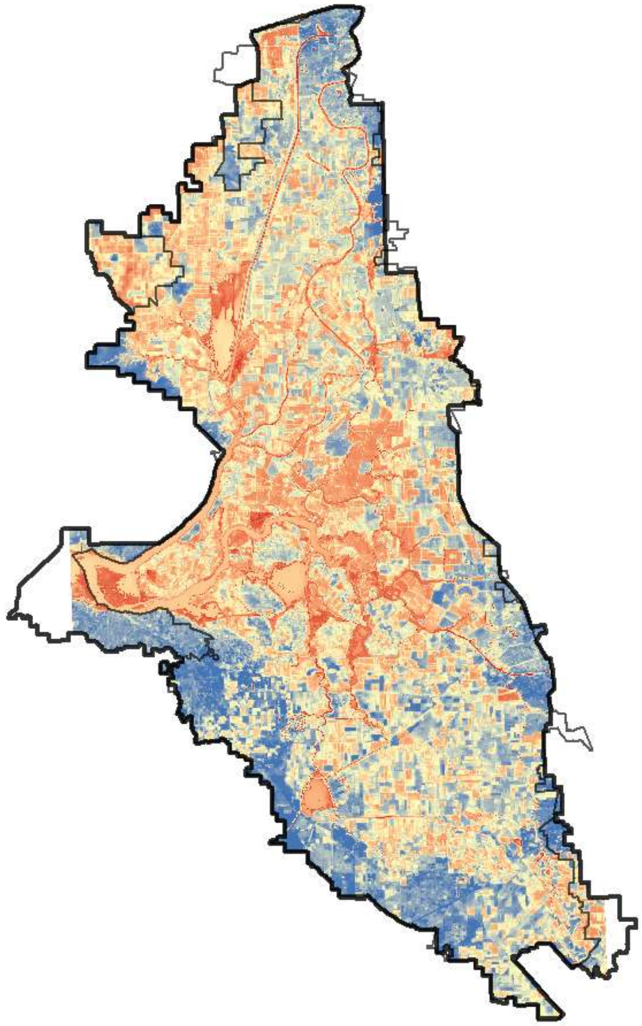
A Comparative Study for Estimating Crop Evapotranspiration in the Sacramento-San Joaquin Delta



A Report for the Office of the Delta Watermaster

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Executive Summary

Consumptive water use by crops, often referred to as evapotranspiration (ET), is frequently the largest component of an agricultural region's water balance. This study investigates crop consumptive use in the Sacramento-San Joaquin Delta ("Delta") of California using a comparative approach with several prominent methods for estimating crop ET, including estimates based on crop coefficients, water balances, energy balance using remote sensing, and field measurements.

Crop ET estimates are provided for both the Legal Delta and the Delta Service Area (DSA) for two water years (2015 and 2016) by seven methods:

CalSIMETAW	California Simulation of Evapotranspiration of Applied Water, by the California Department of Water Resources (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), by the Irrigation Training and Research Center (ITRC) at California Polytechnic State University (Cal Poly).
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	Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), by the University of California (UC) Davis.
UCD-PT	Optimized Priestley-Taylor approach, by UC Davis.

In addition, field-based estimates and measurements of ET using eddy covariance and estimates with surface renewal stations were developed over bare soil during the fall of 2015 and over three predominant crops in the Delta (alfalfa, corn, and pasture) in the 2016 irrigation season. One direct ET measurement station was also deployed in 2016. Five additional California Irrigation Management Information System (CIMIS) stations were deployed in the Delta in 2016 to improve the spatial representation of weather variables and accuracy in input datasets of reference ET estimates. Two annual land use parcel surveys for 2015 and 2016 were conducted by Land IQ, Inc., which provided updated land use maps over the study area with more than 30 land use classes. A total of 26 agricultural classes were used for ET estimates and analysis.

The participating modeling groups were required to estimate average daily ET, in millimeters per day (mm/d), for each month in raster (digital grid at a 30x30-meter resolution) or tabular format. The UC Davis reporting team conducted geostatistical analyses to calculate agricultural ET in the Delta by crop types over various spatial and temporal scales. ET estimates from model ensemble mean and individual models were compared with field-based measurements and estimates in alfalfa, corn and pasture sites. Intercomparisons among model results were also done to quantify the similarities and explain differences between models.

An Interim Report for the 2015 water year produced in early fall 2016 provided the preliminary results of an initial blind comparison from all methods without access to field data. The Interim Report is available on the project website (https://watershed.ucdavis.edu/project/delta-et). Preliminary model results for 2015 deviated up to 20% from the mean estimate of total annual crop ET in the Delta. By incorporating feedback from modeling groups and improvements by some models, such as UCD-PT's calibration to a subset of the field data collected in the Delta in 2016, all seven teams submitted final ET results for both 2015 and 2016 which are presented in this final report. Final model results had an absolute deviation of about 11% from the ensemble mean annual agricultural ET for both years. Remaining differences in model results can be attributed to hard-wired modeling assumptions, variations in model parameterizations, model-specific differences in input datasets, and modeler professional judgement.

An overview of the model estimates and the spatial-temporal coverage of the field measurements is shown in Figure ES-1. The left panel shows the spatial distribution of ensemble mean ET estimates over agricultural lands (in millimeters per year on 30x30-meter pixels) and the location of the deployed field stations by crop. The upper right panel shows crop ET in thousand acre-feet (TAF) estimated by each model and the ensemble average for major crop categories by year. The lower right panel shows the calendar of the field station deployment.

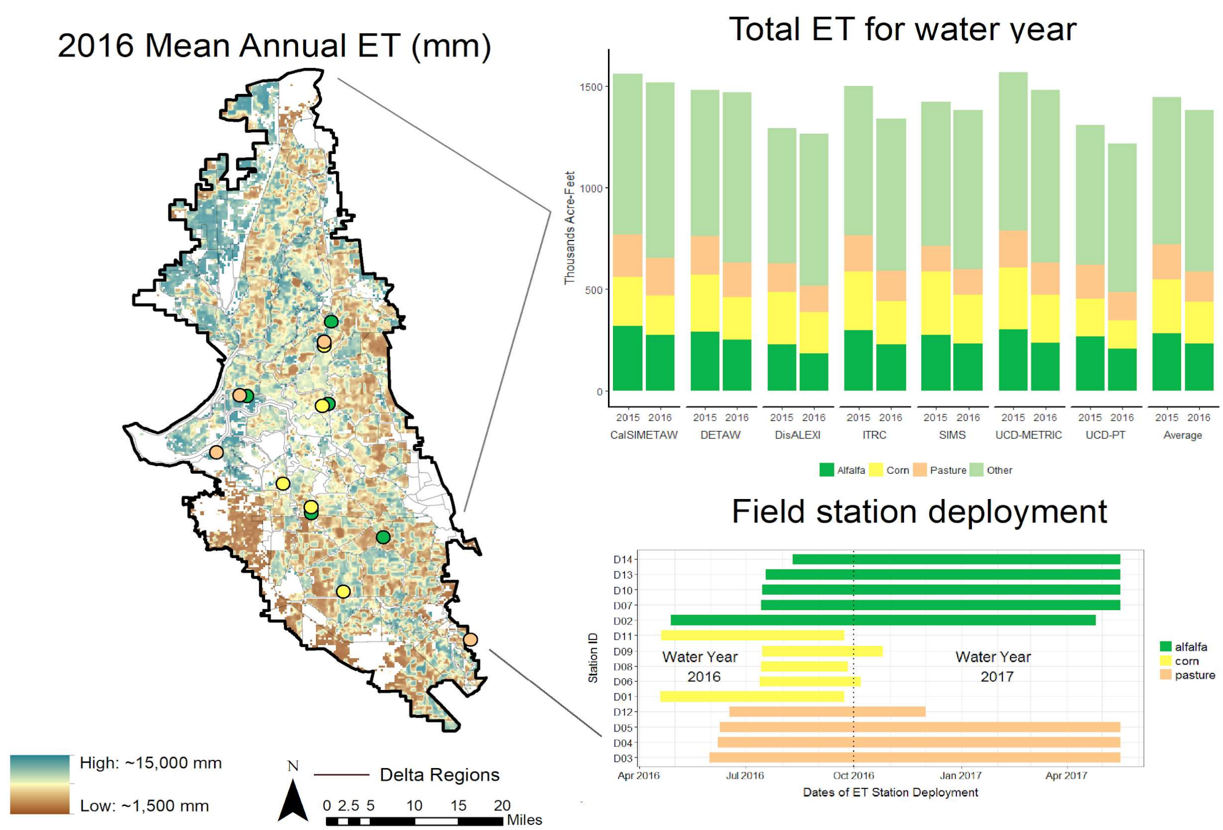

Figure ES-1: Delta Service Area 2016 mean annual ET, 2015 and 2016 total ET by crop and model, and 2016 field campaign stations and deployment timeline.

