

**Consumptive Water Use in California's Sacramento-San Joaquin Delta:  
A Comparison of Estimation Methods and Field Data, with Implications for  
Water Right Diversion Reporting**

By

Jesse Ryan Jankowski  
B.S. (Colorado State University) 2012

Thesis

Submitted in partial satisfaction of the requirements for the degree of

Master of Science

in

Civil and Environmental Engineering

in the

Office of Graduate Studies

of the

University of California

Davis

Approved:

Jay R. Lund, Chair

Josué Medellín-Azuara

Jonathan Herman

Samuel Sandoval Solis

Committee in Charge

2018

## Abstract

Consumptive water use by crops, often referred to as evapotranspiration (ET), is a substantial element of an agricultural region's water balance. In the Sacramento-San Joaquin Delta of California, ET data can inform water resource management in a region with coexisting demands for agriculture, cities, the environment, and inter-basin transfers through large-scale water projects. Established methods for the estimation of ET include two-step crop coefficient approaches and computational models which process remotely sensed data from satellites to estimate ET on larger spatial scales based on vegetation characteristics and energy flux data. Though ET estimation methods are well-documented in the literature and have been applied globally, there are few comparisons of estimation methods which discuss the impacts of using different methodologies and input datasets to quantify ET in a region. Furthermore, to date few studies have used multiple methods, field-measured data, and land use surveys to inform water management in a region as complex and important as the Delta.

This thesis advances analysis and insights from a comparison of seven established ET estimation models which was previously reported by the Center for Watershed Sciences at the University of California Davis (available at <https://watershed.ucdavis.edu/project/delta-et>). It covers agricultural and non-agricultural lands in the 679,594-acre Delta Service Area in the 2015 and 2016 water years (October 2014 through September 2016). Land use survey data was used to analyze monthly ET estimates at 30-meter resolutions, and a field meteorological campaign was also done to estimate ET from bare soil, alfalfa, corn, and pasture using surface renewal, eddy covariance, and water vapor flux stations. The total estimated ET from agricultural lands in the Delta was about 1.44 million acre-feet (MAF) in 2015 and 1.38 MAF in 2016, with all seven models within 12% of the ensemble mean and averaging an absolute difference of 6% for both years. While most of this consumptive use originated from the primary crops in the Delta (alfalfa, corn, pasture, and to a lesser degree almonds, tomatoes, and vineyards), increased fallow lands in 2016, open water, and non-agricultural vegetation were also estimated to consume large amounts of water. A detailed comparison between model estimates on satellite overpass days over fourteen two-acre sites revealed that methodological similarities and common input datasets encouraged agreement among models, but the operator judgement and unique assumptions of each model will frequently cause systematic, regional, and temporal differences between estimates. Field-based ET estimates at the same sites were generally lower than model estimates, with a mean bias of -1.2 mm/d and a RMSE of 2.1 mm/d, suggesting that microclimates and other factors unique to the Delta and not factored into models may impact crop ET.

Some policy implications arise for enhancing collaborative modeling and measurement of ET in California. These include the potential use of ET data to supplement manual diversion reporting, assist with precision irrigation scheduling, inform water management for ecological restoration, and improve the accuracy of data inputs to models for groundwater management, water quality, environmental protection, and inter-basin transfer operations. A preliminary study comparing ET estimates to reported diversions Delta-wide showed strong agreement in timing and magnitude for several islands and large regions of the Delta. With additional data on local conditions and the places and nature of use of water rights, remote ET estimates may help reduce reporting

burdens and streamline water rights administration. Continued and improved land use surveys, field measurement stations, model cooperation and comparison, and a collaborative state consortium to advance ET estimation science and applications in California are recommended and to expand the use of consumptive use data in water resource management.

## Acknowledgements

This thesis represents work contributed by many people towards a collaborative study. Principal investigators Josué Medellín-Azuara (UC Merced), Jay Lund, Kyaw Tha Paw U, and Yufang Jin (UC Davis) provided invaluable guidance, and analysis efforts would have been impossible without technical capabilities of Andy Bell and Nick Santos and the help of Jessica Badillo.

Model operators developed the ET estimates presented here and contributed in-kind time towards project coordination: Morteza Orang from DWR (CalSIMETAW); Lan Liang and Tariq Kadir from DWR (DETAW); Martha Anderson from USDA-ARS (DisALEXI); Dan Howes from Cal Poly (ITRC-METRIC); Forrest Melton and Lee Johnson from NASA-Ames and CSUMB (SIMS); Nadya Alexander from UC Davis (UCD-METRIC); Yufang Jin and Andy Wong from UC Davis (UCD-PT); and other co-authors from each team. The field campaign group from the UC Davis Department of Land, Air and Water Resources also thoroughly participated in all project efforts and discussions: Kyaw Tha Paw U, Eric Kent, Jenae' Clay, and their co-authors, as well Bekele Temesgen and Cayle Little from DWR (CIMIS).

Peer reviewers helped finalize the report on which this thesis was based: Richard Allen of the University of Idaho, Byron Clark of Davids Engineering, Richard Snyder of UC Cooperative Extension, and Thomas Trout of USDA-ARS. The Delta Watermaster's Office guided this work, and financial support was provided by the State Water Resources Control Board, California Department of Water Resources, Delta Protection Commission, Delta Stewardship Council, and the North, Central, and South Delta Water Agencies.

I would personally like to thank Josué Medellín-Azuara and Jay Lund for their mentorship, encouragement, and invaluable insights throughout my research and studies at UC Davis. My employer, Natural Resources Consulting Engineers (NRCE) graciously allowed me to work part-time during school, and I especially thank Wold Mesghinna for advice, mentorship, and valuable experiences which helped shape my career. Thank you also to Jon Herman and Sam Sandoval-Solis for your instruction. I am grateful to the many other researchers, students, staff, and affiliates of the Center for Watershed Sciences who kept me motivated to conduct stimulating interdisciplinary research. Thank you also to the staff and research network of the Public Policy Institute of California (PPIC) for the opportunity to assist exciting work and the inspiration to communicate meaningful public messages. I will always treasure the time I spent in the Grand Canyon with the wonderful people of the 2018 Ecogeomorphology trip.

I would not be here without the love and support of my family and friends. My parents, Paul and Sue, help me believe I can do anything and inspire me to make the world a better place every day. My sister Lindsey keeps me motivated to succeed, beating me to a Master's degree and starting on another this year. Finally, I can never thank my partner Karina enough for encouraging me to go back to school, supporting me endlessly even as she pursued her own degree, and always being up for an adventure. I dedicate this achievement to all of you.

# Contents

Abstract .....	ii
Acknowledgements .....	iv
Contents .....	v
List of Figures .....	vii
List of Tables .....	viii
1. Introduction.....	1
2. Study Area and Methods.....	3
2.1. The Sacramento-San Joaquin Delta and Land Use .....	3
2.2. Consumptive Water Use Models.....	7
2.2.1. Study Approach and Data Sources .....	7
2.2.2. CalSIMETAW .....	8
2.2.3. DETAW .....	9
2.2.4. DisALEXI.....	9
2.2.5. ITRC-METRIC .....	9
2.2.6. SIMS .....	10
2.2.7. UCD-METRIC.....	10
2.2.8. UCD-PT .....	10
2.3. Field Evapotranspiration Measurements .....	11
2.3.1. 2015 Field Campaign on Fallow Lands .....	12
2.3.2. 2016 Field Campaign in Alfalfa, Corn, and Pasture Fields .....	12
2.4. Comparison Method.....	13
3. Consumptive Water Use Estimates.....	16
3.1. Consumptive Water Use in the Delta.....	16
3.2. Consumptive Use by Major Crops .....	20
3.3. Consumptive Use Estimate Variation .....	24
3.4. Field Measurements .....	27
3.4.1. 2015 Measurements in Fallow Fields .....	27
3.4.2. 2016 Measurements in Alfalfa, Corn, and Fields .....	28
4. Comparisons Between Consumptive Use Estimates .....	30
4.1. Model Comparison.....	30
4.1.1. CalSIMETAW .....	34

4.1.2.	DETAW .....	36
4.1.3.	DisALEXI.....	36
4.1.4.	ITRC-METRIC .....	37
4.1.5.	SIMS .....	38
4.1.6.	UCD-METRIC.....	39
4.1.7.	UCD-PT .....	39
4.1.8.	General Model Insights.....	40
4.2.	Field Data Comparison.....	41
4.2.1.	2015 Comparison for Fallow Fields .....	42
4.2.2.	2016 Comparison for Alfalfa, Corn, and Pasture Fields.....	43
4.2.3.	Potential Causes of Differences .....	47
4.2.4.	Improving Model Inputs and Field-Model Comparisons .....	48
5.	Comparing Consumptive Use to Self-Reported Diversions .....	49
5.1.	Water Rights and Diversions in the Delta.....	49
5.2.	Comparison of Diversions and Evapotranspiration .....	52
5.3.	Analysis of Differences Between Diversion and Evapotranspiration.....	54
5.4.	Further Work to Improve Analysis .....	55
6.	Conclusions on Consumptive Water Use in the Delta.....	57
7.	Policy Recommendations for Broader Use.....	60
	References.....	65

## List of Figures

Figure 1: Land uses in the Delta, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018).....	5
Figure 2. Field campaign stations and nearby CIMIS stations, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018).....	14
Figure 3. Maps of ensemble average annual ET in the DSA and its regions, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018). White areas are non-agricultural lands. ....	19
Figure 4. Contribution of significant land uses to agricultural land use area (far left column) and total agricultural ET volume in the DSA, by model, (A) 2015 and (B) 2016 (Medellín-Azuara <i>et al.</i> , 2018).....	23
Figure 5. Monthly average ET rates, by model, averaged over the DSA for significant crops, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018). ....	24
Figure 6. Maps of annual coefficient of variation between all seven models in the DSA, 2015-2016. White areas represent non-agricultural lands (Medellín-Azuara <i>et al.</i> , 2018).....	25
Figure 7. Monthly coefficients of variation between methods for significant crop types in the DSA, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018). ....	26
Figure 8. Monthly absolute variation between methods for significant crop types in the DSA, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018). ....	26
Figure 9. Monthly mean and standard deviation of ET <sub>a</sub> from bare soil stations and nearby CIMIS sites, September 2015 (Medellín-Azuara <i>et al.</i> , 2018). ....	28
Figure 10. Monthly mean and minimum/maximum daily field ET <sub>a</sub> from alfalfa stations and Spatial CIMIS at the same locations, May- September 2016 (Paw U <i>et al.</i> , 2018).....	29
Figure 11. Monthly mean and minimum/maximum daily field ET <sub>a</sub> from corn stations and Spatial CIMIS at the same locations, April-September 2016 (Paw U <i>et al.</i> , 2018).....	29
Figure 12. Monthly mean and minimum/maximum daily field ET <sub>a</sub> from pasture stations and Spatial CIMIS at the same locations, June-September 2016 (Paw U <i>et al.</i> , 2018).....	29
Figure 13. Remote sensing estimates over pasture field on Twitchell Island, June 27, 2016 (Jankowski <i>et al.</i> , 2018). ....	31
Figure 14. Timeseries of model and field-based ET estimates over a pasture field on Twitchell Island, 2015-2016 (Jankowski <i>et al.</i> , 2018). Points represent direct estimates on overpass days and lines represent continuous daily data provided by some models. ....	32
Figure 15a. Comparison of daily ET estimates between models on overpass days over alfalfa, corn, and pasture fields, 2015- 2016 (after Jankowski <i>et al.</i> , 2018). Solid lines represent linear regressions and the gray dashed line represents the 1:1 ratio. ....	33
Figure 16. Challenges of estimating ET remotely (Medellín-Azuara <i>et al.</i> , 2018). ....	41
Figure 17. Comparison of monthly average ET estimates by models and field sites in fallow fields, September 2015 (Medellín-Azuara <i>et al.</i> , 2018). The black dashed line represents Spatial CIMIS ET <sub>o</sub> , the red dashed line SR-based ET <sub>a</sub> estimates, and the solid red line EC-based ET <sub>a</sub> measurements.....	42
Figure 18. Comparison of daily ET estimates between models and field data on overpass days over alfalfa, corn, and pasture fields, April-September 2016 (after Jankowski <i>et al.</i> , 2018). Solid lines represent linear regressions and the gray dashed line represents the 1:1 ratio. ....	45

Figure 19. Delta subareas (Kadir and Liang, 2018) and points of diversion (after SWRCB, 2018). .....	51
Figure 20. Monthly reported diversions (SWRCB, 2018) and ensemble mean ET estimates for select Delta subareas, regions, zones, and the DSA, 2015-2016. ....	53
Figure 21. Analysis of annual differences between reported diversions and ET for all subareas, 2015-2016. ....	55

## List of Tables

Table 1. Land uses in the Delta Service Area, 2015-2016 (Medellín-Azuara <i>et al.</i> , 2018).....	6
Table 2. Field campaign station information, 2015-2016 (after Paw U <i>et al.</i> , 2018). ....	13
Table 3. Summary of ET estimation models and field campaign data, 2015-2016.....	16
Table 4. Total ET volume in the DSA, by model, from agricultural and non-agricultural lands, 2015-2016. ....	17
Table 5. Attributes and agricultural ET estimates for major regions of the DSA, 2015-2016. ....	20
Table 6. Annual ensemble mean ET quantities, by land use, in the DSA, 2015-2016.....	21
Table 7. Comparative statistics between model estimates on overpass days over alfalfa, corn, and pasture fields, 2015-2016 (after Jankowski <i>et al.</i> , 2018). ....	35
Table 8. Comparative statistics between models and field data on overpass days over alfalfa, corn, and pasture fields, April-September 2016 (after Jankowski <i>et al.</i> , 2018). ....	46



# 1. Introduction

Consumptive use in water systems is the quantity of water not returned for reuse elsewhere via surface runoff or deep percolation into groundwater. Evapotranspiration (ET), the combination of water evaporated from the soil and transpired from plants (Womach, 2005), is often the predominant consumptive water use from agriculture or natural vegetation, so consumptive use and ET are often used interchangeably. ET and consumptive use are measured in linear units over time (here in millimeters per day, mm/d), which can be multiplied by land area and time to calculate a volume of water (here in acre-feet, AF, or thousand acre-feet, TAF).

Because consumptively used water is subtracted from the water balance of a watershed and is not available for other uses, a variety of parties are interested in the estimation of ET.

Quantifications of ET may help farmers schedule irrigation to meet crop water needs, manage soil moisture, determine leaching requirements, and anticipate runoff. Water managers use ET data to in the calculation of stream depletions, basin outflow, groundwater recharge, and other hydrologic and hydraulic elements. Other agencies or regulators may also use ET estimates to compute water available for market trading (Hanak *et al.*, 2011) or to administer water rights by estimating actual use (Allen *et al.*, 2005a). In the Sacramento-San Joaquin Delta (“Delta”) of California, a region with many water needs facing complex challenges (Hanak *et al.*, 2013), an understanding of consumptive water use is critical for the allocation of agricultural water, management of inter-basin transfer operations, water quality model calibration, and environmental habitat and species protection. This objective of this thesis was to develop a better understanding of consumptive water use in the Delta by coordinating the modeling, measurement, and comparison of ET across a variety of independent research and estimation efforts.

The science of ET estimation has developed field-based methods using meteorological measurements and empirical desktop approaches for specific crops. Abtew and Melese (2012) describe ways of measuring and calculating ET from crops and other natural and manmade systems in a watershed; direct field ET measurement methods include lysimeters and eddy covariance, while field-based estimates can be made using surface renewal, pan evaporation, or other of micrometeorological techniques. Two-step or so-called “crop coefficient” estimation methods involve measured inputs and empirical approximations, including pan method with coefficients, temperature-based methods such as Thornthwaite, Blaney-Criddle, and Hargreaves-Samani, and radiation-based methods such as Abetew, Priestley-Taylor, Turc, solar radiation maximum temperature, and mass transfer. Crop coefficient approaches also include more complex methods based on a physical model, including Penman and Penman-Monteith (Allen *et al.*, 1998). Satellite images and observations of energy fluxes to and from the earth’s surface have made large amounts of spatial data available, allowing the estimation of ET at large scales using so-called “remote sensing” techniques based on a combination of meteorological inputs, specific assumptions, and empirical methods (Kustas and Norman, 1996). Established remote sensing models include the Surface Energy Balance for Land (SEBAL), the Surface Energy Balance System (SEBS), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), Satellite Irrigation Management Support System (SIMS), and others.

Some simple models work for applications in which meteorological and other data are limited, but more data and computational power may facilitate adoption of more complex and accurate methods.

The study described in this thesis involved the direct comparison of ET estimates from field methods, two-step approaches, and several remote sensing models for two years over a large and predominantly agricultural region of California. Similar efforts have been made to various degrees in scientific literature. Kite and Droogers (2000) compared ET estimates from nine methods (including two field stations, two crop coefficient approaches, two hydrologic models, and three remote sensing models with common input datasets) in western Turkey. Sörensson and Ruscica (2018) completed a large comparison of seven ET estimation methods (two remote sensing approaches and five land surface models) over nine regions of South America.

Other studies have made related remote sensing or field data comparisons with implications for ET estimation. Fisher *et al.* (2008) compared global remote sensing-based estimates of ET to field measurements at 16 sites. Alexandridis *et al.* (2009) developed a customized remote sensing-based ET estimation approach for Greece and compared its results to a crop coefficient-based approach. Itenfisu *et al.* (2003) and Alkaeed *et al.* (2006) compared the results of various methods for computing grass or alfalfa reference evapotranspiration using common input field data, while Senatore *et al.* (2015) compared multiple remote sensing approaches for reference ET calculation. Comparisons of individual energy balance components, rather than the resulting ET estimates, from field sites and remote sensing approaches were made by Timmermans *et al.* (2007), Choi *et al.* (2009), and Paiva *et al.* (2011).

In the Delta, Medellín-Azuara and Howitt (2013) demonstrated a proof-of-concept study for comparing crop consumptive water use data, including one remote sensing model and two crop coefficient-based approaches over about 36,000 cropped acres on five islands. Szilagyi and Jozsa (2018) recently used historic field measurements and empirical soil-air relationships to map and compare ET trends across California's Central Valley from 1979-2015.

This thesis summarizes a unique approach to comparing ET estimation methods for an applied water management problem, covering a large area with a variety of land uses over two years. Multiple estimation methods, including crop coefficients, remote sensing, and multiple types of field stations were integrated, and collaboration yielded results with generally high agreements between model estimates. The impacts of method assumptions on ET estimates at small spatial and temporal scales were examined, field findings suggested unique meteorological conditions potentially not incorporated in models, and further recommendations were made on the use of remote ET estimates by water managers in California. These include precision irrigation scheduling, groundwater model improvement, basin-wide accounting, environmental management, and water rights administration.

A potential application of consumptive use estimates to water rights administration was included in this thesis. Siegfried *et al.* (2014) previously showed that remote estimates of ET, combined with a physical model, could be used to predict diversions and return flows from areas in the Delta. Their study required significant ground-truthing and high-resolution data to model two

islands, and the results showed promise when compared to historic measurements and other models. A more robust Delta-wide analysis was done here to compare ET data to actual diversions reported by water users over the same period. For some Delta islands and larger regions, favorable correlation between ET and reported diversion was found in both timing and magnitude. Results suggest that remotely-estimated ET values show strong promise to aid in the administration of water rights in the Delta. Further examination of local conditions, documentation of water uses, and data collection on irrigation technology, land cover, and places of use would improve this analysis and likely expand the application of consumptive use information for water management, planning, administration, and enforcement.

This thesis summarizes, discusses, and extends a collaborative effort of numerous researchers (see Acknowledgements). Considerable portions of it were previously reported to the Delta Watermaster's Office by Medellín-Azuara *et al.* (2018), and figures and information reproduced from that technical report are noted. This thesis expands upon those efforts and presents additional data, analyses, and applications of consumptive use information to water resource management in the Delta.

## **2. Study Area and Methods**

The comparative study was done in the Sacramento-San Joaquin Delta for the 2015 and 2016 water years (October 2014 through September 2016). Two years of land cover data overlay and support evapotranspiration estimates, aiding comparisons across seven established methods and a field measurement campaign at 18 different sites and four different land uses (Paw U *et al.*, 2018). The following sections describe the study area and its land uses, the different models compared, the field campaign, and the methods employed to compare models and field data.

### **2.1. The Sacramento-San Joaquin Delta and Land Use**

The Sacramento-San Joaquin Delta ("Delta") is the confluence of California's Central Valley, with the Sacramento River flowing from the north and the San Joaquin River in the south. Their waters mix in a series of channels separated by islands and levees, eventually discharging west through the Carquinez Strait into San Francisco Bay and the Pacific Ocean. The Delta estuary system provides habitat for native species, water for irrigation and urban use within its boundary, and is the main transfer hub for California's interconnected water supply system (Hanak *et al.*, 2013).

Since 1965 the California Department of Water Resources (DWR) has defined boundaries of the Delta Service Area as areas irrigated from channels in the Delta, though its official boundaries were defined as the slightly larger Legal Delta by the 1959 Delta Protection Act (DWR, 2017a). The DSA covers 679,594 acres of generally congruent land and water surface and was the primary area addressed in this study; the Legal Delta covers 737,625 acres. Both Delta areas are shown in Figure 1.

Since 1950, DWR (2018d) has done land use surveys of portions of California to quantify crops grown in various regions. In 2015 and 2016, vector land use maps were developed to define field

boundaries and true irrigated area in the Delta during the primary growing season; a 2-by-2-meter resolution was obtained from the Pleiades satellite in July 2015, and National Agricultural Imaging Program (NAIP) imagery at a 0.6-by-0.6-meter resolution was used in May-July 2016 (Land IQ, 2018). The datasets, which were rasterized to match the resolution of remote sensing models for this study, classify all lands within the Delta into 36 categories, 28 of which were considered agricultural for this study. Delta land uses in 2015 and 2016 are mapped in Figure 1 and summarized in Table 1.

Figure 1 and Table 1 show that the Delta's landscape was roughly 70% agricultural in 2015, covering about 477,690 acres, which decreased by 2% to 464,742 acres in 2016. Non-agricultural lands correspondingly increased from 201,904 acres in 2015 to 214,852 acres in 2016. The dominant crops in the Delta in both years were corn, alfalfa, and pasture, though fallow fields became the largest land cover in 2016 (likely driven by land preparation for the planting of permanent crops) and semi-agricultural or right-of-way areas also covered large areas. Other major crops included grape vineyards, tomatoes, rice, almonds, and other field and vegetable crops. Major non-agricultural land use classes were urban areas, open water, and upland herbaceous zones.

The major land use changes from 2015 to 2016 include decreases in alfalfa, corn, and pasture (about 36,000 acres in total, 5% of the DSA), increased fallow land (about 29,000 acres, 4% of the DSA), increased almond and safflower planting (about 16,000 acres in total, 2% of the DSA), and decreases in tomatoes, truck crops, wet herbaceous/sub-irrigated pasture, and other deciduous crops (about 26,000 acres in total, 4% of the DSA). An analysis of lands which changed uses from 2015-2016 showed that the largest shifts were the fallowing of corn (about 19,200 acres), tomatoes (about 13,700 acres), alfalfa (about 9,200 acres), and truck crops (about 4,800 acres), the planting of corn and safflower on fallow lands (each about 5,100 acres), the shift from other deciduous plants to almonds (about 4,200 acres), and the conversion of pasture, fallow, and wet herbaceous/sub-irrigated pasture lands to upland herbaceous areas (about 6,900, 1,500, and 1,200 acres, respectively). Some reported land use shifts may suggest improvements in remote land cover interpretation rather than actual land use changes.

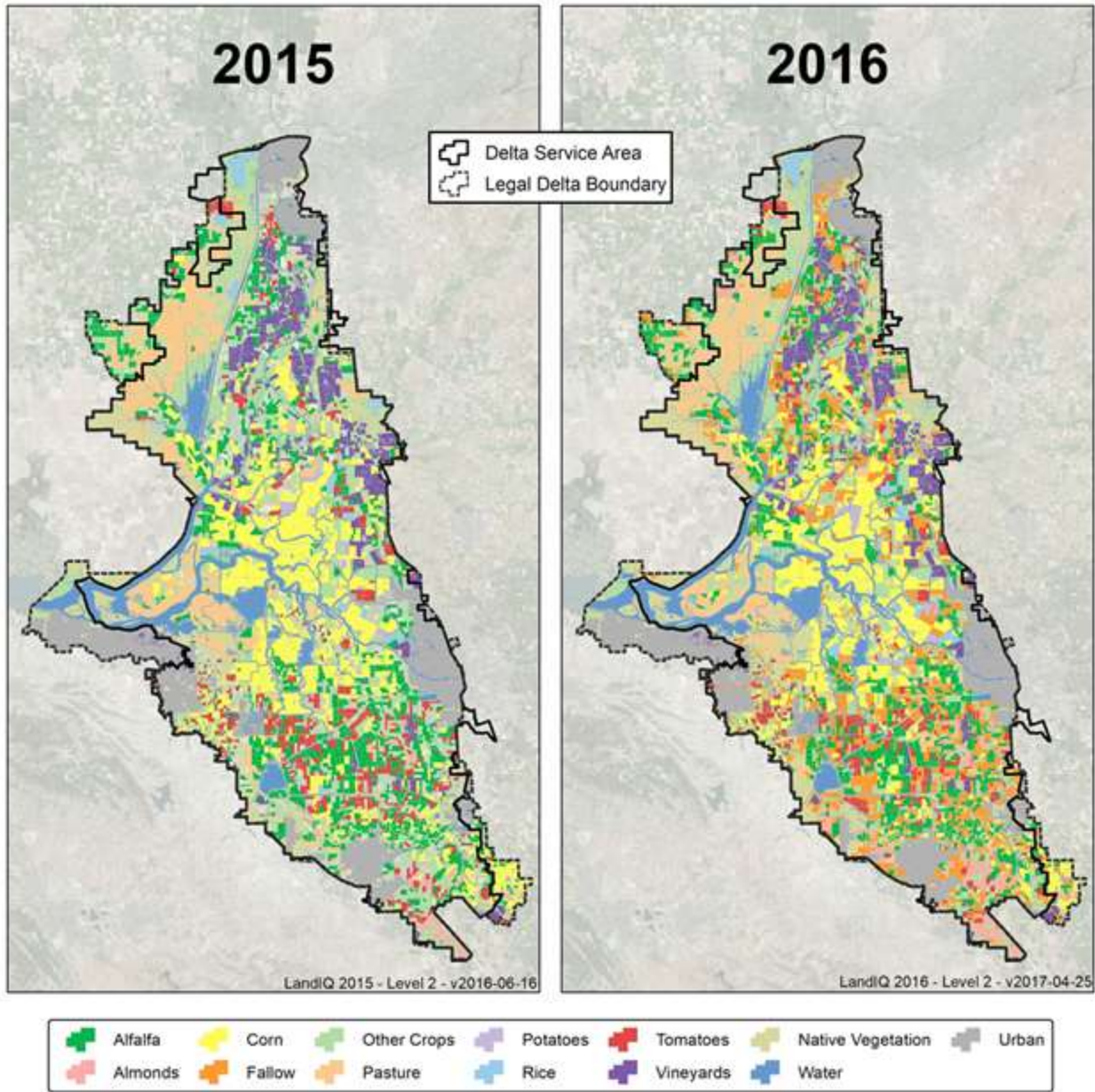


Figure 1: Land uses in the Delta, 2015-2016 (Medellín-Azuara *et al.*, 2018).

**Table 1. Land uses in the Delta Service Area, 2015-2016 (Medellín-Azuara *et al.*, 2018).**

Commodity (* denotes agricultural land use)	2015		2016	
	Acres	Percent of DSA	Acres	Percent of DSA
Alfalfa*	74,267	10.9%	64,946	9.6%
Almonds*	5,216	0.8%	13,275	2.0%
Bush Berries*	1,202	0.2%	1,255	0.2%
Cherries*	2,094	0.3%	2,876	0.4%
Citrus*	9	0.0%	6	0.0%
Corn*	91,712	13.5%	70,845	10.4%
Cucurbit*	3,984	0.6%	3,047	0.5%
Fallow <sup>1</sup> *	51,856	7.6%	80,801	11.9%
Floating Vegetation	3,526	0.5%	2,720	0.4%
Forage Grass*	4,466	0.7%	6,727	1.0%
Olives*	1,474	0.2%	1,531	0.2%
Other Deciduous*	7,702	1.1%	1,744	0.3%
Pasture*	48,097	7.1%	42,418	6.2%
Pears*	5,945	0.9%	5,524	0.8%
Pistachios*	146	0.0%	266	0.0%
Potatoes*	4,115	0.6%	3,823	0.6%
Rice*	7,630	1.1%	7,953	1.2%
Riparian Native Vegetation	21,700	3.2%	22,799	3.4%
Safflower*	5,904	0.9%	13,581	2.0%
Semi-Agricultural/ROW <sup>2</sup> *	48,467	7.1%	48,240	7.1%
Sunflower*	33	0.0%	252	0.0%
Tomatoes*	36,248	5.3%	25,127	3.7%
Truck Crops*	9,557	1.4%	2,620	0.4%
Turf*	2,137	0.3%	2,093	0.3%
Upland Herbaceous <sup>3</sup>	54,379	8.0%	63,446	9.3%
Urban	62,227	9.2%	62,688	9.2%
Vineyards*	36,996	5.4%	37,339	5.5%
Walnuts*	3,469	0.5%	5,261	0.8%
Water	60,072	8.8%	63,045	9.3%
Wet Herbaceous/Sub-Irrigated Pasture <sup>4</sup> *	24,964	3.7%	22,614	3.3%
Other Crops <sup>5</sup> *	-	-	729	0.1%
<i>TOTAL</i>	<i>679,594</i>	<i>100%</i>	<i>679,594</i>	<i>100%</i>

<sup>1</sup> Agricultural lands that show evidence of recent cultivation (past 1-2 seasons) but were not planted with a crop at the time of survey. Actual surface cover varies and may include bare tilled soil, leftover crop residue, or weeds.

<sup>2</sup> Rights-of-Way, includes areas associated with crop cultivation but outside field perimeters (i.e. farmsteads, ditches, fence lines, etc.), roads, levees, transmission lines, and other farm, residential, or commercial/industrial facilities.

<sup>3</sup> Natural vegetation areas with dry soil moisture regimes caused by deeper groundwater conditions or better drainage, including rangeland, annual grassland, oak woodland, and scrub.

<sup>4</sup> Natural vegetation areas with wetter soil moisture conditions that are not within a riparian corridor (i.e. marshlands and meadows). Sub-irrigated meadows and irrigated or sub-irrigated pastures may share similar characteristics, so these lands may oscillate between being classified under this category or pasture depending on land management.

