. Table of surface water allocation amounts for irrigation districts included in this analysis and value sources. Note: This is part 2 of

Crop Type Category	Crop Type
Annual	Beans (Dry)
	Carrots
	Cole Crops
	Corn, Sorghum and Sudan
	Cotton
	Lettuce/Leafy Greens
	Melons, Squash and Cucumbers
	Miscellaneous Field Crops
	Miscellaneous Truck Crops
	Onions and Garlic
	Peppers
	Potatoes and Sweet Potatoes
	Safflower
	Strawberries
	Sunflowers
	Tomatoes
	Rice
	Wheat
Irrigated Forage	Alfalfa and Alfalfa Mixtures
	Miscellaneous Grasses
	Mixed Pasture
	Miscellaneous Grain and Hay
Perennial	Almonds
	Apples
	Avocados
	Bush Berries

	Cherries
	Citrus
	Dates
	Flowers, Nursery and Christmas Tree Farms
	Grapes
	Kiwis
	Miscellaneous Deciduous
	Miscellaneous Subtropical Fruits
	Olives
	Peaches/Nectarines
	Pears
	Pistachios
	Plums, Prunes and Apricots
	Pomegranates
	Walnuts
	Young Perennials

SI Table 21. Table specifying the Land IQ crop types categorized into annual, perennial, and irrigated forage categories.

Crop2016	County	CropName Report	Prod_ Unit	USD_pe r_Unit	Tonpe rAcre	USDp erTon	USDpe rAcre	Peren_An nCrop16
Alfalfa and Alfalfa Mixtures	Kings	Alfalfa Hay	ton	142	7.69	142	1092	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Kern	Alfalfa Hay	ton	153	7.14	153	1092	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Fresno	Alfalfa Hay	ton	167	7.57	167	1264	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Madera	Alfalfa Hay	ton	158	7.24	158	1144	Irrigated Forage
Alfalfa and Alfalfa Mixtures	San Joaquin	Alfalfa hay	ton	143	6.38	143	912	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Merced	Alfalfa hay	ton	170.6	7.25	171	1237	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Tulare	Alfalfa hay	ton	154	7.85	154	1209	Irrigated Forage
Alfalfa and Alfalfa Mixtures	Stanisla us	Alfalfa hay	ton	148	7.08	148	1048	Irrigated Forage
Almonds	Kings	Almonds	ton	4820	1.07	4820	5157	Perennial
Almonds	Kern	Almonds	ton	4920	1.19	4920	5855	Perennial
Almonds	Fresno	Almonds	ton	4633	1.17	4633	5421	Perennial
Almonds	Madera	Almond	ton	4498	1.02	4498	4588	Perennial
Almonds	San Joaquin	Almonds	ton	4800	1.02	4800	4896	Perennial
Almonds	Merced	Almonds	ton	4900	1.14	4900	5586	Perennial
Almonds	Tulare	Almonds	ton	4400	1.09	4400	4796	Perennial
Almonds	Stanisla us	Almonds	ton	4800	1.04	4800	4992	Perennial
Apples	Kings	Apples Kern	ton	900	1.81	900	1629	Perennial
Apples	Kern	Apples	ton	900	1.81	900	1629	Perennial
Apples	Fresno	Apples Fresh	ton	1063	9.22	1063	9801	Perennial
Apples	Madera	Apples Fresh Fresno	ton	1063	9.22	1063	9801	Perennial
Apples	San Joaquin	Apples	ton	413	17.16	413	7087	Perennial
Apples	Merced	Apples San Joaquin	ton	413	17.16	413	7087	Perennial

Apples	Tulare	Apples Kern	ton	900	1.81	900	1629	Perennial
Apples	Stanislaus	Apples San Joaquin	ton	413	17.16	413	7087	Perennial
Avocados	Fresno	NA	0	0	0	-	-	Perennial
Avocados	Tulare	NA	0	0	0	-	-	Perennial
Beans (Dry)	Kings	Beans dry-Tulare	ton	888	1.27	888	1128	Annual
Beans (Dry)	Kern	Beans dry	ton	800	1.3	800	1040	Annual
Beans (Dry)	Fresno	Beans dry lima	ton	1370.82	1.125	1371	1542	Annual
Beans (Dry)	Madera	Beans dry lima-Merced	ton	1370.82	1.125	1371	1542	Annual
Beans (Dry)	San Joaquin	Beans Dry - Merced	ton	1060	1.2	1060	1272	Annual
Beans (Dry)	Merced	Beans dry lima	ton	1370.82	1.125	1371	1542	Annual
Beans (Dry)	Tulare	Beans dry	ton	888	1.27	888	1128	Annual
Beans (Dry)	Stanislaus	Beans Lima	ton	1450	1.15	1450	1668	Annual
Bush Berries	Kings	Blueberries- Tulare	ton	5420	5.93	5420	32141	Perennial
Bush Berries	Kern	Blueberries	ton	7380	5.13	7380	37859	Perennial
Bush Berries	Fresno	Blueberries	ton	3786	1.89	3786	7156	Perennial
Bush Berries	Madera	Blueberries- Fresno	ton	3786	1.89	3786	7156	Perennial
Bush Berries	San Joaquin	Blueberries	ton	4250	5	4250	21250	Perennial
Bush Berries	Merced	Blueberries- San Joaquin	ton	4250	5	4250	21250	Perennial
Bush Berries	Tulare	Blueberries	ton	5420	5.93	5420	32141	Perennial
Bush Berries	Stanislaus	Blueberries- San Joaquin	ton	4250	5	4250	21250	Perennial
Carrots	Kings	NA	0	0	0	-	-	Annual
Carrots	Kern	NA	0	0	0	-	-	Annual
Carrots	Fresno	NA	0	0	0	-	-	Annual
Carrots	Madera	NA	0	0	0	-	-	Annual
Carrots	San Joaquin	NA	0	0	0	-	-	Annual
Carrots	Merced	NA	0	0	0	-	-	Annual

Carrots	Tulare	NA	0	0	0	-	-	Annual
Carrots	Stanislaus	NA	0	0	0	-	-	Annual
Cherries	Kings	Cherries	ton	4410	2.88	4410	12701	Perennial
Cherries	Kern	Cherries	ton	3810	5.93	3810	22593	Perennial
Cherries	Fresno	Cherries	ton	3678	2.22	3678	8165	Perennial
Cherries	Madera	Cherries	ton	3873	3.66	3873	14175	Perennial
Cherries	San Joaquin	Cherries	ton	2480	1.19	2480	2951	Perennial
Cherries	Merced	Cherries-Stanislaus	ton	3420	1.92	3420	6566	Perennial
Cherries	Tulare	Cherries	ton	4620	2.25	4620	10395	Perennial
Cherries	Stanislaus	Cherries	ton	3420	1.92	3420	6566	Perennial
Citrus	Kings	Orange navel - Tulare	ton	665	15.5	665	10308	Perennial
Citrus	Kern	Orange Navel	ton	725	13.76	725	9976	Perennial
Citrus	Fresno	Orange Navel Fresh	ton	430	16.79	430	7220	Perennial
Citrus	Madera	Oranges	ton	475	15.26	475	7249	Perennial
Citrus	San Joaquin	Oranges-Madera	ton	475	15.26	475	7249	Perennial
Citrus	Merced	Oranges-Madera	ton	475	15.26	475	7249	Perennial
Citrus	Tulare	Orange navel	ton	665	15.5	665	10308	Perennial
Citrus	Stanislaus	Oranges-Madera	ton	475	15.26	475	7249	Perennial
Cole Crops	Kings	NA	0	0	0	-	-	Annual
Cole Crops	Kern	NA	0	0	0	0	0	Annual
Cole Crops	Fresno	NA	0	0	0	0	0	Annual
Cole Crops	San Joaquin	NA	0	0	0	-	-	Annual
Cole Crops	Merced	NA	0	0	0	-	-	Annual
Cole Crops	Tulare	NA	0	0	0	-	-	Annual
Cole Crops	Stanislaus	NA	0	0	0	-	-	Annual
Corn, Sorghum and Sudan	Kings	Corn silage	ton	40.1	25.25	40	1013	Annual
Corn, Sorghum and Sudan	Kern	Corn Silage-Tulare	ton	44	26	44	1144	Annual

Corn, Sorghum and Sudan	Fresno	Corn Silage	ton	42	22.97	42	965	Annual
Corn, Sorghum and Sudan	Madera	Corn Silage	ton	39	25.6	39	998	Annual
Corn, Sorghum and Sudan	San Joaquin	Corn grain	ton	156	5.19	156	810	Annual
Corn, Sorghum and Sudan	Merced	Corn Grain	ton	279.21	5.71	279	1594	Annual
Corn, Sorghum and Sudan	Tulare	Corn Silage	ton	44	26	44	1144	Annual
Corn, Sorghum and Sudan	Stanisla us	Corn Silage	ton	39	26.63	39	1039	Annual
Cotton	Kings	Pima	bale-495 lbs	683	0.79	2760	2186	Annual
Cotton	Kern	Upland and Acala	lbs per acre;p rice per poun d	0.67	0.92	1340	1232.8	Annual
Cotton	Fresno	Cotton-Pima	lbs per acre	1.34	0.73	2680	1947.0 2	Annual
Cotton	Madera	Lint	lb;pri ce per lb	0.81	0.82	1620	1323.5 4	Annual
Cotton	San Joaquin	Acala-Merced	500 lb bale	428.45	0.825	1714	1414	Annual
Cotton	Merced	Acala	500 lb bale	428.45	0.825	1714	1414	Annual
Cotton	Tulare	Lint	lbs per acre; $ per every 100 lbs	0.981	0.835	1962	1638.3	Annual
Dates	Fresno	NA	0	0	0	-	-	Perennial
Dates	Madera	NA	0	0	0	-	-	Perennial
Dates	Tulare	NA	0	0	0	-	-	Perennial

Flowers, Nursery and Christmas Tree Farms	Kings	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Kern	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Fresno	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Madera	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	San Joaquin	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Merced	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Tulare	NA	0	0	0	-	-	Perennial
Flowers, Nursery and Christmas Tree Farms	Stanisla us	NA	0	0	0	-	-	Perennial
Grapes	Kings	Wine	ton	286	13.63	286	3898	Perennial
Grapes	Kern	Table Variety Fresh	ton	2230	11.78	2230	26269	Perennial
Grapes	Fresno	Raisin Dried	ton	1100	9.38	1100	10318	Perennial
Grapes	Madera	Raisins Dried	ton	1096	3.09	1096	3387	Perennial
Grapes	San Joaquin	Grapes all	ton	594	7.31	594	4342	Perennial
Grapes	Merced	Wine	ton	524.99	11.23	525	5896	Perennial

Grapes	Tulare	Table Fresh	ton	1340	11.1	1340	14874	Perennial
Grapes	Stanislaus	grapes red	ton	550	10.06	550	5533	Perennial
Greenhouse	Kings	NA	0	0	0	-	-	NA
Greenhouse	Kern	NA	0	0	0	-	-	NA
Greenhouse	Fresno	NA	0	0	0	-	-	NA
Greenhouse	Tulare	NA	0	0	0	-	-	NA
Idle	Kings	NA	0	0	0	-	-	NA
Idle	Kern	NA	0	0	0	-	-	NA
Idle	Fresno	NA	0	0	0	-	-	NA
Idle	Madera	NA	0	0	0	-	-	NA
Idle	San Joaquin	NA	0	0	0	-	-	NA
Idle	Merced	NA	0	0	0	-	-	NA
Idle	Tulare	NA	0	0	0	-	-	NA
Idle	Stanislaus	NA	0	0	0	-	-	NA
Kiwis	Kings	Kiwifruit-Tulare	ton	1780	13.9	1780	24742	Perennial
Kiwis	Fresno	Kiwifruit	ton	1273	1.77	1273	2253	Perennial
Kiwis	Madera	Kiwifruit-Fresno	ton	1273	1.77	1273	2253	Perennial
Kiwis	San Joaquin	Kiwifruit-Fresno	ton	1273	1.77	1273	2253	Perennial
Kiwis	Merced	Kiwifruit-Fresno	ton	1273	1.77	1273	2253	Perennial
Kiwis	Tulare	Kiwifruit	ton	1780	13.9	1780	24742	Perennial
Kiwis	Stanislaus	Kiwifruit-Fresno	ton	1273	1.77	1273	2253	Perennial
Lettuce/Leafy Greens	Kings	Lettuce Head-Kern	ton	470	19.56	470	9193	Annual
Lettuce/Leafy Greens	Kern	Lettuce Head	ton	470	19.56	470	9193	Annual
Lettuce/Leafy Greens	Fresno	Lettuce Leaf	ton	526	15.73	526	8274	Annual
Lettuce/Leafy Greens	Madera	Lettuce Leaf-Fresno	ton	526	15.73	526	8274	Annual
Lettuce/Leafy Greens	Merced	Lettuce Leaf-Fresno	ton	526	15.73	526	8274	Annual

Lettuce/Leafy Greens	Tulare	Lettuce Head-Kern	ton	470	19.56	470	9193	Annual
Managed Wetland	Kings	NA	0	0	0	-	-	NA
Managed Wetland	Kern	NA	0	0	0	-	-	NA
Managed Wetland	Fresno	NA	0	0	0	-	-	NA
Managed Wetland	Madera	NA	0	0	0	-	-	NA
Managed Wetland	San Joaquin	NA	0	0	0	-	-	NA
Managed Wetland	Merced	NA	0	0	0	-	-	NA
Managed Wetland	Tulare	NA	0	0	0	-	-	NA
Managed Wetland	Stanislaus	NA	0	0	0	-	-	NA
Melons, Squash and Cucumbers	Kings	Watermelon_Kern	ton	327	34.3	327	11216	Annual
Melons, Squash and Cucumbers	Kern	Watermelon	ton	327	34.3	327	11216	Annual
Melons, Squash and Cucumbers	Fresno	Honeydew	ton	515	19.92	515	10259	Annual
Melons, Squash and Cucumbers	Madera	Honeydew - Fresno	ton	515	19.92	515	10259	Annual
Melons, Squash and Cucumbers	San Joaquin	melons all	ton	310	48.28	310	14967	Annual
Melons, Squash and Cucumbers	Merced	Melons Cantelope	40lb ctn	4.87	13.433	5	65	Annual
Melons, Squash and Cucumbers	Tulare	Watermelon_Kern	ton	327	34.3	327	11216	Annual
Melons, Squash and Cucumbers	Stanislaus	melons all - Sjoaquin	ton	310	48.28	310	14967	Annual
Miscellaneous Deciduous	Kings	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	Kern	NA	0	0	0	-	-	Perennial

Miscellaneous Deciduous	Fresno	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	Madera	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	San Joaquin	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	Merced	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	Tulare	NA	0	0	0	-	-	Perennial
Miscellaneous Deciduous	Stanislaus	NA	0	0	0	-	-	Perennial
Miscellaneous Field Crops	Fresno	Oriental Veggies	ton	1444	12.12	1444	17501	Annual
Miscellaneous Grain and Hay	Kings	Wheat silage	ton	29.6	17	30	503	Irrigated Forage
Miscellaneous Grain and Hay	Kern	Grain	ton	140	3.95	140	553	Irrigated Forage
Miscellaneous Grain and Hay	Fresno	Hay Other	ton	141	3.07	141	433	Irrigated Forage
Miscellaneous Grain and Hay	Madera	Oat Hay	ton	92	3.2	92	294	Irrigated Forage
Miscellaneous Grain and Hay	San Joaquin	hay all	ton	139	6.03	139	838	Irrigated Forage
Miscellaneous Grain and Hay	Merced	Hay Grain	ton	144.36	3.91	144	564	Irrigated Forage
Miscellaneous Grain and Hay	Tulare	Hay other	ton	93	3.38	93	314.34	Irrigated Forage
Miscellaneous Grain and Hay	Stanislaus	Hay Oat	ton	100	3.18	100	318	Irrigated Forage
Miscellaneous Grasses	Kings	Sorghum silage	ton	27.8	17.97	28	500	Irrigated Forage
Miscellaneous Grasses	Kern	Silage Forage	ton	46.4	19.37	46	899	Irrigated Forage

Miscellaneous Grasses	Fresno	NA	0	0	0	-	-	Irrigated Forage
Miscellaneous Grasses	Madera	Pasture Irrigated	acre	150	0	150	-	Irrigated Forage
Miscellaneous Grasses	San Joaquin	Irrigated Pasture	acre	268	1	268	268	Irrigated Forage
Miscellaneous Grasses	Merced	Pasture irrigated	acre	174	1	174	174	Irrigated Forage
Miscellaneous Grasses	Tulare	Pasture other	acre	40	1	40	40	Irrigated Forage
Miscellaneous Grasses	Stanislaus	Sudan	ton	26	12.76	26	332	Irrigated Forage
Miscellaneous Subtropical Fruits	Kings	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	Kern	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	Fresno	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	Madera	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	San Joaquin	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	Tulare	NA	0	0	0	-	-	Perennial
Miscellaneous Subtropical Fruits	Stanislaus	NA	0	0	0	-	-	Perennial
Miscellaneous Truck Crops	Kings	NA	0	0	0	-	-	Annual

Miscellaneous Truck Crops	Kern	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	Fresno	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	Madera	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	San Joaquin	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	Merced	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	Tulare	NA	0	0	0	-	-	Annual
Miscellaneous Truck Crops	Stanislaus	NA	0	0	0	-	-	Annual
Mixed Pasture	Kings	Pasture range	ton	11.25	0	11.25	11.25	Irrigated Forage
Mixed Pasture	Kern	Range	acre	15	1	15	15	Irrigated Forage
Mixed Pasture	Fresno	Rangeland Grazing	acre	17	1	17	17	Irrigated Forage
Mixed Pasture	Madera	Rangeland	acre	22	0	22	22	Irrigated Forage
Mixed Pasture	San Joaquin	Pasture Range	acre	46.3	1	46	46	Irrigated Forage
Mixed Pasture	Merced	Pasture other	acre	23.41	1	23	23	Irrigated Forage
Mixed Pasture	Tulare	native	acre	20	1	20	20	Irrigated Forage
Mixed Pasture	Stanislaus	Rangeland	acre	21	1	21	21	Irrigated Forage
Olives	Kings	Olives-Tulare	ton	1150	3.23	1150	3715	Perennial
Olives	Kern	Olives-Tulare	ton	1150	3.23	1150	3715	Perennial
Olives	Fresno	Olives-Madera	ton	1500	2.4	1500	3600	Perennial
Olives	Madera	Olives	ton	1500	2.4	1500	3600	Perennial
Olives	San Joaquin	Olives	ton	602	6.34	602	3817	Perennial
Olives	Merced	Olives-Madera	ton	1500	2.4	1500	3600	Perennial
Olives	Tulare	Olives	ton	1150	3.23	1150	3715	Perennial

Olives	Stanislaus	Olives-Sjoaquin	ton	602	6.34	602	3817	Perennial
Onions and Garlic	Kings	Garlic-Kern	ton	1460	7.9	1460	11534	Annual
Onions and Garlic	Kern	Garlic	ton	1460	7.9	1460	11534	Annual
Onions and Garlic	Fresno	Garlic	ton	1500	6.85	1500	10275	Annual
Onions and Garlic	Madera	Garlic-Fresno	ton	1500	6.85	1500	10275	Annual
Onions and Garlic	San Joaquin	Onions	ton	240	22.5	240	5400	Annual
Onions and Garlic	Merced	Garlic-Fresno	ton	1500	6.85	1500	10275	Annual
Onions and Garlic	Tulare	Garlic-Kern	ton	1460	7.9	1460	11534	Annual
Onions and Garlic	Stanislaus	Onions-Sjoaquin	ton	240	22.5	240	5400	Annual
Peaches/Nectarines	Kings	Peaches Freestone	ton	1200	11.23	1200	13476	Perennial
Peaches/Nectarines	Kern	Peaches Freestone-King	ton	1200	11.23	1200	13476	Perennial
Peaches/Nectarines	Fresno	Peach Freeston	ton	1238	10.93	1238	13531	Perennial
Peaches/Nectarines	Madera	Peaches Freestone	ton	469	25.99	469	12189	Perennial
Peaches/Nectarines	San Joaquin	Peaches all	ton	490	17.9	490	8771	Perennial
Peaches/Nectarines	Merced	Peach freestone	ton	463.01	24.57	463	11376	Perennial
Peaches/Nectarines	Tulare	peach freestone	ton	1340	8.35	1340	11189	Perennial
Peaches/Nectarines	Stanislaus	Peaches cling	ton	491	24.28	491	11921	Perennial
Pears	Kings	Pears and asian pear-Tulare	ton	1510	18.6	1510	28086	Perennial
Pears	Kern	Pears and asian pear-Tulare	ton	1510	18.6	1510	28086	Perennial
Pears	Fresno	Pears Asian	ton	1263	19.3	1263	24376	Perennial
Pears	Madera	Pears Asian-Fresno	ton	1263	19.3	1263	24376	Perennial
Pears	San Joaquin	Pears	ton	439	16.44	439	7217	Perennial
Pears	Merced	Pears Asian-Fresno	ton	1263	19.3	1263	24376	Perennial

Pears	Tulare	Pears and asian pear	ton	1510	18.6	1510	28086	Perennial
Pears	Stanisla us	Pears- S Joaquin	ton	439	16.44	439	7217	Perennial
Peppers	Kings	Bell -Kern	ton	970	20.68	970	20060	Annual
Peppers	Kern	Bell	ton	970	20.68	970	20060	Annual
Peppers	Fresno	Pepper Chili	ton	603	16.61	603	10016	Annual
Peppers	San Joaquin	Peppers	ton	469	14.55	469	6824	Annual
Peppers	Merced	Pepper Chili-Fresno	ton	603	16.61	603	10016	Annual
Peppers	Tulare	Bell -Kern	ton	970	20.68	970	20060	Annual
Peppers	Stanisla us	Peppers-Sjoaquin	ton	469	14.55	469	6824	Annual
Pistachios	Kings	Pistachios	ton	4300	1.9	4300	8170	Perennial
Pistachios	Kern	Pistachios	ton	4320	1.62	4320	6998	Perennial
Pistachios	Fresno	Pistachio	ton	1746	1.54	1746	2689	Perennial
Pistachios	Madera	Pistachio	ton	3985	1.75	3985	6974	Perennial
Pistachios	San Joaquin	Pistachio-Merced	ton	3367.31	1.39	3367	4681	Perennial
Pistachios	Merced	Pistachio	ton	3367.31	1.39	3367	4681	Perennial
Pistachios	Tulare	Pistachio	ton	4360	1.28	4360	5581	Perennial
Pistachios	Stanisla us	Pistachio-Merced	ton	3367.31	1.39	3367	4681	Perennial
Plums, Prunes and Apricots	Kings	Plums	ton	1410	7.75	1410	10928	Perennial
Plums, Prunes and Apricots	Kern	apricot	ton	1090	9.76	1090	10638	Perennial
Plums, Prunes and Apricots	Fresno	Plums	ton	1540	9.15	1540	14091	Perennial
Plums, Prunes and Apricots	Madera	Plums dried	ton	2432	3.17	2432	7709	Perennial
Plums, Prunes and Apricots	San Joaquin	Apricots	ton	675	9.36	675	6318	Perennial
Plums, Prunes and Apricots	Merced	Plums Dried	ton	1051.25	3.91	1051	4110	Perennial
Plums, Prunes and Apricots	Tulare	Plum and pluot	ton	1260	9.59	1260	12083	Perennial

Plums, Prunes and Apricots	Stanislaus	Apricot	ton	658	9.76	658	6422	Perennial
Pomegranates	Kings	Pomegranates-Tul	ton	671	3.79	671	2543	Perennial
Pomegranates	Kern	Pomegranates-Tul	ton	671	3.79	671	2543	Perennial
Pomegranates	Fresno	Pomegranates	ton	362	10.06	362	3642	Perennial
Pomegranates	Madera	Pomegranates-Fresno	ton	362	10.06	362	3642	Perennial
Pomegranates	San Joaquin	Pomegranates-Fresno	ton	362	10.06	362	3642	Perennial
Pomegranates	Merced	Pomegranates-Fresno	ton	362	10.06	362	3642	Perennial
Pomegranates	Tulare	Pomegranates	ton	671	3.79	671	2543	Perennial
Pomegranates	Stanislaus	Pomegranates-Fresno	ton	362	10.06	362	3642	Perennial
Potatoes and Sweet Potatoes	Kern	Spring Processing	ton	213	26.27	213	5596	Annual
Potatoes and Sweet Potatoes	Fresno	Sweet potatoes_merced	40lb cnt	17.98	15.0672	18	271	Annual
Potatoes and Sweet Potatoes	San Joaquin	Potatoes	ton	660	18.65	660	12309	Annual
Potatoes and Sweet Potatoes	Merced	Sweet potatoes	40lb cnt	17.98	15.0672	18	271	Annual
Potatoes and Sweet Potatoes	Tulare	Spring Processing-Kern	ton	213	26.27	213	5596	Annual
Potatoes and Sweet Potatoes	Stanislaus	Sweet potatoes	ton	925	18.4	925	17020	Annual
Rice	Fresno	Rice-Sjoaquin	ton	276	3.5	276	966	Annual
Rice	San Joaquin	Rice	ton	276	3.5	276	966	Annual
Rice	Merced	Rice-Sjoaquin	ton	276	3.5	276	966	Annual
Rice	Stanislaus	Rice-Sjoaquin	ton	276	3.5	276	966	Annual
Safflower	Kings	NA	0	0	0	-	-	Annual

Safflower	Kern	NA	0	0	0	-	-	Annual
Safflower	Fresno	NA	0	0	0	-	-	Annual
Safflower	San Joaquin	Safflower	ton	459	1.4	459	643	Annual
Safflower	Merced	NA	0	0	0	-	-	Annual
Safflower	Stanislaus	NA	0	0	0	-	-	Annual
Strawberries	Kings	NA	0	0	0	-	-	Annual
Strawberries	Kern	NA	0	0	0	-	-	Annual
Strawberries	Fresno	NA	0	0	0	-	-	Annual
Strawberries	San Joaquin	NA	0	0	0	-	-	Annual
Strawberries	Merced	NA	0	0	0	-	-	Annual
Strawberries	Tulare	NA	0	0	0	-	-	Annual
Strawberries	Stanislaus	NA	0	0	0	-	-	Annual
Sunflowers	Fresno	NA	0	0	0	-	-	Annual
Tomatoes	Kings	Tomato processed	ton	70.7	56.68	71	4007	Annual
Tomatoes	Kern	Tomato Processed	Acre	72.5	46.4	73	3364	Annual
Tomatoes	Fresno	Processed	ton	72	49.44	72	3560	Annual
Tomatoes	Madera	Processed	ton	75	55.31	75	4148	Annual
Tomatoes	San Joaquin	Tomatoes all	ton	83.4	47.45	83	3957	Annual
Tomatoes	Merced	Processing	25 lb ctn	71.82	0.6415	5746	3686	Annual
Tomatoes	Tulare	Tomato processed =King	ton	70.7	56.68	71	4007	Annual
Tomatoes	Stanislaus	Tomatoes all - Sjoaquin	ton	83.4	47.45	83	3957	Annual
Urban	Kings	NA	0	0	0	-	-	NA
Urban	Kern	NA	0	0	0	-	-	NA
Urban	Fresno	NA	0	0	0	-	-	NA
Urban	Madera	NA	0	0	0	-	-	NA
Urban	San Joaquin	NA	0	0	0	-	-	NA
Urban	Merced	NA	0	0	0	-	-	NA
Urban	Tulare	NA	0	0	0	-	-	NA
Urban	Stanislaus	NA	0	0	0	-	-	NA

Walnuts	Kings	Walnuts	ton	1870	2.01	1870	3759	Perennial
Walnuts	Kern	Walnuts	ton	2030	1.5	2030	3045	Perennial
Walnuts	Fresno	Walnuts		2000	1.82	2000	3640	Perennial
Walnuts	Madera	Walnuts	ton	1778	1.74	1778	3094	Perennial
Walnuts	San Joaquin	Walnuts	ton	1970	2.07	1970	4078	Perennial
Walnuts	Merced	Walnuts	ton	2903.3	1.61	2903	4674	Perennial
Walnuts	Tulare	Walnuts	ton	1790	1.83	1790	3276	Perennial
Walnuts	Stanisla us	Walnuts	tons	1100	1.91	1100	2101	Perennial
Wheat	Kings	Wheat grain	ton	223	2.51	223	560	Annual
Wheat	Kern	Wheat	ton	175	2.7	175	473	Annual
Wheat	Fresno	Wheat Grain	ton	219	1.14	219	250	Annual
Wheat	Madera	Silage	ton	31	13.68	31	424	Annual
Wheat	San Joaquin	Wheat	ton	125	2.93	125	366	Annual
Wheat	Merced	Wheat	ton	168.1	2.29	168	385	Annual
Wheat	Tulare	wheat grain	ton	227	2.42	227	549	Annual
Wheat	Stanisla us	Wheat-Sjoaquin	ton	125	2.93	125	366	Annual
Young Perennials	Kings	NA	0	0	0	-	-	Perennial
Young Perennials	Kern	NA	0	0	0	-	-	Perennial
Young Perennials	Fresno	NA	0	0	0	-	-	Perennial
Young Perennials	Madera	NA	0	0	0	-	-	Perennial
Young Perennials	San Joaquin	NA	0	0	0	-	-	Perennial
Young Perennials	Merced	NA	0	0	0	-	-	Perennial
Young Perennials	Tulare	NA	0	0	0	-	-	Perennial
Young Perennials	Stanisla us	NA	0	0	0	-	-	Perennial

SI Table 22. Table of crop revenue per crop type used for each county; revenue values obtained from each county crop report (2016)..

APPENDIX E. EVAPOTRANSPIRATION DATASET COMPARISONS

The crop water requirement (CWR) values used in Chapter 3 and 4 of this dissertation were derived using the Water Agricultural Water Footprint in R (WAFR) model developed by Booth (2018). The WAFR model estimates gridded daily crop water requirement by making use of local temperature and precipitation data from the Parameter-elevationRegressions on Independent Slopes Model (PRISM), irrigation and evapotranspiration data from the California Irrigation Management Information System (CIMIS), and land cover data (e.g., Land IQ, Kern County Agricultural Commission, and USDA Crop Data Layer). The CWR is calculated for the San Joaquin Valley by accumulating the daily crop evapotranspiration (ET_c), the amount of water transpired by an unstressed crop under standard conditions in a day (units in millimeters, mm), for a complete growing period. The growing period (unit days) is represented from the first to the last day of irrigation application. Booth (2018) uses the following equation for CWR, where $ET_{c,blue}$ is the irrigated, freshwater component of ET_c and $ET_{c, green}$ is the rainwater component of ET_c with the condition that if there is more precipitation than crop evapotranspiration then $ET_{c,blue}$ is equal to zero and the rainwater component, $ET_{c,green}$, is equal to the ET_c (Booth, 2018):

$$CWR = 10\ (\textstyle\sum_t^{lgp}(ET_{c,blue} +\ ET_{c,\ green})$$

$$ET_{c,blue} = \max\ (0, ET_{c,} - P_{eff})$$

$$ET_{c,green} = \min\ (\ ET_{c,} - P_{eff})$$

For more details on the WAFR model see Booth (2018).

The San Joaquin Valley CWR values derived from WAFR were compared with two alternative crop evapotranspiration datasets: the California Department of Water Resources (DWR) detailed analysis unit evapotranspiration (DAU ET) and OpenET, the most recently developed evapotranspiration dataset. The methodology and results of the comparison between WAFR CWR with DWR Cal-SIMETAW derived ET_{aw} are detailed in Section 1 and with OpenET in Section 2.

1. WAFR and DWR Cal-SIMETAW ET Comparisons

1.1. About DWR Cal-SIMETAW Model Derived ET

The downloaded dataset (www.WaterPlan.ca.gov) consists of annual estimates for the 2011-2015 water year. WAFR output and DWR Cal-SIMETAW derived evapotranspiration of applied awater (ET_{aw}) at the detailed analysis unit (DAU) level for the water year 2014 were compared in this analysis. This dataset consists of annual estimates of irrigated crop area, crop evapotranspiration, effective precipitation, evapotranspiration of applied water, and applied water for 20 crop categories. The spatial scale of the analysis is derived at the detailed analysis unit (DAU) and County level. The data is derived by using the California Simulation of Evapotranspiration of Applied Water (Cal-SIMETAW). Like WAFR, the Cal-SIMETAW makes use of daily weather data derived from PRISM climate data and CIMIS near real-time data. Daily U.S. National Climatic Data Center climate station data is used to cover California with a 4x4 kilometer grid of observed evapotranspiration. The evapotranspiration of applied water (ET_{aw}), an estimate of the seasonal irrigation requirement assuming 100% application efficiency. The ET_{aw} is calcualted by generating a hypothetical water balance irrigation schedule using soil-characteristic data from Soil Survey Geographic Database (SSURGO), crop information, precipitation, and daily crop evapotranspiration (ET_c) data. More information is available (https://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Agricultural-Water-Use-Models).

1.2 Methodology

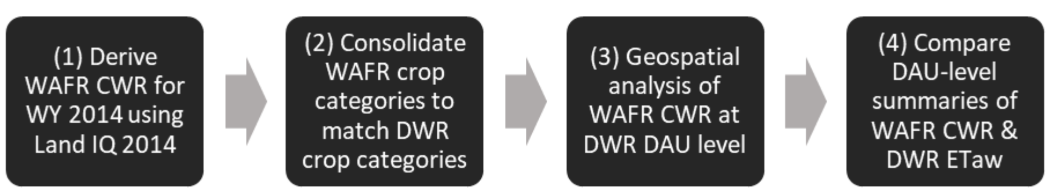
WAFR output for the same 20 crops available for the DWR DAU ET data was used for comparison in this analysis (SI Table 8). The San Joaquin Valley floor was the region of focus for this analysis resulting in a total comparative area within DAUs of 17, 124 acres. Overall this analysis makes use of ArcGIS Pro software and Excel. The following steps were taken to compare WAFR CWR with DWR Cal-SIMETAW ET_{aw} (SI Figure 45):

(1) The WAFR model was run on Land IQ 2014 land use classification data to obtain crop specific CWR values for the 2014 water year. WAFR daily raster output from October 1, 2013 through September 30, 2014 were summed in ArcGIS Pro software to derive monthly and annual CWR values by crop type. The overall CWR of the San Joaquin Valley floor is estimated to be about 15 million acre-feet (MAF).

(2) The CWR for the Land IQ 2014 crop types were consolidated to match the 20 crop categories used by DWR for the ETaw estimates outlined in SI Table 9.

(3) A geospatial analysis was conducted in ArcGIS Pro software to summarize the WAFR derived CWR for DAUs in the San Joaquin Valley. DWR DAU shapefiles were downloaded from (link), cropped to encompass the San Joaquin Valley, and polygons were dissolved by DAU boundary and converted to raster. The ArcGIS Pro 'Zonal Statistics' function was used to summarize the CWR (in millimeters) per DAU boundary resulting in a sum raster file. The raster table was exported to compare with DWR's Cal-SIMETAW ET_{aw} in Excel. The values were converted from millimeters to units of acre-feet (AF).

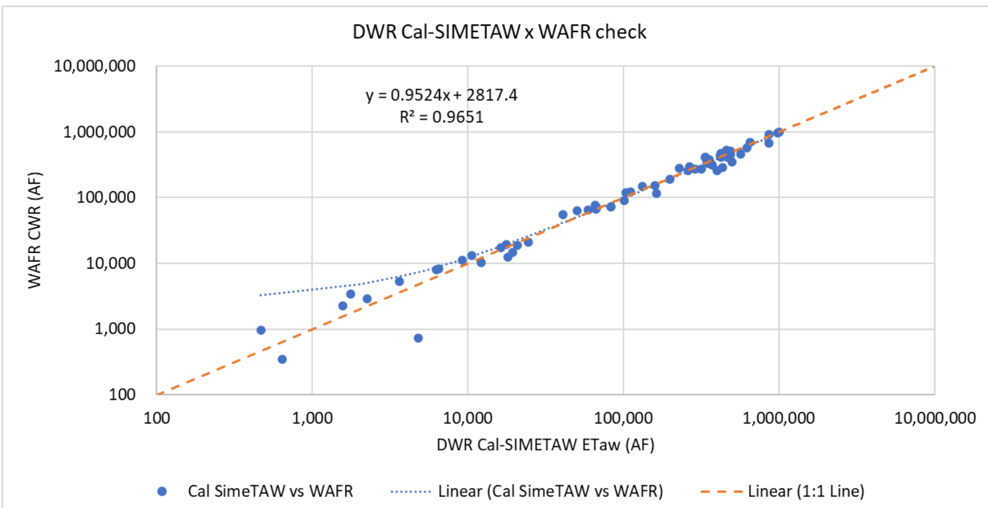
(4) The sum of CWR derived by WAFR and the ETaw derived by Cal-SIMETAW were compared in Excel. The total San Joaquin Valley CWR and ET_{aw} derived for the San Joaquin Valley floor by WAFR and DWR's Cal-SIMETAW, respectively, resulted in about 14 MAF of total CWR.



SI Figure 45. Workflow for the comparison of WAFR derived CWR and DWR CalSIMETAW derived ETaw.

1.3 Results

The comparative results show a small total percent differene of 4% between the CWR derived by WAFR and the ETaw derived by Cal-SIMETAW at the DAU-level for the San Joaquin Valley (SI Table 8). Individual DAU summaries show low difference percentage between WAFR CWR and Cal-SIMETAW ET_{aw} (SI Table 10). The few DAU summaries that have high difference percentages could bedue to the following: some DAUs being partially out of bounds of the San Joaquin Valley floor resulting in unaccounted crop estimates by WAFR calculations, the differing spatial resolution between the models, and consolidation of crop categories between Land IQ and DWR crop categories. A scatterplot between WAFR CWR (SI Figure 41, x-axis) and DWR Cal-SIMETAW (SI Figure 41, y-axis) and fitting a trendline shows great agreement (R^2= 0.97) between the two model ET estimates.



SI Figure 46. Linear fit and R^2 of DWR Cal-SIMETAW and WAFR CWR (blue) and 1:1 line for reference (orange).

Total Area (Acre)	Total WAFR CWR (AF)	Total Cal-SIMETAW ETaw (AF)	Difference (AF)	Difference Normalized by Area (AF/Ac)	Total Percent Difference
4,231,340	14,609,895	15,159,263	(549,368)	(0.13)	-4%

SI Table 23. Summary statistics for comparison of CWR derived by WAFR and ETaw derived by Cal-SIMETAW per DAU in California's San Joaquin Valley.

	DWR DAU Crop Type	WAFR Crop Type
1	Grain (wheat, wheat_winter, wheat_spring, barley, oats, misc._grain & hay)	Wheat; Misc. Grain and Hay
2	Rice (rice, rice_wild, rice_flooded, rice-upland)	Rice; Wild Rice
3	Cotton	Cotton
4	Sugar beet (sugar-beet, sugar_beet_late, sugar_beet_early)	None
5	Corn	Corn, Sorghum, Sudan
6	Dry beans	Dry Beans
7	Safflower	Safflower
8	Other field crops (flax, hops, grain_sorghum, sudan,castor-beans, misc._field, sunflower, sorghum/sudan_hybrid, millet, sugarcane	None
9	Alfalfa (alfalfa, alfalfa_mixtures, alfalfa_cut, alfalfa_annual)	Alfalfa a& Mixed Alfalfa
10	Pasture (pasture, clover, pasture_mixed, pasture_native, misc._grasses, turf_farm, pasture_bermuda, pasture_rye, klein_grass, pasture_fescue)	Mixed Pasture; Misc Grasses
11	Tomato processing (tomato_processing, tomato_processing_drip, tomato_processing_sfc)	Tomatoes
12	Tomato fresh (tomato_fresh, tomato_fresh_drip, tomato_fresh_sfc)	Tomatoes
13	Cucurbits (cucurbits, melons, squash, cucumbers, cucumbers_fresh_market, cucumbers_machine-harvest, watermelon)	Melons, Squash and Cucumbers
14	Onion & garlic (onion & garlic, onions, onions_dry, onions_green, garlic)	Onion & Garlic
15	Potatoes (potatoes, potatoes_sweet)	Potatoes
16	Truck_Crops_misc (artichokes, truck_crops, asparagus, beans_green, carrots, celery, lettuce, peas, spinach, bus h_berries, strawberries, peppers, broccoli, cabbage, cauliflower)	Misc.Truck Crops, carrots, lettuce, bush berries, strawberies, peppers, cole crops
17	Almond & pistacios	Almond; Pistachios
18	Orchard (deciduous) (apples, apricots, walnuts, cherries, peaches, nectarines, pears, plums, prunes, figs, kiwis)	apples, apricots, walnuts, cherries, peaches, nectarines, pears, plums, prunes, kiwis
19	Citrus & subtropical (grapefruit, lemons, oranges, dates, avocados, olives, jojoba)	Citrus; Misc. Subtropical; Olives
20	Vineyards (grape_table, grape_raizin, grape_wine)	Grapes

SI Table 24. Crop water requirement for the following WAFR and DWR DAU crop types were compared in this analysis

DAU	Count*	Area (Ac)	CWR (AF)	ETaw (AF)	Diff. (AF)	Norm.Diff (AF)	Pct
18,239	921,256	204,875	689,092	649,303	39,789	48	6%
18,450	28,973	6,443	21,070	24,441	(3,371)	(129)	-16%
18,539	808,754	179,856	522,120	458,470	63,650	87	12%
19,239	24,913	5,540	17,207	16,204	1,003	45	6%
20,539	262,399	58,354	188,213	199,831	(11,618)	(49)	-6%
20,639	21,746	4,836	14,644	19,295	(4,651)	(238)	-32%
20,650	364,309	81,018	257,636	397,346	(139,709)	(426)	-54%
20,750	155,087	34,489	120,572	103,241	17,331	124	14%
20,824	152,078	33,820	90,836	100,704	(9,868)	(72)	-11%
20,850	433,387	96,380	289,823	432,918	(143,094)	(367)	-49%
20,924	205,730	45,752	152,756	159,910	(7,154)	(39)	-5%
20,950	150,335	33,433	115,224	163,741	(48,517)	(359)	-42%
21,024	390,963	86,945	272,024	289,498	(17,474)	(50)	-6%
21,124	96,265	21,408	70,222	67,572	2,650	31	4%
21,224	574,627	127,790	412,730	424,172	(11,441)	(22)	-3%
21,320	589,167	131,023	473,180	425,225	47,954	90	10%
21,420	344,294	76,566	294,074	265,525	28,549	92	10%
21,520	513,027	114,091	407,446	336,321	71,126	154	17%
21,610	453,218	100,790	339,528	341,306	(1,778)	(4)	-1%
21,624	612,159	136,136	412,412	467,165	(54,753)	(99)	-13%
21,639	29,423	6,543	19,623	17,669	1,955	74	10%
21,650	387,189	86,106	270,112	316,379	(46,267)	(133)	-17%
22,110	7,988	1,776	8,135	6,468	1,667	232	20%
22,310	4,834	1,075	5,244	3,640	1,604	369	31%
22,554	3,041	676	2,875	2,261	614	224	21%
22,754	2,050	456	2,270	1,578	692	375	30%
23,015	781	174	725	4,809	(4,084)	(5,810)	-563%
23,115	5,263	1,170	3,391	1,774	1,617	341	48%
23,310	520,660	115,788	448,220	488,904	(40,685)	(87)	-9%
23,410	14,784	3,288	12,356	18,016	(5,660)	(425)	-46%
23,510	612,814	136,282	511,714	486,922	24,791	45	5%
23,610	492,618	109,552	429,926	420,195	9,731	22	2%
23,616	22,725	5,054	18,949	20,821	(1,872)	(92)	-10%
23,654	11,935	2,654	10,293	12,151	(1,857)	(173)	-18%
23,710	511,384	113,725	407,078	336,391	70,687	154	17%
23,716	86,028	19,132	64,272	59,252	5,019	65	8%
23,816	461,738	102,685	334,238	353,121	(18,882)	(45)	-6%
23,910	80,418	17,884	73,097	82,604	(9,507)	(131)	-13%
23,916	14,285	3,177	11,282	9,205	2,077	162	18%

23,954	307,379	68,357	261,147	260,650	498	2	0%
24,010	64,954	14,445	67,101	66,445	656	11	1%
24,054	58,472	13,003	62,701	50,072	12,629	240	20%
24,116	553,111	123,005	313,807	373,670	(59,863)	(120)	-19%
24,154	806	179	344	641	(297)	(410)	-87%
24,216	182,796	40,651	121,930	111,144	10,786	66	9%
24,254	1,127,815	250,811	925,898	863,700	62,198	61	7%
24,354	1,239,455	275,639	969,590	979,001	(9,411)	(8)	-1%
24,410	1,308,771	291,054	1,003,549	1,004,247	(698)	(1)	0%
24,416	207,724	46,195	147,946	131,548	16,397	88	11%
24,515	8,805	1,958	7,911	6,261	1,649	208	21%
24,516	27,426	6,099	13,030	10,618	2,412	98	19%
24,616	88,967	19,785	72,366	82,581	(10,214)	(128)	-14%
25,415	641,144	142,582	460,350	562,954	(102,604)	(178)	-22%
25,515	705,763	156,952	566,864	619,566	(52,702)	(83)	-9%
25,615	784,407	174,442	682,630	862,070	(179,440)	(254)	-26%
25,715	80,532	17,909	77,397	65,508	11,890	164	15%
25,754	63,932	14,218	55,647	40,985	14,662	255	26%
25,815	468,346	104,154	380,343	356,333	24,010	57	6%
25,915	430,384	95,712	346,284	496,731	(150,447)	(388)	-43%
26,015	859	191	956	467	489	633	51%
26,115	302,433	67,257	277,492	229,725	47,767	175	17%

*SI Table 25. DAU boundary level summary of WAFR derived CWR and DWR's Cal-SIMETAW ETaw along with value differences, normalized difference, and percent difference. *Count of 30 by 30 meter pixels within the DAU.*

2. WAFR and OpenET Comparisons

2.1 About OpenET Derived ET

OpenET dataset derives satellite-based estimates of actual evapotranspiration over specified periods of time. OpenET uses multiple satellite-driven models (i.e., ALEXI/DisALEXI, eeMETRIC, geeSEBAL, PT-JPL, SIMS, SSEBop) and provides the ensemble mean of ET from these models. All models use Landsat satellite data (30 x 30 meter spatial resolution or 0.22 acres per pixel) and gridded weather data (e.g., solar radiation, air temperature, humidity, wind speed, and precipitation). For California, OpenET uses Spatial CIMIS as is the case with WAFR and DWR's Cal-SIMETAW models. OpenET uses Google Earth Engine to compute, store, and visualize the ET data via an Application Programming Interface (API). The OpenET API enables users to request data from OpenET data via scripted queries and a graphical use interface. For more information on OpenET methodologies visit (https://openetdata.org/methodologies/).

