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Informing Water Conservation Initiatives Using
Remotely Sensed Data

A dissertation submitted in partial satisfaction
of the requirements for the degree of Doctor of Environmental
Science and Engineering

by

Robert Barrera Reny

2024

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UNIVERSITY OF CALIFORNIA

Los Angeles

Informing Water Conservation Initiatives Using
Remotely Sensed Data

by

Robert Barrera Reny

Doctor of Environmental Science and Engineering

University of California, Los Angeles, 2024

Professor Richard F. Ambrose, Co-Chair

Professor Alvar Escriva-Bou, Co-Chair

Abstract: Recent intense and record-breaking droughts have greatly impacted California's water supply, driving new large-scale water conservation initiatives. Informing and analyzing these initiatives requires data at similarly large scales, which is primarily only possible with remotely sensed data. Despite its increasing availability, remotely sensed data has not been utilized to the extent that it could be in water conservation, resulting in data gaps and uncertainty. The objective of this dissertation is to evaluate and inform water conservation initiatives using remotely sensed data. In the first chapters of this dissertation, I assessed a fallowing program along the Colorado River intended to produce water savings to protect the Colorado River system. I first identified an appropriate evapotranspiration (ET) model for the fallowing program

using the traditional valley-wide consumptive use estimate since ET is a proxy for consumptive use, I then explored how fallowing savings estimates differ between the standard water-balance approach employed by the Federal Government and an ET-based approach, and finally I explored factors that correlate with higher fallowed field water use. My results showed that the traditional approach for calculating fallowing savings produces higher estimates than an ET-based approach, primarily due to differences in estimated fallowed field water use. I also found evidence that fallowed field water use decreases with older field age, lower surrounding field water use, and larger field size. Fallowing programs may benefit by accounting for fallowed field consumptive use when estimating savings and incentivizing keeping fields in fallow and having larger fallowed fields to potentially reduce lost water. The final chapter of this dissertation used remotely sensed irrigated area estimates to inform the Outdoor Residential Water Use Standard (ORWUs) described under the Conservation as a California Way of Life legislation. The ORWUs are designed to set water budgets for retailers based on their irrigated area as measured by a 2018 snapshot image. I used additional years of imagery data to inform this 2018 value and explore how irrigated area varies by year. I found that irrigated area as measured by this type of snapshot imagery is highly variable between years and that the use of 2018 values results in “winners” and “losers” between agencies. Remotely sensed data has the potential to fill critical data gaps and improve water conservation initiatives as shown throughout this dissertation. However, utilizing remotely sensed data requires modeling and data may not be as high-resolution or as temporally available as desired, resulting in uncertainties. Clearly identifying, addressing, and communicating uncertainties and benefits related to remotely sensed data will be key to maximizing the benefit that this data source has to offer for policy makers.

The dissertation of Robert Barrera Reny is approved.

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University of California, Los Angeles

2024

DEDICATION

To Annelise for your support in every season
of this years-long journey, to Tala for transforming our lives.

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VITA/BIOGRAPHICAL SKETCH

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CHAPTER 1: INTRODUCTION

California's water supply supports the largest agricultural production in the United States as well as tens of millions of residents (CDFA 2020) but drought and overuse have strained this vital resource. Droughts reduce water availability while also increasing crop water demands, which damages agricultural and related sectors (Escriva-Bou 2022). California has experienced multiple droughts in recent years, including two severe droughts (2012-16 and 2020-22), as well as a record breaking Western United States megadrought impacting the Colorado River, a key source of water for California (Williams et al., 2020). Research indicates that droughts will become more common in the face of climate change (Cook et al., 2018). This reality, combined with a need to cut back on general water overuse, necessitates action to generally reduce water use, improve water storage, and better manage water demand within California (Tanaka et al., 2006, PPIC 2018).

Responses to drought by governments throughout the world are generally reactive and are typically characterized as "crisis management" (Wilhite and Pulwarty, 2005). Recent droughts have similarly resulted in conservation initiatives within California. In response to California's 2012 to 2016 drought, the State legislature passed the Conservation as a California Way of Life legislation to help California adapt to water management challenges caused by climate change (A.B. 1668, S.B. 606). A subset of this legislation outlines the Outdoor Residential Water Use Standards (ORWUs), which are meant to set water budgets at the retail agency level based on their irrigated area. In response to the megadrought along the Colorado River, the United States Federal Government provided funds within the Inflation Reduction Act to help conservation along the river, including funds for fallowing payments along the river (H.R. 5376). Fallowing

payments are targeted for large irrigation districts that utilize Colorado River water, including districts within California, where the majority of Colorado River water use occurs.

Each of these conservation initiatives apply at relatively large spatial scales; the ORWUs apply to all of California while fallowing will occur within irrigation districts that are tens of thousands of acres in size. Achieving water conservation goals and understanding impacts from these initiatives requires data at large spatial scales that are also updated over time (García et al., 2016; Hering, 2014; Walker, 2000). However, field-level water use data which would inform fallowing programs are often difficult to estimate (Perry 2023) and conventional methods for measuring irrigated area are time-consuming and tedious (Velpuri et al., 2009). Remote sensing technology offers an alternative method to measure both water resources and landcover without on-the-ground measurements (Lindell et al., 1999, Belward and Skoien 2015).

The monitoring of water resources using satellite remote sensing started in the 1970's with the launch of Landsat-1 (Strong, 1974, Klemas et al., 1974). Satellite remote sensing is increasingly being used as a complementary source of information to traditional monitoring networks and, in many cases, provides the only feasible source of data. Satellite-based sensors are now capable of making direct and indirect measurements of nearly all components of the hydrological cycle (Lettenmaier et al., 2015; McCabe et al., 2017; Y. Zhang et al., 2016), including consumptive use through the measurement of evapotranspiration (ET) (Jensen 1974; Wanniarachchi and Sarukkalige 2022). ET is the transfer of water vapor to the atmosphere through the combined processes of evaporation from the Earth's surface and transpiration through plant tissues. ET models traditionally require expertise to utilize but the recent launch of OpenET in 2021 has made ET data across the Western United States readily available to individuals and governments (Melton et al. 2022). OpenET provides access to six different ET

models, as well as an ensemble model, most of which calculate ET using a surface energy balance approach (Bastiaanssen et al. 1998).

In addition to water resources measurement, there is also a long history of remotely sensed measurements of vegetated area (Belward and Skoien 2015). Historically, visual interpretation and manual digitizing of aerial imagery has been used for land area classification or identification of different land uses (Freeman and Buck 2003; Pauleit, Ennos, and Golding 2005), but this method is impractical for larger areas. To resolve this, machine-learning techniques have been increasingly applied to land use classification using supervised machine learning (Wang et al. 2022; Ramezan et al. 2021) where desired land use classifications are identified by their unique spectral signatures as measured by sensors on aircraft or satellites. Irrigated area, or healthy vegetation, can be identified by the fact that chlorophyll reflects more near infrared light and absorbs more red light compared to non-vegetation (Rouse 1973).

Despite its value, remote sensing is still in the process of being adopted to inform conservation initiatives (Chen et al., 2004, UCRC 2023, Khanal 2020). This is seen even with the recent initiatives explored in this dissertation. Water savings from fallowing programs along the Colorado River are roughly estimated using accounting methods based on physical water balances at the district level due to the challenge of measuring field-level water use (USBR 2022). This method simplifies fallowing savings calculations by attributing all of the district's consumptive use, which may include fallowed field consumptive use, to cropped fields only. The ORWUs utilize remotely sensed data to offer an estimate of irrigated area for all of California but the data has inherent uncertainty that could be informed through the collection of additional data points. In this dissertation I look to inform a USBR fallowing program intended to save water along the Colorado River as well as the ORWUs using remotely sensed data. For the

following program I aim to inform the United States Bureau of Reclamation's standard methodology for calculating fallowed water savings by using an alternative ET-based approach, highlighting the potential that water use by fallowed fields may inflate USBR's calculated water savings. For the ORWUs, I provide context to the irrigated area value as measured and provided by California's Department of Water Resources to retail agencies for use in future water budgets. This dissertation is organized into five chapters; after this introduction chapter I explore the following topics:

- Chapter 2 describes the Palo Verde Irrigation District (PVID) fallowing program and presents an alternative accuracy assessment to determine which evapotranspiration model, as provided by OpenET, provides the most representative data for the district in comparison to the current water accounting method based on a physical water balance. ET models are estimated through surface energy balance approach, but accuracy is uncertain without on-the-ground data. Traditionally these data are provided in the form of eddy covariance towers or lysimeters. However, due to a lack of this data in PVID, an alternative approach was utilized which compared the total valley's estimated water use to the total valley's ET. The model that performed best based on linear regression parameters was then used for field-level estimates in Chapters 3 and 4.
- Chapter 3 explains the standard method USBR utilizes to calculate fallowing savings and outlines the risk for overestimated savings under this methodology. ET data from the model chosen in Chapter 2 is then used to calculate an alternative fallowing savings by directly comparing ET on cropped and fallowed fields. This value is compared against

USBR's estimate to illustrate the potential extent that water savings are overestimated by USBR due to fallowed field water use.

- Chapter 4 aims to inform the PVID fallowing program by identifying factors that correlate with higher fallowed field water use through multi-linear regressions. Fallowed field size, shape, surrounding field water use, and adjacency to PVID's major canal were all assessed as factors that may relate to fallowed field water use. Multi-linear regressions were performed for 2019, 2020, and 2021 data to identify factors that are statistically correlated to fallowed field water use. Factors shown to be related to higher water use could be incorporated into fallowing agreements to improve the effectiveness of the fallowing program.
- Chapter 5 explores the stability of irrigated area measurements as they are calculated for the ORWUs. National Agriculture Aerial Imagery (NAIP) high resolution imagery taken in 2018 was used by the Department of Water Resources to estimate irrigated area across California for use in developing water budgets for retailer agencies. Given temporal changes in healthy vegetation within California, this single measurement may produce unrepresentative result. To inform this potential bias, four total years of classified NAIP imagery from 2014, 2016, 2018, and 2020 were compared to evaluate irrigated area stability within Southern California.

This research informs and provides recommendations for two different conservation initiatives spurred by recent droughts impacting California. For the PVID fallowing program,

recommendations may improve the efficiency and amount of water conserved per fallowed acre and lead to an alternative method of fallowing savings calculations. For the ORWUs, my research identifies potential pitfalls and equity questions that may occur with the current methodology for measuring irrigated area.

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CHAPTER 2: ASSESSMENT OF OPENET MODELS FOR USE IN THE PALO VERDE IRRIGATION DISTRICT

Abstract

As one of the largest users of Colorado River water, the Palo Verde Irrigation District (PVID) is home to multiple water conservation studies and initiatives including a long-term fallowing program. Valley-wide consumptive use estimates are currently used to assess water savings from conservation initiatives due to a lack of field-level consumptive use data. However, fully understanding the effectiveness of these studies and their value for farmers and stakeholders is only possible through field-level data. OpenET recently launched to provide easy access to multiple satellite-based evapotranspiration (ET) models for estimating consumptive use within the Western United States. These models allow for the estimation of field-level consumptive use without the need for installing comprehensive metering systems. ET model accuracies are generally assessed against on-the-ground covariance towers or lysimeters which are not present in PVID and are costly to deploy at scale. To assess the most appropriate OpenET model for use in PVID, an alternative approach was taken which compared valley-wide ET data to valley-wide consumptive use estimates to then recommend a model for field-level data. Regression analysis was performed between PVID's total monthly consumptive use as measured by each OpenET model and the United States Bureau of Reclamation's monthly total PVID consumptive use estimates for the whole PVID system from 2016 to 2021. Although this consumptive use dataset is itself an estimate, it is a useful value to measure against because of its use in official accounting on the river. By comparing regression parameters, I found that the eeMETRIC model best fit USBR's monthly consumptive use estimates, particularly during peak summer consumptive use. These results indicate that the eeMETRIC model is a useful model for

assessing field-level ET within PVID and can be used to help inform conservation at the field-scale.

Introduction

Proper water accounting within irrigation districts is difficult to obtain despite the importance of accurate water measurements for capturing the realities of water use (Young and McColl 2009). Comprehensive measurement systems are complex to install and maintain and are prone to inaccuracies, costly, and deteriorate over time (Benavides et al. 2021). As water resources become more strained a greater emphasis on accurate and available water accounting is needed. The Colorado River system has recently undergone an historic drought (Gangopadhyay et al. 2022), leading to a call for millions of acre-feet of water savings to protect reservoirs in the system (Flavelle 2023). Much of this conservation will come from irrigation districts which calls into question how savings are calculated. Remote-sensed data offers an alternative method to measure water use at a lower cost and easier implementation compared to comprehensive measurement systems.

The Palo Verde Irrigation District (PVID) is an unquantified, first priority irrigation district along the Colorado River (Palo Verde Irrigation District 2002). As a first priority user over Colorado River Water, PVID has the first rights to diversions from the river and PVID's unquantified status means that its water use is not limited. Due to these characteristics, most fields in PVID are flood irrigated through gates generally lacking metering technology. Field-level diversions are commonly estimated via water head which has known inaccuracies (Bradshaw and O'Halloran 1998). Even assuming these measurements are perfectly accurate they are not equal to consumptive use when flooded water returns unmeasured into canals. When metering technology is present, overflows into canals still make it impossible to assess how

much of the flooded water was consumed by a given field. An increasing number of water conservation studies or programs are occurring in PVID, including land fallowing, deficit irrigation for alfalfa, and cover cropping (Montazar et al. 2020; 2018; Daley and LaSalle 2020). Valley-wide consumptive use is measured and has historically been used to assess water savings but the lack of field-level data complicates final understanding the impacts of conservation initiatives.

The longest on-going conservation program in PVID is a federally monitored fallowing program (Guetz 2023). Water savings from the PVID fallowing program are estimated at the valley-wide scale by measuring total diversions from the Colorado River and return flows to the Colorado River (Owen-Joyce and Kimsey 1987). A valley-wide water accounting is the current method used to estimate water savings from this fallowing program as well as other pilot studies occurring the Valley due to a lack of accurate field level consumptive use data. The installation of a comprehensive metering network to measure every field's water use at the size of PVID is impractically expensive and would require a large amount of coordination and buy-in from farmers (Tran and Weger 2018). Satellite data provides a solution for measuring PVID's field-level consumptive use data to help inform conservation studies at a lower cost and without implementation barriers.

Remote sensing has been widely used to monitor irrigated areas over space and time, even in lieu of in-situ monitoring (Folhes, Rennó, and Soares 2009; Senay et al. 2017; Volk et al. 2024). OpenET launched in 2021 as part of a collaboration between NASA, the Environmental Defense Fund, the United States Geological Survey, and several others groups, to provide accessible ET data across the entire Western United States (Melton et al. 2022). OpenET provides access to six different ET models as well as an ensemble model which is an average of

multiple models. The Upper Colorado River Commission and California Bay Delta farmers are already utilizing OpenET data in their studies and work because of its ease of data access, affordability, and accuracy.

Despite the growing data availability and interest in ET there remains uncertainty about the accuracy of satellite-based approaches for monitoring irrigation water use, particularly at the field level. Errors in satellite-based measurement of irrigation water use has the potential to generate negative impacts on farmers (e.g., if their water use is overestimated) or conservation (e.g., if agricultural water users are exceeding estimated water use). Lysimeters and eddy covariance (EC) are often the methods of choice for assessing the accuracy of satellite ET data (Baldocchi, 2003, 2014; Farahani et al., 2007) but sufficient sampling is limited by high costs of installation and the complexity of conventional EC set-ups (Saha et al. 2022).

PVID does not currently have any lysimeters or EC towers so there is no direct method for assessing the accuracy of OpenET's models to recommend a model best designed for PVID. As the home to multiple water conservation studies and programs, an accurate and openly available consumptive use estimate at the field-level would be extremely valuable for both farmers and researchers in the valley. ET is commonly used as a direct measurement of consumptive use when properly calibrated and assessed for accuracy. USBR's valley-wide consumptive use estimates offers a measurement that is the official accounting estimate for PVID despite not necessarily being the true value. USBR's measurement is therefore a useful value to compare ET model estimates to and identify the most representative ET model for PVID. By identifying an OpenET model that aligns with USBR's consumptive use measurement at the valley-wide scale, decision makers can have more confidence in the field-level estimate of the ET model to better inform water conservation studies.

This research will assess the performance of available OpenET models for use in PVID by comparing the monthly ET produced by cropland in PVID with USBR's monthly valley-wide consumptive use measurement from 2016 through 2021. ET data was downloaded through OpenET's API and USBR data was extracted from yearly fallowing reports. It is assumed that the identification of a model that is similar to USBR's consumptive use estimates at the valley-wide scale will also provide useful field-level data. Model performance was assessed via monthly linear regression results with the intent of identifying a useful ET model for the collection of field-level consumptive use data. Accurate field-level consumptive use data can then be used to properly quantify the water savings of conservation programs as well as help inform how those programs are implemented.

Methods

Study Area and Field-Level Shapefiles

PVID is an unquantified, first-priority district, home to 88,000-acres of agricultural land located in Blythe, California (Figure 1) (Guetz 2023). As an unquantified user of Colorado River water, PVID pays for water based on irrigated acreage as opposed to volume of water consumed. As a result, water is relatively inexpensive: farmers pay \$61 per acre to irrigate with any amount of water, disincentivizing the use of efficient irrigation technologies. Flood irrigated alfalfa makes up the majority of fields in PVID. PVID is designed as a relatively closed system, all fields have canals that eventually return water to the Colorado River so that overflows from flood irrigation are not wasted. From a cropping standpoint, alfalfa takes up approximately 60% of the acreage in PVID while fallowed acreage represents another 10% to 25% depending on the year. Annual crops such as cotton or melons, other grasses, and idled fields, which are fields that have not been planted for usually economic reasons, make up the remaining area.

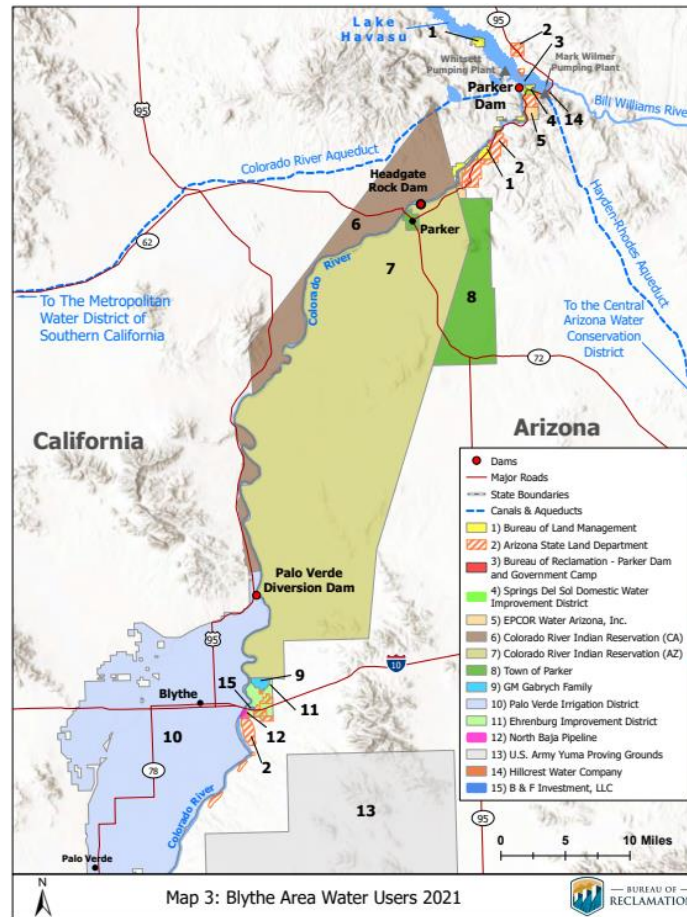


Figure 1. Palo Verde Irrigation District's Location in Comparison to Lake Havasu, the Colorado River, and the Colorado River Aqueduct

LandIQ, Inc. conducted quarterly crop-mapping for PVID from 2019 to 2021 utilizing remote-sensed image analysis combined with on-the-ground verification. This work resulted in the creation of shapefiles for every contiguous field in PVID for each quarter. These shapefiles capture all of the fields in PVID, not including berm areas between fields or canals and will be used for ET data collection.

General Consumptive Use Model

Consumptive use of water is equal to ET, or the combination of evaporation of moisture from the surface of soils and vegetative cover and water loss due to plant transpiration (Blaney 1952; Farahani et al. 2007). Consumptive use of agricultural crops is most commonly measured

by lysimeters, water balances, soil moisture measurements, or through a surface energy balance (SEB) (Erie et al. 1981; Farahani et al. 2007). Lysimeters are tanks filled with soil that are weighed to accurately measure short-term water use. Non-weighing lysimeters and the water balance method require accurate measurement of applied water, rainfall, and change in soil water storage to compute consumptive use. The soil moisture method for computing consumptive use involves the measurement of soil water content over time using soil sampling and gravimetric analysis. These techniques are all limited in scale and would be impractical to employ at the scale of an irrigation district such as PVID. The SEB approach offers a method that is not as limited by area or cost. A SEB computes consumptive use by balancing short and longwave radiation as measured by remote-sensed or aerial imagery with heat fluxes estimated through meteorological parameters. Unaccounted energy in the energy balance is assumed to have gone towards the conversion of water to water vapor, or ET.

Estimate of PVID's Consumptive Use through Water Balance

The measurement of PVID's diversions and return flows to compute consumptive use is complicated by changes in soil and groundwater storage. To help understand the influence of groundwater on PVID's consumptive use, a comprehensive water balance study was conducted in PVID (Owen-Joyce and Kimsey 1987). This water balance was conducted through several data streams, including measured diversions and return flows, a groundwater elevation model built from scattered piezometers across the valley, consumptive use estimates based on crop type and associated typical water use, as well as ET modeling. Through these data, Owen-Joyce and Kimsey concluded that the groundwater's net impact on the valley is through a positive unmeasured return flow to the river. This value was set at 6% of total diversions and is included in USBR's yearly consumptive use estimates for the valley.