<sup>5</sup> Includes Asparagus\*, Carrots\*, Eucalyptus, Nursery, Sudangrass, and Young Orchard\*, which were only included in the 2016 survey. Any land planted with those crops in 2015 was included in another category.

## 2.2. Consumptive Water Use Models

Seven established methods or models which use remotely-sensed data, satellite imagery, and field measurements to estimate ET were compared by Medellín-Azuara *et al.* (2018). Estimates were developed by respective research teams and results were submitted for separate analysis by an independent research team from the Center for Watershed Sciences at the University of California (UC) Davis. The seven methods developed and applied by a variety of academic and governmental research organizations were:

- **CalSIMETAW**: California Simulation of Evapotranspiration of Applied Water, by DWR.
- **DETAW**: Delta Evapotranspiration of Applied Water, by DWR.
- **DisALEXI**: Disaggregated Atmosphere-Land Exchange Inverse method, by the U.S. Department of Agriculture Agricultural Research Service (USDA-ARS).
- **ITRC-METRIC**: Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) method, applied by the Irrigation Training and Research Center (ITRC) at California Polytechnic State University (Cal Poly) San Luis Obispo.
- **SIMS**: Satellite Irrigation Management Support System, by the National Aeronautics and Space Administration Ames Research Center (NASA-ARC) and California State University Monterey Bay (CSUMB).
- **UCD-METRIC**: METRIC method, implemented by UC Davis.
- **UCD-PT**: Priestley-Taylor optimized approach, by UC Davis.

### 2.2.1. Study Approach and Data Sources

ET estimates were developed with improvements developed through collaboration over a two-year study. An interim report (Medellín-Azuara *et al.*, 2016) summarized the results of a “blind” comparison, with all seven models submitting ET estimates for 2015 with access only to the 2015 DWR land use data and common reference ET datasets. Following the release of the interim report, the 2016 land use data, and field data for fallow fields in 2015 and alfalfa, corn, and pasture fields in 2016, models were permitted to make methodological improvements and final updated results were submitted for both 2015 and 2016. Final results presented by Medellín-Azuara *et al.* (2018) are replicated here, reflecting model improvements, lessons from the initial blind data comparison, and access to the two years of field campaign and land use data. Estimates prior to the final submissions are not reported here.

Final model ET estimates were developed for the 2015 and 2016 water years (from October 1, 2014 to September 30, 2016), and input datasets to the models were standardized where possible. Land use information for the Delta were sourced from DWR’s 2015 and 2016 land use datasets (Land IQ, 2018). Grass reference evapotranspiration (ET<sub>o</sub>) data was sourced from the California Irrigation Management Information System (CIMIS) maintained by DWR, specifically the Spatial CIMIS dataset developed by Hart *et al.* (2008). Spatial CIMIS uses satellite observations from the NOAA Geostationary Operational Environmental Satellite (GOES) to interpolate data from over 130 CIMIS field stations and cover California with a 2-by2-km resolution grid of data at a daily interval. ET<sub>o</sub> values are calculated using the ASCE version of the Penman-Monteith equation (EWRI-ASCE, 2005). Spatial CIMIS data for the Delta was developed with data from

15 CIMIS stations in the vicinity, five of which (242-Staten Island, 243-Ryde on Grand Island, 247-Jersey Island, 248-Holt on Roberts Island, and 249-Ripon) were deployed within the Delta as part of this study to improve accuracy for the 2016 water year. ETo values from specific CIMIS stations, calculated from a modified form of the Penman-Monteith equation following Temesgen and Eching (2013), were used for comparison to the field campaign data.

The five remote sensing-based methods (DisALEXI, ITRC-METRIC, SIMS, UCD-METRIC, and UCD-PT) used primarily Landsat 8 multispectral imagery (rows 33 and 34 of path 44) at 30-meter resolution in 16-day intervals to derive ET estimates. To increase temporal frequency, DisALEXI, ITRC-METRIC, and SIMS also used Landsat 7 satellite data after filling Scan Line Corrector (SLC) gaps. All remote sensing methods except for SIMS used Landsat thermal imagery, sharpened from 100 to 30-meter resolution using their own selected methods. The different methods chose Landsat images at their discretion, typically using clear sky scenes with minimal cloud obscuration. On average, remote sensing models used two overpass dates in water year 2014 (usually for interpolation of early water year 2015 data), nine dates from water year 2015 (roughly one successful overpass a month), 18 from water year 2016 (roughly one successful overpass every three weeks), and two from water year 2017 (primarily for interpolation of later water year 2016 images). Overpass dates were more frequently used by models in March through December, when images from California's Central Valley are less likely to have clouds (Jankowski *et al.*, 2018).

Some methods such as DisALEXI, SIMS, and UCD-PT utilized additional satellite data from the Moderate-Resolution Imaging Spectroradiometers (MODIS) and other sources. Though no specific error analysis was conducted by models as part of this study, available ranges of errors based on prior applications are cited below. Kite and Droogers (2000) suggested uncertainties between 32 and 52% in estimating ET from an energy balance residual approach, though improvements in remote sensing techniques and data availability have increased considerably since then.

### **2.2.2. CalSIMETAW**

CalSIMETAW is a crop coefficient-based tool developed by Orang *et al.* (2013) and used by DWR to determine potential crop evapotranspiration (ET<sub>c</sub>) for 26 different land use categories statewide for use in developing California Water Plan Updates. Crop coefficient (K<sub>c</sub>) values determined by regional farm advisors or sourced from available literature, ETo data from Spatial CIMIS, air temperature data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), and other climate data from National Climate Data Center (NCDC) stations are ingested to develop daily ET<sub>c</sub> estimates either at a 4-km resolution or for each of the 482 Detailed Analysis Units and Counties (DAU-COs) across the state; six of these DAU-COs fall within the Delta. The model can also calculate evapotranspiration of applied water (ET<sub>aw</sub>) using soil water holding capacity and depth information from the USDA Soil Survey Geographic (SSURGO) database, though this data was not used in this study (Orang *et al.*, 2018).



### 2.2.3. DETAW

DETAW is a crop coefficient model developed by Kadir (2006) and Snyder *et al.* (2013) to estimate daily actual evapotranspiration (ET<sub>a</sub>) and inform DWR's water balance and water quality models for the Delta. DETAW generates estimates for 15 different land use categories across 168 subareas of the DSA which generally outline major islands and upland areas. K<sub>c</sub> values for either normal or dry years are taken from state crop literature, and ET<sub>o</sub> inputs for each subarea area are generated by spatially correcting data from the Lodi/Stockton CIMIS station. Spatial correction isolines, with reductions up to 20% in the east Delta and increases up to 10% in the west, were developed using modern CIMIS station data so that historical ET<sub>a</sub> estimates can be made back to 1922. DETAW also makes ET<sub>aw</sub> estimates, which were not compared in this study, for each subarea using a daily soil-water balance (Kadir and Liang, 2018). Since its initial release, DETAW was refined by Liang and Suits (2017) through multiple comparisons to remote sensing data, averaging an absolute 16% difference from the SEBAL platform for Delta-wide ET over 14 months.

### 2.2.4. DisALEXI

DisALEXI is a pure energy balance model developed by Anderson *et al.* (2011) to use thermal infrared remote sensing of land surface temperature and separate soil-canopy and atmospheric boundary layers to produce ET<sub>a</sub> estimates at continental and 5-10-km scales. Daily estimates at a disaggregated 30-meter resolution were produced for this study by fusing inputs from Landsat and MODIS (Anderson, 2018). Though DisALEXI is a pure energy balance approach which does not use ET<sub>o</sub> data, it did produce assumed ET<sub>o</sub> estimates for this study. Anderson *et al.* (2011) calibrated and tested DisALEXI through applications for drought monitoring in the continental U.S., irrigation management in Europe, and hydrologic decision support in Africa.

### 2.2.5. ITRC-METRIC

ITRC-METRIC, developed by Howes *et al.* (2012), is a version of the Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) model originally developed by Allen *et al.* (2007a; 2007b). The Irrigation Training and Research Center (ITRC) at Cal Poly modified the original model to use a grass reference crop (ET<sub>o</sub>), incorporated different aerodynamic resistance and albedo computations for certain crops, and developed a semi-automated calibration procedure. METRIC processes remotely sensed data from Landsat and uses an energy balance approach to develop daily average ET<sub>a</sub> estimates on overpass days at 30-meter resolution. These are scaled to monthly average estimates by computing fraction of reference evapotranspiration (ET<sub>oF</sub>) values and temporally interpolating with ET<sub>o</sub> data from Spatial CIMIS; ITRC-METRIC also developed corrected spatial ET<sub>o</sub> datasets which were not used for this study. The METRIC model uses land use data to correct aerodynamic wind resistance values for vegetation and aid the selection of reference "hot" (bare soil) and "cold" (well-watered grass) reference pixels in satellite images. For the Delta, a self-corrected version of the National Agricultural Statistics Service (NASS) Cropland Data Layer from the USDA was used to develop ITRC-METRIC's ET estimates (Howes, 2018). Howes *et al.* (2012) used ITRC-METRIC's estimates to inform groundwater storage computations and irrigation efficiency

management in the Mexicali Valley.

#### **2.2.6. SIMS**

SIMS was developed by Melton *et al.* (2012) to aid agricultural irrigation and water management decisions in California by developing estimates of daily basal crop ET (ET<sub>cb</sub>) at a 30-meter resolution. ET<sub>cb</sub> estimates assume well-watered conditions and dry exposed soil surfaces, approximating a crop's biological water demand, and were assumed to be representative of field conditions for the majority of agricultural land in the Delta (Melton *et al.*, 2018). Field trials by Melton *et al.* (2012) over six years in 15 major California crops indicated that ET<sub>cb</sub> was within  $\pm 10\%$  of ET<sub>a</sub> for well-watered crops and  $\pm 15\%$  overall. SIMS uses NASA's Terrestrial Observation and Predictions System (TOPS) computing framework to process satellite observations from Landsat and MODIS to estimate fractional crop cover (F<sub>c</sub>) and basal crop coefficient (K<sub>cb</sub>) values. Land cover data were used to screen out non-agricultural areas prior to making estimates. ET<sub>cb</sub> was computed by multiplying K<sub>cb</sub> values by ET<sub>o</sub> data from Spatial CIMIS. Melton *et al.* (2012) compared SIMS estimates to remote sensing estimates from SEBAL in the San Joaquin Valley and field-based stations in the Salinas Valley and other areas of California.

#### **2.2.7. UCD-METRIC**

UCD-METRIC follows the original METRIC energy balance approach developed by Allen *et al.* (2007a; 2007b), applied by UC Davis. The first of three models was implemented in the Google Earth Engine platform (Gorelick *et al.*, 2017) to automate processing of Landsat images and provide some diagnostic tools. UCD-METRIC made daily ET<sub>a</sub> estimates at 30-meter resolution which were upscaled to monthly estimates using a proportional mean. UCD-METRIC uses an alfalfa reference crop (ET<sub>r</sub>) to make initial ET<sub>a</sub> estimates, but grass reference ET<sub>o</sub> values from Spatial CIMIS were used for spatial or temporal interpolation when necessary. A procedure to sharpen coarse thermal data from Landsat satellites was developed specifically for the Delta, and DWR's land use data were used to correct aerodynamic resistance values for some crops and aid hot and cold pixel selection processes (Alexander *et al.*, 2018). A METRIC application by Allen *et al.* (2005b) was within an absolute 15% of lysimeter ET measurements over four months, while Allen *et al.* (2005a) showed that difference increase to 30% for eight individual overpass days. The METRIC algorithm has been calibrated and tested in many locations in the U.S. (Allen *et al.*, 2015) and around the world.

#### **2.2.8. UCD-PT**

UCD-PT was developed by Jin *et al.* (2011), following Fisher *et al.* (2008), to use the semi-empirical Priestley-Taylor (PT) equation to estimate ET by approximating eco-physical constraints on ET as a function of crop vegetation characteristics, moisture indicators, and temperature. The approach originally made monthly ET estimates at a 1-km resolution by using MODIS satellite data and AmeriFlux tower measurements, but it was modified by Jin and Wong (2018) for this study to use Landsat data to develop daily and monthly ET<sub>a</sub> estimates at 30-meter resolution. Further improvements were made to net radiation computations, and PT coefficients

were optimized using field measurements over six different crops (alfalfa, almonds, citrus, corn, and rice) in California. These crops were identified in the Delta using DWR’s land use data, and a generalized PT coefficient optimization was done for other crops where no ground measurements were available. UCD-PT was originally applied by Jin *et al.* (2011) to develop ET estimates for the continental U.S. and was refined through calibration to additional field measurements as part of this study (Jin and Wong, 2018).

### 2.3. Field Evapotranspiration Measurements

In addition to the models which developed ET estimates, a series of meteorological field stations were deployed by the Biomicrometeorology Research Team from the Department of Land, Air and Water Resources at UC Davis (Medellín-Azuara *et al.*, 2018; Paw U *et al.*, 2018). Several stations were deployed in the 2015 and 2016 water years to measure weather and energy balance components to determine actual evapotranspiration (ETa) from selected fields in the Delta. The field stations computed ETa as a residual of the surface energy budget equation, which is the same principle upon which many remote sensing ET models are based:

$$LE = Rn - H - G \quad (1)$$

Where:

*LE* = Latent energy flux (energy used in evapotranspiration)

*Rn* = Net radiation

*H* = Sensible heat flux (heating or cooling of the atmosphere by the surface)

*G* = Ground heat flux (heat energy stored in the soil)

Evapotranspiration is calculated as a function of latent energy flux:

$$ETa = \frac{LE}{Lv} \quad (2)$$

Where:

*Lv* = Latent heat of vaporization (amount of energy needed to evapotranspire one unit of water)

Ground-based meteorological measurements were made at multiple field sites to determine values for the elements of Equation (1) and use Equation (2) to calculate ETa. *Rn* was measured with net radiometers, and at most stations *H* was measured with fine-wire thermocouples using the surface renewal (SR) technique described by Paw U *et al.* (1995). At these sites it was assumed that daily average soil and crop temperatures changed little from day-to-day, so for daily ETa estimates there is negligible ground heat flux and  $G \sim 0$ . Snyder *et al.* (2008) demonstrated that high-frequency field measurements with the SR technique showed no mean bias compared to high-precision measurements of ETa using lysimeters. Because SR-based energy budget residual calculations of ETa require specific assumptions and are not a direct measurement of ET, SR results are referred to here as “field-based estimates.”

At one site for each land cover type, additional sensors were employed to measure *H* using a sonic anemometer following the eddy covariance (EC) technique described by Paw U *et al.* (2000). EC stations also measured *G* using ground heat flux plates, soil temperature probes, and

additional meteorological and soil sensors. These measurements were used to develop calibration factors to apply to the data collected at SR sites and to estimate uncertainty with the assumption of negligible  $G$  on the daily scale. Hirschi *et al.* (2017) demonstrated that corrected eddy covariance-based ETa values showed errors of -7% to +5% when compared to lysimeter measurements of ETa on an annual basis, so values developed at EC sites are referred to here as “measurements” of ET.

At one site in 2016, a Campbell Infrared Gas Analyzer and Sonic Anemometer (IRG) was used to directly measure ETa using high-frequency wind speed and humidity measurements, as described by Horst *et al.* (2016). IRG data were also post-processed and corrected following Twine *et al.* (2000). ETa data developed at the IRG site are referred to here as “measurements” of ET. Final cross-comparisons between sensors and against other standard sensors were done before and after the field campaign to calibrate measurements and estimate uncertainty in energy balance components and calculated ETa values. ETo data from Spatial CIMIS and field meteorological measurements from CIMIS field stations, all of which are deployed to well-watered grass pasture fields, were also used for comparison (Paw U *et al.*, 2018).

### **2.3.1. 2015 Field Campaign on Fallow Lands**

Four SR stations and one EC station (which included SR equipment) were installed in fallow fields between September 7 and 9, 2015. All stations had elevations above sea level and were removed on October 5, 2015, resulting in less than a month of measurements. One station, D4, did not yield accurate or precise results in a post-deployment field calibration, so its results were excluded from further analysis in this study. Table 2 summarizes the field stations deployed in 2015, and they are mapped in Figure 2.

### **2.3.2. 2016 Field Campaign in Alfalfa, Corn, and Pasture Fields**

In 2016, field measurements were taken in 14 fields representing the predominant crops in the Delta: five in alfalfa, five in corn, and four in irrigated pasture. One station in each crop (D11, D12, and D13) included both SR and EC instruments, and IRG equipment was also installed in the alfalfa field (D13). Pasture sites D03, D04, and D05 were co-located with CIMIS stations, and alfalfa site D14 was co-located with the AmeriFlux site US-Tw3 maintained by Falge *et al.* (2017). Measurements began at some sites in late April 2016 in an effort to capture the peak growing season, with additional stations being set up through mid-August 2016. If necessary, corn stations were removed shortly before harvest dates in September 2016, but most remained in the field past the end of the 2016 water year (September 30, 2016). Table 2 summarizes the field stations deployed in 2016, and their locations are mapped alongside nearby CIMIS stations in Figure 2.

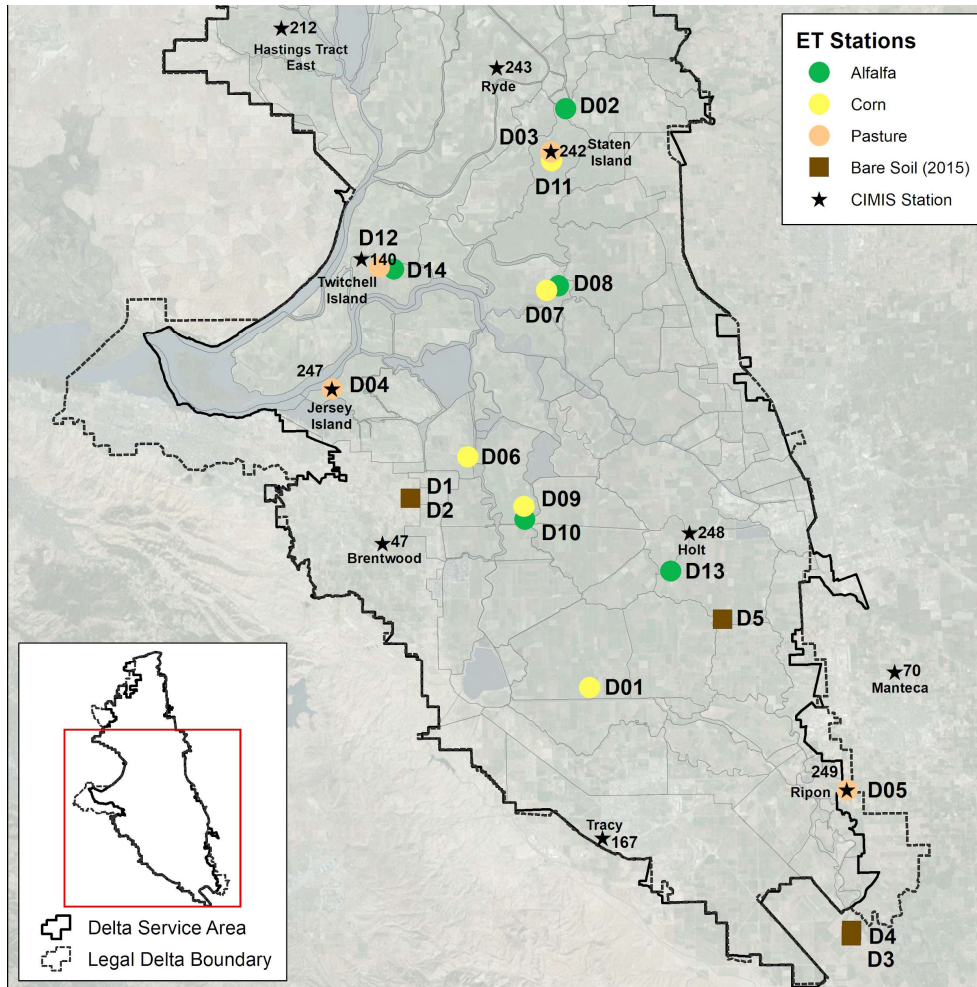
**Table 2. Field campaign station information, 2015-2016 (after Paw U *et al.*, 2018).**

Water Year	Station	Land Use	Island/Area	Elevation (ft.)	Deployed	Removed	Type
2015	D1	Fallow	Knightsen	10	9/11/2015	10/5/2015	SR
	D2	Fallow	Knightsen	10	9/11/2015	10/5/2015	SR
	D3	Fallow	Outside DSA	56	9/10/2015	10/5/2015	SR
	D5	Fallow	Middle Roberts	3	9/9/2017	10/5/2015	SR/EC
2016	D01	Corn	Union	-5	4/19/2016	9/23/2016	SR
	D02	Alfalfa	Staten	-4	4/28/2016	After 9/30/2016	SR
	D03	Pasture	Staten	-11	5/31/2016	After 9/30/2016	SR/CIMIS
	D04	Pasture	Jersey	-12	6/7/2016	After 9/30/2016	SR/CIMIS
	D05	Pasture	Ripon	22	6/9/2016	After 9/30/2016	SR/CIMIS
	D06	Corn	Holland	-12	7/13/2016	After 9/30/2016	SR
	D07	Alfalfa	Bouldin	-11	7/14/2016	After 9/30/2016	SR
	D08	Corn	Bouldin	-12	7/14/2016	9/26/2016	SR
	D09	Corn	Bacon	-18	7/15/2016	After 9/30/2016	SR
	D10	Alfalfa	Bacon	-15	7/15/2016	After 9/30/2016	SR
	D11	Corn	Staten	-13	4/20/2016	9/23/2016	SR/EC
	D12	Pasture	Twitchell	13	6/17/2016	After 9/30/2016	SR/EC
	D13	Alfalfa	Roberts	2	7/18/2016	After 9/30/2016	SR/EC/IRG
	D14	Alfalfa	Twitchell	-11	8/10/2016	After 9/30/2016	SR/AmeriFlux

## 2.4. Comparison Method

Evapotranspiration estimates developed by models and measured in the field varied in spatial and temporal resolution, as well as types of ET estimated and if estimates were made for all land uses. The models and field campaign are summarized in Table 3; years are reported by water year (September of the previous calendar year through October).

To comparatively analyze the study results, independent results collected from models were standardized to 30-meter resolution, with ET estimates in the form of monthly average rates in mm/d or volumes in acre-feet (AF); a 30-by-30-meter pixel is about 0.22 acres and 1 mm/d over this area is equivalent to about 0.02 AF/acre/month (ft./month) of ET. Often an ensemble mean of the seven methods was computed to provide a baseline estimate of ET magnitude and examine when and where some models may deviate from predominant trends.



**Figure 2. Field campaign stations and nearby CIMIS stations, 2015-2016 (Medellín-Azuara *et al.*, 2018).**

Most models submitted monthly estimates for each water year as 12-band geotiff rasters with 30-meter resolution; UCD-METRIC’s results for overpass days were averaged to the monthly scale by a proportional mean. CalSIMETAW and DETAW submitted daily results in spreadsheet format which covered a limited number of crop categories (26 for CalSIMETAW, 15 for DETAW) with coarser resolutions than the other models (DAU-COs for CalSIMETAW, DSA subareas for DETAW) within only the DSA. Their estimates were standardized for the study by cross-matching each of the 36 Delta land uses in Table 1 to one of their limited crop categories, casting ET estimates to 30-meter pixels of the corresponding crop in the corresponding geographic area, and averaging daily estimates to monthly results (Jankowski *et al.*, 2018). SIMS did not make ET estimates for non-agricultural areas, including semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture lands which were considered agricultural land uses for this study, so the ensemble mean ET of the other six models for the DSA was used to represent SIMS results for these pixels.

Land use data, rasterized to 30-meter resolution to match model outputs, and ET estimates were

uploaded to the Google Earth Engine remote sensing cloud computing platform (Gorelick *et al.*, 2017) for analysis. Summary statistics for each land use class were computed for each monthly ET band by reducing all pixels of a given land use over a given region. The data included the number of cells, the mean, standard deviation, and distribution of data (9th, 25th, 75th, and 91th percentiles). Volumetric estimates were calculated by multiplying the average monthly ET rate (mm/d) by the number of days in the month and the number of cells. These monthly estimates and volumes over the 679,594-acre DSA were used for many of the comparative analyses between the seven models in this study (Jankowski *et al.*, 2018).

More specific comparisons required that temporal interpolation processes used by models to extrapolate daily estimates to monthly averages be removed. The finest timescale on which models made ET estimates was on Landsat satellite overpass days, when remote sensing models extrapolate instantaneous satellite observations to make a more “direct” estimate of daily ET. Among the five models, a total of 70 different overpass dates were used from water year 2014 through 2017; a total of eight Landsat 8 overpasses were used commonly by all five of the remote sensing models. Models were compared in pairs only for overpass dates which both methods used for direct ET estimation (Jankowski *et al.*, 2018). Though CalSIMETA and DETA do not utilize satellite data, their daily estimates on the 58 different overpass dates used by the five remote sensing models in 2015-2016 were assumed to be sufficiently representative for comparison purposes. Field data from at least one station were available for comparison on three of the overpass dates in 2015 and 20 of the dates in 2016 (Jankowski *et al.*, 2018); in 2016, only daily average field ETa data were used for comparison since no models provided half-hourly estimates.

Spatial interpolation, often done to mask clouds in satellite images, was also minimized to isolate differences between model and the field data. Model results were averaged over small areas of the predominant crops in the Delta. Since alfalfa, corn, and pasture covered 26-32% of the DSA during the study and field stations were deployed to 14 fields of these crops during water year 2016, these sites (Figure 2) were selected for both model and field data comparisons.

Comparisons between models were not limited to days with field data, however. To eliminate small local variations, model estimates were averaged across a 3-by-3-pixel grid (8,100 m<sup>2</sup> or about two acres) around each field station. It was verified that none of these pixels contained atypical vegetation growth or non-crop areas such as farmstead or roads. A sensitivity analysis was also done to compare these “grid”-scale ET estimates to ET estimates over the entire farmed field (“parcel,” as identified in the vector DWR land use dataset) where stations were located. Statistical testing suggested that that the small differences between the two datasets were not significant within a 95% confidence interval (Jankowski *et al.*, 2018), so grid-scale estimates were used for all comparisons between model and field ET estimates.

Comparative plots and statistics, as well as specific questions tailored to each model, were distributed to modeling teams by the independent analysis group. Individual meetings with each group helped identify key methodological differences models and the prospects for ET estimates converging in the future. A workshop with all study participants and other experts in remote sensing and ET estimation followed these discussions to resolve any remaining issues and

discuss findings. Jankowski *et al.* (2018) provided minutes from each of these meetings which were summarized for this thesis.

**Table 3. Summary of ET estimation models and field campaign data, 2015-2016.**

Model (Operator)	Estimate Made	Land Uses Covered	Spatial Resolution	Temporal Resolution	No. of Landsat Overpasses	Data Format
CalSIMETAW (DWR)	ET <sub>c</sub>	All, in 26 categories	DAU-CO, 6 in DSA	Daily 2015-2016	NA	Spreadsheet database
DETAW (DWR)	ET <sub>a</sub> & ET <sub>o</sub>	All, in 15 categories	168 DSA subareas	Daily 2015-2016	NA	Spreadsheet database
DisALEXI (USDA-ARS)	ET <sub>a</sub> & ET <sub>o</sub>	All	30x30-meter	Daily & Monthly 2015-2016	4 in 2014, 1 in 2015, 20 in 2016, 3 in 2017	Geotiff raster
ITRC-METRIC (ITRC at Cal Poly)	ET <sub>a</sub>	All	30x30-meter	Overpasses & Monthly 2015-2016	1 in 2014, 12 in 2015, 14 in 2016, 2 in 2017	Geotiff raster
SIMS (NASA-Ames & CSUMB)	ET <sub>cb</sub>	All agricultural except semi-agricultural/ROW & wet herbaceous/sub-irrigated pasture	30x30-meter	Daily 2016, Monthly 2015-2016	4 in 2015, 35 in 2016, 3 in 2017	Geotiff raster
UCD-METRIC (UC Davis)	ET <sub>a</sub>	All	30x30-meter	Overpasses 2015-2016	11 in 2015, 10 in 2016	Geotiff raster
UCD-PT (UC Davis)	ET <sub>a</sub>	All	30x30-meter	Daily & Monthly 2015-2016	4 in 2014, 19 in 2015, 17 in 2016, 3 in 2017	Geotiff raster
Field Campaign (UC Davis)	ET <sub>a</sub>	Fallow, Alfalfa, Corn, Pasture	4 sites in 2015, 14 sites in 2016	Half-Hourly 2016, Daily 2015-2016	NA	Spreadsheet database

### 3. Consumptive Water Use Estimates

Estimates of ET by models provide insights into the magnitude of total annual ET in the Delta in 2015 and 2016, as well as the nature of ET from specific crops and non-agricultural land uses. This section presents these results for the seven models, examines general differences between models for various crops, compares ET estimates at various spatial and temporal scales, and presents the results of the two-year field campaign over four different land uses.

#### 3.1. Consumptive Water Use in the Delta

Total ET volumes, in acre-feet (AF), estimated by all seven models were summed for the Delta Study Area. Results were separated by the agricultural and non-agricultural land uses specified in



Table 1. These total Delta ET estimates are summarized for the 2015 and 2016 water years in Table 4.

**Table 4. Total ET volume in the DSA, by model, from agricultural and non-agricultural lands, 2015-2016.**

Model	2015 ET Estimates (AF)		2016 ET Estimates (AF)	
	Agricultural	Non-Agricultural	Agricultural	Non-Agricultural
CalSIMETAW	1,556,298	648,799	1,513,156	718,300
DETAW	1,477,917	709,877	1,468,087	770,473
DisALEXI	1,290,463	448,361	1,262,823	499,669
ITRC-METRIC	1,497,256	625,144	1,338,436	636,006
SIMS	1,419,050*	612,471*	1,379,551*	653,242*
UCD-METRIC	1,565,246	660,842	1,478,065	698,707
UCD-PT	1,307,830	581,803	1,215,091	596,300
<i>Ensemble Mean</i>	<i>1,444,866</i>	<i>612,471</i>	<i>1,379,316</i>	<i>653,242</i>
<i>Ensemble Standard Deviation</i>	<i>110,494</i>	<i>82,846</i>	<i>113,839</i>	<i>88,663</i>

\*SIMS does not estimate ET<sub>cb</sub> for semi-agricultural/ROW, wet herbaceous/sub-irrigated pasture, or any non-agricultural land uses. These values include the average ET of the other six models for those land classes.