The following major conclusions are supported by this study:

1) Using the ensemble average of the seven model estimates, total annual evapotranspiration from crops in the Delta Service Area was estimated at 1,445 TAF in 2015 and 1,379 TAF in 2016. These values are broadly consistent with previously published estimates in the 2013 California Water Plan Update water balances for the Delta. The mean departures of individual models from the ensemble mean were about 91 TAF for the Delta Service Area in both years, representing roughly 6.3% and 6.6% of the estimated ensemble means for 2015 and 2016.
2) Alfalfa, corn, and pasture, the three dominant crops in the Delta, comprised approximately 45% of all agricultural land use in 2015 and 38% in 2016. They contributed to nearly 60% of total annual agricultural ET (or 19.5% of total estimated ET for all land uses) in the Delta Service Area in 2015 based on the seven-model ensemble mean. Alfalfa had the highest estimated ET (282 TAF/year and 3.5 AF/acre in 2015), followed by corn (268 TAF/year and 2.9 AF/acre) and pasture (170 TAF/year and 3.5 AF/acre). Total crop ET decreased in 2016 (229, 208, and 150 TAF for alfalfa, corn, and pasture, respectively); this was likely driven by decreased acreages, as no noticeable change in average ET per unit area occurred.
3) Non-agricultural land use classes, including riparian native, upland herbaceous, and floating vegetation, cover almost 88 thousand acres (13% of the Delta Service Area) with an estimated ensemble mean ET of 247 TAF in 2016. Their estimated consumptive use rates (floating 4.4 AF/acre and riparian 4.0/acre) are larger than the estimated average use rate for agricultural lands in the Delta (3.0 AF/acre). Open water and urban land use classes account for roughly 125 thousand acres (18%) of the Delta Service Area and 406 TAF/year of estimated ET. Not all models are suited to estimate non-agricultural ET, and the classification of non-agricultural land uses will benefit from refinement. The aggregate contribution of natural vegetation to consumptive water use in the Delta is non-trivial and deserves further investigation.
4) The total ET estimated within the Delta differs between methods, but not with statistical significance (95% confidence) for alfalfa, corn, and most months of irrigated pasture. For corn, DETAW was significantly higher than the ensemble mean for November 2015 and January of 2016. For pasture, statistically significant differences from the ensemble mean occurred from November through January of 2016 for CalSIMETAW, DETAW and ITRC-METRIC. All models were consistent with the ensemble mean ET from alfalfa for all months of the study. Even non-statistically significant differences in consumptive water uses represent a substantial economic difference in the use of different ET estimates for water rights or Delta export management, particularly in dry years.
5) Paired model comparisons over small areas and common satellite overpass dates in 2015 and 2016 generally indicate good agreement, with mean biases (average of their differences) ranging from 0.07 mm/day to 0.87 mm/day for the three major crops in the Delta. Differences in input data, model assumptions, model-specific parameter calibration, hard-coded internal estimation steps, and modeler judgment are likely the major sources of discrepancy among models. These model differences could be reduced with use of common and standardized datasets and continued collaboration among ET modeling groups in the future.
6) Comparing monthly model-based ET estimates across the Delta to months with 2016 field-based ET estimates available provides some useful findings. Alfalfa showed no significant differences between field-based estimates and the ensemble mean of model ET estimates across the Delta, though the field data and the ensemble were significantly different for corn and pasture in August and September 2016. ET estimates from individual models were also compared to the field data, with CalSIMETAW and DETAW being significantly different for most months with available

field data and UCD-METRIC being different in August and September 2016. The rest of the models' monthly ET estimates do not differ significantly from the field-estimated ET for the three major crops in any given month. Detailed comparisons at small spatial scales on satellite overpass dates suggested more pronounced differences, with model estimates generally biased higher than field-based estimates for all three crops.

Crop evapotranspiration is one of the largest and most important quantities in local and regional water and flow balances. This study sheds some light on estimation and uncertainty in quantifying consumptive water use by crops. Some policy insights and areas for further development were identified based on results of this study.

1) Idle agricultural land contributed a significant portion of agricultural ET in model-based estimates. However, field-based estimates in late 2015 indicate very low evapotranspiration during the late growing season for a selection of sites above sea level (possibly lacking the seepage issues of lands below sea level). Given the limited field sampling and the importance of this quantification for water management, an enhanced field campaign covering more areas over longer periods of time should be considered and is under development for the 2018 irrigation season.
2) A long-term land use program with enhancements such as the identification of specific site conditions and refined non-agricultural land classification will improve calibration of ET models and could particularly improve ET estimates from non-agricultural land uses.
3) Remote sensing-based ET estimation methods appear to be a cost-effective way to help reduce self-reporting burdens and increase transparency, accuracy, timeliness, and consistency in ET quantification, especially for spatial heterogeneity and interannual variation. However, extrapolating ET estimates to quantify diversions requires additional data acquisition on localized conditions such as irrigation infrastructure, soils and drainage, and periodic comparison with field-based ET measurements. A consortium approach involving stakeholders, government agencies, water professionals, and academic institutions may help establish such a long-term consumptive use estimation program.
4) Reasonably accurate estimates and measurements of ET, particularly in crops, generally facilitates planning and management at the basin scale. The Sustainable Groundwater Management Act (SGMA) requires basins to reach long-term sustainability and will often require quantified local and regional water balances. Remote sensing ET approaches such as those presented in this study may be useful in such quantifications.
5) Given the diversity in expert participation and the broad technical scope of the study, unresolved issues are expected. This report presents some clear discrepancies between the field campaign ET and the modeled ET estimates. The long-term value and credibility of ET estimation for California water management and policy will eventually require a better understanding of this difference between field and model results. Some suggested strategies to reduce these unresolved differences include:
    a) A field campaign focusing on detailed paired comparisons with a few modeled estimates, with uncertainty analyses of measurements and modeled ET estimates.
    b) Involve multiple water experts in the field campaign, including independent networks such as FLUXNET-AmeriFlux, the Department of Water Resources, and other organizations and expert groups.
    c) Explore the use of additional field-obtained data in modeling ET estimates, and compare the outcomes of additional field calibration and validation efforts.
    d) Establish an ET program with some minimal base funding to maintain collaboration and

advancement of ET quantification in the Delta.

6) A consortium of agencies, research centers, academic institutions, and consultants 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 enhances transparency, access to technical information, and collaboration among research groups, agencies, technical consultants, and stakeholders. This requires some pooled minimum funding to maintain the elements of an ET estimation program, including annual land use surveys (accounting for irrigation technology), data curation and storage, documentation, and organization of data to serve various uses and facilitate research and synthesis.

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1 Introduction

Consumptive use (CU) in water systems is the quantity of water use that is not returned for reuse via surface runoff or deep percolation into groundwater (Womach, 2005). Evapotranspiration (ET), the combination of water evaporated from the soil and transpired from plants, is often the predominant consumptive use from agriculture or natural vegetation. Understanding consumptive use in the Sacramento-San Joaquin Delta ("Delta") of California is critical for model calibration, water rights administration, management of export operations, agricultural water distribution, and environmental and water quality protection.

This research project was convened by the Center for Watershed Sciences at the University of California Davis with financial support from the California State Water Resources Control Board Office of the Delta Watermaster and other agencies. Its objective is to develop a better understanding of consumptive water use in the Delta by coordinating modeling, measurement, and other information from a variety of independent research and estimation efforts. Similar research endeavors have been conducted in arid places such as Turkey and have combined remotely sensed data, hydrologic models, and field data (Kite and Droogers, 2000). A proof-of-concept study on estimating CU in the Delta over Fabian Tract and Staten Island was previously completed by Siegfried et al. (2014), and a similar study by Medellín-Azuara and Howitt (2013) employed a three-way comparative approach for five Delta Islands. Government agencies in other states like Idaho have successfully developed open access platforms to host authoritative ET information for agriculture mapped online (https://maps.idwr.idaho.gov/ET/), improving transparency and establishing baseline data for water management and regulation.