Estimate of PVID's Consumptive Use through OpenET Evapotranspiration

ET models using remote sensed data to estimate consumptive use can be generally categorized into semi-empirical methods and analytical methods (Xue et al. 2020). Semi-empirical methods employ empirical relationships and make use of data mainly derived from remote sensing observations with minimum ground-based measurements. Analytical methods identify the physical processes related to ET with varying complexity and require a variety of direct and indirect measurements from remote sensing technology and ground-based instruments. Landsat 8 and 9, as well as other satellites including Sentinel-2 and GOES, are equipped with thermal sensors that can identify vegetation health, surface albedo, and surface temperature, all of which can be utilized in physical models to quantify ET (Xue et al. 2020).

OpenET launched in 2021 to provide accurate and accessible ET data across the Western United States. OpenET provides access to six different ET models, as well as an ensemble model, most of which calculate ET using a surface energy balance approach. These models predict ET from the classical energy balance where ET is set equal to net radiation (R_n) minus heat lost to the soil (G) and heat lost to the air (H). The residual energy is assumed to have been used to convert water to water vapor, or ET (Figure 2) (Junior et al. 2013).

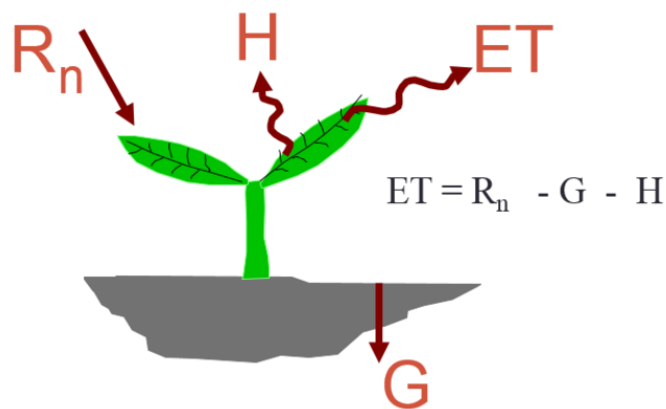


Figure 2. Evapotranspiration Energy Balance. Image from Rickallenidaho licensed under Creative Commons 4.0.

All models, other than SIMS, made available by OpenET are based on full or simplified implementations of the SEB approach (Melton et al. 2022). The SEB approach computes ET by dividing residual surface energy by the energy required to convert water to water vapor. The SEB approach relies on satellite measurements of surface temperature and surface reflectance combined with other key land surface and weather variables to estimate components of the energy balance—net radiation, sensible heat flux, ground heat flux, and latent heat flux. eeMETRIC, geeSEBAL, and DisALEXI estimate each component of the energy balance using short-wave and long-wave data (R. G. Allen et al. 2005; Bastiaanssen et al. 1998; Anderson et al. 2007). The models SSEBop and PT-JPL are simplified SEB approaches in which certain components of the energy balance are not estimated or are calculated using simplifying assumptions (Fisher, Tu, and Baldocchi 2008; Senay et al. 2017). SIMS relies on surface reflectance data and crop type information to compute ET as a function of canopy density using a crop coefficient approach for agricultural lands (Melton et al. 2022). Finally, the ensemble model is an average of all models with a correction for outlying model data.

Another important input to the ET models is on-the-ground weather station data through either California Irrigation Management Information System (CIMIS) stations or gridMET, another remote-sensed dataset. This weather data provides humidity, precipitation, wind, as well as a second data point for temperature and radiation data to compute ET (Hart et al. 2009). In the cases that remote-sensed imagery is blocked by clouds, and for the days in-between satellite passes, weather station data can be used to interpolate and avoid data gaps. Satellite pixels around weather stations also serves as a point of calibration for ET models (R. Allen 1996).

Data Processing

All ET data were downloaded using the OpenET API endpoint `‘/raster/export/multipolygon.’` LandIQ’s 2019 to 2021 PVID field-level shapefiles were uploaded to GoogleEarthEngine for integration with OpenET’s API. Monthly ET data was download for every OpenET model from 2016 to 2021 using the corresponding year’s shapefile. For data before 2019, LandIQ’s 2019 shapefile was utilized to download OpenET data. CIMIS was set as reference ET because PVID has three CIMIS stations located across the valley making it the best data source for reference ET. Monthly ET estimates by field for all of PVID were quantified by summing the mean monthly ET of all pixels within a field. OpenET’s data resolution is 900 square meters and the average field in PVID is approximately 160,000 square meters resulting in an average of 178 pixels per field.

USBR’s monthly consumptive use estimates for PVID were manually obtained through review of annual fallowing reports produced by USBR and the Metropolitan Water District of Southern California. This monthly consumptive use data was adjusted down for canal seepage, evaporation, and transpiration losses as reported by PVID as 37,375 acre-feet per year (Palo Verde Irrigation District 2012). USBR’s monthly consumptive use estimates are occasionally negative in the wintertime, primarily due to precipitation events and groundwater returns via the canal system. A monthly data frame was then created by combining USBR’s monthly PVID consumptive use values with the sum of total PVID ET for each month from January 2016 to December 2021 and every model (Appendix 2-A). A plot of this monthly data frame is shown below in Figure 3.

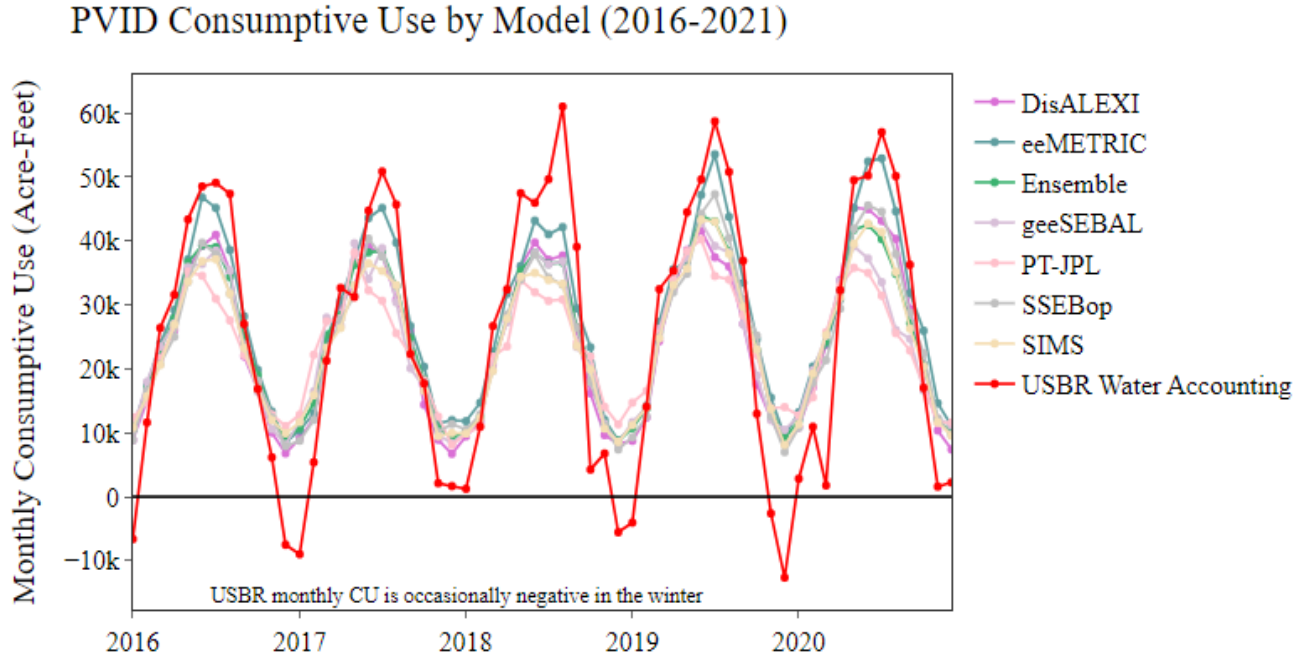


Figure 3. Monthly Consumptive Use Estimates from OpenET and United States Bureau of Reclamation

OpenET Model Accuracy Assessment

To evaluate the most appropriate ET model for us in PVID an ordinary least squares linear regression was performed between each model's monthly ET and USBR's measured monthly consumptive use. This value for each month and each model was then matched with USBR's monthly consumptive use estimate. Model performance was evaluated by the extent to which ET values matched USBR's consumptive use values using mean squared error (Equation 1) primarily. Additionally, models were compared by evaluating the strongest linear relationship between ET and USBR's estimates (R^2) and which model's ETs had the most statistically significant relationship to USBR's estimates (p-value)

$$\text{Mean Squared Error} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Where:

n = number of data points (72 for 72 months of data)

Y_i = observed values (USBR's Total PVID Monthly Consumptive Use Estimate)

$\hat{Y}_i$ = predicted values (Total PVID Monthly ET)

Equation 1. Mean Squared Error

Results

Each OpenET model shared the general trend seen in USBR's monthly consumptive use measurements as seen in Figure 3. USBR consumptive use measurements were highest in the summer when temperatures and the growing season peaked and dipped in the wintertime. ET values were never as low as USBR's winter measurements and never as high as USBR's summer measurements. Of the OpenET models, eeMETRIC consistently recorded the highest monthly ETs of all models while PT-JPL consistently recorded the lowest. The remaining models tended to cluster together. eeMETRIC ET most closely matched the consumptive use as measured by USBR during peak irrigation and plant growth in the summertime.

Of the 7 OpenET models, monthly ET values from eeMETRIC most closely aligned with USBR's monthly consumptive use estimates from 2016 to 2021 (Figure 4). The eeMETRIC model had lowest mean squared error, highest R^2 , and the lowest p-value of all models (Table 1). The SSEBOP, ensemble, and DisALEXI models are also reasonable models to utilize in PVID given their R^2 values of 0.900, 0.905, and 0.905, respectively. There was relatively low variance between all modeled ETs and USBR's consumptive use estimate with R^2 's over 0.9 for all models except PT-JPL which had an R^2 of 0.76. Slopes for all ET models are above 1, meaning that the ET models generally measured lower CU than USBR did (Figure 4).

Monthly Comparison of Model ET to USBR Water Accounting Consumptive Use

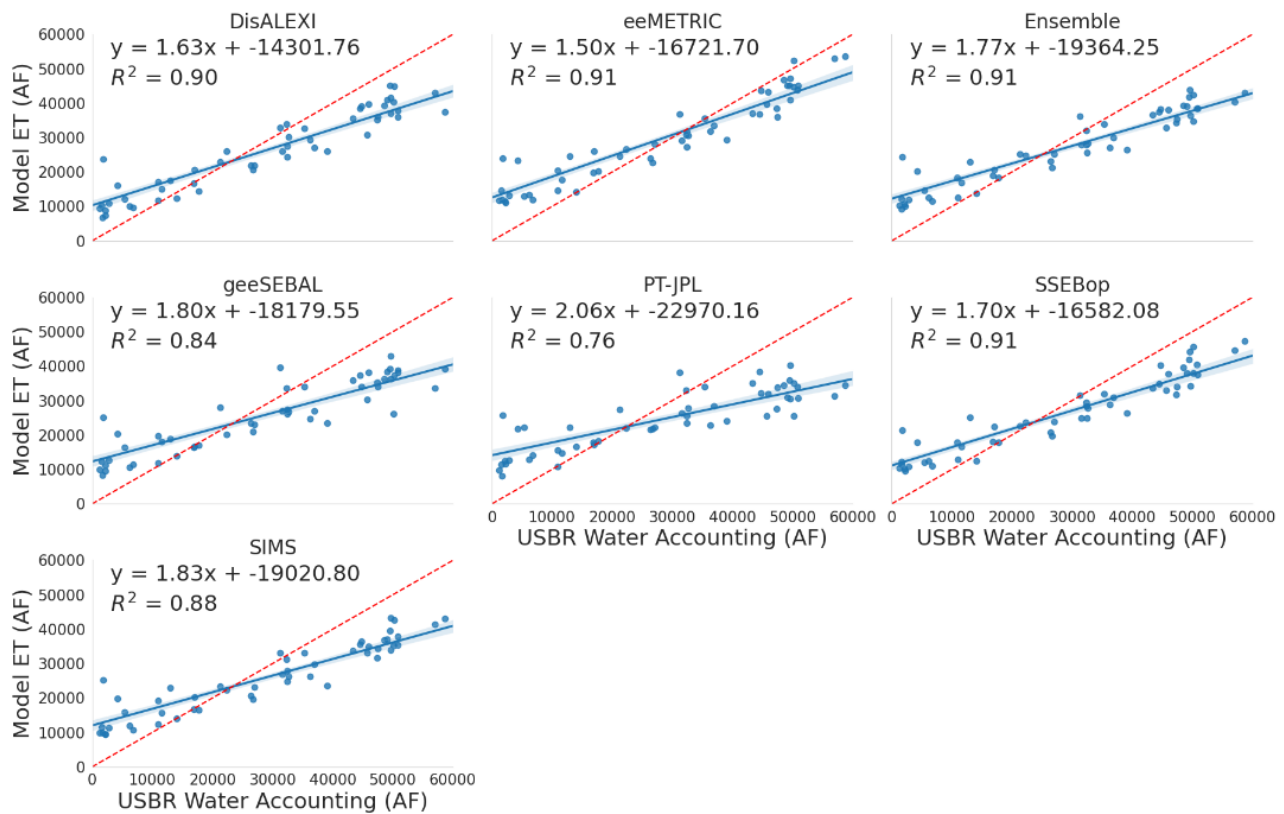


Figure 4. Plots of OpenET Monthly ETs vs USBR Monthly CU Estimates 2016-2021 (red dashed line represents 1:1 relationship)

However, this relationship is seasonal, in the winter ET models measure more CU than USBR while in the summer the ET models measure lower CU than USBR. P-values are significant and low across all models with the highest p-value being 1.414e-19 for the PT-JPL model. Summary results of the linear regressions are shown below in Table 1 and full results can be seen in Appendix 2-B.

Table 1. Linear Regression Results

Model	Mean Squared Error	R ²	p value
eeMETRIC	38428311	0.912	2.309e-32
Ensemble	41518916	0.905	2.184e-31
DisALEXI	43788558	0.900	1.025e-30
SIMS	52006034	0.882	1.518e-28
SSEBop	41484120	0.905	2.131e-31
geeSEBAL	68474652	0.844	4.520e-25
PT-JPL	105744058	0.759	1.414e-19

Discussion

The results indicate that eeMETRIC model is the best model to use for field-level consumptive use data based on similarity to USBR's valley-wide monthly consumptive use estimates for PVID. The SSEBOP, ensemble, and DisALEXI models are also reasonable models to utilize in PVID given their R² values of 0.900, 0.905, and 0.905, respectively. Although USBR's value is an estimate and not the true consumptive use value, it is the value for which accounting on the Colorado River is performed. Therefore, it is useful to have an ET model assessed against this value for the purpose of studying field-level consumptive use within PVID. The result that the eeMETRIC model is the best performing model in PVID is further supported through a recent comprehensive assessment of OpenET's model accuracy by Volk et al., 2024. The eeMETRIC model was identified as the best performing ET model within arid regions,

similar to PVID, and for long-term crops such as alfalfa, which is dominant in PVID (Volk et al. 2024). OpenET models include the most commonly used ET models but the individual models are not necessarily calibrated for specific areas of concern such as PVID. More accurate ET data is likely possible through fine-tuning inputs to the eeMETRIC model for PVID (De la Fuente-Sáiz et al. 2017). However, given the number of stakeholders who may then implement different models, the use of the eeMETRIC OpenET model allows for potentially more widely accepted agreement due to OpenET's availability and transparency.

Each of the OpenET models reflected to some extent the consumptive use pattern in PVID as measured by USBR. Model complexity did not seem to have any significant relationship to a given model's relationship to USBR's estimates. SIMS is the only model that relies on crop data to estimate ET and its estimates tended to fall between the other ET models (Melton et al. 2022). SSEBop and PT-JPL both employ simplifications of the SEB approach (Fisher, Tu, and Baldocchi 2008; Senay et al. 2017), and while PT-JPL produced the lowest estimates of all the model, SSEBop regularly produced the second or third highest estimates. DisALEXI tended to vary widely in terms of its order within the other models which may be due to the fact that DisALEXI is designed to estimate ET at larger extents and utilizes coarser meteorological inputs than the other models (R. G. Allen et al. 2005; Bastiaanssen et al. 1998; Anderson et al. 2007). The eeMETRIC model measured the highest ETs of all ET models evaluated in this study, likely due to the fact that it utilizes alfalfa reference ET when calibrating sensible heat flux while other models generally use grass reference ET which tends to be lower (Irmak et al. 2008).

A key assumption in this paper is that an ET model that produces valley-wide data similar to USBR's consumptive use estimates at the valley-wide scale will also provide useful

field-level data. Only field-level accurate consumptive use data could be used to evaluate an ET models' field-level data and ideally this data will be produced in the future to confirm the conclusion that the eeMETRIC model is most appropriate for PVID. However, until that data is available it is reasonable to assume that the eeMETRIC model can be useful for field-level data based on its aggregate similarity to USBR's values.

Although useful, USBR's valley-wide consumptive use estimates are imperfect as reflected in negative winter consumptive use estimates and by the fact that factors such as weather or groundwater conditions are not accounted for. USBR's reports on consumptive use assume that the system is in balance on an annual time scale but that may not necessarily be the case because of the connection of the river, groundwater, and PVID's canals. Canals in PVID are known to return groundwater and Colorado River water to measured return flow locations (Owen-Joyce and Kimsey 1987) which helps explain the negative winter consumptive use measurements in four out of six years evaluated.

Conclusion

PVID, like many irrigation districts, lacks accurate field-level consumptive use data. Field-level data is often needed to properly evaluate the impacts of water conservation measures but cost and ease of implementation prevent comprehensive measurement systems. This study evaluated OpenET ET models against USBR's monthly valley wide measurement of consumptive use from 2016 through 2021 to recommend a model for field-level consumptive use data. Of all the OpenET models, the eeMETRIC model best matched USBR's monthly consumptive use estimates based on linear regression results and therefore is recommended for studying field-level consumptive use.

In light of the fact that comprehensive field-level data is unlikely to be available in the near future, given its availability, cost, and accuracy, the eeMETRIC model can be a highly useful tool to evaluate conservation studies within PVID for stakeholders and researchers. Valley-wide consumptive use data makes it nearly impossible to understand the actual benefits of small-scale water conservation measures. Much better understanding of water conservation programs within PVID is now possible through the enhanced spatial resolution of ET data. This accurate and readily available field-level data can be used by decision makers to better understand actual water savings of programs and policies within PVID.