Model ET estimates in the Delta (Table 4) were broadly consistent with other published values for the region, though the ensemble mean was slightly higher. DWR (2018b) publishes the annual Dayflow dataset with estimates of daily average outflows from the Delta estuary. The annual datasets also contain estimates of Delta-wide gross channel depletions (GCD) developed using the Delta Island Consumptive Use (DICU) model (Hutton *et al.*, 1995). Dayflow-reported consumptive use totaled 1,669,385 AF in water year 2015 and 1,675,557 AF in water year 2016, an average of 18% lower than the ensemble mean of models here. The Delta Plan (DSC, 2013) estimated that total in-Delta net water use averages about 900 TAF annually based on Dayflow data from 1930-2011. Net channel depletions (CD) in Dayflow are calculated by subtracting precipitation and non-consumptive diversions from ET (GCD) estimates (DWR, 2017b). Net water use is therefore considerably lower than total ET; Dayflow CD totaled 1,176 TAF in 2015 and 955 TAF in 2016, an average of 36% lower than GCD for the same period. The California Water Plan Update 2013 for the Delta region (DWR, 2014) also plotted values from Dayflow, stating that in-Delta consumptive uses are about 1,688 TAF in a wet year (i.e. 1998), 1,690 TAF in an average year (i.e. 2000), or 1,688 in a dry year (i.e. 2001). DWR (2018a) reported that 2016 was a Below Normal year in the Sacramento basin and a Dry year in the San Joaquin basin, while 2015 was a Critical year in both basins, so ET estimates were about 17% higher than the Water Plan Update's numbers. DWR (2018c) will use the CalSIMETAW model to estimate statewide consumptive water use for the upcoming Water Plan Update 2018.

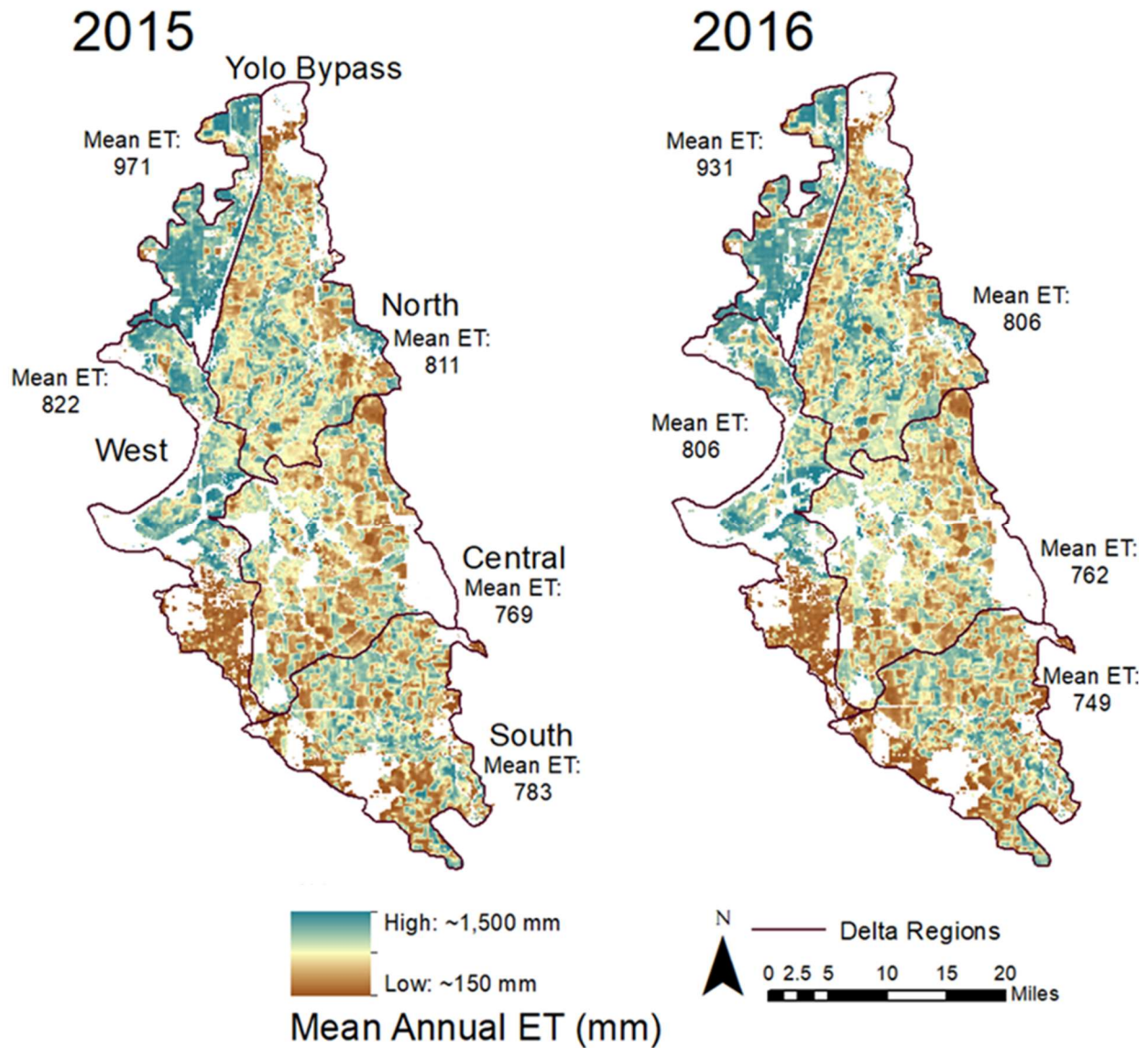
The seven model estimates (Table 4) were within -12% to +10% of the ensemble mean agricultural ET in the Delta for both years of the study, averaging an absolute difference of 6% in 2015 and 7% in 2016. Non-agricultural lands had larger relative differences from -27% to +18%, with absolute average deviations of 9% in 2015 and 10% in 2016. Most remote sensing methods based on a surface energy balance are typically calibrated for agriculturally managed vegetation and are not specifically designed to estimate ET from more heterogeneous natural vegetation, open water, and urban areas, however. Overall total ET estimates differed an absolute 7% in 2015 and 8% in 2016, ranging from -15% to +10%. These model divergences are considerably lower than similar studies. The nine approaches compared by Kite and Droogers (2000) averaged a 23% absolute difference from the mean daily ET for two cropped sites on two satellite overpass days. The seven methods compared by Sörensson and Ruscica, (2018) were within 60% of the ensemble mean total annual ET in any given region of South America, while relative differences were closer to 100%. The three models compared by Medellín-Azuara and Howitt (2013) averaged a 12% absolute difference from the mean total ET for eight different crops on five Delta islands over one water year.

In addition to quantifying total consumptive water use in the Delta, the spatial ET estimates can show effects of geographic land use trends and regional weather patterns on ET. Maps of annual ensemble mean ET, at a 30-meter resolution, are shown in Figure 3; the low range of 150 mm is equal to about 0.5 AF/ac. (ft.) annually, and the high range of 1,500 mm is about 5 ft. annually. Non-agricultural land uses (see Table 1) are shown in white in Figure 3. The Delta was delineated into five major regions based on the jurisdictional boundaries of local water agencies; ET estimates for each region may inform local water management practices. The boundaries of these regions are mapped in Figure 3, and Table 5 summarizes ensemble mean agricultural ET estimates and other information on each region.

Following lands uses (Figure 1), ensemble mean ET estimates in the Delta (Figure 3) varied considerably. The northwest and west-central Delta showed clusters of agricultural areas with higher ET (light and dark blue) where the dominant land uses were pasture and alfalfa. Some areas near Walnut Grove with a diverse crop mix also showed high ET. The southern Delta demonstrated scattered areas of high ET, primarily in alfalfa. The central Delta and agricultural areas near urban centers in the southwest edge of the Delta are among areas with the lowest annual ET (yellow and brown). By region, average per-pixel ET rates decreased from 2015 to 2016 and the largest estimates occurred in the Yolo Bypass both years (971 and 931 mm, about 3.2 and 3.1 ft./year, respectively). The lowest estimates shifted from the Central Delta (769 mm or 2.5 ft./year) in 2015 to the South Delta (749 mm or 2.5 ft./year) in 2016.

The North Delta, being the largest and most agricultural region of the Delta, had the highest estimated annual ET for both years and the highest standard deviation of model ET estimates in 2016 (Table 5). Though the Yolo Bypass had the lowest agricultural ET, it had considerably higher standard deviation and the highest unit ET (total agricultural ET divided by agricultural area, 3.5 AF/acre or ft.) of any region. This suggests that the large-scale pasture fields and patches of rice grown near the bypass are water-intensive, but large bodies of water in the area may make remote ET estimation more difficult. The South and West Delta, which had unit ET

values equal to the average for the DSA (3.0 ft.) and the lowest standard deviation values, had good agreement among models even with very different magnitudes of ET and agricultural areas.



**Figure 3. Maps of ensemble average annual ET in the DSA and its regions, 2015-2016 (Medellín-Azuara *et al.*, 2018). White areas are non-agricultural lands.**

Agricultural lands decreased in all regions of the Delta from 2015 to 2016, causing net reductions in total ET for all regions and an overall reduction of -4.6% in the DSA (Table 5). This decrease was most prominent in the West Delta, with a 3.7% reduction in agricultural acreage causing a decrease of 8.6% in total agricultural ET. Due to the large amount of State-owned land in the West Delta that would be unlikely to change land uses, this was likely caused by increased land fallowing and preparation for permanent crops near Brentwood. The Yolo Bypass had the largest decrease in total ET, which appears to have been caused by large-scale fallowing in the area from 2015 to 2016. The Central and North Delta had the least changes in

total ET. A slight decrease in unit ET for many areas suggests that large-scale land fallowing decreased overall water use and may also indicate changes in irrigation practices which resulted in lower consumptive use.

**Table 5. Attributes and agricultural ET estimates for major regions of the DSA, 2015-2016.**

Delta Region	Total Area (ac.)	Percent Agricultural		Ensemble Mean ET (AF)		Ensemble Standard Deviation of ET (AF)	
		2015	2016	2015	2016	2015	2016
Central Delta	176,718	68.6%	66.8%	352,779	341,899	27,989	16,182
North Delta	175,269	78.9%	77.7%	422,733	411,206	32,614	37,896
South Delta	142,807	76.2%	75.5%	315,921	303,146	25,926	25,408
West Delta	122,321	52.6%	48.9%	194,540	177,985	25,779	23,595
Yolo Bypass	63,119	71.5%	68.2%	158,894	145,080	33,005	27,728
<i>Delta Service Area</i>	<i>679,594</i>	<i>70.2%</i>	<i>68.3%</i>	<i>1,444,866</i>	<i>1,379,316</i>	<i>110,494</i>	<i>82,846</i>

### 3.2. Consumptive Use by Major Crops

Annual land use datasets from DWR were used to examine ET trends by different models for specific land uses. The ensemble mean of the seven models is a reasonable estimate of ET from specific crops and non-agricultural land uses and allows an examination of the general spatial and temporal distribution of ET in the Delta. The DWR land use dataset presents a “snapshot” of planting patterns during the summer (Land IQ, 2018), when most ET occurs; it is unlikely that many crops would be planted in the non-growing season (roughly October through April).

Models generally predicted low ET in the off-season since remote sensing methods observed bare soil, lower energy fluxes, and periodic cloud cover in satellite images. Crop coefficient-based methods include assumed planting and harvest calendars which accounted for low plant growth in the off-season. Even year-round crops such as almonds, pasture, and vineyards would be expected to be dormant during the winter, with correspondingly lower ET relative to the growing season. Table 6 summarizes the ensemble mean total annual ET in the DSA for the same land uses in Table 1, as well as the annual ET per unit area for the entire water year (in ft., which is equivalent to AF/acre) from each crop. Grass reference ET (ET<sub>o</sub>) values from Spatial CIMIS over the entire 679,594-acre DSA are provided at the bottom of Table 6 for comparison.

In both years of the study, all seven models estimated that an average of 60% of the total agricultural ET in the Delta originated from six significant crops which covered about 40% of its land area: alfalfa, almonds, corn, pasture, tomatoes, and vineyards. Non-managed fallow and semi-agricultural/ROW lands, as well as non-agricultural upland herbaceous zones, urban areas, and open water also contributed considerable ET, though most models were not typically calibrated to estimate ET from these surfaces.

**Table 6. Annual ensemble mean ET quantities, by land use, in the DSA, 2015-2016.**

Commodity (* denotes agricultural land use)	Total ET (AF)		Percent of Total ET		Unit ET (ft./yr.)	
	2015	2016	2015	2016	2015	2016
Alfalfa*	282,293	229,046	13.7%	11.3%	3.8	3.5
Almonds*	17,539	37,682	0.9%	1.9%	3.4	2.8
Asparagus*	-	-	-	0.0%	-	2.1
Bush Berries*	3,572	3,839	0.2%	0.2%	3.0	3.1
Carrots*	-	-	-	0.0%	-	2.4
Cherries*	7,089	9,928	0.3%	0.5%	3.4	3.5
Citrus*	19	-	0.0%	0.0%	2.1	1.9
Corn*	267,819	208,197	13.0%	10.2%	2.9	2.9
Cucurbit*	10,152	7,704	0.5%	0.4%	2.5	2.5
Eucalyptus	-	7	-	0.0%	-	1.4
Fallow*	116,638	186,994	5.7%	9.2%	2.2	2.3
Floating Vegetation	14,914	11,861	0.7%	0.6%	4.2	4.4
Forage Grass*	13,947	19,740	0.7%	1.0%	3.1	2.9
Nursery	-	11	-	0.0%	-	1.9
Olives*	4,719	4,711	0.2%	0.2%	3.2	3.1
Other Deciduous*	19,724	5,583	1.0%	0.3%	2.6	3.2
Pasture*	169,449	150,417	8.2%	7.4%	3.5	3.5
Pears*	22,362	20,966	1.1%	1.0%	3.8	3.8
Pistachios*	373	586	0.0%	0.0%	2.6	2.2
Potatoes*	11,283	10,538	0.5%	0.5%	2.7	2.8
Rice*	28,806	29,133	1.4%	1.4%	3.8	3.7
Riparian Native Vegetation	83,735	91,560	4.1%	4.5%	3.9	4.0
Safflower*	-	37,164	-	1.8%	-	2.7
Semi-Agricultural/ROW*	140,793	137,699	6.8%	6.8%	2.9	2.9
Sudangrass	-	0	-	0.0%	-	0.0
Sunflower*	-	699	-	0.0%	-	2.8
Tomatoes*	93,693	63,543	4.6%	3.1%	2.6	2.5
Truck Crops*	25,592	6,947	1.2%	0.3%	2.7	2.7
Turf*	7,493	7,022	0.4%	0.3%	3.5	3.4
Upland Herbaceous	121,528	144,066	5.9%	7.1%	2.2	2.3
Urban	141,772	139,936	6.9%	6.9%	2.3	2.2
Vineyards*	97,965	101,346	4.8%	5.0%	2.6	2.7
Walnuts*	11,091	16,026	0.5%	0.8%	3.2	3.0
Young Orchards*	-	486	-	0.0%	-	2.2
Water	250,521	265,801	12.2%	13.1%	4.2	4.2
Wet Herbaceous/Sub-Irrigated Pasture*	92,454	82,219	4.5%	4.0%	3.7	3.6
<i>TOTAL</i>	<i>2,057,337</i>	<i>2,032,558</i>	<i>100%</i>	<i>100%</i>	-	-
Grass Reference (ETo)	3,917,185	3,899,342	-	-	5.8	5.7

Overall trends in ET and estimates by individual models for the six significant crops were further examined. Figure 4 summarizes the percent of total agricultural land use and total annual agricultural ET volume in the DSA, by model, covered by significant land uses. The “Other” crop category includes almonds and all other agricultural land use categories identified in Table 1. The SIMS columns do not include ET estimates for semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture land uses.

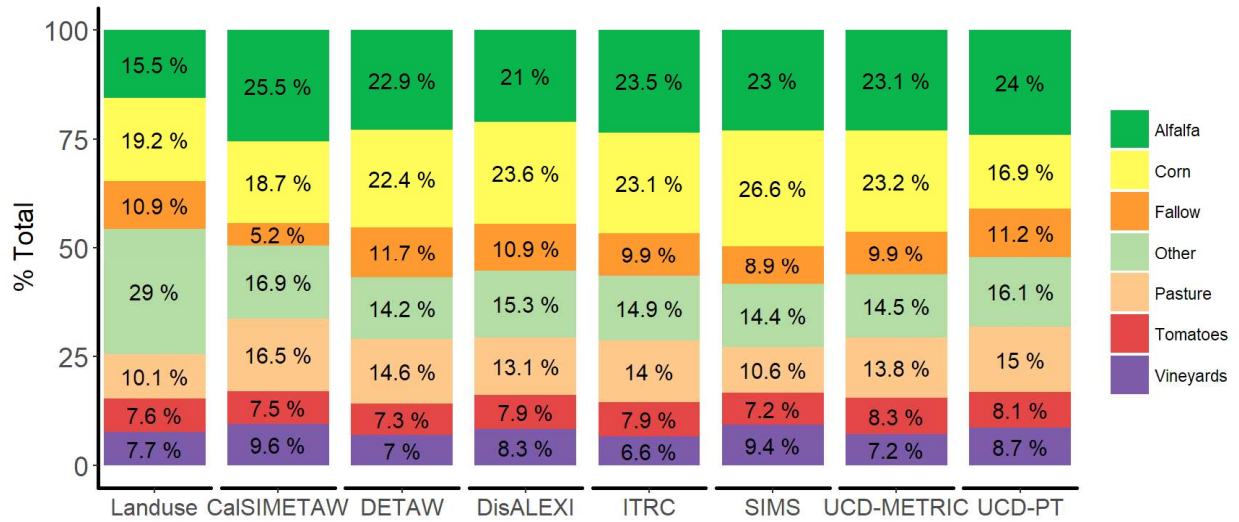
Alfalfa, corn, and pasture totaled 40% and 45% of the land area analyzed in 2015 and 2016, respectively (Figure 4). These three major crops represent nearly three-fifths of DSA crop consumptive use on average. All methods estimated that alfalfa used the most water of a single crop in both water years and pasture was the only single crop which averaged a higher percentage of the DSA’s water use than its land cover in both 2015 and 2016. The total fallow area increased 6.5% from 2015 to 2016, occupying more land than any of the three major crops, and ET estimates increased proportionally from about 10% of total DSA agricultural water use in 2015 to 16% in 2016.

Among the significant crops, corn and fallow showed the greatest differences between models with absolute differences from the mean of  $\pm 2.4\%$  for corn in 2015 and  $\pm 2.2\%$  for fallow in 2016 (Figure 4). Among models, CalSIMETAW tended to deviate the most for all the major crops (an average absolute difference of  $\pm 2.3\%$  from the mean), particularly for fallow where it estimated far lower ET (5-9%) than the other models (10-17% on average).

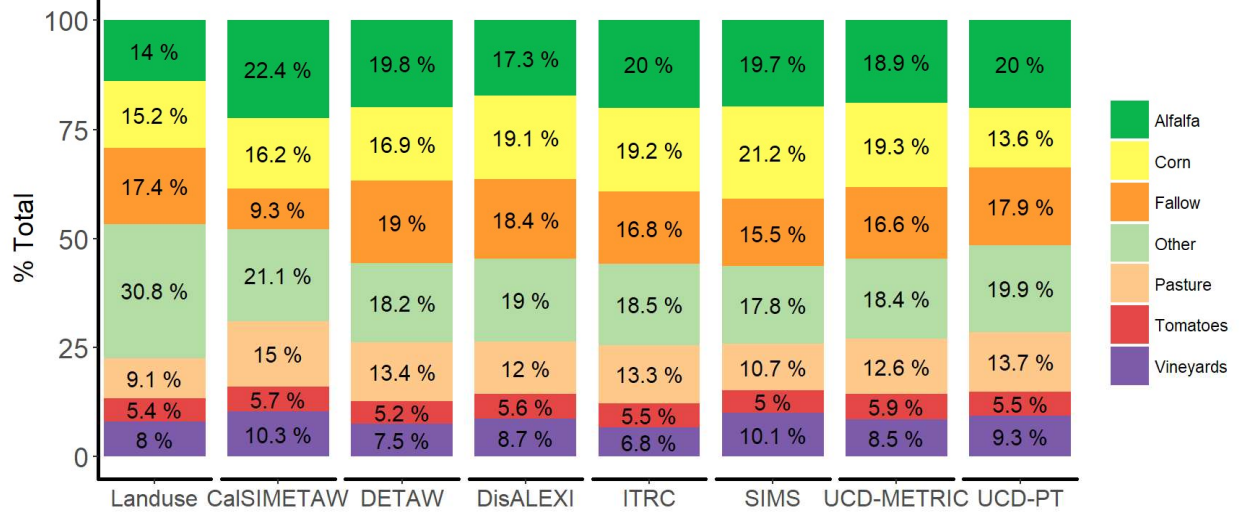
Figure 5 plots monthly ET rates, in mm/d, for the six significant crop categories in the Delta over two years. Each model’s average for the DSA is plotted, and the Spatial CIMIS average ETo rate over the DSA is included for reference.

Monthly ET estimates across all seven methods were generally less than reference ET, with the exception of corn in July for most models (Figure 5). CalSIMETAW estimated that almond ET exceeded ETo during the summer, likely because it did not account for immature orchard crops in its estimates (Orang *et al.*, 2018). All models tracked similar seasonal variation, with occasional outliers or shifts one month earlier or later by some models. ET estimates from CalSIMETAW and the METRIC models were typically on the higher end for most crops, especially during the growing season (March through September). Absolute ET discrepancies between methods were more significant for summer months when ET was the highest, but relative differences between methods increasingly occurred during late fall and winter months for most crops.

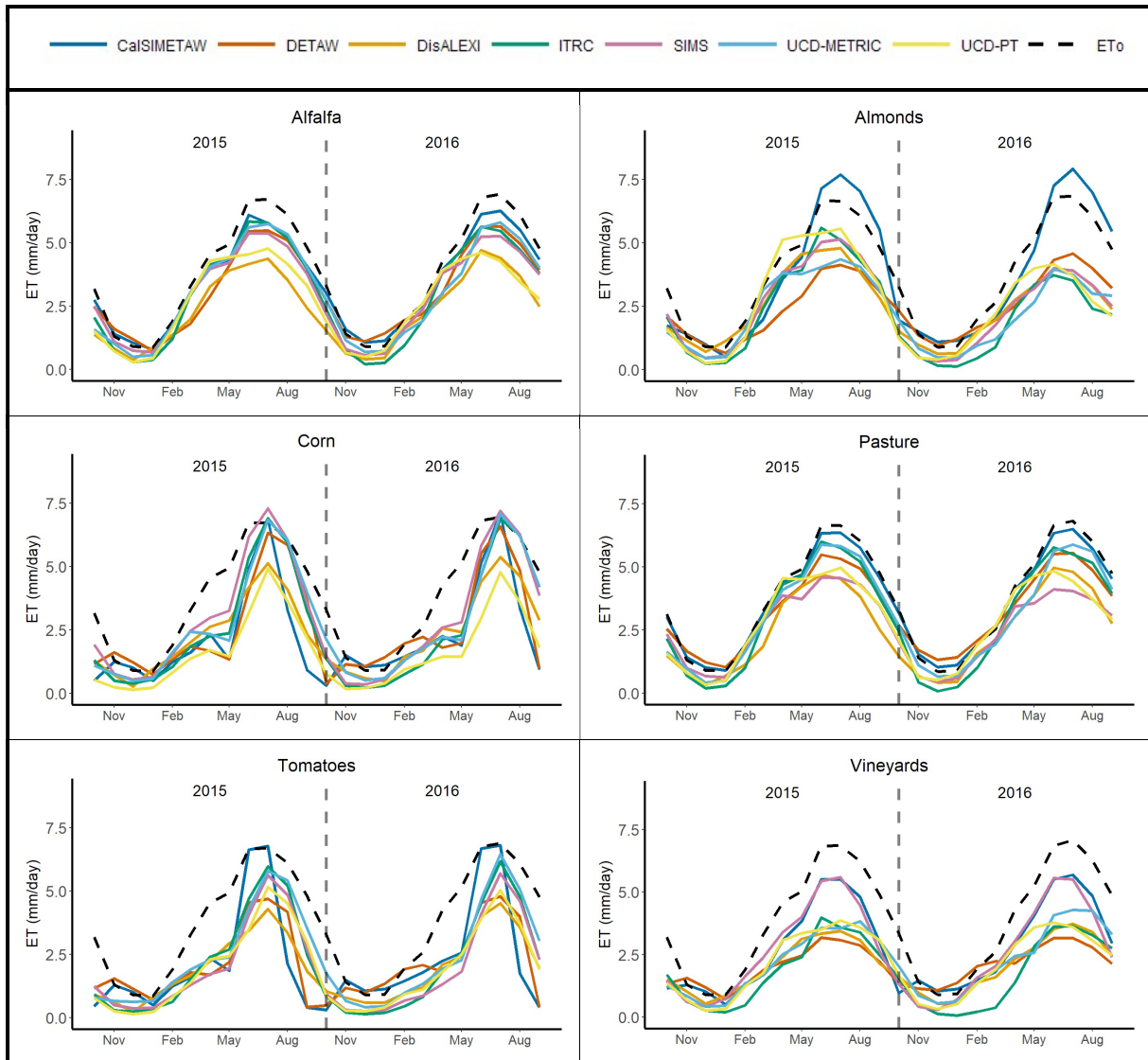
**A) 2015**



**B) 2016**



**Figure 4. Contribution of significant land uses to agricultural land use area (far left column) and total agricultural ET volume in the DSA, by model, (A) 2015 and (B) 2016 (Medellín-Azuara *et al.*, 2018).**



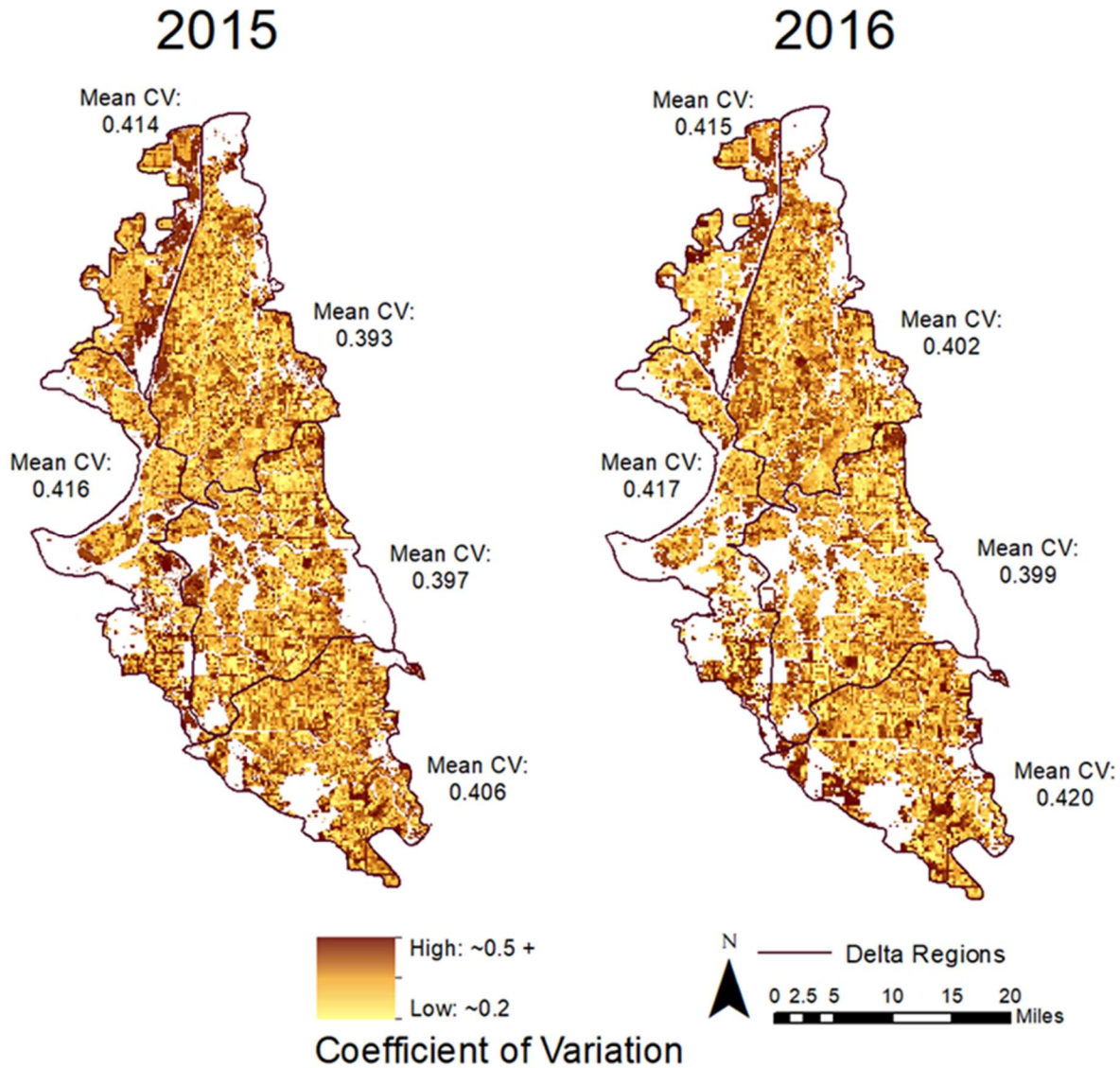
**Figure 5. Monthly average ET rates, by model, averaged over the DSA for significant crops, 2015-2016 (Medellín-Azuara *et al.*, 2018).**

### 3.3. Consumptive Use Estimate Variation

The broad spatial and temporal coverage of ET estimates allows for the examination of differences between individual models and the ensemble mean of all seven methods. These differences may occur spatially across the Delta, especially for specific land uses, as well as for specific times of the year. The coefficient of variation (CV) is a unitless metric which illustrates relative variation between models, calculated by dividing the standard deviation of model estimates by the ensemble mean of estimates. Alternatively, the absolute variation (in mm/d) quantifies the magnitude of model differences from the ensemble mean. The CV was calculated on a pixel-level for agricultural lands across the DSA to quantify differences between models relative to the magnitude of ET estimated for the entire water year. Annual coefficients of variation are mapped in Figure 6, which also shows the mean value for each of the Delta's five



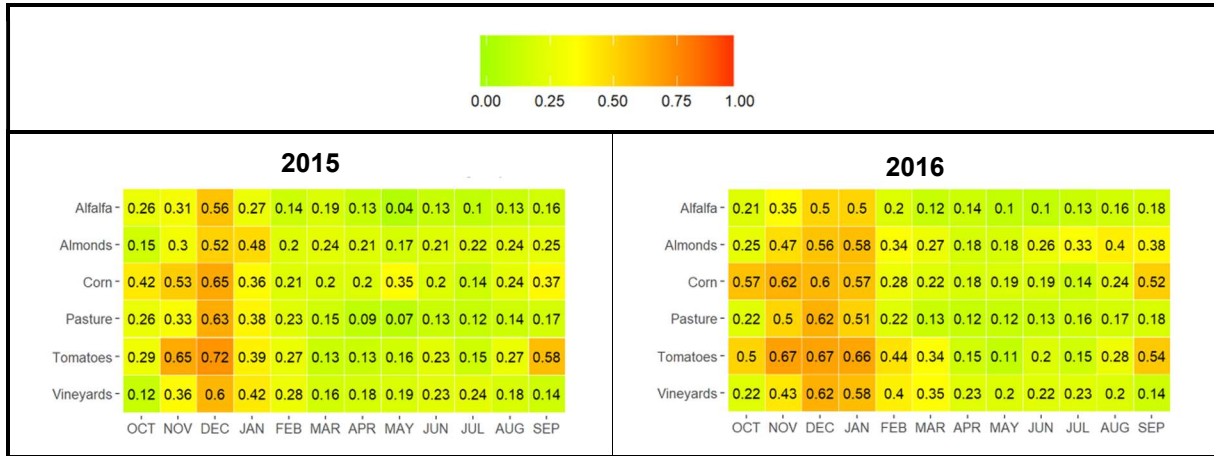
major regions. Monthly CV values are plotted for the eight major crops in the Delta in Figure 7, and monthly absolute variations are plotted for the same crops in Figure 8.