2.2 Methodology

Given that OpenET users currently have a data request/sampling quota, 100 samples (where available) within Kern County were extracted for a comparison with WAFR CWR.

Overall this analysis makes use of ArcGIS Pro, R, and Excel software. The following steps were taken to obain OpenET data for comparison with WAFR CWR:

(1) In ArcGIS Pro I extracted the Land IQ 2016 land use classification dataset for 19 agricultural crops (SI Table 12 for list) in Kern County's valley floor. Each of the fields were encoded with the first two letters of the crop type and automatically generated "OID +100000" (e.g., Gr100958 for Grape field number 958). From this list of agricultural crops, a random selection of 100 fields per crop were selected to extract from OpenET using the following R code:

```
croplist<-read.csv("Land2016_ToRandomSelectFrom.csv")
#randomly select 100 n of each crop type
library(dplyr)
new_df <- croplist %>%
group_by(Crop2016) %>%
slice_sample(n=100)
```

The resulting randomly selected fields were joined with the attiribute table of the Land IQ 2016 dataset for Kern County's valley floor to result in a reduced vector file to be used as input within Open ET's API for data extraction. Given user quota limitations on OpenET, fields were given encoded with 1 for sample priority and 2 second sample priority in the vector file. For this analysis all fields were extracted without meeting user quota limits and 100 fields per crop were extracted for the CWR comparison.

(2) The Open ET retrieval code was developed by Nick Santos (UC Merced). The code evolved with updates to the OpenET API found here along with the Python Package Index. The code used for data extraction for this dissertation can be found here. OpenET's geodatabase API was used to retrieve values for the 100 randomly selected fields per crop for Kern County (documentation this part of OpenET's API can be accessed here). The code below loads the 100 random samples per crop in vector format into a spatial data frame. The centroid coordinates of each field is found and appended to the data frame and sends a request to OpenET's API to find the field IDs that match each set of centroid coordinates, then attaches the field IDs their API returns to the dataframe for each sample to facilitate data lookup. The API then requests the actual ET data associated with the fields of interest. The API uses the timeseries/features/stats/annual endpoint which aggregates data temporally with annual values. Given that only a single year was requested annual aggregations weren't triggered, instead subannual ones were. Once the API returned data, the

code joins the ET values into a new field. Once data for all fields has been retrieved, it exports the data to a new spatial file that can be used in other GIS packages.

(3) The WAFR CWR was run on Land IQ 2016 data for the San Joaquin Valley floor. The same 1,911 randomly selected fields used to obtain OpenET values were extracted from WAFR CWR in ArcGIS Pro through selection of WAFR CWR values with intersecting OpenET centroids. Of the 1,911 random fields, 1,445 fields from WAFR CWR dataset were available for comparison with OpenET (SI Table 12).

(4) WAFR CWR and OpenET values were merged in R software using the code below and exported as a comma-delimited format file. Comparison calculations and related statistics were conducted in Excel.

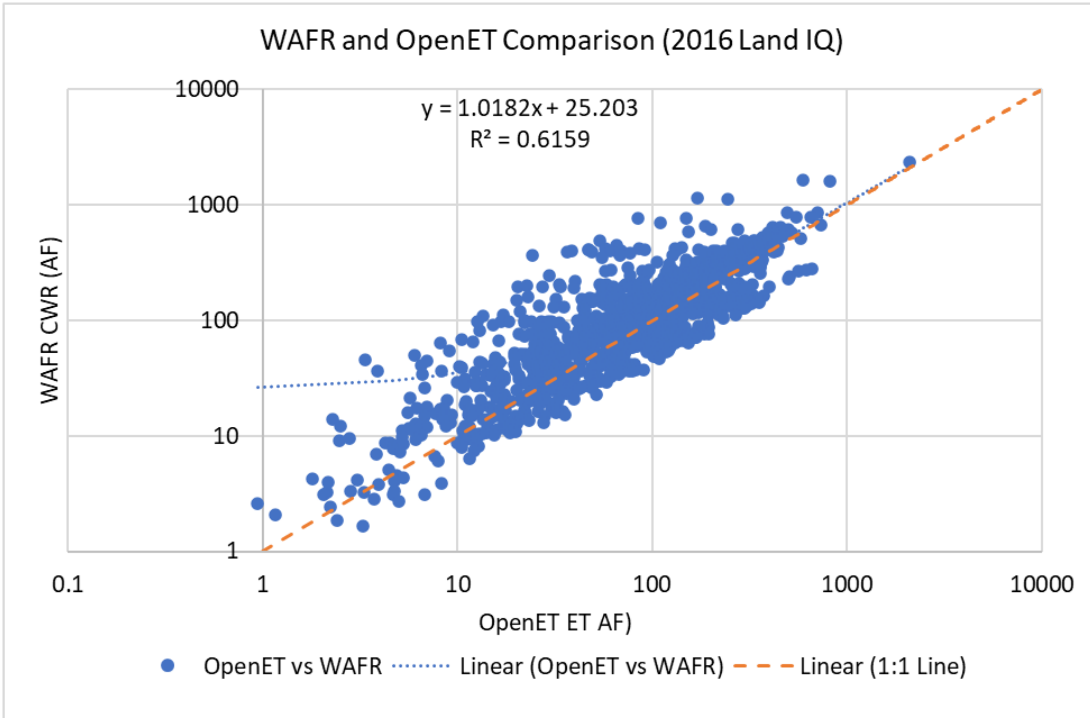
```
OpenET<- read.csv("OpenETvalues.csv")
WAFR<- read.csv("WAFRCWRdata.csv")
combined<- merge(OpenEt, WAFR, by.x ="OBJECTID_1")
write.csv(combined, "combined_openet_wafr.csv")
```

2.3 Results

The comparative results show a total percent differene of 18% between the CWR derived by WAFR and the ET derived by OpenET for Kern County (SI Table 11). Individual field level summaries show variation of difference percentage between WAFR CWR and OpenET (SI Table 13). A scatterplot between WAFR CWR (SI Figure 41, x-axis) and OpenET (SI Figure 42, y-axis) and fitting a trendline shows fair agreement (R^2= 0.61) between the two model ET estimates.

Total Area (Ac)	Total WAFR CWR (AF)	Total OpenET (AF)	Total Diff (AF)	Norm. Diff (AF/Ac)	Diff (%)
64,864	216,773	177,188	39,585	1	18

SI Table 26. Summary statistics for comparison of CWR derived by WAFR and ET derived by OpenET in Kern County.



SI Figure 47. Linear fit and R^2 of OpenET and WAFR CWR (blue) and 1:1 line for reference (orange).

Crop	**Field Count**
Alfalfa and Alfalfa Mixtures	100
Almonds	97
Apples	20
Bush Berries	57
Carrots	86
Cherries	98
Citrus	97
Corn, Sorghum and Sudan	100
Cotton	100
Grapes	88
Idle	97
Peppers	70
Plums, Prunes and Apricots	10
Pomegranates	97
Potatoes and Sweet Potatoes	92
Strawberries	5
Tomatoes	92
Walnuts	39
Wheat	100
Grand Total	**1,445**

SI Table 27. The number of fields sampled from OpenET and WAFR per crop type.

Field ID	Crop	Area (Ac)	Open ET (AF)	WAFR CWR (AF)	Difference (AF)	Norm.Diff (AF/Ac)	Diff (%)
48035	Cotton	584	2,081	2,350	270	0.46	11%
51955	Grapes	313	590	1,638	1,049	3.35	64%
51488	Grapes	311	817	1,619	801	2.58	50%
60207	Idle	227	170	1,148	979	4.30	85%
46363	Idle	222	244	1,132	888	3.99	78%
46130	Corn, Sorghum and Sudan	209	707	853	147	0.70	17%
48709	Wheat	308	490	851	361	1.17	42%
44993	Corn, Sorghum and Sudan	187	649	789	141	0.75	18%
49795	Grapes	155	547	785	238	1.53	30%
42888	Idle	153	84	771	687	4.50	89%
60566	Idle	150	149	770	622	4.14	81%
46918	Idle	133	111	704	594	4.46	84%
47122	Almonds	160	730	673	(57)	-0.36	-8%
43945	Walnuts	155	187	660	473	3.06	72%
42582	Corn, Sorghum and Sudan	156	414	640	226	1.45	35%
43971	Cotton	156	454	635	181	1.16	28%
59875	Walnuts	144	201	617	416	2.90	67%
45155	Carrots	169	273	610	337	1.99	55%
46975	Cotton	148	497	607	110	0.74	18%
46966	Cotton	146	484	595	112	0.77	19%

43946	Walnuts	139	153	593	440	3.17	74%
44228	Cotton	142	420	581	161	1.13	28%
61143	Corn, Sorghum and Sudan	138	517	580	62	0.45	11%
44733	Cotton	141	471	577	106	0.75	18%
43129	Cotton	143	396	576	180	1.26	31%
45183	Corn, Sorghum and Sudan	127	466	537	71	0.56	13%
59784	Carrots	161	368	529	161	1.00	30%
44743	Corn, Sorghum and Sudan	124	392	524	132	1.06	25%
43062	Carrots	157	406	515	109	0.69	21%
50019	Almonds	122	578	510	(69)	-0.56	-13%
43279	Cotton	124	373	502	130	1.05	26%
45698	Corn, Sorghum and Sudan	122	407	497	91	0.75	18%
44132	Cotton	121	375	495	120	0.99	24%
43000	Idle	98	54	494	440	4.50	89%
45363	Cotton	116	299	493	194	1.67	39%
179289	Carrots	150	331	492	161	1.07	33%
59812	Carrots	149	394	488	93	0.63	19%
43994	Cotton	120	355	487	133	1.11	27%
44945	Carrots	139	335	487	152	1.10	31%
61744	Corn, Sorghum and Sudan	121	413	487	74	0.61	15%
43039	Cotton	118	358	477	119	1.01	25%

58468	Wheat	180	264	474	210	1.16	44%
46809	Pomegranates	120	257	466	210	1.75	45%
42778	Corn, Sorghum and Sudan	113	394	463	69	0.61	15%
45129	Carrots	141	351	462	112	0.79	24%
42817	Cotton	112	329	452	123	1.10	27%
42694	Idle	85	66	452	386	4.53	85%
42818	Cotton	107	328	435	108	1.00	25%
45849	Carrots	128	329	432	103	0.81	24%
56266	Walnuts	96	442	431	(11)	-0.12	-3%
46920	Cotton	103	373	431	57	0.56	13%
60216	Wheat	163	142	425	284	1.74	67%
46699	Pomegranates	106	345	424	78	0.74	18%
59706	Walnuts	99	131	423	293	2.97	69%
46697	Pomegranates	106	346	422	76	0.72	18%
46698	Pomegranates	105	333	419	86	0.81	20%
46700	Pomegranates	106	324	419	95	0.90	23%
46701	Pomegranates	106	325	418	93	0.88	22%
45325	Idle	80	85	417	332	4.14	80%
46696	Pomegranates	104	356	416	60	0.58	15%
44802	Corn, Sorghum and Sudan	100	405	416	11	0.11	3%
43711	Idle	78	57	415	358	4.59	86%

46138	Corn, Sorghum and Sudan	100	377	413	36	0.36	9%
46722	Pomegran ates	104	259	413	153	1.47	37%
43280	Cotton	102	307	412	105	1.04	26%
44244	Wheat	157	258	412	154	0.98	37%
45104	Idle	78	173	412	239	3.06	58%
61343	Carrots	117	391	411	20	0.17	5%
46703	Pomegran ates	103	369	410	41	0.40	10%
44843	Carrots	120	372	409	36	0.30	9%
59577	Idle	79	47	409	362	4.60	88%
45438	Idle	77	91	408	317	4.10	78%
60168	Wheat	156	264	407	143	0.92	35%
46704	Pomegran ates	102	357	406	50	0.49	12%
46715	Pomegran ates	102	334	406	72	0.71	18%
43482	Idle	76	47	406	358	4.69	88%
46707	Pomegran ates	102	256	405	149	1.46	37%
45485	Cotton	99	280	404	124	1.25	31%
46710	Pomegran ates	102	235	403	168	1.65	42%
46716	Pomegran ates	101	311	402	91	0.91	23%
47884	Almonds	94	435	402	(33)	-0.35	-8%
46706	Pomegran ates	101	333	402	69	0.68	17%
43917	Wheat	156	317	400	83	0.53	21%

47388	Idle	79	69	400	331	4.21	83%
46709	Pomegranates	101	205	400	195	1.93	49%
45799	Idle	77	38	399	361	4.70	90%
53076	Idle	76	132	398	266	3.51	67%
43828	Wheat	155	354	397	43	0.28	11%
60260	Idle	76	60	397	337	4.41	85%
46708	Pomegranates	100	214	397	183	1.83	46%
52182	Almonds	90	420	392	(28)	-0.31	-7%
48073	Idle	72	49	392	343	4.76	88%
54196	Walnuts	85	184	391	207	2.42	53%
47508	Idle	78	36	390	354	4.57	91%
46720	Pomegranates	98	216	388	172	1.76	44%
60736	Idle	74	67	387	320	4.32	83%
46702	Pomegranates	97	310	387	77	0.79	20%
49720	Idle	76	77	386	309	4.05	80%
59110	Citrus	99	363	384	21	0.21	6%
44878	Cotton	94	314	379	65	0.70	17%
58497	Wheat	144	269	376	108	0.75	29%
42636	Carrots	107	265	374	108	1.02	29%
59787	Idle	74	24	370	346	4.65	93%
44129	Walnuts	86	127	367	240	2.79	65%
58386	Idle	70	68	365	296	4.21	81%
43883	Cotton	88	258	357	98	1.12	27%
43273	Carrots	100	302	354	52	0.52	15%
44246	Cotton	88	250	354	103	1.18	29%

43260	Cotton	87	270	353	83	0.95	24%
53496	Almonds	80	318	352	34	0.43	10%
44212	Wheat	124	286	352	66	0.53	19%
61179	Idle	65	55	350	295	4.56	84%
61171	Cotton	85	195	346	151	1.78	44%
47989	Almonds	81	323	342	18	0.23	5%
44187	Cotton	80	207	338	131	1.64	39%
46565	Almonds	77	211	336	125	1.62	37%
53159	Almonds	78	366	336	(30)	-0.38	-9%
54769	Almonds	78	361	336	(26)	-0.33	-8%
51384	Walnuts	75	328	334	7	0.09	2%
42479	Almonds	80	149	334	185	2.31	55%
50650	Almonds	78	349	334	(15)	-0.20	-5%
51310	Almonds	77	347	332	(15)	-0.19	-4%
55006	Almonds	76	305	332	27	0.35	8%
46735	Almonds	78	223	330	107	1.37	32%
45089	Corn, Sorghum and Sudan	81	232	330	98	1.21	30%
52611	Almonds	77	359	330	(29)	-0.37	-9%
43495	Corn, Sorghum and Sudan	79	259	329	71	0.89	21%
43619	Corn, Sorghum and Sudan	79	282	328	46	0.58	14%
44210	Cotton	81	228	327	100	1.24	31%
44871	Cotton	77	283	327	44	0.57	13%

60740	Corn, Sorghum and Sudan	78	252	327	74	0.95	23%
45058	Corn, Sorghum and Sudan	82	284	327	43	0.52	13%
49885	Almonds	77	293	326	34	0.44	10%
43709	Corn, Sorghum and Sudan	78	294	325	31	0.40	9%
48802	Almonds	77	335	324	(12)	-0.15	-4%
45854	Corn, Sorghum and Sudan	79	240	323	83	1.06	26%
46804	Pomegranates	83	170	322	152	1.83	47%
47730	Almonds	78	337	322	(16)	-0.20	-5%
55442	Almonds	76	364	320	(44)	-0.58	-14%
44668	Corn, Sorghum and Sudan	78	268	320	51	0.66	16%
44606	Cotton	78	105	319	214	2.73	67%
179316	Almonds	76	364	319	(45)	-0.59	-14%
179292	Almonds	76	352	317	(34)	-0.45	-11%
46803	Pomegranates	81	182	317	135	1.66	43%
59901	Carrots	96	278	317	39	0.40	12%
46915	Cotton	75	269	316	47	0.62	15%
44687	Corn, Sorghum and Sudan	77	215	315	101	1.31	32%

44525	Corn, Sorghum and Sudan	78	264	315	51	0.65	16%
46214	Potatoes and Sweet Potatoes	154	203	314	110	0.72	35%
44130	Corn, Sorghum and Sudan	77	221	313	92	1.21	30%
47032	Pomegranates	79	220	313	92	1.17	30%
47712	Almonds	75	341	312	(29)	-0.38	-9%
46916	Cotton	74	260	311	51	0.69	16%
58396	Potatoes and Sweet Potatoes	152	323	311	(12)	-0.08	-4%
44873	Corn, Sorghum and Sudan	73	251	311	60	0.82	19%
48766	Idle	62	157	310	153	2.48	49%
49537	Almonds	73	329	310	(19)	-0.26	-6%
44470	Corn, Sorghum and Sudan	77	257	310	53	0.68	17%
47044	Pomegranates	78	176	310	133	1.70	43%
43691	Cotton	75	280	309	28	0.38	9%
56138	Citrus	77	318	309	(10)	-0.12	-3%
47512	Almonds	74	292	308	17	0.23	5%
45227	Wheat	107	248	308	60	0.56	19%
47161	Pomegranates	78	210	308	98	1.25	32%

44788	Corn, Sorghum and Sudan	75	205	308	102	1.36	33%
49873	Almonds	72	250	307	57	0.79	19%
44508	Corn, Sorghum and Sudan	77	123	307	184	2.40	60%
47874	Pomegran ates	78	190	307	117	1.50	38%
47510	Almonds	74	213	307	94	1.27	31%
46330	Corn, Sorghum and Sudan	76	198	306	108	1.42	35%
45737	Corn, Sorghum and Sudan	74	259	305	46	0.63	15%
47164	Pomegran ates	78	201	305	105	1.35	34%
45860	Corn, Sorghum and Sudan	72	160	304	145	2.00	48%
47142	Pomegran ates	77	205	304	99	1.29	33%
60141	Wheat	116	191	303	112	0.97	37%
45066	Corn, Sorghum and Sudan	76	209	303	94	1.24	31%
45032	Corn, Sorghum and Sudan	74	287	303	16	0.22	5%
46179	Corn, Sorghum and Sudan	73	232	303	70	0.96	23%
47170	Pomegran ates	77	154	302	148	1.92	49%
44117	Cotton	71	201	302	101	1.42	33%

47366	Pomegranates	76	162	301	140	1.83	46%
60204	Carrots	91	209	301	92	1.00	30%
44461	Corn, Sorghum and Sudan	74	253	300	48	0.65	16%
47144	Pomegranates	76	156	300	144	1.88	48%
43760	Cotton	74	224	300	75	1.02	25%
43739	Corn, Sorghum and Sudan	72	256	300	44	0.61	15%
44270	Cotton	73	195	299	104	1.42	35%
47143	Pomegranates	76	211	299	88	1.16	30%
53732	Citrus	78	357	299	(58)	-0.75	-19%
47067	Pomegranates	76	193	298	105	1.39	35%
47048	Pomegranates	76	172	298	126	1.67	42%
45627	Corn, Sorghum and Sudan	74	263	298	35	0.48	12%
47047	Pomegranates	76	171	298	126	1.67	42%
45328	Corn, Sorghum and Sudan	75	245	298	52	0.70	18%
45728	Potatoes and Sweet Potatoes	155	318	297	(20)	-0.13	-7%
50060	Pomegranates	77	155	297	142	1.85	48%
47606	Pomegranates	76	184	297	113	1.49	38%

47168	Pomegranates	76	150	297	147	1.95	50%
47167	Pomegranates	75	188	296	108	1.44	36%
44482	Corn, Sorghum and Sudan	74	258	296	38	0.52	13%
43194	Potatoes and Sweet Potatoes	146	294	296	2	0.02	1%
47146	Pomegranates	75	150	296	146	1.94	49%
45356	Cotton	70	196	296	99	1.43	34%
47042	Pomegranates	75	213	295	82	1.10	28%
56953	Citrus	73	330	294	(36)	-0.49	-12%
46275	Carrots	81	159	294	135	1.66	46%
60529	Cotton	70	248	294	45	0.65	15%
45695	Corn, Sorghum and Sudan	71	245	291	47	0.66	16%
47480	Pomegranates	73	220	291	72	0.98	25%
47145	Pomegranates	74	161	291	131	1.76	45%
44037	Cotton	72	209	291	82	1.14	28%
43642	Corn, Sorghum and Sudan	71	210	290	80	1.13	28%
47365	Pomegranates	73	171	289	118	1.62	41%
48571	Citrus	80	264	289	25	0.31	8%
47165	Pomegranates	73	188	288	100	1.37	35%

52773	Almonds	67	302	288	(14)	-0.21	-5%
47049	Pomegranates	73	150	287	137	1.87	48%
45039	Carrots	77	193	286	94	1.21	33%
44405	Tomatoes	154	360	286	(74)	-0.48	-26%
45794	Carrots	81	75	285	210	2.59	74%
44889	Corn, Sorghum and Sudan	69	257	284	27	0.39	10%
48405	Citrus	78	297	284	(12)	-0.16	-4%
50041	Citrus	78	298	284	(14)	-0.18	-5%
49386	Pomegranates	73	186	282	96	1.32	34%
50057	Citrus	77	296	281	(15)	-0.19	-5%
44583	Carrots	80	121	280	159	2.00	57%
43116	Carrots	78	187	279	92	1.19	33%
43722	Alfalfa and Alfalfa Mixtures	148	659	279	(380)	-2.58	-136%
53948	Citrus	77	238	277	39	0.51	14%
179338	Citrus	77	253	277	25	0.32	9%
60220	Almonds	66	161	277	116	1.76	42%
54490	Carrots	78	208	277	69	0.88	25%
56105	Carrots	78	161	276	115	1.47	42%
46444	Carrots	79	180	275	95	1.21	35%
46018	Carrots	78	126	275	148	1.90	54%
48722	Idle	54	62	274	213	3.94	78%
56785	Almonds	63	280	274	(6)	-0.10	-2%

43982	Walnuts	64	97	273	177	2.76	65%
51573	Apples	106	219	273	54	0.51	20%
43799	Alfalfa and Alfalfa Mixtures	151	616	273	(343)	-2.27	-126%
45224	Cotton	67	221	272	51	0.76	19%
55809	Carrots	77	216	271	55	0.71	20%
55542	Citrus	75	280	270	(10)	-0.13	-4%
46266	Carrots	75	57	270	212	2.85	79%
47362	Pomegranates	68	204	269	64	0.95	24%
44731	Alfalfa and Alfalfa Mixtures	149	564	268	(296)	-1.99	-110%
46028	Carrots	77	161	267	106	1.38	40%
59704	Walnuts	62	89	267	178	2.86	67%
59623	Corn, Sorghum and Sudan	65	189	265	76	1.17	29%
46965	Cotton	65	214	265	51	0.78	19%
46299	Cotton	65	213	265	52	0.80	20%
43893	Cotton	64	227	265	37	0.58	14%
43997	Carrots	77	141	264	122	1.59	46%
47166	Pomegranates	67	161	264	103	1.53	39%
48732	Carrots	77	118	263	145	1.90	55%
44068	Potatoes and Sweet Potatoes	129	208	263	54	0.42	21%
43872	Carrots	78	208	262	55	0.70	21%

61211	Carrots	74	223	262	39	0.52	15%
43571	Carrots	78	205	262	57	0.74	22%
46090	Corn, Sorghum and Sudan	63	166	261	96	1.51	37%
46317	Cotton	63	181	261	80	1.27	31%
43517	Carrots	77	165	261	95	1.23	37%
43658	Corn, Sorghum and Sudan	64	194	260	66	1.03	25%
44198	Cotton	64	190	260	70	1.09	27%
44295	Cotton	63	194	259	65	1.03	25%
44972	Idle	48	93	258	165	3.43	64%
42896	Carrots	76	157	258	101	1.33	39%
46183	Carrots	74	205	258	53	0.72	21%
46153	Wheat	98	358	257	(102)	-1.03	-40%
61092	Carrots	73	215	255	40	0.55	16%
61262	Corn, Sorghum and Sudan	61	195	255	60	0.99	24%
42672	Carrots	73	169	255	86	1.17	34%
45347	Corn, Sorghum and Sudan	60	242	255	12	0.21	5%
51740	Apples	99	227	255	28	0.28	11%
44378	Cotton	62	158	254	96	1.54	38%
45781	Corn, Sorghum and Sudan	61	197	252	55	0.91	22%
47945	Wheat	96	138	252	114	1.18	45%
46952	Pomegranates	65	136	251	115	1.79	46%

42895	Carrots	74	158	250	91	1.24	37%
43605	Carrots	75	241	248	7	0.09	3%
42766	Carrots	74	161	246	84	1.15	34%
43632	Cotton	59	164	245	81	1.37	33%
59936	Idle	48	30	245	215	4.47	88%
44546	Corn, Sorghum and Sudan	60	212	244	33	0.54	13%
44168	Carrots	71	77	243	166	2.34	68%
42572	Carrots	70	140	241	101	1.43	42%
53666	Grapes	47	176	240	64	1.37	27%
44952	Alfalfa and Alfalfa Mixtures	126	508	240	(269)	-2.14	-112%
57901	Cotton	56	205	237	32	0.57	14%
43654	Corn, Sorghum and Sudan	58	138	237	99	1.69	42%
43775	Carrots	71	164	236	72	1.01	30%
44376	Wheat	82	189	234	45	0.55	19%
50015	Pomegranates	60	114	233	120	1.98	51%
48728	Carrots	67	120	231	111	1.65	48%
44240	Corn, Sorghum and Sudan	56	165	231	66	1.17	29%
53510	Almonds	53	215	230	15	0.29	7%
44664	Alfalfa and Alfalfa Mixtures	127	501	229	(272)	-2.14	-119%
57214	Almonds	52	236	227	(8)	-0.16	-4%

54197	Walnuts	50	123	227	105	2.11	46%
44258	Cotton	54	185	223	38	0.70	17%
44673	Cotton	53	128	222	94	1.78	42%
47598	Idle	44	91	221	130	2.95	59%
43255	Carrots	66	156	220	64	0.96	29%
44065	Wheat	78	174	220	46	0.59	21%
46509	Wheat	83	179	219	41	0.49	19%
47139	Pomegranates	57	130	219	89	1.57	41%
42946	Potatoes and Sweet Potatoes	107	181	219	39	0.36	18%
46476	Corn, Sorghum and Sudan	54	193	219	26	0.49	12%
43569	Cotton	53	165	219	54	1.02	25%
42949	Potatoes and Sweet Potatoes	107	199	219	20	0.18	9%
52635	Idle	42	40	218	178	4.25	82%
43907	Corn, Sorghum and Sudan	53	147	217	70	1.31	32%
43119	Wheat	77	184	216	31	0.41	14%
43639	Cotton	52	141	215	74	1.43	34%
43683	Cotton	52	154	214	61	1.17	28%
46279	Corn, Sorghum and Sudan	50	162	214	52	1.04	24%
46248	Wheat	81	166	213	47	0.58	22%
47310	Idle	42	87	212	125	2.95	59%

47137	Pomegranates	54	124	211	88	1.61	42%
43990	Wheat	74	147	211	65	0.87	31%
45508	Wheat	77	115	209	94	1.22	45%
54740	Grapes	39	118	208	91	2.31	44%
44276	Potatoes and Sweet Potatoes	103	280	208	(71)	-0.69	-34%
42718	Wheat	77	78	208	130	1.69	62%
56909	Almonds	49	183	208	26	0.53	12%
45753	Wheat	80	254	208	(46)	-0.57	-22%
43563	Carrots	62	109	208	99	1.61	48%
45645	Corn, Sorghum and Sudan	50	161	207	46	0.92	22%
43180	Carrots	61	183	206	23	0.37	11%
44238	Almonds	48	73	206	133	2.75	64%
44141	Walnuts	48	54	206	152	3.15	74%
60139	Wheat	79	75	206	131	1.66	63%
43026	Idle	37	33	205	172	4.68	84%
43222	Potatoes and Sweet Potatoes	100	328	205	(122)	-1.23	-60%
54891	Grapes	38	108	205	97	2.53	47%
46235	Wheat	78	254	203	(51)	-0.66	-25%
43856	Wheat	77	185	203	18	0.24	9%
42683	Idle	37	58	203	145	3.91	71%
45477	Potatoes and Sweet Potatoes	100	202	202	(1)	-0.01	0%

46810	Pomegranates	52	115	201	87	1.68	43%
58467	Wheat	77	23	201	179	2.32	89%
45556	Wheat	77	163	201	38	0.50	19%
43328	Wheat	73	112	201	89	1.21	44%
48655	Idle	40	79	201	122	3.06	60%
48707	Wheat	75	148	201	53	0.70	26%
46525	Wheat	77	273	201	(72)	-0.93	-36%
43312	Wheat	76	180	201	21	0.27	10%
53050	Grapes	38	149	201	52	1.35	26%
46957	Pomegranates	52	107	201	94	1.82	47%
48617	Idle	40	74	200	126	3.18	63%
55493	Grapes	38	139	200	61	1.60	31%
55410	Grapes	38	165	199	34	0.89	17%
46243	Wheat	75	185	199	14	0.19	7%
53043	Grapes	38	152	199	47	1.23	24%
42922	Corn, Sorghum and Sudan	48	142	198	56	1.17	28%
42705	Wheat	76	299	198	(102)	-1.34	-52%
49961	Pomegranates	51	76	197	121	2.38	61%
43803	Idle	38	27	196	169	4.45	86%
47309	Idle	39	87	196	109	2.79	56%
52830	Grapes	38	151	196	45	1.20	23%
44730	Alfalfa and Alfalfa Mixtures	109	400	196	(204)	-1.88	-104%

47242	Idle	38	93	196	103	2.68	53%
47825	Almonds	46	211	195	(16)	-0.34	-8%
47608	Idle	39	88	195	107	2.75	55%
56728	Idle	38	34	195	162	4.27	83%
47830	Almonds	47	211	195	(16)	-0.34	-8%
46485	Idle	39	20	195	175	4.49	90%
47614	Idle	39	88	195	106	2.74	55%
48087	Idle	38	71	194	123	3.23	63%
46551	Grapes	38	63	194	132	3.50	68%
51484	Grapes	37	84	194	110	2.94	57%
56300	Grapes	35	142	194	52	1.49	27%
59648	Cotton	48	121	194	73	1.53	38%
43473	Wheat	75	171	194	22	0.30	12%
45353	Wheat	72	181	194	13	0.18	7%
57785	Idle	37	55	194	138	3.72	71%
58011	Idle	35	40	194	154	4.42	80%
61109	Cotton	46	168	193	25	0.55	13%
54460	Wheat	70	193	192	(1)	-0.01	0%
47267	Idle	38	90	192	101	2.64	53%
46571	Wheat	73	262	191	(71)	-0.97	-37%
45088	Potatoes and Sweet Potatoes	96	184	191	7	0.07	4%
43311	Idle	38	55	190	136	3.61	71%
48547	Idle	38	84	190	107	2.82	56%
45263	Wheat	70	158	189	31	0.44	16%
49263	Wheat	72	92	187	95	1.31	51%
45030	Carrots	54	125	187	62	1.15	33%

51112	Grapes	36	136	186	50	1.36	27%
43046	Almonds	43	135	185	50	1.17	27%
43478	Corn, Sorghum and Sudan	45	134	185	51	1.12	27%
48394	Almonds	43	156	184	28	0.65	15%
46006	Corn, Sorghum and Sudan	45	131	183	52	1.16	28%
44397	Potatoes and Sweet Potatoes	91	206	183	(22)	-0.25	-12%
44289	Tomatoes	97	195	183	(12)	-0.12	-6%
46238	Carrots	52	112	183	71	1.36	39%
44111	Cotton	43	110	182	72	1.68	40%
42810	Carrots	54	117	182	65	1.20	36%
43735	Wheat	71	152	181	29	0.41	16%
56185	Citrus	47	158	181	23	0.48	12%
48613	Idle	36	66	181	114	3.20	63%
43442	Wheat	71	140	181	41	0.57	23%
58766	Citrus	47	184	181	(4)	-0.08	-2%
60452	Wheat	67	156	181	25	0.37	14%
48088	Idle	36	66	180	114	3.22	63%
42701	Carrots	52	126	179	54	1.04	30%
45547	Corn, Sorghum and Sudan	45	133	179	46	1.02	26%
45060	Corn, Sorghum and Sudan	45	156	178	22	0.49	12%
43445	Wheat	69	194	178	(16)	-0.23	-9%

45132	Corn, Sorghum and Sudan	43	141	178	37	0.85	21%
52523	Grapes	34	116	177	60	1.78	34%
50726	Almonds	41	200	176	(24)	-0.59	-14%
55002	Almonds	40	185	175	(11)	-0.27	-6%
45288	Walnuts	40	59	174	114	2.85	66%
50873	Almonds	40	168	173	5	0.12	3%
45454	Corn, Sorghum and Sudan	41	102	173	71	1.72	41%
45350	Wheat	64	153	173	20	0.31	11%
58368	Walnuts	40	55	173	118	2.96	68%
50167	Walnuts	40	166	172	6	0.15	3%
52627	Walnuts	38	139	172	33	0.85	19%
46770	Cotton	41	139	171	33	0.80	19%
55612	Grapes	30	108	171	64	2.09	37%
42633	Almonds	41	64	171	107	2.62	63%
46967	Cotton	41	139	170	31	0.75	18%
60451	Wheat	63	147	169	22	0.35	13%
49834	Almonds	40	172	169	(3)	-0.08	-2%
43562	Carrots	50	95	168	73	1.47	43%
48708	Corn, Sorghum and Sudan	41	134	168	34	0.83	20%
60941	Tomatoes	91	221	168	(54)	-0.59	-32%
48278	Idle	33	67	167	100	3.00	60%
50217	Walnuts	38	148	167	18	0.48	11%
57866	Wheat	65	68	167	99	1.52	59%

50810	Almonds	38	189	166	(22)	-0.58	-13%
43332	Wheat	63	135	166	31	0.50	19%
58611	Almonds	38	146	166	20	0.52	12%
50374	Almonds	39	167	166	(1)	-0.03	-1%
45538	Wheat	62	220	165	(54)	-0.87	-33%
56134	Cherries	79	313	165	(148)	-1.87	-90%
57362	Almonds	37	177	165	(12)	-0.31	-7%
46360	Almonds	39	85	165	80	2.06	48%
47975	Almonds	40	192	165	(27)	-0.67	-16%
53575	Almonds	38	182	165	(17)	-0.45	-10%
47262	Almonds	40	184	165	(19)	-0.49	-12%
49631	Almonds	39	150	164	14	0.37	9%
53862	Grapes	31	112	164	52	1.69	32%
43425	Alfalfa and Alfalfa Mixtures	91	333	164	(168)	-1.85	-102%
49339	Walnuts	38	135	164	29	0.76	17%
48554	Almonds	39	174	164	(11)	-0.27	-6%
57922	Cotton	39	140	164	24	0.61	15%
55706	Cherries	81	374	164	(211)	-2.62	-129%
47635	Almonds	39	171	163	(8)	-0.21	-5%
52396	Almonds	38	159	163	4	0.10	2%
52158	Almonds	37	183	162	(20)	-0.54	-12%
45215	Corn, Sorghum and Sudan	41	99	162	63	1.54	39%
47682	Almonds	39	169	162	(6)	-0.16	-4%

46310	Corn, Sorghum and Sudan	38	137	162	25	0.67	16%
48493	Almonds	38	172	162	(10)	-0.27	-6%
44723	Carrots	47	58	162	104	2.22	64%
45200	Cotton	38	119	162	42	1.11	26%
48418	Almonds	39	191	162	(29)	-0.75	-18%
61714	Idle	31	23	161	138	4.53	86%
53847	Cherries	79	280	161	(119)	-1.50	-74%
44640	Cotton	38	141	161	20	0.52	12%
43638	Potatoes and Sweet Potatoes	81	192	161	(31)	-0.38	-19%
47633	Almonds	38	162	161	(1)	-0.03	-1%
43686	Corn, Sorghum and Sudan	39	132	160	28	0.72	17%
50010	Almonds	39	181	160	(21)	-0.55	-13%
56104	Cherries	81	246	160	(86)	-1.06	-54%
49338	Walnuts	37	92	160	68	1.85	43%
43785	Corn, Sorghum and Sudan	39	113	159	47	1.20	29%
60928	Potatoes and Sweet Potatoes	81	202	159	(43)	-0.52	-27%
56704	Cherries	77	210	159	(50)	-0.65	-32%
43496	Cotton	39	96	159	64	1.65	40%
52221	Almonds	37	153	159	6	0.17	4%
47443	Almonds	38	64	159	95	2.51	60%

43207	Potatoes and Sweet Potatoes	78	183	159	(24)	-0.31	-15%
50962	Almonds	37	167	159	(9)	-0.24	-6%
44066	Potatoes and Sweet Potatoes	77	201	158	(43)	-0.55	-27%
54703	Cherries	76	311	158	(153)	-2.02	-97%
49328	Almonds	37	150	158	8	0.22	5%
43991	Potatoes and Sweet Potatoes	77	216	157	(59)	-0.76	-37%
43513	Alfalfa and Alfalfa Mixtures	88	271	157	(114)	-1.31	-73%
50053	Pomegran ates	41	56	157	101	2.49	64%
43225	Potatoes and Sweet Potatoes	78	207	157	(51)	-0.65	-32%
49287	Walnuts	36	155	157	2	0.04	1%
57066	Cherries	77	255	157	(98)	-1.27	-63%
47838	Pomegran ates	40	91	157	65	1.62	42%
50673	Almonds	36	118	156	39	1.08	25%
61552	Idle	29	78	156	78	2.72	50%
51023	Almonds	36	48	156	109	2.99	69%
45108	Corn, Sorghum and Sudan	37	114	156	41	1.13	27%
60907	Almonds	37	88	156	68	1.85	43%
43492	Cotton	38	117	156	39	1.03	25%

56051	Cherries	79	339	156	(183)	-2.34	-118%
47686	Almonds	38	158	156	(2)	-0.06	-1%
50090	Almonds	37	134	155	21	0.59	14%
49332	Walnuts	36	122	155	33	0.92	21%
47865	Pomegranates	39	91	155	64	1.62	41%
61594	Tomatoes	77	198	155	(43)	-0.56	-28%
49997	Pomegranates	40	63	155	92	2.30	59%
58260	Idle	30	32	155	123	4.11	79%
43877	Cotton	38	117	154	38	0.99	24%
58551	Pomegranates	37	121	154	34	0.90	22%
46800	Pomegranates	39	88	154	65	1.66	43%
60896	Corn, Sorghum and Sudan	37	123	154	31	0.84	20%
43880	Cotton	37	108	153	46	1.24	30%
50539	Walnuts	35	86	153	67	1.92	44%
49978	Pomegranates	40	84	153	69	1.74	45%
50544	Almonds	36	171	153	(18)	-0.49	-11%
43362	Carrots	45	75	153	78	1.72	51%
43931	Citrus	39	44	153	109	2.79	72%
43987	Alfalfa and Alfalfa Mixtures	84	287	152	(135)	-1.59	-88%
46480	Tomatoes	82	191	152	(39)	-0.48	-26%

60490	Almonds	36	98	152	54	1.51	36%
59705	Walnuts	35	50	152	102	2.87	67%
46503	Cotton	37	119	152	33	0.90	22%
46502	Cotton	37	117	152	35	0.93	23%
49980	Pomegranates	39	83	152	68	1.73	45%
43282	Carrots	44	118	151	34	0.75	22%
43705	Potatoes and Sweet Potatoes	76	210	151	(59)	-0.77	-39%
42856	Potatoes and Sweet Potatoes	74	107	151	44	0.60	29%
46841	Tomatoes	82	188	151	(37)	-0.45	-25%
43375	Cotton	36	104	151	47	1.32	31%
61134	Idle	29	20	151	130	4.44	87%
61624	Tomatoes	74	178	150	(28)	-0.38	-19%
43275	Potatoes and Sweet Potatoes	74	231	150	(81)	-1.09	-54%
60955	Tomatoes	81	160	150	(10)	-0.13	-7%
43529	Potatoes and Sweet Potatoes	79	239	149	(89)	-1.13	-60%
48684	Citrus	40	55	149	94	2.38	63%
46070	Tomatoes	75	174	149	(25)	-0.33	-17%
52628	Walnuts	33	123	149	26	0.77	17%
48897	Almonds	35	44	148	105	3.00	70%
56608	Citrus	37	92	148	56	1.50	38%
43055	Potatoes and Sweet Potatoes	72	94	148	54	0.74	36%