Results from this project are divided into the 2015 (October 1, 2014 – September 30, 2015) and 2016 (October 1, 2015 – September 30, 2016) water years. An Interim Report consisting of preliminary results for the 2015 season was issued in September 2016 (Medellín-Azuara et al., 2016) and can still be viewed on the project website, though model results for the 2015 water year have been updated since the final report to reflect model improvements, lessons from the initial blind data comparison, and access to the two years of field campaign data provided by UC Davis. This peer-reviewed report closes the project's consumptive use modeling and measurement efforts for 2015 and 2016. A project website and online data repository (https://watershed.ucdavis.edu/project/delta-et) has been established as an additional work product of this study.

Participating organizations in this study include the University of California Davis (UC Davis), UC Cooperative Extension, the California Department of Water Resources (DWR), the California Polytechnic Institute San Luis Obispo Irrigation Training and Research Center (ITRC), NASA Ames Research Center (ARC) and California State University Monterey Bay (CSUMB), and the United States Department of Agriculture Agricultural Research Service (USDA-ARS).

Box 1 provides a brief primer on evapotranspiration and defines related terms used throughout this report.

Box 1: A Primer on Evapotranspiration and Consumptive Use

Consumptive water use is water that is lost from a watershed via evapotranspiration (ET) over time and is not available for other uses. Evapotranspiration is the sum of evaporation from soil and transpiration from plants, measured in linear units over time (millimeters per day, mm/d, in this study), which can be multiplied by land area and time period to calculate a volume (thousand acre-feet, TAF, in this study). Consumptive use and evapotranspiration are often used interchangeably.

Several model and field methods exist for determining evapotranspiration. These include direct measurement, two-step calculation, and remote sensing. Abtew and Melese (2012) and others provide a description of 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, a multitude of micrometeorological techniques, or light detection and ranging (LIDAR). Two-step 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. Two-step ET inputs can also be calculated through complex methods such as Penman and Penman-Monteith, which are based on a physical model. Lastly, remote sensing methods including the Surface Energy Balance System (SEBS), Surface Energy Balance for Land (SEBAL), METRIC, SIMS, and others use a combination of satellite and ground-based data to estimate ET. Some simple models work for applications in which meteorological and other data are limited, but more data and time availability may facilitate adoption of more complex and accurate methods.

Some definitions common in evapotranspiration literature are:

ETo: Reference evapotranspiration, based on ET of a well-watered short reference crop. In this report, ETo refers to ET from a grass reference crop, but alfalfa (**ETr**) or pan evaporation can also be used (Allen et al., 2005).

ETc: Potential crop evapotranspiration, the amount of water evaporated from the soil and transpired from the plant assuming ideal or standard conditions and no lack of water.

ETa: Actual crop evapotranspiration, which can be obtained by adjusting ETc based on environmental factors such as soil condition that reflect actual water available to the plant. ETa is typically less than or equal to ETc, but can exceed it depending on irrigation practices and canopy cover.

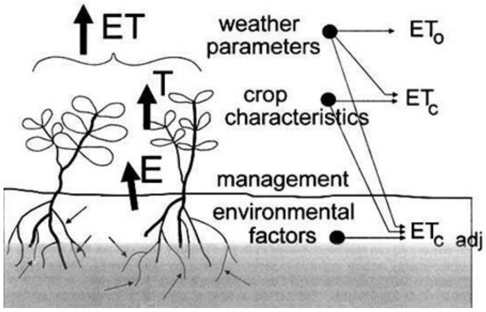
ETaw: Evapotranspiration of applied water, the net amount of irrigation water needed to produce a crop (not including irrigation application efficiency). Soil, crop, precipitation, and ETc data are used to determine ETaw.

ETcb: Basal crop evapotranspiration, the crop ET under well-watered conditions where crops are irrigated so that the exposed soil surface (not beneath the crop canopy) is maintained in a dry condition.

Kc: Crop coefficient, the ratio of a well-watered potential crop ET to a reference ET value (ETc / ETo).

EToF: Fraction of reference ET, the ratio of actual crop ET to reference ET (ETa / ETo). EToF will generally be less than Kc as stress, growing conditions, or management may cause ETa to be less than ETc.

Kcb: Basal crop coefficient, the ratio of the estimated basal crop ET (primarily transpiration) versus a reference ETo under well-watered conditions where crops are irrigated so that the exposed soil surface is dry (ETcb / ETo).



Schematic of evapotranspiration estimation components (Allen et al., 1998).

This project consolidates information on methods for measuring and estimating consumptive water use within the Delta. Seven estimation methods or models using remotely-sensed data, satellite imagery, and ground-level meteorological stations to measure and estimate ET were gathered for comparison in this report. These seven methods include:

CalSIMETAW	California Simulation of Evapotranspiration of Applied Water, by the California Department of Water Resources (DWR) (Appendix C).
DETAW	Delta Evapotranspiration of Applied Water, by DWR (Appendix D).
DisALEXI	Disaggregated Atmosphere-Land Exchange Inverse method, by the U.S. Department of Agriculture Agricultural Research Service (USDA-ARS) (Appendix E).
ITRC-METRIC	Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), by the Irrigation Training and Research Center (ITRC) at California Polytechnic State University (Cal Poly) (Appendix F).
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) (Appendix G).
UCD-METRIC	Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), by the University of California (UC) Davis (Appendix H).
UCD-PT	Optimized Priestley-Taylor approach, by UC Davis (Appendix I).

Land IQ, Inc., an independent consulting firm contracted by DWR, provided parcel-scale land use survey map data for 2015 and 2016 which served as the basis for identifying predominant land uses in the Delta and quantifying ET for specific crop types. A subset of methods also used the Land IQ data in developing their ET estimates, namely CalSIMETAW, DETAW, SIMS, UCD-METRIC and UCD-PT. UC Davis also deployed 23 field stations to 18 sites throughout the Delta in 2015 and 2016 to measure energy balance components to calculate actual ET (ETa) for bare soil in 2015 and three irrigated crops (alfalfa, corn, and pasture) in 2016.

Detailed descriptions of each model's ET estimation method and the field campaign methods, along with figures and descriptions of the study protocol, are provided as technical appendices to this report. The main report body compares ET estimates from the seven methods spatially, temporally, and across agricultural land uses in the Delta for both the 2015 and 2016 water years. Final model results are compared to field-based ET estimates and measurements from UC Davis, and specific comparisons between methods are presented to provide insights into model differences. The report concludes with a discussion of challenges, limitations, potential opportunities, and work ahead to improve long-term estimation of ET in the Sacramento-San Joaquin Delta.

2 Study Area and Methods

This section describes the study area, including hydrologic, water management, and land use features based on past studies and the Land IQ 2015 and 2016 land use surveys. The field data collection methods employed by UC Davis in 2015 and 2016 are explained, and the relative attributes of the seven ET estimation methods are described.

2.1 Delta Land Use

The Sacramento-San Joaquin Delta ("Delta") discharges water from both river basins in California's Central Valley west into the San Francisco Bay. The Delta estuarine system provides habitat for native species, water for irrigation and urban use within its boundary, and also serves as the main hub for California's interconnected water supply system (Hanak et al., 2013). The Delta's area can be defined by either the Legal Delta boundaries, as specified by the 1959 Delta Protection Act, or the Delta Service Area (DSA), which is defined by DWR as areas that are irrigated by channels in the Delta. The boundaries of both regions are shown in Figure 1; the Legal Delta covers 737,625 acres, while the DSA covers 679,594 acres of generally congruent land and water surface.