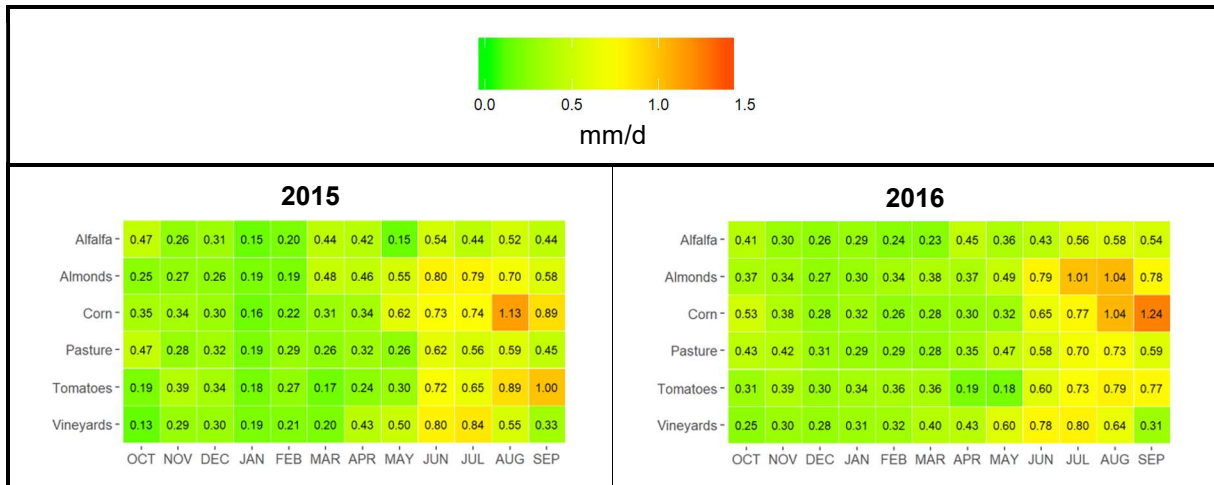
**Figure 6. Maps of annual coefficient of variation between all seven models in the DSA, 2015-2016. White areas represent non-agricultural lands (Medellín-Azuara *et al.*, 2018).**

Spatial relative variations between model ET estimates (Figure 6) did not always correlate with ET (Figure 3); the southwest Delta east of Tracy had low ET with high variation, clusters in the central-eastern and central-southern Delta had both low variation and low ET, and north of the Yolo Bypass and Sherman Island had high ET with wide degrees of variation in small clusters. Generally, model estimates varied more near urban areas (especially in the south Delta), for rice fields around the Yolo Bypass, and areas surrounding flooded fields such as the Cache Slough complex and Frank's Tract. Average coefficients of variation increased slightly in all regions from 2015 to 2016, especially in the North and South Delta. The West Delta had the highest average relative variation between models in both years, while the lowest variation occurred in

the North Delta in 2015 and the Central Delta in 2016.



**Figure 7. Monthly coefficients of variation between methods for significant crop types in the DSA, 2015-2016 (Medellín-Azuara *et al.*, 2018).**



**Figure 8. Monthly absolute variation between methods for significant crop types in the DSA, 2015-2016 (Medellín-Azuara *et al.*, 2018).**

Coefficients of variation among models were generally higher from September through January for most crops, especially corn, tomatoes, and vineyards (Figure 7). ET estimates in these months represented about 23% of annual ET volumes, so these relative differences were more prominent during months with much less ET. Furthermore, the primarily annual crops of the Delta are not typically grown in these months and even year-round crops would typically have considerably lower ET when dormant. The annual “snapshot” of land uses in the DWR dataset did not factor in planting or harvesting dates, so crop coefficient-based methods (CalSIMETAW and DETAW) may differ from remote sensing models in transition months depending on their assumed growth calendars. The masking of remote sensing methods to a single crop each year also reports wintertime ET occurring from crops that may have been observed as bare soil in satellite images. For year round-crops, the lower energy fluxes observed by satellites in the cooler months may also cause uncertainty in residual energy balances. The masking of clouds or the use of fewer wintertime images would also cause variations among models since their spatial and temporal

interpolation methods were not standardized for this study.

Absolute variations (Figure 8) support the above assertions; the higher relative variation among models in the non-growing season represents far less ET than is estimated to occur during the primary growing season (March through August). Some crops had greater absolute differences among models: almonds, corn, and tomatoes, primarily late in the growing season (July through September). Most of these crops also had higher coefficients of variation in other months, suggesting greater uncertainty in extrapolation of remotely-estimated ET values to the transitional and non-growing season for these land uses compared to other crops like alfalfa and pasture. This may be due to their variable ground cover during the growing season or leafy crops like corn and orchards causing shadows in satellite images. As with the coefficient of variation, the “snapshot” of annual land uses could cause disagreement between methods if the assumed planting/harvest schedules in crop coefficient-based methods did not align with bare soils observed in satellite images after harvest.

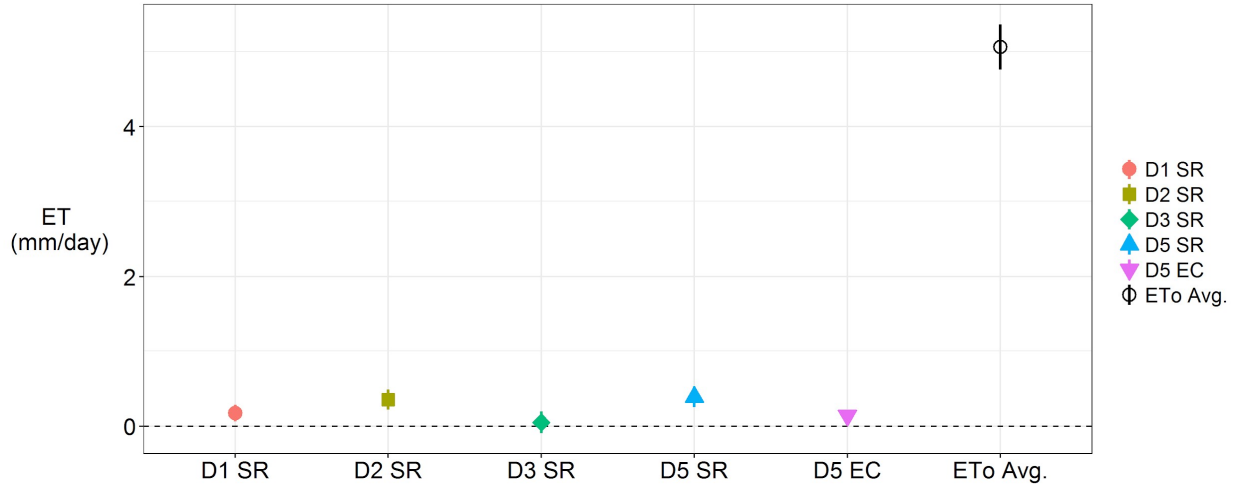
### **3.4. Field Measurements**

A field campaign was deployed to measure meteorological variables at several types of stations to develop estimates and direct measurements of ET which are presented in this section alongside additional field data from CIMIS stations. The 2015 campaign produced data from five fallow sites for less than a month, while the 2016 campaign covered fourteen sites in alfalfa, corn, and pasture with upwards of five months of data at some sites (Paw U *et al.*, 2018).

#### **3.4.1. 2015 Measurements in Fallow Fields**

Field measurements were made in four fallow fields in 2015; daily field-based estimates of actual evapotranspiration (ET<sub>a</sub>) were developed at four surface renewal (SR) stations and direct ET<sub>a</sub> measurements were made at one co-located eddy covariance (EC) station. Due to short deployment timelines (Table 2), less than a full month of data were gathered, so Figure 9 presents monthly mean results and standard deviations for September 2015. Figure 9 also plots grass reference ET (ET<sub>o</sub>) averaged for the three CIMIS sites in the Delta at the time (47-Brentwood, 70-Manteca, and 71-Modesto, see Figure 2).

Fallow field ET<sub>a</sub> estimates and measurements were significantly lower than nearby ET<sub>o</sub> values, with the exception of some rainy days at the end of the deployment period (Figure 9). The four sites showed an average ET<sub>a</sub> of 0.22 mm/d, with values ranging from 0.05-0.39 mm/d for the limited deployment period at low-elevation stations (3-56 ft.). Because of random errors and uncertainty related to the deployed instrumentation, mean values slightly greater than zero fall within the range of zero ET<sub>a</sub> for all stations. Slightly higher ET<sub>a</sub> values may have been observed at both the high elevation site (D3) due to sparse weeds in the field and the low elevation site (D5) due to tidal influences on the local water table which may have enhanced the near-surface soil moisture availability for evaporation. Fallow fields below sea level were not available for study in the initial field campaign (Medellín-Azuara *et al.*, 2016; Paw U *et al.*, 2018).



**Figure 9. Monthly mean and standard deviation of ETa from bare soil stations and nearby CIMIS sites, September 2015 (Medellín-Azuara *et al.*, 2018).**

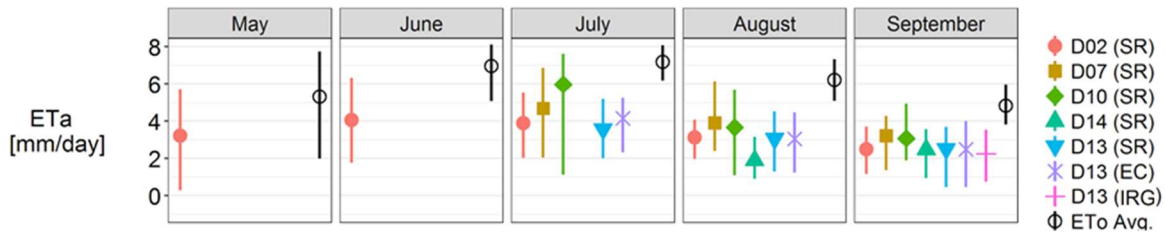
The short period of bare soil field measurements for less than one month of 2015, a drought year, and other factors associated with fallow field selection and conditions limit the ability to draw conclusions about bare soil ET from this study alone. Due to uncertainties related to measuring and estimating ET from bare soil in the Delta, a pilot study employing field equipment and satellite imagery for selected for adjacent fallow and irrigated crop fields is underway in the 2018 growing season.

### 3.4.2. 2016 Measurements in Alfalfa, Corn, and Fields

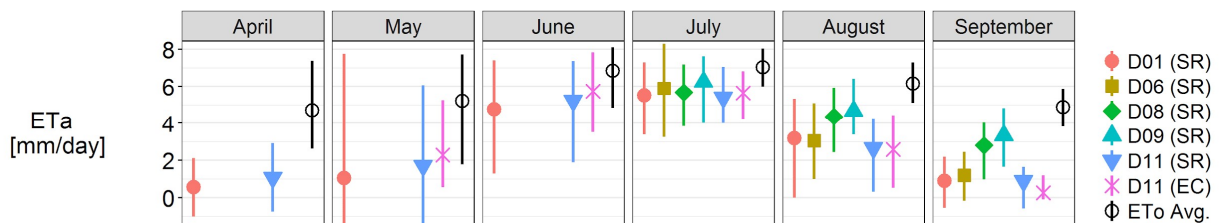
The expanded field campaign in 2016 developed ETa data at fourteen different alfalfa, corn, and pasture sites in the Delta (Figure 2) between April and September (Table 2). Monthly average field-based estimates of ETa from surface renewal (SR) sites, measurements of ETa at one eddy covariance (EC) station in each crop type, and ETa measurements at one IRG station at site D13 are plotted for alfalfa in Figure 10, corn in Figure 11, and pasture in Figure 12. Each station with at least eight days of field data in the given month is plotted, and vertical bars show minimum and maximum daily values for the same period. The plots also include ETo values from Spatial CIMIS, averaged over each 2-by-2-km pixel containing a field station, over the same period. Additional data collected in the 2017 water year at some sites (Paw U *et al.*, 2018) is not reported here.

Monthly mean alfalfa ETa data ranged from 2 to 6 mm/d in 2016, generally lower than ETo values and peaking in July with daily values as high as 7 mm/d (Figure 10). Direct measurements of ETa water vapor flux from the IRG station at site D13 yielded values comparable to the SR and EC energy budget residual methods at the same site. Field-based ETa estimates from at site D07 in September 2016 were broadly consistent with independent ETa measurements at AmeriFlux site US-Bi1 (located about 400 ft. to the east in the same field), while those at site D14 were lower than the co-located AmeriFlux site US-Tw3 (Paw U *et al.*, 2018). Fluctuations in ETa following alfalfa cuttings were generally averaged out on the monthly scale, though values at the beginning of the deployment with less than a month of data could be affected if

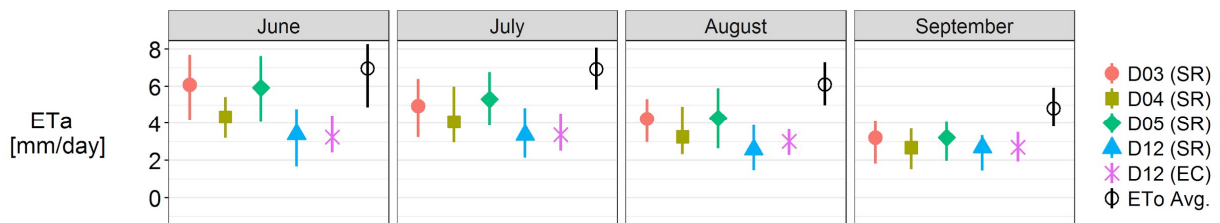
observations did not include a full cutting cycle. For example, measurements at Station D10 began mid-July, more than a week after the last alfalfa cutting, and thus caught only the time of peak ET and not expected low ETa values post-harvest.



**Figure 10. Monthly mean and minimum/maximum daily field ETa from alfalfa stations and Spatial CIMIS at the same locations, May-September 2016 (Paw U *et al.*, 2018).**



**Figure 11. Monthly mean and minimum/maximum daily field ETa from corn stations and Spatial CIMIS at the same locations, April-September 2016 (Paw U *et al.*, 2018).**



**Figure 12. Monthly mean and minimum/maximum daily field ETa from pasture stations and Spatial CIMIS at the same locations, June-September 2016 (Paw U *et al.*, 2018).**

Corn stations showed mean monthly ETa values between 1 and 6 mm/d, with daily values as low as zero in April and peaking at more than 8 mm/d in July (Figure 11). Measurements from the EC station at site D11 were typically higher than the SR estimates at the same site, though they dropped lower prior to harvest in late September. Field-based estimates were broadly similar to independent measurements in a cornfield at AmeriFlux site US-Tw2 on Twitchell Island (where no corn stations were deployed in the 2016 field campaign) in July 2012 (Paw U *et al.*, 2018), though caution should be exercised in comparing 2012 data with 2016 data due to the potential for interannual variability.

Pasture ETa values at individual stations varied widely from 3 to 6 mm/d depending on the measurement method and site, with monthly averages at least 1 mm/d lower than ETo values from Spatial CIMIS (Figure 12). Maximum daily values at sites D03 and D05 were the only ones which generally approached mean Spatial CIMIS ETo values (both sites were co-located with

CIMIS stations). Station D12 yielded the lowest values, from near-zero to 3 mm/d; that site had sparse vegetation inside the measurement enclosure which could have affected net radiation or ground heat flux measurements. These low values could also indicate low amounts of irrigation and significant canopy cover variations, which were observed by field personnel visiting the sites periodically for maintenance. A side study completed following the field campaign indicated that metal panel fencing used to protect the instruments from livestock damage may have increased net radiation observations about 3% compared to an unfenced area (Paw U *et al.*, 2018).

## **4. Comparisons Between Consumptive Use Estimates**

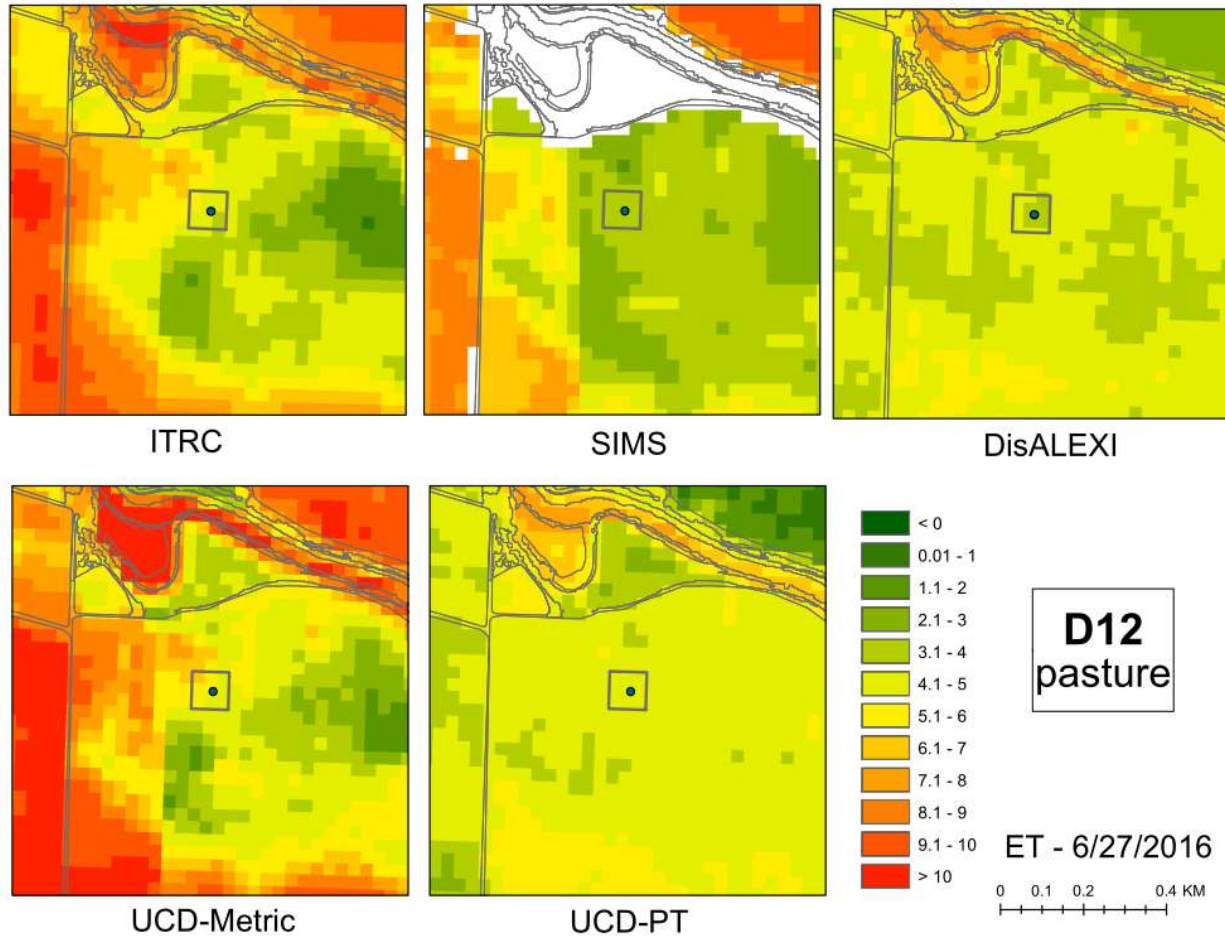
Evapotranspiration estimates for the Delta, presented across a variety of crops and areas, demonstrate reasonable agreement between the seven methods compared in this study. At such a large scale, there are many factors which might influence results and drive differences. To isolate variables of importance and discern key differences between methods, this section presents detailed comparisons at small spatial and temporal scales between methods. Direct comparisons between methods and the field data are also presented, and insights learned from modeling teams are discussed.

### **4.1. Model Comparison**

Though the seven models compared in this study are in fair agreement regarding total evapotranspiration volumes in the Delta, some differences exist between model estimates depending on specific crops, times of the year, and regions of the Delta. Potential reasons for these differences include the type of evapotranspiration estimated (potential, actual, or basal crop), different input datasets, and unique assumptions and procedures employed by each model. To insulate multiple influencing factors and facilitate a detailed identification of methodological differences that may have caused discrepancies in ET estimates, the methods were compared on small spatial and temporal scales; estimates were averaged over a 3-by-3-pixel grid (8,100 m<sup>2</sup> or about two acres) on select days over fourteen fields in the Delta. The fields contained irrigated alfalfa, corn, and pasture, the Delta's three predominant crops, and were chosen based on the location of the field stations deployed in 2016 (Figure 2).

A spatial comparison of the seven methods is shown in Figure 13 for field station D12, located in a pasture field on Twitchell Island. The Landsat 8 overpass date in the summer of 2016 was used by all five remote sensing models to make direct ET estimates. The field station site, pixel grid around it, field boundaries, and non-agricultural areas screened out by SIMS are also shown. On the same day shown in Figure 13, CalSIMETAW estimated a daily ET<sub>c</sub> of 7.70 mm/d and DETAW estimated 6.99 mm/d of ET<sub>a</sub> (these estimates cover the entire area since these models have coarse output resolutions). The deployed SR field station at site D12 estimated a daily average field-based ET<sub>a</sub> of 4.00 mm/d on the same day, while the EC equipment measured a daily average ET<sub>a</sub> of 4.02 mm/d. A two-year timeseries of ET estimates from models for the grid around station D12, including overpass dates and continuous daily estimates for those models that provided them (see Table 3), as well as field-based ET estimates from the SR equipment, is shown in Figure 14. Jankowski *et al.* (2018) provide similar ET maps and timeseries plots for all

14 comparison sites.



**Figure 13. Remote sensing estimates over pasture field on Twitchell Island, June 27, 2016 (Jankowski *et al.*, 2018).**

To eliminate estimate differences caused by temporal interpolation between satellite overpasses, model ET estimates were compared only on overpass days which were used for direct estimation. Following Jankowski *et al.* (2018), detailed graphical and statistical comparisons were made for overpass days which pairs of models had in common. Though comparison sites were selected based on 2016 field station locations, inter-model comparisons were not limited to the field deployment period and covered a total of 58 overpasses in water years 2015 and 2016. Results from CalSIMETAW and DETAW, which do not use Landsat data, were compared on all overpass dates. Field pasture station D05 was outside the DSA, so CalSIMETAW and DETAW did not make ET estimates for that site. Figure 15 presents comparative scatter plots between the 21 possible pairs of ET estimation models, with an axis corresponding with one model's estimates. Comparisons are separated by crop, with each data point representing a pair of ET estimates on a single overpass date at a single site. Linear regression lines for each crop and a 1:1 sloped line are also provided for reference.

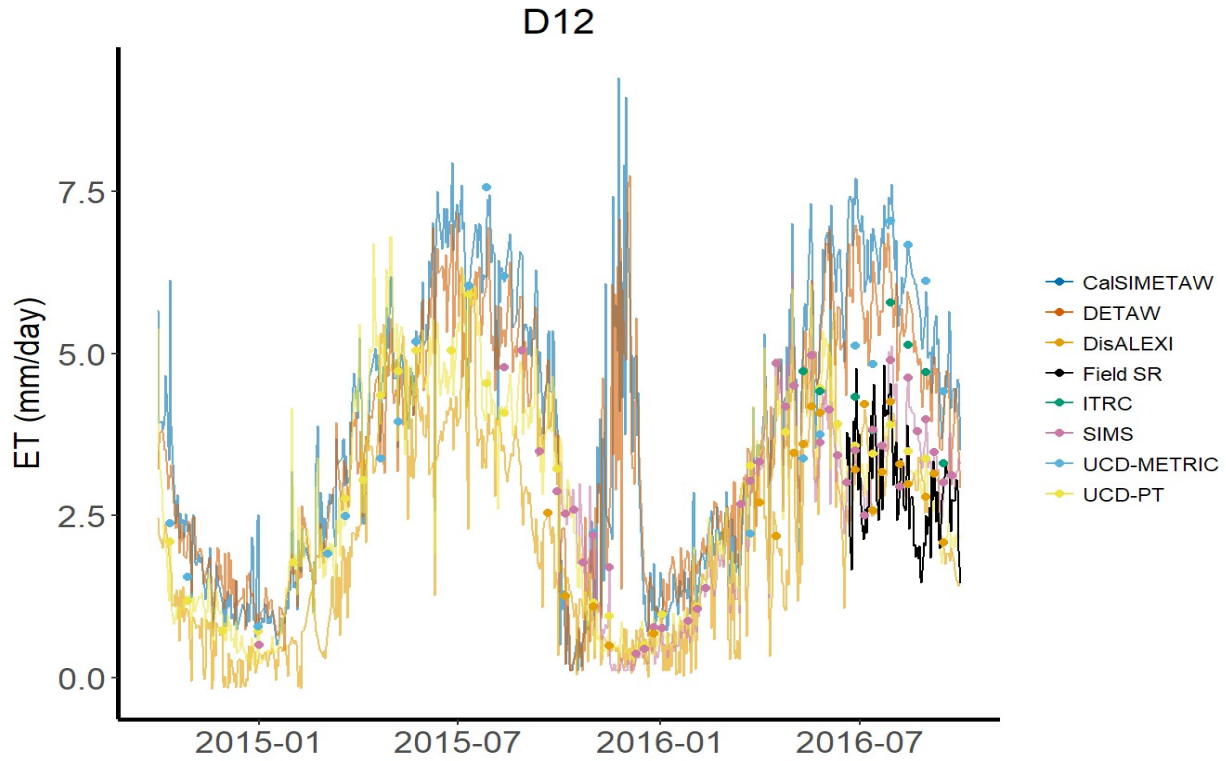


Figure 14. Timeseries of model and field-based ET estimates over a pasture field on Twitchell Island, 2015-2016 (Jankowski *et al.*, 2018). Points represent direct estimates on overpass days and lines represent continuous daily data provided by some models.

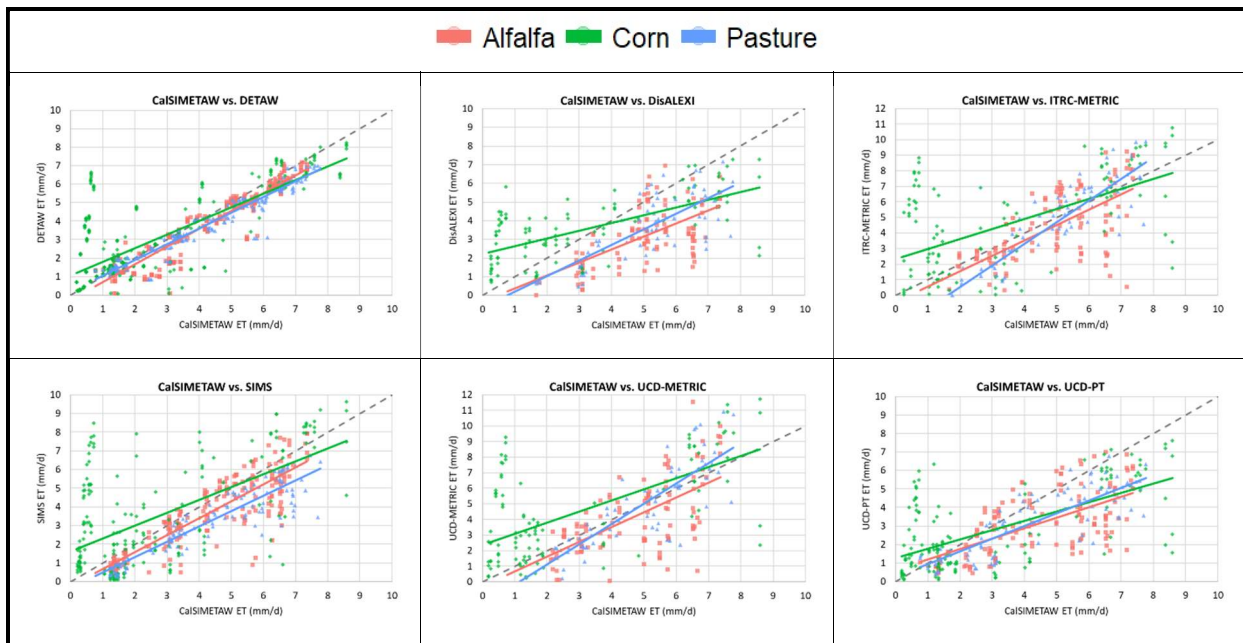
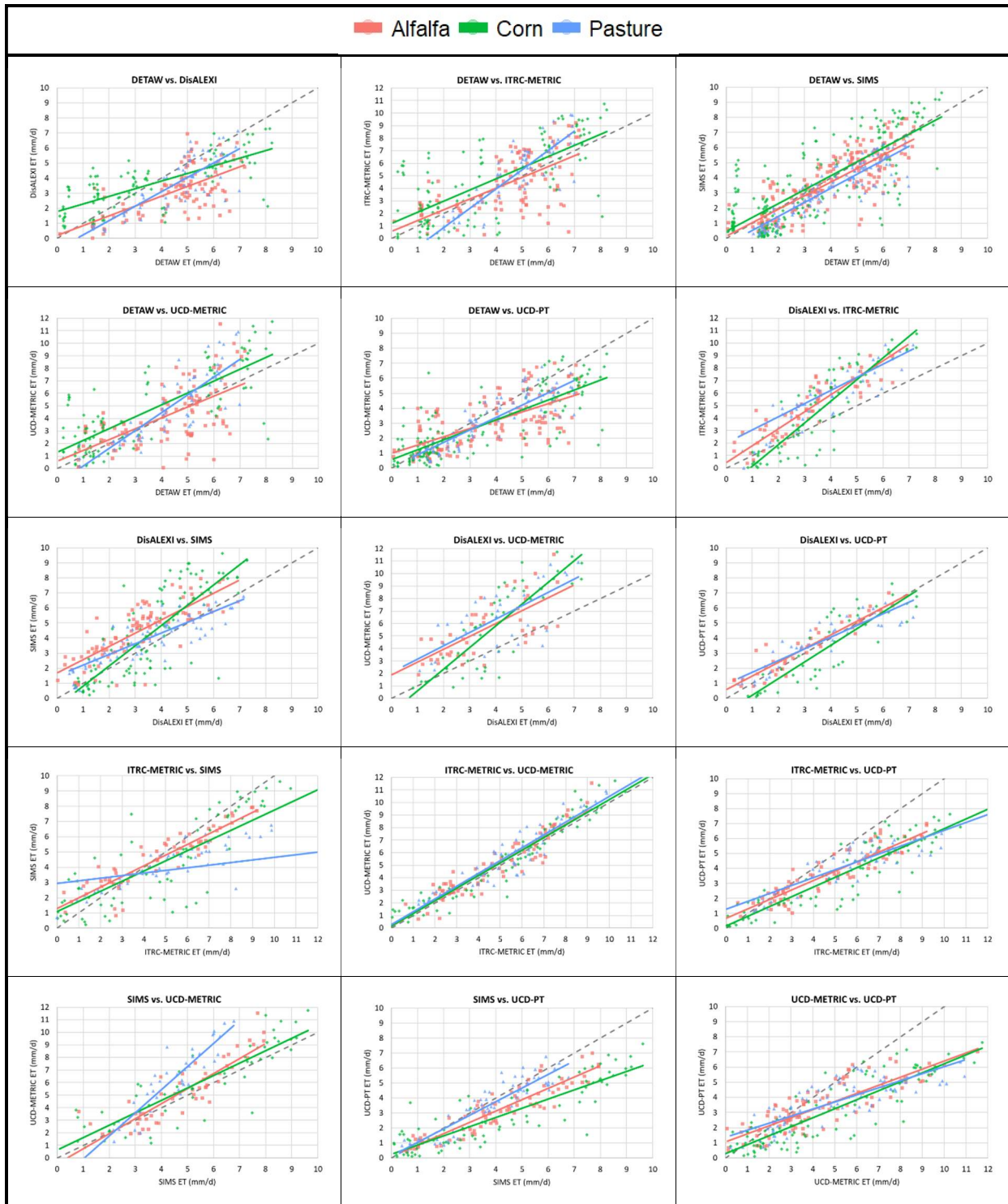


Figure 15a. Comparison of daily ET estimates between models on overpass days over alfalfa, corn, and pasture fields, 2015-2016 (after Jankowski *et al.*, 2018). Solid lines represent linear regressions and the gray dashed line represents the 1:1 ratio.