45713	Tomatoes	79	174	148	(26)	-0.34	-18%
52983	Citrus	39	156	148	(8)	-0.20	-5%
44887	Potatoes and Sweet Potatoes	76	196	148	(48)	-0.63	-32%
45786	Potatoes and Sweet Potatoes	76	209	148	(62)	-0.82	-42%
42731	Cotton	36	110	148	38	1.04	26%
58590	Pomegran ates	35	107	148	40	1.14	27%
45712	Tomatoes	78	177	147	(30)	-0.38	-20%
42544	Tomatoes	78	155	147	(8)	-0.10	-5%
58501	Tomatoes	79	184	147	(37)	-0.47	-25%
60532	Alfalfa and Alfalfa Mixtures	80	274	147	(127)	-1.59	-86%
42585	Tomatoes	76	200	147	(53)	-0.69	-36%
45184	Alfalfa and Alfalfa Mixtures	78	337	147	(190)	-2.44	-130%
179412	Citrus	38	152	146	(6)	-0.15	-4%
59128	Citrus	38	141	146	6	0.15	4%
49970	Pomegran ates	38	72	146	74	1.95	51%
58823	Citrus	38	165	146	(18)	-0.48	-13%
44275	Potatoes and Sweet Potatoes	73	229	146	(83)	-1.14	-56%
57065	Citrus	39	107	146	40	1.02	27%

44007	Potatoes and Sweet Potatoes	75	123	146	23	0.30	16%
48687	Citrus	38	49	146	97	2.52	66%
58013	Tomatoes	77	173	146	(27)	-0.35	-19%
45329	Alfalfa and Alfalfa Mixtures	81	312	146	(166)	-2.06	-114%
55625	Cherries	72	266	146	(120)	-1.67	-82%
54242	Cherries	78	354	146	(209)	-2.69	-144%
45018	Potatoes and Sweet Potatoes	75	258	145	(113)	-1.51	-77%
43776	Tomatoes	78	183	145	(38)	-0.48	-26%
42531	Carrots	44	73	145	73	1.66	50%
50465	Almonds	34	48	145	97	2.88	67%
45120	Corn, Sorghum and Sudan	36	102	145	43	1.20	29%
42657	Tomatoes	75	170	145	(25)	-0.34	-18%
43493	Potatoes and Sweet Potatoes	74	195	145	(50)	-0.67	-34%
46782	Tomatoes	77	199	145	(54)	-0.71	-37%
179425	Citrus	38	160	145	(15)	-0.41	-11%
58204	Citrus	36	142	145	2	0.07	2%
44219	Cotton	34	103	145	41	1.20	28%
45777	Alfalfa and	80	292	144	(147)	-1.85	-102%

	Alfalfa Mixtures						
44063	Alfalfa and Alfalfa Mixtures	76	320	144	(175)	-2.31	-122%
45787	Potatoes and Sweet Potatoes	74	127	144	17	0.24	12%
45964	Potatoes and Sweet Potatoes	75	94	144	50	0.67	35%
45779	Bush Berries	40	55	144	89	2.24	62%
60506	Citrus	40	46	144	98	2.42	68%
43923	Corn, Sorghum and Sudan	35	82	144	62	1.76	43%
51935	Grapes	27	116	143	28	1.01	19%
43790	Alfalfa and Alfalfa Mixtures	79	305	143	(162)	-2.05	-113%
50721	Almonds	33	150	143	(7)	-0.21	-5%
51710	Citrus	39	149	143	(6)	-0.15	-4%
43465	Potatoes and Sweet Potatoes	73	192	143	(49)	-0.68	-34%
46300	Potatoes and Sweet Potatoes	72	165	143	(22)	-0.30	-15%
56740	Citrus	37	136	143	6	0.17	4%
46334	Alfalfa and Alfalfa Mixtures	78	321	142	(179)	-2.30	-126%

50349	Carrots	42	85	142	57	1.37	40%
43463	Alfalfa and Alfalfa Mixtures	78	186	142	(44)	-0.57	-31%
43181	Carrots	42	122	142	20	0.48	14%
42575	Tomatoes	74	164	142	(21)	-0.29	-15%
52013	Citrus	39	145	142	(3)	-0.08	-2%
42753	Potatoes and Sweet Potatoes	70	128	142	14	0.20	10%
54522	Cherries	76	352	142	(210)	-2.76	-148%
44428	Alfalfa and Alfalfa Mixtures	77	315	142	(173)	-2.25	-122%
58109	Wheat	55	149	142	(8)	-0.14	-5%
46244	Alfalfa and Alfalfa Mixtures	76	295	142	(154)	-2.01	-109%
60162	Corn, Sorghum and Sudan	35	113	141	28	0.82	20%
49996	Pomegranates	37	71	141	71	1.93	50%
55727	Cherries	77	168	141	(27)	-0.35	-19%
47038	Pomegranates	36	95	141	46	1.28	32%
44335	Potatoes and Sweet Potatoes	70	118	141	23	0.32	16%
44959	Carrots	40	81	141	60	1.50	43%

44373	Wheat	52	106	141	35	0.66	25%
43809	Cotton	34	97	141	44	1.29	31%
45775	Alfalfa and Alfalfa Mixtures	78	307	141	(166)	-2.14	-118%
45045	Alfalfa and Alfalfa Mixtures	77	311	141	(171)	-2.22	-122%
43557	Corn, Sorghum and Sudan	34	75	141	66	1.96	47%
45075	Corn, Sorghum and Sudan	34	104	140	37	1.07	26%
47842	Pomegranates	36	76	140	64	1.79	46%
44736	Alfalfa and Alfalfa Mixtures	77	294	140	(154)	-1.99	-110%
60954	Tomatoes	76	158	140	(18)	-0.24	-13%
59043	Citrus	37	139	140	1	0.02	1%
43394	Tomatoes	75	105	140	35	0.47	25%
45311	Wheat	52	122	139	17	0.34	12%
55533	Citrus	38	143	139	(3)	-0.09	-2%
51338	Walnuts	31	118	139	22	0.69	15%
53232	Citrus	37	133	139	6	0.16	4%
42658	Tomatoes	72	163	139	(24)	-0.34	-18%
45047	Alfalfa and Alfalfa Mixtures	76	313	139	(174)	-2.29	-126%

51991	Citrus	38	130	139	9	0.23	6%
45286	Alfalfa and Alfalfa Mixtures	75	324	138	(186)	-2.46	-134%
58044	Tomatoes	74	157	138	(18)	-0.25	-13%
45770	Alfalfa and Alfalfa Mixtures	76	307	138	(169)	-2.21	-122%
44500	Alfalfa and Alfalfa Mixtures	75	280	138	(142)	-1.89	-103%
43798	Alfalfa and Alfalfa Mixtures	77	306	138	(168)	-2.19	-122%
46536	Potatoes and Sweet Potatoes	69	155	138	(17)	-0.25	-13%
59622	Bush Berries	38	57	138	80	2.11	58%
43383	Tomatoes	74	149	137	(11)	-0.15	-8%
61243	Carrots	39	118	137	20	0.51	14%
60953	Tomatoes	74	162	137	(25)	-0.33	-18%
49100	Citrus	39	130	137	8	0.20	6%
45048	Alfalfa and Alfalfa Mixtures	75	293	137	(156)	-2.09	-114%
43925	Alfalfa and Alfalfa Mixtures	76	275	137	(138)	-1.81	-101%
60576	Grapes	26	61	137	76	2.95	56%

56041	Citrus	37	136	137	0	0.01	0%
51804	Citrus	38	136	136	1	0.02	1%
43773	Tomatoes	73	155	136	(19)	-0.26	-14%
42594	Carrots	38	100	136	36	0.95	27%
44400	Cotton	33	75	135	60	1.81	45%
43936	Cotton	33	94	135	41	1.26	30%
42809	Idle	26	26	135	109	4.25	81%
44256	Alfalfa and Alfalfa Mixtures	74	287	135	(152)	-2.06	-113%
51827	Citrus	37	107	135	27	0.74	20%
44706	Potatoes and Sweet Potatoes	70	178	134	(44)	-0.63	-33%
44015	Cotton	33	97	134	37	1.12	27%
61249	Tomatoes	72	136	133	(3)	-0.04	-2%
50536	Almonds	31	118	133	15	0.48	11%
44547	Alfalfa and Alfalfa Mixtures	74	258	133	(125)	-1.69	-93%
43396	Alfalfa and Alfalfa Mixtures	74	307	133	(174)	-2.36	-130%
60649	Carrots	38	109	133	24	0.64	18%
43741	Alfalfa and Alfalfa Mixtures	74	301	133	(168)	-2.28	-127%
45584	Alfalfa and	74	249	133	(116)	-1.58	-87%

	Alfalfa Mixtures						
57920	Cotton	31	111	132	21	0.68	16%
45219	Corn, Sorghum and Sudan	31	111	132	21	0.67	16%
46236	Carrots	38	31	132	101	2.67	77%
55704	Citrus	34	139	132	(8)	-0.23	-6%
43052	Alfalfa and Alfalfa Mixtures	73	232	131	(101)	-1.38	-77%
42619	Tomatoes	69	162	131	(31)	-0.45	-24%
49223	Almonds	31	137	131	(6)	-0.20	-5%
46783	Pomegranates	34	35	130	95	2.84	73%
45280	Alfalfa and Alfalfa Mixtures	69	195	130	(65)	-0.94	-50%
45294	Alfalfa and Alfalfa Mixtures	71	298	129	(169)	-2.37	-131%
58713	Citrus	34	63	129	66	1.96	51%
58099	Tomatoes	68	167	129	(38)	-0.56	-30%
44294	Carrots	38	75	129	54	1.43	42%
43744	Alfalfa and Alfalfa Mixtures	71	291	128	(162)	-2.28	-127%
52010	Citrus	35	131	128	(3)	-0.08	-2%
46891	Tomatoes	69	157	128	(29)	-0.42	-22%

58272	Potatoes and Sweet Potatoes	63	96	128	32	0.51	25%
51341	Walnuts	29	100	128	28	0.97	22%
45726	Potatoes and Sweet Potatoes	66	142	127	(15)	-0.22	-11%
60292	Almonds	30	44	127	83	2.81	65%
44286	Carrots	38	81	126	45	1.21	36%
43469	Potatoes and Sweet Potatoes	66	226	126	(100)	-1.50	-79%
60925	Tomatoes	68	140	126	(14)	-0.21	-11%
61254	Carrots	35	68	125	57	1.61	46%
46833	Tomatoes	67	146	125	(21)	-0.31	-17%
49088	Almonds	30	100	124	24	0.81	19%
45001	Carrots	37	45	124	79	2.15	64%
44080	Cotton	31	93	124	31	1.01	25%
55554	Cherries	60	221	123	(98)	-1.62	-80%
47660	Pomegranates	31	80	121	41	1.31	34%
58360	Citrus	30	114	121	7	0.23	6%
58034	Potatoes and Sweet Potatoes	62	211	121	(90)	-1.43	-74%
59950	Idle	24	21	120	100	4.14	83%
58390	Tomatoes	64	156	120	(36)	-0.57	-30%
42643	Peppers	74	158	120	(38)	-0.51	-32%
44589	Almonds	27	62	120	58	2.12	49%
50984	Grapes	23	92	119	27	1.17	23%
54039	Citrus	32	107	119	13	0.39	10%

46007	Corn, Sorghum and Sudan	29	98	119	21	0.71	17%
61530	Carrots	33	81	119	37	1.14	32%
51625	Apples	46	95	118	23	0.50	19%
47066	Pomegran ates	30	75	118	43	1.44	37%
44305	Alfalfa and Alfalfa Mixtures	66	172	118	(54)	-0.82	-46%
61093	Potatoes and Sweet Potatoes	60	143	118	(25)	-0.42	-22%
45536	Grapes	22	97	117	20	0.88	17%
49465	Cherries	63	142	117	(26)	-0.40	-22%
46358	Cotton	28	66	116	50	1.78	43%
61384	Idle	21	72	116	44	2.07	38%
43059	Cotton	29	77	116	39	1.37	34%
17930 2	Pomegran ates	30	75	116	40	1.35	35%
47296	Almonds	27	130	115	(15)	-0.55	-13%
42588	Peppers	71	161	115	(47)	-0.66	-41%
46528	Potatoes and Sweet Potatoes	58	118	115	(4)	-0.07	-3%
58872	Citrus	30	74	114	40	1.32	35%
58554	Wheat	42	72	114	42	1.01	37%
61780	Corn, Sorghum and Sudan	28	89	114	25	0.89	22%
43263	Cotton	28	74	113	39	1.42	35%
46125	Tomatoes	59	123	113	(10)	-0.16	-9%

43692	Alfalfa and Alfalfa Mixtures	62	267	113	(154)	-2.48	-136%
61728	Corn, Sorghum and Sudan	28	76	113	37	1.32	33%
43898	Alfalfa and Alfalfa Mixtures	63	228	113	(116)	-1.85	-103%
46382	Idle	22	17	112	95	4.34	85%
51599	Apples	44	97	112	16	0.36	14%
42798	Potatoes and Sweet Potatoes	56	194	112	(82)	-1.46	-73%
46789	Pomegranates	29	67	112	45	1.56	40%
54847	Grapes	20	74	111	37	1.87	33%
47198	Almonds	27	104	111	7	0.27	7%
55579	Grapes	20	85	111	26	1.32	24%
45992	Alfalfa and Alfalfa Mixtures	61	220	111	(109)	-1.81	-99%
48670	Almonds	27	116	111	(5)	-0.19	-4%
55769	Grapes	21	63	110	47	2.29	43%
61024	Tomatoes	58	109	110	1	0.02	1%
61431	Carrots	30	44	110	66	2.18	60%
46799	Pomegranates	28	64	109	45	1.62	41%
59496	Idle	22	14	109	96	4.41	88%
44138	Alfalfa and	60	66	109	43	0.71	39%

	Alfalfa Mixtures						
43976	Potatoes and Sweet Potatoes	57	143	109	(35)	-0.60	-32%
45639	Corn, Sorghum and Sudan	26	74	109	35	1.34	32%
45738	Corn, Sorghum and Sudan	26	63	109	46	1.77	42%
45509	Wheat	39	52	109	57	1.45	53%
44923	Wheat	39	89	108	19	0.48	17%
45203	Wheat	40	97	107	10	0.26	9%
53385	Wheat	39	119	107	(12)	-0.31	-11%
60232	Corn, Sorghum and Sudan	26	73	107	34	1.30	32%
44957	Wheat	39	108	107	(1)	-0.02	-1%
55551	Citrus	29	122	107	(15)	-0.53	-14%
42533	Peppers	67	123	107	(16)	-0.24	-15%
51657	Grapes	20	85	107	21	1.08	20%
46917	Cotton	25	84	106	22	0.88	21%
46546	Wheat	41	99	106	7	0.16	6%
51598	Apples	41	98	106	8	0.18	7%
60582	Grapes	19	81	106	24	1.27	23%
44439	Alfalfa and Alfalfa Mixtures	59	231	106	(126)	-2.14	-119%
46564	Wheat	38	63	105	42	1.10	40%

45859	Corn, Sorghum and Sudan	25	57	105	48	1.92	46%
58519	Cotton	25	69	105	36	1.42	34%
61424	Potatoes and Sweet Potatoes	51	69	105	36	0.70	35%
43284	Potatoes and Sweet Potatoes	52	141	105	(37)	-0.71	-35%
42803	Tomatoes	56	114	105	(10)	-0.17	-9%
44677	Wheat	39	90	104	14	0.36	14%
43539	Wheat	39	81	104	23	0.59	22%
55097	Grapes	19	49	104	55	2.83	53%
58045	Corn, Sorghum and Sudan	25	65	104	39	1.60	38%
54383	Grapes	19	82	104	21	1.11	21%
58950	Grapes	20	77	104	27	1.35	26%
59389	Grapes	20	66	102	36	1.82	35%
53267	Grapes	20	66	102	37	1.88	36%
56135	Plums, Prunes and Apricots	30	99	102	4	0.12	4%
53382	Wheat	37	105	102	(3)	-0.07	-2%
58532	Wheat	38	46	102	56	1.47	55%
51461	Apples	40	106	102	(4)	-0.09	-4%
42655	Carrots	30	54	102	48	1.62	47%
58127	Wheat	39	74	102	27	0.71	27%
49499	Walnuts	23	59	102	42	1.80	42%

56131	Plums, Prunes and Apricots	30	126	102	(25)	-0.83	-25%
54674	Grapes	18	57	101	44	2.39	43%
43951	Cotton	25	72	101	29	1.17	29%
44874	Corn, Sorghum and Sudan	24	83	101	18	0.75	18%
45943	Potatoes and Sweet Potatoes	52	123	101	(22)	-0.43	-22%
59237	Grapes	19	63	100	37	1.90	37%
57704	Grapes	19	56	100	44	2.31	44%
48705	Wheat	37	73	100	27	0.71	27%
45748	Wheat	38	127	100	(27)	-0.72	-27%
52239	Grapes	19	67	100	33	1.71	33%
60052	Wheat	38	41	99	58	1.54	59%
60331	Idle	19	22	99	77	4.09	78%
59381	Grapes	19	73	99	26	1.38	27%
61737	Corn, Sorghum and Sudan	24	79	99	20	0.82	20%
57033	Idle	19	17	99	82	4.27	83%
44149	Wheat	38	66	99	33	0.87	33%
44274	Wheat	38	79	99	19	0.52	20%
59940	Idle	20	13	99	86	4.40	87%
57642	Grapes	19	73	98	25	1.32	25%
53772	Grapes	18	73	98	25	1.37	25%
55367	Idle	19	24	98	74	3.94	76%
45925	Wheat	37	70	98	28	0.74	28%

50924	Grapes	19	72	98	26	1.35	26%
59529	Idle	19	18	98	80	4.19	81%
58126	Wheat	37	75	98	22	0.60	23%
60993	Tomatoes	53	114	98	(16)	-0.31	-17%
45495	Wheat	37	69	98	29	0.78	29%
59406	Grapes	19	30	98	67	3.57	69%
59341	Grapes	19	55	97	43	2.26	44%
58760	Grapes	19	29	97	68	3.66	70%
56389	Grapes	19	70	97	28	1.48	29%
57552	Idle	19	27	97	70	3.76	72%
53130	Grapes	19	80	97	17	0.91	17%
45021	Tomatoes	50	130	97	(33)	-0.66	-34%
44930	Potatoes and Sweet Potatoes	48	81	97	16	0.33	17%
42733	Cotton	24	63	97	34	1.44	36%
50105	Cherries	51	193	97	(96)	-1.88	-99%
57407	Grapes	19	30	97	66	3.58	69%
53185	Citrus	25	112	97	(16)	-0.62	-16%
58528	Idle	19	33	96	63	3.33	65%
57776	Grapes	18	65	95	30	1.63	31%
59292	Grapes	18	45	95	50	2.73	53%
43859	Corn, Sorghum and Sudan	23	31	95	64	2.79	67%
59750	Grapes	19	22	95	73	3.91	77%
54450	Grapes	18	71	94	24	1.35	25%
59153	Grapes	18	29	94	65	3.62	69%
51101	Grapes	18	73	94	21	1.15	23%

45029	Tomatoes	49	121	94	(26)	-0.54	-28%
54478	Grapes	17	44	94	50	2.85	53%
46434	Alfalfa and Alfalfa Mixtures	52	128	94	(34)	-0.66	-37%
59174	Grapes	18	60	93	33	1.84	35%
48817	Walnuts	21	76	92	16	0.76	17%
51295	Grapes	18	79	92	13	0.70	14%
42535	Idle	18	15	92	77	4.30	83%
61794	Alfalfa and Alfalfa Mixtures	48	113	92	(21)	-0.43	-23%
58965	Grapes	17	70	91	21	1.23	23%
53374	Citrus	24	111	91	(19)	-0.80	-21%
60021	Carrots	28	67	91	24	0.87	27%
45159	Alfalfa and Alfalfa Mixtures	46	187	90	(97)	-2.08	-107%
53119	Citrus	24	103	90	(12)	-0.52	-14%
58724	Citrus	24	63	90	27	1.15	30%
53643	Grapes	17	58	90	32	1.85	36%
51512	Grapes	17	69	90	21	1.29	24%
43020	Alfalfa and Alfalfa Mixtures	47	65	89	24	0.50	27%
53343	Citrus	24	91	89	(2)	-0.08	-2%
44826	Alfalfa and	47	172	89	(83)	-1.75	-94%

	Alfalfa Mixtures						
57312	Grapes	17	55	89	34	1.98	38%
43806	Alfalfa and Alfalfa Mixtures	48	148	88	(59)	-1.22	-67%
46911	Almonds	21	82	88	6	0.30	7%
48696	Citrus	23	35	88	53	2.31	60%
59258	Grapes	17	27	88	61	3.64	70%
46396	Wheat	33	82	88	5	0.16	6%
45043	Alfalfa and Alfalfa Mixtures	48	195	88	(107)	-2.24	-123%
45354	Alfalfa and Alfalfa Mixtures	46	86	88	2	0.04	2%
45146	Idle	17	26	87	62	3.64	70%
59649	Wheat	34	87	87	0	0.00	0%
51243	Grapes	17	63	87	24	1.42	28%
46397	Alfalfa and Alfalfa Mixtures	47	139	87	(52)	-1.10	-59%
58909	Grapes	17	61	87	26	1.57	30%
45997	Corn, Sorghum and Sudan	21	79	86	8	0.37	9%
46429	Alfalfa and Alfalfa Mixtures	48	182	86	(96)	-2.01	-111%

46798	Pomegranates	22	54	85	31	1.41	36%
57903	Peppers	52	128	84	(44)	-0.84	-52%
59326	Almonds	19	66	84	18	0.96	22%
56899	Grapes	16	69	83	14	0.89	17%
49286	Walnuts	19	51	83	33	1.71	39%
44440	Alfalfa and Alfalfa Mixtures	46	179	83	(96)	-2.08	-116%
44777	Tomatoes	42	97	83	(14)	-0.33	-17%
54127	Cherries	41	110	83	(27)	-0.66	-33%
44660	Alfalfa and Alfalfa Mixtures	46	172	83	(89)	-1.96	-108%
44932	Tomatoes	43	79	83	3	0.07	4%
48250	Almonds	20	93	82	(11)	-0.54	-13%
49897	Walnuts	19	82	82	0	0.02	0%
61648	Wheat	30	42	82	40	1.33	49%
42982	Potatoes and Sweet Potatoes	42	68	82	14	0.33	17%
48879	Walnuts	19	74	82	8	0.42	10%
59821	Corn, Sorghum and Sudan	20	48	82	34	1.68	41%
45975	Tomatoes	42	79	81	2	0.05	3%
59533	Idle	16	13	81	68	4.33	84%
56145	Cherries	39	171	81	(90)	-2.28	-110%

56394	Cherries	39	180	81	(99)	-2.53	-123%
60747	Tomatoes	42	93	81	(12)	-0.30	-15%
42691	Cotton	19	51	80	29	1.53	37%
46294	Tomatoes	43	105	80	(25)	-0.58	-31%
56133	Cherries	39	184	80	(104)	-2.68	-129%
53734	Cherries	41	129	80	(49)	-1.20	-61%
55578	Cherries	39	177	80	(97)	-2.45	-121%
44051	Potatoes and Sweet Potatoes	42	105	80	(25)	-0.61	-32%
48080	Tomatoes	41	101	80	(21)	-0.51	-27%
54471	Wheat	29	76	80	3	0.12	4%
56574	Cherries	38	183	79	(104)	-2.72	-131%
61291	Carrots	23	45	79	35	1.49	44%
55407	Grapes	15	62	79	17	1.11	21%
54822	Cherries	38	84	79	(4)	-0.11	-6%
60219	Almonds	18	55	79	24	1.32	31%
56639	Bush Berries	20	47	79	32	1.60	40%
42860	Potatoes and Sweet Potatoes	40	59	79	20	0.50	26%
43028	Potatoes and Sweet Potatoes	38	117	79	(38)	-1.01	-49%

56647	Grapes	15	61	78	18	1.16	22%
56641	Bush Berries	20	49	78	29	1.50	37%
49661	Almonds	19	71	78	7	0.39	9%
55631	Cherries	39	173	78	(95)	-2.46	-122%
56167	Citrus	19	82	78	(4)	-0.22	-5%
50074	Citrus	21	84	78	(6)	-0.28	-8%
58552	Cherries	39	107	78	(30)	-0.75	-38%
56393	Cherries	38	180	78	(102)	-2.69	-131%
56638	Bush Berries	19	49	77	28	1.46	37%
47776	Pomegranates	20	23	77	53	2.72	69%
48681	Alfalfa and Alfalfa Mixtures	41	153	77	(76)	-1.87	-99%
44046	Carrots	23	21	77	56	2.48	73%
51812	Cherries	41	185	77	(108)	-2.66	-141%
43953	Cotton	19	55	77	22	1.17	29%
44374	Potatoes and Sweet Potatoes	38	83	77	(7)	-0.18	-9%
43984	Potatoes and Sweet Potatoes	37	102	77	(25)	-0.67	-33%
55398	Cherries	40	196	76	(119)	-3.02	-156%

44201	Cotton	19	51	76	25	1.36	33%
44325	Potatoes and Sweet Potatoes	37	60	76	17	0.44	22%
56640	Bush Berries	19	46	76	30	1.58	39%
43593	Cotton	18	49	76	27	1.47	36%
60988	Tomatoes	41	90	76	(14)	-0.35	-19%
45451	Cotton	19	51	76	25	1.35	33%
56603	Bush Berries	19	30	76	46	2.42	61%
54697	Cherries	37	84	76	(8)	-0.23	-11%
179378	Citrus	20	59	76	17	0.83	22%
47071	Pomegranates	19	51	76	24	1.26	32%
44115	Cotton	18	42	75	34	1.90	45%
45156	Potatoes and Sweet Potatoes	37	49	75	26	0.71	35%
56604	Bush Berries	19	29	75	46	2.45	61%
46117	Tomatoes	38	83	75	(8)	-0.21	-11%
44033	Potatoes and Sweet Potatoes	37	104	75	(29)	-0.77	-38%
58772	Citrus	20	77	75	(1)	-0.07	-2%
43717	Potatoes and Sweet Potatoes	39	45	75	30	0.77	40%
44133	Tomatoes	40	85	75	(10)	-0.26	-14%
43190	Tomatoes	40	71	75	4	0.09	5%
46388	Cotton	18	54	74	20	1.12	27%

56342	Citrus	19	76	74	(2)	-0.11	-3%
44206	Potatoes and Sweet Potatoes	37	106	74	(32)	-0.86	-43%
58446	Corn, Sorghum and Sudan	18	58	74	16	0.86	21%
45710	Tomatoes	39	92	74	(18)	-0.46	-25%
51939	Cherries	40	150	74	(76)	-1.88	-102%
44106	Potatoes and Sweet Potatoes	38	120	74	(47)	-1.22	-63%
44034	Potatoes and Sweet Potatoes	37	96	74	(22)	-0.60	-30%
56192	Citrus	19	57	73	16	0.86	22%
51454	Pomegranates	19	22	73	51	2.71	70%
45600	Wheat	29	56	73	17	0.61	24%
43069	Potatoes and Sweet Potatoes	36	60	73	13	0.37	18%
45788	Potatoes and Sweet Potatoes	38	125	73	(52)	-1.39	-71%
45241	Corn, Sorghum and Sudan	18	61	73	12	0.67	16%
44284	Wheat	28	65	73	8	0.28	11%
47193	Cherries	40	140	73	(67)	-1.68	-91%
46508	Alfalfa and Alfalfa Mixtures	41	142	73	(69)	-1.68	-94%

42904	Corn, Sorghum and Sudan	18	61	73	12	0.67	16%
58876	Citrus	19	52	73	21	1.09	29%
46749	Pomegranates	19	42	73	31	1.67	43%
60355	Corn, Sorghum and Sudan	18	55	73	17	0.99	24%
59776	Potatoes and Sweet Potatoes	36	100	73	(27)	-0.77	-38%
60441	Alfalfa and Alfalfa Mixtures	38	112	73	(39)	-1.03	-54%
60783	Tomatoes	37	72	73	0	0.00	0%
59817	Potatoes and Sweet Potatoes	38	93	72	(21)	-0.54	-28%
60118	Tomatoes	38	93	72	(21)	-0.55	-29%
59729	Corn, Sorghum and Sudan	18	57	72	15	0.85	21%
57950	Potatoes and Sweet Potatoes	38	96	72	(24)	-0.63	-33%
54777	Grapes	13	37	72	35	2.65	49%
61630	Potatoes and Sweet Potatoes	36	106	72	(33)	-0.92	-46%
45110	Alfalfa and Alfalfa Mixtures	38	168	72	(96)	-2.49	-133%
42714	Tomatoes	37	74	72	(2)	-0.05	-3%

47438	Potatoes and Sweet Potatoes	37	135	72	(63)	-1.71	-88%
55208	Citrus	19	76	72	(4)	-0.20	-5%
46892	Tomatoes	39	86	72	(14)	-0.36	-20%
60443	Corn, Sorghum and Sudan	17	26	72	46	2.63	64%
46563	Wheat	26	39	72	33	1.27	46%
60704	Potatoes and Sweet Potatoes	37	41	72	30	0.82	42%
46228	Potatoes and Sweet Potatoes	37	90	71	(18)	-0.49	-25%
55284	Citrus	19	68	71	4	0.19	5%
60876	Tomatoes	37	79	71	(8)	-0.22	-11%
60674	Tomatoes	36	86	71	(15)	-0.41	-21%
44332	Potatoes and Sweet Potatoes	36	104	71	(33)	-0.93	-47%
50633	Almonds	16	69	71	2	0.13	3%
56532	Wheat	25	63	71	8	0.31	11%
59551	Potatoes and Sweet Potatoes	36	86	71	(15)	-0.42	-21%
51813	Cherries	38	167	71	(96)	-2.55	-135%
50662	Grapes	14	40	71	31	2.22	44%
46065	Potatoes and Sweet Potatoes	36	87	71	(17)	-0.45	-23%
59100	Grapes	13	42	71	28	2.11	40%

57789	Bush Berries	19	60	70	10	0.54	14%
43384	Tomatoes	38	64	70	6	0.16	9%
46526	Alfalfa and Alfalfa Mixtures	39	128	70	(58)	-1.50	-84%
57136	Almonds	16	37	70	33	2.08	47%
46258	Alfalfa and Alfalfa Mixtures	38	118	70	(48)	-1.27	-69%
46751	Pomegran ates	18	43	69	26	1.47	38%
46497	Alfalfa and Alfalfa Mixtures	38	125	69	(56)	-1.47	-81%
51790	Cherries	37	158	69	(89)	-2.42	-128%
60460	Corn, Sorghum and Sudan	17	59	69	10	0.59	15%
46217	Alfalfa and Alfalfa Mixtures	38	140	69	(71)	-1.85	-103%
44811	Tomatoes	36	84	69	(15)	-0.42	-22%
60874	Tomatoes	36	81	69	(12)	-0.33	-17%
44953	Alfalfa and Alfalfa Mixtures	36	126	68	(58)	-1.61	-84%
56053	Carrots	19	40	68	28	1.47	42%
61350	Alfalfa and	37	136	68	(68)	-1.84	-99%

	Alfalfa Mixtures						
61125	Pomegranates	18	10	68	57	3.27	85%
46005	Corn, Sorghum and Sudan	17	51	68	17	1.03	25%
49383	Cherries	36	134	68	(66)	-1.84	-98%
60621	Tomatoes	35	84	68	(17)	-0.48	-25%
60875	Tomatoes	35	78	68	(11)	-0.30	-16%
43728	Alfalfa and Alfalfa Mixtures	36	122	68	(55)	-1.51	-81%
43301	Alfalfa and Alfalfa Mixtures	37	137	67	(70)	-1.90	-103%
44598	Tomatoes	35	90	67	(23)	-0.65	-34%
46323	Alfalfa and Alfalfa Mixtures	37	130	67	(63)	-1.73	-95%
57193	Grapes	13	44	67	22	1.73	33%
49245	Cherries	35	145	67	(78)	-2.20	-117%
46465	Carrots	19	16	66	50	2.67	75%
54397	Citrus	17	73	66	(7)	-0.40	-11%
56524	Potatoes and Sweet Potatoes	32	52	66	14	0.45	22%
44616	Alfalfa and Alfalfa Mixtures	37	132	66	(67)	-1.82	-101%

61209	Carrots	19	44	66	21	1.11	33%
43808	Alfalfa and Alfalfa Mixtures	36	128	66	(63)	-1.77	-96%
60034	Idle	12	12	65	54	4.36	82%
59693	Tomatoes	35	79	65	(14)	-0.40	-21%
56375	Citrus	17	31	65	34	2.03	52%
46101	Peppers	41	98	65	(33)	-0.81	-51%
59722	Carrots	18	53	65	12	0.64	18%
47273	Pomegranates	17	43	65	22	1.30	33%
61540	Peppers	39	102	65	(37)	-0.95	-58%
59621	Bush Berries	18	27	64	38	2.12	58%
58292	Alfalfa and Alfalfa Mixtures	35	153	64	(89)	-2.52	-138%
44790	Wheat	24	69	64	(5)	-0.21	-8%
61407	Peppers	39	94	64	(30)	-0.79	-47%
58503	Carrots	19	47	64	17	0.89	27%
60353	Alfalfa and Alfalfa Mixtures	34	130	64	(66)	-1.93	-104%
43696	Corn, Sorghum and Sudan	16	40	64	23	1.51	37%
49018	Pomegranates	16	45	64	18	1.13	29%
53353	Citrus	17	63	63	(0)	-0.01	0%
43144	Tomatoes	34	73	63	(9)	-0.28	-15%

59606	Idle	13	8	63	55	4.34	87%
42842	Peppers	38	73	62	(10)	-0.27	-17%
60890	Bush Berries	17	25	62	37	2.18	60%
46295	Tomatoes	33	78	62	(16)	-0.47	-25%
59585	Bush Berries	17	31	62	31	1.83	51%
56950	Cherries	30	83	62	(21)	-0.72	-35%
57949	Potatoes and Sweet Potatoes	32	83	62	(21)	-0.66	-35%
59591	Bush Berries	17	29	61	32	1.92	53%
56637	Cherries	29	112	61	(52)	-1.76	-85%
55458	Grapes	11	39	61	22	1.97	36%
59830	Tomatoes	32	38	61	22	0.70	36%
60492	Tomatoes	33	71	60	(11)	-0.32	-18%
59626	Alfalfa and Alfalfa Mixtures	34	83	60	(22)	-0.66	-37%
44140	Alfalfa and Alfalfa Mixtures	33	117	60	(57)	-1.71	-95%
44956	Alfalfa and Alfalfa Mixtures	31	114	60	(55)	-1.77	-92%
60129	Peppers	38	79	60	(20)	-0.52	-33%
60342	Alfalfa and Alfalfa Mixtures	32	115	60	(55)	-1.72	-92%

43174	Peppers	37	80	60	(21)	-0.55	-34%
46263	Alfalfa and Alfalfa Mixtures	32	97	59	(37)	-1.16	-63%
44939	Alfalfa and Alfalfa Mixtures	31	124	59	(65)	-2.11	-110%
60080	Alfalfa and Alfalfa Mixtures	32	79	59	(20)	-0.62	-34%
46421	Alfalfa and Alfalfa Mixtures	32	112	59	(53)	-1.67	-90%
51951	Cherries	32	122	59	(63)	-1.95	-106%
60937	Tomatoes	32	68	59	(9)	-0.28	-15%
56287	Cherries	31	121	59	(62)	-2.04	-106%
46788	Pomegranates	15	33	59	26	1.73	44%
47152	Almonds	14	48	58	10	0.74	18%
43487	Corn, Sorghum and Sudan	14	43	58	15	1.05	26%
56601	Bush Berries	14	38	58	20	1.39	35%
56338	Corn, Sorghum and Sudan	14	31	57	26	1.91	46%
43457	Alfalfa and	31	123	57	(66)	-2.14	-115%

	Alfalfa Mixtures						
43627	Wheat	21	73	57	(16)	-0.77	-28%
61090	Carrots	16	50	57	7	0.44	13%
48697	Alfalfa and Alfalfa Mixtures	30	110	57	(53)	-1.75	-93%
57185	Almonds	13	58	56	(2)	-0.12	-3%
58052	Tomatoes	30	74	56	(17)	-0.56	-30%
56888	Idle	11	30	56	26	2.45	46%
60942	Tomatoes	30	64	56	(8)	-0.26	-14%
58050	Tomatoes	30	68	56	(12)	-0.41	-22%
56602	Bush Berries	14	36	56	20	1.44	36%
61457	Wheat	19	26	55	29	1.52	53%
58420	Idle	11	9	55	46	4.25	84%
57685	Citrus	14	60	55	(5)	-0.37	-10%
54850	Cherries	27	121	55	(66)	-2.43	-120%
45507	Wheat	20	25	54	30	1.51	55%
45931	Alfalfa and Alfalfa Mixtures	31	99	54	(45)	-1.45	-82%
45816	Potatoes and Sweet Potatoes	28	94	54	(40)	-1.42	-73%
58269	Tomatoes	28	29	54	25	0.90	47%
46591	Alfalfa and	29	117	54	(64)	-2.16	-118%

	Alfalfa Mixtures						
54489	Potatoes and Sweet Potatoes	27	49	54	5	0.17	8%
47315	Almonds	13	39	53	14	1.08	26%
44390	Alfalfa and Alfalfa Mixtures	30	94	53	(40)	-1.37	-76%
52932	Citrus	14	34	53	19	1.35	36%
60226	Cotton	13	26	53	27	2.08	51%
57788	Bush Berries	14	47	53	6	0.44	12%
61287	Tomatoes	27	60	53	(7)	-0.27	-14%
60781	Tomatoes	27	58	53	(6)	-0.21	-11%
43189	Tomatoes	28	61	52	(9)	-0.32	-17%
45414	Potatoes and Sweet Potatoes	26	44	52	8	0.31	15%
45578	Citrus	14	26	52	26	1.94	51%
42836	Idle	10	20	52	32	3.16	62%
54155	Idle	10	21	52	30	3.14	58%
46349	Alfalfa and Alfalfa Mixtures	28	105	52	(53)	-1.89	-103%
60625	Tomatoes	27	65	52	(14)	-0.51	-27%
42664	Wheat	20	40	52	11	0.57	22%
58087	Cotton	12	31	51	21	1.66	40%
42795	Tomatoes	27	57	51	(6)	-0.20	-11%
55296	Citrus	14	22	51	29	2.14	56%

60725	Idle	10	21	51	30	3.07	59%
42639	Peppers	32	72	51	(21)	-0.65	-40%
55010	Grapes	10	24	51	27	2.86	53%
54506	Citrus	14	54	51	(3)	-0.22	-6%
44419	Plums, Prunes and Apricots	16	33	51	18	1.09	35%
61627	Potatoes and Sweet Potatoes	26	34	50	16	0.62	32%
43223	Tomatoes	27	56	50	(6)	-0.21	-11%
59269	Plums, Prunes and Apricots	16	33	50	17	1.08	34%
59957	Cotton	12	33	50	18	1.43	35%
61511	Idle	9	6	50	44	4.68	88%
61218	Tomatoes	25	66	50	(16)	-0.63	-32%
44781	Wheat	19	48	50	1	0.08	3%
48836	Walnuts	11	45	50	5	0.43	10%
47507	Pomegranates	12	29	49	20	1.63	41%
42979	Apples	18	36	49	13	0.72	27%
51938	Cherries	27	102	49	(53)	-1.98	-108%
52008	Bush Berries	13	36	49	13	0.97	27%
46792	Pomegranates	13	28	49	21	1.66	42%
56763	Citrus	13	32	49	17	1.35	35%
46794	Pomegranates	12	26	49	23	1.85	47%

51850	Bush Berries	13	19	49	29	2.26	60%
43849	Cotton	11	32	48	16	1.41	34%
46143	Tomatoes	25	55	48	(6)	-0.26	-13%
60737	Tomatoes	24	64	48	(16)	-0.68	-34%
58203	Walnuts	10	16	48	32	3.16	67%
58574	Grapes	9	33	48	14	1.57	30%
54792	Grapes	9	30	48	18	1.98	37%
58032	Peppers	29	70	47	(23)	-0.78	-48%
56765	Cherries	25	108	47	(61)	-2.45	-129%
47210	Cherries	26	55	47	(9)	-0.34	-19%
43304	Grapes	9	23	47	24	2.71	52%
51972	Bush Berries	12	25	46	21	1.72	45%
55260	Grapes	9	35	46	12	1.31	25%
46150	Corn, Sorghum and Sudan	11	36	46	10	0.91	22%
59974	Idle	9	3	46	43	4.65	93%
59934	Apples	17	34	46	12	0.68	25%
45942	Peppers	28	71	46	(26)	-0.91	-56%
58453	Potatoes and Sweet Potatoes	24	56	45	(10)	-0.43	-22%
179304	Pomegranates	12	28	45	18	1.51	39%
59670	Carrots	13	27	45	18	1.43	40%
61791	Carrots	13	43	45	2	0.14	4%
61517	Idle	8	7	45	38	4.52	85%

45792	Tomatoes	23	63	44	(19)	-0.82	-43%
42686	Peppers	27	56	44	(12)	-0.43	-26%
61219	Tomatoes	22	56	44	(12)	-0.55	-28%
61682	Bush Berries	12	16	44	28	2.36	63%
53074	Citrus	12	42	44	1	0.13	3%
56545	Idle	8	13	44	31	3.84	70%
55436	Pomegran ates	11	24	44	20	1.77	45%
61526	Peppers	26	55	44	(12)	-0.44	-26%
59870	Apples	16	33	43	10	0.62	23%
59813	Carrots	13	33	43	10	0.79	24%
61585	Tomatoes	22	57	43	(14)	-0.63	-33%
44209	Cotton	10	34	43	9	0.85	21%
61681	Bush Berries	11	13	43	29	2.59	69%
61527	Peppers	25	56	43	(13)	-0.52	-31%
61680	Bush Berries	11	16	42	26	2.32	62%
59273	Wheat	16	51	42	(9)	-0.57	-21%
45944	Potatoes and Sweet Potatoes	22	75	42	(33)	-1.50	-77%
61679	Bush Berries	11	15	42	27	2.40	64%
56948	Cherries	20	77	42	(35)	-1.74	-84%
55068	Grapes	8	24	42	18	2.22	42%
53397	Citrus	11	29	42	13	1.18	31%
60906	Peppers	25	54	42	(12)	-0.47	-29%

56397	Bush Berries	10	31	42	11	1.05	26%
60341	Alfalfa and Alfalfa Mixtures	23	80	42	(39)	-1.72	-92%
43645	Carrots	12	23	42	19	1.52	45%
55435	Pomegran ates	11	20	42	22	2.09	53%
56943	Cherries	19	66	41	(25)	-1.31	-63%
43115	Peppers	24	55	41	(14)	-0.59	-35%
61773	Idle	8	7	41	34	4.29	84%
61528	Peppers	24	58	41	(17)	-0.72	-43%
56002	Citrus	11	37	40	3	0.28	8%
43114	Potatoes and Sweet Potatoes	20	26	40	15	0.74	36%
59953	Idle	8	10	40	30	3.74	75%
58558	Wheat	15	30	40	10	0.68	25%
59449	Plums, Prunes and Apricots	13	28	40	12	0.95	30%
60324	Wheat	15	53	40	(13)	-0.87	-33%
61480	Potatoes and Sweet Potatoes	20	32	40	8	0.41	20%
44350	Cotton	10	29	40	11	1.12	27%
56136	Bush Berries	10	26	40	13	1.36	34%
58068	Idle	8	10	39	29	3.82	73%
56464	Cherries	20	81	39	(41)	-2.04	-106%