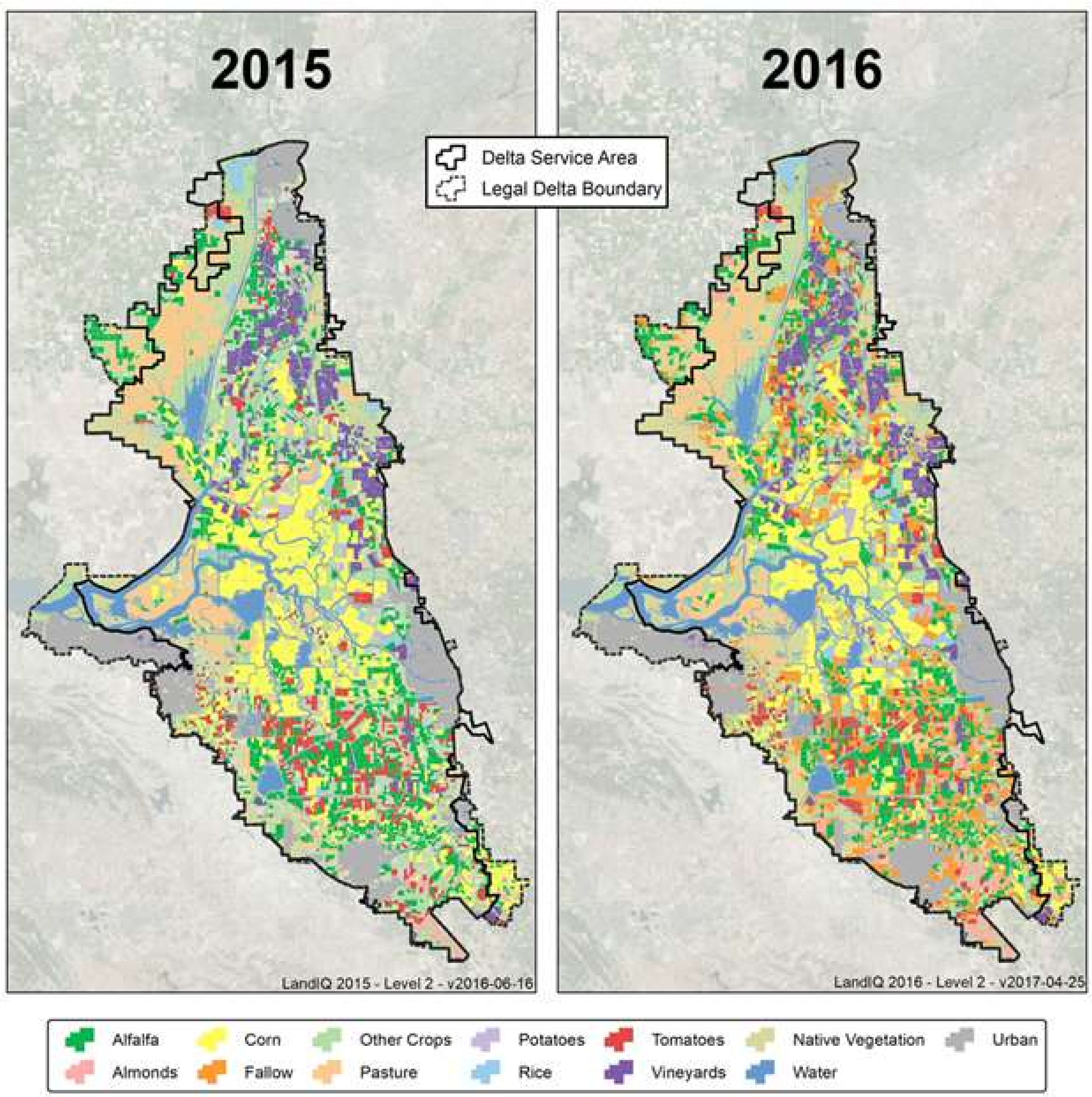


Figure 1. Land use classes in the Delta in 2015 and 2016.

Since 1950, DWR has conducted land use surveys of portions of California to quantify crops grown in various regions. In November 2015, DWR contracted with Land IQ to develop high-resolution land use maps for the Legal Delta and the DSA. The 2015 survey used satellite data from July 13-14, 2015, while the 2016 survey covered May 27 - July 31, 2016, to develop a representative dataset of crops planted during the predominant growing season. The preliminary results of these surveys, after initial quality control and assurance by DWR, were provided to the UC Davis study team for analysis and further distribution to ET modeling groups for this study. Additional information about the land use surveys, ground-truthing, and their verified accuracy appears in Appendix J, and DWR's Water Use and Efficiency Branch can provide additional information upon request. Maps of Land IQ's 2015 and 2016 surveys appear in Figure 1, and the survey's findings are summarized by land use in Table 1.

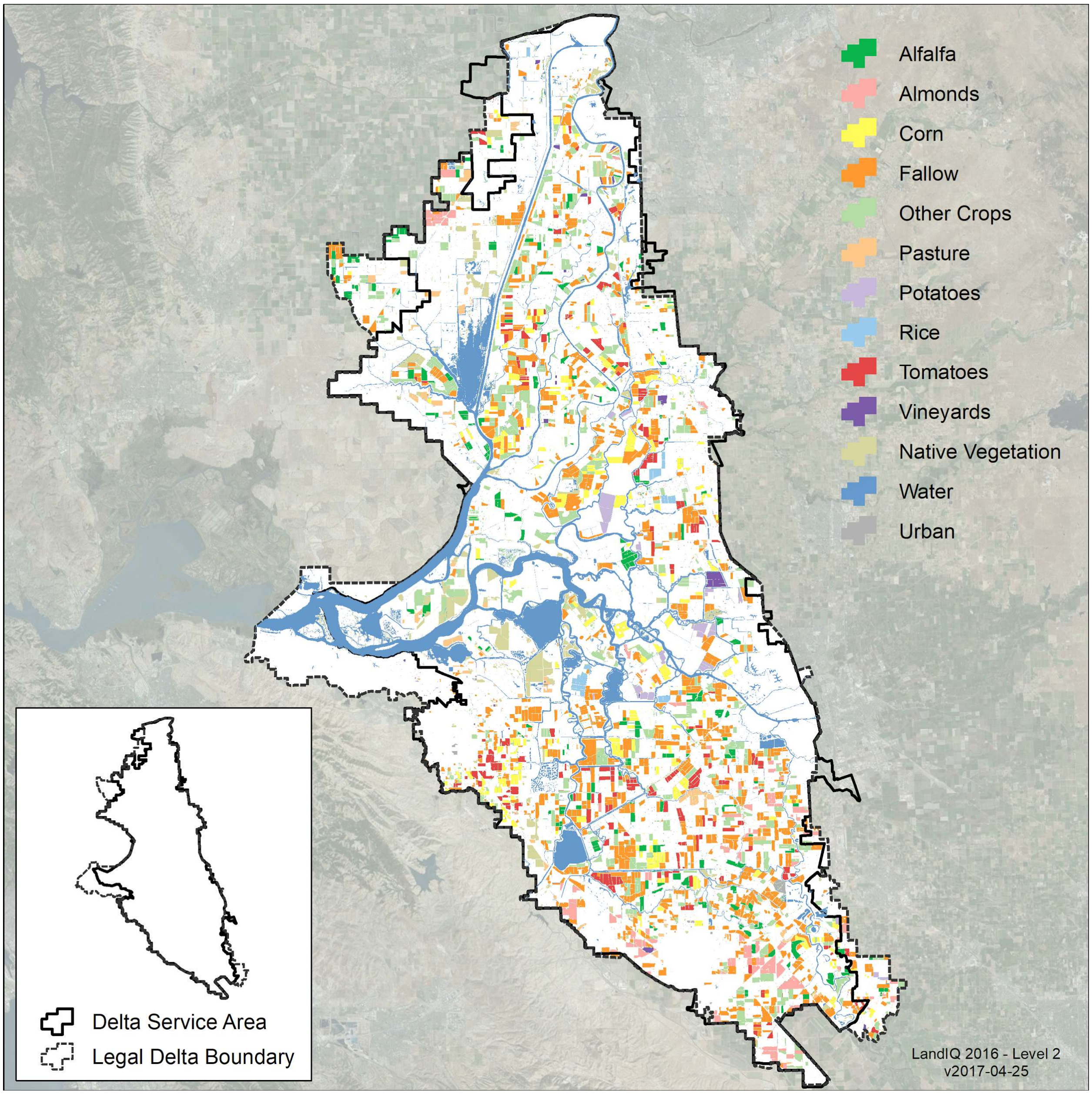


Figure 2. Changes in Delta land use classes from 2015 to 2016, showing classes identified in 2016.

Based on Land IQ's datasets, the Delta's agricultural landscape within the DSA consisted of about 477,690 acres of land in 2015, which decreased by 12,948 acres to about 464,742 acres in 2016 (Table 1 identifies which land uses were considered agricultural for this study). Non-agricultural lands in the DSA correspondingly increased from 201,904 acres in 2015 to 214,852 acres in 2016. Areas where the survey reported land use changes between the 2015 and 2016 are mapped in Figure 2, which shows the land use surveyed in 2016 (consistent open water areas are also shown for geographic reference).