**Figure 15b. Comparison of daily ET estimates between models on overpass days over alfalfa, corn, and pasture fields, 2015- 2016 (after Jankowski *et al.*, 2018). Solid lines represent linear regressions and the gray dashed line represents the 1:1 ratio.**

Linear regressions between models (Figure 15) show the correlation and bias between ET estimates of paired models. A regression slope of one with a y-intercept of zero would indicate perfect agreement in ET estimates; a positive slope suggests the model on the y-axis biases towards higher ET estimates than the model on the x-axis, and a positive y-intercept indicates positive bias by the model on the y-axis for lower-end ET estimates (the opposite is true for negative slopes and/or negative y-intercepts). The coefficient of determination ( $R^2$ ) value for a given regression represents the strength of the correlation; a value of one would indicate perfect correlation between estimates but not necessarily agreement. Table 7 summarizes linear regression results for each model pair; the values are for combined datasets of all three crops, so they do not directly relate to the regression lines in Figure 15; Jankowski *et al.* (2018) provide statistics for individual crops. Additional comparative statistics were also computed using combined data from all three crops together to quantify major differences between pairs of models. Mean bias (in mm/d), the average of the differences between two sets of estimates, quantifies which model estimated higher on average. Root-mean-square error (RMSE, also in mm/d) quantifies the absolute deviation between two models. These statistics are also presented in Table 7. The sections below discuss comparisons (Figure 15 and Table 7) with respect to each model.

#### 4.1.1. CalSIMETAW

CalSIMETAW's typically positive mean bias (Table 7) would be expected since it estimates potential ET (ET<sub>c</sub>) rather than the actual ET (ET<sub>a</sub>) that most other models estimate; ET<sub>c</sub> would typically exceed ET<sub>a</sub> during times of plant-water stress since it assumes ideal conditions and no lack of water, though ET<sub>a</sub> could be greater depending on unique irrigation practices and canopy cover. Agreements between CalSIMETAW's ET<sub>c</sub> and other ET<sub>a</sub> values at a given time and location therefore suggest minimal plant stress. CalSIMETAW generally had the lowest slope compared to other models, meaning it estimated higher ET on the low end (also demonstrated by its positive y-intercepts) and lower ET on the high end. It also generally had lowest linear regression  $R^2$  values of any models, meaning its estimates were least well-correlated with other ET values.

CalSIMETAW showed zero mean bias compared to UCD-METRIC in pasture and was also close to UCD-PT in corn, but overall it matched closest with DETAW (biased slightly higher for alfalfa and pasture but lower for corn). This was expected since they are both crop coefficient-based methods developed by the California Department of Water Resources (DWR). The two models still had slightly elevated RMSE values, however, caused by several outlying corn estimates where DETAW estimated much higher ET and some alfalfa sites where CalSIMETAW estimated higher ET at the low end. Timeseries plots at individual sites (i.e. Figure 14) demonstrate that these discrepancies typically occurred in late August through mid-September, meaning that they were caused by different assumed harvest dates; if CalSIMETAW assumed that crops were harvested earlier than DETAW it would experience a rapid drop in ET<sub>c</sub> for the days afterward. CalSIMETAW's assumed planting, irrigation, and harvest periods were developed with input from DWR's Regional Offices, who surveyed local farm advisors and

farmers directly (Orang *et al.*, 2013; Orang *et al.*, 2018). These assumed calendars, which are needed by crop coefficient models, could also drive other temporal differences between models depending on the crop growth stage assumed at a given time.

**Table 7. Comparative statistics between model estimates on overpass days over alfalfa, corn, and pasture fields, 2015-2016 (after Jankowski *et al.*, 2018).**

Model 1 (x)	Model 2 (y)	n	Slope	Y-Intercept	Linear R <sup>2</sup>	Mean Bias (mm/d)	RMSE (mm/d)
CalSIMETAW	DETAW	754	0.79	0.65	0.73	0.10	1.19
	DisALEXI	272	0.42	1.60	0.31	0.92	2.11
	ITRC-METRIC	299	0.74	1.30	0.35	-0.19	2.40
	SIMS	507	0.67	1.02	0.45	0.19	1.85
	UCD-METRIC	273	0.71	1.59	0.35	-0.41	2.39
	UCD-PT	367	0.53	0.98	0.45	0.81	1.98
DETAW	DisALEXI	272	0.55	1.16	0.44	0.73	1.73
	ITRC-METRIC	299	0.94	0.59	0.49	-0.35	2.09
	SIMS	507	0.89	0.24	0.64	0.18	1.39
	UCD-METRIC	273	0.95	0.80	0.54	-0.58	1.99
	UCD-PT	367	0.66	0.62	0.60	0.62	1.56
DisALEXI	ITRC-METRIC	195	1.40	0.19	0.51	-1.48	2.86
	SIMS	265	0.98	0.92	0.58	-0.86	1.66
	UCD-METRIC	125	1.29	0.91	0.57	-2.05	2.77
	UCD-PT	125	0.91	0.28	0.75	0.03	0.98
ITRC-METRIC	SIMS	196	0.44	2.04	0.44	0.63	2.64
	UCD-METRIC	210	1.02	0.16	0.90	-0.24	0.87
	UCD-PT	222	0.61	0.63	0.80	1.34	1.91
SIMS	UCD-METRIC	140	1.09	0.43	0.70	-0.90	1.76
	UCD-PT	222	0.69	0.40	0.75	0.87	1.48
UCD-METRIC	UCD-PT	277	0.55	0.81	0.71	1.27	2.05
<i>Average</i>		294	0.80	0.82	0.58	0.03	1.89

CalSIMETAW’s coarse spatial coverage, including only six different DAU-COs in the Delta, would cause spatial differences compared to models with finer resolutions; this can be observed in the CalSIMETAW plots in Figure 15, where a single CalSIMETAW value has a range of estimates from other models. Land use classifications required to produce estimates could also drive differences; at site D09 the DWR land use survey identified fallow land rather than corn, likely biasing estimates lower than they would have been from corn (Medellín-Azuara *et al.*, 2018). Though CalSIMETAW produces estimates for only 26 different land uses (compared to the 36 surveyed uses in Table 1), this would not manifest in this detailed comparison since alfalfa, corn, and pasture are all unique crops in the model. CalSIMETAW is undergoing additional improvements to account for immature tree crops and will be adapted for groundwater planning under California’s Sustainable Groundwater Management Act (SGMA).

#### **4.1.2. DETAW**

DETAW was generally in the best agreement with ET estimates by other models; it had linear regression slopes close to one, mean bias values that were slightly positive but close to zero, and the lowest average RMSE when paired with other models (Table 7). DETAW had its highest mean bias over DisALEXI (largely driven by alfalfa, as it was very low for corn) and largest RMSE with ITRC-METRIC (though their mean bias was near-zero for alfalfa); its methodological differences from both remote sensing-based models are considerable.

As discussed above, DETAW's estimates most closely matched those of CalSIMETAW. Because the two models are based on the same principles, they would be expected to produce similar results if used on the spatial scale with the same inputs, including ETo, Kc, irrigation periods, and temperature. However, the two models estimated different forms of ET and are used on different spatial scales, CalSIMETAW for statewide water planning and DETAW for water accounting in the Delta. This coarser spatial scale limits the potential range of DETAW estimates over smaller areas of the Delta and may drive differences compared to models with finer spatial outputs. DETAW also assumes that crop coefficients are uniform (i.e. all corn in the Delta has the same Kc curve), further limiting its spatial variation. DETAW's use of unique ETo values instead of Spatial CIMIS may also drive regional differences, especially at the far western and eastern edges where DETAW applies the largest corrections to the Lodi/Stockton CIMIS station's reading (Kadir, 2006). As with CalSIMETAW, DETAW's estimates may have been biased low at corn site D09 due to incorrect fallow classification (Medellín-Azuara et al., 2018). DETAW also estimates ETa from only 15 different land use categories, which may have been an issue for fallow lands (classified as native vegetation) but would not impact its separate alfalfa, corn (designated a field crop), and pasture categories.

Convergence between DETAW and other models could be improved through common spatial scales, ETo values, temperatures, crop coefficients (for models that use them, including CalSIMETAW and SIMS), and planting/irrigation/harvest schedules. DETAW's inputs and methods are being recalibrated using the 2016 field data presented here and incorporating CalSIMETAW's larger range of 26 land uses. More active communication and cooperation between modeling groups at DWR was fostered as a direct result of this study.

#### **4.1.3. DisALEXI**

DisALEXI had the least overpass dates in common with other remote sensing models and frequently estimated lower than them, with the most negative mean bias values and relatively high RMSE values (Table 7). It had the greatest agreement with UCD-PT, with the lowest overall mean bias and second-lowest RMSE of any model pair; their alfalfa estimates had the lowest RMSE values for the all comparisons. The biggest discrepancies between the two models was over corn fields, where DisALEXI biased higher. DisALEXI had the greatest differences from the METRIC approaches, where it biased several mm/d lower and had RMSE values of almost 3 mm/d for all three crops (pasture had the greatest RMSE value of any comparison, exceeding 4 mm/d).

DisALEXI has considerable methodological differences from other remote sensing approaches,

as it is a strict energy balance method fusing large amounts of satellite data which include GOES sensible heat flux measurements at a 1-by-1-km resolution and global-scale insolation inputs from the University Corporation for Atmospheric Research (UCAR) Climate Forecast System Reanalysis (CFSR). This differed from many models' use of local-scale meteorological measurements from CIMIS stations, so depending on the heterogeneity of the study area the sharpening of this data could bias DisALEXI's estimates compared to other models. Though its use of land surface temperature as a primary input is similar to the METRIC methods, this did not appear to encourage agreement between ETa estimates. DisALEXI also uses a Priestley-Taylor component to make an initial estimate of transpiration based on net radiation divergence within the canopy, so it would be expected to agree with UCD-PT in times of full vegetation cover and minimal water stress.

DisALEXI's use of higher temporal resolution satellite data such as GOES and MODIS could cause outliers in comparison to remote sensing models that use net radiation data from Landsat at a daily scale. Finally, DisALEXI does not explicitly use any input ET measurements such as the field data collected for this study. These data would only be used to correct the physical process assumptions made by the model, and the model was previously calibrated by Anderson *et al.* (2011) to other locations worldwide. Thus, DisALEXI's estimates would not be expected to converge further with other models unless significant process changes and input datasets changes were made to the model.

#### 4.1.4. ITRC-METRIC

ITRC-METRIC generally had the highest RMSE values when compared to other models, with higher ET estimates evinced by positive mean bias values (Table 7). This is particularly true on the low end of ET estimates, as it had linear regression slopes generally less than one and the highest y-intercept values on average. ITRC-METRIC diverged considerably from DisALEXI and UCD-PT, where it biased more than 1 mm/d higher and had RMSE values close to 3 mm/d.

ITRC-METRIC's ETa estimates were very similar to UCD-METRIC, with the lowest overall RMSE of any model pair. This would be expected since both are an implementation of the METRIC model originally developed by Allen *et al.* (2007a; 2007b). These systematic differences are likely caused by small methodological updates made in ITRC's approach, as well as the modeler judgement that is required to run the METRIC model. METRIC operation largely depends on its internal calibration procedure, which requires the selection of bare soil ("hot") and well-irrigated reference crop ("cold") pixels in satellite images. Each model has developed its own semi-automated approach to this procedure with quantitative checks, but ultimately the process requires manual tuning which reflect the operator's professional judgement and agronomic experience. This is especially true for leafy crops such as corn, orchards, and vineyards, which may cause shadows in satellite images that can alter ETa estimates. While UCD-METRIC uses an alfalfa reference crop (ETr) to develop ET estimates from satellite data, ITRC modified the model to utilize the grass reference crop (ETo) more commonly used in California. These different inputs would not inherently cause differences between the models as long as the cold pixel's fraction of reference ET was appropriately adjusted. However, the

hourly-to-daily upscaling computation of reference ET that is built into each model (i.e. the use of instantaneous Landsat overpasses data and daily Spatial CIMIS ETo values) may potentially cause systematic differences (Alexander *et al.*, 2018).

Some input datasets also varied between the ITRC and UCD METRIC models. Thermal data is a required input to the METRIC model, though it does not include a default process for converting it from the 100-meter Landsat 8 resolution into the 30-meter resolution used to report ETa estimates. ITRC used the default cubic spline-interpolated thermal data from the U.S. Geologic Survey (USGS), though it has developed a custom procedure that was not implemented for this study (Howes, 2018). Though land use data is not directly used to make ET estimates in the METRIC model, general classifications are required to identify agricultural areas for hot/cold pixel selection and to adjust roughness length for orchards and vineyards. ITRC used a quality-controlled version of the National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) from the USDA (2016), but this would not be expected to cause major differences with models that used the DWR land use dataset. Further modifications made to ITRC's custom METRIC model could result in ETa estimates diverging to some degree rather than converging. Nevertheless, similar operator experience, internal sensitivity analysis and model iterations, and consistent input datasets would all be expected to improve convergence between ITRC and other models.

#### **4.1.5. SIMS**

SIMS's estimates of basal crop ET (ETcb) assume well-watered conditions and dry soil surfaces; they would be expected to exceed ETa estimates if crops were water-stressed, but ETa could be higher in cases of high evaporation from exposed soils (i.e. early season irrigation or precipitation events which resulted in evaporation from exposed topsoil). High positive linear regression slopes and low negative y-intercepts suggest that both of these differences occurred; SIMS estimated lower than other models in the low end of ET and higher ET at the high end (Figure 15 and Table 7). However, SIMS was generally in good agreement with other models. It had mean bias values closest to zero (though slightly negative) and relatively low RMSE values, which may have been encouraged by SIMS having the most overpass dates in common with other remote sensing models.

SIMS's ETcb estimates were closest to ETc estimates by CalSIMETAW and ETa estimates by DETAW, biased slightly less. This suggests that the basal crop coefficients developed by SIMS using the relationship between normalized difference vegetation index (NDVI) and fractional crop cover reasonably matched the literature-based crop coefficients in the DWR models. However, RMSE values above 1 mm/d suggest that SIMS observed greater spatial variation in ET since its coefficients are corrected to account for meteorological differences and local crop conditions. SIMS had the greatest differences from ETa estimates by the METRIC, models, UCD-METRIC having a high positive bias and ITRC having high RMSE values. These differences were greatest for pasture sites, where both models were biased more than 1.5 mm/d and where ITRC had a RMSE greater than 4 mm/d compared to SIMS (though SIMS and ITRC had a near-zero mean bias for alfalfa). Timeseries plots of single stations (i.e. Figure 14) suggest

that large discrepancies occurred over short periods during the peak growing season.

SIMS is specifically targeted to inform field-level water management and irrigation scheduling (Jankowski *et al.* (2018) showed that its estimates averaged at the parcel-scale biased slightly lower than the grid-scale averages compared here) without thermal input data, so its results may not be expected to converge with other models in the near-future due to their inherently different purposes and methods. However, increased consistency in input datasets and communication between modeling groups regarding assumptions are promising avenues to explore prospects for convergence.

#### **4.1.6. UCD-METRIC**

UCD-METRIC generally estimated higher ET<sub>a</sub> than other models, with the highest average mean bias and relatively high RMSE values (Table 7). However, with y-intercept values very close to zero it was considerably closer to other models on the low end of ET. As previously discussed, its ET<sub>a</sub> estimates differed considerably from DisALEXI but were very close to those of ITRC-METRIC. Though ITRC-METRIC used Landsat thermal inputs with default sharpening, UCD-METRIC developed a custom process for the Delta to mask out open water and riparian areas before sharpening thermal data (Alexander *et al.*, 2018). METRIC software may have a small impact on model differences, as the model is continually being updated by the University of Idaho with respect to individual energy balance components and in functions for specific crop types such as trees and vines. UCD-METRIC used 2014 v4B of the METRIC software, while ITRC-METRIC is based on the 2013 version and includes many modifications (some of which were made in parallel to the University of Idaho's efforts, some of which were developed specifically by ITRC).

UCD-METRIC is still in the development stage and is being refined with additional iterations, analysis software tools, and analyst experience. More work is anticipated to fine-tune METRIC's parameters for California's regional microclimates (i.e. not "perfect days," fog, and the "Delta breeze") and unique crop mixes (especially empirical equations for corn, vineyards, and oranges). These efforts would be expected to increase agreement between UCD-METRIC and other remote sensing models as better diagnostic tools are developed and its estimation procedure is streamlined.

#### **4.1.7. UCD-PT**

UCD-PT was the only remote sensing model which directly used the field data collected in 2016 for model development, with 70% used to calibrate its coefficients for alfalfa, corn and pasture and 30% used for validation (Jin and Wong, 2018). Thus, any differences between field data and other models (discussed in the next section) would drive differences between them and UCD-PT's ET<sub>a</sub> estimates. This was particularly true in the low end of ET, where UCD-PT generally had the lowest negative y-intercept values and high slopes (Figure 17 and Table 7). Nevertheless, UCD-PT's relatively low (slightly negative) mean bias and RMSE values suggest good agreement with other models. It also had the highest R<sup>2</sup> values, meaning its ET<sub>a</sub> estimates correlated well with those of other estimates regardless of magnitude.

As discussed above, UCD-PT had excellent agreement with DisALEXI for corn and was biased slightly higher for alfalfa and pasture. Its estimates differed most from those of CalSIMETA and the METRIC models. UCD-PT's approach to remote sensing differs slightly from other energy balance-based models, as it uses field data to optimize coefficients specific to certain land uses. These Priestley-Taylor (PT) coefficients capture ecophysiological constraints on plant water needs due to environmental conditions such as drought (Jin *et al.*, 2011). This was done for the three primary crops in the Delta using the field data, as well as for almonds, citrus, and rice using data from AmeriFlux towers; other land covers used a generalized optimization pooling data from all crops (Jin and Wong, 2018).

While UCD-PT can produce ET<sub>a</sub> estimates without field data calibration, its modeling team believes that calibration to additional field data increases its model accuracy and makes it more robust and optimized. This may cause issues if the model is calibrated to less than a full season of field data, which was the case for corn in this study. UCD-PT is undergoing refinements to use additional field and satellite data, so the accuracy of its estimates is expected to increase further and may better converge with other models.

#### **4.1.8. General Model Insights**

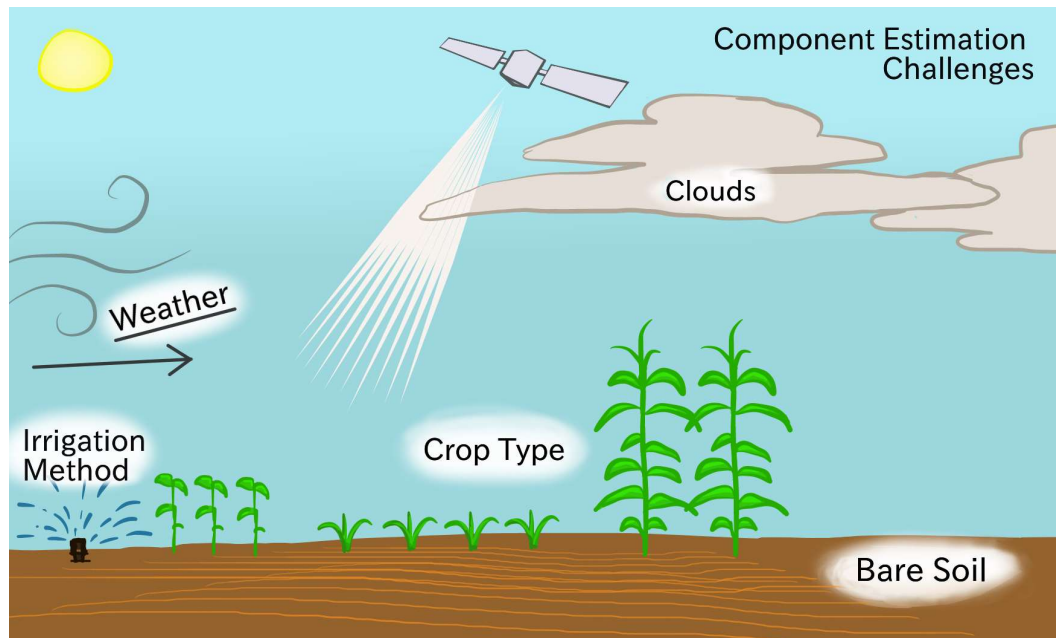
For the fine-scale comparisons presented between the seven models, differences in ET estimates can be attributed to several factors: the estimation of different types of ET (impacting crops which are maintained in less than optimal condition), non-standardized input datasets (i.e. ET<sub>o</sub>, thermal inputs, land use data), hardcoded assumptions (i.e. planting and harvesting calendars for CalSIMETA and DETAW), and the modeler judgement inherently required to fine-tune model operations and estimates. Broader differences for many crops across the entire Delta may have also been impacted by the use of different Landsat overpass dates (which were selected at each modeling team's discretion), interpolation methods (both temporal, between overpasses, and spatial, over clouds in satellite images), and empirical relationships used by each model to account for spatial variation in ET and behaviors by specific crops (i.e. METRIC's relationship between hot and cold pixels, SIMS's determination of crop coefficients based on NDVI, and UCD-PT's partitioning of available energy to latent heat).

The unique characteristics of the Delta, such as its many water channels and wind corridors, may cause differences between models depending on the accuracy of their assumptions. Each of the seven methods compared in this study was developed and tested with various calibration and validation datasets collected over various time periods and locations, often outside the Delta study area, chosen at the discretion of each model's operator. Estimates of total ET over larger areas of the Delta would be expected to converge among methods if increasingly standardized datasets and assumptions were used, but the requirement for occasional data interpolation and the complex relationships between model inputs and estimates will likely always result in some disagreement.

Remote sensing methods are generally best suited for large regional ET estimates, where field measurements cannot practically provide broad areal coverage cost-effectively. Crop coefficient approaches offer similar results in a simplified format, but they may fail to capture field



responses to local conditions on fine spatial scales. Advantages of remote sensing methods include consistency in aerial image acquisition time, relatively low costs for publicly available data, and efficient processing of new images. However, challenges remain in estimating ET using remotely-sensed thermal observations due to the complex energy and water exchange processes among crops, soil, and the atmosphere, as illustrated in Figure 16.



**Figure 16. Challenges of estimating ET remotely (Medellín-Azuara *et al.*, 2018).**

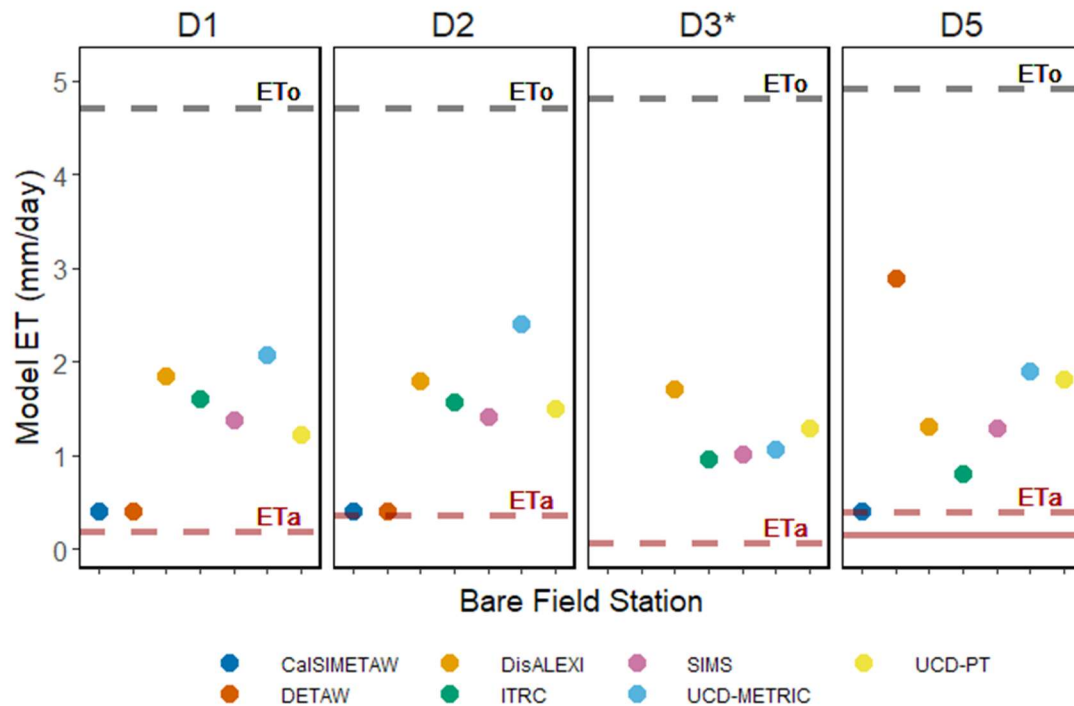
A 30-meter pixel may encompass soil and crops with a variety of root and canopy systems in vertical layers, affecting the accuracy of calculations which assume homogeneity. Short-term irrigation or precipitation and the presence of some atmospheric gases may influence thermal signals from the land surface, especially when they occur in localized areas that may be different from calibration sites. While some remote sensing approaches avoid such complexities by not using thermal data, they may not capture crop water stress or bare-soil evaporation. Cloud masking and the removal of shadows also pose challenges, especially if they occur in a sequence of satellite images. Other scientific advances such as enhanced regional-scale weather modeling, soil-plant-atmosphere land surface models, and remote sensing technologies will substantially improve ET estimation and potentially improve forecasting of future water use. Higher spatiotemporal resolution in satellite-based data will also help overcome limitations in current platforms.

## 4.2. Field Data Comparison

The field data collected for this study, over four fallow fields in 2015 and 14 alfalfa, corn, and pasture fields in 2016 (Paw U *et al.*, 2018), was compared to ET estimates by models on fine spatial and temporal scales to examine notable differences and discuss the reasons they may have occurred.

#### 4.2.1. 2015 Comparison for Fallow Fields

Fallow field evapotranspiration estimates were compared between the seven models and four field stations in the Delta in 2015. Because field measurements were taken for less than a complete month, from September 7 through October 5, 2015, field-based estimates and model data (both in mm/d) were averaged for September 2015. Model estimates were averaged across a 3-by-3-pixel grid (8,100 m<sup>2</sup> or about two acres) around each of the 2015 field stations (see Figure 2), all of which included field-based ET<sub>a</sub> estimates from SR equipment and one EC site with ET<sub>a</sub> measurements. Comparisons between field data and model ET estimates, as well as Spatial CIMIS ET<sub>o</sub> values at the corresponding locations, are plotted in Figure 17.



**Figure 17. Comparison of monthly average ET estimates by models and field sites in fallow fields, September 2015 (Medellín-Azuara *et al.*, 2018). The black dashed line represents Spatial CIMIS ET<sub>o</sub>, the red dashed line SR-based ET<sub>a</sub> estimates, and the solid red line EC-based ET<sub>a</sub> measurements.**

\*Station D3 was located just outside the DSA, so CalSIMETAW and DETAW did not produce ET estimates at its corresponding pixel. Station D4 was excluded due to uncertain calibration of a sensor.