56498	Citrus	10	32	39	7	0.67	17%
42740	Alfalfa and Alfalfa Mixtures	21	49	39	(10)	-0.47	-25%
52662	Citrus	10	32	39	7	0.65	17%
55465	Cherries	19	42	39	(4)	-0.20	-10%
53917	Cherries	19	42	38	(3)	-0.17	-9%
60013	Wheat	15	38	38	(0)	-0.01	0%
55998	Citrus	10	39	38	(1)	-0.07	-2%
53444	Cherries	19	83	38	(45)	-2.29	-117%
47661	Pomegranates	10	24	38	14	1.39	36%
56575	Cherries	19	75	38	(37)	-2.01	-98%
55392	Cherries	20	79	38	(41)	-2.11	-109%
57364	Bush Berries	10	41	38	(3)	-0.29	-8%
57487	Bush Berries	10	40	38	(3)	-0.27	-7%
52715	Cherries	19	90	38	(52)	-2.67	-138%
46140	Alfalfa and Alfalfa Mixtures	21	76	38	(38)	-1.86	-102%
53109	Cherries	20	79	38	(42)	-2.13	-111%

59450	Plums, Prunes and Apricots	12	25	37	12	1.02	33%
56578	Cherries	18	82	37	(45)	-2.49	-120%
54267	Grapes	7	16	37	22	3.11	58%
46801	Pomegranates	10	20	37	17	1.81	46%
61361	Peppers	23	61	37	(24)	-1.04	-65%
56593	Cherries	18	76	37	(39)	-2.17	-106%
42906	Corn, Sorghum and Sudan	9	32	37	4	0.50	12%
60601	Idle	7	4	37	33	4.60	89%
58029	Almonds	9	8	37	28	3.29	78%
53328	Citrus	10	27	37	10	0.98	26%
56633	Cherries	18	78	36	(42)	-2.35	-115%
61089	Tomatoes	18	43	36	(7)	-0.37	-19%
56379	Citrus	9	32	36	4	0.43	11%
50106	Cherries	19	69	36	(33)	-1.74	-92%
47587	Idle	7	12	36	24	3.29	66%
57674	Citrus	9	39	36	(4)	-0.38	-10%
55281	Citrus	9	31	36	4	0.45	12%
60777	Cherries	17	30	35	5	0.31	15%
54912	Grapes	7	16	35	19	2.85	54%
53211	Citrus	9	36	35	(1)	-0.11	-3%

52973	Bush Berries	9	25	34	9	1.00	26%
43199	Plums, Prunes and Apricots	11	14	34	20	1.77	59%
57650	Citrus	9	36	34	(1)	-0.14	-4%
52963	Bush Berries	9	27	34	7	0.83	22%
60482	Idle	7	7	34	28	4.15	81%
42604	Peppers	21	67	34	(33)	-1.60	-97%
52964	Bush Berries	9	28	34	6	0.68	18%
52962	Bush Berries	9	25	34	9	0.97	26%
59979	Wheat	13	36	34	(2)	-0.19	-7%
52975	Bush Berries	9	25	34	8	0.96	25%
61662	Pomegran ates	8	15	34	19	2.33	56%
61498	Cherries	16	61	33	(27)	-1.70	-82%
57695	Citrus	9	32	33	1	0.16	4%
58121	Peppers	21	48	33	(15)	-0.72	-45%
58116	Cotton	8	21	33	12	1.55	37%
58071	Almonds	8	17	33	16	2.02	47%
52965	Bush Berries	9	26	33	7	0.78	20%
52957	Bush Berries	9	26	33	7	0.81	21%
52968	Bush Berries	9	24	33	8	0.96	25%
52966	Bush Berries	9	29	33	4	0.43	11%

44827	Alfalfa and Alfalfa Mixtures	17	61	33	(29)	-1.64	-88%
52967	Bush Berries	9	25	33	7	0.83	22%
57656	Citrus	8	29	32	3	0.38	10%
58845	Citrus	8	31	32	1	0.17	4%
59011	Cherries	16	40	32	(8)	-0.47	-23%
57003	Citrus	8	33	32	(1)	-0.07	-2%
61473	Peppers	19	53	32	(21)	-1.11	-65%
43024	Potatoes and Sweet Potatoes	15	33	32	(2)	-0.11	-5%
58378	Cotton	7	17	32	15	1.99	47%
45719	Tomatoes	16	35	31	(4)	-0.22	-11%
56230	Wheat	11	21	31	10	0.91	32%
61263	Carrots	9	21	31	10	1.18	34%
61487	Citrus	8	11	31	20	2.48	64%
61459	Potatoes and Sweet Potatoes	15	33	31	(2)	-0.12	-6%
55604	Wheat	11	17	31	13	1.23	44%
55470	Cherries	15	29	30	1	0.06	3%
43056	Peppers	18	53	30	(24)	-1.35	-80%
61678	Citrus	8	16	30	13	1.70	45%
52969	Bush Berries	8	24	30	6	0.74	20%
54507	Cherries	16	54	30	(24)	-1.52	-81%
45994	Potatoes and Sweet Potatoes	15	30	29	(1)	-0.06	-3%

50139	Almonds	7	25	29	4	0.54	13%
48719	Citrus	8	13	29	17	2.13	57%
61884	Idle	6	10	29	19	3.37	66%
42540	Alfalfa and Alfalfa Mixtures	16	58	29	(29)	-1.83	-101%
60989	Tomatoes	16	28	29	0	0.02	1%
59895	Citrus	8	12	29	17	2.17	58%
52958	Bush Berries	7	22	28	6	0.80	21%
45420	Alfalfa and Alfalfa Mixtures	15	39	28	(11)	-0.71	-39%
59143	Grapes	5	17	28	11	2.12	41%
51872	Bush Berries	7	13	28	15	2.06	55%
51434	Pomegranates	7	13	28	14	2.03	52%
46785	Pomegranates	7	16	28	12	1.65	42%
54750	Cherries	14	30	27	(2)	-0.15	-8%
46406	Wheat	10	28	27	(0)	-0.03	-1%
57913	Peppers	17	46	27	(19)	-1.10	-68%
53905	Grapes	5	12	27	15	2.96	54%
59632	Carrots	8	16	27	11	1.38	41%
61405	Peppers	16	49	27	(22)	-1.40	-83%
61020	Peppers	17	35	27	(8)	-0.48	-30%
54449	Grapes	5	11	27	16	3.26	60%
59559	Peppers	16	40	27	(13)	-0.84	-50%

45720	Peppers	16	40	27	(14)	-0.85	-52%
58030	Peppers	16	44	26	(17)	-1.06	-65%
61192	Peppers	16	43	26	(17)	-1.01	-63%
42637	Peppers	16	34	26	(8)	-0.49	-31%
58130	Peppers	16	38	26	(12)	-0.74	-46%
44263	Alfalfa and Alfalfa Mixtures	14	49	26	(23)	-1.63	-87%
45321	Idle	5	7	26	19	3.98	74%
42611	Peppers	16	34	26	(8)	-0.49	-30%
52149	Apples	10	32	26	(6)	-0.64	-24%
55592	Cherries	13	28	26	(2)	-0.15	-7%
61358	Peppers	16	42	25	(16)	-1.04	-65%
52148	Apples	9	31	25	(6)	-0.67	-25%
56951	Cherries	12	33	25	(9)	-0.72	-34%
52263	Apples	9	30	25	(6)	-0.62	-23%
55657	Cherries	12	20	25	5	0.37	18%
55699	Cherries	12	27	25	(3)	-0.22	-11%
52152	Apples	9	28	25	(4)	-0.41	-15%
58377	Cotton	6	15	25	10	1.67	39%
51793	Citrus	6	24	24	(0)	-0.05	-1%
45490	Potatoes and Sweet Potatoes	12	24	24	(0)	-0.02	-1%
53244	Cherries	12	36	23	(13)	-1.07	-55%
61362	Peppers	15	34	23	(11)	-0.74	-46%
53335	Citrus	6	16	23	7	1.13	30%

52970	Bush Berries	6	17	23	5	0.90	24%
55393	Cherries	12	52	23	(29)	-2.44	-126%
55601	Cherries	11	23	23	(0)	-0.03	-2%
56842	Citrus	6	17	22	5	0.95	25%
59869	Apples	8	17	22	5	0.57	21%
59019	Cherries	11	27	22	(6)	-0.51	-26%
59018	Cherries	11	25	22	(4)	-0.32	-16%
52974	Bush Berries	6	16	21	6	1.01	26%
60485	Idle	4	6	21	16	3.77	73%
55602	Cherries	11	23	21	(2)	-0.20	-10%
58557	Cherries	11	26	21	(5)	-0.46	-23%
56877	Peppers	13	40	21	(19)	-1.48	-89%
59073	Citrus	5	22	21	(1)	-0.20	-5%
52980	Citrus	5	21	21	(0)	-0.05	-1%
59534	Peppers	13	33	21	(12)	-0.96	-60%
51675	Grapes	4	9	20	12	3.04	57%
57916	Cotton	5	13	20	7	1.47	36%
59558	Peppers	12	26	20	(5)	-0.45	-27%
61178	Tomatoes	11	24	20	(3)	-0.32	-17%
58379	Wheat	7	19	20	1	0.16	6%
57765	Bush Berries	5	17	20	3	0.50	13%
51568	Bush Berries	5	11	20	9	1.70	45%

57914	Potatoes and Sweet Potatoes	10	29	20	(9)	-0.86	-45%
58153	Wheat	8	23	20	(3)	-0.45	-17%
57679	Bush Berries	5	17	19	1	0.30	8%
60551	Peppers	11	26	19	(8)	-0.70	-41%
57012	Grapes	3	11	19	8	2.20	41%
55463	Wheat	6	13	18	5	0.75	27%
57218	Citrus	5	15	18	3	0.73	19%
42586	Peppers	11	33	18	(15)	-1.34	-83%
61639	Idle	3	7	18	11	3.18	61%
56910	Walnuts	4	8	18	9	2.27	52%
61655	Idle	3	6	17	11	3.37	65%
57881	Peppers	11	30	17	(13)	-1.23	-76%
56606	Bush Berries	4	8	17	9	2.07	52%
52971	Bush Berries	4	12	17	5	1.20	32%
44698	Cherries	9	15	17	1	0.15	8%
44683	Cherries	9	18	17	(1)	-0.11	-6%
50117	Cherries	9	32	17	(15)	-1.71	-91%
52972	Bush Berries	4	12	17	4	1.01	26%
52170	Almonds	4	15	17	1	0.34	8%
53075	Citrus	4	13	17	4	0.89	24%
56944	Cherries	8	22	17	(6)	-0.70	-34%
46462	Wheat	6	11	16	5	0.81	30%
42532	Peppers	10	26	16	(10)	-0.92	-58%

47768	Strawberries	4	7	16	10	2.19	58%
58166	Peppers	10	34	16	(18)	-1.85	-113%
58886	Citrus	4	16	16	(0)	-0.02	0%
51852	Pomegranates	4	6	16	10	2.52	65%
58167	Peppers	10	32	16	(16)	-1.65	-101%
56914	Walnuts	4	8	16	8	2.19	50%
58080	Peppers	10	22	16	(7)	-0.73	-45%
58448	Alfalfa and Alfalfa Mixtures	8	36	15	(20)	-2.42	-132%
61484	Walnuts	3	11	15	4	1.18	26%
61472	Peppers	9	22	15	(6)	-0.71	-42%
53798	Grapes	3	8	15	7	2.42	45%
42935	Potatoes and Sweet Potatoes	7	9	15	6	0.79	39%
54685	Grapes	3	7	15	8	3.03	55%
58459	Alfalfa and Alfalfa Mixtures	8	28	15	(13)	-1.59	-87%
61481	Cherries	7	16	15	(1)	-0.09	-4%
58168	Peppers	9	22	15	(7)	-0.77	-47%
61500	Cherries	7	20	15	(5)	-0.70	-34%
45099	Wheat	5	12	15	3	0.53	20%
58465	Peppers	9	22	14	(8)	-0.90	-57%

43209	Peppers	9	21	14	(7)	-0.79	-50%
61080	Potatoes and Sweet Potatoes	7	14	14	(0)	-0.02	-1%
58972	Citrus	4	15	14	(1)	-0.19	-5%
56983	Idle	3	2	14	12	4.45	84%
60776	Cherries	7	14	14	0	0.04	2%
61637	Carrots	4	8	14	5	1.40	39%
56891	Peppers	8	23	14	(10)	-1.21	-73%
61730	Tomatoes	7	17	13	(4)	-0.57	-31%
58081	Peppers	8	19	13	(6)	-0.69	-42%
58522	Peppers	8	18	13	(5)	-0.63	-40%
56631	Bush Berries	3	9	13	4	1.18	30%
48558	Alfalfa and Alfalfa Mixtures	7	28	13	(14)	-2.02	-111%
44820	Peppers	8	17	13	(4)	-0.54	-33%
56605	Bush Berries	3	7	13	6	1.92	48%
61502	Cherries	6	20	13	(7)	-1.20	-58%
43224	Peppers	8	19	13	(6)	-0.73	-46%
58223	Walnuts	3	6	13	7	2.45	52%
56875	Peppers	7	19	12	(7)	-0.90	-54%
58366	Plums, Prunes and Apricots	4	11	12	1	0.35	11%
55462	Wheat	4	9	12	3	0.80	28%
60036	Idle	2	3	12	10	4.23	79%
59020	Cherries	6	14	12	(2)	-0.38	-19%

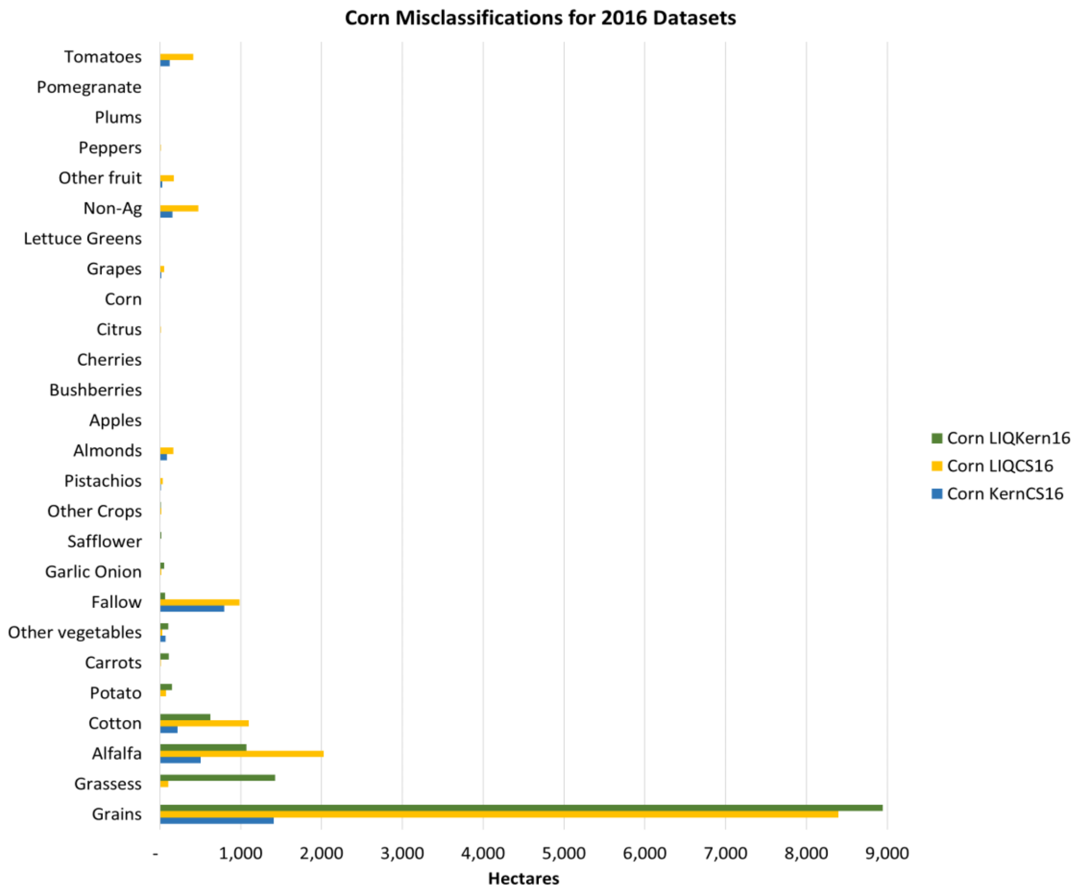
58400	Cotton	3	7	12	5	1.74	42%
59873	Apples	4	6	12	6	1.35	50%
55705	Bush Berries	3	11	12	0	0.12	3%
59874	Apples	4	6	12	6	1.31	49%
59872	Apples	4	6	12	6	1.39	52%
60975	Peppers	7	18	12	(6)	-0.84	-52%
60976	Peppers	7	16	12	(5)	-0.65	-40%
52771	Cherries	6	19	11	(7)	-1.23	-65%
53271	Cherries	6	18	11	(7)	-1.11	-57%
59871	Apples	4	6	11	5	1.28	47%
59274	Grapes	2	6	11	6	2.56	49%
61710	Strawberries	3	5	11	6	2.03	54%
60773	Cherries	6	11	11	1	0.09	5%
61474	Peppers	7	14	11	(3)	-0.50	-29%
43793	Alfalfa and Alfalfa Mixtures	6	20	11	(9)	-1.57	-85%
54129	Cherries	5	14	11	(3)	-0.67	-33%
56878	Peppers	6	19	11	(8)	-1.25	-75%
58170	Peppers	6	13	10	(2)	-0.36	-22%
58255	Potatoes and Sweet Potatoes	5	13	10	(3)	-0.53	-28%
57962	Cotton	2	7	10	4	1.50	36%
59690	Peppers	6	15	10	(5)	-0.80	-51%
52009	Bush Berries	3		10	#VALUE!	#VALUE!	#VALUE!

58169	Peppers	6	12	10	(2)	-0.39	-24%
56386	Cherries	5	11	10	(1)	-0.16	-8%
54035	Grapes	2	5	10	4	2.51	46%
58083	Peppers	6	12	10	(2)	-0.41	-25%
60067	Idle	2	3	10	7	3.65	71%
44586	Peppers	6	12	9	(2)	-0.43	-26%
58164	Peppers	6	13	9	(3)	-0.55	-34%
56632	Bush Berries	2	6	9	3	1.36	34%
61757	Idle	2	2	9	7	3.77	73%
60004	Alfalfa and Alfalfa Mixtures	5	11	9	(2)	-0.32	-18%
58538	Tomatoes	4	10	9	(1)	-0.27	-14%
44041	Cotton	2	4	9	4	2.14	51%
59508	Strawberri es	2	4	9	4	1.82	49%
45163	Bush Berries	2	5	9	3	1.52	38%
53909	Pomegran ates	2	5	8	3	1.77	42%
44324	Alfalfa and Alfalfa Mixtures	5	13	8	(5)	-1.04	-59%
56947	Cherries	4	11	8	(3)	-0.66	-32%
61483	Walnuts	2	5	8	3	1.81	40%
56876	Peppers	5	12	8	(5)	-1.02	-62%
56630	Bush Berries	2	5	7	2	1.21	31%
60017	Walnuts	2	4	7	3	1.95	45%

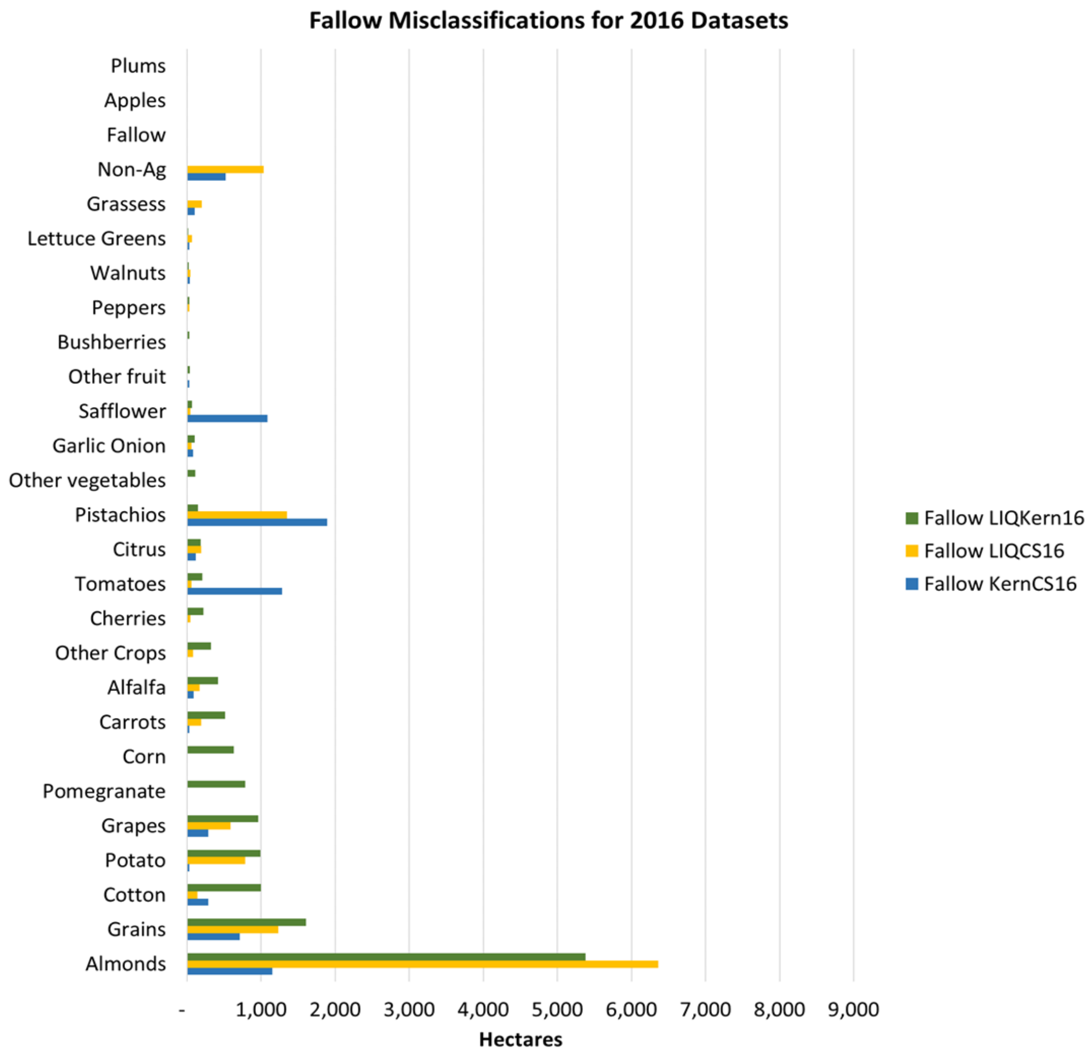
60504	Peppers	4	8	7	(1)	-0.24	-15%
54248	Cherries	3	11	6	(5)	-1.52	-81%
60899	Peppers	4	8	6	(2)	-0.51	-31%
35559	Citrus	1	4	5	1	0.52	13%
61632	Tomatoes	2	5	5	(0)	-0.12	-6%
61633	Tomatoes	2	5	4	(1)	-0.41	-21%
35647	Idle	1	2	4	2	2.89	58%
35680	Carrots	1	3	4	1	0.90	26%
60552	Peppers	2	5	4	(1)	-0.27	-16%
35623	Corn, Sorghum and Sudan	1	2	4	2	1.90	46%
54554	Cherries	2	8	4	(4)	-2.16	-113%
35607	Plums, Prunes and Apricots	1	4	4	(0)	-0.11	-4%
56949	Cherries	2	5	3	(1)	-0.86	-41%
35677	Plums, Prunes and Apricots	1	3	3	0	0.46	15%
179399	Apples	1	3	3	(0)	0.00	0%
35605	Almonds	1	2	3	1	1.52	34%
56582	Cherries	2	5	3	(2)	-1.00	-49%
54280	Cherries	2	7	3	(4)	-2.25	-118%
35587	Bush Berries	1	2	3	1	1.34	34%
35717	Cherries	1	4	3	(1)	-0.66	-32%

35541	Cherries	1	5	3	(2)	-1.64	-86%
35732	Strawberries	1	1	3	2	2.41	64%
179400	Apples	1	2	2	0	0.28	10%
35528	Bush Berries	1	1	2	1	1.67	44%
35478	Strawberries	0		2	#VALUE!	#VALUE!	#VALUE!
35718	Cherries	1	2	2	(1)	-0.66	-32%
35738	Grapes	0		2	#VALUE!	#VALUE!	#VALUE!
35564	Cherries	1	3	2	(2)	-2.02	-97%

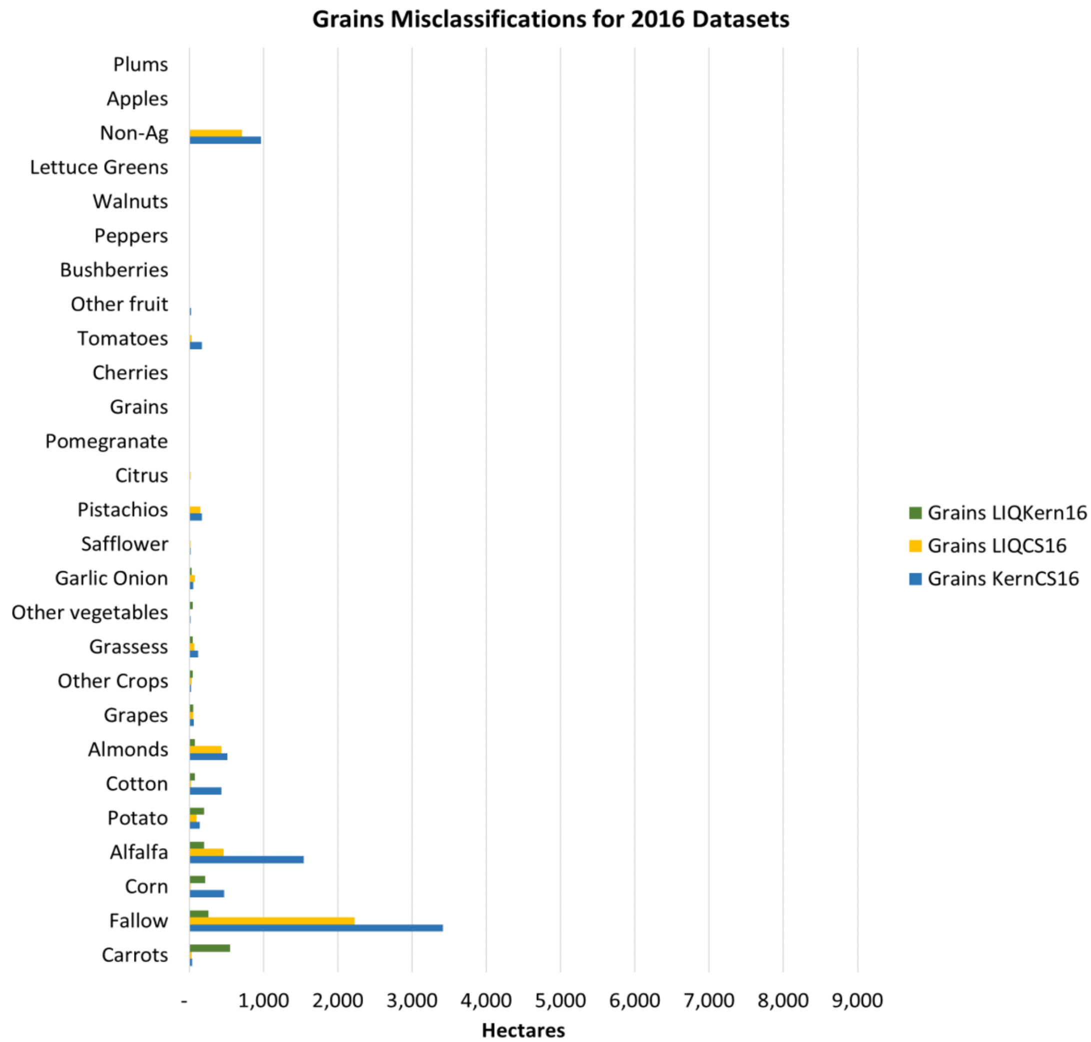
SI Table 28. Summary of WAFR derived CWR and OpenET derived ET along with value differences, normalized difference, and percent difference.



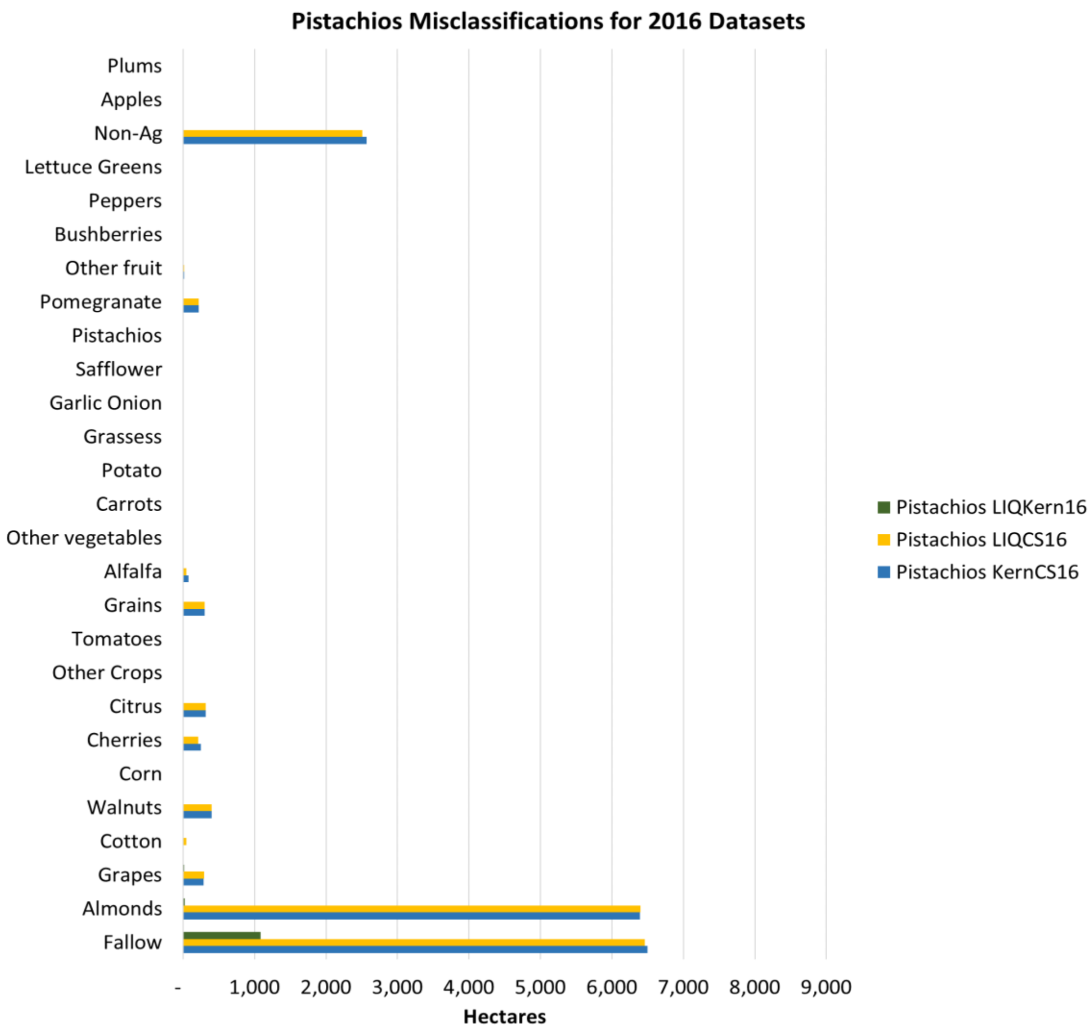
SI Figure 48. Specific crop misclassification for corn in 2016 datasets.



SI Figure 49. Specific crop misclassification for fallow in 2016 datasets.



SI Figure 50. Specific crop misclassification for grains in 2016 datasets.



SI Figure 51. Specific crop misclassification for pistachios in 2016 datasets.

FAO Crop Category	Reconciled Crop Category	Kenr Ag Crop Type	LIQ Crop Type	CropScape Crop Type
Cereals	***Grains***	Wheat Sorghum Milo Oat For/Fod Wheat For/Fod Sorghum For/Fod Barley Oat Barley For/Fod Ryegrass For/Fod Rye Vetch Triticale	Wheat Miscellaneous Grain and Hay	Rice Barley Durum Wheat Winter Wheat Rye Oats Other Hay/Non-Alfalfa Triticale Vetch Dbl Crop WinWht/Corn Dbl Crop Oats/Corn Dbl Crop Durum Wht/Sorghum Dbl Crop Barley/Sorghum Dbl Crop WinWht/Sorghum Dbl Crop Barley/Corn Dbl Crop WinWht/Cotton
Vegetables	***Carrots***	Carrot Carrot Seed	Carrots	Carrots
	Garlic and Onion	Garlic Onion Dry Etc. Onion Seed Onion Green	Onions and Garlic	Garlic Onions
	Lettuce and Greens	Lettuce Leaf Sd Cabbage Cabbage Seed Lettuce Head Swiss Chard Kale Collard Arugula Leek	Lettuce/Leafy Greens	Greens Lettuce

		Lettuce Leaf		
	Peppers	Pepper Fruitng Pepper Spice	Peppers	Peppers
	Tomatoes	Tomato Process Tomato	Tomatoes	Tomatoes
	Other Vegetables	Watermelon Beets, Red Beet Turnip Eggplant Squash, Winter Squash Broccoli Broccoli Seed Gai Lon Tght Hd Asparagus Pumpkin Cantaloupe Honeydew Melon Napa Cbg Tght H Melon Musk Melon Bok Choy Lse Lf Celery Cilantro Radish Cauliflower Sugarcane Cucumber Chive Bean Succulent Bean Dried Garbanzo Bean	Melons, Squash, and Cucumbers Beans (Dry)	Peas Watermelons Misc Vegs & Fruits Sugarbeets Asparagus Broccoli Dry Beans
Fruit	***Apples***	Apple	Apples	Apples
	Bush Berries	Blueberry Blackberry Fruit, Berry Boysenberry	Bush Berries	Blueberries
	Grapes	Grape Grape, Wine Grape, Raisin	Grapes	Grapes
	Plum	Plum	Plums, Prunes, Apricots	Plums
	Pomegranate	Pomegranate	Pomegranates	Pomegranates
	Strawberries	Strawberry	Strawberries	Strawberries
	Citrus	Orange Tangelo Grapefruit Tangerine/Sdls Tangerine Lemon	Citrus	Oranges Citrus

		Pomelo		
	Cherries	Cherry	Cherries	Cherries
	Other Fruit	Nectarine Peach Persimmon Apricot Pear Avocado Kiwi Fig Prune Kumquat	Peaches/Nectarines Pears Kiwis Miscellaneous Subtropical Fruits Avocados Olives	Nectarines Apricots Olives
Root Crops	***Potatoes***	Potato Sweet Potato Yam	Potatoes and Sweet Potatoes	Potatoes
Spices	***Safflower***	Parsley Dill Parsnip	Safflower	Herbs Clover/Wildflowers Safflower
Other Crops	***Alfalfa***	Alfalfa	Alfalfa and Alfalfa Mixtures	Alfalfa
	Cotton	Cotton	Cotton	Cotton
	Grasses	Sudangrass Pastureland Turf/Sod	Miscellaneous Grasses	Sorghum Sod/Grass Seed
	Corn	Corn For/Fod Corn, Sweet Corn, Grain	Corn, Sorghum, and Sudan	Corn
	Other Crops	N-Outdr Plants Op-Rose Op-Vine N-Grnhs Plants Op-Palm Op- Chrstmas Tree OP-Dec. Tree Dandelion Green Rutabaga Op-Flwring Plant Mustard Pecans	Miscellaneous Truck Crops Flower, Nursery, and Christmas Tree Farms Young Perennials Miscellaneous Field Crops	Other Crops Other Tree Crops Pecans Sunflower
Nuts	***Pistachio***	Pistachio	Pistachios	Pistachios
	Walnuts	Walnut	Walnuts	Walnuts
	Almonds	Almond	Almonds	Almonds
Idle	***Fallow***	Uncultivated Ag	Idle	Fallow/Idle Cropland

SI Table 29. Kern County Ag. Commission, Land IQ, and CropScape (USDA NASS CDL) crop types associated with FAO and the Reconciled crop categories for 2014 and 2016 land use classifications.

Study Category	Crop	Production Per Acre	Unit	Unit Value (USD)	Report Crop Name	Source
Alfalfa	Alfalfa	8	Ton	247	Hay-Alfalfa	Kern County Crop Report 2014
Almonds	Almonds	1	Ton	7,125	Almonds	Kern County Crop Report 2014
Apples	Apples	14	Ton	575	Apples	USDA CA Crop 2014, statewide
Bushberries	Bushberries	7	Ton	5,300	Blueberries	Kern County Crop Report 2014
Carrots	Carrots	35	Ton	289	Carrots, unspecified	USDA CA Crop 2014, statewide
Cherries	Cherries	1	Ton	6,840	Cherries	Kern County Crop Report 2014
Citrus	Citrus	10	Ton	942	Kern County Crop Report 2014	Kern County Crop Report 2014
Corn	Corn	26	Ton	61	Corn Silage	USDA CA Crop 2014, statewide
Cotton	Cotton	1,640	Pounds Per Acre	2	Cotton Lint-Pima	Kern County Crop Report 2014
Fallow	Fallow	-	Ton	-		
Garlic Onion	Onions, Fresh	22	Ton	246	Onions, Fresh	Kern County Crop Report 2014
Grains	Grains	5	Ton	212	Hay-Grain	Kern County Crop Report 2014
Grapes	Grapes	13	Ton	2,070	Table Variety-Fresh Market	Kern County Crop Report 2014
Grasses	Silage & Forage	19	Ton	50	Silage and Forage	Kern County Crop Report 2014
Lettuce Greens	Lettuce Greens	17	Ton	694	Lettuce, Head	USDA CA Crop 2014, Kern
Non-Ag	Non-Ag	-	Ton	-		

Other Crops	Other Crops	4	Ton	179	Field Crops, Misc.	Kern County Crop Report 2014
Other Fruit	Other Fruit	6	Ton	1,322	Fruit and Nuts, Misc	Kern County Crop Report 2014
Other Vegetables	Other veggies	36	Ton	326	Vegetable Crops, Misc.	Kern County Crop Report 2014
Peppers	Peppers	22	Ton	1,620	Peppers, Bell	Kern County Crop Report 2014
Pistachios	Pistachios	1	Ton	5,020	Pistachios	Kern County Crop Report 2014
Plums	Plums	9	Ton	1,220	Plums	Kern County Crop Report 2014
Pomegranate	Pomegranate	5	Ton	1,024	Pomegranates	USDA CA Crop 2014, statewide
Potato	Potato	28	Ton	256	Potatoes, Spring, Fresh Market	Kern County Crop Report 2014
Safflower	Safflower	1	Ton	501	Safflower	USDA CA Crop 2014, statewide
Strawberries	Strawberries	33	Ton	1,947	Berries, strawberries, fresh market	USDA CA Crop 2014, statewide
Tomatoes	Tomatoes	53	Ton	90	Tomatoes Processed	Kern County Crop Report 2014
Walnuts	Walnuts	1	Ton	3,390	Walnuts	Kern County Crop Report 2014

SI Table 30. Values used to derive crop revenue for 2014 datasets. Note: Main source for crop revenue values is the Kern County Crop Report 2014 provided by the Kern County Agricultural Commission. USDA California 2014 crop revenue dataset is used to supplement any categories that may be missing or reconciled in broader crop categories in the Kern County Crop Report (see Source and Notes section of the table for more details).

Study Category	Crop	Production Per Acre	Unit	Unit Value (USD)	Report Crop Name	Source
Alfalfa	Alfalfa	7	Ton	153	Hay, Alfalfa	Kern County Crop Report 2016
Almonds	Almonds	1	Ton	4,920	Almonds	Kern County Crop Report 2016

Apples	Apples	2	Ton	900	Apples	Kern County Crop Report 2016
Bushberries	Bushberries	5	Ton	7,380	Blueberries	Kern County Crop Report 2016
Carrots	Carrots	29	Ton	380	Carrots, Unspecified, statewide	USDA CA Crop Report 2016
Cherries	Cherries	6	Ton	3,810	Cherries	Kern County Crop Report 2016
Citrus	Citrus	14	Ton	725	Navel Oranges	Kern County Crop Report 2016
Corn	Corn	26	Ton	41	Corn Silage, statewide	USDA CA Crop Report 2016
Cotton	Cotton	1,580	Pound per Acre	1	Cotton Lint, Pima	Kern County Crop Report 2016
Fallow	Fallow	-	NA	-		
Garlic Onion	Garlic	8	Ton	1,460	Garlic, Fresh and Processing	Kern County Crop Report 2016
Grains	Grains	4	Ton	140	Hay, Grain	Kern County Crop Report 2016
Grapes	Grapes	12	Ton	2,230	Table Variety Fresh Market	Kern County Crop Report 2016
Grasses	Silage and Forage	19	Ton	46	Silage and Forage	Kern County Crop Report 2016
Lettuce Greens	Lettuce Greens	20	Ton	470	Lettuce Head	Kern County Crop Report 2016
Non-Ag	Non-Ag	-	NA	-		
Other Crops	Other Crops	8	Ton	128	Field Crops, Misc	Kern County Crop Report 2016
Other Fruit	Other fruit	15	Ton	880	Fruit & Nuts, Misc	Kern County Crop Report 2016
Other Vegetables	Other vegetables	24	Ton	467	Vegetable Crop, Misc.	Kern County Crop Report 2016
Peppers	Peppers	21	Ton	970	Peppers, Bell	Kern County Crop Report 2016
Pistachios	Pistachios	2	Ton	4,320	Pistachios	Kern County Crop Report 2016

Plums	Plums	9	Ton	1,410	Plums, statewide	USDA CA Crop Report 2016
Pomegranate	Pomegranate	12	Ton	663	Pomegranates, statewide	USDA CA Crop Report 2016
Potato	Potato	26	Ton	213	Potatoes, Spring, Processing	Kern County Crop Report 2016
Safflower	Safflower	1	Ton	441	Safflower, statewide	USDA CA Crop Report 2016
Strawberries	Strawberries	35	Ton	2,067	Berries, strawberries, fresh market	USDA CA Crop Report 2016
Tomatoes	Tomatoes	46	Ton	73	Tomatoes, Processed	Kern County Crop Report 2016

SI Table 31. Values used to derive crop revenue for 2016 datasets. Note: Main source for crop revenue values is the Kern County Crop Report 2014 provided by the Kern County Agricultural Commission. USDA California 2016 crop revenue dataset is used to supplement any categories that may be missing or reconciled in broader crop categories in the Kern County Crop Report (see Source and Notes section of the table for more details).