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Appendices

Appendix 2-A: Data frame of Monthly PVID Consumptive Uses 2016-2021 (acre-feet)

model	USBR Water Accounting	disalexi	eemetric	ensemble	ptjpl	seebop
0	-3769.0	8880.639	10535.697	10394.451	12413.810	8840.876
1	14455.0	14993.167	17662.434	16908.801	14662.390	16532.437
2	29260.0	21801.536	23940.259	23072.553	21646.709	20729.161
3	34447.0	26032.328	29209.053	27903.827	26466.590	25021.556
4	46233.0	35569.894	37132.338	36663.898	35188.525	33623.478
5	51387.0	39241.215	46827.207	39329.263	34553.466	39716.851
6	51955.0	40956.310	45179.256	39036.651	30965.139	37905.997
7	50235.0	35243.661	38592.647	34387.481	27574.740	31766.884
8	29874.0	21977.596	28210.776	25120.746	22145.029	23892.899
9	19693.0	16710.028	19858.726	19059.563	17900.844	18142.780
10	9012.0	10022.918	13335.781	12640.436	12865.100	12377.658
11	-4667.0	6783.334	8493.428	8983.131	11037.891	7893.837
12	-6144.0	9134.391	10338.045	10765.355	12843.089	8762.046
13	8244.0	12185.300	13055.125	14680.558	22205.686	12004.102
14	24129.0	23027.384	24613.450	25313.484	27413.572	22639.628
15	35500.0	30200.437	30676.555	28398.915	27879.424	27728.975
16	34100.0	32986.641	36837.416	36283.141	38161.378	31499.969
17	47589.0	39212.064	43586.597	38219.526	32279.006	40365.681
18	53730.0	37827.085	45169.736	38462.728	30643.183	37557.366
19	48552.0	30810.671	39721.635	32934.468	25553.521	32921.742
20	25188.0	25963.385	26710.336	24812.669	22102.659	23694.252
21	20574.0	14381.139	20315.292	18343.197	18222.577	17857.184
22	4974.0	8911.206	11498.957	10712.614	12526.270	10147.221
23	4506.0	6714.326	11977.978	9171.599	8109.840	11355.368

model	USBR Water Accounting	disalexi	eemetric	ensemble	ptjpl	seebop
24	4083.0	9456.652	11815.860	10252.321	9886.315	10488.508
25	13829.0	11768.722	14693.244	12497.257	10855.427	12859.224
26	29554.0	20663.078	22683.320	21354.424	21898.579	19757.410
27	35280.0	27439.752	31742.962	27902.425	23503.404	28480.813
28	50333.0	35956.692	36089.745	35378.947	33890.901	33970.826
29	48822.0	39755.807	43179.151	38154.320	31991.680	37851.612
30	52520.0	37084.976	41049.679	36437.808	30622.554	34282.553
31	63874.0	37720.584	42171.934	36652.717	30848.956	33154.204
32	41937.0	25963.579	29455.805	26510.860	24087.553	26472.315
33	7099.0	16165.704	23380.354	20233.254	21900.323	17933.210
34	9609.0	9643.305	12021.662	11468.692	14048.777	11101.607
35	-2713.0	8255.385	8801.446	8674.668	11318.608	7396.893
36	-1195.0	8739.466	11122.432	10745.763	14707.441	9297.102
37	16913.0	12377.353	14185.195	13759.873	16556.438	12581.063
38	35311.0	24357.499	27357.167	25739.847	25512.416	24981.588
39	38197.0	32636.281	35596.365	33850.693	33969.922	31984.080
40	47365.0	38562.057	36821.281	37487.941	38424.810	34885.453
41	52489.0	41635.087	47214.314	43958.869	40239.542	44285.310
42	61567.0	37462.634	53548.320	43050.292	34515.846	47306.293
43	53666.0	36006.383	43788.725	38410.425	33967.920	40452.194
44	39763.0	27031.286	33430.629	29975.615	28393.254	30884.297
45	15835.0	17543.748	24639.193	22901.281	22165.720	25195.804
46	243.0	12193.934	15495.579	13632.055	13869.495	12594.390
47	-9797.0	8341.122	9463.889	9117.115	14011.386	6983.689
48	5660.0	10862.909	13215.261	11914.176	12737.976	10807.116
49	13790.0	17139.629	20366.811	18450.976	15552.975	17812.877
50	4618.0	23760.010	23904.069	24306.054	25723.441	21355.956

model	USBR Water Accounting	disalexi	eemetric	ensemble	ptjpl	seebop
51	35165.0	33887.003	30881.843	32012.443	32947.318	29418.262
52	52368.0	45224.300	45124.939	41763.527	35814.690	41912.507
53	53077.0	44986.102	52438.724	42514.329	35012.056	45564.687
54	59876.0	43141.003	52913.496	40304.143	31440.860	44585.221
55	53005.0	40317.458	44644.780	34855.009	25575.572	37964.307
56	39137.0	29390.121	31840.229	27154.059	22870.951	28763.858
57	19871.0	20590.107	25960.840	20653.920	17248.146	22449.898
58	4433.0	10364.095	14623.682	12092.205	11535.654	12216.609
59	5085.0	7391.136	11095.124	10039.660	11612.988	9661.076

Appendix 2-B: Linear Regression Results of OpenET models monthly Consumptive Use Estimates for PVID compared to USBR's Monthly Consumptive Use 2016-2021

DisALEXI vs USBR Consumptive Use eeMETRIC vs USBR Consumptive Use

OLS Regression Results										OLS Regression Results									
Dep. Variable: USBR Water Accounting R-squared: 0.900										Dep. Variable: USBR Water Accounting R-squared: 0.912									
Model: OLS Adj. R-squared: 0.899										Model: OLS Adj. R-squared: 0.911									
Method: Least Squares F-statistic: 523.4										Method: Least Squares F-statistic: 604.5									
Date: Mon, 19 Feb 2024 Prob (F-statistic): 1.03e-30										Date: Mon, 19 Feb 2024 Prob (F-statistic): 2.31e-32									
Time: 08:57:52 Log-Likelihood: -612.98										Time: 08:57:53 Log-Likelihood: -609.07									
No. Observations: 60 AIC: 1230.										No. Observations: 60 AIC: 1222.									
Df Residuals: 58 BIC: 1234.										Df Residuals: 58 BIC: 1226.									
Df Model: 1										Df Model: 1									
Covariance Type: nonrobust										Covariance Type: nonrobust									
coef	std err	t	P> t	[0.025	0.975]					coef	std err	t	P> t	[0.025	0.975]				
const	-1.43e+04	1930.692	-7.408	0.000	-1.82e+04	-1.04e+04					const	-1.672e+04	1887.290	-8.860	0.000	-2.05e+04	-1.29e+04		
disalexi	1.6283	0.071	22.877	0.000	1.486	1.771					ee metric	1.5038	0.061	24.586	0.000	1.381	1.626		

Ensemble vs USBR Consumptive Use

PTJPL vs USBR Consumptive Use

OLS Regression Results										OLS Regression Results									
Dep. Variable: USBR Water Accounting R-squared: 0.905										Dep. Variable: USBR Water Accounting R-squared: 0.759									
Model: OLS Adj. R-squared: 0.904										Model: OLS Adj. R-squared: 0.755									
Method: Least Squares F-statistic: 555.1										Method: Least Squares F-statistic: 182.7									
Date: Mon, 19 Feb 2024 Prob (F-statistic): 2.18e-31										Date: Mon, 19 Feb 2024 Prob (F-statistic): 1.41e-19									
Time: 08:57:53 Log-Likelihood: -611.39										Time: 08:57:53 Log-Likelihood: -639.43									
No. Observations: 60 AIC: 1227.										No. Observations: 60 AIC: 1283.									
Df Residuals: 58 BIC: 1231.										Df Residuals: 58 BIC: 1287.									
Df Model: 1										Df Model: 1									
Covariance Type: nonrobust										Covariance Type: nonrobust									
coef	std err	t	P> t	[0.025	0.975]					coef	std err	t	P> t	[0.025	0.975]				
const	-1.936e+04	2069.737	-9.356	0.000	-2.35e+04	-1.52e+04					const	-2.297e+04	3806.529	-6.034	0.000	-3.06e+04	-1.54e+04		
ensemble	1.7734	0.075	23.562	0.000	1.623	1.924					ptjpl	2.0551	0.152	13.518	0.000	1.751	2.359		

geeSEBAL vs USBR Consumptive Use

SIMS vs USBR Consumptive Use

OLS Regression Results										OLS Regression Results									
Dep. Variable: USBR Water Accounting R-squared: 0.844										Dep. Variable: USBR Water Accounting R-squared: 0.862									
Model: OLS Adj. R-squared: 0.841										Model: OLS Adj. R-squared: 0.879									
Method: Least Squares F-statistic: 313.8										Method: Least Squares F-statistic: 431.5									
Date: Mon, 19 Feb 2024 Prob (F-statistic): 4.52e-25										Date: Mon, 19 Feb 2024 Prob (F-statistic): 1.52e-28									
Time: 08:57:53 Log-Likelihood: -626.40										Time: 08:57:53 Log-Likelihood: -618.14									
No. Observations: 60 AIC: 1257.										No. Observations: 60 AIC: 1240.									
Df Residuals: 58 BIC: 1261.										Df Residuals: 58 BIC: 1244.									
Df Model: 1										Df Model: 1									
Covariance Type: nonrobust										Covariance Type: nonrobust									
coef	std err	t	P> t	[0.025	0.975]					coef	std err	t	P> t	[0.025	0.975]				
const	-1.818e+04	2676.121	-6.793	0.000	-2.35e+04	-1.28e+04					const	-1.902e+04	2327.318	-8.173	0.000	-2.37e+04	-1.44e+04		
geesebal	1.7951	0.101	17.714	0.000	1.592	1.998					sims	1.8281	0.088	20.773	0.000	1.652	2.004		

SSEBop vs USBR Consumptive Use

OLS Regression Results									
Dep. Variable: USBR Water Accounting R-squared: 0.905									
Model: OLS Adj. R-squared: 0.904									
Method: Least Squares F-statistic: 555.7									
Date: Mon, 19 Feb 2024 Prob (F-statistic): 2.13e-31									
Time: 08:57:53 Log-Likelihood: -611.36									
No. Observations: 60 AIC: 1227.									
Df Residuals: 58 BIC: 1231.									
Df Model: 1									
Covariance Type: nonrobust									
coef	std err	t	P> t	[0.025	0.975]				
const	-1.658e+04	1961.674	-8.453	0.000	-2.05e+04	-1.27e+04			
seebop	1.7022	0.072	23.572	0.000	1.558	1.847			

CHAPTER 3: EVALUATING USBR’S FALLOWING SAVINGS CALCULATION THROUGH THE PVID FALLOWING PROGRAM USING EVAPOTRANSPIRATION DATA

Abstract

In response to a record drought along the Colorado River, the United States Bureau of Reclamation (USBR) has set aside funding to incentivize increased fallowing based upon the amount of water saved. However, USBR employs a water balance method at the district level for calculating water savings that assumes zero consumptive use in fallowed fields, potentially overestimating water conservation. To demonstrate this risk, remotely sensed evapotranspiration (ET) data was used to calculate an alternative fallowing savings using a long-term fallowing program in the Palo Verde Irrigation District (PVID). Fields in PVID were divided into cropped and fallowed fields and the respective average ET of both categories over the years 2019 to 2021 were calculated. Fallowing savings were calculated as the yearly difference between cropped field ET and fallowed field ET and these savings were then compared to USBR’s approach. Using the alternative ET approach, USBR’s estimated annual savings at the field level are overestimated by 14% on average (ranging from 4%-26% for the three years of analysis), as a result of not accounting for consumptive use on fallowed fields—which averaged 1 acre-foot/acre. Any amount of overestimate caused by USBR’s approach would result in missed savings targets as well as overpayment for savings. Although ET models are not fully intended for measurement of idle ground ET, which might represent a limitation of our results, this study demonstrates the potential for using remote sensed data to improve water accounting at finer spatial scales.

Introduction

The Colorado River supplies water to seven U.S. states, several tribes, and Mexico. These users are currently allocated 15 million acre-feet of water from the river, however, this allocation exceeds the actual annual supply of the river (Stern and Sheikh 2019). This supply and demand imbalance is only projected to grow as climate change studies project that the Colorado River's supplies will decline in the future (Lukas and Payton 2020). Negative outcomes along the river are already occurring, the rivers overallocation along with a recent long-term drought has greatly reduced storage in Lake Powell and Lake Mead, the two largest reservoirs in the U.S. (Gangopadhyay et al. 2022). USBR projections estimate that without intervention both reservoirs may potentially reach dead pool elevations in the coming years, where water levels lower to the point that deliveries downstream would no longer be possible. In response to this risk, the Federal government called for the conservation of 2 to 4 million acre-feet of water along the river beginning in 2023 (James 2022). The stakeholders along the Colorado River came to an agreement on water cuts in May 2023, heavily relying on land fallowing to produce adequate water savings to protect the reservoirs (Flavelle 2023).

Land fallowing is a common method for water conservation, involving halting irrigation on normally productive agricultural lands (Clay et al. 2019; Medellin-Azuara et al. 2023). Large-scale fallowing along the Colorado River began in the early 2000s for the purposes of transferring agricultural water to Southern California urban users through a program known as the Quantification Settlement Agreement (QSA) (PPIC 2018). Additional fallowing along the Colorado River began in 2005 in the Palo Verde Irrigation District (PVID) to again shift agricultural supplies to urban Southern California. Due to the interstate and international nature

of water rights to the Colorado River, the United States Bureau of Reclamation (USBR) plays a role in managing and accounting for fallowing programs along the river (USBR 2022).

As already decided by stakeholders (Flavelle 2023), fallowing is going to play a major role in achieving the conservation goals of the 2023 Colorado River agreement due to its effectiveness and relatively easy implementation. To incentivize conservation, USBR, via the Lower Colorado River Basin System Conservation and Efficiency Program, has already set payments for land fallowing at \$330 per acre-foot of water saved for a one-year agreement with a grower, \$365 per acre-foot for two years, and \$400 per acre-foot for a three-year commitment. This program design of paying specific amounts of money for realized water savings necessitates accurate water saving accounting. On-going fallowing programs, like the PVID program, are a useful data point for understanding how water savings accounting will be done and potential risks related to that accounting.

But while water conservation will be paid individually to each farmer, the quantification of savings is determined with a water accounting approach at the irrigation district. USBR quantifies savings from the PVID fallowing through the use of an Irrigation Use Factor (IUF) (USBR 2022). The IUF methodology distributes all of the consumptive use in a given irrigable area to irrigated fields while assuming that fallowed fields have zero consumptive use. This methodology has the potential to overestimate savings, if there is any evapotranspiration from fallowed fields as demonstrated by recent studies (Anderson et al. 2018; Senay et al. 2017; Paw U et al. 2019; Medellín-Azuara et al. 2018), resulting in both overpayments to farmers as well as inadequate water savings in Lake Mead and Lake Powell, an important concern when the volumes of water saved need to be accurate to protect reservoir elevations.

Until recently, estimating consumptive use of fallowed fields has been difficult due to a lack of field-level crop and water use data. Historical water use data is available for a subset of fields in the form of applied water volumes. However, this data does not account for the large amounts of water that flow off of fields and into canals which is necessary to measure consumptive use. Evapotranspiration (ET) estimation through remote sensing is an alternative way to measure the consumptive use of individual fields and compare use between fallowed and cropped fields without the need for comprehensive water measurement systems that do not currently exist. As a long-term fallowing program, PVID represents a test case to explore how the use of ET data for quantifying fallowing savings may inform savings as calculated by USBR. In this chapter I compare fallowing water savings as calculated through USBR's IUF approach with estimates from an ET-based approach. IUF values will be collected directly from USBR fallowing reports for PVID and the ET fallowing savings will be calculated through the difference of average fallowed field ET and average cropped field ET. Results will provide an estimate for the risk that USBR's approach creates by ignoring fallowed field water use which may then be used to adjust estimated savings or fallowing payment amounts.

Methods

Current Quantification of Fallowing Water Savings

USBR estimates the amount of water savings in PVID using an irrigation use factor estimate which divides total consumptive use by total irrigated acres. PVID's total consumptive use is defined as PVID's total diversions from the Colorado River as measured at the PVID diversion dam minus the total return flows to the Colorado River as measured by eight spillways and three drainage ditches (Owen-Joyce and Kimsey 1987) (Equation 2). This consumptive use is then divided by PVID's total irrigated or non-fallowed acres (Equation 3). This results in an

acre-ft/acre water usage factor that is then multiplied by the total amount of fallowed acres to calculate a volumetric water savings. Embedded in this calculation is the assumption that fallowed fields have zero consumptive use.

$$\textbf{\textit{Total PVID Consumptive Use}} = \textbf{PVID Diversions} - \textbf{PVID Return Flows}$$

Equation 2. PVID Consumptive Use

$$\textbf{\textit{USBR Fallowing Savings Estimate}} = \frac{\textbf{\textit{Total PVID Consumptive Use}}}{\textbf{\textit{Total Irrigated Acres}}}$$

Equation 3. USBR's Irrigation Use Factor Fallowing Savings Estimate

Studies have shown that fallowed fields can consume a small amount of water within irrigation districts (Anderson et al. 2018; Senay et al. 2017; Paw U et al. 2019; Medellín-Azuara et al. 2018). PVID has several characteristics that make it particularly prone to irrigation water getting consumed on fallowed fields. The majority of fields in PVID are flood irrigated which increases the risk of spillover between fields. The average groundwater depth in PVID is approximately 10 feet although this varies seasonally and there is evidence that the groundwater mounds in the summer and acts as a reservoir that returns water to the river in the winter. This groundwater mounding caused by irrigations may also be a source of consumptive use on fallowed lands (Morway, Gates, and Niswonger 2013). The exact source of consumptive use on fallowed fields is a topic of further study in PVID but for the purposes of this analysis it is assumed that the water consumed by fallowed fields originates from diversions. The following conceptual model (CM) further motivates the theory behind this analysis through a 5-field irrigation district. Each field is a 1-acre flood-irrigated alfalfa field consuming 5 acre-feet/acre/year (AF/A/Y) of water. Initially, the total diversion for the system is 50 acre-feet (AF) and the total return flows is 25 AF, resulting in a total consumptive use of 25 AF (Figure 5).

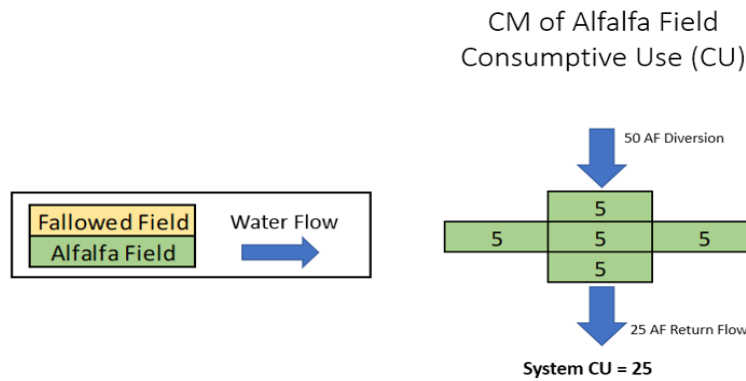


Figure 5. Conceptual Model of Alfalfa Field Consumptive Use

The following depicts what may occur if the center field is turned into fallow, with the assumption that the CU on that fallowed field is due to irrigation water infiltration. This fallowed field consumes 1 AF/A/year of water while the alfalfa fields continue to consume 5 AF/A/year. The total system CU drops from 25 AF to 21 AF. From this example the savings of changing a alfalfa field into fallow is the difference of average CU on the alfalfa field (5 AF) to the CU on the fallowed field (1 AF), or 4 AF (Figure 6).

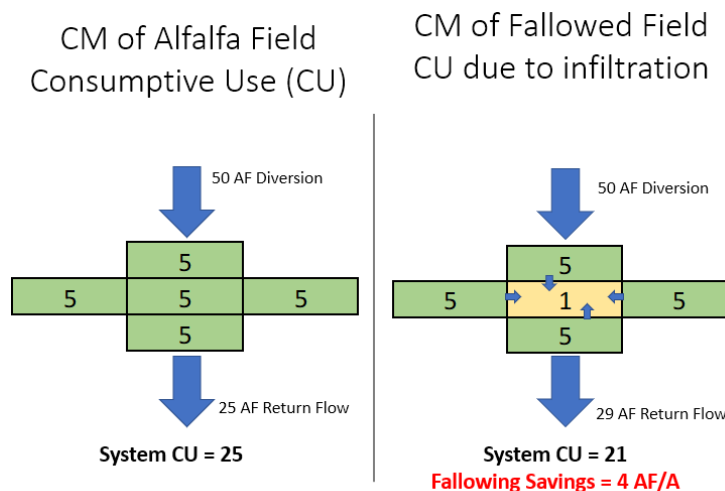


Figure 6. Conversion of Alfalfa Field to Fallow Conceptual Model

Under USBR's irrigation use factor method (Equation 3), the 21 AF of CU in the fallowed field model is solely attributed to the four acres of alfalfa fields (Equation 4).

$$5.25 \text{ AF/A} = \frac{21 \text{ AF}}{4 \text{ Acres}}$$

Equation 4. Conceptual Model Irrigation Use Factor Example

This has the unintended effect of increasing the amount of CU on the cropped fields from 5 to 5.25 AF/A while the true savings value is 4 AF/A in this scenario. The larger 5.25 AF/A value is assumed to represent the amount of water each acre of fallowed land saves, thereby increasing the calculated fallowing savings (Figure 7).

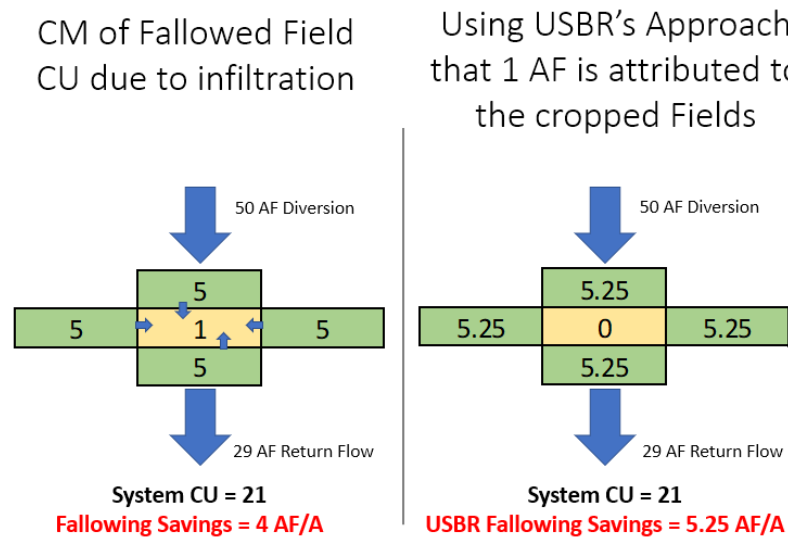


Figure 7. Fallowing Savings Conceptual Model Under IUF Approach

Study Area and Crop Data

As discussed in Chapter 1, PVID is an unquantified, first-priority district, home to 88,000-acres of agricultural land located in Blythe, California on the border of Arizona (Guetz 2023). As an unquantified user of Colorado River water, PVID pays for water based on irrigated acreage as opposed to volume of water consumed. As a result, it costs farmers \$61 per acre to irrigate any amount of water, effectively incentivizing the use of flood irrigation. PVID is designed as a closed system, all fields have canals that eventually return water to the Colorado

River so that overflows from flood irrigation are not wasted. From a cropping standpoint, alfalfa takes up approximately 60% of the acreage in PVID while fallowed acreage represents another 10% to 25% depending on the year. Annual crops such as cotton or melons, other grasses, and idled fields make up the remaining area.

Quarterly crop identification data at the field-level in PVID was collected by LandIQ, Inc. between 2019 and 2021. Through a combination of remote-sensed image analysis and on-the-ground verification, every field in PVID was categorized into its given crop type by quarter. The image analysis involved the use of Normalized Difference Vegetation Index (NDVI) timeseries curves to identify crops. NDVI is a measure of photosynthetic activity and vegetation vigor (Huang et al. 2021) and is computed using Equation 5 where Red represents the intensities of reflected red light and NIR represents the intensity of reflected near infrared light:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Equation 5. NDVI Formula

NDVI identifies vegetation because chlorophyll reflects more NIR and green light while also absorbing more red light compared to non-vegetation. Equation 5 results in values from -1 to +1, with more positive values indicating greater plant vigor. LandIQ, Inc. used daily NDVI data from commercial satellite imagery (maybe state the name and the pixel size) to create unique NDVI curves for the most common crop types in PVID for classification purposes. These crops included alfalfa, fallow, wheat, leafy greens, onions, Sudan grass, garlic, potatoes, cotton, corn, melons, squash, and broccoli. Each quarter approximately one-third of fields were used for on-the-ground verifications to ensure classification accuracies of greater than 97%. Crop data was provided in the form of shapefiles where each shape represents a contiguous field of as small as 2 acres with its corresponding crop type for that quarter.