Seepage from bare soil in areas below sea level and recent precipitation can both increase evaporation from bare soil. All 2015 field stations were above sea level (3 to 56 ft.) and precipitation had not occurred for well over a month before the start of field measurements, though precipitation did occur on September 30. All model and field-based estimates of bare soil ET in September 2015 were well below ETo values for the same time and location (Figure 17). The ensemble mean model estimate was about 1.5 mm/d for stations D1 and D2, 1.8 mm/d for station D3, and 1.8 mm/d for station D5, all of which were larger than field data. The bias of models over the field estimates ranged from fractions of a millimeter per day to nearly 3 mm/d

for UCD-METRIC at station D2 and DETAW at station D5. Where available, CalSIMETAW generally reported bare soil ET<sub>c</sub> values closest to ET<sub>a</sub> reported at field stations, and DETAW's ET<sub>a</sub> values for all but station D5 were also very close to field values. UCD-METRIC generally estimated the highest ET for the period.

Satellite-acquired data (i.e. radiation and thermal) would be expected to capture conditions matching the actual bare fields as long as images were used within the field equipment deployment period. Three different Landsat overpasses occurred in September 2015, and all remote sensing-based methods except for UCD-METRIC used at least one of these overpasses to make a direct ET estimate. UCD-METRIC's closest overpass date used was in mid-August, so the high values estimated by the model for D1 and D2 were likely due to temporal interpolation from a time with higher evaporation (neither of these fields had a crop planted during the 2015 irrigation season), though it appears the mid-August overpass still captured lower post-harvest ET in fields D3 and D5. CalSIMETAW and DETAW's lower estimates were produced using a two-stage evaporation model developed to account for ET from fields during the non-growing season (Orang *et al.*, 2013; Snyder *et al.*, 2013).

Field-based monthly average estimates may have been biased slightly lower than methods since the first six days of the month were not measured and ET<sub>o</sub> was likely declining throughout the month at the sites. Limited model parameterizations for bare soil may have also caused variations. For example, UCD-PT used a generalized PT coefficient for fallow lands because there were insufficient bare soil field measurements available for calibration (Jin and Wong, 2018). Though SIMS ET<sub>cb</sub> estimates do not include evaporation from bare soil, basal crop coefficient (K<sub>cb</sub>) values are set to 0.15 for bare soil observed in satellite images (Jankowski *et al.*, 2018). Any residual vegetation left in fields D3 (where corn was planted during the growing season) or D5 (where alfalfa and oats were planted) following harvest would further elevate K<sub>cb</sub> values and cause higher ET estimates, however.

Other discrepancies between model estimated and field data may have been caused by methodological differences that were resolved in the 2016 season. No bare soil field ET measurements were available in 2016, so these methodological changes pertaining to bare soil are difficult to evaluate. The short duration of the fallow field campaign and other uncertainties around measurements from bare soil limit the ability to draw definite conclusions about bare soil ET measurements and modeling from this study alone.

#### **4.2.2. 2016 Comparison for Alfalfa, Corn, and Pasture Fields**

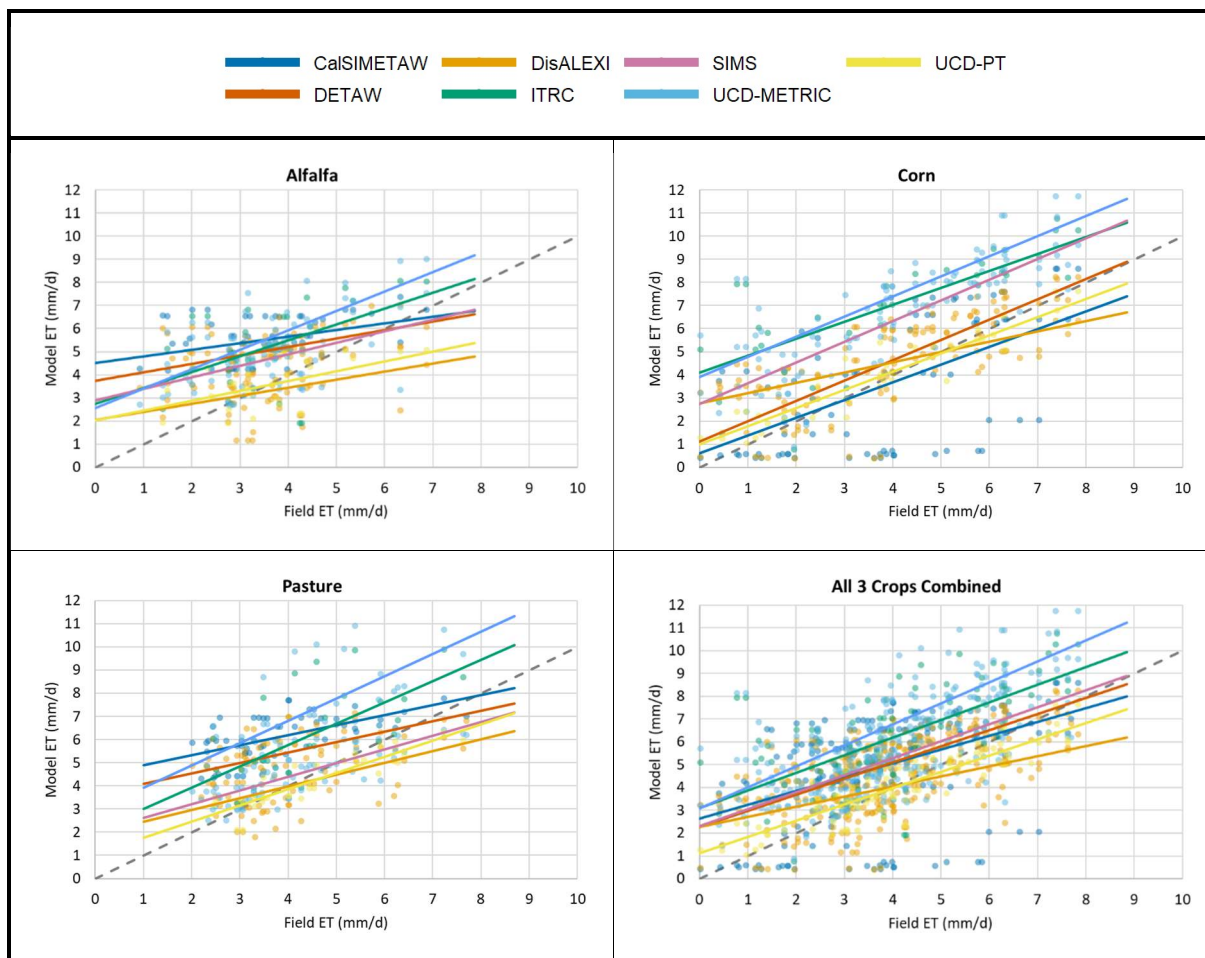
In 2016, daily evapotranspiration estimates from each of the seven models were obtained for satellite overpass dates on which imagery was used to estimate ET. Daily average field-based estimates and measurements of ET were compared for the same days between April 19 and September 30, 2016 (though deployment timelines varied, see Table 2). This method allowed for the most detailed comparison and minimized discrepancies in monthly ET<sub>a</sub> estimates among models that may have been caused by interpolation between satellite images. Model estimates were averaged over a 3-by-3-pixel grid around each of 14 field stations in alfalfa, corn, and pasture fields in 2016 (see Figure 2 and Figure 13). A total of 20 Landsat overpass dates had at

least one station with available measurements for comparison (Jankowski *et al.*, 2018). Model estimates were only compared to field data on overpass dates which were used to make direct estimates; CalSIMETAW and DETAW were compared for all 20 overpass dates during deployment. Field pasture station D05 was outside the DSA, so CalSIMETAW and DETAW did not make ET estimates for that site.

Comparison scatter plots between the field data and each model are plotted by crop, including linear regression lines, in Figure 18. In these plots a single point represents a model estimate and a field data point for a given field station on a given satellite overpass date. The SR sites provided the most data for comparison ( $n = 168$ ), and measurements from EC ( $n = 37$ ) and IRG ( $n = 2$ ) sites were limited, so no distinction is given between field station types in Figure 18. Comparative statistics between models and the field data for each individual crop and all three datasets together appear in Table 8. These statistics include the dimensionless index of agreement (IOA) (Willmott, 1981) and coefficient of efficiency (COE) (Nash and Sutcliffe, 1970). Both normalized performance metrics measure the degree of model prediction error, with a value of 1 representing perfect agreement. An IOA value of zero indicates no agreement, while a COE of zero means model and field data have equal variance. A negative COE value indicates that model variance is greater than observed field variance.

Field-based ET estimates and measurements in 2016 ranged from slightly negative to 8 mm/d across all stations, while the model-estimated ET range on overpass dates varied from near-zero to 12 mm/d depending on the crop (Figure 18). Estimated ET values from all methods showed similar trends to field-based values, capturing temporal and spatial variation between stations, though most models showed a systematic positive bias over field data for all three crops. In the high ET range ( $> 6$  mm/d) for alfalfa and pasture, however, models were biased slightly less than field data. UCD-PT used partial 2016 UC Davis field data to calibrate its model, randomly selecting 70% of the field-based ET estimates and measurements to optimize its PT coefficient parameterization for alfalfa, corn, and pasture. The remaining 30% were used for independent validation (Jin and Wong, 2018). Thus, UCD-PT had the lowest mean bias and RMSE values when compared to the field-based estimates on its overpass dates (Table 8).

IOA values were very similar for most models (Table 8), with DETAW and SIMS have the highest on average (excluding UCD-PT) and CalSIMETAW and UCD-METRIC having the lowest. COE values generally followed IOA values, being lowest and negative for CalSIMETAW and UCD-METRIC while slightly positive for DisALEXI and, as expected, very high for UCD-PT. Corn showed the greatest general correlation, with high IOA and slightly positive COE, while alfalfa had the lowest IOA and the most negative COE values. The comparison metrics scored fairly for all three crops across all seven models, with a high IOA and a near-zero but slightly negative COE. Since these metrics were designed to evaluate hydrologic models, further investigation may be merited to examine their application for ET model comparisons.



**Figure 18. Comparison of daily ET estimates between models and field data on overpass days over alfalfa, corn, and pasture fields, April-September 2016 (after Jankowski *et al.*, 2018). Solid lines represent linear regressions and the gray dashed line represents the 1:1 ratio.**

Excluding UCD-PT, DisALEXI was generally the closest to available field data on overpass dates over the three major crops in the Delta; it was generally the only model with a mean bias of less than 1 mm/d over the field data and an RMSE just over 1 mm/d (Table 8). However, CalSIMETAW and DETAW were also close to field data from corn fields and SIMS very closely matched the pasture field data. UCD-METRIC had both the highest RMSE and mean bias over field data for most of the individual crops; ITRC-METRIC showed a similar slope for each crop but with less upward bias. While CalSIMETAW and DETAW had relatively low overall mean bias compared to the field data, their high RMSE values and shallower slope compared to the 1:1 line (Figure 18) indicate considerable outliers in the upper and lower end of ET estimates, especially for CalSIMETAW in alfalfa. As a whole, the seven models generally had the lowest differences from field data in alfalfa.

**Table 8. Comparative statistics between models and field data on overpass days over alfalfa, corn, and pasture fields, April-September 2016 (after Jankowski *et al.*, 2018).**

Model (y)	Crop	n	Slope	Y-Intercept	Linear R <sup>2</sup>	Mean Bias (mm/d)	RMSE (mm/d)	IOA	COE
CalSIMETA	Alfalfa	60	0.28	4.51	0.15	1.99	2.12	0.38	-2.47
	Corn	78	0.77	0.62	0.34	-0.28	2.19	0.75	-0.24
	Pasture	55	0.43	4.45	0.36	2.04	2.00	0.52	-1.55
	All 3	193	0.61	2.63	0.20	1.17	2.39	0.62	-0.93
DETA	Alfalfa	60	0.37	3.74	0.25	1.52	1.72	0.47	-1.23
	Corn	78	0.88	1.12	0.63	0.54	1.40	0.86	0.42
	Pasture	55	0.45	3.65	0.41	1.31	1.43	0.62	-0.35
	All 3	193	0.71	2.27	0.49	1.18	1.76	0.74	-0.04
DisALEXI	Alfalfa	44	0.35	2.04	0.10	-0.34	1.24	0.58	0.08
	Corn	58	0.44	2.77	0.52	0.64	1.32	0.76	0.57
	Pasture	49	0.51	1.95	0.22	-0.02	1.32	0.69	0.34
	All 3	151	0.45	2.27	0.27	0.11	1.46	0.71	0.43
ITRC-METRIC	Alfalfa	28	0.68	2.75	0.23	1.68	2.04	0.54	-0.53
	Corn	34	0.73	4.11	0.58	2.97	2.96	0.69	-0.19
	Pasture	30	0.92	2.07	0.44	1.91	2.17	0.75	-0.09
	All 3	92	0.77	3.10	0.42	2.18	2.75	0.68	-0.22
SIMS	Alfalfa	59	0.50	2.89	0.27	1.10	1.48	0.56	-0.66
	Corn	76	0.90	2.73	0.77	2.27	2.23	0.73	-0.48
	Pasture	69	0.59	2.03	0.58	0.36	0.92	0.86	0.53
	All 3	204	0.74	2.31	0.48	1.33	1.88	0.73	-0.27
UCD-METRIC	Alfalfa	28	0.84	2.56	0.36	2.07	2.25	0.53	-0.71
	Corn	34	0.87	3.92	0.59	3.19	3.20	0.67	-0.47
	Pasture	30	0.96	2.95	0.47	2.94	2.93	0.66	-1.13
	All 3	92	0.92	3.09	0.51	2.76	3.22	0.65	-0.67
UCD-PT	Alfalfa	28	0.43	2.03	0.31	-0.06	0.94	0.74	0.66
	Corn	37	0.79	1.00	0.89	0.12	0.75	0.96	0.92
	Pasture	32	0.70	1.05	0.79	-0.34	0.68	0.93	0.88
	All 3	97	0.71	1.11	0.77	-0.06	0.88	0.93	0.87
<i>Average</i>	<i>Alfalfa</i>	<i>44</i>	<i>0.49</i>	<i>2.93</i>	<i>0.24</i>	<i>1.14</i>	<i>1.68</i>	<i>0.54</i>	<i>-0.70</i>
	<i>Corn</i>	<i>56</i>	<i>0.77</i>	<i>2.32</i>	<i>0.62</i>	<i>1.35</i>	<i>2.01</i>	<i>0.77</i>	<i>0.08</i>
	<i>Pasture</i>	<i>46</i>	<i>0.65</i>	<i>2.59</i>	<i>0.47</i>	<i>1.17</i>	<i>1.64</i>	<i>0.72</i>	<i>-0.20</i>
	<i>All 3</i>	<i>146</i>	<i>0.70</i>	<i>2.40</i>	<i>0.45</i>	<i>1.24</i>	<i>2.05</i>	<i>0.72</i>	<i>-0.12</i>

### 4.2.3. Potential Causes of Differences

Participating research groups proposed several reasons which may explain discrepancies between model estimates and the field-based estimates and measurements, which vary by both the crop type and the specific field station. Several modeling groups expressed concern that field-based ET estimates and measurements were lower than expected for well-irrigated crops, suggesting that field station installations may have affected measurements due to trampling crops or that the fetch distance of the stations was insufficient to capture ET variations across a field. However, the field campaign team believes its ETa estimates are supported by independent data in the Delta and its micrometeorological techniques were tested in extensive post-deployment comparisons. Low field ETa values observed in the Delta may have been caused by deficit irrigation, unique soil and nutrient conditions, low water availability, short depths to groundwater, plant physiological response to local wind climatology (commonly called the “Delta Breeze”), and other variables. Field techniques did not involve plant trampling at levels significant enough to discernibly affect turbulent transfer and radiation sensor footprints, and adequate fetch was obtained by careful sensor placement height and location (Paw U *et al.*, 2018).

Any systematic biases between CalSIMETA W or DETAW and the field data would be caused when field conditions did not match observations used to develop crop coefficient (Kc) literature. The models may be particularly sensitive to crop coefficients during dry initial and final cropping periods, where Kc values are typically set to around 0.15. At other times of the season the assumed growth, irrigation, and cutting schedules within these models may have differed from actual field conditions. For example: an alfalfa cutting not assumed within crop coefficients might bias field data lower than models, assumed corn senescence dates could bias models higher or lower than the field if the actual dates did not line up, and a pasture irrigation not accounted for in models could bias field-based estimates higher due to surface evaporation. Since there were fewer pasture sites overall and one was outside the DSA, there was also less pasture data available for comparison to the two models (Table 8). Since the models rely on land use classifications to develop crop-specific estimates, they are also sensitive to misclassifications. At site D09 the DWR land use dataset mistakenly showed fallow land rather than corn (Medellín-Azuara *et al.*, 2018), which likely caused some negative bias at the higher end of ET values for corn. Finally, the coarse spatial resolution of CalSIMETA W and DETAW alone may have caused discrepancies compared to field-scale data which captured finer regional ET variations and on-farm practices. Irrigation schedules and soil data were not available for the fields where stations were deployed for this study.

DisALEXI’s differences from field data may be accounted for by unique meteorological processes in the Delta not captured in the large-scale model. Corn estimates by the ITRC and UCD-METRIC models also have some uncertainties from leaf shadows which must be corrected to prevent underestimation of albedo. Systematic differences between models and the field data are unlikely to be caused by the hot/cold pixel selection; this would be more likely to skew the comparative scatter (with a high y-intercept and a slope less than one or a low y-intercept with a slope greater than one) rather than the consistent mean bias observed (slopes close to one with positive y-intercepts for all three crops). Therefore, it’s more likely that both models share a

consistent calibration philosophy which could have biased results over the field data.

SIMS ET<sub>cb</sub> estimates would be expected to have a high bias over field-based ET<sub>a</sub> estimates in the presence of crop water stress or if atypical conditions such as crop speciation or unique physiology, water stress, canopy variation (i.e. stomatal resistance caused by water shortage), pest damage, waterlogging, regional microclimates, or different soils (which affect crop coefficient values rather than explicit inputs to the model) were present at the field sites. Some of the fields where stations were installed were irrigated only sporadically (Paw U *et al.*, 2018); if farmers were to delay irrigation to aid with harvesting (i.e. mid-season alfalfa cutting), sweeten fruit crops (i.e. orchards or vineyards), or adjust for inadequate water supplies, then SIMS estimates would be higher than other models and field data. This would also be the case if there were residual biomass (i.e. corn stalks) left in the field after harvest. Finally, SIMS is sensitive to canopy height variations which affect the empirical relationship between observed NDVI, calculated, fractional crop cover, and resulting crop coefficients.

Remote sensing models which extrapolate instantaneous satellite overpass data to develop daily estimates, particularly the METRIC models, could bias ET<sub>a</sub> estimates if data observed in the field did not match the assumption that the overpass (which passes over the Delta at around 11:00 am PST) was representative of the entire day. The presence of clouds of any type during an overpass (i.e. over station D12 on August 30, 2016, during a Landsat 8 overpass) could also bias model estimates depending on their method for masking out clouds. Absolute temperature measurements by satellites could also be impacted if the vertical atmospheric profiles of major greenhouse gases (i.e. water vapor and carbon dioxide) differed from those assumed by thermal datasets. Vegetation canopy radiative or turbulence transfer simplification assumptions may also differ from actual field surface conditions. Other assumptions inherent to remote sensing and ET modeling, including the basic methodological differences among models described previously, may also be responsible for observed differences between model and field-based ET measurements and estimates.

In general, remote sensing methods would be expected to capture crop growth and land use changes on fairly short temporal scales (every 8 to 16 days based on Landsat overpass frequency), depending on cloud obscuration and interpolation methods. However, the effects of microclimates on ET<sub>a</sub> values in the Delta suggested by the field-based estimates and measurements could cause differences from models if spatial homogeneity was assumed for a given crop (i.e. that a corn field in the north Delta would have similar ET to a corn field in the south Delta if they had the same soil and water conditions and were managed in the same way).

#### **4.2.4. Improving Model Inputs and Field-Model Comparisons**

Existing differences between model estimates and field data could be further investigated and potentially reduced through the collection of additional field data. This includes irrigation timing, crop conditions such as plant-water stress, soil properties such as soil-water content, and a full season of measurements. While field data collection over homogeneous, well-irrigated sites would be expected to converge with some modeled ET estimates which assume more ideal crop conditions, most models are also designed to represent actual field conditions. Further



comparisons to field-collected data, examinations of embedded variables, and incremental modifications are crucial parts of model development, but agreement on the value and use of field data by modeler developers is required. Further meteorological and physical data collection in the field, combined with increased cooperation with remote sensing models through studies such as this, may help increase agreement between field studies and models over time.

## 5. Comparing Consumptive Use to Self-Reported Diversions

Remote estimates of evapotranspiration (ET) show promise to improve the estimation of agricultural diversions in the Delta (Siegfried *et al.*, 2014), which may aid in the administration of water rights by supplementing manual measurements and reporting by water users. To test this broader application of ET data, a preliminary study was done to compare the ET estimates developed for the Delta to diversions reported by water users.

A hypothetical island in the Delta surrounded by water might consist entirely of agricultural lands irrigated by points of diversion (*PODs*) from adjacent surface water channels. Precipitation (*P*) or seepage (*S*) through levees or the subsurface might supplement this irrigation. Water would leave the island via evapotranspiration (*ET*) from crops, pumping of agricultural drainage (*D*), and recharge (*R*) to groundwater. For this conceptual island model, a water balance may be represented as follows:

$$PODs + P + S = ET + D + R \quad (3)$$

If *P* and *S* are assumed to be roughly equal to *D* and *R*, or if all four variables are negligible compared to the magnitude of water gained from *PODs* and lost from *ET*, Equation (3) could be simplified as follows:

$$PODs = ET \quad (4)$$

Estimates of ET and user-reported diversions were compared for actual islands in the Delta to test the hypothesis of Equation (4). For water years 2015 and 2016, information was gathered on the location diversion points and the volume of water diverted monthly. Comparisons were made for specific islands or upland areas, as well as larger geographic regions and the Delta Service Area (DSA) as a whole. Discrepancies between diversions and ET were investigated, and recommendations were developed to expand this work further in the California.

### 5.1. Water Rights and Diversions in the Delta

To develop the conceptual model presented in Equation (4) for actual land areas, the boundaries of Delta islands and the location of water rights points of diversion were defined. The boundaries of islands and upland areas in the Delta are specified by the 168 subareas of the 679,594-acre DSA over which the DETAW model develops ET estimates (Kadir, 2006). The California Department of Water Resources (DWR) has also adapted these subareas for use in the California Simulation (CalSim 3.0) model, Delta Simulation Model (DSM2), and other water planning and analysis models for the Delta (DWR, 2017a). The boundaries of subareas are generally defined by channels surrounding major Delta islands or large canals or roads separating upland areas; a

map of these subareas is shown in Figure 19. Of the 168 DSA subareas, 122 are classified as “lowland” areas and 46 are “upland” zones. Average elevation data for each subarea were obtained from a 10-meter digital elevation model (DEM) to verify these classes. Without additional information on places of use for individual water rights, an application of the conceptual model in Equation (4) to a finer spatial scale than a Delta island would be unlikely to yield reasonable comparisons between diversions and ET because applied water would be more likely to flow outside the specified area. Related prospects for improving this analysis are discussed further below.

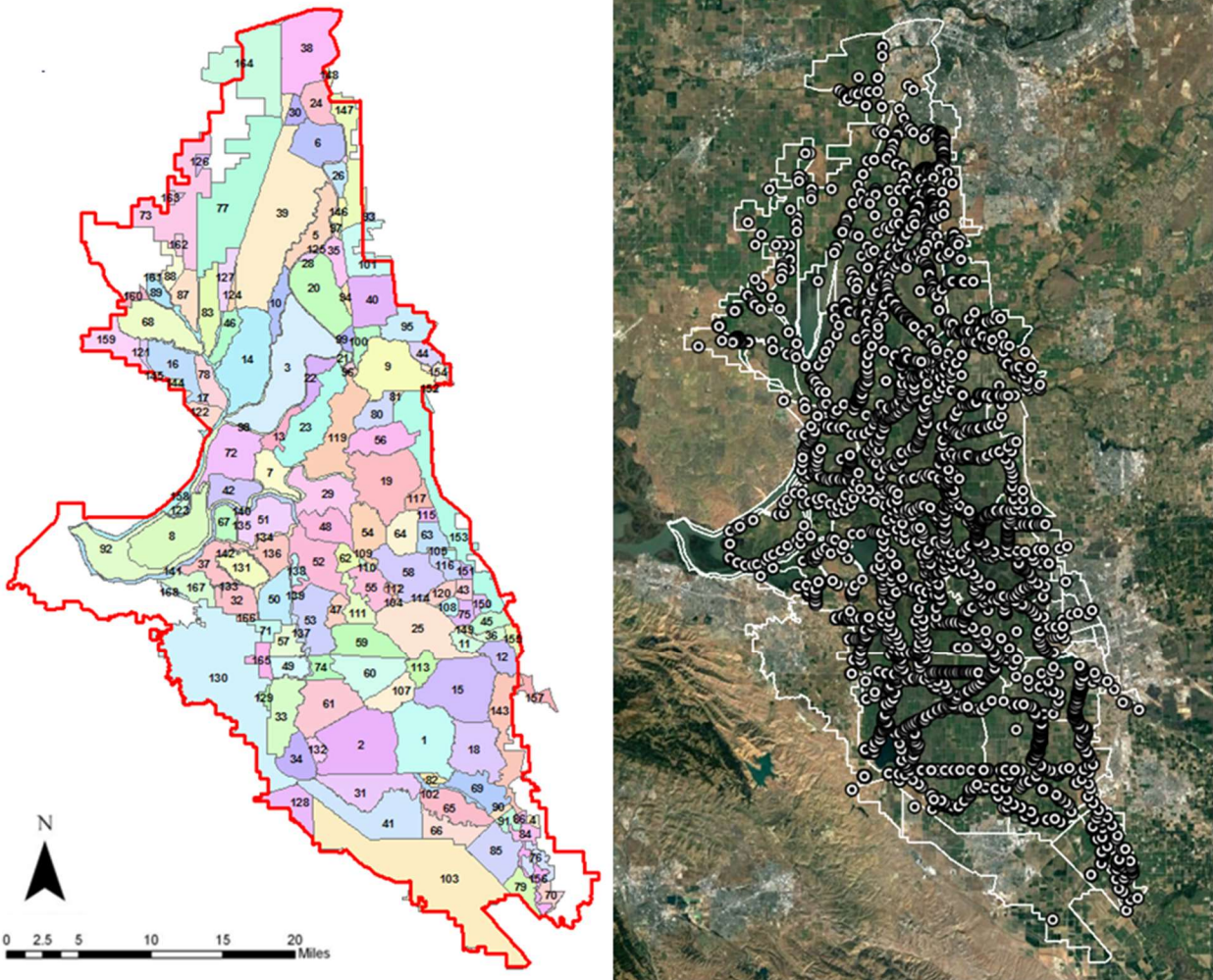
Water users in the Delta hold rights to divert from its channels to serve a variety of demands; these include agricultural irrigation through siphons to subsided islands or longer canals to upland areas, urban areas pumping water from the Delta, State and Federal inter-basin transport projects, and environmental uses supporting wildlife habitat or recreation. The California State Water Resources Control Board (SWRCB) maintains the online Electronic Water Rights Information Management System (eWRIMS) database, which contains information about water rights points of diversion with attributes that include priority date, owner, nature of use, and other information (SWRCB, 2018). Grantham and Viers (2014) presented a summary of California’s water rights system and utilized data from the eWRIMS database to give a comprehensive overview of water rights in the state.

A spatial dataset of water rights PODs across the State of California, updated May 1, 2018, was downloaded from the eWRIMS Water Rights Web Mapping Application. Using geographic information system (GIS) software, PODs in the DSA were identified and assigned to the subarea where their diversion was located. Manual quality control of the dataset was done using aerial images to ensure that each POD was properly assigned to the subarea to which it actually diverts. A total of 3,121 unique water rights divert from 135 of the Delta’s 168 subareas, with 130 of these rights diverting from multiple PODs that may be located in different subareas. The locations of PODs in the DSA are mapped in Figure 19 (this map shows individual PODs documented under each individual water right; many PODs may be used by multiple water rights but not precisely co-located in the dataset).

Diversions made under the 3,121 water rights (as identified by unique Application Numbers) in the Delta were retrieved for comparison to remote ET estimates for the DSA’s subareas. The California Water Code requires, with some exceptions, users of surface waters to file annual water reports supporting beneficial water use and documenting monthly diversions. Depending on the type of water right, these reports are referred to as Supplemental Statements of Water Diversion and Use, Reports of Licensee, or Progress Reports by Permittee (SWRCB, 2017). Wilson (2011) described the history of diversion reporting in California and the program’s impacts and benefits in the Delta.

During California’s historic 2012-2016 drought, reporting and diversion requirements were further expanded under Senate Bill 88 and a Board-adopted Emergency Regulation for Measuring and Reporting Water Diversions (SWRCB, 2017). The SWRCB (2015) also issued Order WR 2015-0002-DWR (“Informational Order”), requiring specific water rights holders in the Sacramento and San Joaquin watershed to provide information on the location, amount, and

nature of their diversions. The Informational Order impacted 1,061 riparian and senior (pre-1914) water rights owned by 445 different parties, representing 90 percent of reported water use in the Delta and 90 percent of water use in the Sacramento and San Joaquin River watersheds; 958 of the impacted water rights were in the DSA POD database developed for this study. Ekdahl and George (2018) summarized an initial review of responses to the Informational Order and provided a spreadsheet database which was used to obtain additional information on the affected water rights in the Delta.