Study Category	**LIQ Category**	**LIQ CWR (ML/Ha)**	**Kern Ag Category**	**Kern CWR (ML/Ha)**	**CropScape Category**	**CropScape CWR (ML/Ha)**
Alfalfa	Alfalfa and Alfalfa Mixtures	16.2	Alfalfa	15.9	Alfalfa	15.7
Almonds	Almonds	11.5	Almond	11.5	Almonds	11.7
Apples	Apples	12.8	Apple	12.7	Apples	12.9
Bushberries	NA	0.0	Blueberry	4.4	Blueberries	12.5
Carrots	Carrots	4.3	Carrot	5.4	Carrots	4.4
Cherries	Cherries	11.7	Cherry	11.7	Cherries	12.1
Citrus	Citrus	16.6	Orange	16.7	Citrus	16.3
Corn	Corn, Sorghum and Sudan	5.7	Corn For/Fod	9.6	Corn	5.9
Cotton	Cotton	7.8	Cotton	7.8	Cotton	8.0
Fallow	Idle	11.3	Uncultivated Ag	8.1	Fallow/Idle Cropland	9.4
Garlic Onion	Onions and Garlic	13.6	Garlic	7.4	Garlic	8.2
Grains	Wheat	5.1	Wheat	5.9	Winter Wheat	5.4
Grapes	Grapes	12.1	Grape	12.2	Grapes	12.2
Grasses	NA	0.0	Sorghum For/Fod	12.5	Grass/Pasture	12.4

Lettuce Greens	Lettuce/Leafy Greens	6.2	Lettuce Head	9.0	Lettuce	5.9
Non-Ag	NA	0.0	NA	0.0	NA	0.0
Other Crops*	Other Crops Avg.	9.7	Other Crops Avg.	8.6	Other Crops Avg.	12.3
Other Fruit*	Other Fruit Avg.	14.9	Other Fruit Avg.	14.2	Other Fruit Avg.	13.1
Other Vegetables*	Other Vegetables Avg.	8.4	Other Vegetables Avg.	8.5	Other Vegetables Avg.	8.9
Peppers	Peppers	10.8	Pepper Fruitng	10.7	Peppers	10.4
Pistachios	Pistachios	13.0	Pistachio	13.0	Pistachios	12.9
Plums	Plums, Prunes and Apricots	12.1	Plum	12.1	Plums	11.6
Pomegranate	Pomegranates	4.2	Pomegranate	4.2	Pomegranates	5.0
Potato	Potatoes and Sweet Potatoes	8.4	Potato	7.2	Potatoes	8.3
Safflower	Safflower	6.1	Safflower	6.1	Safflower	6.5
Strawberries	Strawberries	5.9	Strawberry	5.7	Strawberries	12.6
Tomatoes	Tomatoes	8.0	Tomato Process	8.2	Tomatoes	8.3
Walnuts	Walnuts	12.4	Walnut	12.4	Walnuts	12.2

SI Table 32. The 2014 crop water requirement (CWR) values used per crop within each dataset to derive CWR implications. Note: Each raster dataset was run through WAFR model to obtain CWR tailored to dataset (i.e., LIQ, Kern Ag, CropScape). Values in asterisk are general crop categories that were derived by taking the average of CWR values available for the components of that category.

Dataset	General Category	Category Components	CWR (AF)	CWR (ML)
LIQ	Other Crops	Miscellaneous Truck Crops	3.3	4.0
		Flower, Nursery, and Christmas Tree Farms		
		Young Perennials	3.1	3.8
		Miscellaneous Field Crops		
	Other Fruit	Peaches/Nectarines	5.6	6.9
		Pears		
		Kiwis		
		Miscellaneous Subtropical Fruits		
		Avocados		
		Olives	4.2	5.1
	Other Vegetables	Melons, Squash, and Cucumbers	3.9	4.8
		Beans (Dry)	1.6	2.0
Kern Ag	Other Vegetables	Watermelon	3.7	4.6
		Beets, Red		
		Beet	1.7	2.1
		Turnip	2.1	2.6

		Eggplant		
		Squash, Winter		
		Squash	4.0	4.9
		Broccoli	1.8	2.2
		Broccoli Seed	4.6	5.6
		Gai Lon Tght Hd		
		Asparagus	3.7	4.6
		Pumpkin		
		Cantaloupe		
		Honeydew Melon	4.0	4.9
		Napa Cbg Tght H		
		Melon	1.8	2.2
		Musk Melon		
		Bok Choy Lse Lf		
		Celery		
		Cilantro		
		Radish		
		Cauliflower	1.6	2.0
		Sugarcane		
		Cucumber	4.0	4.9
		Chive		
		Bean Succulent	1.4	1.8
		Bean Dried	1.6	2.0
		Garbanzo Bean		
	Other Fruit	Nectarine	5.7	7.0
		Peach	4.3	5.2
		Persimmon	4.1	5.0
		Apricot		
		Pear		
		Avocado		
		Kiwi		
		Fig		
		Prune		
		Kumquat		
	Other Crops	N-Outdr Plants	2.8	3.4
		Op-Rose	1.7	2.1
		Op-Vine		
		N-Grnhs Plants		
		Op-Palm		
		Op- Chrstmas Tree		
		OP-Dec. Tree	3.7	4.6
		Dandelion Green	1.8	2.2
		Rutabaga	1.4	1.8
		Op-Flwring Plant	3.7	4.5
		Mustard	4.6	5.7
		Pecans		
CropScape	Other Crops	Other Crops	3.2	4.0
		Other Tree Crops	4.8	6.0
		Pecans		
		Sunflower		

	Other Fruit	Nectarines	4.9	6.1
		Apricots	3.8	4.7
		Olives	4.1	5.1
	Other Vegetables	Peas	1.3	1.7
		Watermelons	4.0	5.0
		Misc Vegs & Fruits	3.4	4.1
		Sugarbeets	3.7	4.5
		Asparagus	4.8	5.9
		Broccoli	1.7	2.1
		Dry Beans	1.6	2.0

SI Table 33. Crop water use (CWR) of specific crops that were averaged to derive the CWR for the general category in 2014 datasets.

Study Category	LIQ Category	LIQ CWR (ML/Ha)	Kern Ag Category	Kern CWR (ML/Ha)	CropScape Category	CropScape CWR (ML/Ha)
Alfalfa	Alfalfa and Alfalfa Mixtures	15.63	Alfalfa	15.43	Alfalfa	14.71
Almonds	Almonds	11.41	Almond	11.40	Almonds	11.53
Apples	Apples	12.57	Apple	12.65	Apples	12.71
Bushberries	NA	0.00	Blueberry	4.64	Blueberries	13.73
Carrots	Carrots	3.93	Carrot	5.50	Carrots	4.21
Cherries	Cherries	11.74	Cherry	11.52	Cherries	11.43
Citrus	Citrus	16.07	Orange	16.16	Citrus	15.54
Corn	Corn, Sorghum and Sudan	5.69	Corn For/Fod	10.43	Corn	6.09
Cotton	Cotton	7.90	Cotton	7.92	Cotton	7.98
Fallow	NA	0.00	Uncultivated Ag	8.14	Fallow/Idle Cropland	9.19
Garlic Onion	Onions and Garlic	13.41	Garlic	8.16	Garlic	7.66
Grains	Wheat	4.62	Wheat For/Fod	11.29	Winter Wheat	5.08
Grapes	Grapes	12.09	Grape	12.15	Grapes	12.17
Grasses	NA	0.00	Sudangrass	14.19	Sorghum	9.64
Lettuce Greens	Lettuce/Leafy Greens	5.91	Lettuce Head	5.12	Lettuce	6.65
Non-Ag	NA	0.00	NA	0.00	NA	0.00
Other Crops*	Other CropsAvg	9.61	Other Crops Avg	4.02	Other Crops Avg	11.42
Other Fruit*	Other FruitAvg	14.38	Other Fruit Avg	12.97	Other Fruit Avg	14.29
Other* Vegetables	Other VegetablesAvg	8.39	Other Vegetables Avg	7.86	Other Vegetables Avg	7.53
Peppers	Peppers	10.54	Pepper Fruitng	10.89	Peppers	10.57
Pistachios	Pistachios	12.94	Pistachio	12.88	Pistachios	12.83
Plums	Plums, Prunes and Apricots	11.76	Plum	12.67	Plums	11.44
Pomegranate	Pomegranates	4.20	Pomegranate	4.25	Pomegranates	4.57
Potato	Potatoes and Sweet Potatoes	8.37	Potato	6.69	Potatoes	8.26
Safflower	Safflower	5.75	Safflower	5.79	Safflower	5.76
Strawberries	Strawberries	5.68	Strawberry	5.76	NA	0.00
Tomatoes	Tomatoes	7.95	Tomato Process	7.91	Tomatoes	8.18
Walnuts	Walnuts	12.20	Walnut	12.12	Walnuts	12.13

SI Table 34. . The 2016 crop water use (CWR) values used per crop within each dataset to derive CWR implications. Note: Each raster dataset was run through WAFR model to obtain CWR tailored to dataset (i.e., LIQ, Kern Ag, CropScape). Values in asterisk are general crop categories that were derived by taking the average of CWR values available for the components of that category.

Dataset	General Category	Categories Averaged	CWR (AF)	CWR (ML)
LIQ	Other Crops	Miscellaneous Truck Crops	3.15	3.89
	Other Crops	Flower, Nursery, and Christmas Tree Farms		
	Other Crops	Young Perennials		
	Other Crops	Miscellaneous Field Crops		
	Other Fruit	Peaches/Nectarines	5.41	6.67
	Other Fruit	Pears		
	Other Fruit	Kiwis		
	Other Fruit	Miscellaneous Subtropical Fruits		
	Other Fruit	Avocados		
	Other Fruit	Olives	4.03	4.97
	Other Vegetables	Melons, Squash, and Cucumbers	3.90	4.81
	Other Vegetables	Beans (Dry)	1.60	1.97
Kern Ag	Other Vegetables	Watermelon	3.87	4.77
	Other Vegetables	Beets, Red	1.32	1.63
	Other Vegetables	Beet	1.59	1.96
	Other Vegetables	Turnip	1.28	1.58
	Other Vegetables	Eggplant	2.65	3.26
	Other Vegetables	Squash, Winter		
	Other Vegetables	Squash	3.95	4.87
	Other Vegetables	Broccoli	2.01	2.48
	Other Vegetables	Broccoli Seed	2.49	3.07
	Other Vegetables	Gai Lon Tght Hd		
	Other Vegetables	Asparagus	4.55	5.61
	Other Vegetables	Pumpkin		
	Other Vegetables	Cantaloupe	4.83	5.96
	Other Vegetables	Honeydew Melon	3.16	3.90
	Other Vegetables	Napa Cbg Tght H		
	Other Vegetables	Melon	2.57	3.16
	Other Vegetables	Musk Melon		
	Other Vegetables	Bok Choy Lse Lf	1.44	1.77
	Other Vegetables	Celery		

	Other Vegetables	Cilantro		
	Other Vegetables	Radish	1.51	1.86
	Other Vegetables	Cauliflower	2.32	2.87
	Other Vegetables	Sugarcane		
	Other Vegetables	Cucumber	3.95	4.87
	Other Vegetables	Chive		
	Other Vegetables	Bean Succulent	1.30	1.61
	Other Vegetables	Bean Dried	2.09	2.58
	Other Vegetables	Garbanzo Bean	2.12	2.62
	Other Fruit	Nectarine	5.02	6.18
	Other Fruit	Peach	4.11	5.07
	Other Fruit	Persimmon	4.03	4.97
	Other Fruit	Apricot	4.09	5.04
	Other Fruit	Pear		
	Other Fruit	Avocado		
	Other Fruit	Kiwi		
	Other Fruit	Fig	4.03	4.97
	Other Fruit	Prune		
	Other Fruit	Kumquat		
	Other Crops	N-Outdr Plants		
	Other Crops	Op-Rose		
	Other Crops	Op-Vine		
	Other Crops	N-Grnhs Plants		
	Other Crops	Op-Palm		
	Other Crops	Op- Chrstmas Tree		
	Other Crops	OP-Dec. Tree		
	Other Crops	Dandelion Green	1.316	1.62
	Other Crops	Rutabaga	1.323	1.63
	Other Crops	Op-Flwring Plant		
	Other Crops	Mustard	1.319	1.63
	Other Crops	Pecans		
CropScape	Other Crops	Other Crops	3.08	3.79
	Other Crops	Other Tree Crops	3.91	4.82
	Other Crops	Pecans	4.24	5.24
	Other Crops	Sunflower		
	Other Fruit	Nectarines	5.23	6.45
	Other Fruit	Apricots		
	Other Fruit	Olives	4.15	5.12
	Other Vegetables	Peas	1.21	1.50

	Other Vegetables	Watermelons	3.89	4.80
	Other Vegetables	Misc Vegs & Fruits		
	Other Vegetables	Sugarbeets	3.75	4.63
	Other Vegetables	Asparagus		
	Other Vegetables	Broccoli	1.66	2.05
	Other Vegetables	Dry Beans	1.83	2.26

SI Table 35. Crop water requirement (CWR) of specific crops that were averaged to derive the CWR for the general category in 2016 datasets.

Study Category	Crop	GHG Emission Per-Area Total (Mg CO_2e per Hectare)
Alfalfa	alfalfa	0.90
Almonds	almond	0.23
Apples	apple	0.95
Bushberries	blueberry	3.07
Carrots	carrot	1.49
Cherries	cherry	0.75
Citrus	orange	2.01
Corn	greencorn	2.87
Cotton	cotton	0.61
Fallow	NA	0.00
Garlic Onion	garlic	1.09
Grains	mixedgrain	2.00
Grapes	grape	0.38
Grasses	mixedgrass	1.47
Lettuce Greens	lettuce	1.18
Non-Ag	NA	0.00
Other Crops	NA	-
Other Fruit	fruitnes	0.68
Other Vegetables	vegetablenes	0.94
Peppers	pepper	3.32
Pistachios	pistachio	0.68
Plums	plum	0.38
Pomegranate	NA	-
Potato	potato	1.33
Safflower	safflower	0.40
Strawberries	strawberry	1.55
Tomatoes	tomato	1.45
Walnuts	walnut	0.37

SI Table 36. Greenhouse gas (GHG) emission values used (Carlson et al., 2017) to derive misclassification implications on GHG emissions for the 2014 and 2016 datasets.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 1											
		Kern Ag 2014									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2014	Alfalfa	-	(18.28)	(0.07)	(0.49)	(11.53)	(0.76)	(8.39)	0.59	(0.71)	2.77
	Almonds	2.53	-	(0.06)	(0.22)	(2.32)	2.72	(12.77)	0.99	1.22	10.26
	Apples	0.00	0.10	-	(0.01)	-	0.00	(0.98)	-	0.00	0.43
	Berries	0.04	0.31	-	-	-	0.01	0.76	0.01	-	0.10
	Carrots	0.18	0.49	-	(0.02)	-	0.19	0.04	0.02	0.28	1.52
	Cherries	0.02	(0.56)	(0.01)	(4.17)	(0.73)	-	(14.72)	0.01	0.02	0.71
	Citrus	0.05	1.67	0.00	(3.39)	(0.01)	2.41	-	0.01	0.00	1.67
	Corn	(0.15)	(0.90)	-	(0.21)	(4.72)	(0.03)	(0.18)	-	(0.78)	1.70
	Cotton	0.35	(1.02)	-	-	(1.65)	(0.01)	(0.38)	0.22	-	7.32
	Fallow	(1.66)	(46.44)	(3.44)	(6.41)	(42.34)	(1.13)	(36.97)	(1.69)	(8.12)	-
	Garlic Onion	0.36	(0.10)	(0.00)	-	(2.38)	(0.00)	(0.03)	0.02	0.08	3.30
	Grains	(3.11)	(5.56)	(0.00)	(0.02)	(16.91)	(0.13)	(2.76)	(2.52)	(0.99)	4.60
	Grapes	3.17	24.02	0.18	(0.72)	6.51	8.37	69.04	0.49	3.60	15.56
	Grasses	(0.06)	(0.00)	-	-	(0.32)	(0.00)	-	(0.00)	(0.00)	0.02
	Lettuce Greens	0.01	0.00	-	-	0.00	-	-	0.14	0.00	0.01
	Non-Ag	(2.92)	(71.10)	(0.37)	(5.46)	(19.32)	(3.69)	(132.94)	(0.55)	(1.89)	-
	Other Crops	(0.00)	(0.25)	(0.00)	(0.01)	(0.23)	(0.03)	(1.41)	(0.00)	(0.03)	0.00
	Other fruit	0.05	0.09	-	-	(0.27)	-	(0.03)	0.13	0.18	0.94
	Other Veg	0.52	0.10	0.00	-	0.10	0.02	0.33	0.52	1.22	3.30
	Peppers	0.17	1.47	-	-	0.51	0.01	-	0.25	0.09	3.82
	Pist.	0.26	(18.91)	(0.03)	(0.39)	(0.59)	(0.38)	(10.70)	0.10	0.33	2.19
	Plums	-	0.02	0.00	-	-	-	0.00	-	-	-
	Pome.	0.01	(0.01)	-	-	-	-	(0.00)	-	-	-
	Potato	0.08	0.02	(0.00)	(0.06)	(6.73)	0.00	(0.36)	0.07	0.06	0.78
	Saff.	(0.01)	(0.01)	-	-	(0.01)	-	-	(0.00)	-	0.00
	Strwb	-	-	-	-	-	-	-	-	0.01	-
	Tomato	0.19	(0.60)	-	(0.02)	(4.15)	(0.00)	(0.05)	0.53	0.10	6.72
	Waln	0.03	(0.09)	(0.00)	-	(0.02)	(0.01)	(0.44)	0.00	0.07	0.09
	Total	0.12	(135.53)	(3.80)	(21.58)	(107.09)	7.55	(152.92)	(0.66)	(5.22)	67.80

SI Table 37. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 2											
		Kern Ag 2014									
		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg	Peppers
CropScape 2014	Alfalfa	(1.14)	4.21	(159.20)	1.17	(0.31)	0.02	0.54	(0.84)	(2.97)	(3.44)
	Almonds	0.30	4.63	(147.06)	0.53	(0.13)	0.00	2.99	(0.11)	(1.22)	(0.40)
	Apples	-	-	(13.75)	0.01	-	-	0.04	0.00	(0.00)	(0.09)
	Berries	-	0.38	12.60	0.01	-	-	0.02	-	-	-
	Carrots	1.70	1.40	(3.27)	0.03	(0.02)	-	0.76	0.18	(0.17)	(1.50)
	Cherries	0.00	0.11	(46.99)	0.06	(0.06)	-	0.81	(0.36)	(0.20)	(0.37)
	Citrus	0.02	0.43	(112.26)	0.10	-	-	1.26	0.29	(0.02)	(0.14)
	Corn	(0.51)	0.45	(3.54)	0.16	(0.34)	0.00	0.03	(0.36)	(2.69)	(3.35)
	Cotton	(0.04)	0.71	(39.23)	1.11	(0.06)	0.06	0.54	(1.14)	(4.91)	(5.14)
	Fallow	(2.86)	(5.69)	(167.97)	(0.59)	(3.12)	-	(0.45)	(7.90)	(20.22)	(0.78)
	Garlic Onion	-	1.41	(0.07)	0.25	(0.14)	-	0.26	(0.01)	(0.71)	(0.10)
	Grains	(3.34)	-	(14.93)	0.62	(0.14)	0.07	0.12	(0.56)	(4.21)	(1.51)
	Grapes	0.56	3.52	-	5.04	0.05	-	11.40	5.00	1.17	(2.70)
	Grasses	-	(0.02)	(0.22)	-	-	0.00	0.00	(0.00)	(0.12)	(0.36)
	Lettuce Greens	-	0.01	(0.00)	-	-	-	-	-	-	(0.01)
	Non-Ag	(2.04)	(2.97)	(200.07)	(0.40)	(0.15)	-	(0.32)	(4.50)	(2.54)	(5.55)
	Other Crops	(0.29)	(0.00)	(5.08)	(0.00)	-	-	-	(0.36)	(0.09)	-
	Other fruit	0.08	0.12	(2.44)	0.29	(0.00)	0.00	0.06	-	(0.06)	(9.11)
	Other Veg	0.01	0.37	(2.77)	0.41	-	-	0.10	0.21	-	(0.17)
	Peppers	0.02	0.64	0.27	3.04	-	-	0.15	0.79	0.24	-
	Pist.	(0.03)	0.75	(21.77)	0.03	(0.09)	0.06	0.29	(0.44)	(0.16)	(0.05)
	Plums	-	-	(0.18)	-	-	-	0.00	-	-	-
	Pome.	-	0.01	(0.40)	0.00	-	0.00	-	-	-	-
	Potato	0.98	2.69	(1.67)	0.51	(0.01)	-	0.62	(0.00)	(0.53)	(0.32)
	Saff.	-	(0.00)	(0.28)	(0.00)	-	0.01	-	-	(0.01)	(0.02)
	Strwb	-	0.01	-	-	-	-	-	-	-	-
	Tomato	(0.45)	0.50	(3.93)	0.31	(0.17)	0.01	0.33	(1.29)	(1.88)	(5.24)
	Waln	-	0.02	(5.30)	0.00	-	0.02	0.06	(0.00)	(0.00)	-
	Total	(7.04)	13.68	(939.49)	12.69	(4.69)	0.26	19.60	(11.41)	(41.31)	(40.35)

SI Table 38. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 3										
	Kern Ag 2014									
		Pist.	Plum	Pome.	Potato	Saff	Strwb	Tomato	Waln.	Total
CropScape 2014	Alfalfa	(0.78)	-	(0.11)	(3.98)	0.19	-	(1.23)	(0.02)	(204.79)
	Almonds	50.62	-	3.08	(0.01)	0.05	-	0.14	1.28	(82.94)
	Apples	0.49	-	-	-	-	-	-	-	(13.74)
	Berries	0.66	-	-	-	0.01	-	-	0.01	14.90
	Carrots	0.04	-	0.00	2.93	0.07	-	0.66	-	5.52
	Cherries	0.42	(0.00)	0.01	(0.11)	0.02	(0.04)	0.01	0.00	(66.12)
	Citrus	7.66	(0.00)	0.96	0.06	0.02	-	0.02	0.06	(99.14)
	Corn	(0.16)	-	(0.00)	(0.79)	0.00	-	(0.44)	(0.00)	(16.78)
	Cotton	(0.10)	-	(0.18)	(0.78)	-	-	(0.10)	-	(44.41)
	Fallow	(51.06)	-	(7.03)	(6.02)	(0.01)	(0.22)	(2.12)	(0.02)	(424.24)
	Garlic Onion	0.02	-	-	(0.45)	0.00	-	0.02	-	1.74
	Grains	(1.48)	-	(0.04)	(5.56)	0.26	-	(0.11)	-	(58.20)
	Grapes	9.17	0.00	27.01	4.78	0.43	(0.02)	1.39	0.15	197.16
	Grassess	(0.00)	-	-	-	-	-	(0.00)	-	(1.08)
	Lettuce Greens	-	-	-	0.00	-	-	0.00	-	0.17
	Non-Ag	(72.69)	(0.02)	(16.96)	(17.70)	(0.03)	(0.45)	(1.15)	(0.22)	(565.99)
	Other Crops	(0.00)	-	(0.00)	(0.01)	-	-	(0.00)	-	(7.81)
	Other fruit	1.66	-	1.52	0.03	0.06	-	0.09	-	(6.61)
	Other Veg	0.01	-	-	0.10	-	-	0.30	-	4.68
	Peppers	-	-	-	-	-	-	0.05	-	11.52
	Pist.	-	(0.00)	(2.31)	(0.19)	0.07	-	(0.01)	(0.04)	(52.00)
	Plums	0.01	-	0.02	-	-	-	-	-	(0.13)
	Pome.	0.02	-	-	-	-	-	-	-	(0.37)
	Potato	0.01	-	0.00	-	0.01	(0.04)	0.08	-	(3.81)
	Saff.	(0.02)	-	-	-	-	-	-	-	(0.35)
	Strwb	-	-	-	-	-	-	-	-	0.03
	Tomato	0.01	-	0.00	(0.86)	0.01	(0.01)	-	-	(9.96)
	Waln	0.39	-	0.29	(0.00)	-	-	-	-	(4.89)
	Total	(55.13)	(0.02)	6.25	(28.55)	1.17	(0.77)	(2.42)	1.19	(1,427.66)

SI Table 39. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy CWR Discrepancy (in Acre-feet) Part 1

CropScape 2014	Kern Ag 2014								
	Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton
Alfalfa		4,919	11	48	4,792	278	(357)	2,371	2,826
Almonds	(684)		(18)	16	1,593	(17)	(8,493)	121	350
Apples	(0)	43		1		1	(886)		1
Berries	(1)	3				0	(35)	0	
Carrots	(83)	(380)		0		(101)	(314)	(4)	(42)
Cherries	(8)	68	(1)	313	352		(5,588)	2	11
Citrus	1	1,073	2	449	57	914		2	1
Corn	(963)	(292)		3	87	(13)	(77)		(416)
Cotton	(1,404)	(266)			183	(5)	(157)	(103)	
Fallow	(4,145)	(24,324)	(1,737)	(238)	(7,446)	(767)	(20,930)	(3,331)	(7,573)
Garlic Onion	(275)	(58)	(0)		451	(2)	(20)	(2)	4
Grains	(10,789)	(1,814)	(1)	0	(11)	(58)	(1,187)	(6,954)	(468)
Grapes	(155)	302	(2)	148	882	69	(5,919)	17	220
Grassess	(59)	0			78	0		6	4
Lettuce Greens	(4)	(1)			0			(17)	(0)
Non-Ag	(7,289)	(37,242)	(185)	(202)	(3,397)	(2,499)	(75,254)	(1,080)	(1,767)
Other Crops	(1)	11	(0)	1	56	1	(223)	1	20
Other fruit	(8)	83			276		(19)	25	64
Other Veg	(122)	(18)	(0)		66	(2)	(391)	(11)	50
Peppers	(9)	(19)			33	(0)		2	2
Pist.	(139)	2,600	0	31	228	82	(2,320)	45	466
Plums		0	(0)				(1)		
Pome.	(12)	(7)					(1)		
Potato	(39)	(195)	(1)	3	2,170	(2)	(416)	(5)	2
Saff.	(16)	(3)			1			(1)	
Strwb									0
Tomato	(181)	(258)		1	707	(2)	(28)	(73)	8
Waln	(13)	10	(0)		8	2	(137)	1	47
Total	(26,400)	(55,764)	(1,933)	573	1,166	(2,121)	(122,754)	(8,990)	(6,188)

SI Table 40. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy CWR Discrepancy (in Acre-feet) Part 2									
	Kern Ag 2014								
CropScape 2014	Fallow	Garlic Onion	Grains	Grapes	Grassess	Lettuce Greens	Non-Ag	Other Crops	Other fruit
Alfalfa	6,829	934	13,595	7,409	1,091	72	41	891	71
Almonds	5,463	238	1,429	(1,307)	(22)	27	3	466	(163)
Apples	221			170	0			8	(1)
Berries	10		21	91	0			1	
Carrots	217	(344)	(76)	(506)	(8)	(16)		(110)	(244)
Cherries	494	8	47	(107)	(2)	11		185	(124)
Citrus	923	10	169	8,902	14			355	105
Corn	2,073	(63)	(2)	(291)	(545)	(34)	2	(28)	(159)
Cotton	6,985	3	289	(2,287)	(915)	(2)	56	(55)	(466)
Fallow		(1,277)	(10,080)	(25,277)	(2,507)	(793)	-	(1,830)	(4,755)
Garlic Onion	1,638		242	(4)	(78)	(6)		(7)	(4)
Grains	7,452	(491)		(1,301)	(9,863)	(15)	120	(297)	(244)
Grapes	2,347	42	285		(14)	3		526	(173)
Grassess	80		229	0			19	2	(0)
Lettuce Greens	1		(0)	(0)					
Non-Ag	-	(908)	(5,259)	(30,108)	(1,726)	(39)		(1,296)	(2,711)
Other Crops	25	101	1	8	(0)				(32)
Other fruit	519	63	41	38	9	1	1	13	
Other Veg	817	0	34	(201)	(44)			1	(88)
Peppers	372	1	28	(18)	(59)			3	(36)
Pist.	2,360	37	608	209	1	15	68	124	(51)
Plums				(2)				0	
Pome.			(1)	(43)	(2)		1		
Potato	291	155	333	(112)	(110)	(1)		(10)	(4)
Saff.	4		0	(20)	(1)		29		
Strwb			0						
Tomato	3,852	194	105	(232)	(114)	(6)	4	(9)	(834)
Waln	72		8	(1)	(0)		12	15	(0)
Total	43,045	(1,295)	2,047	(44,992)	(14,892)	(782)	354	(1,052)	(9,913)

SI Table 41. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy CWR Discrepancy (in Acre-feet) Part 3												
	Kern Ag 2014											
		Other Veg	Pepper	Pist.	Plums	Pome	Potato	Saff.	Strwb	Tomato	Waln.	Total
CropScape 2014	Alfalfa	724	171	375		167	2,124	409		1,141	9	50,942
	Almonds	278	5	(6,792)		2,985	157	15		63	(142)	(4,430)
	Apples	2	2	(5)								(444)
	Berries			(3)				0			0	87
	Carrots	(136)	(123)	(18)		0	(932)	(4)		(151)		(3,374)
	Cherries	39	6	(75)	(0)	26	109	7	1	10	(0)	(4,216)
	Citrus	23	10	1,435	1	761	72	7		13	16	15,316
	Corn	(217)	(155)	(159)		1	(58)	(0)		(104)	(1)	(1,412)
	Cotton	(87)	(141)	(135)		115	42			(4)		1,645
	Fallow	(4,740)	(78)	(55,686)		(2,069)	(1,955)	(23)	(6)	(1,208)	(16)	(182,791)
	Garlic Onion	(9)	(3)	(17)			77	0		(0)		1,927
	Grains	(389)	(76)	(1,305)		4	(527)	(115)		(29)		(28,359)
	Grapes	98	163	(104)	0	3,252	407	34	1	84	(0)	2,512
	Grassess	15	6	(0)						0		379
	Lettuce Greens		(1)				(0)			(0)		(23)
	Non-Ag	(594)	(553)	(79,280)	(5)	(4,991)	(5,752)	(80)	(13)	(655)	(182)	(263,067)
	Other Crops	11		(0)		2	4			1		(14)
	Other fruit	22	265	11		1,434	113	19		49		3,017
	Other Veg		(4)	(1)			13			10		109
	Peppers	7								1		307
	Pist.	29	1		0	8,840	102	48		27	5	13,417
	Plums			(1)		7						4
	Pome.			(64)								(128)
	Potato	(7)	(9)	(3)		1		1	1	1		2,044
	Saff.	(1)	(1)	(15)								(23)
	Strwb											1
	Tomato	(16)	(136)	(20)		1	116	2	0			3,081
	Waln	0		(100)		2,398	1					2,324
	Total	(4,949)	(650)	(141,962)	(5)	12,934	(5,890)	321	(16)	(752)	(313)	(391,170)

SI Table 42. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 1											
		Kern Ag 2014									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2014	Alfalfa		980	(0)	(11)	(337)	13	(496)	(944)	132	486
	Almonds	(135)		(15)	(8)	(398)	(379)	(3,745)	(189)	(42)	131
	Apples	0	27		(0)		0	(307)		0	20
	Berries	1	11				0	11	0		3
	Carrots	5	84		(0)		13	(17)	(1)	14	90
	Cherries	(0)	77	(0)	(117)	(49)		(1,887)	(2)	0	38
	Citrus	3	491	1	(49)	3	309		(0)	0	140
	Corn	234	171		(0)	308	6	8		625	1,237
	Cotton	(65)	35			(79)	(0)	(31)	(177)		656
	Fallow	(291)	(595)	(159)	(204)	(2,508)	(61)	(3,114)	(1,230)	(727)	
	Garlic Onion	8	19	0		(80)	0	(3)	(3)	6	270
	Grains	1,401	656	0	(0)	390	14	(1)	(1,785)	342	3,394
	Grapes	(28)	75	(2)	(63)	(178)	(60)	(2,693)	(20)	(14)	89
	Grassess	12	0			(0)	0		(4)	1	12
	Lettuce Greens	0	0			(0)			(10)	0	0
	Non-Ag	(511)	(910)	(17)	(174)	(1,144)	(197)	(11,198)	(399)	(170)	-
	Other Crops										
	Other fruit	(1)	29			(36)		(9)	(19)	1	33
	Other vegetables	1	6	(0)		(13)	0	(67)	(40)	18	106
	Peppers	5	66			15	0		1	3	146
	Pist.	(13)	1,062	(1)	(11)	(31)	(6)	(1,001)	(37)	9	155
	Plums		0	(0)				(0)			
	Pome.										
	Potato	3	82	0	(1)	(150)	0	(42)	(7)	4	58
	Saff.	(1)	0			(1)			(1)		0
	Strwb									0	
	Tomatoes	16	120		(0)	(12)	1	(2)	(98)	17	832
	Waln	(2)	2	(0)		(2)	(2)	(62)	(1)	(3)	3
	Total	641	2,490	(194)	(640)	(4,300)	(348)	(24,655)	(4,965)	216	7,899

SI Table 43. Table of the resulting GHG Emission discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emissions is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 2

CropScape 2014	Kern Ag 2014									
	Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg	Peppers
Alfalfa	(26)	(1,896)	1,387	(235)	(4)	3		13	(5)	(102)
Almonds	(59)	(546)	(456)	(42)	(12)	0		(36)	(76)	(18)
Apples			174	(0)				0	0	(3)
Berries		4	1,102	0						
Carrots	57	(32)	89	0	1			25	23	(45)
Cherries	(1)	(12)	339	(4)	(2)			5	(3)	(13)
Citrus	1	0	4,379	2				82	4	(3)
Corn	96	318	143	145	23	1		52	205	(18)
Cotton	(3)	(247)	153	(216)	(1)	5		(7)	(73)	(175)
Fallow	(234)	(4,197)	(962)	(364)	(128)	-		(282)	(651)	(30)
Garlic Onion		(120)	1	(8)	(1)			0	7	(3)
Grains	285		386	933	4	54		45	169	(24)
Grapes	(8)	(91)		(87)	(1)			(33)	(18)	(378)
Grassess		(24)	4			3		0	2	(8)
Lettuce Greens		(0)	0							(0)
Non-Ag	(166)	(2,190)	(1,146)	(251)	(6)			(161)	(82)	(213)
Other Crops										
Other fruit	(6)	(9)	16	(14)	(0)	0			(1)	(356)
Other vegetables	(0)	(15)	43	(8)				5		(7)
Peppers	1	10	38	67				31	10	
Pist.	(3)	(143)	119	(4)	(2)	4		(0)	(2)	(2)
Plums			0							
Pome.										
Potato	50	(119)	33	(4)	0			1	18	(9)
Saff.		(1)	0	(0)		2			(0)	(1)
Strwb		(0)								
Tomatoes	94	(31)	78	(1)	3	1		132	54	(131)
Waln		(3)	(1)	(0)		0		(0)	(0)	
Total	77	(9,343)	5,918	(90)	(125)	75		(128)	(417)	(1,537)

SI Table 44. Table of the resulting GHG Emission discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emissions is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with Kern Ag 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 3										
	Kern Ag 2014									
		Pist.	Plums	Pome.	Potato	Saff.	Strwb	Tomatoes	Waln.	Total
CropScape 2014	Alfalfa	38			(132)	26		(103)	2	(1,212)
	Almonds	(2,842)			(48)	(1)		(27)	(33)	(8,977)
	Apples	12								(77)
	Berries	18				0			0	1,151
	Carrots	2			65	3		2		378
	Cherries	6	0		(16)	0	(0)	(2)	0	(1,641)
	Citrus	716	0		7	1		1	8	6,098
	Corn	61			86	2		80	1	3,783
	Cotton	(3)			(50)			(16)		(294)
	Fallow	(3,603)			(444)	(2)	(2)	(263)	(1)	(20,051)
	Garlic Onion	2			(23)	0		(4)		68
	Grains	281			245	366		7		7,165
	Grapes	(50)	(0)		(96)	(0)	(0)	(27)	0	(3,683)
	Grassess	0						0		(2)
	Lettuce Greens				(0)			(0)		(10)
	Non-Ag	(5,130)	(0)		(1,307)	(7)	(4)	(142)	(7)	(25,531)
	Other Crops									
	Other fruit	0			(15)	1		(9)		(394)
	Other vegetables	0			(4)			(9)		18
	Peppers							1		394
	Pist.		0		(14)	2		(6)	5	82
	Plums	(0)								(0)
	Pome.									
	Potato	1				0	(0)	(1)		(83)
	Saff.	(1)								(2)
	Strwb									0
	Tomatoes	4			16	1	(0)			1,094
	Waln	(47)			(0)					(118)
	Total	(10,535)	0		(1,730)	396	(7)	(519)	(24)	(41,843)

SI Table 45. Table of the resulting GHG Emission discrepancy reflecting user's accuracy of CropScape 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emissions is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 1										
	Kern Ag 2016									
CropScape 2016	Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
Alfalfa	-	(12.58)	(0.00)	(0.52)	(4.82)	(2.76)	(6.09)	0.03	(0.47)	0.25
Almonds	4.54	-	0.96	(3.09)	(2.28)	(39.11)	(50.00)	1.01	0.95	16.60
Apples	-	(0.00)	-	-	-	-	(0.01)	-	-	-
Berries	-	0.01	-	-	-	0.01	0.01	-	-	-
Carrots	1.07	0.12	-	(0.35)	-	(0.15)	0.04	0.05	0.01	0.72
Cherries	0.04	0.55	-	(0.05)	0.00	-	3.05	-	-	0.03
Citrus	0.11	6.47	0.02	(2.86)	(0.04)	(12.12)	-	0.01	0.01	2.91
Corn	(0.01)	(0.13)	-	(0.05)	(1.88)	(0.16)	(0.02)	-	(0.35)	0.02
Cotton	0.67	(0.55)	0.01	(0.01)	(0.97)	(0.61)	(0.22)	0.60	-	1.53
Fallow	(1.84)	(43.98)	(0.13)	(2.77)	(27.95)	(2.74)	(29.58)	(2.10)	(5.08)	-
Garlic Onion	1.01	0.09	-	(0.06)	0.13	(0.04)	0.00	0.12	0.17	2.38
Grains	(1.68)	(5.74)	-	(0.95)	(29.09)	(1.37)	(1.88)	(1.79)	(0.47)	0.97
Grapes	2.19	31.30	0.10	(1.01)	2.96	3.51	69.34	1.02	2.00	18.64
Grassess	(0.01)	(0.31)	-	(0.21)	(8.48)	-	(0.18)	(0.00)	(0.03)	0.22
Lettuce Greens	0.01	0.03	-	-	(0.21)	-	(0.01)	0.11	0.09	0.67
Non-Ag	(1.46)	(41.87)	(0.01)	(7.08)	(7.76)	(6.53)	(98.87)	(0.40)	(1.02)	-
Other Crops	(0.00)	(0.18)	-	(0.12)	(4.49)	(0.06)	(0.36)	(0.00)	(0.00)	0.02
Other Fruit	0.78	0.44	-	(0.05)	0.10	(0.43)	2.25	0.90	2.80	0.89
Other Veg	0.81	0.04	0.00	(0.09)	0.03	-	0.00	1.84	2.86	0.02
Peppers	0.33	0.18	-	(0.01)	0.30	(0.01)	0.32	0.39	0.04	0.04
Pist.	2.34	7.64	0.23	(0.77)	(1.09)	(2.18)	(7.96)	0.16	2.51	32.63
Plums	0.01	0.09	-	-	0.00	(0.02)	0.01	-	-	-
Pome.	0.07	0.87	-	-	(0.00)	(0.45)	(0.00)	0.01	0.11	0.12
Potato	0.19	(0.00)	0.00	(0.16)	(22.25)	(0.02)	(0.04)	0.03	0.03	0.40
Saff.	(0.02)	(0.04)	-	-	(0.15)	(0.00)	(0.00)	(0.00)	(0.01)	1.40
Strwb	-	-	-	-	-	-	-	-	-	-
Tomatoes	0.44	(0.97)	0.04	(0.01)	(9.19)	(0.56)	(0.70)	0.68	0.67	10.65
Waln	0.05	(1.30)	0.01	-	(0.15)	(0.31)	(0.60)	0.03	0.02	0.26
Total	9.63	(59.84)	1.24	(20.20)	(117.28)	(66.11)	(121.49)	2.68	4.87	91.36

SI Table 46. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 2										
	Kern Ag 2016									
CropScape 2016		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg
	Alfalfa	(2.69)	2.05	(97.92)	0.09	(0.18)	-	0.01	(1.51)	(2.36)
	Almonds	(1.61)	6.66	(263.78)	0.15	(0.22)	-	1.77	(2.51)	(0.48)
	Apples	-	-	(0.03)	-	-	-	0.00	-	-
	Berries	-	-	0.01	-	-	-	-	-	-
	Carrots	(0.10)	0.91	(2.20)	0.25	0.27	-	0.56	(0.00)	(0.02)
	Cherries	0.00	0.41	(0.41)	0.00	-	-	0.03	-	-
	Citrus	(0.01)	0.16	(49.92)	0.23	0.00	-	0.51	(0.07)	(0.01)
	Corn	(0.57)	0.60	(0.20)	0.00	(0.04)	-	0.00	(0.72)	(0.73)
	Cotton	(0.12)	1.72	(33.09)	0.56	(0.70)	-	0.26	(0.89)	(5.03)
	Fallow	(6.63)	(4.66)	(103.65)	(0.39)	(3.01)	-	(1.11)	(4.01)	(14.84)
	Garlic Onion	-	1.50	(0.23)	0.10	0.03	-	0.06	(0.01)	0.03
	Grains	(7.07)	-	(12.30)	(0.62)	(1.91)	0.00	(0.22)	(0.47)	(5.22)
	Grapes	1.10	3.65	-	1.06	0.23	-	10.63	4.87	0.84
	Grasses	(0.18)	0.10	(11.07)	-	(0.30)	-	(0.02)	(0.03)	(1.74)
	Lettuce Greens	(0.02)	0.07	(0.03)	0.01	-	-	0.06	-	(0.07)
	Non-Ag	(2.91)	(1.32)	(106.54)	(0.09)	(0.39)	-	(0.22)	(1.53)	(1.93)
	Other Crops	(0.19)	0.03	(5.03)	0.01	(0.56)	-	-	(0.48)	(4.39)
	Other Fruit	0.09	0.73	(4.03)	0.22	0.00	-	0.58	-	0.04
	Other Veg	(0.00)	0.41	(0.78)	0.07	0.01	-	0.85	(0.01)	-
	Peppers	0.84	0.29	(4.19)	0.20	0.18	-	0.19	1.09	0.13
	Pist.	(0.20)	2.73	(22.36)	0.07	(0.01)	-	1.00	(1.29)	(0.73)
	Plums	-	-	(1.18)	-	-	-	-	0.00	-
	Pome.	(0.00)	0.05	(12.04)	-	(0.00)	-	0.05	(0.28)	(0.01)
	Potato	(3.61)	1.76	(0.23)	0.41	(0.72)	-	0.15	(0.01)	(1.46)
	Saff.	(0.26)	(0.00)	(0.15)	(0.00)	(0.02)	-	(0.00)	-	(0.05)
	Strwb	-	-	-	-	-	-	-	-	-
	Tomatoes	(5.20)	1.18	(10.79)	0.06	(0.33)	-	0.46	(5.91)	(2.22)
	Waln	(0.03)	0.06	(7.94)	0.00	(0.01)	-	0.04	(0.03)	(0.08)
	Total	(29.37)	19.08	(750.09)	2.39	(7.67)	0.00	15.61	(13.81)	(40.32)