The use of aerial imagery and NDVI curves cannot differentiate between lands that are idle or fallowed. Under PVID's fallowing program, fallowed lands must be disced and kept free of plant growth which may not be the case on idle lands (USBR 2022). Idle lands are also commonly idled due to low productivity or other practical reasons. Separation of idle lands from fallowed lands was done using fallowing verification reports produced yearly by USBR. PVID submits a yearly map of all fallowed fields to USBR who then verifies 5% of the fields and produces a pdf report containing the map of fallowed lands. This map was digitized and used to manually verify which lands identified as fallowed by Land IQ, Inc. were actually fallowed as defined by the fallowing program. In the years evaluated for this study, no fields were found to be cropped when they were enrolled as fallowed.

ET Data

ET is the transfer of water vapor to the atmosphere through the combined processes of evaporation from the Earth's surface and transpiration through plant tissues. The ET that occurs as a result of agricultural field irrigation is equivalent to CU and thus provides a methodology for measuring field level CU (Farahani et al. 2007). OpenET launched in 2021 to provide accurate and accessible ET data across the Western United States. OpenET provides access to six different ET models, as well as an ensemble model, most of which calculate ET using a surface energy balance approach (Melton et al. 2022). These models predict ET from the classical energy balance where ET is set equal to net radiation (R_n) minus heat lost to the soil (G) and heat lost to the air (H). The residual energy is assumed to have been used to convert water to water vapor, or ET (Junior et al. 2013).

OpenET's eeMETRIC model was chosen as the model for estimating ET at the field scale in this study given the results found in Chapter 1 that eeMETRIC adequately reflects USBR's

consumptive use estimates across the valley. Although an estimate, USBR's value is used in official Colorado River water accounting and is therefore the best available datapoint available for valley-wide consumptive use. The use of eeMETRIC is further supported through a recent comprehensive assessment of OpenET's model accuracy which concluded that eeMETRIC performs best of all OpenET models in arid regions with long-term crops like alfalfa (Volk et al. 2024). Additionally, eeMETRIC has been officially adopted by stakeholders in the Upper Colorado River Basin for future water use studies.

An important input to the ET models is on-the-ground weather station data through either California Irrigation Management Information System (CIMIS) stations or gridMET, another remote sensed dataset. This weather data provides humidity, precipitation, wind, as well as a second data point for temperature and radiation data to compute ET (Hart et al. 2009). In the cases that remote-sensed imagery is blocked by clouds, and for the days in-between satellite passes, weather station data can be used to interpolate and avoid data gaps. Satellite pixels around weather stations also serves as a point of calibration for ET models (Allen 1996). CIMIS data was chosen as the accompanying weather dataset for this study because PVID is home to three CIMIS stations located across the valley.

Data Processing

Quarterly crop data was joined by matching field shapes or “geometries” to build out a yearly data frame for 2019, 2020, and 2021. To control for inconsistent water use related to crop rotations and transitioning fields in and out of fallow, only fields planted with the same crop for the entire year were included in this analysis. Approximately 70% of fields in PVID remain the same crop the entire year which predominantly includes the highest water using fields, alfalfa, and the lowest, fallow. Actions on the remaining fields, including variable crop rotations, and

field maintenance, are not consistent year-to-year and therefore add too much randomness to a given year's water use. The shapefiles of annual fields were then combined with eeMETRIC ET data obtained through OpenET's API. CIMIS was set as the reference ET for eeMETRIC because of the presence of three CIMIS stations across PVID. OpenET data was downloaded at the monthly time step using the annual fields shapefiles. The monthly ET data was then summed across years to obtain yearly consumptive use estimates by field. The average yearly ET on fallowed fields and cropped fields were then compared to estimate fallowing savings. All ET data was corrected for the monthly precipitation across the valley as measured by the PVID CIMIS stations.

Estimation of Water Saving Through Remote Sensing

To estimate water savings for fallowed fields as measured by ET, the difference in CU on fallowed fields and cropped fields was computed. The CU of each field in PVID was calculated by computing the average pixel-level ET within a field boundary as defined by PVID's crop shapefiles. Field type was then averaged by fallowed or non-fallowed crop identifications and summed over a year to obtain average consumptive use estimates for fallowed fields and cropped fields. Mean annual fallowed field consumptive use estimate was subtracted from the mean annual cropped field consumptive use estimate to calculate an alternative fallowing savings per acre (Equation 6). This ET estimate of fallowing savings was then directly compared with the savings calculated via USBR's IUF approach to assess the difference between the approaches. Yearly IUF factors and total fallowed acreage were obtained directly from yearly fallowing verification reports published by USBR.

$$ET \text{ Fallowing Estimate} = (Irrigated \text{ Fields}_{Avg \text{ ET}} - Fallowed \text{ Fields}_{Avg \text{ ET}})$$

Equation 6. ET Fallowing Savings Estimate

Results

The yearly ET of all fields in PVID can be seen below in Figure 8. PVID consists of about 88,000 acres divided into approximately 2600 distinct field polygons. Yearly ET values are plotted on a red to blue scale where blue colors represent higher ETs while red colors represent low ETs. All maps are shown with the same data scale from 0.3 AF/A to 6.2 AF/A. Fallowed fields are shown in bold to help depict the general location of fallowed fields as well as there generally low ET values as seen in orange and red field color. There are fallowed fields throughout the valley but they do tend to cluster towards the edges of the valley as seen in the clusters of fallowed fields in the southern edge, northwest edge, and northeast edges of PVID. Fields move in or out of fallow within these clusters overtime, but the clusters generally remain consistent. Fields in blue are predominately alfalfa or other hay crops while fields in yellow to orange tend to be seasonal crops that are planted for a portion of the year. Blue alfalfa fields are heavily prevalent throughout the middle and western sides of the valley.

Yearly distributions of ET are relatively consistent from 2019 through 2021 as shown by the three most common crops in PVID (Figure 9). Although there are long tales in the distributions, for alfalfa the median yearly ET in AF/A/Y changes from 5.19, to 5.26, to 4.97 from 2019 through 2021. The 25th percentile changes from 4.82, to 4.85, to 4.48 and the 75th percentile for alfalfa changes from 5.51, to 5.60, to 5.32 from 2019 through 2021. For fallow fields the median ET changes from 1.03, to 1.38, to 1.35 while for forage grass the median ET changes from 4.00, to 3.69, to 3.77, from 2019 through 2021.

Annual ET of Fields in PVID 2019 to 2021 (Fallowed Fields in Bold)

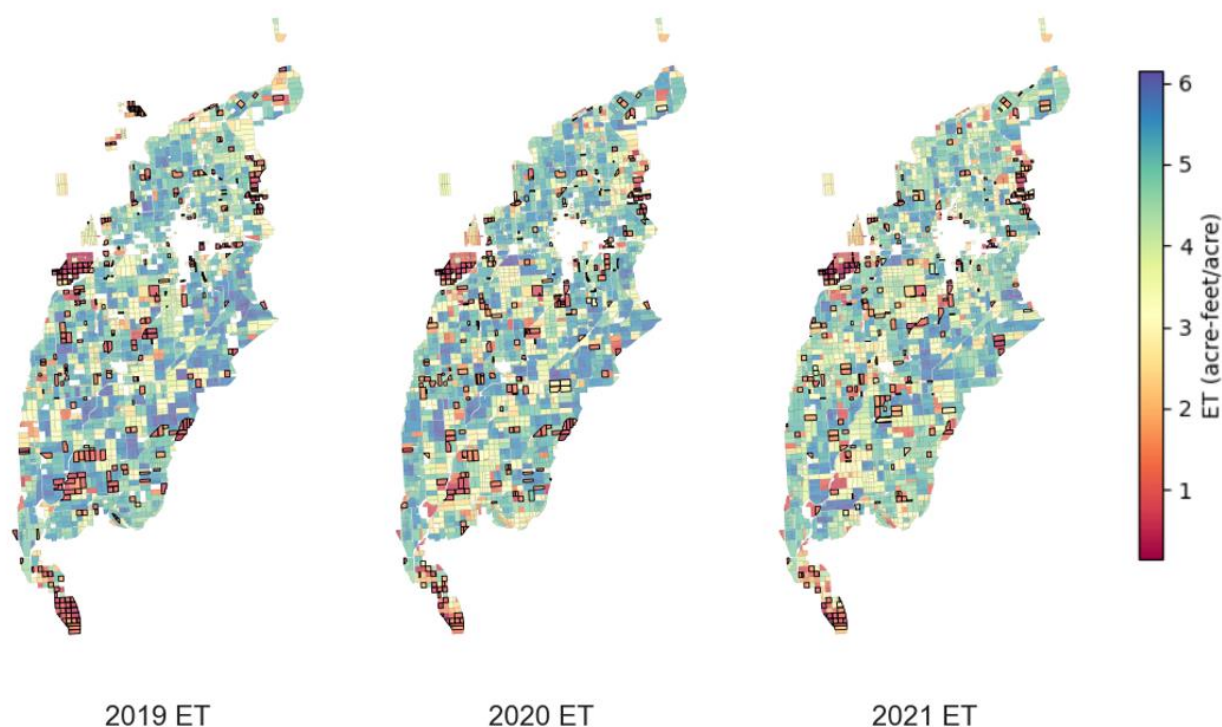


Figure 8. Annual Evapotranspiration of Fields in the Palo Verde Irrigation District 2019-2021

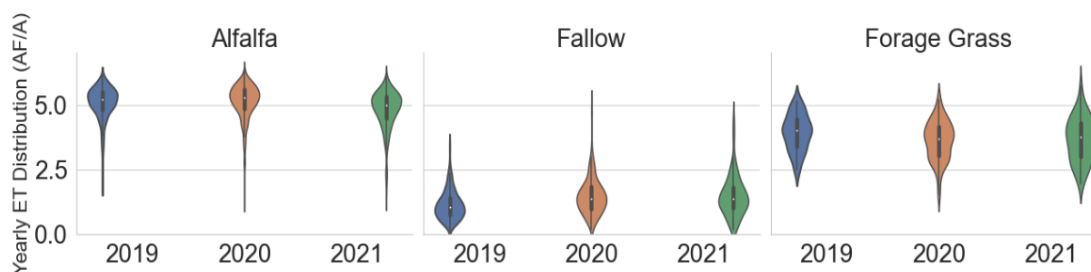


Figure 9. Yearly ET Distribution of the Most Common Palo Verde Irrigation District Crops (2019-2021)

Alternative Fallowing Savings Results

The results of the alternative fallowing savings analysis, in comparison to USBR's estimates, are shown in Table 2. PVID Fallowing Program Water Savings Estimate Method Comparison. The average IUF from 2019 to 2021 was 4.37 acre-feet/acre (AF/A) with 2021 recording the highest IUF and 2020 the lowest. Fallowed field ET averaged 1.16 AF/A while

non-fallowed fields averaged 4.96 AF/A. Average non-fallowed field ET peaked in 2020 and was lowest in 2021. The peak coincided with the best agreement between ET calculated savings and USBR's calculated savings (3.66% difference) while the low coincided with the worst agreement between the two savings calculations (25.75% difference). Fallowed field ET was relatively consistent for the 2019-21 period, with a range of 1.15 to 1.18 AF/A. Therefore, differences in ET calculated fallowing savings was primarily driven by variable non-fallowed field ET. The eeMETRIC model estimates an average of 14% less water saved from fallowing as compared to USBR's IUF approach.

Table 2. PVID Fallowing Program Water Savings Estimate Method Comparison

	USBR Calculated Irrigation Use Factor (Acre- feet/Acre (AF/A))	Average Fallowe d Field ET (AF/A)	Average Non- Fallowed Field ET (AF/A)	Average Savings per Fallowed Acre (AF/A)	Percent Reduction in Savings Using ET
2019	4.29	1.16	4.82	3.66	-14.60%
2020	4.23	1.18	5.26	4.08	-3.66%
2021	4.60	1.15	4.8	3.65	-25.75%
Avg	4.37	1.16	4.96	3.80	-14.04%

Evaluating these differences in fallowing savings using the PVID fallowing program reveals the potential risk introduced by USBR's IUF methodology. Fallowed land acreage in PVID was approximately 10,376 acres from 2019 through 2021. This three-year period coincided with stable fallowing calls resulting in the same acreage fallowed for each year. Assuming the ET methodology is the true value, the IUF methodology overestimated fallowing savings by an average of 14.0% in 2019 through 2021, with a range of 3.7% to 25.8%. At the water price of 400\$/AF USBR will pay for a three-year fallowing agreement, this results in a cumulative overpayment of \$7 million and a reduction in savings of 20,025 AF (Table 3).

Table 3. Comparison of Following Savings Between USBR's and an ET-Based Approach

CY	CY Fallowed Acreage	Fallowing Savings Based on IUF Factor in Table 2 (AF)	Fallowing Savings Based on ET Calculated Savings in Table 2 (AF)	Potential Water Savings Overestimate under IUF	Overpayment Based on Overestimated Savings
2019	10,376	44,513	37,976	6,537	\$2,614,800
2020	10,376	43,890	42,334	1,556	\$622,592
2021	10,376	49,804	37,872	11,932	\$4,772,800
Average	10,376	46,069	39,394	6,675	\$2,670,064
Cumulative	31,128	134,207	125,182	19,025	\$7,362,192

Discussion

Evaluating PVID's savings from 2019 to 2021 resulted in a range of USBR overestimates, from 1,556 AF to 11,932 AF. Financially this overestimate range results in overpayment from \$622,592 to \$4,772,800. This range in water savings overestimate as well as overpayment is driven by differences in cropped field ET because fallowed field ET was stable between these three years. Cropped field ET peaked in 2020, potentially due to the planting of cotton fields not present in 2019 and 2021, since alfalfa acreage was similar between the years. This year also coincided with higher peak air temperatures compared to 2019 and 2021. This peak in cropped ET drove up the expected fallowing savings. Non-fallowed field water use in 2019 and 2021 was separated by 0.02 AF/A while fallowed field water use was separated by 0.01 AF/A. Despite these close values, fallowing savings overestimates differed by 5,500 AF which was driven by a 5,500 AF lower fallowing savings in 2019 as calculated by USBR.

A benefit of SEB ET models is that they do capture water loss from bare land but modeled values are sensitive to calibration and data inputs (R. G. Allen et al. 2013). The METRIC model has been found to measure higher ET than other models on fallowed fields and alfalfa fields. Of multiple models evaluated, including SIMS, DisALEXI, and two METRIC

approaches, only a subset of models agreed with each other (Medellín-Azuara et al. 2018; Tasumi 2019). It is important to approach a true value for field level water use through the continual refinement of model inputs but the potential variability in calibration and model inputs does highlight a benefit of using OpenET models. OpenET models are publicly available and useable by all stakeholders for evaluation and potential agreement. Despite this benefit there is still a need in PVID for OpenET model assessment against on-the-ground ET data from eddy-covariance stations or lysimeters to verify field-level data results.

ET models measure the water consumption within a field but they cannot separate out where the consumed water originated from. For example, fallow field consumed water may come from diversions, groundwater, or precipitation (Condon and Maxwell 2019). In this study we corrected ET for average precipitation across the valley but we cannot differentiate between what may be groundwater or diverted water consumption on fallowed fields. From the perspective of USBR's IUF approach, only diverted water that is consumed by fallowed fields would inflate savings. A comprehensive study using ET and subsurface data would be needed to properly breakout these components of fallowed field consumptive use (Ryken, Gochis, and Maxwell 2022). Any contribution of groundwater to fallow field ET would ultimately decrease the actual value of diverted water consumed by fallowed fields as reported in this study.

Conclusion

USBR has called for water savings through fallowing along the Colorado River to protect key elevations at Lake Mead and Lake Powell but this calls into question how exactly water saving estimates are computed. With the catastrophic risk of dead pool elevations possible it is important that anticipated water savings are actualized. Using OpenET ET data I show that USBRs default method for fallowing savings estimates has the potential to overestimate savings,

leading to less water for the reservoirs and overpayment from USBR. This overestimate results directly from ET on fallowed fields which serves to reduce the effectiveness of fallowed savings since these fields are assumed to have zero consumptive use. Verification is needed to demonstrate that these fields are consuming diverted water but with the threat of dead pool elevations, the potential for an overestimate should be fully evaluated to ensure protection of reservoir levels.

The lack of measurement or imperfect measurement of water use on agricultural lands is a common hurdle for conservation programs which is why regional water use may be used to estimate savings. It is important that these programs understand the risks associated with regional estimates with regards to their particular conservation targets. ET data, while still an estimated value, can be a useful data point to help inform conservation at the field-level. In the case of fallowing saving estimates from USBR, ET data shows that there is a risk for inadequate conservation savings intended to protect Lake Mead from reaching critically low elevations.

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CHAPTER 4: EXPLORATION OF FACTORS THAT INFLUENCE FALLOWED FIELD WATER USE WITHIN THE PALO VERDE IRRIGATION DISTRICT FALLOWING PROGRAM

Abstract

In response to a record drought along the Colorado River, the United States Bureau of Reclamation (USBR) has set aside funding to incentivize agricultural land fallowing to produce water saving and protect water elevations in Lake Mead and Lake Powell. Fallowing is a well-known and accepted method for producing agricultural water savings but studies have shown that fallowed fields consume some water which reduces the water savings impact of fallowing. Understanding the different factors that affect this fallowed field consumption can be key in minimizing their water use. This study evaluated traits that potentially correlate with consumptive use on fallowed fields using the Palo Verde Irrigation District Fallowing Program as a study site. Using evapotranspiration (ET) data from OpenET and crop shapefiles I show that fallowed field consumptive use is generally positively and statistically significantly correlated with the ET of its surrounding fields, smaller field size, and field narrowness, while being negatively and statistically significantly correlated with time fallowed. Future and on-going fallowing programs may be able to be made more efficient by adopting regulations to prioritize field traits that minimize fallowed water consumption. This could include ensuring larger and squarer fallowed fields, increasing the allowable time that a field can be fallowed, and locating fallowed fields away from high water use crops.

Introduction

Land fallowing is a common and well accepted method for achieving water conservation targets on farmlands (Clay et al. 2019; Medellin-Azuara et al. 2023). In the wake of an historic 22-year drought (Gangopadhyay et al. 2022) along the Colorado River, the United States Government has set aside billions of dollars to help conserve 2 to 4 million acre-feet of water per year along the river (Flavelle 2023). A significant portion of these monies will go toward fallowing payments for farmers. Compared to other agricultural water conservation measures, land fallowing is easily implementable, relatively affordable, and produces higher water savings (Song and Song 2023). Fallowing has been regularly implemented along the Colorado River, particularly in the Imperial Irrigation District, the Palo Verde Irrigation District, and Bard Water District (Medellin-Azuara et al. 2023; MWD 2021). Imperial Irrigation District's fallowing programs have produced approximately 100 thousand acre-feet per year, Palo Verde Irrigation District's produces 10 to 25 thousand acre-feet per year, and Bard Water District's program produces about 6 thousand acre-feet of water per year. It is often assumed that fallowed fields have zero consumptive use, but studies have shown that fallowed fields can consume small amounts of water within irrigation districts (Medellin-Azuara et al. 2023; Fu et al. 2019; Zheng et al. 2016; Hunter et al. 2019; Lian et al. 2021). Fallowing programs regularly include a disking requirement to ensure that vegetation does not grow on the fields (USBR 2022) because any water consumption on fallowed fields represents losses in conserved water and potentially missed conservation targets. Understanding factors that influence the actual water consumption from a fallowed field can help improve the effectiveness and efficiency of current and future fallowing programs.

Consumptive use from fallowed fields has potentially several different sources. Spillover can occur from cropped fields to fallowed fields, either through surface or groundwater flows

(Morway, Gates, and Niswonger 2013). Surface flows are likely more of a concern for fallowed fields that may be a portion of or right next to larger cropped fields. Fallowed fields surrounded by higher water use crops or fields next to canals have higher potential for infiltration as water traverses the surface or subsurface of the fields (Fu et al. 2019; Ouyang 2009; LaHue and Linquist 2019). There is also a temporal factor that influences consumptive use on fallowed fields, recently fallowed fields have been shown to lose water through evaporation of soil column moisture (Hunter et al. 2019; Lian et al. 2021). Several of these traits can be explored in relation to fallowed field consumptive use given an appropriate study site and consumptive use dataset.

In this study I used evapotranspiration (ET) data as a measure of consumptive use to explore fallowed field consumptive use within a long-term fallowing program in the Palo Verde Irrigation District (PVID). A multiple regression analysis was performed to explore whether selected parameters have a significant correlation to fallowed field ET. These parameters will include: the consumptive use of fields surrounding a fallowed field, fallowed field adjacency to canals, fallowed field area, fallowed field perimeter squared over area ratio, and fallowed field age. The results of this study will be used to provide recommendations to improve the efficiency of on-going and future fallowing programs.

Methods

Study Area and Crop Fallowing Identification

As discussed in Chapter 1, PVID is an unquantified, first-priority irrigation district, home to 88,000-acres of agricultural land located in Blythe, California on the border of Arizona (Guetz 2023). As an unquantified user of Colorado River water, PVID pays for water based on irrigated acreage as opposed to volume of water consumed. As a result, it costs farmers \$61 per acre to irrigate any amount of water. This is a relatively inexpensive source of water with respect to

other sources in California, reducing the incentive to transition away from flood irrigation (Taghvaeian Saleh et al. 2018) which increases the risk of spillover between fields (Morway, Gates, and Niswonger 2013). From a cropping standpoint, alfalfa takes up approximately 60% of the acreage in PVID while fallowed acreage represents another 10% to 25% depending on the year. Annual crops such as cotton or melons, other grasses, and idled fields make up the remaining area.