**Figure 19. Delta subareas (Kadir and Liang, 2018) and points of diversion (after SWRCB, 2018).**

Annual water use reports are filed by calendar year, so water use reports from 2014-2016 were required to match ET estimates for all months of water years 2015-2016. A Python program was developed (available at <https://github.com/jessejanko/pyWRIMS>) to query the eWRIMS Water Rights Records site based on the Water Right ID attribute of individual water rights, accessing annual water use reports for each. Monthly direct diversions, typically in acre-feet (AF), were

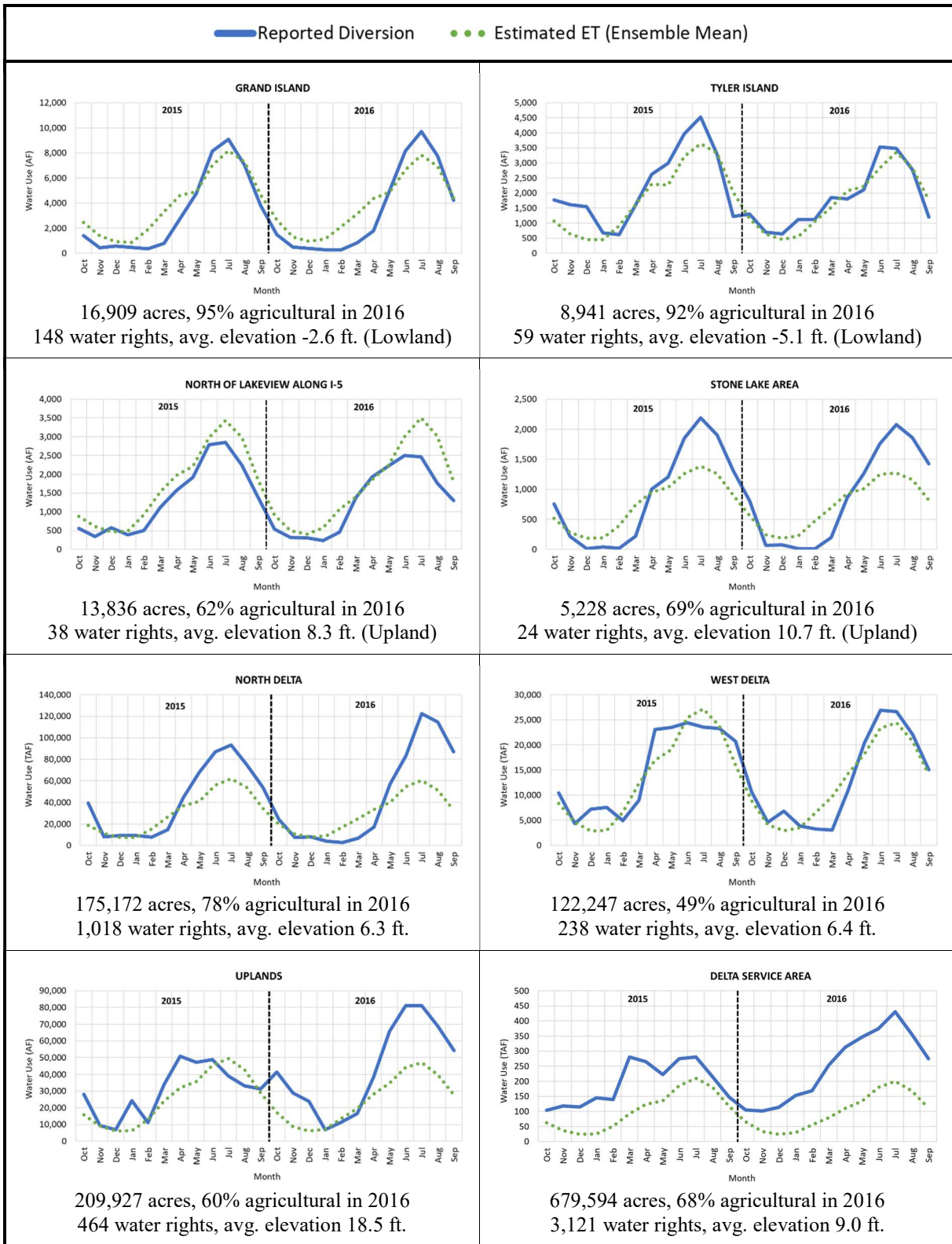
obtained for at least one year from 2,741 of the 3,121 water rights in the DSA; the status of all but 38 of the remaining rights was marked as Cancelled, Inactive, or Revoked. Manual quality control was done on water rights with annual diversions exceeding 1,000 to ensure the proper units were used, as some users occasionally reported diversions in gallons. Additional manual quality control of smaller diversions was not done, as it would take considerable time.

Though water use reports are filed for individual water rights (as identified by Application Numbers), 130 of the water rights in the Delta have multiple PODs that may divert to multiple subareas. Since no supporting information was available to split these diversions to multiple PODs, each water right's diversion was assigned to its first numbered POD and associated subarea. Not all water rights in the Delta divert water solely for agricultural irrigation; other beneficial uses identified in water rights attributes include stockwatering, domestic or municipal, fish and wildlife preservation and enhancement, recreational, power or industrial, fire protection, and other incidental uses. No water rights were excluded from the analysis, which would be expected to drive reported diversions greater than ET estimates if diversions were reported for non-agricultural uses. Available user-reported monthly diversions were summed for each of the DSA subareas to produce a dataset which could be compared to ET estimates over the same areas and times.

## **5.2. Comparison of Diversions and Evapotranspiration**

For comparison to monthly user-reported diversions in water years 2015-2016, monthly average ET volumes from each of the seven models compared in this study were averaged to produce an ensemble mean; SIMS results included the DSA-wide average of the other six models for semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture lands (which covered about 11% of the DSA). Though some user-reported diversions were for non-agricultural land uses, managed natural vegetation (i.e. hunting clubs) is likely a small percentage of the total land area covered by riparian, floating or wetland vegetation in the Delta. Therefore, most non-agricultural ET is unlikely to originate from intentional diversions, so only ET estimates from the 26 agricultural classes identified in DWR's land use survey (Table 1) were used. Monthly ensemble mean ET volumes from agricultural lands were summed by subarea for direct comparison to reported diversions.

Available reported diversions from all 3,121 water rights in the DSA totaled 2,309,710 AF in 2015 and 2,991,783 AF in 2016, while ensemble mean ET estimates for the DSA's agricultural lands totaled 1,444,866 AF in 2015 and 1,379,316 AF in 2016 (Table 4). Monthly timeseries plots were developed for each of the DSA's 168 subareas, its five major regions (see Figure 3), the lowland and upland zones specified in the subarea dataset, and the entire DSA. Figure 20 presents eight sample plots for various areas, as well average elevation and other attributes for each.



**Figure 20. Monthly reported diversions (SWRCB, 2018) and ensemble mean ET estimates for select Delta subareas, regions, zones, and the DSA, 2015-2016.**

The timeseries comparison plots shown in Figure 20 represent large Delta islands and upland areas with sizable volumes of ET and diversions which matched well in both monthly timing and magnitude. These areas demonstrated very good agreement between diversion and ET in transitional seasons, with roughly equal discrepancies during the peak growing season (June-August) and wintertime (November-February). However, neither ET nor diversions were consistently higher or lower for all areas; Grand Island and the Stone Lake Area had higher diversions in summer and higher ET in winter, Tyler Island had consistently higher diversions, and the subarea North of Lakeview Along I-5 had consistently higher ET. Some larger geographic (North and West) and topographic (Uplands) areas of the Delta also showed excellent agreement between diversions and ET for volumes exceeding 25,000 AF per month.

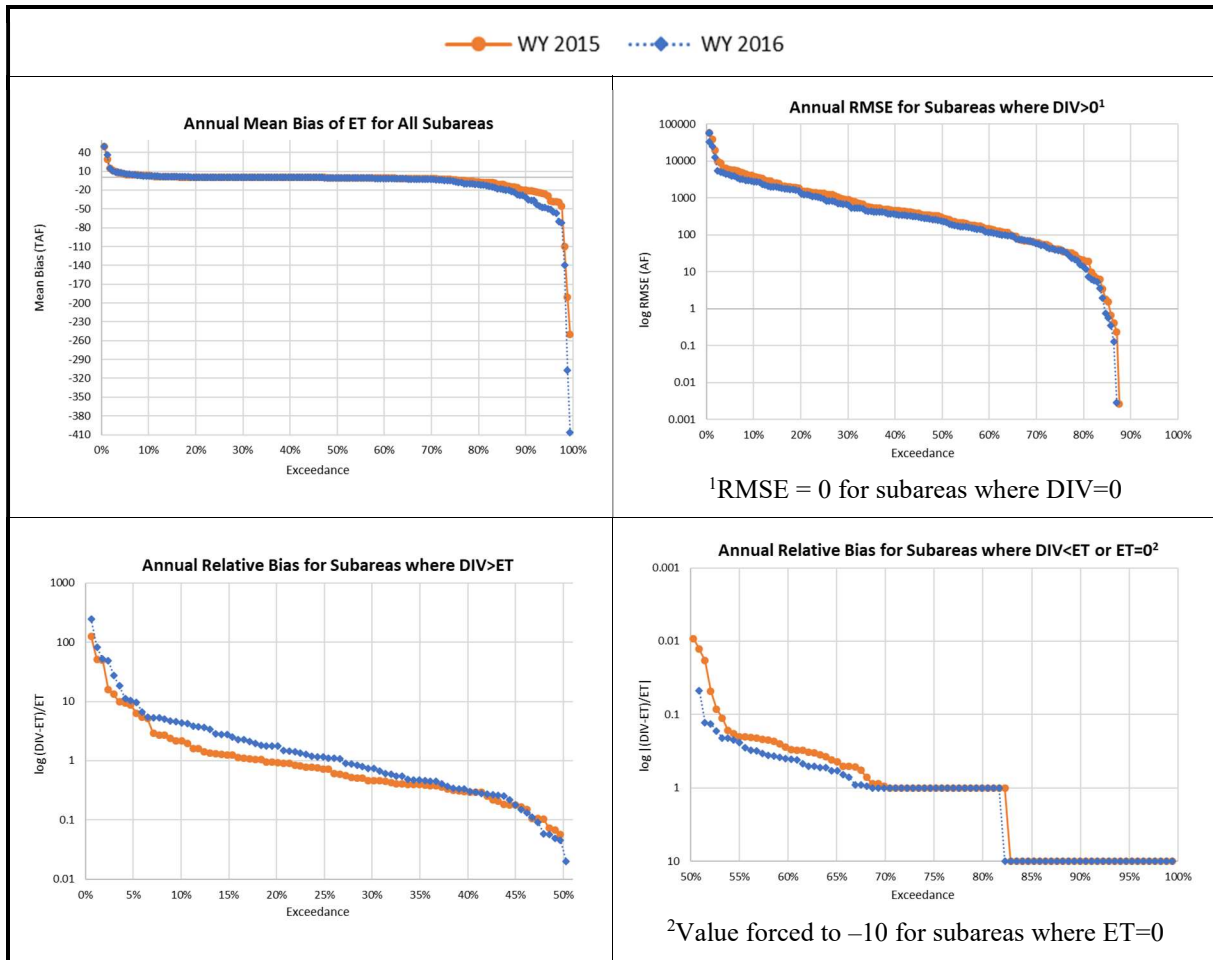
Many other subareas not plotted in Figure 20 had less strong correlations between ET and diversions, often small in magnitude but more substantial for some subareas. Large discrepancies often depended on the nature of water right uses within a subarea and other local factors (these are discussed further below). In the DSA overall, reported diversions exceeded ET in every month; notably, diversions which spiked in March 2015 and increased overall in 2016 were not reflected in ET estimates. The comparison suggests some promise for ET estimates to accurately quantify diversion in some areas, and a more comprehensive evaluation of errors in the analysis can indicate the magnitude of major differences and suggest venues for improvement.

### 5.3. Analysis of Differences Between Diversion and Evapotranspiration

Annual total diversions and agricultural ET estimates were compared for all 168 subareas of the DSA to examine systematic differences. Several comparative statistics were used to quantify these differences: mean bias, root-mean-square error (RMSE), index of agreement, coefficient of efficiency, and relative bias. Relative bias, a quantification of the difference between diversions (*DIV*) and ET relative to the magnitude of ET, was computed for individual subareas as follows:

$$\text{Annual Relative Bias} = \frac{\sum \text{DIV} - \sum \text{ET}}{\sum \text{ET}} \quad (5)$$

The result of Equation (5) would be positive if *DIV* exceeded *ET* (which occurred in 85 subareas in 2016), negative if *ET* exceeded *DIV* (32 subareas in 2016), equal to -1 if there was zero reported *DIV* (21 subareas in 2016), or equal to zero if *ET* was equal to *DIV* (no subareas in either year). Since an *ET* value of zero would cause a mathematical error, annual mean bias values for subareas with zero agricultural ET (30 in 2016) were forced to a value of -10 for plotting purposes. Figure 21 contains exceedance plots of annual mean bias, RMSE (for all monthly values for a given subarea and year), and relative bias for all 168 subareas, separated by water year. RMSE and relative bias are plotted on log scales, so the RMSE plot does not show zero values and the negative relative bias values are plotted by absolute value in reverse order.



**Figure 21. Analysis of annual differences between reported diversions and ET for all subareas, 2015-2016.**

Mean bias values for all subareas show that absolute differences were small, with ET biased lower than diversions: -6 TAF on average in 2015 and -11 TAF in 2016 (Figure 21). Very good agreement was found for about 75% of subareas, where mean bias was less than  $\pm 10$  TAF, and about a third of the subareas had a mean bias of less than  $\pm 1$  TAF. The major outliers were three subareas with biases lower than -100 TAF (Clifton Court, Byron Tract, and Merritt Island in both years). RMSE values show that monthly relative differences between diversion and ET were even smaller, averaging about 1 TAF in 2015 and 2 TAF in 2016 with 23 subareas having a RMSE of less than 1 AF in both years. Relative bias values, averaging 2.3 in 2015 and 4.3 in 2016 for areas with nonzero ET, indicate that subareas were roughly split between having greater ET and greater diversion. Higher diversions in 2016 were likely due to a wetter year with increased water availability, especially for water project transfers (discussed further below). Conversely, the estimated total agricultural ET in the Delta decreased by about 66,000 AF from 2015-2016 due to land fallowing and other previously discussed trends.

#### 5.4. Further Work to Improve Analysis

The hypothesis of Equation (4) appears accurate for islands surrounded by water with largely

agricultural water rights, even up to larger regions of the Delta; estimated ET was within about one magnitude of reported diversions for more than half of the Delta's subareas (Figure 21), with many having excellent agreement in both timing and magnitude (Figure 20). However, the simplified assumption of an isolated agricultural island appears less accurate for certain areas with specific water uses. Further investigation of individual water rights will improve the results of this analysis and allow for similar comparisons on even finer spatial scales.

Major differences between reported diversions and estimated ET are likely driven by the nature of beneficial water use associated with individual rights, and reported diversions for non-agricultural uses would exceed ET estimates made from exclusively agricultural lands. Though ET estimates exist for non-agricultural lands, water use on managed lands such as hunting clubs is difficult to separate from consumptive use by entirely natural vegetation. More than 200 of the Delta's water rights have beneficial uses for Recreation or Fish and Wildlife Enhancement, and diversions reported under these rights totaled more than 800 TAF in 2016; removing rights associated exclusively with these uses would improve the accuracy of this analysis, but several hundred additional water rights have multiple beneficial uses which include Irrigation, making them difficult to separate. Other specific agricultural practices may be included in reported diversions but not well-represented in ET estimates: pre-season field wetting, land subsidence reversal activities, or the flooding of rice paddies to aid in post-harvest decomposition. This knowledge of local practices and water use is crucial to understand the data gaps and limitations of this initial analysis.

In upland areas not surrounded by water, the hypothesis of Equation (4) further breaks down as water may be sourced from or used in other subareas of the Delta. In areas around Tracy and Yolo, ET estimates exceeded diversions because irrigation water was sourced from outside the subarea where the water was consumptively used. Conversely, when water was transported outside a subarea its reported diversions exceeded ET by several magnitudes. Diversions by Reclamation Districts 150 and 999 did not match agricultural ET estimates on Merritt Island, and pumping by the State Water Project and the Central Valley Project were also much higher than the small amounts of ET in the Clifton Court Forebay and Byron Tract. Diversions under these large-scale projects are well-monitored, and their water rights could potentially be excluded entirely from the analysis; any deliveries within the Delta would require further investigation of their reported diversions, as they may include water uses upstream in the Trinity and Sacramento River basins.

The database of water rights and diversions in the Delta developed for this study allows for further evaluation of individual water rights in specific subareas where diversion and ET showed significant differences, and additional data would improve the accuracy and applicability of this information. The unaddressed elements of Equation (3), pumping, recharge, precipitation, and seepage, may not be negligible in comparison to the magnitude of ET and diversions. This may be particularly true on finer timescales than months, as diverted water may not yet have returned to surrounding channels due to moisture held in soil pores. Desktop estimates of runoff fractions and gridded precipitation datasets like PRISM could be used to improve this analysis, but it would be difficult to obtain comprehensive pumping data or precise recharge and seepage



numbers across the Delta. A pilot study in an area with available information, ideally for the same period of this study (water years 2015-2016), might reveal how ET estimates could better match reported diversions with additional water balance data.

Additional data is also needed for the 380 water rights with no reported diversions in this study, though about 90% of them are marked as cancelled or currently inactive. The 130 rights in the Delta which divert to multiple PODs are also a concern, as their potential use of water in multiple subareas is not accounted for in this analysis. These rights represented about 42% of Delta diversions in 2016 and could impact water balances within certain subareas if reported diversions were split between several PODs. Information on water use by individual PODs is not available in the eWRIMS database, so this expansion would likely require coordination with individual water right holders.

The value of this study would increase if ET estimates could be compared to diversions made under individual water rights, and differences between the two would be expected to decrease when made over the specific field(s) or other non-agricultural areas where diverted water was applied. This improvement would require significant data on place(s) of use for individual water rights and would be best paired with detailed land use data and information on water infrastructure (i.e. irrigation canal conditions) to help determine carriage and application efficiency. States such as Utah have mapped places of use for all water rights and posted the data online, along with other information on points of diversion and nature of use for independent analysis (UDWR, 2018). In California, recent documentation collected for senior water rights under the Informational Order (Ekdahl and George, 2018) may make this type of analysis possible if care is taken to develop sufficiently accurate, precise, and accessible datasets.

## **6. Conclusions on Consumptive Water Use in the Delta**

Evapotranspiration is one of the largest and most important quantities in local and regional water balances. It is also one of the most uncertain water balance components, as it is invisible, hard to estimate, and subject to varying estimation methods and data. This study expands on previously-reported efforts (Jankowski *et al.*, 2018; Medellín-Azuara *et al.*, 2018) to summarize and discuss information on evapotranspiration from lands in the Delta, with important method and field insights learned from detailed data comparisons. It highlights a broad range of ET estimates by multiple methods, from annual values totaled over large areas to daily results at the two-acre scale and half-hourly point field data. Despite discrepancies at small spatial and temporal scales, the study's results show some convergence of long-term models estimates over large areas (i.e. Delta-wide over a water year).

State agencies and other stakeholders currently support a wide range of methods for measuring and estimating ET from crops and other ecosystems, and crop ET measurement and estimation methods continue to evolve and improve. However, few efforts have been made to compare these methods, particularly for applied water management problems. Given the wide ranges of ET estimates and sometimes high economic values of water uses, systematic comparison and development of ET estimation methods is critical and should yield substantial value. On average, the seven models in this study estimated that total evapotranspiration in the Delta totaled about

2,057 thousand acre-feet (TAF) in 2015 and 2,033 TAF in 2016, about 70% of which came from agricultural lands in both years. These values were broadly consistent (though about 18% higher) with values published by state agencies (DWR, 2017b). For agricultural lands, all models were within  $\pm 12\%$  of the ensemble mean in both years and averaged an absolute difference of 6% or about 91 TAF. These average differences were considerably lower than similar comparisons of consumptive use estimates published in the literature (Kite and Droogers, 2000; Medellín-Azuara and Howitt, 2013; Sörensson and Ruscica, 2018).

Alfalfa, corn, and pasture covered 40-45% of the Delta and averaged about 60% of all agricultural consumptive water use in the Delta (654 TAF) across all models. Among these three, alfalfa had the highest average annual ET per unit area (3.7 AF/acre or ft.) and accounted for 12% of all consumptive use in the Delta; pasture had similar unit ET (3.5 ft.) and corn had the lowest (2.9 ft.). Almonds, tomatoes, and vineyards covered an additional 10% of the Delta land area and consumed about 10% of its agricultural ET. Land use changes from 2015 to 2016 included decreases in the three main crops and increased fallow land (nearly 29,000 acres, some of which was likely driven by land preparation for the planting of permanent crops), resulting in a 5% (66 TAF) decrease in total agricultural ET. Models estimated that non-agricultural riparian, upland, and floating vegetation may have larger per-area ET rates than many crops and consume considerable volumes of water across the Delta. However, not all methods are suited to estimate ET for these land uses, and no corroborating field data was available for this study.

Different areas of the Delta often have varying major crops, drainage, and climate conditions (winds, temperatures, elevations, soils, etc.). Estimates for larger regions are useful for Delta water flow and quality management, particularly as inputs to models. The five remote sensing-based methods captured some spatial variability in ET estimates which often corresponded with specific crop types, and certain Delta regions corresponding with water agency service areas had observable trends in ET and land use. The greatest relative differences between methods were from October to January, when only about 13% of annual agricultural ET occurs, and larger relative differences and early or late-season increases in absolute differences were seen in corn, tomatoes (which may not be grown outside the summer, indicating the differences likely occur for post-harvest fallow fields), almonds, and vineyards.

Field measurements collected by UC Davis represent a coordinated effort to deploy multiple instrumentation to several land covers in the Delta and develop datasets for common comparison to ET models. Measurements and estimates from surface renewal, eddy covariance, and water vapor flux equipment generally agreed (Paw U *et al.*, 2018), so trade-offs between equipment cost, apparent accuracy, and correlation of measurement deserve further investigation. Field-based estimates of actual evapotranspiration (ET<sub>a</sub>) from upland fallow fields sampled in late summer 2015 were nearly zero, considerably lower than most modeled values which ranged from 1-2 mm/d for the same period and locations. Additional fallow field measurements, particularly over an entire year, are needed to better support the findings of this study. A pilot study comparing ET from fallow fields to adjacent cropped fields is underway for the 2018 growing season.

Field measurements in 2016 from alfalfa, corn, and pasture fields provided considerably more

data for analysis and comparison, including half-hourly ET<sub>a</sub> estimates and measurements along with individual energy balance component datasets (Medellín-Azuara *et al.*, 2018; Paw U *et al.*, 2018). These data are critical in assessing the field-scale uncertainties and accuracy of ET<sub>a</sub> estimates made by larger-scale models, and expanding a field campaign to other major crops and natural lands during the entire water year could be useful to assess ET<sub>a</sub> values across the Delta and enhance model performance under a wider set of land uses. Daily average field estimates and measurements of ET were compared to model estimates on concurrent satellite overpass days which were used to make direct estimates. While remote sensing-based estimates were well-correlated with field-based estimates, models generally estimated higher ET from all three crops (ensemble mean bias of +1.2 mm/d and RMSE of 2.1 mm/d). Differences were generally greatest for corn, with lower bias for alfalfa and lower RMSE for pasture. Remote ET estimation methods may be improved by increased temporal resolution, validation of interpolation methods, and error assessment of model assumptions in cooperation with field campaign teams.

Detailed comparisons between ET estimation methods on small spatial and temporal scales yielded insights into methodological assumptions and input datasets which may cause differences between ET estimates. Models were compared over 14 two-acre areas around alfalfa, corn, and pasture field stations on common satellite overpass dates used for direct estimation. These comparisons generally indicate good agreement between models; mean biases ranged from zero to 2.4 mm/d, and RMSE values ranged from 0.7-4.2 mm/d and averaged 1.8 mm/d across all comparisons for all three crops. The greatest agreements were found between models with similar methods and inputs: CalSIMETA<sub>W</sub> and DETAW, DisALEXI and UCD-PT, ITRC-METRIC and UCD-METRIC. Though standardization of input datasets was pursued in this study, major sources of discrepancy likely included types of ET estimates (actual, ET<sub>a</sub>, potential, ET<sub>c</sub>, or basal crop, ET<sub>cb</sub>), selected input data, assumptions, specific parameter calibration, hard-coded internal estimation steps, and modeler judgment. Improved communication among modeling groups and standardization of input datasets such as land use, satellite overpass dates, and data sharpening and interpolation procedures should improve convergence in ET estimations, but unique approaches, assumptions, and parameterizations may always result in some disagreements.

The initial comparison between reported diversions and modeled consumptive use in the Delta shows promise. Mean biases between diversions and ensemble mean agricultural ET in the DSA's 168 subareas averaged -8.5 TAF, with about 75% of subareas less than ±10 TAF and a third less than ±1 TAF. RMSE values were even smaller, averaging about 1.5 TAF, and 23 subareas had a RMSE of less than 1 AF. Average relative biases of 3.3 indicated that subareas were roughly split between having greater ET and greater diversion. Errors increased alongside diversions in the wetter 2016 water year, even as ET decreased due to land use changes. Major outliers occurred in subareas with large water transfers outside the Delta or upland regions sourcing water from elsewhere. Water rights in the Delta have a multitude of dedicated purposes that include agricultural, human, environmental, and recreational uses which all affect the amount of water they might consumptively use, so further examination of individual water rights and local practices is needed to improve the usability of this analysis. With information about points of diversion and places of use, remote consumptive use estimates would be expected to

more closely approximate direct diversions, potentially supplementing manual measurements and aiding in the administration of water rights.

This study demonstrates how to improve the quality, transparency, and accessibility of remote evapotranspiration data for large agricultural regions. The approach employed for this study was inclusive and collaborative, involving major research groups and agencies estimating ET across California and globally. The collection of data by an independent research team allowed for the unbiased analysis and presentation of results, the cooperation of modeling teams helped advance knowledge of how unique methods impact ET estimates, and iterative improvements over two years encouraged collaborative development to better represent local conditions. In-depth model and field comparisons and related discussions helped identify method gaps, demonstrate the uncertainties and challenges involved in modeling and measuring ET, and improve collaboration on technical efforts to quantify consumptive water use in California.

## **7. Policy Recommendations for Broader Use**

Remote estimates of evapotranspiration (ET) from agricultural crops, natural vegetation, and developed lands have a range of potential uses by state agencies, stakeholders, researchers, and other water professionals. In the Sacramento-San Joaquin Delta, ET estimates may impact water management models and practices affecting agricultural uses, urban diversions, pump operations to transfer water outside the basin, and environmental water uses for aquatic, riparian, and upland wildlife habitat. Water professionals and practitioners statewide may benefit from the accurate estimation of ET to improve water accounting, inform groundwater modeling, monitor land uses, and manage irrigation practices on fine scales. Learning from this study and practices in other places, the State of California can pursue innovative applications of remote ET estimates and advance technical capabilities to use them for water management.

Governments, agencies, and districts may put consumptive water use information to use in the management and planning of water resources and the administration of laws and regulations. In California, agencies like the State Water Resources Control Board and the Department of Water Resources may use ET estimates to advance basin water budgets, quantify idle land water transfers, permit and administer water rights, supplement regional water accounting, monitor and assess the impacts of drought, estimate the impacts of land use changes on streamflows, develop water conservation targets, manage Delta inflows and exterior transfers, and improve water balances which inform water quantity and quality estimates. The State of Idaho's Department of Water Resources (IDWR) uses remote sensing-based estimates of ET for a variety of water management, accounting, and water right purposes. An online platform deployed by IDWR (2018) allows users to interactively obtain crop irrigation requirements and other information, improving transparency and reducing conflict. Allen *et al.* (2015) documented more than 20 additional applications of the METRIC model and Landsat data to ET estimation across the U.S.

The ensemble average of seven models demonstrated in this study provides a reasonable assessment of ET over large spatial and temporal scales (i.e. annual ET volumes for the Delta Service Area). Water managers and regulatory agencies may place value on having a single ET value, but it is important to understand the scientific uncertainties associated with ET estimation.

While a multi-model approach is an avenue to explore in a long-term ET estimation program for California, additional effort will be required to integrate multiple estimation approaches (i.e. weighted averaging of methods for select crops or data applications). The trade-offs of cost and practicality versus accuracy and comprehensiveness incurred in a multi-model approach merit further examination.

Given the diversity in expert participation and the broad technical scope of the study, unresolved issues are expected. This thesis and Medellín-Azuara *et al.* (2018) present some clear discrepancies between the field campaign ET and the modeled ET estimates in the Delta, though many models have cited greater agreement with field data from other locations in their respective literature. The long-term value and credibility of ET estimation for California water management and policy will eventually require a better understanding of these differences, and some strategies may help reduce these unresolved differences. Field measurement campaigns could focus on detailed paired comparisons with a few modeled estimates, with uncertainty analyses of both measurements and estimates. Multiple water experts, such as independent field networks (i.e. FLUXNET-AmeriFlux), DWR, and other expert groups should be involved. The potential benefits of model calibration and validation with additional field-obtained data should be examined, and an ET measurement and estimation program with some base funding would be best-suited to maintain collaboration and advancement of ET quantification statewide.

This study's sample comparison of ET estimates to user-reported diversions in the Delta demonstrates the potential value of remotely-sensed consumptive use estimates in water rights administration. Estimates of ET may supplement self-reported data and help water users meet regulatory requirements. Recent increases in reporting requirements have imposed significant costs and labor requirements on water users and present questions of consistency and accuracy across many different diversions. Remote sensing-based ET estimation methods could provide a cost-effective approximation of water use, increasing transparency, accuracy, and consistency across the state; such methods have been used successfully in other states such as Idaho (IDWR, 2018). Most water rights in the Delta have senior priority and are overseen by a variety of reclamation districts, water agencies, and other legislative groups created to address local water issues (Wilson, 2014). Collaborative consumptive use estimation groups may help establish trust in estimates and innovative approaches to administration. A similar approach is currently being sponsored among Delta water users by the Office of the Delta Watermaster, although results have not yet been reported.

The extrapolation of ET estimates to quantify diversions requires, at minimum, information on the places of water diversion and use. Additional data on the nature of water uses (i.e. agricultural, human, or environmental beneficial uses) and localized conditions such as irrigation infrastructure, soil, and drainage will aid analysis efforts considerably. Additional work is needed to maintain comprehensive water right records, ensure the accuracy of point of diversion datasets, make diversion report data more accessible for interested parties, and ascertain how water is diverted under rights with multiple points of diversion. More information on the places of use for individual water rights and quantifications of seepage, pumping, recharge, and precipitation on Delta islands would further improve this work. Similar datasets have been made

available by other states for independent analysis (UDWR, 2018).

Remote ET estimates may aid in on-farm water management and precision irrigation practices when presented in a usable format with sufficient resolution and timeliness. The present resolution of Landsat satellite data, passing over a region every eight days and outputting estimates at 30-meter resolution, can provide farmers with estimates of consumptive water use by entire fields in the past. This retrospective data might inform upcoming irrigation if schedules are designed to meet plant ET requirements and can also help farmers manage for variable soils, meet leaching requirements, ground-truth crop coefficients, and enhance ditch banks for off-season habitat. Improved irrigation practices may lead to increased crop yields and economic benefits. Higher-resolution estimates of ET using data from unmanned aerial vehicles (UAVs) shows promise to provide ET estimates at the centimeter and minute-level, potentially improving irrigation uniformity across fields or allowing time to adjust irrigation practices in real-time to meet crop water requirements (Morandé *et al.*, 2018).