SI Table 47. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 3											
		Kern Ag 2016									
		Peppers	Pist.	Plums	Pome.	Potato	Saff	Strwb	Tomatoes	Waln	Total
CropScape 2016	Alfalfa	(0.51)	(1.11)	-	(0.06)	(2.29)	0.02	-	(0.54)	(0.02)	(133.99)
	Almonds	(0.18)	(18.07)	-	(0.88)	0.02	0.28	(0.03)	0.31	1.17	(347.82)
	Apples	-	-	-	(0.09)	-	-	-	-	-	(0.14)
	Berries	-	-	-	-	-	-	-	-	-	0.04
	Carrots	(0.11)	0.01	-	-	3.95	0.03	-	0.50	-	5.57
	Cherries	-	9.57	-	0.14	-	-	-	-	0.00	13.37
	Citrus	(0.40)	2.31	(0.00)	0.03	0.28	0.03	-	0.00	0.02	(52.31)
	Corn	(0.70)	(0.01)	-	-	(0.40)	0.00	-	(0.06)	-	(5.40)
	Cotton	(0.44)	(0.12)	-	(0.21)	(0.92)	0.03	-	(0.03)	-	(38.52)
	Fallow	(1.76)	(112.35)	-	(16.52)	(7.00)	(0.18)	(0.08)	(2.42)	(0.35)	(395.12)
	Garlic Onion	(0.03)	0.02	-	0.00	0.64	0.15	-	0.15	-	6.22
	Grains	(0.61)	(4.84)	-	(0.15)	(5.71)	0.00	(0.02)	(0.15)	(0.00)	(81.28)
	Grapes	0.35	13.77	0.01	0.94	4.84	0.05	-	0.54	0.48	173.40
	Grassess	(0.21)	(0.01)	-	-	(0.52)	0.01	-	(0.02)	-	(23.00)
	Lettuce Greens	-	0.01	-	0.00	0.04	0.01	-	0.00	-	0.75
	Non-Ag	(1.50)	(44.36)	(0.02)	(5.38)	(4.16)	(0.01)	(0.05)	(1.23)	(0.13)	(336.76)
	Other Crops	(0.19)	(0.18)	-	(0.00)	(1.49)	0.00	-	(0.00)	(0.00)	(17.69)
	Other Fruit	(1.61)	0.22	-	-	0.25	0.36	-	0.14	0.01	4.68
	Other Veg	(0.00)	0.00	-	-	0.75	0.00	-	0.01	-	6.81
	Peppers	-	-	-	-	0.10	0.02	-	0.42	-	0.87
	Pist.	(0.17)	-	-	(0.36)	0.13	0.09	-	0.08	1.20	13.70
	Plums	-	0.01	-	-	-	-	-	-	-	(1.07)
	Pome.	-	0.52	-	-	-	-	-	0.02	0.04	(10.94)
	Potato	(0.04)	(0.00)	-	(0.00)	-	0.64	-	0.08	-	(24.85)
	Saff.	(0.00)	(0.01)	-	-	(0.28)	-	-	(0.01)	-	0.37
	Strwb	-	-	-	-	-	-	-	-	-	-
	Tomatoes	(10.43)	(0.09)	-	(0.07)	(0.46)	0.11	-	-	-	(32.65)
	Waln	(0.02)	(3.90)	-	(0.04)	(0.01)	-	-	(0.00)	-	(13.94)
	Total	(18.54)	(158.61)	(0.00)	(22.66)	(12.23)	1.63	(0.17)	(2.19)	2.42	(1,289.68)

SI Table 48. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet)
Part 1

		Kern Ag 2016									
	Row Labels	Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2016	Alfalfa		2,871	2	46	1,458	135	(324)	1,761	955	1,089
	Almonds	(1,218)		(84)	218	860	6	(18,409)	76	307	10,723
	Apples		0					(2)			
	Berries		0				0	(0)			
	Carrots	(395)	(55)		(2)		(32)	(156)	(10)	(2)	90
	Cherries	(3)	0		7	0		(375)			5
	Citrus	0	2,130	3	367	114	1,265		2	4	1,489
	Corn	(1,491)	(48)		1	35	(13)	(7)		(187)	32
	Cotton	(1,494)	(169)	(28)	0	88	(35)	(76)	(435)		1,832
	Fallow	(8,537)	(28,096)	(322)	(111)	(4,569)	(458)	(15,715)	(6,713)	(6,057)	
	Garlic Onion	(246)	(19)		2	204	(5)	(7)	(11)	(2)	519
	Grains	(10,537)	(2,244)		4	(394)	(131)	(725)	(6,097)	(268)	2,914
	Grapes	(93)	389	(1)	216	425	204	(5,558)	23	116	2,833
	Grasses	(100)	(37)		9	1,127		(43)	(3)	14	782
	Lettuce Greens	(3)	(12)			41		(22)	(16)	(5)	158
	Non-Ag	(6,768)	(26,744)	(30)	(284)	(1,268)	(1,093)	(52,526)	(1,293)	(1,211)	-
	Other Crops	(18)	0		7	866	(0)	(63)	4	2	57
	Other fruit	(25)	59		6	161	40	(480)	97	549	324
	Other Veg	(203)	(10)	(0)	3	66		(1)	(169)	(40)	4
	Peppers	(28)	(3)		1	55	(1)	(59)	1	2	8
	Pist.	(337)	3,143	3	67	644	60	(2,914)	21	840	19,632
	Plums	(1)	0			0	(0)	(5)			
	Pome	(35)	(924)			(0)	(70)	(8)	(2)	(21)	23
	Potato	(100)	(14)	(1)	6	3,652	(1)	(22)	(4)	1	195
	Saff	(117)	(15)			1	(0)	(1)	(12)	(2)	5,076
	Strwb										
	Tomatoes	(459)	(410)	(37)	0	1,041	(32)	(275)	(217)	47	8,490
	Waln	(25)	110	(1)		40	3	(115)	8	34	342
	Total	(32,230)	(50,095)	(495)	565	4,648	(158)	(97,887)	(12,990)	(4,925)	56,616

SI Table 49. Table of the resulting crop water requirement discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The crop water requirement is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 2										
	Kern Ag 2016									
	Row Labels	Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg
CropScape 2016	Alfalfa	553	4,286	3,255	78	69		452	73	515
	Almonds	313	104	(2,680)	(27)	138		903	(172)	105
	Apples			0				1		
	Berries			1						
	Carrots	(284)	(200)	(378)	(81)	(42)		3	(3)	(64)
	Cherries	0	1	(27)	(0)			4		
	Citrus	13	24	3,394	11	1		217	21	10
	Corn	(37)	(1,967)	(16)	(57)	1		19	(139)	(41)
	Cotton	(1)	(1,148)	(1,886)	(900)	94		292	(137)	20
	Fallow	(1,540)	(31,205)	(15,743)	(2,001)	(549)		(1,404)	(1,331)	(3,360)
	Garlic Onion		(163)	(23)	(20)	11		6	(9)	(14)
	Grains	(652)		(1,110)	(5,374)	(3)	0	156	(99)	(440)
	Grapes	98	42		(28)	31		1,126	(97)	80
	Grasses	8	(156)	(361)		53		284	(3)	97
	Lettuce Greens	(5)	(12)	(4)	(2)			6		(12)
	Non-Ag	(677)	(8,836)	(16,183)	(469)	(71)		(278)	(508)	(437)
	Other Crops	20	3	(49)	(36)	142			(21)	495
	Other fruit	142	59	210	1	3		165		53
	Other Veg	(1)	(46)	(79)	(14)	3		94	(7)	
	Peppers	78	(3)	(352)	(13)	30		21	(120)	13
	Pist.	67	216	256	(5)	12		484	(11)	271
	Plums			(21)					(0)	
	Pome	(0)	(15)	(1,637)		(0)		1	(161)	(2)
	Potato	18	(346)	(14)	(170)	206		46	(3)	32
	Saff	(19)	(71)	(12)	(12)	1		1		(3)
	Strwb									
	Tomatoes	2	(427)	(616)	(50)	57		268	(984)	28
	Waln	4	7	(4)	(1)	2		50	(1)	13
	Total	(1,900)	(39,855)	(34,080)	(9,171)	189	0	2,916	(3,711)	(2,640)

SI Table 50. Table of the resulting crop water requirement discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The crop water requirement is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 3											
	Kern Ag 2016										
CropScape 2016	Row Labels	Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa	34	112		31	1,338	124		530	11	19,454
	Almonds	3	(7,069)		1,005	137	97	1	147	(82)	(14,598)
	Apples				40						39
	Berries										1
	Carrots	(26)	(6)			(591)	(1)		(79)		(2,312)
	Cherries		(295)		22					(0)	(659)
	Citrus	60	674	0	46	187	11		1	3	10,047
	Corn	(58)	(4)			(18)	0		(16)		(4,010)
	Cotton	(24)	(39)		44	112	15		0		(3,873)
	Fallow	(313)	(67,907)		(2,886)	(2,752)	(674)	(2)	(1,868)	(458)	(204,573)
	Garlic Onion	(4)	(8)		0	34	8		(2)		255
	Grains	(59)	(1,925)		6	(603)	(9)	(0)	(49)	(2)	(27,642)
	Grapes	24	(169)	(0)	134	420	4		33	0	255
	Grasses	(4)	(3)			106	29		5		1,804
	Lettuce Greens		(8)		0	(0)	0		(0)		104
	Non-Ag	(267)	(26,810)	(6)	(939)	(1,634)	(48)	(1)	(952)	(165)	(149,498)
	Other Crops	2	(14)		2	506	8		2	(0)	1,912
	Other fruit	249	17			87	81		31	1	1,829
	Other Veg	(0)	(1)			35	0		(0)		(366)
	Peppers					9	1		22		(337)
	Pist.	8			1,049	181	31		37	70	23,827
	Plums		(1)								(27)
	Pome		(1,480)						(4)	(19)	(4,354)
	Potato	(2)	(3)		1		102		4		3,583
	Saff	(0)	(5)			(17)			(1)		4,791
	Strwb										-
	Tomatoes	(554)	(37)		20	100	31				5,985
	Waln	0	(248)		22	8			2		252
	Total	(930)	(105,228)	(5)	(1,403)	(2,355)	(188)	(3)	(2,156)	(641)	(338,111)

SI Table 51. Table of the resulting crop water requirement discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The crop water requirement is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emissions Discrepancy (in $MgCO_2e$) Part 1

		Kern Ag 2016									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2016	Alfalfa		723	(0)	(12)	(114)	8	(307)	(996)	52	82
	Almonds	(261)		(67)	(111)	(222)	(493)	(8,749)	(225)	(40)	261
	Apples		0					(1)			
	Berries		1				1	0			
	Carrots	25	12		(8)		4	(8)	(3)	1	39
	Cherries	(0)	7		(3)	(0)		(123)			0
	Citrus	5	1,131	1	(44)	7	490		(0)	1	237
	Corn	387	30		(0)	105	6	1		284	18
	Cotton	(74)	23	(2)	(0)	(39)	(2)	(16)	(496)		172
	Fallow	(617)	(692)	(30)	(91)	(1,520)	(37)	(2,412)	(2,280)	(572)	
	Garlic Onion	7	5		(2)	(46)	1	(1)	(8)	4	91
	Grains	1,384	779		(11)	579	32	(0)	(1,218)	163	1,418
	Grapes	(19)	92	(1)	(95)	(88)	(144)	(2,813)	(41)	(8)	108
	Grasses	12	32		(4)	(7)		(4)	(7)	9	147
	Lettuce Greens	0	3			(14)		(2)	(9)	3	34
	Non-Ag	(489)	(659)	(3)	(232)	(422)	(88)	(8,060)	(439)	(114)	-
	Other Crops										
	Other fruit	(6)	11		(2)	(18)	(1)	(422)	(68)	8	19
	Other Veg	1	2	(0)	(3)	(22)		(0)	(139)	42	1
	Peppers	17	16		0	24	3	17	4	2	3
	Pist	(35)	1,231	(5)	(24)	(87)	(4)	(1,436)	(24)	16	1,289
	Plums	(0)	1			(0)	(0)	(2)			
	Pome										
	Potato	7	6	0	(3)	(260)	0	(2)	(4)	2	39
	Saff	(7)	1			(6)	(0)	(0)	(8)	(0)	438
	Strwb										
	Tomatoes	42	192	5	(0)	(19)	8	(24)	(170)	192	1,854
	Waln	(5)	26	(2)		(8)	(2)	(58)	(14)	(2)	13
	Total	376	2,972	(103)	(646)	(2,179)	(219)	(24,422)	(6,145)	42	6,265

SI Table 52. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emissions Discrepancy (in $MgCO_2e$) Part 2

		Kern Ag 2016									
		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg	Peppers
CropScape 2016	Alfalfa	(20)	(1,695)	830	(107)	(2)			11	(3)	(27)
	Almonds	(99)	(903)	(778)	(15)	(25)			(66)	(25)	(16)
	Apples			0							
	Berries			1							
	Carrots	35	(18)	65	0	18			0	12	(9)
	Cherries	(0)	(9)	17	(0)						
	Citrus	2	0	2,025	6	0			13	2	(21)
	Corn	39	405	8	12	3			54	55	(7)
	Cotton	(3)	(600)	128	(153)	(23)			(3)	(74)	(27)
	Fallow	(254)	(6,843)	(601)	(255)	(156)			(86)	(496)	(118)
	Garlic Onion		(50)	5	(1)	(0)			1	13	(3)
	Grains	237		315	392	74	0		20	208	(17)
	Grapes	(22)	(94)		(18)	(4)			(45)	(13)	(68)
	Grasses	3	(63)	192		4			1	35	(8)
	Lettuce Greens	0	(3)	1	(0)					3	
	Non-Ag	(112)	(1,938)	(618)	(60)	(20)			(33)	(65)	(100)
	Other Crops										
	Other fruit	(12)	(32)	37	(6)	(0)				(3)	(238)
	Other Veg	(0)	(16)	12	(1)	(0)			0		(0)
	Peppers	89	8	804	8	15			162	14	
	Pist	(7)	(227)	144	(4)	(1)			(0)	(17)	(14)
	Plums			0					(0)		
	Pome										
	Potato	58	(96)	4	(5)	13			1	40	(2)
	Saff	(7)	(26)	0	(2)	(1)				(1)	(0)
	Strwb										
	Tomatoes	91	(95)	204	(0)	6			193	57	(474)
	Waln	(1)	(16)	(1)	(0)	(0)			(0)	(2)	(1)
	Total	18	(12,309)	2,795	(210)	(101)	0		223	(261)	(1,149)

SI Table 53. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emissions Discrepancy (in $MgCO_2e$)
Part 3

		Kern Ag 2016								
		Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
CropScape 2016	Alfalfa	17			(88)	9		(52)	3	(1,688)
	Almonds	(2,910)			(39)	(4)	(0)	(61)	(24)	(14,872)
	Apples									(0)
	Berries									2
	Carrots	1			46	1		1		214
	Cherries	17							0	(95)
	Citrus	417	0		18	2		0	2	4,295
	Corn	2			55	0		15		1,473
	Cotton	(1)			(79)	2		(8)		(1,275)
	Fallow	(4,436)			(673)	(58)	(1)	(421)	(17)	(22,665)
	Garlic Onion	1			(10)	4		(3)		5
	Grains	402			309	26	0	12	1	5,103
	Grapes	(89)	(0)		(90)	(0)		(10)	0	(3,461)
	Grasses	1			6	10		0		357
	Lettuce Greens	1			(1)	0		(0)		16
	Non-Ag	(1,751)	(0)		(400)	(4)	(0)	(214)	(6)	(15,828)
	Other Crops									
	Other fruit	0			(9)	3		(5)	0	(740)
	Other Veg	0			(20)	0		(0)		(144)
	Peppers				6	1		19		1,212
	Pist				(24)	2		(7)	39	805
	Plums	(0)								(2)
	Pome									
	Potato	1				47		(2)		(156)
	Saff	(0)			(21)			(1)		360
	Strwb									
	Tomatoes	7			10	17				2,098
	Waln	(126)			(2)			(1)		(204)
	Total	(8,449)	0		(1,005)	58	(1)	(738)	(2)	(45,190)

SI Table 54. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 1											
	Kern Ag 2014										
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
LIQ 2014	Alfalfa	-	(0.04)	-	-	(0.42)	(0.00)	-	0.00	(0.01)	0.08
	Almonds	0.30	-	-	-	(0.00)	0.06	(0.10)	0.18	0.03	0.12
	Apples	-	-	-	-	-	-	-	-	-	-
	Berries	-	-	-	-	0.21	0.45	-	-	-	-
	Carrots	0.06	0.01	-	(0.10)	-	-	0.00	0.13	0.05	0.19
	Cherries	0.01	(0.03)	-	(1.14)	-	-	-	-	-	0.03
	Citrus	-	0.00	-	-	-	-	-	-	-	0.09
	Corn	(0.00)	(0.25)	-	-	(0.00)	-	-	-	(0.00)	0.04
	Cotton	0.00	(0.01)	-	-	(0.00)	-	-	-	-	0.02
	Fallow	(0.01)	(0.70)	-	-	(0.23)	-	(0.17)	-	(0.44)	-
	Garlic Onion	-	(0.01)	-	-	(0.20)	-	-	0.07	-	0.01
	Grains	(0.15)	(0.00)	-	-	(0.05)	(0.00)	(0.01)	(0.02)	(0.01)	0.09
	Grapes	0.25	0.25	-	(0.02)	0.06	0.11	0.21	-	-	0.58
	Grasses	-	-	-	-	-	-	-	-	-	-
	Lettuce Greens	-	-	-	(0.35)	0.03	-	0.00	-	0.06	-
	Non-Ag	-	-	-	-	-	-	-	-	-	-
	Other Crops	-	(1.99)	-	-	(0.11)	(0.66)	(0.09)	(0.02)	-	0.12
	Other fruit	0.00	-	-	-	(0.05)	-	(0.01)	-	-	0.68
	Other Veg	-	0.00	-	-	-	-	-	-	-	-
	Peppers	-	-	-	-	0.07	-	-	-	-	-
	Pist	0.05	(0.16)	-	-	-	(0.01)	(0.01)	-	0.00	0.01
	Plums	-	-	0.00	(0.06)	-	0.16	-	-	-	-
	Pome	-	(0.00)	-	-	-	-	-	-	0.00	0.03
	Potato	-	-	-	-	(0.02)	-	(0.04)	-	0.02	0.05
	Saff	-	-	-	-	-	-	-	-	-	0.00
	Strwb	-	-	-	-	-	-	-	-	-	-
	Tomatoes	-	(0.00)	-	-	(0.00)	-	-	-	-	-
	Waln	-	(0.00)	-	-	-	-	-	-	-	-
	Total	0.51	(2.93)	0.00	(1.68)	(0.70)	0.10	(0.19)	0.33	(0.30)	2.13

SI Table 55. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 2										
		Kern Ag 2014								
LIQ 2014		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg
	Alfalfa	-	0.21	(0.11)	0.01	-	-	0.00	(0.04)	(0.01)
	Almonds	0.01	0.03	(0.50)	-	-	-	0.02	-	(0.02)
	Apples	-	-	-	-	-	-	-	0.00	-
	Berries	-	-	0.02	-	-	-	-	-	-
	Carrots	0.10	0.29	(0.10)	0.04	(0.00)	-	-	-	(0.02)
	Cherries	-	0.05	(0.04)	-	-	-	0.00	(0.00)	-
	Citrus	-	0.02	(0.76)	-	-	-	-	0.00	(0.00)
	Corn	(0.04)	0.07	-	4.99	-	-	-	-	(0.00)
	Cotton	-	0.01	(0.28)	0.00	-	-	0.07	-	(0.03)
	Fallow	-	(1.04)	(1.52)	(0.00)	-	-	(0.00)	(0.05)	(0.01)
	Garlic Onion	-	0.03	(0.00)	-	-	-	1.01	-	(0.05)
	Grains	(0.15)	-	(0.09)	0.02	-	-	0.00	(0.02)	-
	Grapes	0.00	0.15	-	-	-	-	0.04	0.00	-
	Grasses	-	-	-	-	-	-	-	-	-
	Lettuce Greens	-	0.02	-	-	-	-	2.02	-	(0.68)
	Non-Ag	-	-	-	-	-	-	-	-	-
	Other Crops	(0.04)	-	(17.19)	-	-	-	-	(0.10)	(9.27)
	Other fruit	-	0.02	(0.07)	-	-	-	0.05	-	(0.49)
	Other Veg	-	-	(0.05)	-	-	-	0.06	-	-
	Peppers	-	0.14	0.08	-	-	-	-	-	0.16
	Pist	-	0.00	(0.12)	-	-	-	0.01	-	-
	Plums	-	-	-	-	-	-	-	0.30	-
	Pome	-	-	-	-	-	-	-	(0.01)	-
	Potato	0.08	-	(0.16)	-	-	-	0.33	(0.00)	-
	Saff	-	(0.00)	-	-	-	-	-	-	-
	Strwb	-	-	-	-	-	-	-	-	-
	Tomatoes	(0.01)	-	-	-	-	-	-	(0.12)	-
	Waln	-	-	-	-	-	-	-	-	-
	Total	(0.04)	0.01	(20.89)	5.05	(0.00)	-	3.60	(0.04)	(10.44)

SI Table 56. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3

	Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 3										
	Kern Ag 2014										
LIQ 2014		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa	-	(0.03)	-	-	-	-	-	-	(0.37)	-0.37
	Almonds	-	0.09	0.00	-	-	-	0.00	-	0.21	0.21
	Apples	-	-	-	-	-	-	-	-	0.00	0.00
	Berries	-	-	-	-	-	(0.01)	-	-	0.67	0.67
	Carrots	(1.97)	-	-	0.05	-	-	0.04	-	(1.22)	-1.22
	Cherries	-	0.01	-	-	-	-	-	-	(1.12)	-1.12
	Citrus	(0.01)	0.00	-	0.01	-	-	-	-	(0.65)	-0.65
	Corn	-	-	-	-	-	-	-	-	4.81	4.81
	Cotton	-	(0.00)	-	(0.02)	-	-	(0.00)	-	(0.24)	-0.24
	Fallow	-	(0.11)	(0.16)	(0.14)	-	-	-	-	(4.57)	-4.57
	Garlic Onion	(0.76)	-	-	(0.02)	-	-	0.00	-	0.09	0.09
	Grains	-	(0.03)	(0.00)	(0.03)	-	-	-	-	(0.45)	-0.45
	Grapes	(0.02)	0.24	0.07	-	-	-	-	0.03	1.95	1.95
	Grasses	-	-	-	-	-	-	-	-	-	0.00
	Lettuce Greens	-	-	-	-	-	-	-	-	1.10	1.10
	Non-Ag	-	-	-	-	-	-	-	-	-	0.00
	Other Crops	-	(0.48)	-	(0.77)	-	-	(0.01)	-	(30.63)	-30.63
	Other fruit	-	0.00	-	-	-	-	0.09	-	0.23	0.23
	Other Veg	-	-	-	-	-	-	-	-	0.02	0.02
	Peppers	-	-	-	0.28	-	-	-	-	0.74	0.74
	Pist	-	-	-	-	-	-	(0.00)	-	(0.23)	-0.23
	Plums	-	-	0.06	-	-	-	-	-	0.46	0.46
	Pome	-	0.00	-	-	-	-	-	-	0.02	0.02
	Potato	(0.16)	-	-	-	-	-	0.00	-	0.08	0.08
	Saff	-	-	-	-	-	-	-	-	(0.00)	0.00
	Strwb	-	-	-	0.01	-	-	-	-	0.01	0.01
	Tomatoes	(0.27)	-	-	(0.00)	-	-	-	-	(0.41)	-0.41
	Waln	-	-	-	-	-	-	-	-	(0.00)	0.00
	Total	(3.19)	(0.31)	(0.04)	(0.62)	-	(0.01)	0.13	0.03	(29.49)	-29.49

SI Table 57. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The revenue is normalized by 1million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 1											
		Kern Ag 2014									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
LIQ 2014	Alfalfa		12			182	0		9	60	208
	Almonds	(84)				1	(3)	(67)	20	7	64
	Apples										
	Berreis										
	Carrots	(30)	(11)		(0)			(40)	(26)	(8)	26
	Cherries	(3)	2		82						18
	Citrus		1								49
	Corn	(15)	(85)			0				(1)	50
	Cotton	(15)	(3)			0					20
	Fallow	(23)	(366)			(40)		(94)		(408)	
	Garlic Onion		2			111			23		9
	Grains	(523)	(0)			(1)	(2)	(3)	(61)	(3)	138
	Grapes	(12)	3		5	8	1	(18)			87
	Grasses										
	Lettuce Greens				7	4		(5)		(4)	
	Non-Ag										
	Other Crops		(180)			15	(87)	(24)	1		563
	Other fruit	(0)				59		(2)			427
	Other Veg		(1)								
	Peppers					5					
	Pist	(24)	24				2	(2)		1	10
	Plums			(0)	5		3				
	Pome		(4)							(0)	9
	Potato					8		(43)		1	18
	Saff										2
	Strwb										
	Tomatoes		(1)			0					
	Waln		1								
	Total	(729)	(607)	(0)	99	353	(86)	(296)	(33)	(356)	1,696

SI Table 58. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 2										
	Kern Ag 2014									
LIQ 2014	Row Labels	Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other fruit	Other Veg
	Alfalfa		731	6	6			3	5	3
	Almonds	9	8	(6)				2		5
	Apples								(0)	
	Berreis									
	Carrots	(22)	(17)	(16)	(11)	(0)				(18)
	Cherries		21	(0)				0	(1)	
	Citrus		10	65					0	1
	Corn	(5)	(12)		(17,395)					(0)
	Cotton		2	(17)	(2)			(8)		(1)
	Fallow		(1,834)	(229)	(12)		-	(15)	(29)	(3)
	Garlic Onion		17	0				355		12
	Grains	(25)		(8)	(267)			(8)	(10)	
	Grapes	0	12					2	(0)	
	Grasses									
	Lettuce Greens		0					(149)		(1,934)
	Non-Ag									
	Other Crops	7		(545)					(21)	340
	Other fruit		10	3				14		257
	Other Veg			(4)				(0)		
	Peppers		7	(4)						5
	Pist		2	1				4		
	Plums								(59)	
	Pome								(7)	
	Potato	14		(11)				(3)	(7)	
	Saff		0							
	Strwb									
	Tomatoes	4							(82)	
	Waln									
	Total	(19)	(1,044)	(764)	(17,681)	(0)	-	197	(211)	(1,331)

SI Table 59. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 3

	Kern Ag 2014									
LIQ 2014	Row Labels	Peppers	Pist	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa		18							1,244
	Almonds		(13)	1				1		(55)
	Apples									(0)
	Berreis									
	Carrots	(166)			(18)			(9)		(366)
	Cherries		(3)							116
	Citrus	1	1		12					140
	Corn									(17,464)
	Cotton		(7)		1			(0)		(29)
	Fallow		(121)	(46)	(44)					(3,265)
	Garlic Onion	25			23			12		590
	Grains		(24)	0	(4)					(800)
	Grapes	1	(3)	8					(0)	92
	Grasses									
	Lettuce Greens									(2,079)
	Other Crops		(164)		95			1		0
	Other fruit		0					67		835
	Other Veg									(5)
	Peppers				12					25
	Pist							1		19
	Plums			21						(29)
	Pome		(6)							(8)
	Potato	(4)						0		(28)
	Saff									2
	Strwb				(0)					(0)
	Tomatoes	(8)			0					(86)
	Waln									1
	Total	(151)	(320)	(16)	77			72	(0)	(21,150)

SI Table 60. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 1											
		Kern Ag 2014									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
LIQ 2014	Alfalfa		2			(12)	0		(3)	3	14
	Almonds	(16)				(0)	(8)	(28)	(34)	(1)	2
	Apples										
	Berries					5	13				
	Carrots	2	2		(2)			(2)	(8)	3	11
	Cherries	(0)	5		(32)						1
	Citrus		0								7
	Corn	4	48			0				2	31
	Cotton	(1)	0			(0)					2
	Fallow	(2)	(9)			(14)		(14)		(39)	
	Garlic Onion		1			(7)			(13)		1
	Grains	66	0			1	0	(0)	(15)	2	66
	Grapes	(2)	1		(2)	(2)	(1)	(8)			3
	Grasses										
	Lettuce Greens				(10)	(2)		(0)		2	
	Other Crops										
	Other Fruit	(0)				(6)		(1)			24
	Other Veg		0								
	Peppers					2					
	Pist	(2)	9				(0)	(1)		0	1
	Plums			(0)	(2)		(4)				
	Pome										
	Potato					(1)		(4)		1	3
	Saff										0
	Strwb										
	Tomatoes		0			(0)					
	Waln		0								
	Total	49	60	(0)	(48)	(35)	(0)	(60)	(73)	(28)	167

SI Table 61. Table of the resulting GHG emission discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User’s Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 2										
	Kern Ag 2014									
		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
LIQ 2014	Alfalfa		(97)	1	(1)				1	(0)
	Almonds	(2)	(3)	(2)						(1)
	Apples								0	
	Berries			2						
	Carrots	3	(7)	3	0	0				3
	Cherries		(6)	0					0	
	Citrus		0	30					0	0
	Corn	7	49		4,442					0
	Cotton		(2)	1	(0)					(0)
	Fallow		(764)	(9)	(2)		-		(2)	(0)
	Garlic Onion		(2)	0						0
	Grains	13		2	24				2	
	Grapes	(0)	(4)						(0)	
	Grasses									
	Lettuce Greens		(1)							243
	Other Crops									
	Other Fruit		(2)	0						(13)
	Other Veg			1						
	Peppers		2	12						6
	Pist		(0)	1						
	Plums								(10)	
	Pome									
	Potato	4		3					1	
	Saff		(2)							
	Strwb									
	Tomatoes	2							12	
	Waln									
	Total	27	(838)	46	4,463	0	-		4	239

SI Table 62. Table of the resulting GHG emission discrepancy reflecting user’s accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of LIQ 2014 with Kern Ag 2014Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 3										
	Kern Ag 2014									
		Peppers	Pist.	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
LIQ 2014	Alfalfa		2							(91)
	Almonds		(5)					(0)		(99)
	Apples									0
	Berries						0			19
	Carrots	(59)			1			0		(50)
	Cherries		0							(31)
	Citrus	(0)	0		1					39
	Corn									4,582
	Cotton		(0)		(1)			(0)		(1)
	Fallow		(8)		(10)					(871)
	Garlic Onion	(23)			(1)			(1)		(44)
	Grains		5		1					169
	Grapes	(2)	(1)						0	(18)
	Grasses									
	Lettuce Greens									232
	Other Crops									
	Other Fruit		0					(9)		(7)
	Other Veg									1
	Peppers				8					31
	Pist							(0)		6
	Plums									(17)
	Pome									
	Potato	(5)						(0)		3
	Saff									(2)
	Strwb				0					0
	Tomatoes	(7)			0					9
	Waln									0
	Total	(95)	(7)		(0)		0	(11)	0	3,859

SI Table 63. Table of the resulting GHG emission discrepancy reflecting user's accuracy of LIQ 2014 compared with Kern Ag 2014 (actual; ground truth) dataset. The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 1											
		Kern Ag 2016									
LIQ 2016		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
	Alfalfa	-	(0.48)	-	-	(0.03)	(0.00)	-	0.00	(0.19)	0.06
	Almonds	0.09	-	-	-	(0.06)	(0.38)	(0.18)	0.05	0.02	1.60
	Apples	-	-	-	-	-	-	-	-	-	0.02
	Berries	-	-	-	-	0.20	-	-	-	-	-
	Carrots	4.26	0.02	-	-	-	-	-	0.73	-	1.71
	Cherries	0.05	0.05	-	(0.52)	-	-	0.00	-	-	0.01
	Citrus	-	0.03	-	-	(0.00)	-	-	-	-	0.19
	Corn	(0.06)	(0.02)	-	-	(2.72)	-	-	-	(1.72)	0.17
	Cotton	0.37	-	-	-	-	-	-	0.33	-	1.32
	Fallow	(1.13)	(77.85)	-	(2.88)	(14.01)	(12.36)	(4.54)	(1.67)	(5.35)	-
	Garlic Onion	0.01	0.02	-	-	0.11	-	-	0.42	-	2.38
	Grains	(0.27)	(0.96)	-	-	(14.27)	-	(0.03)	(0.27)	(0.30)	0.35
	Grapes	0.13	3.01	-	(0.02)	0.07	0.08	0.22	-	-	4.28
	Grasses	-	-	-	-	-	-	-	-	-	-
	Lettuce Greens	-	0.04	-	-	(1.10)	-	-	-	0.47	0.38
	Non-Ag	-	-	-	-	-	-	-	-	-	-
	Other Crops	(0.00)	(0.01)	-	(0.13)	(2.51)	(0.09)	(5.83)	(0.00)	(0.04)	0.10
	Other Fruit	-	0.02	-	-	0.00	-	0.00	-	-	2.24
	Other Veg	1.24	0.00	-	-	-	-	-	1.56	2.51	-
	Peppers	-	0.15	-	-	0.87	-	-	-	-	-
	Pist	0.00	0.06	-	-	-	(0.06)	(0.01)	0.05	0.14	18.82
	Plums	-	-	0.00	(0.05)	-	-	-	-	-	-
	Pome	-	0.00	-	-	-	-	(0.00)	-	-	0.00
	Potato	-	(0.00)	-	(0.42)	(12.06)	-	(0.01)	-	-	0.31
	Strwb	-	-	-	-	-	-	-	-	-	-
	Saff	-	-	-	-	(0.78)	-	-	(0.04)	(0.00)	1.51
	Tomatoes	-	(0.00)	-	-	(3.76)	-	-	-	-	10.66
	Waln	-	(0.00)	-	-	-	-	-	-	-	-
	Total	4.69	(75.91)	0.00	(4.02)	(50.06)	(12.80)	(10.38)	1.15	(4.47)	46.11

SI Table 64. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 2										
	Kern Ag 2016									
LIQ 2016		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	(0.82)	0.29	(0.09)	0.00	-	-	0.01	-	-
	Almonds	(0.01)	0.28	(2.79)	-	(0.01)	-	-	-	-
	Apples	-	-	-	-	-	-	-	(0.01)	-
	Berries	-	-	0.02	-	-	-	-	-	-
	Carrots	(0.12)	4.24	(0.08)	-	0.29	-	0.59	-	(0.04)
	Cherries	-	-	(0.00)	-	-	-	0.20	0.01	-
	Citrus	-	0.02	(0.76)	-	-	-	-	(0.02)	-
	Corn	(1.42)	11.39	-	0.60	-	-	0.00	-	(2.73)
	Cotton	(0.10)	0.04	-	-	(0.02)	-	-	-	(0.94)
	Fallow	(2.97)	(2.20)	(62.28)	(0.02)	(0.35)	-	(0.82)	(1.27)	(3.11)
	Garlic Onion	-	0.54	-	-	0.01	-	1.03	(0.01)	0.01
	Grains	(0.82)	-	(3.13)	(0.04)	-	-	(0.05)	-	(1.13)
	Grapes	-	0.01	-	-	-	-	0.81	0.16	-
	Grasses	-	-	-	-	-	-	-	-	-
	Lettuce Greens	(0.03)	0.01	(0.13)	-	-	-	4.23	-	(5.40)
	Non-Ag	-	-	-	-	-	-	-	-	-
	Other Crops	(1.55)	0.03	(4.01)	-	(1.31)	-	-	(0.95)	(6.85)
	Other Fruit	0.27	0.29	(0.05)	-	0.05	-	0.87	-	0.18
	Other Veg	-	-	-	-	-	-	-	-	-
	Peppers	1.16	-	(0.01)	-	-	-	1.43	-	-
	Pist	-	0.01	(0.90)	-	-	-	0.02	-	(0.00)
	Plums	-	-	-	-	-	-	-	0.00	-
	Pome	-	-	-	-	-	-	-	(0.01)	-
	Potato	(2.20)	1.79	-	-	(0.36)	-	-	(0.02)	(1.16)
	Strwb	-	-	-	-	-	-	-	-	-
	Saff	(0.48)	(0.00)	-	-	-	-	(0.01)	-	-
	Tomatoes	(3.16)	-	-	0.00	(0.16)	-	0.03	(0.75)	(0.04)
	Waln	-	-	-	-	-	-	-	-	-
	Total	(12.24)	16.74	(74.24)	0.54	(1.85)	-	8.35	(2.86)	(21.22)

SI Table 65. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy Revenue Discrepancy (in 1 Million USD) Part 3											
	Kern Ag 2016										
LIQ 2016		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa	-	(0.50)	-	-	(0.55)	-	-	-	-	(2.31)
	Almonds	-	(0.08)	-	-	-	-	-	-	-	(1.48)
	Apples	-	-	-	-	-	-	-	-	-	0.01
	Berries	-	-	-	-	-	-	(0.01)	-	-	0.21
	Carrots	(0.01)	-	-	-	6.62	-	-	0.05	-	18.24
	Cherries	-	0.10	-	-	-	-	-	-	-	(0.09)
	Citrus	-	0.01	-	-	0.02	-	-	-	-	(0.52)
	Corn	-	(0.02)	-	-	(1.66)	0.02	-	-	-	1.82
	Cotton	-	(0.00)	-	-	(0.23)	-	-	-	-	0.77
	Fallow	(1.44)	(2.51)	-	(15.39)	(13.66)	(0.08)	-	(1.73)	(0.16)	(227.76)
	Garlic Onion	(0.03)	-	-	-	1.59	-	-	0.02	-	6.10
	Grains	-	(0.02)	-	(0.01)	(2.43)	0.00	-	-	-	(23.37)
	Grapes	0.01	0.09	-	0.05	-	-	-	0.09	0.03	9.02
	Grasses	-	-	-	-	-	-	-	-	-	-
	Lettuce Greens	-	-	-	-	-	-	-	-	-	(1.55)
	Non-Ag	-	-	-	-	-	-	-	-	-	-
	Other Crops	(2.62)	(0.96)	(0.02)	(0.03)	(0.24)	-	-	-	-	(27.02)
	Other Fruit	(0.10)	-	-	-	-	-	-	0.04	-	3.81
	Other Veg	-	-	-	-	-	-	-	-	-	5.31
	Peppers	-	-	-	-	0.11	-	-	-	-	3.73
	Pist	-	-	-	-	-	-	-	0.01	0.04	18.17
	Plums	-	-	-	-	-	-	-	-	-	(0.05)
	Pome	-	0.00	-	-	-	-	-	-	-	0.00
	Potato	-	-	-	-	-	-	-	0.11	-	(14.01)
	Strwb	-	-	-	-	-	-	-	-	-	-
	Saff	-	(0.01)	-	-	-	-	-	-	-	0.18
	Tomatoes	(0.88)	-	-	-	-	-	-	-	-	1.95
	Waln	-	-	-	-	-	-	-	-	-	(0.00)
	Total	(5.07)	(3.92)	(0.02)	(15.37)	(10.43)	(0.06)	(0.01)	(1.41)	(0.09)	(228.83)

SI Table 66. Table of the resulting revenue discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 1											
		Kern Ag 2016									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
LIQ 2016	Alfalfa		140			11	0		10	432	272
	Almonds	(25)				21	(1)	(67)	3	6	1,020
	Apples										44
	Berries					(13)					
	Carrots	(1,608)	(9)						(154)		199
	Cherries	(3)	0		80			(0)			2
	Citrus		11			2					98
	Corn	(8,459)	(7)			16				(1,130)	304
	Cotton	(831)							(246)		1,572
	Fallow	(5,214)	(49,729)		(116)	(2,290)	(2,068)	(2,414)	(5,337)	(6,380)	
	Garlic Onion	(0)	3			592			39		908
	Grains	(1,748)	(401)			(393)		(10)	(996)	(197)	974
	Grapes	(6)	34		4	10	4	(18)			646
	Grasses										
	Lettuce Greens		(20)			76				(44)	80
	Non-Ag										
	Other Crops	(87)	(1)		6	335	(3)	(1,402)	(0)	19	305
	Other Fruit		2			7		(1)			823
	Other Veg	(278)	(0)						(101)	41	
	Peppers		(3)			160					
	Pist	(1)	28				2	(4)	7	48	11,429
	Plums			(0)	5						
	Pome		(4)					(4)			1
	Potato		(11)		16	2,048		(9)			151
	Safflower					6			(124)	(2)	5,479
	Strwb										
	Tomatoes		(1)			390					8,274
	Waln		0								
	Total	(18,259)	(49,968)	(0)	(5)	978	(2,065)	(3,929)	(6,900)	(7,206)	32,579

SI Table 67. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 2

		Kern Ag 2016								
		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
LIQ 2016	Alfalfa	193	763	4	2			482		
	Almonds	3	2	(34)		5				
	Apples								(0)	
	Berries			(6)						
	Carrots	(366)	(972)	(15)		(59)		(2)		(174)
	Cherries			(0)				24	(1)	
	Citrus		3	60					8	
	Corn	(110)	(40,437)		(9,844)			15		(188)
	Cotton	(1)	(29)			3				1
	Fallow	(690)	(14,699)	(9,459)	(96)	(63)	-	(1,039)	(420)	(705)
	Garlic Onion		34			15		302	2	144
	Grains	(86)		(301)	(349)			22		(110)
	Grapes		0					85	(3)	
	Grasses									
	Lettuce Greens	(9)	(1)	(16)				322		(1,571)
	Non-Ag									
	Other Crops	70	(34)	(134)		236			(89)	377
	Other Fruit	420	24	3		42		252		268
	Other Veg									
	Peppers	106		(1)				161		
	Pist		1	12				8		0
	Plums								(51)	
	Pome								(3)	
	Potato	22	(342)			105			(3)	32
	Safflower	(34)	(2)					6		
	Strwb									
	Tomatoes	(27)			(2)	26		18	(130)	0
	Waln									
	Total	(509)	(55,688)	(9,887)	(10,290)	308	-	656	(692)	(1,925)

SI Table 68. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet)
Part 3

		Kern Ag 2016									
		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
LIQ 2016	Alfalfa		76			356					2,742
	Almonds		(36)								897
	Apples										44
	Berries							(0)			(20)
	Carrots	(3)				(1,100)			(8)		(4,272)
	Cherries		(3)								99
	Citrus		3			12					197
	Corn		(9)			(121)	(1)				(59,971)
	Cotton		(1)			27					494
	Fallow	(256)	(1,517)		(2,689)	(5,370)	(306)		(1,335)	(210)	(112,401)
	Garlic Onion	3				591			5		2,636
	Grains		(9)		0	(328)	(3)				(3,936)
	Grapes	1	(1)		7				5	(0)	769
	Grasses										
	Lettuce Greens										(1,184)
	Non-Ag										
	Other Crops	(58)	(174)	(1)	7	51					(578)
	Other Fruit	16							9		1,867
	Other Veg										(339)
	Peppers					10					434
	Pist								3	3	11,536
	Plums										(47)
	Pome		(6)								(17)
	Potato								7		2,017
	Safflower		(5)								5,324
	Strwb										
	Tomatoes	(51)									8,498
	Waln										0
	Total	(348)	(1,683)	(1)	(2,674)	(5,873)	(310)	(0)	(1,313)	(207)	(145,212)

SI Table 69. Table of the resulting CWR discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in $MGCO_2e$) Part 1											
		Kern Ag 2016									
LIQ 2016		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
	Alfalfa		28			(1)	0		(5)	21	19
	Almonds	(5)				(6)	(5)	(31)	(10)	(1)	25
	Apples										4
	Berries					5					
	Carrots	101	2						(41)		93
	Cherries	(0)	1		(32)			(0)			0
	Citrus		5			0					15
	Corn	2,110	4			152				1,418	189
	Cotton	(41)							(272)		149
	Fallow	(377)	(1,225)		(94)	(762)	(166)	(370)	(1,813)	(602)	
	Garlic Onion	0	1			(36)			(29)		91
	Grains	220	130			284		(0)	(184)	103	520
	Grapes	(1)	9		(2)	(2)	(3)	(9)			25
	Grasses										
	Lettuce Greens		4			(74)				15	20
	Non-Ag										
	Other Crops										
	Other Fruit		0			(1)		(0)			48
	Other Veg	2	0						(118)	37	
	Peppers		14			72					
	Pist	(0)	10				(0)	(2)	(7)	1	743
	Plums			(0)	(2)						
	Pome										
	Potato		5		(9)	(141)		(1)			30
	Saff					(33)			(81)	(0)	473
	Strwb										
	Tomatoes		0			(8)					1,858
	Waln		0								
	Total	2,008	(1,012)	(0)	(140)	(550)	(174)	(414)	(2,558)	992	4,302

SI Table 70. Table of the resulting GHG emission discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in MGCO$_2$e) Part 2										
	Kern Ag 2016									
LIQ 2016		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	(6)	(238)	1	(1)					
	Almonds	(1)	(38)	(8)		(1)				
	Apples								0	
	Berries			2						
	Carrots	42	(84)	3		19				30
	Cherries			0					0	
	Citrus		0	31					4	
	Corn	97	7,736		2,005					206
	Cotton	(2)	(15)			(1)				(14)
	Fallow	(114)	(3,223)	(361)	(12)	(18)	-		(27)	(104)
	Garlic Onion		(18)			(0)			2	5
	Grains	27		80	24					45
	Grapes		(0)						(1)	
	Grasses									
	Lettuce Greens	0	(0)	3						233
	Non-Ag									
	Other Crops									
	Other Fruit	(34)	(13)	0		(3)				(13)
	Other Veg									
	Peppers	123		1						
	Pist		(1)	6						(0)
	Plums								(16)	
	Pome									
	Potato	35	(97)			6			1	31
	Saff	(12)	(1)							
	Strwb									
	Tomatoes	55			(0)	3			24	1
	Waln									
	Total	211	4,007	(243)	2,016	6	-		(13)	421