Quarterly crop identification data at the field-level in PVID was collected by LandIQ, Inc. between 2019 and 2021 as described in Chapter 2 Methods. Through a combination of remote-sensed image analysis and on-the-ground verification of a third of fields, every field in PVID was categorized into its given crop type by quarter, including fallowed fields. Each quarter approximately one-third of fields were used for on-the-ground verifications to ensure classification accuracies of greater than 97%. Crop data was provided in the form of shapefiles where each shape represents a contiguous field of as small as 2 acres with its corresponding crop type for that quarter.

The use of aerial imagery and NDVI curves cannot differentiate between lands that are idle or fallowed. Idle lands are also commonly idled due to low productivity or other practical reasons. Separation of idle lands from fallowed lands was performed using fallowing verification reports produced yearly by USBR. PVID submits a yearly map of all fallowed fields to USBR who then verifies 5% of the fields and produces a pdf report containing the map of program fallowed lands. This map was digitized and used to manually verify which lands identified as fallowed by Land IQ, Inc. were actually fallowed as defined by the PVID fallowing program.

ET Data

Estimating ET through remotely sensed data is a common method for measuring field-level consumptive use when field-level consumptive use data is lacking like in in PVID. The ET that occurs as a result of agricultural field irrigation is equivalent to CU and thus provides a methodology for measuring field level CU (Farahani et al. 2007). OpenET launched in 2021 to provide accurate and accessible ET data across the Western United States. OpenET provides access to seven different ET models (Melton et al. 2022). These models predict ET from the classical energy balance where ET is set equal to net radiation (R_n) minus heat lost to the soil (G) and heat lost to the air (H). The residual energy is assumed to have been used to convert water to water vapor, or ET (Junior et al. 2013).

OpenET's eeMETRIC model was chosen as the model for estimating ET at the field scale in this study given the results found in Chapter 1 that eeMETRIC adequately reflects USBR's consumptive use estimates across the valley. Although an estimate, USBR's value is used in official Colorado River water accounting and is therefore the best available datapoint available for valley-wide consumptive use. The use of eeMETRIC is further supported through a recent comprehensive assessment of OpenET's model accuracy which concluded that eeMETRIC performs best of all OpenET models in arid regions with long-term crops like alfalfa (Volk et al. 2024). Additionally, eeMETRIC has been officially adopted by stakeholders in the Upper Colorado River Basin for future water use studies (UCRC 2022).

An important input to the ET models is on-the-ground weather station data through either California Irrigation Management Information System (CIMIS) stations or gridMET, another remote sensed dataset. This weather data provides humidity, precipitation, wind, as well as a second data point for temperature and radiation data to compute ET (Hart et al. 2009). In the

cases that remote-sensed imagery is blocked by clouds, and for the days in-between satellite passes, weather station data can be used to interpolate and avoid data gaps. Satellite pixels around weather stations also serves as a point of calibration for ET models (Allen 1996). CIMIS data was chosen as the accompanying weather dataset for this study because PVID is home to three CIMIS stations located across the valley.

Parameter Building for Regression Analysis

In order to perform a regression analysis between fallowed field ET and the selected parameters, each parameter was first calculated for every field. Parameters were selected based on the fact that they were measurable and associated with fallowed field water use based on previous studies. These parameters are described below:

- **Average ET of fields surrounding the fallowed field:** The consumptive use of fields surrounding a fallowed field was used as a proxy for applied water. Higher levels of applied water surrounding a fallowed field have been shown to increase the lateral flow potential into the fallowed field (Fu et al. 2019; Ouyang 2009). To compute the average ET of surrounding fields for every fallowed field, a spatial weighting with normalization approach was taken using Python 3.8, libpysal package version 4.5.1, geopandas version 0.9.0, and pysal version 1.14.4. A queen weighting approach with regularization was chosen as the method for spatial analysis. Queen weighting describes a type of spatial connection where every polygon neighboring the polygons of interest is linked to the polygon of interest (Rey et al. 2022). Regularization refers to the averaging of the variable of interest from the linked polygons, in this case ET, to control for fields that have more neighbors than others. For this study every field touching a given fallowed field was linked to the fallowed field. The average ET of every field touching the

fallowed field was then computed and that value was the ET lag of the given fallowed field. For example, a center field surrounded by four fields of 4.0, 5.0, 4.0, and 5.0 AF/A/Y of ET each, would have an ET lag of 4.5 AF/A/Y (Figure 10).

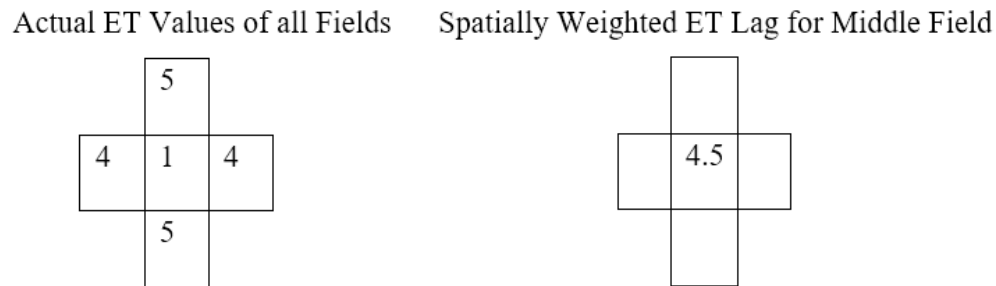


Figure 10. Spatial Weighting Calculation Example for Middle Field

- **Canal adjacency:** Unlined canals carrying water represent a potential for lateral flows into a fallowed field (Zheng et al. 2016). A shapefile of PVID canals was used to spatially link the shapefile of fallowed fields from PVID that were located adjacent to a canal resulting in values of 0 or 1, with 1 indicating the field is adjacent to a canal.
- **Fallowed field area:** Fallowed field area was included as small fields tend to be located at the edge of a fully cropped field as opposed to representing their own separate field. This design leaves very little barrier for lateral flows between fields. Field area was directly computed using the geometry of every field as captured by Land IQ, Inc. and then log-transformed to normalize the area distribution of the data.
- **Fallowed field square perimeter over area:** Fallowed field square perimeter over area is a metric that reflects fallowed field thinness. Squarer fields will have a square perimeter over area value closer to 16 while more rectangular fields will have larger square perimeter over area ratios. Similar to field area, thinner fields are more likely to be a part of a larger field that may be irrigated resulting in higher potential for lateral flows

into the fallowed portion of the field. Field area and perimeter were directly computed using the geometry of every field as captured by Land IQ, Inc.

- **Fallowed field consecutive years fallowed:** Fallowed field age or consecutive years fallowed was included because latent soil moisture, another source of ET, is often present in recently fallowed fields and has been shown to decrease overtime (Hunter et al. 2019; Lian et al. 2021). Fallowed field age was calculated by linking fields together that had been fallowed each year. LandIQ, Inc. provided crop identification data from 2019 to 2021 which were used in conjunction with pdf fallowing verification reports published by USBR to calculate fallowed field age. USBR's fallowing verification reports include a image of PVID fields with fallowed fields for that year highlighted. Three additional years of fallowing verification reports from 2016 to 2018 were digitized to further increase the history of the fallowed field age dataset.

Regression Analysis

Correlations were explored between fallowed field ETs and field traits including the sum of their neighboring field's ETs, fallowed field area, fallowed field canal adjacency, and fallowed field age using a linear multi-regression analysis. Each year of data from 2019 through 2021 was included in the analysis and analyzed separately. To aid in the interpretation of results, all parameters including the dependent variable, fallowed field ET, were scaled from 0 to 1 using the sklearn MinMaxScaler. This scaler measures the minimum and maximum values for each given column of data, subtracts the minimum from each datapoint, and divides by the range. The statsmodels package in Python was utilized to perform the multilinear regression between the selected parameters and fallowed field ET with an added coefficient (Equation 6).

$$F_{ET} = \beta_0 + F_{ET_{Lag}}\beta_1 + F_{Area}\beta_2 + F_{P^2/Area}\beta_3 + F_{Age}\beta_4 + F_C\beta_5 + e_i$$

Equation 6. Multiple Regression Formula

Where:

F_{ET} = Fallowed field yearly ET

$F_{ET_{Lag}}$ = Fallowed field yearly ET Lag

F_{Area} = Log(Fallowed field area)

$F_{P^2/Area}$ = Fallowed field square perimeter over area ratio

F_{Age} = Fallowed field age

F_C = Fallowed field canal adjacency

β = Coefficients

β_0 = Intercept

e_i = Error term

Results

Results of the Regression Analysis

The yearly ET of all fields within PVID for 2019 through 2021 are shown in Figure 11. Fields in bold are fields that were identified as fallowed for that year. Fields in red and orange had ET's of 2 acre-feet/acre/year and below while green and blue fields had ET's above 4 AF/A/Y. Fallowed fields occurred throughout the Valley but did tend to cluster next to each other and appeared regularly on the edges of the Valley. The ET range of all fields fell generally between 0.3 AF/A/Y to 6.2 AF/A/Y.

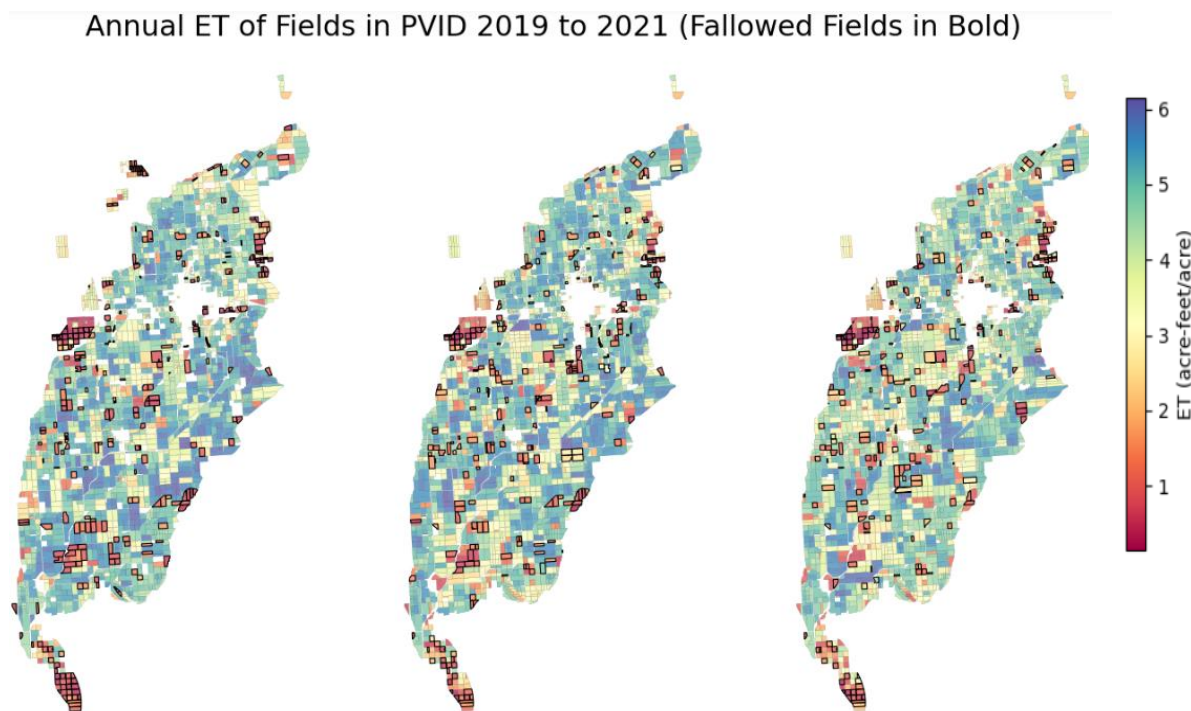


Figure 11. Annual ET of Fields in PVID 2019-2021 (Fallowed Fields are Shown Outlined)

Figure 12, Figure 13, and Figure 14 depict distribution plots of yearly ET on the x axis for different crops planted for the whole year. Within a year a given crop had a relatively large range of yearly ET and between years there was relative consistency in yearly ET for any given crop. Each year of data represents over 1000 alfalfa fields, over 150 fallow fields, over 50 forage grass fields and over 30 irrigated pasture fields. Fallow fields had median ET's of 1.0, 1.4 and 1.4 AF/A/Y for 2019, 2020 and 2021 respectively. Distributions of fallow field ET showed a wide range with minimums of 0.4, 0.2, and 0.3 and maximums of 3.1, 4.6, and 4.5 AF/A/Y for 2019, 2020, and 2021, respectively. Alfalfa, forage grass, and irrigated pasture had similar lower values of ET around 1 AF/A/Y while the high end values were generally separated by about 1 AF/A/Y from irrigated pasture, to forage grass, to alfalfa.

Yearly Crop ET Distributions for Annual PVID Crops 2019

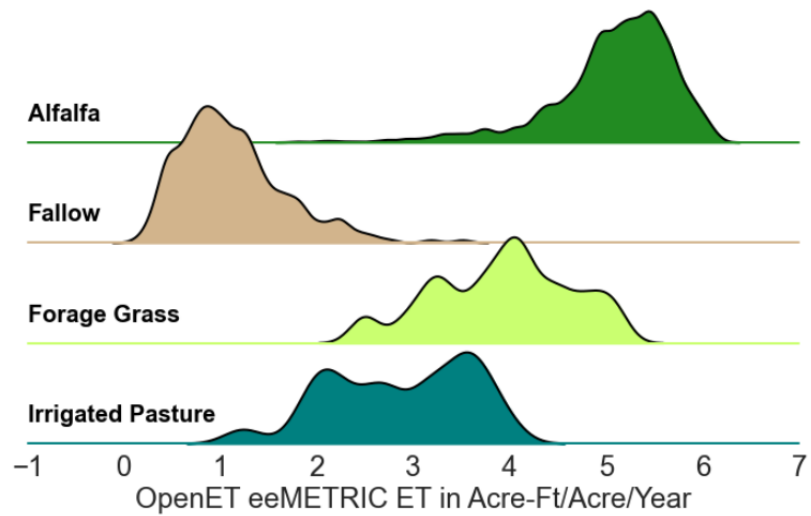


Figure 12. Distribution of Yearly ETs for Perennial Crops in PVID 2019

Yearly Crop ET Distributions for Annual PVID Crops 2020

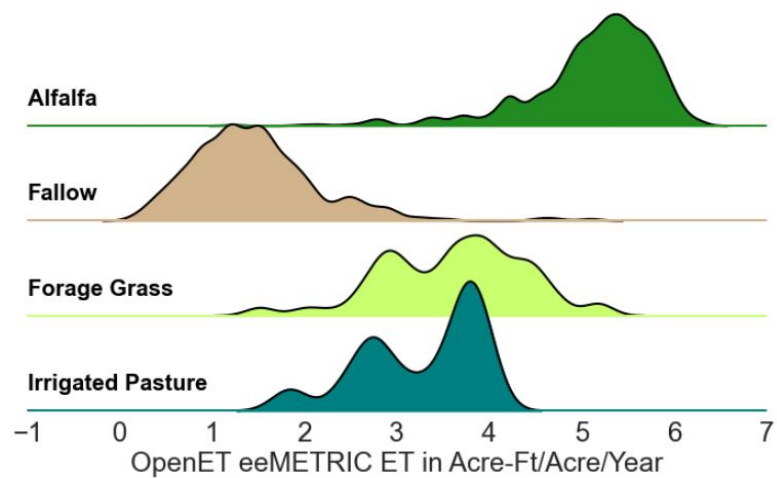


Figure 13. Distribution of Yearly ETs for Perennial Crops in PVID 2020

Yearly Crop ET Distributions for Annual PVID Crops 2021

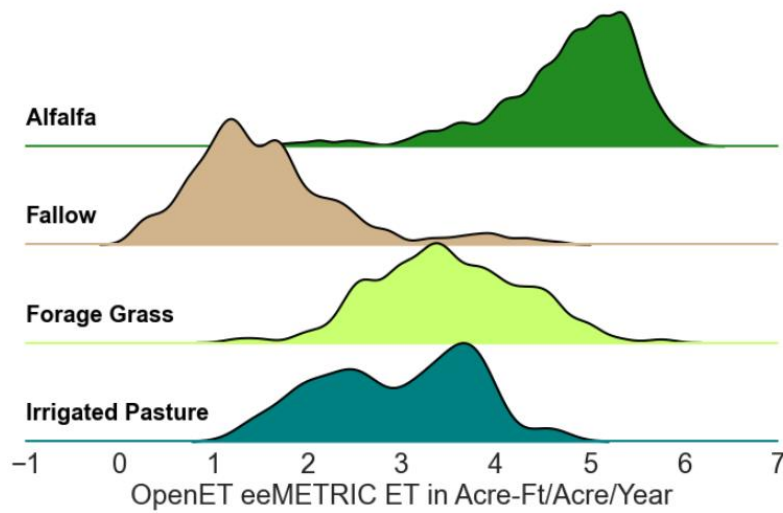


Figure 14. Distribution of Yearly ETs for Perennial Crops in PVID 2021

Regression Analysis

As an initial data exploration step, selected parameters were first plotted against fallowed field yearly ET (Figure 15). Every year of data is represented in these graphs where each point is

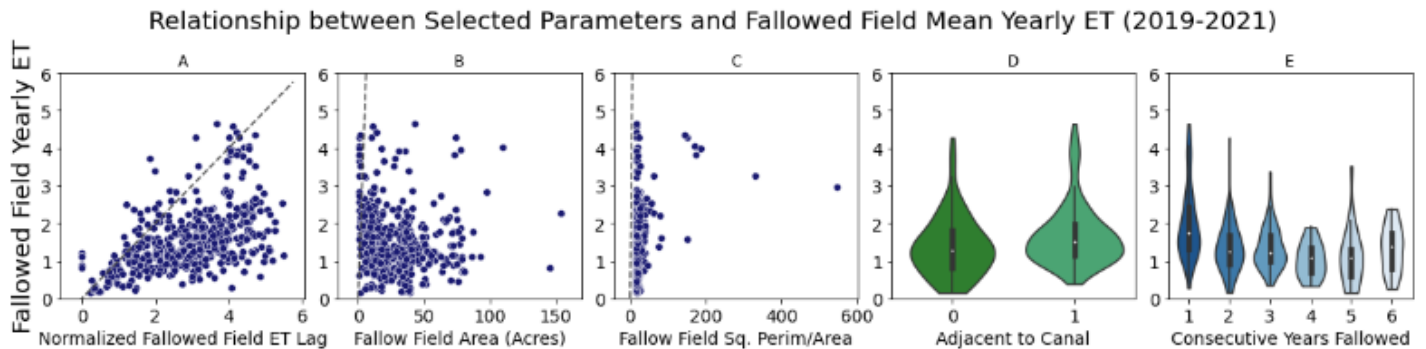


Figure 15. Plots of Fallowed Field Yearly ET Vs. Selected Regression Parameters (Dashed line represents 1:1 fit)

Plot A shows a roughly positive and linear relationship between normalized fallowed field ET lag and fallowed field ET, meaning that as surrounding field consumptive use increased fallowed field consumptive use also tended to increase. The majority of data points are below the 1:1 dashed line indicating that fallowed field consumptive use only weakly responds to increased surrounding field consumptive use. Fallowed field yearly ET is scattered when plotted against

fallowed field area (Plot B), high and low ETs occurred at all area values but there is a slight negative trend in the data. Plot C shows that the majority of fallow field square perimeter over area values are low, below 100, but higher ratio values primarily represent higher ET values as well. Plot D shows that adjacency to canal raises the minimum, median, and maximum of the fallowed field yearly ET distribution. Finally, Plot E shows that the number of consecutive years fallowed appeared to correlate with decreasing fallowed field ET. The largest range of ET values as well as maximum ET values occurred on fallowed fields most recently converted to fallow. The range and maximum ET values generally decreased as the fields aged.

The multi-linear regression results between these parameters and fallowed field yearly ET are shown below in Table 4. Each row shows the results for a given year. Only the ET lag of a fallowed field was positively correlated with fallowed field ET each year, with 2019 showing the strongest impact of surrounding field ET with modeled fallowed field ET. Fallowed field area and shape were both correlated with fallowed field ET but in 2019 both coefficients had the opposite sign of the expected relationship. Increasing fallowed field age was correlated with lower fallowed field ETs in 2 of 3 years while canal adjacency was correlated with higher fallowed field ETs in 1 of 3 years. Overall these results showcase that fallowed field ET is not completely explained by these parameters and results are mixed for most parameters other than ET lag. Full regression results can be seen in Appendix 4-A.

Table 4. Regression Results of Selected Parameters Vs. Fallowed Field Yearly ET

Year of Data	Normalized ET Lag	Log(Fallowed Field Area)	Fallowed Field Square Perimeter/Area	Fallowed field age	Canal Adjacency
2019	0.7***	0.4***	-0.4*	-0.2***	0.3***
2020	0.3***	-0.3***	0.4***	0.001	0.01
2021	0.3***	-0.2***	0.3***	-0.08***	0.01
Values shown are regression coefficients. All parameters have been scaled 0-1 * p < 0.05 ** p < 0.01 *** p < 0.001					

Discussion

Fallowed field consumptive use in PVID was found to be significantly and positively correlated with the consumptive use of surrounding fields. Results for other parameters are mixed but there is evidence that fallowed field consumptive use decreases with larger field size, wider shape, and field age. Canal adjacency was found to have a positive impact on fallowed field consumptive use but this result was only statistically significant in a single year. These results are largely in line with previous research and expected findings. As traits that can be controlled by farmers or program managers, fallowing programs within PVID and elsewhere can incentivize less wasteful fallowing practices by targeting these traits.

Greater amounts of applied water is expected to increase the potential spillover between fields (Fu et al. 2019) which is in line with my findings that the higher surrounding ET of a fallowed field is correlated with higher fallowed field consumptive use. ET and applied water are not perfectly correlated, in fact lower applied water volumes can result in greater crop yields and ET (Grafton et al. 2018). However, in PVID, flood irrigation is the primary irrigation method so differences in ET are expected to be due differences in applied water volumes and crop water use, not change in irrigation efficiency.