The dominant crops in the Delta in both 2015 and 2016 were corn, alfalfa, and pasture. Other major crops included grape vineyards, tomatoes, rice, almonds, and other field and vegetable crops. The remainder of the survey categories for the Delta consisted of open water, urban areas, other vegetation, fallow agricultural fields, and non-irrigated forage areas. The 2016 survey included asparagus, carrots, eucalyptus, nurseries, sudangrass, and young orchards as new land use types; any acreage planted with these crops in 2015 was included in another land use category. Acreages and respective percentages of the DSA for all crops identified by Land IQ in 2015 and 2016 are summarized in Table 1, which includes the change in acreage and percent of the DSA area from 2015 to 2016 for each crop. Table 1 also notes those agricultural land uses which were used to calculate total ET in the Delta for this study.

The major land use changes from 2015 to 2016 reported by the survey include decreases in alfalfa, corn, and pasture (about 36,000 acres in total, 5% of the DSA), increased fallowing of land (about 29,000 acres, 4% of the DSA), increased almond and safflower planting (about 16,000 acres in total, 2% of the DSA), increased upland herbaceous areas (about 9,100 acres or 1% 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). These land use changes suggest a likely decrease in agricultural consumptive water use in the Delta from 2015 to 2016.

The main land use change from 2015 to 2016 indicated by the survey data was the conversion of corn (about 19,200 acres), tomatoes (about 13,700 acres), alfalfa (about 9,200 acres), and truck crops (about 4,800 acres) to fallow fields. This fallowing may have been in response to the drought, which approached its fifth year in the summer of 2016. The Office of the Delta Watermaster has also suggested that it may signal a shift from seasonal crops as lands are prepared for the planting of permanent crops such as orchards or vineyards. Alternatively, some lands identified as fallow may have been between crop rotations or prepared for the planting of winter grains at the time of the surveys. Other large shifts between crops from 2015 to 2016 were the planting of corn and safflower on previously fallow lands, (each about 5,100 acres) and the shift from other deciduous to almonds (about 4,200 acres). The largest shifts from survey-identified agricultural to non-agricultural lands from 2015 to 2016 included the conversion of pasture, fallow, and wet herbaceous/sub-irrigated pasture lands to upland herbaceous (about 6,900, 1,500, and 1,200 acres, respectively). The largest shifts from non-agricultural to agricultural lands occurred when upland herbaceous areas were fallowed (about 760 acres) or converted to pasture (about 500 acres).

The largest urbanization from 2015 to 2016 (461 acres, 0.1% of the DSA) occurred on lands previously classified as upland herbaceous (about 130 acres), corn, or tomatoes (each about 120 acres). Open water areas increased from 2015 to 2016 (2,973 acres, 0.4% of the DSA) in small channels and canals throughout the Delta which had previously been classified as riparian (about 1,500 acres), floating vegetation, or wet herbaceous/sub-irrigated pasture (each about 1,100 acres) in 2015. Some of the reported land use shifts, rather than indicating actual land use changes, may have resulted from misclassification of grasses or Land IQ's improvements in identification accuracy as perennial crops mature. Crops included as new categories in the 2016 land use survey (see note below Table 1) were primarily classified as fallow (about 200 acres) or forage grass (about 100 acres) in 2015.

Table 1. Land use classes and changes in the Delta Service Area.

Commodity (* denotes agricultural land use)	2015		2016		2015-2016 Change	
	Acres	Percent of DSA	Acres	Percent of DSA	Acres	Percent of DSA
Alfalfa*	74,267	10.9%	64,946	9.6%	-9,321	-1.4%
Almonds*	5,216	0.8%	13,275	2.0%	+8,059	+1.2%
Bush Berries*	1,202	0.2%	1,255	0.2%	+53	+0.0%
Cherries*	2,094	0.3%	2,876	0.4%	+782	+0.1%
Citrus*	9	0.0%	6	0.0%	-2	-0.0%
Corn*	91,712	13.5%	70,845	10.4%	-20,868	-3.1%
Cucurbit*	3,984	0.6%	3,047	0.5%	-937	-0.1%
Fallow[1]*	51,856	7.6%	80,801	11.9%	+28,945	+4.3%
Floating Vegetation	3,526	0.5%	2,720	0.4%	-806	-0.1%
Forage Grass*	4,466	0.7%	6,727	1.0%	+2,260	+0.3%
Olives*	1,474	0.2%	1,531	0.2%	+57	+0.0%
Other Deciduous*	7,702	1.1%	1,744	0.3%	-5,958	-0.9%
Pasture*	48,097	7.1%	42,418	6.2%	-5,679	-0.84%
Pears*	5,945	0.9%	5,524	0.8%	-421	-0.1%
Pistachios*	146	0.0%	266	0.0%	+120	+0.0%
Potatoes*	4,115	0.6%	3,823	0.6%	-292	-0.0%
Rice*	7,630	1.1%	7,953	1.2%	+323	+0.1%
Riparian Native Vegetation	21,700	3.2%	22,799	3.4%	+1,099	+0.2%
Safflower*	5,904	0.9%	13,581	2.0%	+7,678	+1.1%
Semi-Agricultural/ROW[2]*	48,467	7.1%	48,240	7.1%	-227	-0.0%
Sunflower*	33	0.0%	252	0.0%	+219	+0.0%
Tomatoes*	36,248	5.3%	25,127	3.7%	-11,121	-1.6%
Truck Crops*	9,557	1.4%	2,620	0.4%	-6,936	-1.0%
Turf*	2,137	0.3%	2,093	0.3%	-44	-0.0%
Upland Herbaceous[3]	54,379	8.0%	63,446	9.3%	+9,067	+1.3%
Urban	62,227	9.2%	62,688	9.2%	+461	+0.1%
Vineyards*	36,996	5.4%	37,339	5.5%	+344	+0.1%
Walnuts*	3,469	0.5%	5,261	0.8%	+1,792	+0.3%
Open Water	60,072	8.8%	63,045	9.3%	+2,973	+0.4%
Wet Herbaceous/Sub-Irrigated Pasture[4]*	24,964	3.7%	22,614	3.3%	-2,350	-0.4%
Other Crops[5]*	-	-	729	0.1%	+729	+0.1%
TOTAL	*679,594*	*100%*	*679,594*	*100%*	*0*	*0%*

[1] 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.

[2] 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.

[3] Encompasses natural vegetation areas with dry soil moisture regimes caused by deeper groundwater conditions or better drainage, including rangeland, annual grassland, oak woodland, and scrub.

[4] 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.

[5] 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 Field Evapotranspiration Estimates, Measurements, and Regional Weather Modeling

The UC Davis Land, Air and Water Resources (LAWR) Department deployed a series of field stations in 2015 and 2016 to measure and estimate weather and energy balance components for the purpose of determining ET in selected fields in the Delta. The methods employed to estimate and measure ET at these stations are described in this section. A detailed report of the two-year field campaign, including peer-reviewed references, appears in Appendix B. A description of the LAWR Department's wind field modeling efforts appears in this section. The field-based ET measurements and estimates are presented in Section 3.1 and compared to model estimates in Section 4.2.

2.2.1 Field Campaign Approach and Methodology

The surface energy budget equation and the micrometeorological technique called eddy covariance were employed to measure and estimate evapotranspiration, which is defined as the amount of water evaporated and transpired from a surface. Basic conservation of energy dictates that all energy flowing into and out of a surface, such as bare soil or a crop surface, must sum to zero. This energy conservation equation can be expressed as the net radiation (Rn) being set equal to all the non-radiative processes. These non-radiative energy flows are primarily composed of the latent energy flux (LE), representing the energy used in evapotranspiration; the sensible heat flux (H), representing the heating or cooling of the atmosphere by the surface; and the ground heat flux (G), representing the heat energy stored in the soil. The energy budget residual equation can be arranged as LE = Rn – H – G. Once LE is determined, actual evapotranspiration (ETa, Box 1) can be calculated by dividing the energy used (LE) by the amount of energy needed to evaporate one unit of water (latent heat of vaporization, Lv). This general energy budget residual method is employed by many remote sensing-based methods to develop ETa estimates. Most models and measurement methods simplify energy budget exchange to vertical fluxes, which is reasonable for relatively homogeneous surfaces. Thus, to calculate LE using the energy budget residual method, independent measurements and estimates were used to obtain Rn, G, and H values.