SI Table 71. Table of the resulting GHG emission discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. GHG emission is in units of MgCO$_2$e. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of LIQ 2016 with Kern Ag 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in $MGCO_2e$) Part 3											
	Kern Ag 2016										
LIQ 2016		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa		8			(21)					(195)
	Almonds		(13)								(95)
	Apples										4
	Berries							0			7
	Carrots	(1)				77			0		240
	Cherries		0								(31)
	Citrus		1			1					58
	Corn		4			229	40				14,189
	Cotton		(0)			(20)					(215)
	Fallow	(96)	(99)			(1,314)	(26)		(301)	(8)	(11,113)
	Garlic Onion	(3)				(26)			(0)		(13)
	Grains		2			132	5				1,388
	Grapes	(2)	(1)						(2)	0	10
	Grasses										
	Lettuce Greens										201
	Non-Ag										
	Other Crops										
	Other Fruit	(15)							(1)		(31)
	Other Veg										(79)
	Peppers					6					216
	Pist								(1)	1	751
	Plums										(18)
	Pome										
	Potato								(2)		(143)
	Saff		(0)								347
	Strwb										
	Tomatoes	(40)									1,894
	Waln										0
	Total	(157)	(99)			(935)	19	0	(307)	(6)	7,373

SI Table 72. Table of the resulting GHG emission discrepancy reflecting user's accuracy of LIQ 2016 compared with Kern Ag 2016 (actual; ground truth) dataset. GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 1											
		LIQ 2014									
CropScape 2014		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
	Alfalfa	-	(18.33)	(0.07)	(0.38)	(11.45)	(0.76)	(8.38)	1.09	(0.69)	2.73
	Almonds	2.38	-	(0.06)	(0.18)	(2.31)	2.68	(12.77)	1.69	1.21	10.61
	Apples	0.00	0.10	-	(0.01)	-	0.00	(0.98)	0.03	0.00	0.41
	Berries	0.04	0.31	-	-	-	0.01	0.76	0.02	-	0.10
	Carrots	0.19	0.49	-	(0.01)	-	0.19	0.03	0.05	0.28	1.56
	Cherries	0.02	(0.56)	(0.01)	(3.71)	(0.73)	-	(14.70)	0.06	0.02	0.79
	Citrus	0.05	1.75	0.00	(3.33)	(0.01)	2.41	-	0.10	0.00	1.77
	Corn	(0.15)	(1.07)	-	(0.06)	(4.86)	(0.03)	(0.18)	-	(0.78)	1.69
	Cotton	0.34	(1.02)	-	-	(1.67)	(0.01)	(0.38)	0.93	-	7.58
	Fallow	(1.68)	(46.34)	(3.44)	(6.21)	(42.09)	(1.15)	(36.97)	(2.51)	(7.96)	-
	Garlic Onion	0.36	(0.09)	(0.00)	-	(2.38)	(0.00)	(0.03)	0.24	0.08	3.30
	Grains	(3.17)	(5.55)	(0.00)	(0.01)	(17.06)	(0.12)	(2.75)	(4.68)	(0.98)	5.05
	Grapes	3.52	23.98	0.18	(0.67)	6.52	8.23	69.53	5.76	3.63	15.17
	Grasses	(0.06)	(0.00)	-	-	(0.32)	(0.00)	-	(0.01)	(0.00)	0.02
	Lettuce Greens	0.01	0.00	-	-	0.00	-	-	0.14	0.00	0.01
	Non-Ag	(2.92)	(71.06)	(0.37)	(5.46)	(19.24)	(3.67)	(132.81)	(1.22)	(1.89)	-
	Other Crops	(0.00)	(0.25)	(0.00)	(0.01)	(0.23)	(0.03)	(1.41)	(0.00)	(0.03)	0.00
	Other Fruit	0.07	0.09	-	-	(0.38)	-	(0.03)	0.40	0.19	0.94
	Other Veg	0.52	0.10	0.00	-	0.10	-	0.33	0.91	1.24	3.30
	Peppers	0.21	1.47	-	-	0.82	0.01	-	3.24	0.09	3.84
	Pist	0.25	(18.88)	(0.03)	(0.39)	(0.60)	(0.41)	(10.69)	0.12	0.32	2.27
	Plums	-	0.02	0.00	-	-	-	0.00	-	-	-
	Pome	0.01	(0.01)	-	-	-	-	(0.00)	0.00	-	0.00
	Potato	0.11	0.02	(0.00)	(0.06)	(6.78)	0.00	(0.36)	0.49	0.06	0.78
	Saff	(0.01)	(0.01)	-	-	(0.01)	-	-	(0.00)	-	0.01
	Strwb	-	-	-	-	-	-	-	-	0.01	-
	Tomatoes	0.20	(0.60)	-	(0.02)	(4.03)	(0.00)	(0.04)	0.78	0.09	6.71
	Waln	0.03	(0.09)	(0.00)	-	(0.01)	(0.01)	(0.44)	0.01	0.07	0.11
	Total	0.34	(135.53)	(3.81)	(20.50)	(106.72)	7.35	(152.26)	7.65	(5.00)	68.74

SI Table 73. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 2										
		LIQ 2014								
CropScape 2014		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	(1.22)	4.22	(156.33)	-	(1.59)	-	0.80	(0.89)	(0.78)
	Almonds	0.32	4.63	(145.51)	-	(0.86)	-	5.39	(0.12)	(0.26)
	Apples	-	-	(13.75)	-	-	-	0.05	0.00	-
	Berries	-	0.38	12.54	-	-	-	0.15	-	-
	Carrots	1.72	1.38	(3.13)	-	(0.08)	-	0.71	0.18	(0.08)
	Cherries	0.00	0.10	(46.53)	-	(0.26)	-	1.28	(0.26)	(0.00)
	Citrus	0.02	0.38	(110.79)	-	(0.02)	-	2.13	0.27	-
	Corn	(0.61)	0.45	(3.44)	-	(1.27)	-	0.13	(0.38)	(0.58)
	Cotton	(0.03)	0.71	(37.09)	-	(0.92)	-	0.77	(1.15)	(3.55)
	Fallow	(3.19)	(5.28)	(166.85)	-	(18.89)	-	(0.58)	(8.17)	(3.16)
	Garlic Onion	-	1.40	(0.07)	-	(0.67)	-	0.51	(0.01)	(0.01)
	Grains	(3.40)	-	(14.66)	-	(3.51)	-	0.14	(0.57)	(0.35)
	Grapes	0.83	2.98	-	-	1.69	-	14.69	4.90	0.11
	Grasses	-	(0.02)	(0.22)	-	-	-	0.00	(0.00)	(0.12)
	Lettuce Greens	-	0.01	-	-	-	-	-	0.00	-
	Non-Ag	(2.23)	(2.90)	(198.73)	-	(1.60)	-	(0.46)	(5.10)	(0.78)
	Other Crops	(0.30)	(0.00)	(5.08)	-	(0.08)	-	-	(0.36)	(0.00)
	Other Fruit	0.08	0.10	(2.41)	-	(0.03)	-	0.08	-	(0.00)
	Other Veg	0.00	0.37	(2.73)	-	-	-	1.39	0.21	-
	Peppers	0.11	0.61	0.27	-	0.25	-	-	0.79	-
	Pist	(0.06)	0.75	(21.31)	-	(0.16)	-	0.29	(0.44)	(0.08)
	Plums	-	-	(0.18)	-	-	-	0.00	-	-
	Pome	-	0.01	(0.40)	-	-	-	-	-	-
	Potato	0.93	2.68	(1.65)	-	(0.39)	-	0.80	(0.00)	(0.03)
	Saff	(0.00)	(0.00)	(0.28)	-	(0.01)	-	-	-	-
	Strwb	-	0.01	-	-	-	-	-	-	-
	Tomatoes	(0.46)	0.49	(3.91)	-	(0.70)	-	1.07	(1.35)	(0.01)
	Waln	-	0.02	(5.31)	-	(0.00)	-	0.06	(0.00)	-
	Total	(7.47)	13.48	(927.54)	-	(29.10)	-	29.41	(12.43)	(9.70)

SI Table 74. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 3											
	LIQ 2014										
CropScape 2014		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa	(3.06)	(0.76)	(0.01)	(0.11)	(3.99)	0.19	-	(1.23)	(0.02)	(201.02)
	Almonds	(0.39)	50.71	(0.00)	3.08	(0.01)	0.05	-	0.13	1.28	(78.26)
	Apples	(0.09)	0.49	-	-	-	-	-	-	-	(13.73)
	Berries	-	0.66	-	-	-	0.01	-	-	0.01	14.98
	Carrots	(1.63)	0.04	(0.00)	0.00	2.97	0.07	-	0.66	-	5.60
	Cherries	(0.36)	0.42	(0.42)	0.01	(0.14)	0.02	(0.04)	0.01	0.00	(64.97)
	Citrus	(0.14)	7.66	(0.01)	0.95	0.06	0.02	-	0.02	0.06	(96.63)
	Corn	(3.04)	(0.16)	-	(0.00)	(0.78)	0.00	-	(0.43)	(0.00)	(15.55)
	Cotton	(5.04)	(0.11)	-	(0.18)	(0.80)	-	-	(0.10)	-	(41.73)
	Fallow	(0.67)	(50.89)	(0.31)	(6.87)	(6.04)	(0.01)	(0.22)	(2.10)	(0.02)	(421.58)
	Garlic Onion	(0.03)	0.02	-	-	(0.40)	0.00	-	0.02	-	2.25
	Grains	(1.51)	(1.46)	-	(0.03)	(5.28)	0.26	-	(0.10)	-	(59.73)
	Grapes	(2.77)	9.17	0.17	27.02	5.03	0.43	(0.02)	1.42	0.14	201.62
	Grasses	(0.36)	(0.00)	-	-	(0.00)	-	-	(0.00)	-	(1.09)
	Lettuce Greens	(0.01)	-	-	-	0.00	-	-	0.00	-	0.17
	Non-Ag	(5.66)	(72.14)	(0.06)	(16.97)	(17.57)	(0.03)	(0.43)	(1.15)	(0.22)	(564.67)
	Other Crops	-	(0.00)	-	(0.00)	(0.01)	-	-	(0.00)	-	(7.80)
	Other Fruit	(7.99)	1.66	-	1.52	0.03	0.06	-	0.08	-	(5.56)
	Other Veg	(0.17)	0.01	-	-	0.11	-	-	0.30	-	5.98
	Peppers	-	-	-	-	0.02	-	-	0.05	-	11.75
	Pist	(0.05)	-	(0.01)	(2.31)	(0.18)	0.07	-	(0.01)	(0.04)	(51.59)
	Plums	-	0.01	-	0.02	-	-	-	-	-	(0.13)
	Pome	-	0.02	-	-	-	-	-	-	-	(0.37)
	Potato	(0.33)	0.01	(0.00)	0.00	-	0.01	(0.05)	0.08	-	(3.70)
	Saff	(0.01)	(0.02)	-	-	-	-	-	-	-	(0.35)
	Strwb	-	-	-	-	-	-	-	-	-	0.03
	Tomatoes	(4.61)	0.01	-	0.00	(0.83)	0.01	(0.01)	-	-	(7.18)
	Waln	-	0.39	-	0.29	(0.00)	-	-	-	-	(4.89)
	Total	(37.90)	(54.29)	(0.64)	6.40	(27.83)	1.17	(0.77)	(2.37)	1.18	(1,398.17)

SI Table 75. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The revenue is normalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 1										
		LIQ 2014								
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton
CropScape 2014	Alfalfa		4,935	11		5,306	274	(343)	7,245	2,759
	Almonds	(692)		(19)		1,886	(23)	(8,420)	595	344
	Apples	(0)	43				1	(876)	10	1
	Berries	(1)	3				0	(35)	1	
	Carrots	(93)	(380)				(102)	(253)	(2)	(42)
	Cherries	(8)	68	(1)		416		(5,534)	31	11
	Citrus	0	1,126	2		60	912		42	1
	Corn	(995)	(348)			308	(13)	(77)		(420)
	Cotton	(1,415)	(264)			272	(5)	(157)	610	
	Fallow	(4,272)	(24,271)	(1,742)		(5,807)	(776)	(20,876)	(2,926)	(7,449)
	Garlic Onion	(287)	(56)	(0)		644	(1)	(20)	52	4
	Grains	(11,305)	(1,810)	(1)		714	(54)	(1,181)	(756)	(467)
	Grapes	(187)	302	(2)		1,035	67	(5,907)	495	221
	Grasses	(64)	0			91	0		30	4
	Lettuce Greens	(4)	(1)			0			1	(0)
	Non-Ag	(7,436)	(37,219)	(189)		(2,654)	(2,487)	(74,999)	(1,419)	(1,768)
	Other Crops	(1)	11	(0)		64	1	(221)	6	20
	Other Fruit	(12)	83			454		(19)	156	65
	Other Veg	(127)	(18)	(0)		89		(389)	95	50
	Peppers	(12)	(18)			66	(0)		150	2
	Pist	(149)	2,599	0		271	87	(2,296)	124	457
	Plums		0	(0)				(1)		
	Pome	(12)	(7)					(1)	(0)	
	Potato	(55)	(193)	(1)		3,094	(2)	(422)	73	2
	Saff	(16)	(3)			1			0	
	Strwb									0
	Tomatoes	(200)	(256)			973	(2)	(24)	213	7
	Waln	(15)	10	(0)		7	2	(136)	5	47
	Total	(27,359)	(55,665)	(1,944)	-	7,287	(2,121)	(122,186)	4,834	(6,153)

SI Table 76. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 *compared with LIQ 2014 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.*

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 2

		LIQ 2014								
		Fallow	Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit
CropScape 2014	Alfalfa	6,718	246	14,756	7,398		525		1,129	39
	Almonds	5,649	(117)	1,629	(1,149)		356		539	(229)
	Apples	211			184				7	(1)
	Berries	10		24	110				3	
	Carrots	224	(1,094)	(35)	(481)		(34)		(129)	(261)
	Cherries	552	(3)	49	(64)		85		199	(119)
	Citrus	982	3	162	8,911		33		515	65
	Corn	2,062	(403)	235	(280)		(9)		(179)	(181)
	Cotton	7,226	(19)	401	(2,132)		62		(214)	(525)
	Fallow		(2,635)	(8,088)	(24,988)		(3,298)		(2,681)	(5,157)
	Garlic Onion	1,638		326	(4)		73		(53)	(12)
	Grains	8,172	(2,120)		(1,266)		(80)		(481)	(265)
	Grapes	2,288	(18)	272			224		472	(229)
	Grasses	100		257	1				1	(0)
	Lettuce Greens	1		0						(1)
	Non-Ag	-	(1,845)	(4,448)	(29,763)		(279)		(2,109)	(3,220)
	Other Crops	25	(27)	2	12		16			(43)
	Other Fruit	519	(6)	39	40		17		13	
	Other Veg	817	(1)	42	(195)				(32)	(103)
	Peppers	373	(4)	31	(18)		15			(42)
	Pist	2,444	(10)	672	222		47		93	(77)
	Plums				(2)				0	
	Pome	1		(0)	(43)					
	Potato	291	(875)	445	(108)		64		(56)	(10)
	Saff	33	(1)	1	(20)		0			
	Strwb			1						
	Tomatoes	3,850	(1,175)	138	(227)		71		(124)	(973)
	Waln	84		9	3		1		11	(1)
	Total	44,270	(10,102)	6,919	(43,860)	-	(2,114)	-	(3,076)	(11,346)

SI Table 77. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 3												
	LIQ 2014											
CropScape 2014		Other Veg	Pepper	Pist	Plum	Pome	Potato	Saff	Strwb	Tomato	Waln	Total
	Alfalfa	191	147	360	1	167	1,834	412		1,168	8	55,286
	Almonds	59	4	(6,833)	(0)	2,986	117	15		63	(143)	(3,383)
	Apples		2	(5)								(424)
	Berries			(3)				0			0	113
	Carrots	(62)	(136)	(18)	(1)	0	(1,337)	(4)		(144)		(4,384)
	Cherries	0	5	(75)	(0)	25	103	7	1	11	(0)	(4,239)
	Citrus		10	1,434	7	752	63	7		13	16	15,116
	Corn	(46)	(145)	(159)		1	(111)	(0)		(96)	(1)	(860)
	Cotton	(57)	(146)	(156)		115	(25)			(1)		3,571
	Fallow	(737)	(68)	(55,534)	(107)	(2,023)	(2,278)	(23)	(6)	(1,173)	(16)	(176,932)
	Garlic Onion	(0)	(1)	(17)			(14)	0		2		2,273
	Grains	(32)	(78)	(1,295)		4	(828)	(116)		(24)		(13,267)
	Grapes	9	151	(105)	1	3,253	329	34	1	89	(0)	2,793
	Grasses	15	5	(0)			0			0		440
	Lettuce Greens		(1)				(0)			(0)		(5)
	Non-Ag	(183)	(571)	(78,714)	(21)	(4,995)	(6,634)	(82)	(13)	(642)	(183)	(261,873)
	Other Crops	0		(0)		2	3			1		(129)
	Other Fruit	1	218	10		1,434	86	19		44		3,160
	Other Veg		(5)	(1)			4			12		238
	Peppers						0			1		545
	Pist	15	1		0	8,840	80	48		28	5	13,504
	Plums			(1)		7						4
	Pome			(64)								(126)
	Potato	(0)	(10)	(3)	(0)	1		1	1	2		2,236
	Saff		(0)	(15)								(20)
	Strwb											1
	Tomatoes	(0)	(127)	(20)		1	(13)	2	0			2,113
	Waln			(100)		2,398	1					2,326
	Total	(825)	(745)	(141,315)	(120)	12,969	(8,619)	322	(16)	(647)	(315)	(361,926)

SI Table 78. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 1											
		LIQ 2014									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2014	Alfalfa		983	(0)	(9)	(335)	13	(496)	(1,756)	129	478
	Almonds	(128)		(15)	(6)	(396)	(373)	(3,743)	(323)	(42)	136
	Apples	0	27		(0)		0	(307)	(3)	0	19
	Berries	1	11				0	11	0		3
	Carrots	6	84		(0)		13	(13)	(3)	14	92
	Cherries	(0)	77	(0)	(104)	(49)		(1,884)	(13)	0	42
	Citrus	3	514	1	(49)	3	310		(4)	0	149
	Corn	235	204		(0)	317	6	8		623	1,231
	Cotton	(63)	35			(80)	(0)	(31)	(745)		679
	Fallow	(294)	(593)	(159)	(197)	(2,493)	(61)	(3,114)	(1,825)	(713)	
	Garlic Onion	8	18	0		(80)	0	(3)	(45)	6	270
	Grains	1,426	655	0	(0)	394	13	(1)	(3,311)	338	3,721
	Grapes	(31)	74	(2)	(59)	(178)	(59)	(2,712)	(232)	(14)	87
	Grasses	12	0			(0)	0		(8)	1	15
	Lettuce Greens	0	0			(0)			(10)	0	0
	Non-Ag	(512)	(910)	(17)	(173)	(1,139)	(196)	(11,186)	(885)	(169)	-
	Other Crops										
	Other Fruit	(1)	29			(51)		(9)	(57)	1	33
	Other Veg	1	6	(0)		(13)		(67)	(69)	18	106
	Peppers	6	66			24	0		18	3	147
	Pist	(12)	1,060	(1)	(11)	(31)	(6)	(1,000)	(47)	9	160
	Plums		0	(0)				(0)			
	Pome										
	Potato	4	82	0	(1)	(151)	0	(42)	(53)	4	58
	Saff	(1)	0			(1)			(1)		3
	Strwb									0	
	Tomatoes	17	120		(0)	(12)	1	(2)	(144)	16	832
	Waln	(2)	2	(0)		(1)	(2)	(62)	(2)	(3)	3
	Total	674	2,546	(194)	(611)	(4,273)	(342)	(24,655)	(9,521)	222	8,264

SI Table 79. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 2

		LIQ 2014								
		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
CropScape 2014	Alfalfa	(28)	(1,902)	1,362		(18)			14	(1)
	Almonds	(64)	(547)	(452)		(75)			(40)	(16)
	Apples			174					0	
	Berries		4	1,097						
	Carrots	58	(32)	86		8			25	10
	Cherries	(1)	(11)	336		(8)			3	(0)
	Citrus	1	0	4,322		3			77	
	Corn	115	317	139		87			54	44
	Cotton	(2)	(246)	145		(24)			(7)	(53)
	Fallow	(261)	(3,890)	(956)		(777)			(292)	(102)
	Garlic Onion		(120)	1		(4)			1	0
	Grains	290		379		113			46	14
	Grapes	(11)	(77)			(36)			(32)	(2)
	Grasses		(24)	4					0	2
	Lettuce Greens		(0)						0	
	Non-Ag	(183)	(2,140)	(1,138)		(66)			(182)	(25)
	Other Crops									
	Other Fruit	(6)	(8)	16		(1)				(0)
	Other Veg	(0)	(15)	42					5	
	Peppers	3	9	38		9			31	
	Pist	(6)	(142)	117		(4)			(0)	(1)
	Plums			0						
	Pome									
	Potato	47	(118)	33		6			1	1
	Saff	(0)	(1)	0		(0)				
	Strwb		(0)							
	Tomatoes	96	(30)	77		11			138	0
	Waln		(3)	(1)		(0)			(0)	
	Total	48	(8,974)	5,819		(777)			(158)	(127)

SI Table 80. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2014 with LIQ 2014 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 3											
	LIQ 2014										
CropScape 2014		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
	Alfalfa	(91)	37	0		(132)	26		(103)	2	(1,829)
	Almonds	(17)	(2,847)	(0)		(49)	(1)		(26)	(33)	(9,056)
	Apples	(3)	12								(81)
	Berries		18				0			0	1,146
	Carrots	(48)	2	0		66	3		2		371
	Cherries	(13)	6	11		(20)	0	(0)	(2)	0	(1,628)
	Citrus	(3)	717	4		7	1		1	8	6,066
	Corn	(17)	61			86	2		80	1	3,593
	Cotton	(171)	(3)			(51)			(17)		(635)
	Fallow	(26)	(3,592)	(4)		(445)	(2)	(2)	(260)	(1)	(20,060)
	Garlic Onion	(1)	2			(21)	0		(5)		29
	Grains	(24)	278			233	368		6		4,938
	Grapes	(388)	(50)	(0)		(101)	(0)	(0)	(28)	0	(3,853)
	Grasses	(8)	0			0			0		(6)
	Lettuce Greens	(0)				(0)			(0)		(10)
	Non-Ag	(217)	(5,091)	(1)		(1,297)	(7)	(4)	(143)	(7)	(25,689)
	Other Crops										
	Other Fruit	(312)	0			(15)	1		(8)		(387)
	Other Veg	(7)	0			(4)			(9)		(4)
	Peppers					1			1		356
	Pist	(2)		0		(14)	2		(6)	5	69
	Plums		(0)								(0)
	Pome										
	Potato	(10)	1	0			0	(0)	(1)		(141)
	Saff	(0)	(1)								(3)
	Strwb										0
	Tomatoes	(115)	4			16	1	(0)			1,025
	Waln		(47)			(0)					(118)
	Total	(1,471)	(10,493)	10		(1,742)	398	(7)	(517)	(24)	(45,905)

SI Table 81. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2014 compared with LIQ 2014 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 1

CropScape 2016	LIQ 2016									
	Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
Alfalfa	-	(11.65)	(0.00)	(0.54)	(8.90)	(2.62)	(6.09)	0.12	(0.36)	0.46
Almonds	3.83	-	0.99	(2.03)	(1.73)	(30.55)	(49.60)	1.95	0.66	92.02
Apples	-	(0.00)	-	-	-	-	(0.01)	-	-	-
Berries	-	0.01	-	-	-	0.01	0.01	-	-	-
Carrots	1.04	0.07	-	(0.07)	-	(0.15)	0.02	0.37	0.01	5.20
Cherries	0.04	0.44	-	(0.05)	0.00	-	2.81	0.00	-	2.48
Citrus	0.11	6.49	0.02	(2.45)	(0.03)	(12.22)	-	0.29	0.01	4.68
Corn	(0.00)	(0.13)	-	(0.05)	(1.58)	(0.02)	(0.02)	-	(0.05)	0.01
Cotton	0.32	(0.52)	0.01	-	(0.86)	(0.60)	(0.22)	3.03	-	0.74
Fallow	(1.28)	(39.61)	(0.13)	(2.13)	(22.30)	(2.79)	(27.79)	(2.60)	(1.26)	-
Garlic Onion	1.01	0.08	-	-	0.08	(0.04)	0.00	0.54	0.01	1.57
Grains	(1.06)	(5.37)	-	(0.85)	(21.07)	(1.35)	(1.67)	(10.69)	(0.28)	1.69
Grapes	2.12	27.48	0.15	(0.99)	4.24	3.49	69.25	3.44	1.71	38.02
Grasses	(0.00)	(0.32)	-	(0.02)	(7.04)	(0.03)	(0.17)	(0.04)	(0.01)	0.45
Lettuce Greens	0.01	0.03	-	-	(0.01)	(0.01)	(0.01)	0.02	0.08	1.51
Non-Ag	(1.35)	(39.58)	(0.01)	(6.05)	(6.05)	(6.04)	(92.58)	(1.26)	(0.89)	-
Other Crops	(0.00)	(0.18)	-	(0.03)	(2.03)	(0.06)	(0.36)	(0.00)	(0.00)	0.20
Other Fruit	0.51	0.36	-	(0.05)	0.07	(0.41)	2.25	4.99	0.36	0.30
Other Veg	0.35	0.04	0.00	(0.05)	0.02	-	0.00	0.81	1.28	0.16
Peppers	0.03	0.17	-	(0.01)	0.06	(0.01)	0.32	0.70	0.30	1.54
Pist	0.71	7.39	0.23	(0.77)	(1.11)	(2.20)	(7.96)	0.54	0.36	23.37
Plums	0.01	0.09	-	-	-	(0.02)	0.01	-	-	-
Pome	0.06	0.86	-	-	(0.00)	(0.44)	(0.00)	0.03	0.11	0.10
Potato	0.10	(0.00)	0.00	(0.03)	(14.07)	(0.02)	(0.04)	0.88	0.02	10.80
Saff	(0.02)	(0.04)	-	-	(0.38)	(0.00)	(0.00)	(0.01)	(0.00)	0.05
Strwb										
Tomatoes	0.43	(0.97)	0.04	(0.02)	(3.35)	(0.56)	(0.70)	2.33	0.29	0.50
Waln	0.04	(1.29)	0.01	-	(0.12)	(0.29)	(0.60)	0.06	0.02	0.31
Total	6.99	(56.12)	1.31	(16.19)	(86.16)	(56.93)	(113.14)	5.51	2.38	186.15

SI Table 82. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). Revenue is nortmalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 2										
	LIQ 2016									
CropScape 2016		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	(2.95)	0.61	(98.16)		(0.80)		0.01	(2.16)	(0.77)
	Almonds	(1.37)	5.68	(252.41)		(0.47)		2.22	(2.13)	(0.19)
	Apples	-	-	(0.03)		(0.00)		-	-	-
	Berries	-	-	0.01		-		-	-	-
	Carrots	(0.00)	0.76	(2.04)		0.07		0.28	(0.01)	-
	Cherries	-	0.41	(0.41)		-		0.02	0.01	-
	Citrus	(0.01)	0.44	(48.94)		0.00		0.51	(0.07)	-
	Corn	(0.52)	0.02	(0.20)		(0.77)		0.00	(0.87)	(0.00)
	Cotton	(0.00)	0.08	(31.67)		(1.06)		0.43	(0.85)	(1.11)
	Fallow	(7.26)	(3.04)	(77.51)		(13.50)		(0.85)	(3.29)	(0.48)
	Garlic Onion	-	2.03	(0.22)		0.16		0.94	(0.00)	0.00
	Grains	(6.75)	-	(9.27)		(6.06)		(0.15)	(0.51)	(0.34)
	Grapes	0.90	3.43	-		0.82		10.42	4.68	0.23
	Grasses	(0.52)	0.06	(9.73)		(1.60)		(0.01)	(0.07)	(0.02)
	Lettuce Greens	(0.01)	0.13	(0.03)		-		0.04	-	-
	Non-Ag	(2.16)	(0.97)	(103.46)		(1.58)		(0.80)	(1.23)	(0.51)
	Other Crops	(0.48)	0.03	(5.03)		(3.28)		-	(0.04)	(0.02)
	Other Fruit	0.01	0.06	(4.02)		0.06		0.74	-	0.01
	Other Veg	-	0.07	(0.77)		0.13		1.12	(0.01)	-
	Peppers	0.03	0.24	(4.21)		0.05		0.42	1.17	-
	Pist	(0.27)	2.37	(21.12)		(0.26)		0.69	(1.25)	(0.01)
	Plums	-	0.00	(1.18)		-		-	0.00	-
	Pome	(0.00)	0.02	(12.02)		(0.00)		0.09	(0.29)	(0.00)
	Potato	(1.02)	1.22	(0.07)		(1.63)		0.46	(0.01)	-
	Saff	(0.13)	(0.00)	(0.15)		(0.05)		-	-	(0.01)
	Strwb									
	Tomatoes	(1.17)	0.20	(10.79)		(1.36)		0.47	(7.87)	(0.30)
	Waln	(0.03)	0.03	(7.89)		(0.10)		0.02	(0.03)	(0.02)
	Total	(23.72)	13.87	(701.33)		(31.22)		17.07	(14.83)	(3.52)

SI Table 83. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). Revenue is nortmalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy Revenue Discrepancy (in Million USD) Part 3

		LIQ 2016									
		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
CropScape 2016	Alfalfa	(0.52)	(0.69)	(0.02)	(0.06)	(0.76)	0.07	-	(0.56)	(0.02)	(136.35)
	Almonds	(0.21)	(18.08)	(0.47)	(0.85)	0.01	0.26	(0.03)	0.34	1.03	(251.12)
	Apples	-	-	-	(0.09)	-	-	-	-	-	(0.14)
	Berries	-	-	-	-	-	-	-	-	-	0.04
	Carrots	(0.13)	0.01	-	-	3.99	0.04	-	0.47	-	9.93
	Cherries	-	8.30	-	0.14	-	-	-	-	0.00	14.19
	Citrus	(0.40)	2.33	(0.02)	0.02	0.10	-	-	0.01	0.02	(49.10)
	Corn	(0.72)	(0.01)	-	-	(0.04)	0.00	-	(0.10)	-	(5.05)
	Cotton	(0.39)	(0.53)	(0.00)	(0.20)	(0.57)	0.01	-	(0.07)	-	(34.04)
	Fallow	(1.70)	(111.68)	(0.12)	(1.44)	(4.97)	(0.24)	(0.08)	(1.47)	(0.34)	(327.86)
	Garlic Onion	(0.02)	0.02	-	0.00	0.53	0.19	-	0.20	-	7.08
	Grains	(0.62)	(4.84)	(0.04)	(0.14)	(3.42)	0.00	(0.02)	(0.16)	(0.00)	(72.98)
	Grapes	0.34	13.87	0.40	0.90	0.69	0.03	-	0.89	0.46	186.98
	Grasses	(0.21)	(0.01)	-	-	(0.48)	0.00	-	(0.02)	-	(19.83)
	Lettuce Greens	-	0.01	-	0.00	0.02	0.01	-	0.02	-	1.82
	Non-Ag	(1.80)	(43.43)	(0.16)	(5.20)	(2.69)	(0.04)	(0.03)	(1.38)	(0.12)	(319.37)
	Other Crops	(0.24)	(0.18)	-	(0.00)	(1.36)	0.00	-	(0.01)	(0.00)	(13.07)
	Other Fruit	(1.37)	0.22	(0.00)	-	0.24	0.38	-	0.27	0.01	4.99
	Other Veg	(0.00)	0.00	-	-	0.72	0.00	-	0.01	-	3.90
	Peppers	-	0.00	-	-	0.11	-	-	0.55	-	1.45
	Pist	(0.17)	-	(0.01)	(0.35)	0.10	0.17	-	0.13	1.18	1.78
	Plums	-	0.01	-	-	-	-	-	-	-	(1.07)
	Pome	-	0.52	-	-	-	-	-	0.01	0.04	(10.93)
	Potato	(0.04)	(0.00)	-	(0.00)	-	0.68	-	0.03	-	(2.74)
	Saff	(0.00)	(0.01)	-	-	(0.12)	-	-	(0.01)	-	(0.88)
	Strwb										
	Tomatoes	(10.84)	(0.09)	-	(0.07)	(1.07)	0.24	-	-	-	(34.65)
	Waln	(0.02)	(3.89)	(0.00)	(0.04)	-	-	-	(0.00)	-	(13.84)
	Total	(19.05)	(158.16)	(0.44)	(7.41)	(8.96)	1.83	(0.16)	(0.85)	2.27	(1,060.84)

SI Table 84. Table of the resulting revenue discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). Revenue is nortmalized by 1 million USD. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User’s Accuracy CWR Discrepancy (in acre-feet)
Part 1

		LIQ 2016									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2016	Alfalfa		2,660	2	71	3,154	119	(304)	14,789	733	2,038
	Almonds	(1,084)		(79)	240	827	(123)	(17,901)	780	215	59,450
	Apples		0					(2)			
	Berries		0				0	(0)			
	Carrots	(389)	(31)		3		(33)	(85)	(18)	(2)	649
	Cherries	(3)	0		13	1		(338)	0		412
	Citrus	(0)	2,140	3	448	110	1,208		103	4	2,390
	Corn	(128)	(46)		3	111	(2)	(7)		(25)	18
	Cotton	(737)	(158)	(28)		129	(36)	(75)	2,035		890
	Fallow	(5,990)	(25,301)	(328)	-	(2,597)	(476)	(14,682)	(4,547)	(1,499)	
	Garlic Onion	(253)	(17)			216	(5)	(7)	33	(0)	342
	Grains	(6,797)	(2,099)		38	756	(133)	(639)	(4,201)	(160)	5,087
	Grapes	(96)	342	(1)	341	754	137	(5,423)	290	100	5,780
	Grasses	(45)	(37)		2	1,296	(1)	(39)	334	6	1,570
	Lettuce Greens	(3)	(12)			5	(1)	(22)	1	(5)	359
	Non-Ag	(6,355)	(25,285)	(32)	-	(704)	(1,029)	(48,908)	(2,213)	(1,056)	-
	Other Crops	(19)	0		3	498	(0)	(61)	98	1	711
	Other Fruit	(19)	49		9	129	35	(457)	1,194	71	109
	Other Veg	(89)	(10)	(0)	4	84		(1)	47	(17)	35
	Peppers	(2)	(3)		2	14	(1)	(57)	59	15	266
	Pist	(110)	3,039	4	105	794	51	(2,831)	214	121	14,058
	Plums	(1)	0				(0)	(5)			
	Pome	(32)	(921)			0	(71)	(8)	(2)	(20)	20
	Potato	(54)	(12)	(1)	2	3,645	(2)	(21)	163	1	5,230
	Saff	(126)	(13)			22	(0)	(1)	0	(1)	190
	Strwb										
	Tomatoes	(465)	(411)	(36)	1	606	(34)	(273)	824	23	396
	Waln	(21)	109	(1)		42	2	(111)	61	31	403
	Total	(22,818)	(46,015)	(497)	1,286	9,889	(395)	(92,257)	10,047	(1,464)	100,402

SI Table 85. Table of the resulting CWR discrepancy reflecting user’s accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet) Part 2										
		LIQ 2016								
CropScape 2016		Garlic Onion	Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	121	3,765	3,341		285		436	20	154
	Almonds	(149)	2,422	(2,317)		259		291	(285)	35
	Apples			0		0				
	Berries			1						
	Carrots	(30)	(10)	(348)		(21)		(50)	(16)	
	Cherries		41	(24)				1	(1)	
	Citrus	4	166	3,387		8		111	9	
	Corn	(119)	21	(16)		6		(8)	(202)	(0)
	Cotton	(1)	54	(1,779)		102		(199)	(168)	(16)
	Fallow	(2,768)	(8,367)	(11,714)		(2,848)		(2,583)	(1,210)	(115)
	Garlic Onion		184	(22)		40		(57)	(6)	(0)
	Grains	(1,678)		(830)		(191)		(463)	(128)	(34)
	Grapes	(25)	330			99		349	(253)	19
	Grasses	(60)	276	(310)		235		1	(10)	1
	Lettuce Greens	(10)	10	(4)				(5)		
	Non-Ag	(823)	(2,672)	(15,636)		(333)		(2,412)	(450)	(122)
	Other Crops	(30)	155	(45)		727			(3)	2
	Other Fruit	2	16	216		42		96		12
	Other Veg		6	(77)		31		(74)	(9)	
	Peppers	(3)	24	(340)		7		7	(204)	
	Pist	(11)	988	263		265		122	(109)	4
	Plums		0	(19)					(1)	
	Pome	(1)	(0)	(1,621)		(0)		(21)	(193)	(1)
	Potato	(291)	287	(4)		348		(44)	(2)	
	Saff	(30)	12	(12)		(0)				(1)
	Strwb									
	Tomatoes	(245)	83	(606)		173		(94)	(1,692)	(2)
	Waln	(1)	29	3		32		10	(2)	3
	Total	(6,149)	(2,178)	(28,514)		(734)		(4,585)	(4,915)	(61)

SI Table 86. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy CWR Discrepancy (in acre-feet)
Part 3

		LIQ 2016									
		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
CropScape 2016	Alfalfa	37	67	2	31	351	378		550	10	32,809
	Almonds	5	(7,390)	(5)	971	52	93	1	160	(79)	36,387
	Apples				40						39
	Berries										1
	Carrots	(30)	(6)			(989)	(2)		(75)		(1,482)
	Cherries		(266)		22					(0)	(142)
	Citrus	64	663	10	45	54			4	3	10,934
	Corn	(56)	(4)			(7)	0		(28)		(487)
	Cotton	(18)	(179)	(0)	44	(21)	6		0		(155)
	Fallow	(293)	(67,824)	(35)	(250)	(2,432)	(879)	(2)	(1,143)	(444)	(158,327)
	Garlic Onion	(2)	(7)		0	(20)	11		(2)		427
	Grains	(57)	(1,941)	(6)	5	(728)	(12)	(0)	(52)	(1)	(14,265)
	Grapes	29	(184)	4	128	42	3		54	(0)	2,817
	Grasses	(3)	(3)			43	3		5		3,265
	Lettuce Greens		(8)		0	(4)	0		(1)		302
	Non-Ag	(310)	(26,375)	(49)	(903)	(1,315)	(136)	(1)	(1,071)	(157)	(138,348)
	Other Crops	4	(15)		2	300	9		6	(0)	2,343
	Other Fruit	233	16	0		65	87		60	1	1,968
	Other Veg	(0)	(1)			(34)	0		(0)		(103)
	Peppers		(0)			5			28		(182)
	Pist	10		0	1,051	106	60		59	63	18,316
	Plums		(1)								(26)
	Pome		(1,493)						(2)	(19)	(4,386)
	Potato	(2)	(3)		1		110		1		9,353
	Saff	(0)	(4)			(19)			(2)		15
	Strwb										
	Tomatoes	(505)	(37)		21	(28)	68				(2,233)
	Waln	0	(267)	0	23				5		349
	Total	(894)	(105,261)	(80)	1,232	(4,577)	(199)	(2)	(1,446)	(625)	(200,812)

SI Table 87. Table of the resulting CWR discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The CWR is in units of acre-feet. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 1

		LIQ 2016									
		Alfalfa	Almonds	Apples	Berries	Carrots	Cherries	Citrus	Corn	Cotton	Fallow
CropScape 2016	Alfalfa		670	(0)	(13)	(211)	8	(307)	(3,979)	39	154
	Almonds	(220)		(68)	(73)	(169)	(385)	(8,679)	(436)	(28)	1,448
	Apples		0					(1)			
	Berries		1				1	0			
	Carrots	25	7		(2)		4	(5)	(21)	1	283
	Cherries	(0)	6		(3)	(0)		(113)	(0)		33
	Citrus	5	1,136	1	(38)	6	494		(11)	1	381
	Corn	33	28		(0)	88	1	1		39	11
	Cotton	(35)	22	(3)		(35)	(2)	(16)	(2,496)		84
	Fallow	(427)	(623)	(31)	(70)	(1,212)	(38)	(2,266)	(2,824)	(142)	
	Garlic Onion	7	5			(28)	1	(1)	(37)	0	60
	Grains	875	729		(10)	419	31	(0)	(7,263)	98	2,475
	Grapes	(18)	81	(1)	(93)	(125)	(143)	(2,809)	(138)	(7)	220
	Grasses	5	32		(0)	(6)	0	(4)	(147)	3	294
	Lettuce Greens	0	3			(1)	0	(2)	(2)	3	78
	Non-Ag	(453)	(623)	(3)	(199)	(329)	(81)	(7,548)	(1,374)	(100)	-
	Other Crops										
	Other Fruit	(4)	10		(2)	(12)	(1)	(422)	(375)	1	6
	Other Veg	1	2	(0)	(2)	(16)		(0)	(61)	19	5
	Peppers	1	15		0	5	2	17	7	19	103
	Pist	(11)	1,190	(5)	(24)	(89)	(4)	(1,435)	(81)	2	923
	Plums	(0)	1				(0)	(2)			
	Pome										
	Potato	4	5	0	(1)	(164)	0	(2)	(121)	2	1,039
	Saff	(8)	0			(16)	(0)	(0)	(16)	(0)	16
	Strwb										
	Tomatoes	42	192	5	(0)	(7)	8	(24)	(584)	83	87
	Waln	(4)	26	(2)		(7)	(2)	(57)	(29)	(2)	15
	Total	(183)	2,914	(106)	(528)	(1,909)	(107)	(23,676)	(19,988)	31	7,717

SI Table 88. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 1 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 2									
		LIQ 2016							
CropScape 2016		Grains	Grapes	Grasses	Lettuce Greens	Non-Ag	Other Crops	Other Fruit	Other Veg
	Alfalfa	(507)	832		(11)			16	(1)
	Almonds	(770)	(744)		(54)			(56)	(10)
	Apples		0		(0)				
	Berries		1						
	Carrots	(15)	61		5			2	
	Cherries	(9)	17					0	
	Citrus	0	1,985		1			12	
	Corn	16	8		65			66	0
	Cotton	(28)	122		(35)			(3)	(16)
	Fallow	(4,466)	(450)		(698)			(71)	(16)
	Garlic Onion	(68)	4		(2)			0	0
	Grains		238		236			22	14
	Grapes	(88)			(16)			(43)	(4)
	Grasses	(37)	169		23			2	0
	Lettuce Greens	(5)	1						
	Non-Ag	(1,426)	(600)		(82)			(26)	(17)
	Other Crops								
	Other Fruit	(3)	37		(3)				(1)
	Other Veg	(3)	12		(6)			0	
	Peppers	7	809		4			174	
	Pist	(196)	136		(23)			(0)	(0)
	Plums	(0)	0					(0)	
	Pome								
	Potato	(66)	1		28			0	
	Saff	(21)	0		(2)				(0)
	Strwb								
	Tomatoes	(16)	204		26			257	8
	Waln	(8)	(1)		(5)			(0)	(1)
	Total	(7,710)	2,843		(549)			352	(43)

SI Table 89. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 2 of 3.