Newly enrolled fallowed fields have been shown to lose soil column moisture overtime (Hunter et al. 2019; Lian et al., 2021) which was observed in my data as older fields produced less ET than newer fields. Figure 15 did show that some fallowed fields enrolled for longer than four years produced slightly higher ETs, which may be due to changing water use on surrounding fields (Fu et al. 2019) or the fact that extremely dry soils that crack can provide a conduit for increased groundwater consumptive use (Zeng et al. 2023). Fluctuating groundwater elevations may play a role in changing fallowed field consumptive use as well. PVID's groundwater is known to fluctuate and reach to within a couple of meters of the surface (Owen-Joyce and Kimsey 1987) and shallow groundwater flows can lift water tables beneath fallow land causing water to be non-beneficially consumed (Morway, Gates, and Niswonger 2013).

Fallowed field area and thinness partially reflects the impact of farmer decisions and practices on fallowed field ET. Smaller and thinner fallowed fields are more likely to be a portion of another field and have less permanent barriers between cropped areas and fallowed areas (USBR 2022) would be expected to increase the risk of surface water spillover between fields (Morway, Gates, and Niswonger 2013). This relationship was not seen in 2019 though, the same year that surrounding field ET had the strongest influence on fallowed field ET.

Canal adjacency was generally not correlated with fallowed field ET. PVID's canals tend to be full for most of the year creating potential for fallowed field water consumption through infiltration although these results do not support that. Most canals in PVID are unlined dirt canals but compaction over decades may have created canals that are impermeable (Kalybekova et al. 2023). Despite the lack of a statistically significant result, Figure 15 did show that fields adjacent to a canal increased the minimum and median of the fallowed field ET distribution.

Alfalfa, forage grass, and irrigated pasture fields showed large ranges of ET within each year from 2019 through 2021. The range of ET on these cropped fields is likely due to a number of factors like soil conditions, crop age, and crop health (Jia et al. 2009; Hatfield, Sauer, and Prueger 2001) and individual farmer practices such as the frequency of crop cuttings (Shewmaker, Allen, and Neibling 2013). A portion of the variation may be explained by errors in ET measurement but this variation cannot be evaluated without a proper accuracy assessment.

The use of ET as a proxy for consumptive use can be complicated by several factors. Precipitation is a common source of ET on fallowed fields as water evaporates from the surface of fallowed fields (Peterson and Westfall 2004). In this study I removed precipitation from ET data, additionally, PVID averages about 3 inches of precipitation per year which is about 5% of alfalfa's average annual ET. Groundwater elevations and differences in soil type across the valley may both contribute to differing ET on fallowed fields. Although groundwater was not assessed in this study, USBR data indicates that the groundwater returns water to PVID canals in the wintertime meaning that groundwater is within several feet of the surface and may be a source of evapotranspiration. Fully explaining fallowed field consumptive use is outside the scope of this research and would require field-based studies. However, these findings are largely in line with previous research and represent easily implementable program adjustments that may improve the water savings per area for fallowing programs being implemented to protect reservoirs along the Colorado River.

Lower surrounding field ET, larger field size and shape, younger field age, and location away from canals were all found to be statistically significant predictors of lower fallowed field ET in at least 2 of 3 years analyzed. Anecdotally, the traits seen in the fifteen highest water using fallowed fields in PVID support this finding. Thirteen of fifteen high water using fields were

under 15 acres in size and also thinly shaped. Ten of fifteen were fully bordered by cropped fields and none were fully bordered by fallowed fields or on the edge of the valley. Adopting guidance that encourages or mandates practices that utilizes this information would likely improve the water savings efficiency of the PVID fallowing program and potentially other fallowing programs. Fallowed field consumptive use may always be present within large irrigated areas but by ensuring fields are located away from high water use crops, are generally larger in size, and fallowed for a longer time should result in a gain in conserved water for systems like the Colorado River.

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Appendix 4-A Fallowed Field ET Multilinear Regression Results

2019 ET Regression Results for Normalized ET lag, Field shape, Field age, Canal Adjacency, and Field area

OLS Regression Results

Dep. Variable: Fallowed Field ET R-squared: 0.472

Model: OLS Adj. R-squared: 0.469

Method: Least Squares F-statistic: 195.5

Date: Fri, 19 Jul 2024 Prob (F-statistic): 6.09e-149

Time: 10:08:21 Log-Likelihood: 291.75

No. Observations: 1101 AIC: -571.5

Df Residuals: 1095 BIC: -541.5

Df Model: 5

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	-0.1324	0.037	-3.593	0.000	-0.205	-0.060
Normalized ET Lag	0.6866	0.027	25.630	0.000	0.634	0.739
SqPerim/Area	-0.3517	0.158	-2.219	0.027	-0.663	-0.041
Field Age	-0.2186	0.024	-9.166	0.000	-0.265	-0.172
Adjacent to Canal	0.0298	0.012	2.422	0.016	0.006	0.054
logarea	0.4427	0.065	6.782	0.000	0.315	0.571

2020 ET Regression Results for Normalized ET lag, Field shape, Field age, Canal Adjacency, and Field area

OLS Regression Results

Dep. Variable: Fallowed Field ET R-squared: 0.351

Model: OLS Adj. R-squared: 0.343

Method: Least Squares F-statistic: 46.38

Date: Fri, 19 Jul 2024 Prob (F-statistic): 2.79e-38

Time: 10:08:22 Log-Likelihood: 385.21

No. Observations: 435 AIC: -758.4

Df Residuals: 429 BIC: -734.0

Df Model: 5

Covariance Type: nonrobust

coef

std err

t

P>|t|

[0.025

0.975]

const

0.1432

0.029

4.885

0.000

0.086

0.201

Normalized ET Lag

0.2737

0.023

12.094

0.000

0.229

0.318

SqPerim/Area

0.4149

0.111

3.740

0.000

0.197

0.633

Field Age

0.0011

0.018

0.064

0.949

-0.034

0.036

Adjacent to Canal

0.0108

0.010

1.056

0.291

-0.009

0.031

logarea

-0.2697

0.044

-6.083

0.000

-0.357

-0.183

2021 ET Regression Results for Normalized ET lag, Field shape, Field age, Canal Adjacency, and Field area

OLS Regression Results

Dep. Variable: Fallowed Field ET

R-squared: 0.355

Model: OLS

Adj. R-squared: 0.348

Method: Least Squares

F-statistic: 50.98

Date: Fri, 19 Jul 2024

Prob (F-statistic): 4.38e-42

Time: 10:08:22

Log-Likelihood: 348.32

No. Observations: 470

AIC: -684.6

Df Residuals: 464

BIC: -659.7

Df Model: 5

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.1514	0.030	5.091	0.000	0.093	0.210
Normalized ET Lag	0.2827	0.027	10.311	0.000	0.229	0.337
SqPerim/Area	0.2900	0.070	4.117	0.000	0.152	0.428
Field Age	-0.0817	0.019	-4.213	0.000	-0.120	-0.044
Adjacent to Canal	0.0121	0.012	1.035	0.301	-0.011	0.035
logarea	-0.1888	0.033	-5.771	0.000	-0.253	-0.124

CHAPTER 5: INFORMING IRRIGATED AREA MEASUREMENTS DERIVED FROM NAIP IMAGERY: A CASE STUDY

Abstract

California's residential outdoor water use represents a significant portion of overall residential water use and is therefore a potential target for water conservation needed to respond to climate change and droughts. California's Department of Water Resources (DWR) and the State Water Resources Control Board are in the process of finalizing a regulatory framework to set water budgets for urban suppliers across the state, part of which will be calculated based on a given agency's irrigated area. Irrigated area is defined as healthy grass and tree area and measurements of irrigated area based on remote sensing data are provided to water agencies in the state by DWR. DWR contracted with external vendors to calculate this irrigated area through a machine learning classification analysis of remote sensed National Agricultural Imagery Program (NAIP) imagery taken in 2018. The snap-shot nature of this imagery, combined with the seasonally varying nature of healthy vegetation in Southern California's climate, may produce unrepresentative irrigated area measurements. There is a need for additional data to provide context for retailers to understand any sampling bias in their irrigated area measurement as provided by DWR. In this study I evaluate four total years of classified NAIP imagery across Metropolitan Water District's (MWD) service area from 2014 to 2020 to begin to add context to the 2018 irrigated area estimates provided by DWR. I found that irrigated area at the MWD service area was within 3% of each other from 2014 to 2018 but increased by 17% in 2020, the year of highest rainfall and earliest imagery timing. At the MWD Member Agency scale, irrigated area had an average coefficient of variance of 9%, which could translate into 9% swings in a calculated outdoor water budget purely due to the NAIP year chosen for the analysis. For

three agencies 2018 represented a maximum while for seven other agencies 2018 represented a minimum irrigated area measurement compared to the other years analyzed. Overall, these results indicate that there is significant uncertainty in using NAIP imagery to measure irrigated area for the purpose of a water budget estimation. Overestimated water budgets would result in less effective conservation as intended by the legislation while underestimated water budgets would result in a greater barrier to compliance for retail agencies. The irrigated area variability seen in this study supports a more flexible approach for computing a retailer's outdoor water budget that use irrigated estimates derived from 2018 NAIP imagery as a baseline, rather than an absolutely accurate value, which can be improved upon as more data is made available.

Introduction

California's water supply, which supports millions of people and the largest agricultural industry in the United States, is increasingly threatened by drought and shortage (California 2023; Escriva-Bou and Sencan 2020). The effects of climate change on the water resources of California have begun as water supplies have reached record lows in recent years (Woodhouse et al., 2020). Further detrimental effects of climate change are likely to emerge throughout this century, creating larger challenges for water resources management and necessitating increased conservation (Dettinger et al., 2011) Historically, California's conservation policies have been passed in response to droughts (DWR 1993, Dziegielewski et al., 1993, Shaw et al., 1992). As a response to the 2012-2016 drought, the California legislature passed in 2018 Assembly Bill 1668 and Senate Bill 606, commonly known as the *Making Conservation a California Way of Life* regulatory framework, that established individualized efficiency goals for each urban retail water supplier based on the unique characteristics of the supplier's service area (California Water Board 2024).

Outdoor irrigation accounts for roughly half of California's urban water use (PPIC Water for cities 2018) and therefore represents a major strategic area for water conservation.

California's Department of Water Resources (DWR) and the State Water Resources Control Board (SWRCB) are in the process of considering the adoption of the Conservation as a California Way of Life regulation, which, if adopted would go into effect January 2025. The Outdoor Residential Water Use Standard (ORWUS) is one of the components of the Urban Water Use Objective (UWUO) proposed under the regulation which will set a water use budget for each of California's 398 urban retail water suppliers. The ORWUS are set partially through a given retailer's irrigated area.

DWR contracted with Quantum Spatial Inc. (QSI) and Eagle Aerial Solutions (EA) to produce irrigated area estimates for every retailer in California using large-scale aerial imagery. EA utilized National Agricultural Imagery Program (NAIP) imagery taken in 2018 to estimate irrigated areas for all of California. NAIP is administered through the United States Department of Agriculture and imagery is collected by aircraft to obtain high resolution imagery originally intended for agricultural use (USDA 2018). In any given year, NAIP flyovers for Southern California occur over a range of dates, all of the images taken over this range of dates are stitched together and represent a single snapshot for the entire year.

Southern California's Mediterranean climate results in variability in healthy vegetation within a year. In Mediterranean climates, water is often limited and vegetation regularly experiences seasonal precipitation variation which influences how healthy vegetation appears in aerial imagery (Hanson and Weltzin 2000). For the tree-grass mosaics of urban regions in California, seasonal climatic responses are further complicated by varying irrigation restrictions, microclimatic effects, increasing diversity of vegetative cover through climate appropriate and

low water landscaping, and canopy conditions, making estimates of vegetative cover inconsistent even outside of seasonal variation. (Buyantuev and Wu 2012; Allen, Roberts, and McFadden 2021; Savi et al. 2014; Leuzinger, Vogt, and Körner 2010). Irrigated area as measured by aerial imagery will likely vary substantially depending on when imagery is taken within a year.

Given the many driving factors of variability in seasonal vegetation, the use of a single year of NAIP imagery for setting water limits raises concerns about the consistency of data across years. The UWUO standard is intended to save water by setting water-use limits for retail agencies based on their populations, local climate conditions, and irrigated area—broadly defined as healthy turfgrass and tree cover or vegetation (DWR 2022). Retail agencies will have to meet water budgets set by their unique UWUO which is heavily influenced by irrigated area. Over time these budgets are designed to become more restrictive to further increase water savings. It is important that calculated budgets are accurate and reasonable for fairness, effective conservation, and buy-in from retail suppliers. As currently quantified under the legislation, irrigated area is measured through remote sensed data. The remote sensed data used for the proposed legislation is effectively a snapshot image taken in 2018. For retailers without their own data, this snapshot measurement lacks any context to identify whether irrigated areas have been accurately estimated.

There are risks associated with inaccurate estimates of irrigated area. Overestimated irrigated area would result in increased water budgets and therefore less effective conservation. Underestimated irrigated area would create stricter budgets than what would be required to support healthy vegetation either resulting in unintended watering restrictions or retailer penalties for exceeding budgets. Although there are negative outcomes with either over or underestimates of irrigated area, most of the risk from a mandated water budget falls on retailers

if their budgets are unreasonable. There is no way for retailers relying on DWR's classified imagery for irrigated area measurements to judge how accurate the irrigated area measurement is for their area.

As home to approximately half of the state's residential water use (Mount and Hanak 2016), the Metropolitan Water District of Southern California (MWD) and was used as the study site for this study (Figure 16). MWD supplies water to 26 Southern California Member Agencies which in turn supply water to over two hundred retail agencies.

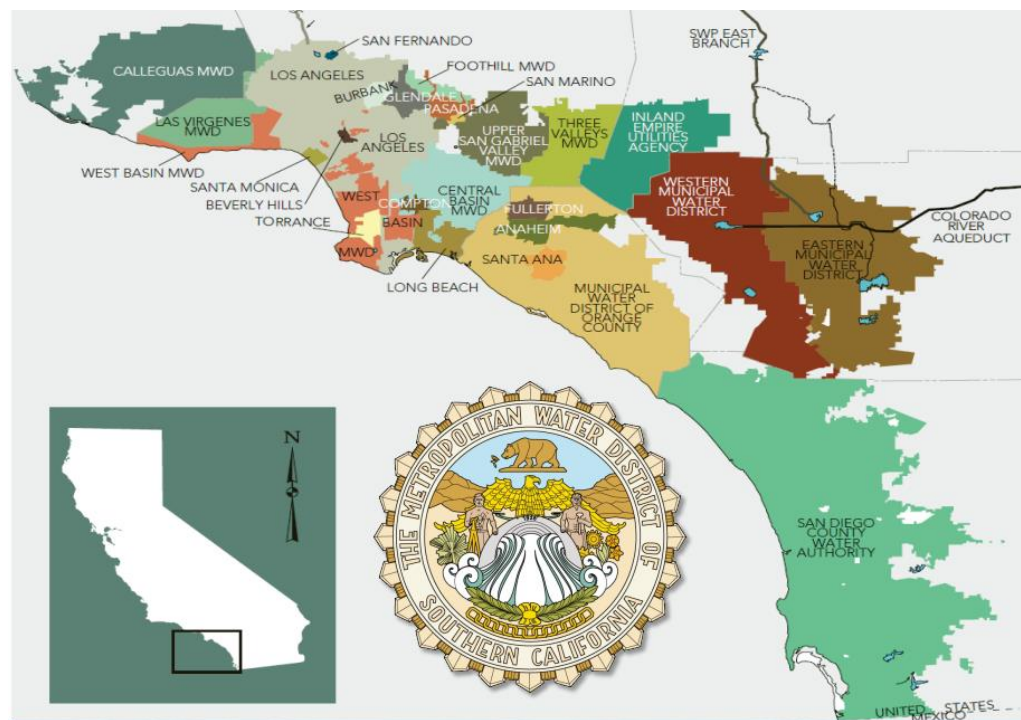


Figure 16. Metropolitan Water District Service Area and Member Agencies

In this study I analyzed four separate years (2014, 2016, 2018, and 2020) of classified NAIP imagery within MWD's service area provided independently by DCSE, Inc. (DCSE) to inform the values produced by DWR's analysis in 2018. As a single point-in-time image, no assessment has been done to understand the variability created by using 2018's NAIP classified imagery to measure irrigated area. Analyzing multiple years of NAIP data provides an opportunity to understand the potential bias that the use of 2018 imagery may create for setting

the ORWU standard to help inform both retailers and DWR. First, DWR's 2018 NAIP classification results were compared with DCSE's 2018 NAIP imagery to assess comparability between the datasets. Total irrigated area changes as measured by DCSE's 2014 through 2020 NAIP data were then assessed to evaluate stability in irrigated area as measured by NAIP imagery at the Member Agency and MWD-wide scale. Finally, to better understand year-to-year changes in vegetative irrigated area, classification changes over time were assessed through pixel-level raster changes year-to-year.

Methods

Landscape Area Measurements

Regional-scale land cover products have been made available through both aerial imagery and satellite earth observation missions (Belward and Skøien 2015; Fensham and Fairfax 2002). Land cover identification requires the presence of multispectral sensors that detect red, green, blue, and near infrared (NIR) spectral bands. NIR bands are necessary for quantifying the normalized difference vegetation index (NDVI) which is effective in highlighting vegetation in remotely sensed imagery (Yuan et al. 2019; Ding et al. 2016). NDVI is a measure of vegetation vigor and is computed using Equation 5. NDVI works to identify vegetation because chlorophyll reflects more NIR and green light and absorbs more red light compared to green non-vegetation. Equation 5 results in values from -1 to +1, with more positive values indicating greater plant vigor.

The advancement of large-scale imaging has sparked significant interest in applying machine-learning algorithms to remotely-sensed imagery for land use classification (Maxwell, Warner, and Fang 2018; Adam et al. 2014). Historically, visual interpretation and manual digitizing was used for land area classification (Freeman and Buck 2003; Pauleit, Ennos, and Golding 2005), but this method is impractical for large areas like Southern California. Machine-

learning techniques for land use classification are commonly performed using supervised machine learning (Wang et al. 2022; Ramezan et al. 2021), which involves labeling a training set of data which the algorithm trains on to learn how to classify a test set of data. The accuracy of the algorithm is computed by comparing the true values of the test set of data to the algorithm's predicted values. In the case of land area classification, grid points and areas are manually labeled vegetation, impervious surface, bare land, etc., and the machine learning algorithm identifies the spectral patterns in the red, green, blue, and NIR bands that separate these classes.

Accurate classification methods rely upon adequate image resolution for the types of land area classes analyzed. Urban environments consist of a mosaic of small-scale features made up of different materials (Jong et al. 2000; Mathieu, Freeman, and Aryal 2007). This high degree of spectral heterogeneity requires very high-resolution imagery for accurate land use classification in urban environments. Starting in 2003, NAIP has acquired once-a-year aerial imagery for the entire United States at a resolution of 30 cm primarily for agricultural use (Sha 2016). Although intended for agricultural use, NAIP produces high-resolution imagery that is useful for land area classifications in urban environments.

Landscape Area Data Processing and Analysis

DWR's 2018 LAM data for MWD's service area and DCSE's 2018 verification LAM data for MWD's service area did not use identical classification schemes and were not provided in the exact same format. DWR's classification scheme included irrigated area, pools, horse corrals, and agricultural land. Agricultural lands and horse corrals are not included in the ORWU budget but can be included as an added variance to the ORWU budget on a case-by-case basis. DCSE provided estimates for grass and tree area while DWR provided an irrigated area measurement which is the sum of grass and tree area as illustrated in Table 5 below. Note that classifications from DWR's consultant, Eagle Aerial, included the labels under the *Level 1*

column and DCSE’s classification was performed with the labels under the *Class Name* category seen in Table 5. The **Irrigated** category under *Level 1* is the value that is used in the ORWU standard and was compared to the sum of **Turf** and **Trees** within DCSE’s *Class Name* category. Although the Classification Status column labels pools as irrigated, pools are not included in the **Irrigated** category provided by DWR.

Table 5. DWR (Eagle/Quantum) and DCSE LAM Classification Crosswalk

Eagle/Quantum Classifications			DCSE Classifications		
Level 1	Level 2	Classification Status	Class Name	Class Examples	Class Category
1. Impervious	Impervious	Not Irrigable	Impervious Surfaces	Concrete, asphalt, parking lots, buildings, roads and freeways	Not Irrigable
2. Pools	Swimming pools/ man-made water features	Irrigated		Pools	Swimming pools, spas, hot tubs
3. Irrigated	3.1 Turf grass/ ground cover	Irrigated	Turf (Grass)	Grass fields, lawns, athketic fields, golf courses	Irrigated
	3.2 Canopy/ planting beds	Irrigated			
4. Irrigable Not Irrigated	4.1 Turf grass/ ground cover 4.2 Canopy/ other	Irrigable Not Irrigated Irrigable Not Irrigated	Bare Land	Bare soil, undeveloped land, dead vegetation, brown lawns, mulch, dirt lots	Irrigable Not Irrigated
5. Non irrigated vegetation	Undeveloped for the purposes of irrigation	Not Irrigable			
6. Undeveloped lands	Undeveloped lands	Not Irrigable			
7. Horse corrals	Horse corrals	Irrigated			
8. Open Water	Other open natural water (rivers/ponds)	Not Irrigable	Water Bodies	Lakes, ponds, reservoirs, estuaries, marshes, rivers	Not Irrigable
9. Artificial Turf	Artificial Turf	Not Irrigable	Artificial Turf	Artificial athletic fields, artificial front lawns	Not Irrigable
10. Agricultural Land	Agricultural land (1 acre mmu)	Irrigated	Not specified as a classification by DCSE		

The actual calculation of the ORWU standard is shown below in Equation 6.

$$\text{ORWU} = (\text{ETo} - \text{Peff}) * (0.62) * (0.80) * (\text{II} + 0.20 * \text{INI})$$

ETo = reference evapotranspiration (inches)

Peff = effective precipitation (inches)

II = irrigated area (acres)

INI = irrigable not irrigated area (acres)

Equation 6. Outdoor Residential Water Use Standard

Reference evapotranspiration (ETo) and effective precipitation (Peff) are unique to any given retail agency’s local weather conditions and are easily available through weather station data. Irrigable not irrigated area (INI) is defined as “Area(s) of planted and previously maintained vegetation that appears water stressed (brown or leafless plants). These are areas that

are not currently being irrigated but were irrigated in the past or are intended to be irrigated in the future.” DWR assumes 20% of what is classified as INI should be added to the ORWU budget. DCSE’s LAM data was intended to approximate DWR’s irrigated area and not DWR’s INI area. DCSE’s data does not separate out unirrigated lawn and tree area from underdeveloped land, dirt lots, and bare soil, therefore DCSE’s data was not used to assess DWR’s INI category over time. Pools are included in DWR’s irrigated area calculation but make up a minor amount of area compared to grass and trees and were not expected to change significantly with the seasons. The purpose of this study is to assess inherent variability in NAIP imagery measurement of vegetated areas, so pools were not included in the analysis.