While the above equation should be valid for any time frame, such as hourly or half-hourly averages, it can be simplified for daily summed estimates of LE and ETa. Under such conditions, there is usually negligible ground heat flux; that is, the daily average soil and crop temperatures do not change much from day-to-day, so G ~ 0 for daily estimates of ETa and the above equation simplifies to LE = Rn – H. Measurements of G can be used to check that daily average of G ~ 0, and measured non-zero values of daily average G can be accounted for in the uncertainty of the calculated ETa. Because the surface renewal energy budget residual method used to calculate ETa requires specific assumptions and is not a direct measurement of ET energy components, results of the field campaign are referred to herein as "field-based estimates" of ET; however direct eddy covariance data are referred to as measurements (see below).

Field measurements and estimates from both 2015 and 2016 relied on very similar sets of sensors. Rn was measured with net radiometers (including a 'four-stream' net radiometer at one UC Davis site) and H was measured with fine-wire thermocouples using the surface renewal technique at all sites. At most stations, the simplified equation discussed above was applied and G was assumed to be zero for daily ET calculations. Stations using this bare minimum set of sensors are referred to as 'lite' stations.

At one site for each land cover type (fallow, alfalfa, corn, pasture), additional sensors were employed for calibration and to check the simplifying assumptions used by the other 'lite' stations; these stations with additional sensors are referred to as 'full' stations. H was measured using a sonic anemometer and the eddy covariance technique, and calibration factors were developed to apply to the surface renewal measurements at the 'lite' stations. G was measured with ground heat flux plates and soil temperature probes in order to estimate uncertainty associated with the assumption of negligible G on the daily scale. Additional meteorological and soil sensors were also deployed as part of these 'full' stations. Cross-calibrations between the sensors used in this project, in some cases against other sensors used as 'standards,' were also conducted before and after the field campaign.

In addition to the energy balance residual method described above, direct eddy covariance measurements of water vapor flux were taken with a DWR-provided Campbell Infrared Gas Analyzer and Sonic Anemometer (IRGASON) system at one of the 'full' station sites during the 2016 field campaign for purposes of comparison. The IRGASON values, which measure wind velocity and humidity at high-frequency, represent a direct measurement of ET; those specific data are referred to herein as "direct measurements" of ET. This station also had a 'four-stream' net radiometer. Finally, field results were compared to eddy covariance water vapor flux data collected in the Delta by the University of California Berkeley for the past several years as part of the global FLUXNET network.

Related peer-reviewed literature report that, with high-frequency (half-hour) data collection, field-based ET estimation by calibrated surface renewal energy budget methods show no mean bias compared to high precision lysimeter-based ET measurements (Snyder et al., 2008). Direct eddy covariance ET measurements, when properly corrected, have been shown to have ET measurement errors of +5% to -7% on an annual basis, when compared to lysimeters, in a recent Swiss study (Hirschi et al., 2017). Shorter-term intercomparisons with eddy covariance show random errors around double the annual values cited above, and surface renewal has uncertainty higher than that of eddy covariance. Further background and details on methodology, instruments, and data processing for the field campaign appear in Appendix B.

2.2.2 2015 Field Campaign over Fallow Fields

Four 'lite' stations and one 'full' station were installed in fallow fields between September 7 and 9, 2015, using the energy budget residual methods described above. The locations of these stations are mapped in Figure 3 and coordinates are available on the project website (https://watershed.ucdavis.edu/project/delta-et). The sites were chosen by arrangement through the Office of the Delta Watermaster with growers who had voluntarily fallowed their fields as participants in the 2015 Diversion Reduction Program (George, 2016). 'Lite' stations D1 and D2 were installed in a single field off of Byron Highway near Brentwood, CA. Unlike the other fallow fields where measurements were taken, this field had sparse weeds growing in it. 'Lite' stations D3 and D4 were deployed in two adjacent fallow fields off of S. Kasson Road near Tracy, CA. 'Full' station D5 was deployed in a field off of Crocker Road on Middle Roberts Island near Manteca, CA. All stations had elevations above sea level. The stations were all removed on October 5, 2015, resulting in less than a month of measurements. Some limitations inherent to this relative short time frame and coverage of this field campaign call for further study to better characterize ET from fallow lands in the Delta.

In addition to the measurements recorded over fallow fields, meteorological measurements from nearby California Irrigation Management Information System (CIMIS) stations were also used. These measurements were used to calculate reference evapotranspiration (ETo, Box 1). Daily ETo data from three CIMIS stations, which are also mapped in Figure 3, were used for comparison against the field-based ETa estimates developed for the fallow fields.

2.2.3 2016 Field Campaign over Alfalfa, Corn, and Pasture

Measurements were taken in five alfalfa fields, five corn fields, and four pasture fields spread across the Delta in the 2016 water year. These sites are mapped in Figure 3 and other site metadata are available on the project website (https://watershed.ucdavis.edu/project/delta-et). Stations D11, D12, and D13 were 'full' stations and the rest were 'lite' stations. In addition, DWR's IRGASON direct eddy covariance station for water vapor flux was installed at site D13. Measurements began at some sites in late April 2016, with additional stations being set up through mid-August 2016. Corn stations were removed shortly before harvest dates in September and October 2016, but most of the stations in alfalfa and pasture remained into the 2017 water year and were still deployed as of mid-May 2017. Deployment timelines for the 2016 field campaign are plotted in Figure 4. The results of the field campaign are primarily focused on the 2016 water year, when field-based ET measurements and estimates at multiple sites can be compared to the results of the seven ET estimation methods described in Section 2.3.

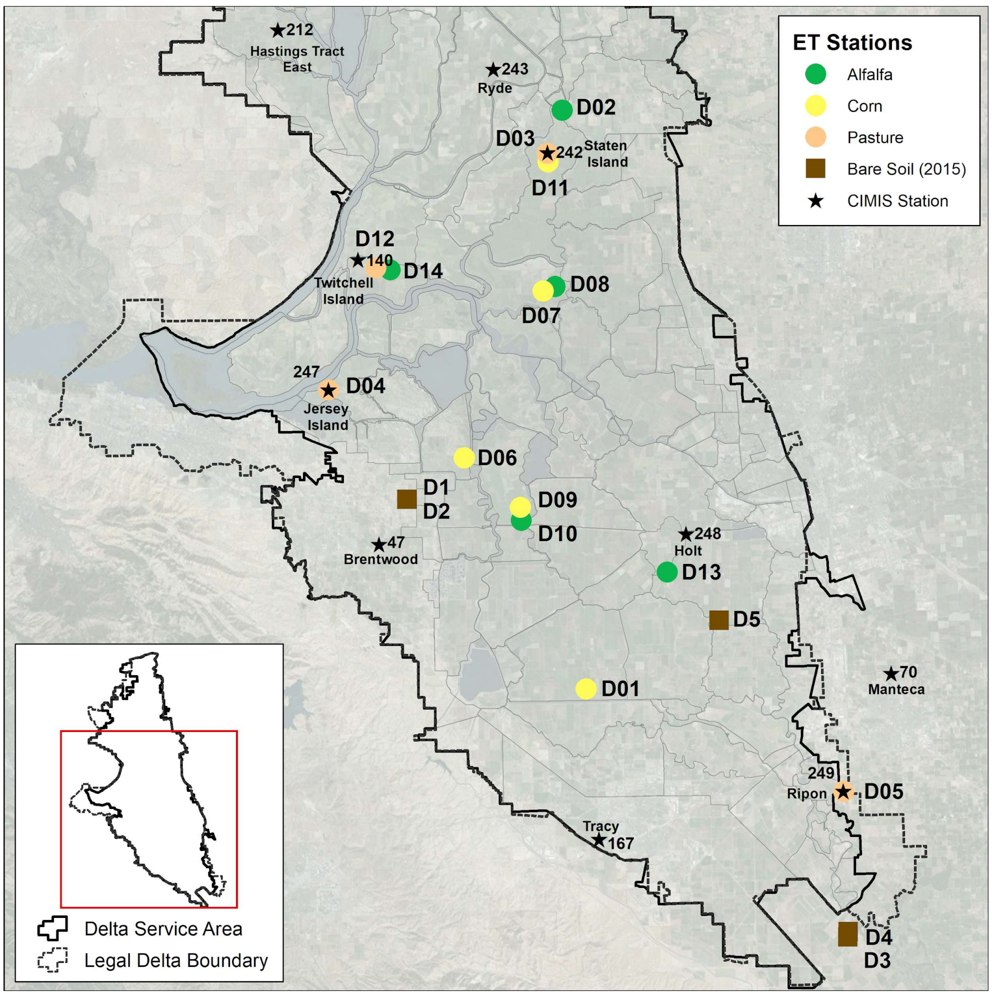


Figure 3. Locations of 2015 and 2016 field campaign ET stations and nearby CIMIS stations.