Crosstab of CropScape 2016 with LIQ 2016 Reflecting User's Accuracy GHG Emission Discrepancy (in $MgCO_2e$) Part 3

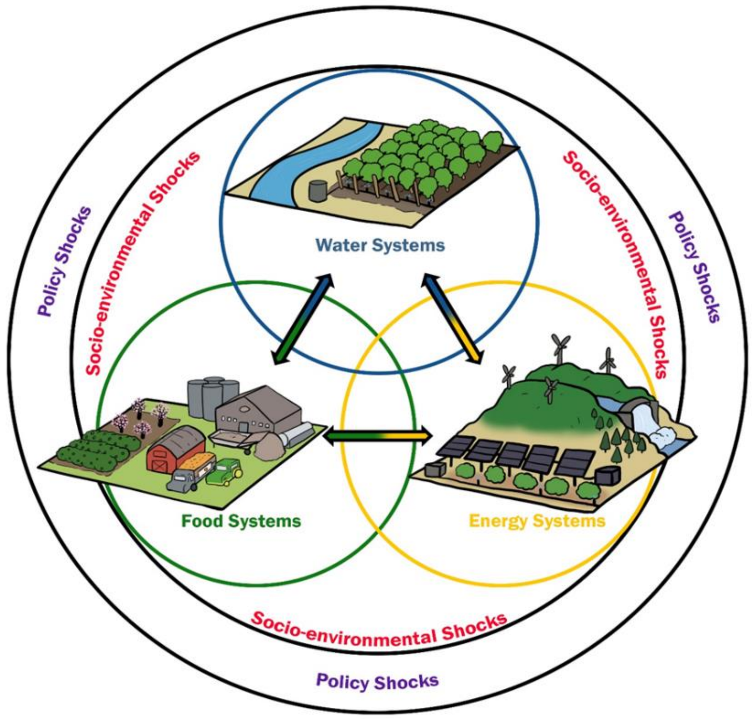
		LIQ 2016									
		Peppers	Pist	Plums	Pome	Potato	Saff	Strwb	Tomatoes	Waln	Total
CropScape 2016	Alfalfa	(27)	10	0		(29)	26		(55)	3	(3,402)
	Almonds	(18)	(2,912)	(4)		(22)	(4)	(0)	(67)	(21)	(13,378)
	Apples										(0)
	Berries										2
	Carrots	(11)	1			47	1		1		384
	Cherries		14							0	(56)
	Citrus	(21)	420	5		6			0	2	4,390
	Corn	(7)	1			6	2		26		419
	Cotton	(24)	(3)	0		(49)	1		(20)		(2,536)
	Fallow	(114)	(4,410)	(1)		(478)	(76)	(1)	(257)	(16)	(18,965)
	Garlic Onion	(2)	1			(8)	5		(4)		(67)
	Grains	(17)	402	2		185	35	0	12	0	(1,291)
	Grapes	(65)	(89)	(0)		(13)	(0)		(17)	0	(3,386)
	Grasses	(8)	1			6	1		0		342
	Lettuce Greens		1			(0)	0		(0)		75
	Non-Ag	(121)	(1,715)	(2)		(258)	(12)	(0)	(240)	(6)	(15,298)
	Other Crops										
	Other Fruit	(203)	0	0		(9)	4		(9)	0	(986)
	Other Veg	(0)	0			(20)	0		(0)		(68)
	Peppers		0			6			25		1,196
	Pist	(14)		0		(19)	3		(11)	38	371
	Plums		(0)								(2)
	Pome										
	Potato	(2)	1				50		(1)		791
	Saff	(0)	(0)			(9)			(1)		(59)
	Strwb										
	Tomatoes	(493)	7			23	36				(127)
	Waln	(1)	(126)	(0)					(2)		(208)
	Total	(1,148)	(8,397)	(0)		(635)	73	(1)	(619)	0	(51,858)

SI Table 90. Table of the resulting GHG emission discrepancy reflecting user's accuracy of CropScape 2016 compared with LIQ 2016 (assumed ground truth for the statewide dataset). The GHG emission is in units of $MgCO_2e$. Values in parenthesis are negative. Note: this table was broken up into three parts to facilitate inclusion of this table and readability. This table is Part 3 of 3.

APPENDIX G. INFEWS- WHAT'S ALL THE FUSS?

1. Introduction

Food, energy, and water are critical resources for human survival worldwide. These resources underpin economic vitality, social well-being, and ecosystem health and are increasingly stressed by climate change (Vörösmarty et al., 2018). Therefore, it is imperative to find long-term, resilient, and sustainable solutions to feed 9 billion people by 2050 (Alexandratos & Bruinsma, 2012), which will require about a 60% increase in agricultural production and increase water demands (Alexandratos & Bruinsma, 2012; Rosenberg, 1992). Climate change impacts on water availability will have repercussions on food, energy, and water security globally. Agriculture is the largest user of freshwater resources, withdrawing about 70% of water (FAO, 2017a), making it highly vulnerable to climate change while also being a large contributor to greenhouse gas (GHG) emissions globally (IPCC, 2001).

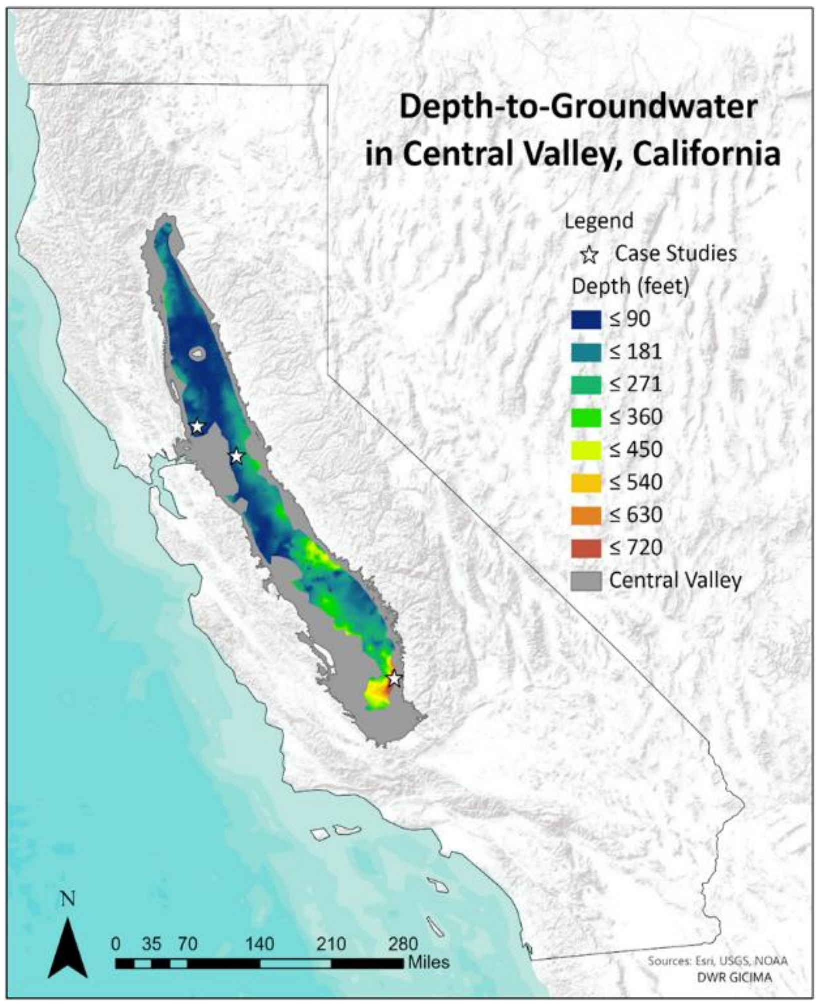


SI Figure 52. Relationships between food, energy, and water components and system impacts to California-specific food systems due to policy changes aiming to address a changing climate.

California is uniquely positioned to play a central role in addressing global food, energy, and water security issues as an epicenter of climate change risk and leader in food production and innovation. The state can play a prominent role in developing climate-smart agricultural practices. To do this, California needs to develop and implement climate change adaptation strategies that simultaneously advance social equity, protect the environment, and promote human well-being while managing limited natural resources and building resilience to climate change. This is no small feat. A foundational step to developing climate change adaptation strategies that lead to equitable and effective solutions is to address energy and water needs in California's food systems.

Strategies narrowly focused on maximizing food production that fail to address energy and water use needs can increase system risk to policy changes that aim to address a changing climate. A comprehensive understanding of food-energy-water systems (FEWS) for California (SI Figure 52, Box1) can help develop solutions targeted to specific food system inefficiencies and prevent unforeseen outcomes. It is evident that of the three sectors, water in California drives, constrains, and creates competition between energy and food sectors due to the natural variability of precipitation, the financially and energetically costly conveyance of water, and the policy and management decisions that restrict its use. Given that California uses groundwater for roughly 40% of its irrigation applications (Chappelle et al., 2017), it is not surprising that water from overexploited aquifers is embedded in California's agricultural exports. Virtually exporting scarce freshwater resources makes it more critical to quantify embedded water and energy of food systems in water-scarce, drought-prone regions, like California. Monitoring water resources has become more urgent now that the state is addressing groundwater overdraft under the 2014 Sustainable Groundwater Management Act (SGMA), which also has implications for agricultural land use (Hanak et al., 2019). Policies and management strategies add a layer of complexity if not in their impact on sustainability, then in the price paid at the marketplace because of not accounting for the water and energy needs throughout food systems.

To ensure that solutions are durable and effective, an integrated approach is needed that accounts for FEWS relationships. This paper illustrates the importance of a FEWS approach to developing agricultural policies that support food production while enhancing system resilience to climate change. This paper will (i) quantify embedded energy and water for three key food production systems in California and (ii) illustrate how a FEWS approach can lead to better policy and management decisions. This paper also (iii) highlights key barriers to translating a FEWS-nexus understanding of agricultural systems into practical, on-the-ground solutions.



SI Figure 53. California's Central Valley (gray outline) has a north to south gradient of depth to groundwater. The case studies (stars) reviewed in this paper fall within shallow to deep depth to groundwater levels.

2. Methods

2.1 Data and Assumptions

Embedded water (acre-feet; AF) and energy (kilowatt-hour; kWh) are estimated per ton of product produced for each of the California-specific food system examples by consolidating and applying findings and methods from published case studies (SI Table 17). Summarized in SI Table 18, reported normalized yield values allow California agricultural professionals to apply reported estimates to different yield outputs and allow for the cross-comparison across different yield scenarios and food system scales (e.g., acreage). The GHG emissions associated with energy use for each example are calculated and reported as carbon dioxide equivalent (CO_2e), which allows other GHG emissions to be expressed in terms of carbon dioxide based on their global warming potentials.

Table 1. Food System Example Parameters, Equations, and Data Sources

Example 1- Almond Production					
Case Study Area	**Yield**	**Water Use**	**Energy Use**	**Cost of Energy**	**CO_2e**
100-acres	1 ton per acre	4 acre-feet per acre (AF/ac); based on range of 3 AF/ac to 4.33 AF/ac	Energy to pump groundwater from x feet depth= (Weight of water (lbs.)*Lift (ft) *(kWh/(2,655,220 ft-lbs.))); simplified equation from (Peacock, 1996)	Cost of electricity at $0.15 per kWh	7.07 × 10-4 metric tons CO_2/kWh
			50 PSI sprinkler pressure; (Minton et al., 2011)		
			Energy to pressurize sprinklers to x PSI using pump with 70% efficiency=3.3795 4 * X PSI; simplified equation from (Peacock, 1996)		

(Almond Board of California, 2019)	(Almond Board of California, 2019)	(Almond Hullers and Processors Association, 2015; Haviland *et al.*, 2019)	0.586 kWh of total energy are required per kilogram (kg) of almond kernels; Equation: 0.586 kWh * 94,800 kg of almond kernels; (Kendall et al., 2015)	(U.S. Energy Information Administration, 2019);	(U.S. Environmental Protection Agency, 2019)
Example 2- Wine Grape Production: Frost Protection					
Case Study Area	**Yield**	**Water Use**	**Energy Use**	**Cost of Energy**	**CO_2e**
141- acres	6.5 tons per acre	21 acre-feet total; Water supply required to prevent radiation frost using sprinklers of about 55 gallons per minute per acre	50 PSI sprinkler pressure; (Minton et al., 2011) Energy to pressurize sprinklers to x PSI using a pump with 70% efficiency=3.37954 * X PSI; (Peacock, 1996) one machine per 10 acres; 13 gallons per hour (Snyder and Melo-Abreu, 2005);	Cost of electricity at \$0.15 per kWh; (U.S. Energy Information Administration, 2019)	7.07 × 10-4 metric tons CO_2/kWh
(Alston et al., 2018)	(Goodhue et al., 2008)	(Verdegaal, 2009)	Propane wind machine uses on average 13 gallons per hour; (Venner and Blank, 1995)	Cost of propane at \$3 per gallon (U.S. Energy Information Administration, 2021)	(U.S. Environmental Protection Agency, 2019)
Example 3- Food Processing: Tomatoes					
Case Study Area	**Yield**	**Water Use**	**Energy Use**	**Cost of Energy**	**CO_2e**

N/A	170,860 tons	340,781,948 gallons	Electrical energy 4,442,360 kWh	Cost of electricity at $0.15 per kWh	7.07 × 10-4 metric tons CO_2/kWh
	Amon *et al.*, 2017)	Amon *et al.*, 2017)	Amon *et al.*, 2017)	(U.S. Energy Information Administration, 2019);	(U.S. Environmental Protection Agency, 2019)

SI Table 91. Data sources of parameters and equations used to obtain water-energy use and CO2e emissions for each California-specific food system example.

2.2 Example Selection

The most prominent food systems in California—(i) almond production, (ii) wine grape production, and (iii) food processing—were selected to quantify embedded energy and water and illustrate how a FEWS approach could lead to better policy and management decisions. Almond production in California is the 2nd leading commodity generating $6.1 billion in cash receipts (CDFA, 2019). This study focuses on almond production in Kern County as it dedicates the highest acreage (~21,000 acres) to almond production in the Central Valley (CDFA, 2020). This study makes use of Kendall et al. (2015) to deduce energy-water use and CO2e emissions at the hulling and shelling stage of almond production. The next California-heavy production system analyzed in this study is frost protection in wine grape production, which garnered a total retail value of $43.6 billion in 2019 California wine shipments (Wine Institute, 2020). In addition to accounting for on-farm water and energy use, this study considers a tomato processing facility to represent the post-farm food stage. Few studies have detailed quantification of the embedded water and energy use at food processing facilities. This study makes use of Amon et al. (2017) to address the implications of energy and water use at food processing facilities.

The food system examples are chosen across regions that encompass varying depth to groundwater levels (SI Figure 53), since groundwater in the state plays a critical role in meeting irrigation demands, especially during drought, it is important to demonstrate how varying groundwater levels impact water and energy use. The specific locations are also regions where these food systems are most prominent in the Central Valley. Food system size and regional characteristics reflect regional climate conditions and average food system sizes. The next section provides specifics on the region and the assumptions made to derive energy and water use for each example.

2.3 Location & Assumptions

Almond Production

Consider a mature six-year-old almond orchard of 100 acres located in Kern County that yields about 100 tons of almonds in a season. The selected acreage for this example is based on the average size of almond orchards reported by the Almond Board of California (2019) and the yield range used for this analysis of ~1 ton of almonds per acre is the average of the expected yield range of 0.7-1.5 tons of almonds per acre (Doll et al., 2010; Haviland et al., 2019). The required water for irrigation of an almond orchard ranges from three acre-feet per acre (AF/ac) (Almond Hullers and Processors Association, 2015) to 4.33 AF/ac (Haviland *et al.*, 2019). Water use for almond production in this example is assumed to be four AF/ac, which results in a total of ~400 AF of seasonal water requirement for this 100-acre orchard. On-site energy requirements are calculated for groundwater pumping from 700 feet of depth and pressurizing the micro-sprinkler system at 25 pounds per square inch (PSI) with a pump efficiency of 70% (Peacock, 1996).

Wine Grape Production

Many of California's wine grape regions are prone to frost damage during cold winter nights. Frost protection methods, like sprinklers and wind machines, have different water and energy implications. Consider approximately 15-hours of overnight frost protection in January at an average-sized vineyard of 141-acres in Lodi (Alston et al., 2018). This vineyard yields a total of 916.5 tons of grapes (Goodhue et al., 2008). For this case study, the total amount of water required to provide frost protection for 15-hours via overhead sprinklers pressurized at 50 PSI is 21 acre-feet. The amount of water required is based on 55 gallons per minute (gpm) per acre for overhead sprinkler water application (based on the maximum of the range of 50-55 gpm per acre; Minton *et al.*, 2011). It is assumed that electricity supplies the energy for the sprinklers at $0.15/kWh, and propane supplies the wind machines' energy at $3/gallon. There are two stages of the frost protection process that require energy—1) the electricity to pump water from 600 feet of groundwater depth and 2) to pressurize the sprinkler system at 50 pounds-per-square-inch (PSI) (Minton et al., 2011). For this scenario, assume one machine requiring 13 gallons per hour is needed per 10 acres to protect 141-acres of grapes from frost damage (Snyder & Melo-abreu, 2005) requiring a total of ~2,730 gallons of propane for 15-hours (Venner & Blank, 1995). This analysis does not consider the cost of installing and maintaining sprinkler systems or wind machines.

Food Processing: Tomatoes

An assessment of energy-water use at a tomato processing facility conducted by Amon *et al.* (2017) was used to inform this example and calculate overall system CO_2e emissions. The study by Amon *et al.* (2017) provides data on energy-water use for all stages at a tomato processing facility in Dixon over an around-the-clock processing season (July-September). This tomato processing plant yields about 170,860 tons of tomato product per season. In this example, energy and water use and CO_2e emissions per ton of product include significant functions at a tomato processing facility—groundwater pumping, unloading, and sorting, steam generation and utilization, cooling, cleaning, and wastewater treatment**.** Reported results reflect the total water-energy use and CO_2e emissions encompassing all components of the tomato processing facility.

3. Results & Discussion

This section reviews the results of the embedded energy-water and CO_2e emissions analysis for each California-specific food systems reported in SI Table 18. This section uses the examples to discusses how a taking a FEWS approach could lead to resilient climate change adaption strategies and prevent unwarranted outcomes.

Table 2. Results of Embedded Water, Energy, and CO_{2e} for California Food System Examples						
Example 1- Almond Production						
Total Acreage	100	**Total Water Use (AF/ton)**	**Total Energy (kWh/ton)**	**Total Cost of Energy ($USD/ton)**	**CO_2e (Metric Ton/ton)**
Total Yield (tons)	100				
At the Orchard		4	4,339	650	3.1
Hulling & Shelling		–	532	80	0.38
Example 2- Wine Grape Production: Frost Protection					
Total Acreage	141	**Total Water Use (AF/ton)**	**Total Energy (kWh/ton)**	**Total Cost of Energy ($USD/ton)**	**CO_2e (Metric Ton/ton)**
Total Yield (tons)	916.5				
Sprinkler Systems		0.02	24	4	0.02
Wind Machines		0	80	9	0.06
Total		–	3,719	558	2.64
Example 3- Food Processing: Tomatoes					
Total Acreage	N/A	**Total Water Use (AF/ton)**	**Total Energy (kWh/ton)**	**Total Cost of Energy ($USD/ton)**	**CO_2e (Metric Ton/ton)**
Total Yield (tons)	170,860				
Tomato Processing		0.006	26	4	0.02

SI Table 92. The total water, energy, and CO_2e emissions of three California-specific examples normalized by ton of product.

3.1 Almond Production: Field to Processor

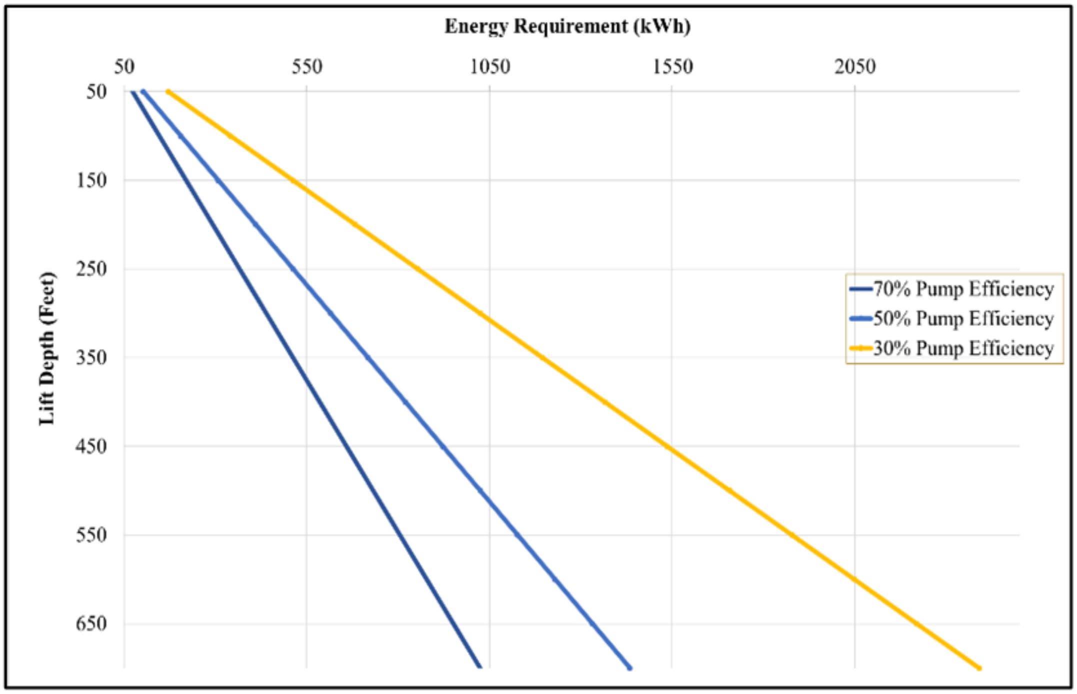
3.1.1 Water and Energy Use

On-Farm– The amount of energy required to pump groundwater to meet seasonal water requirements for almond production results in ~4,096 kWh/ton of almonds at ~$614/ton of almonds. In comparison, the amount of energy required to pressurize the micro-sprinklers is ~243 kWh/ton at ~$36/ton. The total energy required, and costs associated with on-farm almond production are ~4,339 kWh/ton with a cost of ~$650/ton of almonds, respectively. The CO_2e emissions resulting from energy to pump groundwater and pressurize sprinkler systems are ~3.1 metric tons CO_2e/ton of almonds. (US EPA, 2019). Thinking of these CO_2e emissions in the carbon market context, if a metric ton of CO_2 is worth $8 (Woo et al., 2017), then the CO_2e associated price with this food system example would be ~$2,480 per season per 100 acres.

Hulling and Shelling– Calculations for the energy requirements of hulling and shelling for this example aided by Kendall *et al.* (2015) resulted in ~532 kWh/ton of energy at the cost of ~$80/ton of almonds and result in ~0.38 metric tons of CO_2e emissions/ton of almonds (US EPA, 2019). Overall, the hulling and shelling process requires less energy than pumping groundwater and pressurizing the micro-sprinklers for irrigation combined. Something to consider is that the energy and water footprints per ton of almonds differ based on the source of water (i.e., surface water or groundwater), local climate conditions, and water availability. Energy requirements for pumping groundwater vary based on the pump's energy efficiency and the region's depth-to-groundwater characteristics. More energy is required to run less efficient pumps and pump water from deeper aquifers (SI Figure 54), which was the case for this food system in Kern County.

3.1.2 Policy and Management Decisions Affecting Almond Production

California agricultural production is affected by policy and management, especially those related to water and land use. Water scarcity is a major driver in water policy and management in California. The 2014-2016 drought led to more than five million acre-feet (MAF) of groundwater overdraft (Howitt et al., 2015) and in part led to the passing of the 2014 Sustainable Groundwater Management Act, commonly referred to as SGMA. This new groundwater law aims to address groundwater overdraft by 2040 (see Box 2). Although the implications of SGMA remain primarily unknown, governing water agencies under SGMA, known as GSAs, are proposing potential changes in water prices, restrictions in drilling new groundwater wells, and agricultural land-use changes. A recent study projects that a more than 500,000 acre reduction in irrigated land may be needed to address groundwater overdraft by 2040 (Hanak et al., 2019). This potential reduction in agricultural land comes with socio-economic and environmental implications. For example, consider the socio-economic impacts during the 2015 drought on the state: fallowing of about 540,000 irrigated acres in the Central Valley, about 1.84 billion dollars of direct costs of the drought on agriculture, and a loss of about 10,100 direct seasonal jobs (Howitt et al., 2015). During the drought, surface water shortages of about 8.7 MAF were offset by about 6 MAF of groundwater, which allowed some crops (e.g., almonds, pistachios, other orchards) to continue production business-as-usual. Under SGMA, groundwater offsets may not be possible, making the detrimental socio-economic impacts observed during the 2015 drought permanent further impacting already vulnerable disadvantaged communities (DACs; for definition, see Box 2). The complete implications of SGMA remain unknown since it is in its preliminary implementation stages. However, one can begin to put together the magnitude of collateral outcomes resulting from a single law aiming to fix one sector of FEWS if management strategies are developed without considering where water is dedicated throughout the food system.



SI Figure 54. Graph of energy requirements (kWh) to lift one-acre foot of water from various depths (50-650 feet) for pumping efficiencies of 30, 50, and 70%.

3.1.3 Almond Production Climate Change Adaptation Strategies with FEWS Lens

The FEWS approach to identifying which stage of almond production was the most energy-intensive highlights that on-farm energy required to pump groundwater is the most intensive and costly. This FEWS perspective can help target technological investments or funding incentives that may help improve this energy-intensive stage of almond production. For example, at the farm level, a farmer may consider implementing renewable energy, like solar, to offset high costs associated with groundwater pumping. A FEWS approach allows one to pinpoint production stages that take up more energy than others, like pumping having higher energy requirements than pressurizing of sprinkler systems. Trends in reduced energy use in sprinkler systems could be attributed to the transition to energy and water-efficient irrigation systems and irrigation methods, like regulated deficit irrigation. Pumping of groundwater is more energy-intensive than pressurizing of sprinkler systems because it takes more energy and costs more to lift large amounts of heavy water hundreds even thousands of feet in some part of the state (SI Figure 53). Solutions to the high depth to groundwater levels lead back to SGMA’s objective to replenish groundwater levels, which may require land use to be repurposed other, multi-benefit land use (for examples see Box 3). Land use transitions are complicated. Agriculture in California is an essential part of the local, national, and global economy and is the livelihood for many people across the state. A FEWS approach with a detailed breakdown of water, energy, and

GHG emissions tradeoffs is necessary to facilitate decisions that result in practical solutions at the local and watershed levels and account for decision tradeoffs.

3.2 Wine Grape Production: Frost Protection

3.2.1 Energy and Water Use

Water and Energy for Sprinklers– Water use for frost protection results in about 0.02 acre-feet/ton (AF/ton) of wine grapes (based on the required 21 AF for 15-hours of wine grape frost protection). For this wine grape frost protection scenario, lifting the total required 21 AF of water 600 feet with a pump that runs at 70% efficiency requires about 20 kWh/ton of grapes and costs about $3/ton of grapes. Additionally, energy requirements to pressurize the sprinkler system to 50 PSI requires ~4 kWh/ton of grapes and costs ~$0.60/ton of grapes. In total, using sprinklers for 15-hours of frost protection for wine grapes requires ~24 kWh/ton of energy and costs ~$4/ton of grapes, which is not high compared to the price per ton of wine (Penn, 2021; ~$2.5 to $4K per ton of wine grapes).

Energy for Wind Machines– Most wind machines are driven by propane or diesel, for this example we assume the 14 wind machines are fueled by propane to provide frost protection. The total energy use for wine grape frost protection ~80 kWh/ton of grapes based on the conversion of gallon of propane to 27 kWh of energy (Propane 101, 2019), and would cost ~$9/ton of grapes for 15-hours of frost protection. Wind machines do not utilize water, but wind machines require higher energy use and costs than sprinkler methods.

GHG emissions– For this example, the sprinkler system results in less CO_2e emissions/ton of grapes (~0.02 metric tons) compared to wind machines (~0.06 metric tons CO_2e /ton of grapes) (US EPA 2019). Within a carbon market context, sprinkler systems result in $150 worth of CO_2e emissions (total of ~18 metric tons of CO_2e) and about $440 of CO_2e emissions for wind machines (total of ~60 metric tons of CO_2e) for 15 hours of frost protection.

3.2.2 Policy and Management Decisions Affecting Wine Grape Production

California has an objective to achieve carbon neutrality by 2045 (Mahone et al., 2020), which requires an estimated 125 million tons of carbon emissions to be removed from the atmosphere annually—equivalent to removing 26 million cars from the road annually (Baker *et al.*, 2020). This intense carbon removal is possible with policies that address pollution sources from transportation, industrial sectors, and agriculture. Having a FEWS perspective to meeting carbon neutrality in the next 20 years can effectively account for GHG emission inventory across the life cycle of food production and target solutions within food systems that are hot spots for emissions. For example, in a life cycle assessment of wine grape production conducted by Steenwerth *et al.* (2015), authors identified pest and weed management, pesticide manufacturing, on-farm truck use and associated fuel, and field nitrous oxide emissions from N-fixing legumes in cover crop mixes to be the highest sources of energy use and GHG emissions. Agriculturally universal practices applicable to grape production and other crop-type systems result in high GHG emissions and energy, indicating the opportunity to develop technology or viticulture practices that address energy use emission hotspots. Proposed management solutions like implementing cover crops applicable across various crop types and regions and therefore, should be done with an account of potential tradeoffs whether in yield, crop quality, GHG emissions, and water-energy use. An example of a GHG emission strategy best approached through a

FEWS lens that is tailored to a specific crop and region is applying N-fixing legumes as cover crops in grape production. While applying N-fixing legume to other crops or grapes in regions outside of California may be an ideal approach, a study found that the implementation of annual cover crops with N-fixing legumes in wine grapes in Napa and Lodi resulted in ~19% higher global warming potential from higher nitrous oxide emissions (Steenwerth et al., 2015). Furthermore, N-fixing legumes may not be ideal for low-yielding California coastal wine grapes but may be a more beneficial approach for high-yielding table grapes or wine grapes in the Central Valley.

3.2.3. Wine Grape Production Climate Change Adaptation with FEWS Lens

The quality and yield of wine grape production are strongly dependent on climatic conditions and dynamic interactions between temperature, water, viticulture techniques, and varietals (Van Leeuwen et al., 2019). Warming temperatures, drier conditions, and water scarcity will drive changes in techniques and regionally suitable varietals (Mozell & Thachn, 2014). Some climate change adaptation strategies for vineyards include changing varietals and rootstock, modifying viticulture techniques (e.g., physical, biological, and chemical), modifying training systems, moving to higher altitudes or regions where soils have greater water holding capacity (Nicholas & Durham, 2012; Van Leeuwen et al., 2019). Some adaptation strategies to address limited water supply include switching to varietals with drought-resistant germplasm (McElrone et al., 2013) and variation in grape phenology increase climate change resilience (Morales-Castilla et al., 2020).

3.3. Food Processing: Tomatoes

3.3.1 Water and Energy Use

The tomato processing facility's overall energy requirement is ~26 kWh/ton of tomato, which has CO_2e emissions of ~0.02 metric tons CO_2e/ton of tomatoes (US EPA, 2019) and costs about $4/ton of tomato for three months of 24-hour processing. The most prominent water use is present in unloading tomatoes from trucks, removing grit, and conveying tomatoes to the facility, and electrical energy is highest for pumping and thermal energy for generating steam—all forms of managing water (Amon et al., 2017).

3.3.2 Policy and Management Decisions Affecting Food Processing Facilities

Wildfires, heatwaves, and wind intensity have been increasing with changing climate conditions (Jones et al., 2020) with indirect effects on California's food producers and processors. In 2019, for example, California public utilities (CPUs) implemented a public safety management strategy known as the Public Safety Power Shutoff (PSPS) to reduce wildfire risk during extreme weather events with high winds and elevated temperatures. Taking a processing facility offline not only results in loss of product for every hour without power, but also increases in water and energy to clean and restart the facility for continued production. Customers affected by PSPS events criticized CPUs for poor execution of rules, regulations, and communication, which led to an investigation to examine recent PSPS events to ensure utilities are held accountable for outcomes during these events (Balaraman, 2019). Implementing the PSPS management highlights how crucial it is to develop climate change adaptation strategies and management with a FEWS understanding and approach to prevent unwarranted outcomes and ensure effective communication between resource managers and impacted entities.

Increases in heatwaves have also driven changes in food standards. For example, the Food and Drug Administration's Food Safety Modernization Act (US FDA, 2011) makes food production standards and processing more stringent to prevent foodborne illnesses, which case ~48 million people to get sick, ~128,000 to become hospitalized, and ~3,000 to die each year in the United States (CDC, 2020). These regulations have many implications in terms of water and energy embedded in food processing and handling facilities—increases in refrigeration capacity at the facility and transportation of products and water increases to ensure proper cleaning and sanitation of products and facilities. As changes in climate lead to changes in food standards, FEWS quantification is important to targeting where there is a need to focus technological and financial investments withing California food systems.

3.3.3. Food Processing Climate Adaptation with FEWS Lens

Comprehensive and detailed analysis of water and energy use for California-specific food systems help identify components or stages of food processing that could become water or energy saving. For example, the water-energy analysis by Amon *et al.* (2017) highlighted high energy use for pumping and steam generation, which could lead to technological developments that increase energy efficiency for these critical steps of food processing. Furthermore, understanding that the preliminary fruit preparation—the washing and the conveyance of fruit from the truck to the processing facility—is water-intensive could lead to increased automation coupled with water recapture and reuse methods that reduce the energy-water footprint at this processing stage.

4. Conclusions

The foundation of developing solutions that take a FEWS approach is understanding the intricate interconnections and relationships between FEWS, which have been assessed in the literature through research, modeling, and technological developments. A gap persists in effectively translating a conceptual understanding of FEWS and current food system water and energy consumption to develop practical solutions to water and energy efficiency and GHG emission reduction. Not only is a guided action plan needed to bridge theory and practical implementation, but "detailed research-based evidence" at various scales, different environments, and contexts are needed (Leck et al., 2015). United States federal funding has steered the evolution of FEWS research with a global reach worldwide, but most of this research has tended to be conceptual and lacking the ability to lead to actionable solutions.

For example, the National Science Foundation's funding of Innovation at the Nexus of Food, Energy, and Water Systems (NSF-INFEWS) projects to date are primarily theoretical approaches, and the most common research method is modeling with emphases on irrigation, biogas and biochar, and renewable energy. FEWS research focusing on California-specific food systems could take climate change adaptation strategies to the next level by focusing on artificial intelligence and blockchain for food traceability, transparency, and reliability (Creydt & Fischer, 2019; Galvez et al., 2018; Kamath, 2018). Solutions to FEWS developed for commodity crops like corn or wheat have less relevance to the complex agricultural landscape found in California, where specialty crops have specific growing conditions and unique production logistics. The NSF-INFEWS projects with the most practical solution developments for California, to date, focus on technology development for recycling agricultural byproducts for use as renewable power or soil remediation (Fang et al., 2020; Qaramaleki et al., 2020). Other aspects of FEWS research, such as automation technology, artificial intelligence, and blockchain, could help catalyze conceptual understanding to applied solutions for California's food systems.

Overall, there is a need for research in California that not only evolves the understanding of the relationships between FEWS but also facilitates the transformation of theoretical findings into practical solutions. In addition to research that bridges theory and practice, detailed studies of California's food production systems' water-energy footprints are needed. Such assessments could inform effective policies, management implementation, and technological investments that promote socio-economic and environmental well-being. Detailed FEWS studies—especially localized life-cycle assessments (Amon et al., 2017; Kendall et al., 2015; Steenwerth et al., 2015)—can help identify inefficiencies and potential cost savings.

Generally, FEWS research has involved diverse professional communities (e.g., academia, industry, and agencies) and increasingly with stakeholder input (Endo et al., 2017), yet further inclusion of can help bridge theory and practice. This approach could also decrease negative and unwarranted tradeoffs in action plans (Leck et al., 2015; Opejin et al., 2020). By working with multiple key stakeholders (see Box 4), California can develop policy and management approaches that are community informed and essential for developing timely, relevant, and long-term solutions to California agriculture FEWS issues.

Box 1. Food-Energy-Water Nexus—What's all the fuss?

The nexus of food, energy, and water systems (FEWS) is the concept of considering food, energy, and water sectors as reliant and influential on one another since the changes or actions of one sector impacts one or both other sectors. FEWS is not a new concept, having been formalized in 2011 (Waughray, 2011) as an outcome of needing to address food, energy, and water security under rapid global change (Simpson & Jewitt, 2019). Although many FEWS studies focus on single or coupled systems (Helmstedt *et al.*, 2018), the scientific community has recognized the interconnectedness of these sectors in response to weather extremes (e.g., flooding, drought, wildfires) and human population pressures (Wada *et al.*, 2016).

Understanding FEWS can be complicated due to locally, regionally, and globally variable factors like climate, water availability, energy sources, land use, policy, and management strategies.

California food systems are complicated due to the varying size and scale of agricultural production, diversity of commodities, water resources availability, and regional climatic differences. Food systems include all the natural resources, human capital, and labor involved at every stage of the food production system: from growing crops to food processing to the distribution chain. Energy plays a vital role at every stage of the food system: energy from the Sun to grow the crops to energy from renewable (e.g., solar, wind, water) or nonrenewable (e.g., coal, diesel) sources to generate electricity for pumping groundwater, conveying surface water, or pressurizing irrigation systems; to energy for powering food processing facilities and fueling distribution trucks. Both food and energy systems rely on freshwater resources—groundwater and surface water—for growing crops, irrigation, sanitation, cooling and heating, and electricity generation, to list a few.

Box 2. Addressing Groundwater Overdraft Under SGMA

What is SGMA?

The Sustainable Groundwater Management Act aims to bring critically overdrafted basins into sustainable use and prevent undesirable outcomes that result from groundwater overdraft by 2040 (DWR, 2014). The undesirable outcomes or six "sins" of groundwater overdraft are lowering groundwater levels, land subsidence, reducing aquifer storage, degraded water quality, surface water depletion, and seawater intrusion. SGMA requires local agencies (e.g., irrigation districts, water agencies, water storage districts, and city and county agencies) to coordinate and collaborate to form Groundwater Sustainability Agencies (GSAs). GSAs are responsible for developing and implementing Groundwater Sustainability Plans (GSPs), which are the roadmaps for how GSAs will address groundwater overdraft and associated issues by 2040. Strategies for addressing groundwater overdraft vary by region since SGMA recognized the need for local management of this resource and places management control to local GSAs.

Potential Implications of SGMA?

Although the implications of SGMA remain unknown, studies have projected that more than 500,000 acres of agricultural land may go out of production to address groundwater overdraft by 2040 as per SGMA (Hanak et al., 2019). Potential land-use changes (see Box 3) could offer the opportunity to implement land uses that address groundwater overdraft and its associated six "sins" while also offering other socio-economic and environmental benefits. Water scarcity and SGMA offer a new way to think about how surface water and groundwater are being used and managed, especially in the most critically overdrafted basins in the state. So far, GSAs have considered ways to augment supplies (e.g., recharge, reclaimed water, and surface storage), shift surface water use (e.g., surface water trading, conveyance, surface water treatment, and recycled water), and manage demand (e.g., land fallowing, pumping restrictions, urban conservation, and irrigation efficiency) (Hanak et al., 2020).

Disadvantaged Communities (DACs): Disadvantaged communities are areas in the state that are burdened with economic (e.g., poverty, high unemployment), health (e.g., cardiovascular disease, asthma), and environmental issues (e.g., poor air and water quality). The California Department of Water Resources defines DACs as communities in the state with an annual median household income (MHI) of less than 80% of the statewide annual MHI. Communities with an annual MHI of less than 60% of the statewide annual MHI are referred to as ***Severe Disadvantaged Communities (SDACs)*** (Balazs et al., 2019).

Box 3. Land Repurposing Options for Groundwater Sustainability

Groundwater Sustainability Agencies (GSAs) have considered land fallowing as one of the major approaches to managing water demand. Leaving land fallow long-term can have socio-economic impacts (e.g., loss of jobs, impact the local economy, risks to food security). Leaving land fallowed can also lead to worsening air quality which can have negative health repercussions (e.g., asthma and spread of valley fever) that already burden many rural communities, especially in the Central Valley. Land repurposing options can give fallowed land another use that offers multiple benefits, could work with agriculture, and benefit communities, the environment, and the economy. The following are some land repurposing options:

Habitat Restoration—provides species with habitat, can offer increased soil carbon storage. One thing to consider is the distance to the existing habitat since large, connected areas are most successful. Although funding is available, it may not be easy to access. It is recommended that first-time applicants consider partnering with local conservation non-profits, resource conservation districts, or Natural Resources Conservation Service (NRCS) offices for application support. Suggested reading: Butterfield et al., 2017; Lortie et al., 2018

Dryland Agriculture—provides some revenue, is flexible year to year, and offers soil health and pollinator potential. Before implementation, some things to consider are that yields are unpredictable, and this land use is not viable in some regions with limited rainfall. Another consideration is that it generally involves shallow soil tillage to control weeds and to help preserve stored soil moisture, which may worsen air quality conditions. Suggested reading: Pottinger, 2021

Pollinator-Friendly Cover Crops—can offer soil quality improvements and support pollinators. Some considerations are that seed mixes need to be based on local rainfall patterns, soil conditions, and crop types. Suggested reading: Mitchell *et al.*, 2017

Renewable Energy—like low impact solar, can provide substantial revenue and offers a clean energy source. Some considerations are that it is not possible to implement everywhere, and location depends on areas with the proper physical conditions. The solar implementation also needs to be near transmission infrastructure. Suggested reading: Butterfield *et al.*, 2013; Pearce *et al.*, 2016

Recharge—groundwater recharge can store water for future use, improve well reliability, and provide habitat and support groundwater-dependent ecosystems. Some considerations are that it requires conveyance and permitting and may have potential water quality impacts that depend on soil and present aquifer contamination characteristics. Another consideration is that successful recharge projects depend on suitable soil characteristics. Suggested reading: Bourque *et al.*, 2019; Mayzelle *et al.*, 2015

Parks and Green Space—provide recreational opportunities for communities that currently lack these areas, like DACs. Green spaces also play as a buffer against environmental health threats, especially in rural agricultural communities. It is essential to consider places this land uses in communities that are currently lacking these spaces. Suggested reading: Lee, 2020

Less Water-Intensive Crops—could promote water savings, keeps specialty crops in production, and promotes crop diversity. Less water-intensive crops could be more flexible in that they can be annually fallowed during drought. Some considerations are that some crops require more labor, result in changes in revenue, markets differ among crops, and different needs in fertilizer amounts and those associated costs.

Box 4. Recommendations for Diversity and Inclusion in Codeveloping California Agriculture FEWS Solutions

For California, key stakeholders to involve in the co-development of solutions include researchers, government agencies, industry, local communities, and agricultural professionals— including farmers and small-scale farmers. There is a persistent knowledge and decision-making equity gap in California, especially in the San Joaquin Valley. More than 500 DACs and small-scale farmers have been excluded from decisions that impact their livelihood due to language barriers, limited broadband access, or lack of access to information in their native language or communication through appropriate means. A solution to this is disseminating and translating policy, management plans, and critical research that impacts community members that are non-English speakers. Another is to diversify how information is disseminated among different implementing and impacted entities (e.g., mail-in, in-person, multilingual digital communications). Acknowledging an increase in mobile communications in the future, there is a need to strategize how to bridge communities without broadband and lower literacy. The future for making knowledge and information accessible is in artificial intelligence and developing on the spot translation. Acknowledging and accommodating the diversity in languages spoken in the state can lead to equitable, collaborative, and inclusive decision-making and lead to innovative solutions stemming from diverse perspectives and lived experiences. An example is CaliWaterAg YouTube channel, a trilingual—English, Spanish, and Hmong—channel that aims to make the science and policy behind California water and land use management accessible to community members and farmers in the state (www.tinyurl.com/caliwaterag). Overall, collaboration and co-development of solutions are critical for California's success in addressing California agriculture FEWS security moving forward.