Total irrigated area as measured by DWR and DSCE were first directly compared at the Metropolitan Member Agency level to assess percent difference between the datasets. To assess the stability in irrigated area measurement over time, total irrigated area as measured by 2014, 2016, 2018, and 2020 NAIP images were summed at the Member Agency level as well as at the Metropolitan-wide scale. Total irrigated areas and percent differences over time were then calculated at both scales.

To explore changes in NAIP-classified irrigated area, a raster analysis was conducted for Member Agency Santa Ana due to observed irrigated area similarity between DWR and DCSE’s dataset as well as high year-to-year irrigated area variability seen from 2014 to 2020. NAIP imagery for 2014, 2016, and 2020 was reprojected to match the 2018 NAIP projection. NAIP images taken over the same location will not result in perfectly aligned pixels due to the imperfect precision of a flyover. In order to create a link between each raster, the pixels were forcefully aligned through a nearest neighbor approach. After reprojection, a change analysis was

conducted from 2014's grass and tree pixels to each following year's raster classification, whether grass, trees, bare land, pools, impervious surfaces, water bodies, or artificial turf.

Results

DWR irrigated area and DCSE grass and tree area measurements were within 3% of each other in 2018. DWR and DCSE measured 232,952 and 239,024 acres residential irrigated area within MWD's service area, respectively. The results of the data intercomparison at the Member Agency level are shown below in Figure 17 which plots the percent difference in irrigated area as classified by DWR and irrigated area as defined as the sum of DCSE's grass and tree classification. Positive values indicate that DCSE measured more irrigated area than DWR and each bar represents a MWD Member Agency. At the Member Agency level there was a wide spread between the two datasets. Fourteen agencies had irrigated area measurements that were within 10% between the two datasets. Four agencies had a percent difference above 20%, Foothill (+66%), Central Basin (+24%), Santa Monica (-22%), and Torrance (-36%). Eight agencies had a percent difference above 10% but below 20%, West Basin (-11%), Burbank (-13%), Compton (-13%), Anaheim (-15%), Glendale (-17%), Pasadena (+13%), San Diego (+17%), San Fernando (-19%). DCSE measured less irrigated area in Member Agencies on average than DWR did.

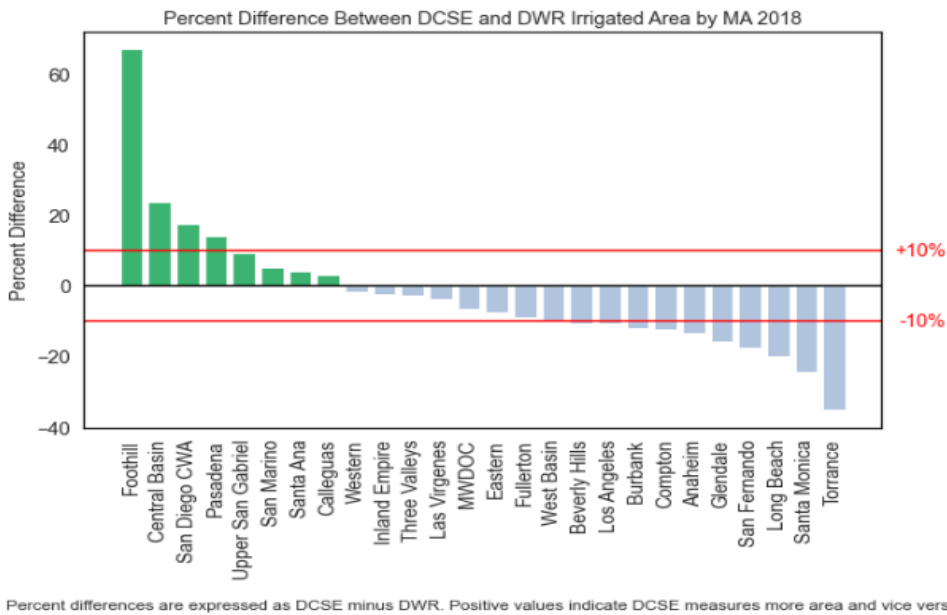


Figure 17. DCSE and DWR 2018 Residential Irrigated Area Comparison by Member Agency

At the total scale of MWD’s service area, irrigated area as measured by DCSE was relatively consistent from 2014 through 2018 (230 thousand acres, 224 thousand acres, 237 thousand acres) but increased in 2020 (274 thousand acres) (Table 6). Total land area did not change from 2014 through 2020 as the same area was evaluated each year. Tree canopy cover made up a larger portion of the irrigated area than grass every year evaluated, though this does not consider that area under trees could include turf area. Grass area was at its lowest in 2018 and largest in 2020 while tree area was lowest in 2016 and highest in 2020 (Table 6). Using the 2014 measurement as the initial value, absolute changes in irrigated area year-to-year resulted in percent differences of 2.7%, 3.0%, and 17.5%, respectively.

Table 6. MWD Residential Irrigated Area as Measured by DCSE. DWR measured 232.1 thousand acres in 2018.

	2014	2016	2018	2020
Grass (Acres)	67.4	60.4	50.4	82.0
Trees (Acres)	163.5	163.2	186.1	192.1
Irrigated (Acres)	230.9	223.6	236.5	274.1

Irrigated area was more variable year-to-year at the Member Agency scale than at the MWD scale (Appendix 5-C). Several member agencies show high year-to-year variation in residential irrigated area, many with annual changes of over $\pm 15\%$. Eastern MWD stands out with an 80% increase in irrigated area between 2018 and 2020. Coefficients of variance for each agency averaged 9.4% and ranged from 2.3% for Torrance to 37.6% for Eastern MWD. The seven agencies in the highest quartile of irrigated area variance were located predominately in the southern half of MWD's service area while the seven agencies in the lowest quartile of irrigated area variance are primarily located in the northwest of MWD's service area (Appendix 5-D). Only four Metropolitan Member Agencies had less irrigated area in 2020 than in 2018 (Calleguas, Beverly Hills, Las Virgenes, and Santa Monica). Seventeen Member Agencies saw peaks in irrigated area in 2020, three saw peaks in 2018, five in 2016, and one in 2014. Eleven agencies had minimums in 2016, seven in 2018, six in 2014, and two in 2020. When summed to the MWD service area, many of these differences in peak and minimum irrigated area cancelled out, resulting in relative irrigated area stability over the whole service area from 2014 to 2018.

To begin to understand the variation in irrigated area over time, the Member Agency Santa Ana, with irrigated area within 5% between DCSE and DWR's estimates and a relatively high coefficient of variance of 12.7%, was further evaluated at the raster level. Santa Ana irrigated acreage was 1579 acres in 2014 and had a 9.0% decline in 2016 to 1436 acres, a 16.4% increase to 1672 acres in 2018, and a 15.9% increase to 1937 acres in 2020 15.9% (Appendix 5-B). Similar to what was seen at the MWD scale, trees make up the majority of the irrigated area category and as tree area became larger in 2018 and 2020, grass area shrunk to a minimum value of the years evaluated. This pattern of trees peaking in 2020 while grass hit a minimum is seen in eight other Member Agencies (Appendix 5-A). Figure 18 shows the evolution of NAIP pixel

classifications in Santa Ana over time. This figure follows the classification of Santa Ana's 2014 grass and tree pixels through 2020. In 2014 initially, there are 21.2 million tree pixels and 15.9 million grass pixels. In 2016 only 35% of pixels classified as grass in 2014 were still classified as grass, as the majority of 2014 grass pixels were classified as bare land (24%), trees (26%), or impervious (13%). Of the tree pixels in 2014, 60% remained trees in 2016 with the remainder becoming impervious (17%), bare land (13%), and grass (9%). Of 2016 grass about 30% became trees in 2018 and of 2016 trees about 7% became grass in 2018. From 2016 to 2018, 32% of bare land and 26% of impervious surface became trees. The pattern of a portion of grass, bare land, and impervious classifications becoming trees continued again from 2018 to 2020. Other classifications are shown in this flow diagram but overall have a minimal impact on the total area. The general pattern in this flow diagram is seen in other Member Agencies as well (Appendix 5-C)

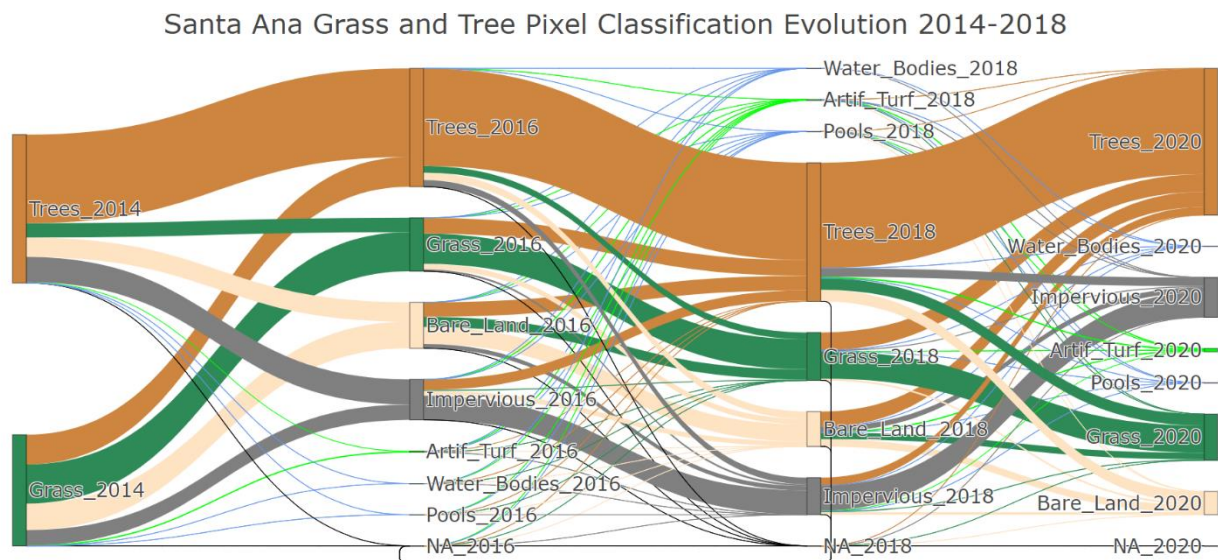


Figure 18. Santa Ana Grass and Tree Pixel Flow Diagram

Discussion

Residential outdoor watering represents a large portion of household water use, particularly within Southern California. As conservation targets are set, it is important that retail

water agencies understand how their budget is generated and any uncertainty in that budget. Setting retailer water budgets based partially on irrigated area measured via 2018 NAIP imagery assumes that the estimated irrigated area for any given retail agency measurement is accurate and representative. This study used multiple years of classified NAIP imagery data to provide context for the 2018 NAIP measurement provided by DWR and which will be used for setting retail agency water budgets. Results showed that at the MWD scale, irrigated area identified by 2018 NAIP imagery analysis performed by DCSE is similar in value to irrigated area as measured by 2014 and 2016 NAIP ($\pm 3\%$) but is about 18% lower than 2020 estimates. Comparing estimates between DWR and DCSE shows that the datasets are dissimilar. Between the two data sets, four agencies had a percent difference above 20%, Foothill (+66%), Central Basin (+24%), Santa Monica (-22%), and Torrance (-36%) while eight agencies had a percent difference above 10% but below 20%. At the Member agency level, irrigated area was highly variable from 2014 to 2020 with an average irrigated area coefficients of variance of 9% which, for agencies with low INI area, can translate directly to 9% variances in ORWU budgets (Equation 6). Irrigated area for three Member Agencies peaked in 2018 while seven saw a minimum, which illustrates the potential for “winners” and “losers” if water budgets are based only on 2018 data. These results support the use of a region-wide water budget for compliance or for the use of coarser but more regularly available imagery to more easily identify a representative irrigated area value that could be updated over time.

Seasonal weather variation and the timing of NAIP flyovers would be expected to influence how much healthy vegetation is identified by aerial imagery (Hanson and Weltzin 2000). NAIP flyovers in 2018 occurred later in the summer for most of Southern California

compared to the other years, when imagery was taken during or just after the wet season. The specific timings of NAIP flyovers over the majority of Southern California are shown below:

- 2014 NAIP: 5/13 – 6/3
- 2016 NAIP: 4/24 – 7/19
- 2018 NAIP: 7/22 – 8/23; March 2019 for southern San Diego
- 2020 NAIP: 4/15 – 6/21

Peak irrigated area was measured by 2020 NAIP imagery, which was flown in spring, during the wet season. Seasonal changes in tree cover would also be expected to influence overall land area measurements as tree canopy covers up other land types (Bucini et al., 2017). This may explain the large amounts of bare land and impervious surface that become trees from 2016 to 2018 in Santa Ana. Tree canopy effects are also likely seen in the eight agencies which had peak tree area but minimum grass area in 2020. Tree area did peak with the spring flyover timing, but it appears that tree area may have blocked out grass area since the two land types are often co-located. A previous study of urban forestry in Los Angeles did not capture this tree canopy effect because the intent of that study was to measure the number of trees, not tree area in Los Angeles (Gillespie et al., 2012). Irrigated area hit a minimum in 2016 for MWD's service area, despite the fact that 2018 NAIP imagery was flown later in the year, which should have reduced the amount of non-irrigated vegetation that appeared healthy.

Assessing irrigated area as measured by 2018 NAIP data in the context of additional years of data is further complicated by the fact that the other year's wet seasons were impacted by interannual droughts (2012-2016 and 2020-2022) (DWR 2021, DWR 2022). Southern California has experienced multiple multi-year droughts in recent years resulting in both decreased precipitation and irrigation restrictions (Robeson et al., 2015, Swain et al., 2014). During multi-year droughts, different types of vegetation may show effects at different seasons and at different times (Miller et al. 2022), further increasing the difficulty of capturing a

representative irrigated area from a single image. Irrigated area in MWD's service area was at a minimum in 2016 when a multi-year drought was just coming to an end, during which there were watering restrictions (Nagourney and Lovett 2016). Although 2020 was technically a drought year in California, precipitation within Southern California peaked compared to the other NAIP years (6.1, 9.7, 4.8, and 14.9 inches of Los Angeles County precipitation in 2014, 2016, 2018, and 2020, respectively (NWS 2024)). This peak rainfall, combined with a wet season NAIP image capture, likely combined to produce the irrigated area peak seen in 2020.

In addition to the potential influence of seasons and droughts on NAIP classifications, there are other complications inherent in using very high-resolution fly over imagery for classification purposes. High resolution fly over imagery often contains clouds and cast shadows that interfere with expected spectral signatures of land types (Makarau et al., 2011). Shadows can cause partial or total loss of radiometric signature and therefore the process of classification and object detection can be biased or even fail (Adeline et al., 2013, Bhaskaran et al., 2013, Domenech and Mallet, 2014). Shadows are present in NAIP imagery since flyovers cannot all occur at a time where the sun is directly overhead, which may explain classification error and differences year-to-year. Time series analysis of spectral imagery also requires radiometric calibration (Schowengerdt 2005) to account for sun positioning and angle. NAIP images are the result of hundreds of flyovers stitched together, making this type of correction extremely difficult to perform and likely resulting in errors when comparing pixel change over time. Another potential source of error when classifying a single year of data or analyzing change across multiple years of data are fuzzy land-cover classifications (Masiliūnas, Tsendbazar, and Verbesselt 2017). Soil surfaces, especially those covered by sparse grasses, are considered fuzzy land-surface classifications. These types of surfaces will be labeled either vegetation or bare land

but in reality the soil has a gradation of vegetation that may not fully match either category. In addition, soil is also difficult to differentiate from some impervious surface types due to spectral similarities, e.g. bricks that are composed of clay (Chen et al., 2017a). These potential sources of error may explain some of the differences seen in year-to-year irrigated area changes in this study.

DWR's classification algorithm is not available for use to replicate their methodology for the other NAIP years. Although DCSE did not use the same algorithm, the purpose of the 2018 intercomparison was to validate whether DCSE's algorithm is an appropriate proxy for DWR's. The intercomparison showed that the two datasets are not the same, which makes conclusions difficult to assess for all of Southern California. In addition, to what will be differences in training and test machine learning datasets, both DWR and DCSE make manual data adjustments that will impact irrigated area measurements, including how undeveloped land is included in the dataset as well as how irrigated areas outside of residential parcel boundaries are classified. Both DCSE's and DWR's classification accuracies were reported to be greater than or equal to 90%. DWR's classification accuracy is not reported. Although irrigated area as identified by DCSE in 2014, 2016, and 2020 may not replicate what DWR would identify for the same years given different methods, the relative changes observed by DCSE in the NAIP imagery should still reflect the changes that DWR would observe given that there is only a single NAIP image available to be analyzed in 2014, 2016, and 2020.

Irrigated area measured via NAIP imagery has inherent drawbacks but should be seen as a useful data point for setting the ORWUS. Remote-sensed image analysis is possibly the only feasible and cost-effective option for quantifying irrigated area over extensive areas (Lunetta et al., 2004) and imagery other than NAIP is generally not high resolution enough for accurate

irrigated area measurements, is high cost, or lacks the full spatial extent of California (EOS 2024). The variability seen in this study creates uncertainty for a water budget set by 2018 NAIP imagery, both for proper conservation targets and for realistic retail agency compliance. This uncertainty should be recognized by both DWR and retailers, and budgets as well as any penalties for missed budgets should be adaptable enough to change as improved data becomes available. Overall conservation targets may not be as sensitive to the use of NAIP year as seen in the relative stability of irrigated area at Metropolitan's total service area as compared to retailer water budgets. Improved data may include additional years of NAIP analysis, utilizing higher frequency commercial imagery, or including seasonal data products with NAIP imagery (Zheng and Qiu 2012). Future work should include further analysis of the range in irrigated area variability seen across MWD's service area, which appeared to have some geographic correlation, to inform what areas and traits result in increased instability in irrigated area as measured by aerial imagery. Additionally, retail agency boundaries should be evaluated using the same process outlined in this study to provide directly applicable data to retail agencies. Given the variance increase from MWD's service area to Member Agency areas, retail agency areas may see even higher amounts of irrigated area variability across years.

Conclusion

This study was performed to inform the use of 2018 NAIP classified imagery for measuring irrigated areas to be used as an input to the ORWU budget calculation. Analyzing four years of classified NAIP imagery for MWD's service area showed that, particularly at smaller scales like Member Agency areas, the estimates of irrigated area are highly variable both between DWR and DCSE's estimates as well as overtime in DCSE's estimates. Depending on the agency, 2018 NAIP produced 3 peak irrigated area estimates and 7 minimum irrigated area estimates. Year-to-year coefficients of variance in irrigated area averaged 9% indicating that

irrigated area is unstable as measured by these four years of NAIP imagery. These results highlight uncertainty in the use of 2018 NAIP classified imagery as an estimate for irrigated areas to then be used in enforceable water budgets, especially when the data appears variable and results may not be easily reproduced.

NAIP imagery is likely the most realistic and best currently available data source for measuring irrigated area across all of California but produces data with inherent uncertainties. These uncertainties should be recognized by both DWR and retail agencies and as irrigated area data is improved and updated, either through additional NAIP imagery analysis by DWR, or through alternative methods, water budgets should also be updated. Perfectly agreed upon irrigated area data is unlikely to be available in the near future but conservation actions are needed in the present to reduce California's water use in the midst of climate change and drought. Irrigated area as measured by NAIP imagery can help inform water budgets but should not be viewed as a completely accurate and unchangeable value to set water budgets on.