Groundwater management is informed by water balance models that require the quantification of water entering and exiting a system. Consumptive use of water is a substantial and often uncertain part of this equation, so accurate estimates of ET may increase the overall accuracy of groundwater balance calculations. The determination of groundwater recharge by irrigation or banking practices is valuable to water users and managers alike. Managers may also use remote ET estimates to monitor groundwater uses, predict pumping in the absence of data, or to compliment and verify meter readings. Spatial ET estimates across large regions may further aid in management of entire groundwater basins. Additional information on local soil and groundwater conditions may help refine the estimates of other components in the water balance, such as recharge fractions and runoff, but ET from irrigated crops is the largest water balance component in agricultural areas.

California's Sustainable Groundwater Management Act (SGMA) requires basins across the state to take steps towards long-term sustainability. This includes the formation of Groundwater Sustainability Agencies (GSAs) and the drafting of Groundwater Sustainability Plans (GSPs). Remote ET estimates may facilitate groundwater management at multiple scales and ease the amount of technical work required model, monitor, and maintain groundwater balances across the state as part of these efforts. Uncertainties in ET estimates may affect long-term groundwater planning, however: underestimation of ET could overstate sustainability, while overestimation may risk the integrity of water balances used in transfers, exchanges, and net accounting.

This study reveals the need for more information on consumptive use from non-irrigated but actively managed lands. This includes fallow fields, which were estimated to represent nearly 10% of total ET in the Delta in 2016. However, preliminary field-based estimates from a selection of areas above sea level in late summer 2015 were considerably lower than most models. The quantification of bare soil ET from specific areas is critical because it is the amount of water potentially saved in comparison to a fully-irrigated crop during the growing season, establishing the net consumptive water use of crops. Depending on regulations, this net water use may be available for transfer to other uses, banking to groundwater, environmental flow benefits, or compensation through voluntary fallowing programs. Current data presents high uncertainties

for the quantification of potential fallowing water savings. A more rigorous field-based study comparing similarly cropped and fallowed areas is needed, particularly on subsided land affected by subsurface seepage, and such a study is underway for the 2018 growing season.

The quantification of water consumptively used by non-agricultural lands, especially from non-crop vegetation, is also valuable for water managers. This study's ET estimates from natural vegetation, including floating, riparian, and native classes, indicate their consumptive use rates per-unit area might be higher than those of irrigated crops in the Delta. However, because most estimation methods are primarily developed for agricultural land uses, these estimates need further examination. Additional model refinements may also be needed to account for unique growth characteristics and land cover variation in non-managed vegetation. There is considerable interest in the remote identification and mapping of different vegetation types, especially native versus non-native species. Lands use classifications could be improved through collaboration with other agencies and research groups with specialized experience. In tandem with increased model applications to non-cropped areas, additional field work to measure ET and other meteorological fluctuations should also be done to obtain calibration and validation data. A comprehensive review of previous field studies in these land use classes may improve accuracy for estimating this potentially large consumptive use in the Delta. Improved data on ET from vegetation may help quantify habitat water needs, evaluate the impacts of restoration on local water uses, and better incorporate natural landscapes into regional water balances.

The full-coverage Delta land use survey program completed by DWR for this study aided ET estimation efforts by individual models and made comparisons for specific crops possible. Multiple years of data also allowed for the evaluation of crop planting and land use trends for the Delta, though some inaccuracies in classifications were possible due to the inherent difficulty of distinguishing very similar vegetation types in satellite images. Delta land use surveys for 2015-2016 and other statewide data are planned to be made available online by DWR (2018d). An accurate, consistent, and long-term land use and crop type mapping survey program for the Delta and the state of California would substantially improve the basis for ET estimation and general water accounting and management at all scales. Such a program will benefit from including winter crop data (multi-cropping) and irrigation method and frequency information, potentially extending the quantification of elements in the water balance beyond consumptive use. Further refinement of non-agricultural land classes, including the separation of managed habitat areas (i.e. hunting clubs) and distinguishing between native versus invasive vegetation would inform both ET estimation efforts and broader land use, ecosystem, and watershed planning.

Expansions to the California Irrigation Management Information System (CIMIS) network made in this study will continue to provide benefits. Five new CIMIS stations were deployed in the Delta to gather field meteorological data and provided point ETo values. The increased station density decreased the interpolation distances for making the Spatial CIMIS ETo maps used by most remote sensing methods. Though any increased accuracy due to the new stations remains to be assessed, the additional data to be collected at these stations in the future is still valuable to the CIMIS program. Field measurement sensors are becoming simpler to use and more affordable, which could translate to the ability to make direct ETo measurements over multiple

crops in standardized stations similar to the CIMIS network.

Though extensive, this study does exhaustively investigate ET results for the Delta. Further analysis of model estimates, field measurements, land use information, and other data may yield additional valuable findings. All results analyzed in this study, presented as monthly geospatial rasters of ET estimates from each model and spreadsheets of field data, have been released publicly by Medellín-Azuara *et al.* (2018). This transparency encourages scrutiny and broader use of this valuable information, but more work can be done to present data in a format understandable to a broader audience. This may include interactive mapping and plotting tools, options to import additional data, and supportive documentation. Ideally such work could be accessible from a web browser or mobile device using a guided user interface (GUI). Hall *et al.* (2018) have begun the development of such an effort, called OpenET, which plans to present near-real-time ET estimates from multiple remote sensing models across the entire Western United States in an online tool. Several use cases of OpenET are proposed to demonstrate the tool's capability for water trading, groundwater modeling, and irrigation management. Similar efforts to increase access to ET and promote the understanding of estimation methods are expected to increase trust in the data and promote the broader use of consumptive use information worldwide. However, care should be taken to explain the limitations of ET estimates and their appropriate applications in water management.

This study helped advance the understanding of several models and field methods for consumptive use estimation and measurement with an application to a particular area of concern. The State of California should continue to pursue efforts to accurately quantify consumptive water use and promote related collaboration between scientists, water managers, practitioners, policymakers, and the public. A consortium including agencies, educational institutions, research centers, consultants, and stakeholders would greatly improve prospects for estimating ET in the Delta and elsewhere in California. Creating venues for collaborative exchange of common datasets and methodological standards for estimating ET promotes trust, enhances transparency, improves accuracy, and encourages further innovation. This type of program may require some pooled minimum funding to maintain ET estimation program elements, including accurate annual land use surveys, data curation and storage, documentation, and organization of data to serve various uses and facilitate research and synthesis.



## References

- Abtew, W., and Melesse, A.M. (2012). *Evaporation and evapotranspiration: measurements and estimations*. Springer Science & Business Media.
- Alexander, N., Merz, J., Santos, N., Hart, Q., Jankowski, J., and Medellín-Azuara, J. (2018). Mapping Evapotranspiration at High Resolution with Internalized Calibration, University of California Davis Approach (UCD-METRIC). Center for Watershed Sciences, University of California Davis. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix H. Available at <<https://watershed.ucdavis.edu/project/delta-et>>, last visit September 11, 2018.
- Alexandridis, T.K., Cherif, I., Chemin, Y., Silleos, G.N., Stavrinos, E., and Zalidis, G.C. (2009). Integrated Methodology for Estimating Water Use in Mediterranean Agricultural Areas. *Remote Sensing* 1, 445-465.
- Alkaeed, O., Flores, C., Jinno, K., and Tsutsumi, A. (2006). Comparison of Several Reference Evapotranspiration Methods for Itoshima Peninsula Area, Fukoka, Japan. *Memoirs of the Faculty of Engineering, Kyushu University* 66(1).
- Allen, R.G., Pereira, L.S., Raes, D., and Smith, M. (1998). Crop evapotranspiration - Guidelines for computing crop water requirements. Food and Agriculture Organization of the United Nations (UN-FAO) irrigation and drainage paper 56. Available at <<https://www.kimberly.uidaho.edu/water/fao56/fao56.pdf>>, last visit September 11, 2018.
- Allen, R.G., Tasumi, M., Morse, A.T., and Trezza, R. (2005a). A Landsat-based energy balance and evapotranspiration model in Western US water rights regulation and planning. *Irrigation and Drainage Systems* 19(3-4), 251-268.
- Allen, R.G., Tasumi, M., and Morse, A.T. (2005b). Satellite-based evapotranspiration by METRIC and Landsat for Western States water management. U.S. Bureau of Reclamation Evapotranspiration Workshop, Fort Collins, Colorado.
- Allen, R.G., Tasumi M., Morse A.T., Trezza, R., Kramber, W., Lorite, I. and Robinson, C.W. (2007a). Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC) – Applications. *Journal of Irrigation and Drainage Engineering* 133(4), 395-406.
- Allen, R.G., Tasumi, M., and Trezza, R. (2007b). Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC) – Model. *Journal of Irrigation and Drainage Engineering* 133(4), 380-394.
- Allen, R.A., Trezza, R., Kramber, B., Morse, A.T., Hendrickx, J., Irmak, A., Huntington, J., Robison, C., Kelly, C., Kjaersgaard, J., Greth, J., Tasumi, M., and Martin, T. (2015). ET Investigations involving METRIC/Landsat – Applications for Water Management. Kimberly Research and Extension Center, University of Idaho. Available at

- <https://www.idwr.idaho.gov/files/gis/METRIC-in-Other-States.pdf>}, last visit September 11, 2018.
- Anderson, M.C., Kustas, W.P., Norman, J.M., Hain, C.R., Mecikalski, J.R., Schultz, L., González-Dugo, M.P., Cammalleri, C., d'Urso, G., Pimstein, A. and Gao, F. (2011). Mapping daily evapotranspiration at field to continental scales using geostationary and polar orbiting satellite imagery. *Hydrology and Earth System Sciences* 15(1), 223-239.
- Anderson, M.C. (2018). Atmosphere-Land Exchange Inverse Flux Disaggregation Approach (DisALEXI). Agricultural Research Service, U.S. Department of Agriculture. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix E. Available at <https://watershed.ucdavis.edu/project/delta-et>}, last visit September 11, 2018.
- California Department of Water Resources (DWR) (2014). California Water Plan Update 2013: Sacramento-San Joaquin Delta. Sacramento, California. Available at <https://water.ca.gov/Programs/California-Water-Plan/Water-Plan-Updates>}, last visit September 11, 2018.
- DWR (2017a). A Water Resources System Planning Model for State Water Project (SWP) & Central Valley Project (CVP)- CalSim 3.0 Draft Report. Sacramento, California. Available at [http://baydeltaoffice.water.ca.gov/modeling/hydrology/CalSim3/Document\\_Calsim3.cfm](http://baydeltaoffice.water.ca.gov/modeling/hydrology/CalSim3/Document_Calsim3.cfm)}, last visit September 11, 2108.
- DWR (2017b). Dayflow: An Estimate of Daily Average Delta Outflow. Sacramento, California. Available at <https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/Environmental-Services/Compliance-Monitoring-Assessment/Dayflow/Files/Publications/Current-Dayflow-Documentation.pdf>}, last visit September 11, 2018.
- DWR (2018a). California Data Exchange Center. Sacramento, California. Available at <http://cdec.water.ca.gov/>}, last visit September 11, 2018.
- DWR (2018b). Dayflow. Sacramento, California. Available at <https://water.ca.gov/Programs/Environmental-Services/Compliance-Monitoring-And-Assessment/Dayflow-Data>}, last visit September 11, 2018.
- DWR (2018c). Draft Assumptions and Estimates for California Water Plan Update 2018. Sacramento, California. Available at <https://water.ca.gov/-/media/DWR-Website/Web-Pages/Programs/California-Water-Plan/Water-Plan-Updates/Files/Update-2018/Water-Plan-Update-2018-Draft-Assumptions-and-Estimates-Report.pdf>}, last visit September 11, 2018.
- DWR (2018d). Land Use Surveys. Sacramento, California. Available at <https://www.water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Land-Use-Surveys>}, last visit September 11, 2108.

- California State Water Resources Control Board (SWRCB) (2015). Order WR 2015-0002-DWR: Order for Additional Information in the Matter of Diversion of Water from the Sacramento and San Joaquin Watersheds. Sacramento, California. Available at [https://www.waterboards.ca.gov/waterrights/water\\_issues/programs/drought/docs/2015sacsjinfororder.pdf](https://www.waterboards.ca.gov/waterrights/water_issues/programs/drought/docs/2015sacsjinfororder.pdf), last visit September 11, 2018.
- SWRCB (2017). Water Rights: Statement of Water Diversion and Use Program. Sacramento, California. Available at [https://www.waterboards.ca.gov/waterrights/water\\_issues/programs/diversion\\_use/](https://www.waterboards.ca.gov/waterrights/water_issues/programs/diversion_use/), last visit September 11, 2018.
- SWRCB (2018). eWRIMS – Electronic Water Rights Information Management System. Sacramento, California. Available at [https://www.waterboards.ca.gov/waterrights/water\\_issues/programs/ewrims/](https://www.waterboards.ca.gov/waterrights/water_issues/programs/ewrims/), last visit September 11, 2018.
- Choi, M., Kustas, W.P., Anderson, M.C., Allen, R.G., Li, F., and Kjaersgaard, J.H. (2009). An intercomparison of three remote sensing-based surface energy balance algorithms over a corn and soybean production region (Iowa, U.S.) during SMACEX. *Agricultural and Forest Meteorology* 149, 2082-2097.
- Delta Stewardship Council (DSC) (2013). The Delta Plan: Ensure a reliable water supply for California, a healthy Delta ecosystem, and a place of enduring value, amended April 2018. Available at <http://deltacouncil.ca.gov/delta-plan-0>, last visit September 11, 2018.
- Ekdahl, E. and George, M.P. (2018) Summary of Preliminary Review of Responses to Order WR 2015-0002-SWR. State Water Resources Control, California Water Boards. Sacramento, California. Available at [https://www.waterboards.ca.gov/water\\_issues/programs/delta\\_watermaster/docs/20180215\\_cvr\\_memo\\_dwr\\_info\\_order\\_spreadsheet.pdf](https://www.waterboards.ca.gov/water_issues/programs/delta_watermaster/docs/20180215_cvr_memo_dwr_info_order_spreadsheet.pdf), last visit September 11, 2018.
- Environmental and Water Resources Institute of the American Society of Civil Engineers (EWRI-ASCE) (2005). The ASCE Standardized Reference Evapotranspiration Equation. Available at <https://www.kimberly.uidaho.edu/water/asceewri/ascestzdetmain2005.pdf>, last visit September 11, 2018.
- Falge, E., Aubinet, M. Bakwin, P.S., Baldocchi, D., Berbigier, P., Bernhofer, C., Black, T.A., Ceulemans, R., Davis, K.J., Dolman, A.J., Goldstein, A., Goulden, M.L., Granier, A., Hollinger, D.Y., Jarvis, P.G., Jensen, N., Pilegaard, K., Katul, G, Paw U, K.T., Law, B.E., Lindroth, A., Loustau, D., Mahli, Y., Monson, R., Moncrieff, P., Moors, E., Munger, J.W., Meyers, T., Oechel, W., Schulze, E.D., Thorgeirsson, H., Tenhunen, J., Valentini, R., Verma, S.B., Vesala, T., and Wofsy, S.C. (2017). Fluxdata: The Data Portal serving the FLUXNET community. ORNL DAAC, Oak Ridge, Tennessee, USA. Available at <http://fluxnet.fluxdata.org/>, last visit September 11, 2018.

- Fisher, J. B., Tu, K. P., and Baldocchi, D. D. (2008). Global estimates of the land-atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. *Remote Sensing of Environment* 112(3), 901–919
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202, 18-27.
- Grantham, T.E. and Viers, J.H. (2014). 100 years of California’s water rights system: patterns, trends and uncertainty. *Environmental Research Letters* 9(8), 084012.
- Hall, M., Grimm, R., Melton, F., Huntington, J., Erickson, T.A., Herring, J., Johnson, L., Guzman, A., Morton, C., Harding, J., Daudert, B., Anderson, M., Schull, M., Hain, C., Ozdogon, M., Senay, G., Bastiaanssen, W., Hessels, T., van Opstal, J., Fisher, J., and Serrat-Capdevila, A. (2018). OpenET. Available at <<https://etdata.org/>>, last visit September 11, 2018.
- Hanak, E., Lund, J.R., Dinar, A., Gray, B., Howitt, R., Mount, J., Moyle, P., and Thompson, B. (2011). Managing California’s Water: From Conflict to Reconciliation. Public Policy Institute of California, San Francisco, California. Available at <[http://www.ppic.org/content/pubs/report/R\\_211EHR.pdf](http://www.ppic.org/content/pubs/report/R_211EHR.pdf)>, last visit September 11, 2018.
- Hanak, E., Lund, J., Durand, J., Fleenor, W., Gray, B., Medellín-Azuara, J., Mount, J. and Jeffres, C. (2013) Stress Relief Prescriptions for a Healthier Delta Ecosystem. Public Policy Institute of California, San Francisco, California. Available at <[http://www.ppic.org/content/pubs/report/R\\_413EH2R.pdf](http://www.ppic.org/content/pubs/report/R_413EH2R.pdf)>, last visit September 11, 2018.
- Hart, Q.J., Brugnach, M., Temesgen, B., Rueda, C., Ustin, S.L., and Frame, K. (2008). Daily reference evapotranspiration for California using satellite imagery and weather station measurement interpolation. *Civil Engineering and Environmental Systems* 26(1), 19-33.
- Hirschi, M., Michel, D., Lehner, I., and Seneviratne, S.I. (2017). A site-level comparison of lysimeter and eddy covariance flux measurements of evapotranspiration. *Hydrology and Earth System Sciences* 21(3), 1809-1825.
- Horst, T.W., Vogt, R., and Oncley, S.P. (2016). Measurements of Flow Distortion within the IRGASON Integrated Sonic Anemometer and CO<sub>2</sub>/H<sub>2</sub>O Gas Analyzer. *Boundary-layer Meteorology* 160(1), 1–15.
- Howes, D.J., Burt, C.M., Feist, K. (2012). Basin-wide Remote Sensing of Actual Evapotranspiration and its Influence on Regional Water Resources Planning. Research Paper ITRC P-12-002. Irrigation Training and Research Center, California Polytechnic Institute San Luis Obispo.
- Howes, D.J. (2018). 2015 Delta Consumptive Use Analysis, ITRC-METRIC Process and Evaluations. ITRC Report to the California Department of Water Resources and the Delta

- Stewardship Council. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix F. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Hutton, P., Mahadevan, N., Guivetchi, K., Schreiner, P., Ito, S., Taylor, D., Pate, N., and Ullrey, N. (1995). Estimation of Delta Island Diversions and Return Flows. California Department of Water Resources, Sacramento, California. Available at <http://baydeltaoffice.water.ca.gov/modeling/deltamodeling/models/dicu/DICU%20Report.pdf>, last visit September 11, 2018.
- Idaho Department of Water Resources (IDWR) (2018). Evapotranspiration Viewer. Available at <https://maps.idwr.idaho.gov/ET/>, last visit September 11, 2018.
- Itenfisu, D., Elliott, R.L., Allen, R.G., and Walter, I.A. (2003). Comparison of Reference Evapotranspiration Calculations as Part of the ASE Standardization Effort. *Journal of Irrigation and Drainage Engineering* 129(6), 440-448.
- Jankowski, J., Bell, A., Santos, N., and Badillo, J. (2018). Comparative Study Methodology and Additional Data. Center for Watershed Sciences, University of California Davis. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix A. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Jin, Y., Randerson, J.T., and Goulden, M.L. (2011). Continental-scale net radiation and evapotranspiration estimated using MODIS satellite observations. *Remote Sensing of Environment* 115(9), 2302–2319.
- Jin, Y. and Wong, A. (2018). Priestley-Taylor UC Davis Approach (UCD-PT). Department of Land, Air and Water Resources, University of California Davis. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix I. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Kadir, T. (2006). Estimates for Consumptive Water Demands in the Delta using DETAW. Methodology for Flow and Salinity Estimates in the Sacramento-San Joaquin Delta and Suisun Marsh, 27th Annual Progress Report. California Department of Water Resources. Sacramento, California. Available at <http://baydeltaoffice.water.ca.gov/modeling/deltamodeling/delta/reports/annrpt/2006/2006Ch7.pdf>, last visit September 11, 2018.
- Kadir, T. and Liang, L. (2018). Delta Evapotranspiration of Applied Water (DETAW): A Layperson’s Guide to DETAW. California Department of Water Resources. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix D. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Kustas, W.P. and Norman, J.M. (1996). Use of remote sensing for evapotranspiration monitoring

over land surfaces. *Hydrological Sciences* 41(4), 495-516.

- Land IQ, Inc. (2018). Summary of 2016 Land Use Mapping of the Sacramento-San Joaquin Delta. Technical Memorandum to California Department of Water Resources. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix J. Available at <<https://watershed.ucdavis.edu/project/delta-et>>, last visit September 11, 2018.
- Liang, L. and Suits, B. (2017). Implementing DETAW in Modeling Hydrodynamics and Water Quality in the Sacramento-San Joaquin Delta. Methodology for Flow and Salinity Estimates in the Sacramento-San Joaquin Delta and Suisun Marsh, 38th Annual Progress Report. California Department of Water Resources. Sacramento, California. Available at <[https://www.water.ca.gov/-/media/DWR-Website/Web-Pages/Library/Modeling-And-Analysis/DETAW/Files/Method\\_2017\\_Chapter3.pdf](https://www.water.ca.gov/-/media/DWR-Website/Web-Pages/Library/Modeling-And-Analysis/DETAW/Files/Method_2017_Chapter3.pdf)>, last visit September 11, 2018.
- Medellín-Azuara, J. and Howitt, R.E. (2013). Comparing Consumptive Agricultural Water Use in the Sacramento-San Joaquin Delta: A Proof of Concept Using Remote Sensing. Center for Watershed Sciences, University of California Davis. Available at <[https://watershed.ucdavis.edu/files/biblio/DPC\\_ComparativeStudy\\_ET\\_Final\\_Report\\_UCD.pdf](https://watershed.ucdavis.edu/files/biblio/DPC_ComparativeStudy_ET_Final_Report_UCD.pdf)>, last visit September 11, 2018.
- Medellín-Azuara, J., Paw U, K.T., Jin, Y., Hart, Q., Kent, E., Clay, J., Wong, A., Bell, A., Anderson, M., Howes, D., Melton, F., Kadir, T., Orang, M., Leinfelder-Miles, M.M., and Lund, J.R. (2016). Estimation of Crop Evapotranspiration in the Sacramento San Joaquin Delta: Preliminary Results for the 2014-2015 Water Year, Interim Report. Available at <<https://watershed.ucdavis.edu/project/delta-et>>, last visit September 11, 2018.
- Medellín-Azuara, J., Paw U, K.T., Jin, Y., Jankowski, J., Bell, A.M., Kent, E., Clay, J., Wong, A., Alexander, N., Santos, N., Badillo, J., Hart, Q., Leinfelder-Miles, M., Merz, J., Lund, J.R., Anderson, A., Anderson, M., Chen, Y., Edgar, D., Eching, S., Freiberg, S., Gong, R., Guzmán, A., Howes, D., Johnson, L., Kadir, T., Lambert, J.J., Liang, L., Little, C., Melton, F., Metz, M., Morandé, J.A., Orang, M., Pyles, R.D., Post, K., Rosevelt, C., Sarreshteh, S., Snyder, R.L., Trezza, R., Temesgen, B., and Viers, J.H. (2018). A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta. Center for Watershed Sciences, University of California Davis. Available at <<https://watershed.ucdavis.edu/project/delta-et>>, last visit September 11, 2018.
- Melton, F.S., Johnson, L.F., Lund, C.P., Pierce, L.L., Michaelis, A.R., Hiatt, S.H., Guzman, A., Adhikari, D.D., Purdy, A.J., Rosevelt, C., and Votava, P. (2012). Satellite irrigation management support with the terrestrial observation and prediction system: a framework for integration of satellite and surface observations to support improvements in agricultural water resource management. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 5(6), 1709-1721.
- Melton, F.S., Guzman, A., Johnson, L.F., Rosevelt, C., and Post, K. (2018). NASA Satellite Irrigation Management Support System (SIMS). Cooperative for Research in Earth

Science and Technology, NASA Ames Research Center and California State University Monterey Bay. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix G. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.

- Morandé, J.A., Trezza, R., Anderson, A., Paw U, K.T., Jin, Y., Jankowski, J., Badillo, J., Medellín-Azuara, J., Viers, J., and Chen, Y.Q. (2018). Evapotranspiration Estimation from Unmanned Aerial Vehicle Imagery: Multispectral/Thermal Imagery for High Spatial Resolution METRIC-ET Maps and Relative Humidity-Air Temperature Spatial Profile in Alfalfa, Pasture, and Corn in the Sacramento-San Joaquin Delta, California. Center for Watershed Sciences, University of California Davis. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix L. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Nash, J.E. and Sutcliffe, J.V. (1970). River flow forecasting through conceptual models, Part I – A discussion of principles. *Journal of Hydrology* 10, 282-290.
- Orang, M.N., Snyder, R.L., Shu, G., Hart, Q.J., Sarreshteh, S., Falk, M., Beaudette, D., Hayes, S. and Eching, S. (2013). California Simulation of Evapotranspiration of Applied Water and Agricultural Energy Use in California. *Journal of Integrative Agriculture* 12(8), 1371-1388.
- Orang, M., Snyder, R.L., Hart, Q., Sarreshteh, S., and Eching, S. (2018) California Simulation of Applied Water (CalSIMETAW). California Department of Water Resources. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix C. Available at <https://watershed.ucdavis.edu/project/delta-et>, last visit September 11, 2018.
- Paiva, C.M., França, G.B., Liu, W.T.H., and Rotunno, O.C. (2011). A comparison of experimental energy balance components data and SEBAL model results in Dourados, Brazil. *International Journal of Remote Sensing* 32(6), 1731-1745.
- Paw U, K.T., Qiu, J., Su, H.B., Watanabe, T., and Brunet, Y. (1995). Surface renewal analysis: a new method to obtain scalar fluxes. *Agricultural and Forest Meteorology* 74(1-2), 119-137.
- Paw U, K.T., Baldocchi, D.D., Meyers, T. P., and Wilson, K. (2000). Correction of eddy-covariance measurements incorporating both advective effects and density fluxes. *Boundary-layer Meteorology* 97(3), 487-511.
- Paw U, K.T., Kent, E., Clay, J., Leinfelder-Miles, M., Lambert, J.J., McAuliffe, M., Edgar, D., Freiberg, S., Gong, R., Metz, M., Little, C., and Temesgen, B. (2018). Field Campaign Report for Water Years 2015-2016 and 2016-2017. Biomicrometeorology Research Team, Department of Land, Air and Water Resources, University of California Davis. A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta, Appendix B. Available at <https://watershed.ucdavis.edu/project/delta-et>

- et>, last visit September 11, 2018.
- Senatore, A., Mendicino, G., Cammalleri, C., and Ciraolo, G. (2015). Regional-Scale Modeling of Reference Evapotranspiration: Intercomparison of Two Simplified Temperature- and Radiation-Based Approaches. *Journal of Irrigation and Drainage Engineering*, 141(12), 04015022.
- Siegfried, L.J., Fleenor, W.E., and Lund, J.R. (2014). Physically Based Modeling of Delta Island Consumptive Use: Fabian Tract and Staten Island, California. *San Francisco Estuary and Watershed Science* 12(4).
- Snyder, R.L., Spano, D., Duce, P., Paw U, K.T., and Rivera, M. (2008). Surface Renewal Estimation of Pasture Evapotranspiration. *Journal of Irrigation and Drainage Engineering*, 134(6), 716-721.
- Snyder, R.L., Orang, M.N., Matyac, J.C., Sarreshteh, S. and Kadir, T. (2013). Delta Evapotranspiration of Applied Water – DETAW. California Water Plan Update 2013, Vol. 4 Reference Guide. California Department of Water Resources. Sacramento, California. Available at <<https://www.water.ca.gov/-/media/DWR-Website/Web-Pages/Library/Modeling-And-Analysis/DETAW/Files/08DETAW.pdf>>, last visit September 11, 2018.
- Sörensson, A.A. and Ruscica, R.C. (2018). Intercomparison and Uncertainty Assessment of Nine Evapotranspiration Estimates Over South America. *Water Resources Research* 54, 2891-2908.
- Szilagyi, J. and Jozsa, J. (2018). Evaporation Trends (1979-2015) in the Central Valley of California, USA: Contrasting Tendencies During 1981-2007. *Water Resources Research* 54.
- Temesgen, B. and Eching, S. (2013). PM Equation. California Irrigation Management Information System, California Department of Water Resources. Available at <<https://cimis.water.ca.gov/Content/PDF/PM%20Equation.pdf>>, last visit September 11, 2018.
- Timmermans, W.J., Kustas, W.P., Anderson, M.C., and French, A.N. (2007). An intercomparison of the Surface Energy Balance Algorithm for Land (SEBAL) and the Two-Source Energy Balance (TSEB) modeling schemes. *Remote Sensing of Environment* 108, 369-384
- Twine, T.E., Kustas, W.P., Norman, J.M., Cook, D.R., Houser, P.R, Meyers, T.P., Prueger, J.H., Starks, P.J., and Wesley, M.L. (2000). Correcting eddy-covariance flux underestimates over a grassland. *Agricultural and Forest Meteorology* 103(3), 279-300.
- U.S. Department of Agriculture (USDA) (2016). National Agricultural Statistics Service Cropland Data Layer. Available at <<https://nassgeodata.gmu.edu/CropScape/>>, last visit September 11, 2018.



Utah Division of Water Rights (UDWR) (2018). Searching Water Right Records. Available at <<https://www.waterrights.utah.gov/wrinfo/query.asp>>, last visit September 11, 2018.

Willmott, C.J. (1981). On the validation of models. *Physical Geography* 2(2), 184-194.

Wilson, C.M. (2011). Statements of Water Diversions and Use: Providing a Better Picture of Water Use in the Delta. Delta Watermaster's Report to the State Water Resources Control Board and the Delta Stewardship Council. Available at <[https://www.waterboards.ca.gov/board\\_info/agendas/2011/nov/rev\\_stmnts.pdf](https://www.waterboards.ca.gov/board_info/agendas/2011/nov/rev_stmnts.pdf)>, last visit September 11, 2018.

Wilson, C.M. (2014). Local Water Governance in the Delta. Delta Watermaster's Report to the State Water Resources Control Board and the Delta Stewardship Council. Available at <[https://www.waterboards.ca.gov/water\\_issues/programs/delta\\_watermaster/docs/governance\\_092514.pdf](https://www.waterboards.ca.gov/water_issues/programs/delta_watermaster/docs/governance_092514.pdf)>, last visit September 11, 2018.

Womach, J. (2005). Agriculture: A Glossary of Terms, Programs, and Laws, 2005 Edition. Congressional Research Service, Library of Congress, Washington D.C. Available at <<https://digital.library.unt.edu/ark:/67531/metacrs7246/>>, last visit September 11, 2018.