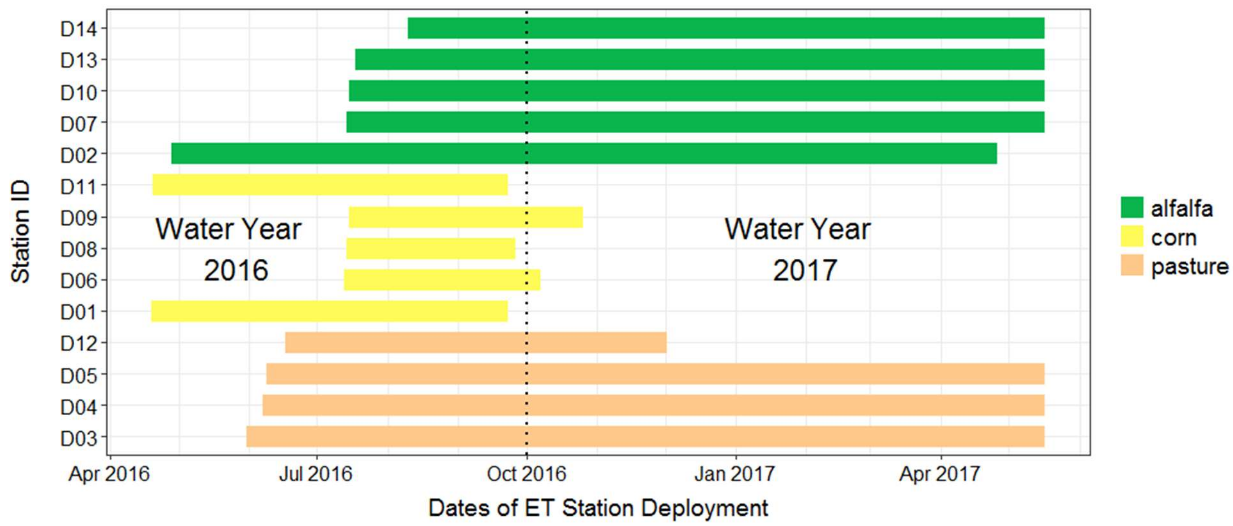


Figure 4. Deployment timelines for 2016 field campaign ET stations. Stations not removed before May 2017 were still deployed in the field as of May 18th, 2017.

Spatial CIMIS (Hart et al., 2009), which uses a combination of satellite data and interpolated ground-based meteorological measurements, provided reference ETo estimates for comparison with the field-based ETa estimates developed at field stations. All of the ETa stations in pasture fields were nearby or co-located with CIMIS stations, so ETo values calculated directly from these station measurements were also used for comparison.

Following field station removal, cross-comparisons of 14 net radiometers, 14 fine-wire thermocouples, and four sonic anemometers were carried out at UC Davis Campbell Tract Research Facility fields in Fall 2016. Uncertainty in energy balance components and evapotranspiration due to random instrument uncertainty was evaluated using these measurements.

2.2.4 Regional Meteorological Modelling

The Weather Research and Forecasting (WRF) model, a regional-scale model developed at the National Center for Atmospheric Research (NCAR), was combined with the UC Davis Atmosphere Canopy Soil Algorithm (ACASA) with the objective of developing a method to model wind fields across the Delta region for potential use with remotely-sensed ET estimation methods. After the two models were combined and specifically tailored to the Delta, pilot runs were made to simulate wind fields across the Delta and at selected sites where field measurements were made. Comparisons between modeled and field-measured wind data are presented in Section 3.1.3, and details of the regional-scale modeling appear in Appendix M.

2.3 Evapotranspiration Estimation Methods and Comparison Protocol

Seven core ET estimation methods (hereinafter referred as “methods,” “models,” or “groups”) were intercompared to help quantify, map, and compare the different approaches to estimating consumptive crop water uses in the Delta for the 2015 and 2016 water years. These comparisons were refined following the initial intercomparison summarized in the 2015 Interim Report for the project (Medellín-Azuara et al., 2016) and access to field campaign data provided by UC Davis. This section presents a short description of each method alongside its attributes, as provided by each modeling group. A summary description of the model comparison protocol follows; a detailed description appears in Appendix A. The results of these estimation methods are presented in Section 3.2, and several method comparisons are discussed in Section 4.

2.3.1 Estimation Methods

A summary of the seven ET estimation methods compared in this study, along with peer-reviewed references, appears in Table 2, with information provided by the participating modeling groups. The majority of the methods calculate individual components in the energy balance equation (net radiation, sensible heat flux, and ground heat flux) using satellite data as main inputs, estimating ET as the residual of the surface energy balance (see description in Section 2.2.1). CalSIMETAW, DETAW, and to an extent SIMS, however, use the crop coefficient-based approach to directly estimate ET as a fraction of reference ET. Appendices C through I detail the methodology of each ET estimation method.

Table 2. Method description, attributes, and published references.

Method	Description	Attributes (relative)
CalSIMETAW (Orang et al., 2013, also described in Appendix C)	CalSIMETAW is a soil-water balance model developed to estimate ETc and ETaw from 26 different land use categories by a two-step crop coefficient method for use in the California Water Plan. CalSIMETAW employs near-real-time daily ETo information from Spatial CIMIS, daily air temperature data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), and other climate data from National Climate Data Center (NCDC) stations. ETo is estimated using the Hargreaves-Samani equation, which was calibrated to estimate regional Penman-Monteith ETo to improve spatial heterogeneity. The model uses Soil Survey Geographic Database (SSURGO) data and crop information with precipitation and ETc data to generate hypothetical water balance irrigation schedules to determine ETaw. CalSIMETAW can also be used to study the impacts of climate change scenarios on water demand.	*Implementation Cost* *Initial*: Low *Annual*: Low *Expertise*: Medium *Intrusiveness*: Low *Spatial Resolution*: Detailed Analysis Unit/County (DAU-CO) (size varies, in the Delta 296.5 - 1,241 km^2) *Temporal Resolution*: Daily 2015-2016
DETAW (Snyder et al., 2006 and Kadir, 2006, also described in Appendix D)	DETAW is a soil-water balance model that estimates ETa by a two-step crop coefficient approach for 15 different land use categories in 168 subareas within the Delta. ETo is computed using the Hargreaves-Samani equation with historical weather data then adjusted with calibration factors to match the Penman-Monteith-based estimates from CIMIS stations. Both depth and volumetric daily ETa are estimated, and ETaw is estimated for 11 crop categories, native vegetation, riparian vegetation, urban, and open water areas from water year 1922 to the present. Since its initial release, DETAW has been refined based on multiple SEBAL applications.	*Implementation Cost* *Initial*: Low *Annual*: Low *Expertise*: Medium *Intrusiveness*: Low *Spatial Resolution*: 168 Delta subareas (size varies, 0.23 - 138 km^2) *Temporal Resolution*: Daily 2015-2016
DisALEXI (Anderson et al., 2011, also described in Appendix E)	DisALEXI is a multi-scale energy balance approach using land-surface temperature retrieved from thermal infrared satellite sensors, aircraft, or unmanned aerial vehicles (UAVs). The two-source land-surface representation partitions surface temperature and fluxes between soil and canopy elements, estimating total ETa and its soil evaporation and transpiration components. Daily ETa is estimated by fusing maps retrieved from Landsat and Moderate-Resolution Imaging Spectroradiometers (MODIS).	*Implementation Cost* *Initial*: Medium *Annual*: Medium *Expertise*: Medium *Intrusiveness*: Low *Spatial Resolution*: 30x30-meter pixel *Temporal Resolution*: Daily 2015-2016