References

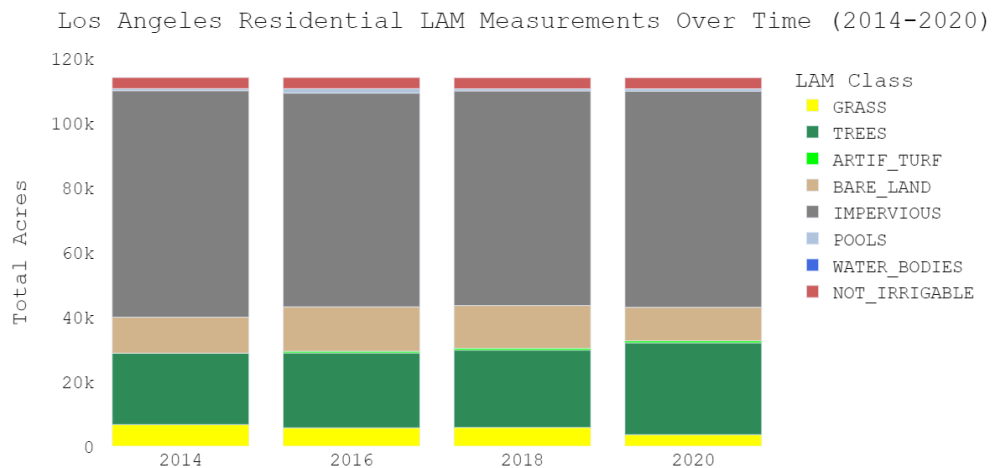
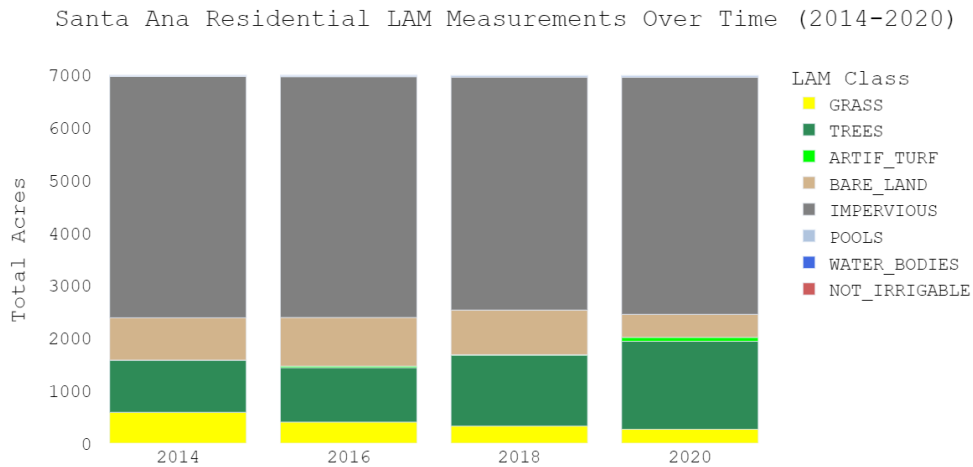
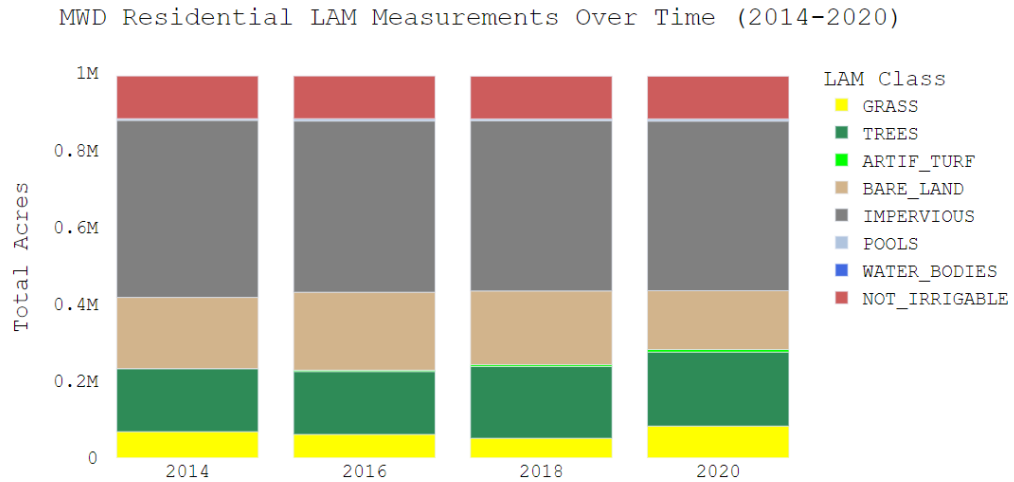
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Appendix

Appendix 5-A LAM Bar Charts for Metropolitan Water District and Selected Member Agencies

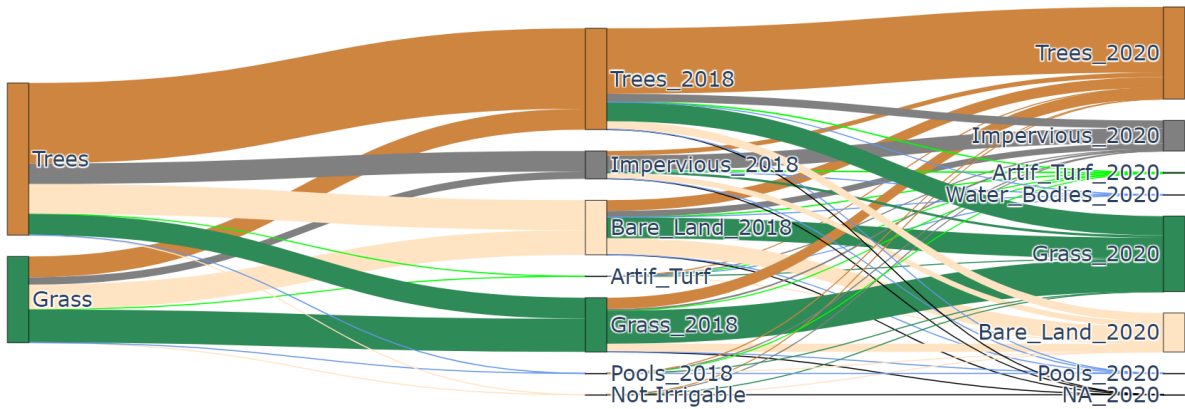


Appendix 5-B. Member Agency Irrigated Area by Year and Percent Changes
(Acres)

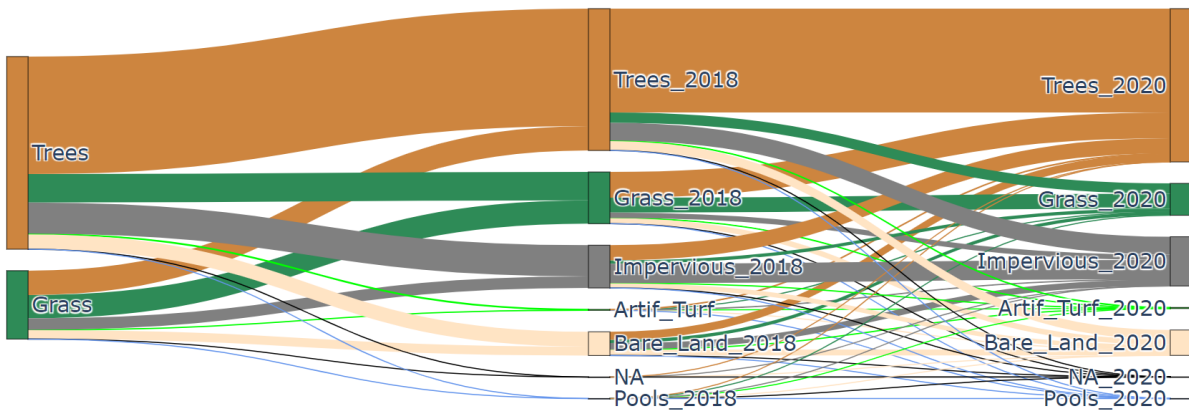
Member Agency	2014	2016	2018	2020	Coefficient of Variance
Anaheim	2789.2	2427.1	2792.2	3171.4	10.873148
BeverlyHills	820.7	798.9	871.8	793.5	4.348141
Burbank	937.9	902.7	936.6	1028.3	5.656037
Calleguas	11583.2	10446.4	10856.0	11573.7	5.046139
CentralBasin	10626.9	9281.2	8689.2	11874.0	14.075201
Compton	493.7	463.2	417.9	615.7	17.011355
EasternMWD	12090.8	10566.1	11666.1	21940.5	37.601065
Foothill	2575.8	2990.3	2729.9	2715.6	6.279257
Fullerton	1798.8	1629.9	1791.4	2168.1	12.332138
Glendale	1597.0	1864.4	1624.8	1778.2	7.399186
InlandEmpireUtilityAgency	11045.6	10033.9	11929.5	11995.2	8.174627
LasVirgenes	2588.8	2741.1	2601.3	2457.1	4.469579
LongBeach	2141.7	2714.1	2089.0	2550.7	12.917159
LosAngeles	28760.8	28829.9	29711.3	31957.9	5.006572
MWDOC	26084.2	21636.5	26948.9	27932.2	10.839673
Pasadena	2841.3	2926.2	2886.2	3087.6	3.654681
SDCWA	63618.5	66024.7	71526.7	82710.1	11.973863
SanFernando	146.0	145.5	161.1	149.1	4.848019
SanMarino	719.1	722.6	709.7	756.0	2.776674
SantaAna	1579.2	1436.5	1672.7	1937.8	12.747059
SantaMonica	565.1	494.8	636.0	512.4	11.488188
ThreeValleys	8615.7	7366.0	7467.4	8930.9	9.818559
Torrance	946.6	957.7	923.0	975.3	2.303223
UpperSGV	10691.7	9763.8	8768.0	11586.4	11.876655
WestBasin	8046.9	8428.7	7838.5	8119.9	3.015454
WesternMWD	17294.2	17962.2	18232.1	20803.5	8.282831

Appendix 5-C Flow Diagrams for Selected Member Agencies

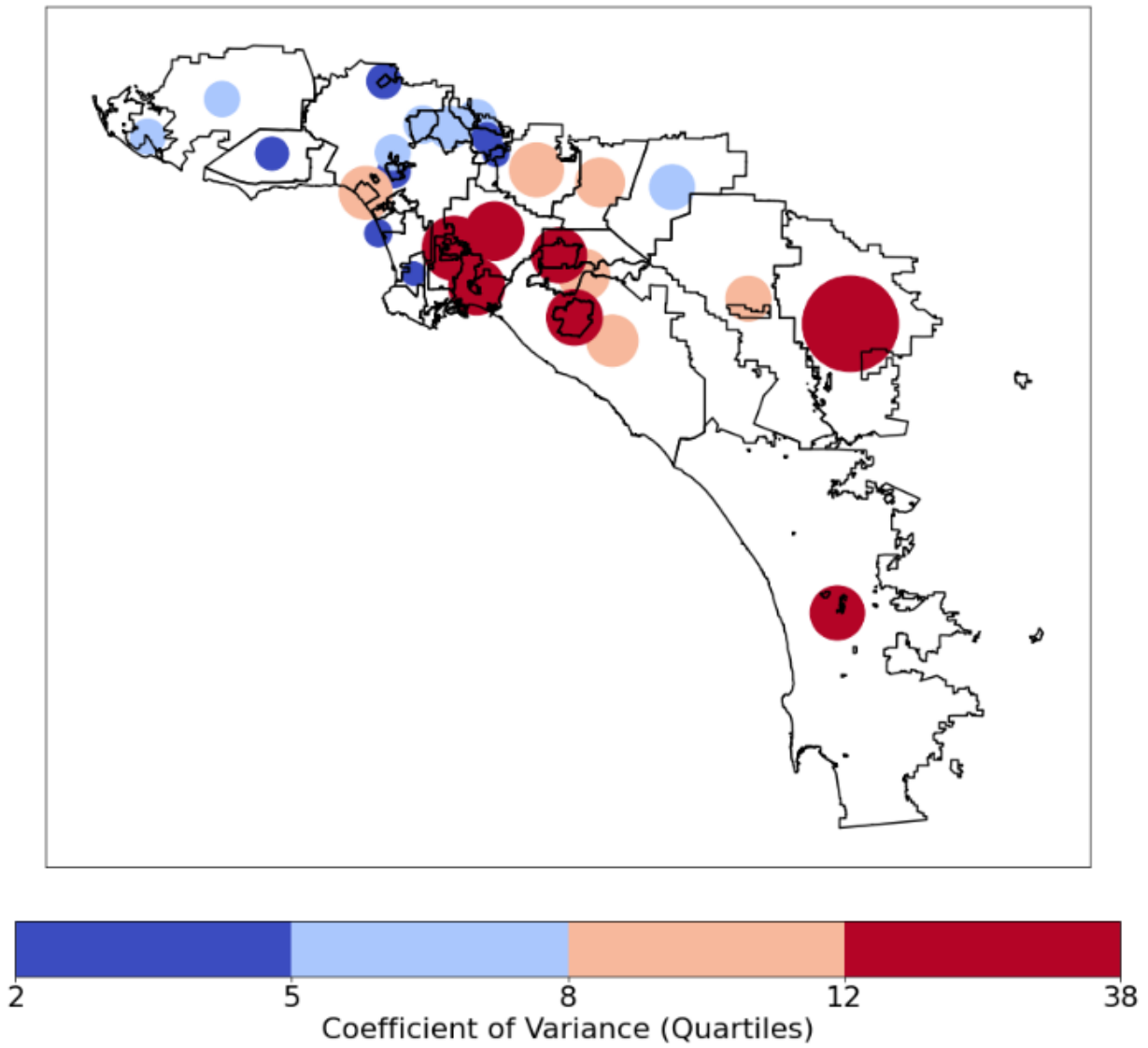
Compton Grass Trees Pixel Sankey NAIP Classification 2016, 2018, 2020



San Fernando Grass Trees Pixel Sankey NAIP Classification 2016, 2018, 2020



Appendix 5-D. Map of Coefficient of Variation Quartiles



CHAPTER 6: CONCLUSION

Dissertation Summary and Recommendations

Large-scale water conservation initiatives, including those addressed in this dissertation, are being implemented and will continue to be necessary to respond to water resource constraints due to drought and unsustainable consumption. At the same time, remotely sensed data is improving in quality, quantity, and accessibility. Decision makers have the opportunity to leverage this data to improve and inform these large-scale water conservation initiatives for the benefit of stakeholders and water systems. Sufficiently addressing the uncertainty inherent in remotely sensed data will be key in obtaining stakeholder approval and maximizing the benefit that the data source has to offer. The following is a summary of the results from the water conservation initiatives explored in this dissertation as well as recommendations for future study and policy considerations.

Chapter 2: Assessment of OpenET Models for Use in PVID

OpenET's eeMETRIC model was identified as the most representative evapotranspiration (ET) model, although other models performed well, for use in PVID based on linear regression results and is therefore the recommended model for studying field-level consumptive use. However, before fully adopting an ET model for consumptive use measurement there are at least one major technical and one major social consideration that should be addressed which arise due to my recommendation of using remote sensing to produce ET estimates. The technical consideration is the need for a field-level accuracy assessment with flux towers or lysimeters to inform the accuracy of modeled results and any biases that would result by adopting modeled ET as a consumptive use measure. The social consideration involves addressing and generating buy-in among stakeholders. Beyond concerns about model accuracy and the source of the water consumed on fallowed fields, there may also be secondary political or historical impacts from

changing the fallowing savings calculation method. Impacts of changing methods on stakeholders and the Colorado River system should be extensively evaluated both in the past and into the future and be well understood by all before any official adoption of a new calculation method. For example, if savings have been overestimated, this may call into question water volumes saved in the Colorado River system or priority system water use.

Chapter 3: Evaluating USBR's Fallowing Savings Calculation through the PVID Fallowing Program using Evapotranspiration Data

ET estimates show that fallowed fields in PVID consume water which, depending on the source of this water, would inflate fallowing savings as calculated by USBR. An ET-based approach for estimating fallowing savings may be more accurate but this would require understanding where the water that is consumed on fallowed fields originates from. Whether the consumed water is latent water left over from cropping, groundwater, or infiltration from neighboring irrigated fields, has implications for understanding whether water loss should count against the program benefits. Evidence in Chapter 4 points to infiltration as one origin for this consumed water but the exact contribution cannot be concluded. This uncertainty can only be understood with an extensive and likely impractical groundwater and soil study applied across the valley. Even if this is not realistic, smaller scale soil and groundwater studies would still be useful in understanding where the water consumed on fallowed fields originates from.

Chapter 4: Exploration of Factors that Influence Fallowed Field Water Use within the PVID Fallowing Program

I found evidence that smaller fallowed fields, higher surrounding field water use, older fallowed field age, and thinner field shape, had some correlation with higher fallowed field water use. The statistical significance of these correlations exhibited some variability, as all

parameters, besides surrounding field water use had a year where the coefficient sign was opposite of expected. There may be a benefit to performing a statistical analysis that includes a spatial or geographical element, which may help to explain differences in fallowed field consumptive use across the valley, may aid in any potential adoption of rules or incentives within a fallowing program. Logistically, adopting rules or incentives to attempt to minimize fallowed field water use will take widespread stakeholder buy-in and coordination. The recommendations provided in this chapter are all possible but assume complete control over fallowed fields. For example, positioning fallowed fields away from high water use fields is likely not in the complete control of a single farmer and would require coordination by administrators.

Chapter 5: Assessment of Irrigated Area measurements

I found that irrigated area as estimated through NAIP imagery classification varies significantly in magnitude over four consecutive measurements from 2014 to 2020 and that the use of 2018 imagery for the Outdoor Residential Water Use Standard likely does not result in a representative water budget for all agencies. Identification of irrigated area within all of California is an extremely difficult task and NAIP imagery is likely the best available data source to estimate this area. However, given the variability in irrigated area as shown in my results, it may be reasonable to allow retailers to choose a representative year of data as more data is collected on top of including the irrigable not irrigated area buffer going forward. This would increase water budgets initially but would have the added benefit of showcasing an understanding that irrigated area as measured by NAIP is an imperfect value. Given the extensive public comment and delays in adopting this legislation, it may be reasonable to lower demands on retailers in order to set a baseline that can be improved upon in future years as more data are collected.

Addressing Uncertainty in Water Conservation Initiatives

Water conservation initiatives like the Outdoor Residential Water Use Standards (ORWUs) and the Palo Verde Irrigation District (PVID) fallowing program require large-scale water use and land area data to evaluate and inform (García et al., 2016, Hering, 2014, Walker, 2000). These types of large-scale initiatives will likely become more common and necessary in the future given the expected increase in drought due to climate change (Cook et al., 2018). However, traditional methods for estimating both field water use and land area are generally impractical for sizeable areas (Perry 2023, Velpuri et al., 2009). Remotely sensed data provides a more accessible data source, and in some cases the only data source, to fill this gap. This dissertation sought to leverage remotely sensed data to provide an alternative method for calculating fallowing savings, identify factors that may improve fallowing program efficiency, and illustrate variability in irrigated area measurements as applied to the ORWUs. A common thread through these chapters is the multiple levels of uncertainty that arises with the use of remotely sensed data, likely one of the reasons that utilization of the data source is not more widespread despite its increasing availability.

Uncertainty is inherent in many methods of data collection but is particularly highlighted when attempting to adopt newer methods (Fernandez and Rodrik 1991). Remotely sensed data has more than one source of inaccuracy or uncertainty, including model accuracy, pixel resolution, (Maxwell et al., 2021, Reddy & Kumar 2021) and lack of sufficient accuracy assessments (Stehman & Foody 2009). The impact of these uncertainties appears in two primary ways within my dissertation. For the fallowing chapters there is uncertainty in the absolute accuracy of the chosen evapotranspiration model and uncertainty in the origin of the water consumed through evapotranspiration. These uncertainties and a bias for the status quo are likely

key reasons for the continued use of an antiquated district-wide method for calculated following savings by USBR when field-level estimates are readily available.

The State Water Board (SWB) and Department of Water Resources (DWR) are embracing remotely sensed data to estimate irrigated area for the ORWUs; however, there appears to be not enough recognition of the uncertainty created by a single point-in-time measurement. My irrigated area results showcase the uncertainty in how representative the 2018 measurement itself is due to the changing nature of irrigated area over time. The uncertainty in the 2018 measurement has been brought up in numerous public comments during the rule making of the legislation. Even during the adoption of the legislation in which the ORWUs fall under in July 2024, stakeholders expressed concerns with how the irrigated area data was collected. DWR and the SWB have attempted to address some of this uncertainty through what is termed irrigable but not irrigated area, which was not addressed in this dissertation. DWR has determined that 20% of this area applies to water budgets as a catch-all factor to account for the uncertainty present in differentiating between healthy vegetated (irrigated) and unhealthy vegetated (irrigable not irrigated) area. However, DWR will remove this buffer once an updated data point for irrigated area is collected through another year of National Agriculture Imagery Program (NAIP) imagery analysis (July 3, 2024 SWB Board Meeting). DWR is assuming that this second measurement will resolve uncertainty in irrigated area measurements, but my results show that two data points is likely not enough to achieve this. Two datapoints may inaccurately make the data appear to be representative since they would represent a straight line. My data shows that, at four data points, it becomes clear that irrigated area as measured by NAIP imagery is unstable and any given year of data will likely result in different results for a given agency.

Assuming DWR continues to update LAM data it is highly likely this same result will be found through their own analysis.

Sufficiently understanding and addressing the uncertainty surrounding remotely sensed data will be key in maximizing the benefit that the data type offers. Political considerations must be addressed, as the adoption of a particular ET model or decisions made regarding irrigated area measurements will have differing impacts between stakeholders, potentially resulting in resistance. Addressing and communicating these different impacts and levels of uncertainty will make adoption more likely (Manski 2019). Adaptive Policy Pathways (APP) provides a framework for addressing and handling uncertainties that can be applied to uncertainties discussed in this dissertation (Walker et al., 2013). APP combines two approaches for dealing with uncertainties, from adaptation pathways (Haasnoot et al., 2013) and dynamic adaptive policy making (APM) (Kwakkel et al., 2016, Walker et al., 2001). This approach broadly addresses: relevant uncertainties which may change over time; different types of policy actions to handle vulnerabilities and opportunities; adaptation pathways describing sequences of promising policy actions; and a monitoring system with related contingency actions to keep the policy on track of a preferred pathway (Walker et al., 2013). Integral to APP is the reassessment of the problem through on-going monitoring and reiteration of potential policy actions and pathways as efficacy, vulnerabilities, and opportunities are assessed. Applying this type of approach to the initiatives discussed in this dissertation would not only demonstrate an active understanding that there are uncertainties present, it would also improve policy implementation as multiple pathways forward under different scenarios are identified ahead of time and would be readily implementable as the problem shifts to match a new scenario. While an adaptive approach like APP would add to the workload of decision makers, I think it offers a pathway

forward for using remotely sensed data where the alternative may be not benefitting from the data at all. Remotely sensed data can only be a valuable resource if it is utilized, therefore taking steps, even small steps, toward its utilization should be a focus of decision makers.

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