ITRC-METRIC (Howes et al., 2012, also described in Appendix F)	The METRIC energy balance algorithm (see UCD-METRIC below) was modified by ITRC to use a grass reference crop (ETo) instead of alfalfa (ETr). It ETa computations include thermal data from Landsat satellites, and the METRIC procedure was also modified to use a semi-automated calibration procedure, spatially-interpolated ETo from Spatial CIMIS, and different aerodynamic resistance and albedo computations for specific crops.	*Implementation Cost* *Initial*: Medium *Annual*: Medium *Expertise*: High *Intrusiveness*: Low *Spatial Resolution*: 30x30-meter pixel *Temporal Resolution*: Overpasses 2015-2016, Monthly 2015-2016
SIMS (Melton et al., 2012, also described in Appendix G)	SIMS uses satellite measurements in red and near-infrared wavelengths to track crop canopy development and estimate fractional cover and basal crop coefficient (Kcb) values in real-time. Spatial CIMIS ETo is then used in a two-step approach to estimate basal crop evapotranspiration (ETcb), assuming well-watered conditions and dry exposed soil surfaces; ETcb estimates include only the transpiration component of ET and do not explicitly consider evaporation. Field comparisons in California have shown that SIMS seasonal ETcb estimates are within 10% of measured seasonal ET for well-watered crops, which were assumed to constitute much of the Delta's agricultural acreage.	*Implementation Cost* *Initial*: Low *Annual*: Low *Expertise*: Low *Intrusiveness*: Low *Spatial Resolution*: 30x30-meter pixel *Temporal Resolution*: Daily 2016, Monthly 2015-2016
UCD-METRIC (Allen et al., 2007a and 2007b, also described in Appendix H)	METRIC is an energy balance approach that calculates ET as a residual, employing both satellite multispectral imagery and ground-based reference evapotranspiration data. UCD-METRIC uses the original METRIC approach developed by the University of Idaho Kimberly Research Center, with the first of three models implemented in Google Earth Engine for automated processing of Landsat images and other diagnostic tools.	*Implementation Cost* *Initial*: Medium *Annual*: Low *Expertise*: High *Intrusiveness*: Low *Spatial Resolution*: 30x30-meter pixel *Temporal Resolution*: Overpasses 2015-2016, Monthly 2015-2016

UCD-PT (Jin et al., 2011, also described in Appendix I)	The UCD-PT approach was originally developed to use the semi-empirical Priestley-Taylor equation to estimate monthly ETa at a 1x1-km resolution by integrating primarily MODIS satellite data and AmeriFlux tower measurements. The approach was refined at UC Davis for this study to use Landsat data as primary inputs to develop daily 30x30-meter ETa estimates. In addition to improved net radiation estimates, the eco-physical constraint on ET (as represented by the PT coefficient) was optimized as a function of crop vegetation characteristics and moisture indicator for each of six crop types (Alfalfa, Almond, Citrus, Corn, and Rice) using field measurements in California. A generalized PT coefficient optimization was done for other crops where no ground measurements were available.	*Implementation Cost* *Initial*: Low to medium *Annual*: Low *Expertise*: Low *Intrusiveness*: Low *Spatial Resolution*: 30x30-meter pixel *Temporal Resolution*: Daily 2015-2016, Monthly 2015-2016

2.3.2 Input Datasets

To reduce the impacts of differences in input datasets on ET estimates for this study, following the Interim Report each of the seven methods in Table 2 used consistent key input data whenever possible to develop final ET estimates. The five remote sensing-based methods (DisALEXI, ITRC-METRIC, SIMS, UCD-METRIC, and UCD-PT) used primarily Landsat 8 multispectral imagery at 30x30-meter resolution in 16-day intervals to derive ET estimates. To increase temporal frequency, DisALEXI and SIMS also used Landsat 7 satellite data after filling Scan Line Corrector (SLC) data gaps using their own selected approaches (Appendices E and G). All remote sensing methods except for SIMS used Landsat thermal imagery, sharpened from a coarser resolution of approximately 100-meter to 30-meter resolution (sharpening methods varied, see respective appendices for more information about each model's method). The different methods chose Landsat images at their discretion, typically using clear sky scenes with minimal cloud obscuration (common in winter and early spring). Among the five models, a total of 70 different overpass dates (the Delta is covered by two separate scenes, rows 33 and 34 of path 44, in each overpass) were used from water year 2014 through 2017; late 2014 scenes were necessary to interpolate ET in early 2015, and early 2017 scenes were used to interpolate in late 2016 (lists of Landsat overpass dates used by each model are provided in Appendix A). A total of eight Landsat 8 overpasses were used commonly by all five of the teams which used satellite data. A detailed method comparison for dates common among paired methods is presented in Section 4.1. Some methods such as DisALEXI, SIMS, and UCD-PT utilized additional satellite data from MODIS and other sources, which are further described in their respective technical appendices.

Reference ET (ETo, Box 1) data from Spatial CIMIS (Hart et al., 2009) at 2-km resolution was provided by DWR. Fifteen CIMIS stations in the vicinity of the Delta (6-Davis, 70-Manteca, 71-Modesto, 121-Dixon, 131-Fair Oaks, 139-Winters, 155-Bryte, 166-Lodi West, 170-Concord, 191-Pleasanton, and 196-Esparto), including four stations in the Delta (47-Brentwood, 140-Twitchell Island, 167-Tracy, and 212-Hastings Tract East) and five additional stations newly deployed to the Delta by DWR in 2016 as part of this project (242-Staten Island, 243-Ryde (on Grand Island), 247-Jersey Island, 248-Holt (on Roberts Island), and 249-Ripon) were used to update Spatial CIMIS ETo for the study region (Little, 2017). The CIMIS stations nearest the Delta are mapped in Figure 3. Data collected at CIMIS stations are quality-controlled and gap-filled based on procedures outlined by Meek and Hatfield (1994), and Spatial CIMIS calculates ETo using the ASCE version of the Penman-Monteith equation (EWRI-ASCE, 2005). Land use datasets for 2015 and 2016 were produced by Land IQ at 30x30-meter resolution by combining land use surveys and satellite image classification (Section 2.1 and Appendix J) and were used as needed by modeling groups.

Each independent research group used its particular model along with satellite data and standard land use and weather datasets to provide monthly estimates of evapotranspiration in millimeters per day (mm/d; 1 mm/d of ET on a 30x30-meter pixel is equivalent to about 0.02 ft./month, or AF/ac./month). Results in a tabular format (CalSIMETAW and DETAW) were converted to a 30x30-meter resolution raster by applying the evapotranspiration estimate for each crop type to all the pixels in the region having that land use in Land IQ's dataset. Limited comparisons also used daily ET estimates from each model for select days. Monthly results were aggregated over the corresponding water year (either October 1, 2014 – September 30, 2015, or October 1, 2015 – September 30, 2016) to calculate annual cumulative evapotranspiration. Detailed comparisons of paired methods and different input datasets that may have caused differences in ET estimates are discussed in Section 4.1 and additional information and figures appear in Appendix A.

2.3.3 Other Considerations

The methods employed in the study vary in implementation costs (subdivided into initial startup costs and annual maintenance costs), expertise requirements, level of intrusiveness, and resolution. While there are not consistent and perfect metrics for measuring these characteristics, they should be considered on a case-by-case basis in selecting among the methods for a particular purpose. Each modeling group was surveyed to identify the relative cost, expertise, intrusiveness, and accuracy of each method. These relative attributes appear in Table 2 and are discussed further below.

2.3.3.1. Implementation Costs

Up-front infrastructure needs for all ET estimation models include computer processing capacity and software licenses. Advances in computing technology, cloud storage, distributed parallel processing, and the proliferation of open-source software should continue to decrease these costs in the years to come. Nevertheless, the highest investment cost is for expert human capital to establish and calibrate each model's framework. Once an estimation model is established and calibrated, annual maintenance costs may be much lower for most methods. These costs include maintaining software licenses, data backup and storage, and personnel required to run, maintain, inspect results, and periodically upgrade each system. Although the majority of satellite imagery datasets used by models are publicly available from the USGS and NASA, methods that rely on computer analysis of remote sensing data sometimes use proprietary software that can be costly for some applications. The complex and constantly evolving algorithms used by some methods merit a high degree of expert involvement and corresponding initial investments. For fully-automated methods that rely on cloud computing resources, implementation costs can be substantially reduced.

2.3.3.2. Expertise

Most methods and applications require a combination of agronomic, geographic information system (GIS), and computer science expertise. Some routine tasks demand less training in some of these areas; however, general knowledge of the ranges of crop ET under various conditions is needed to conduct quality assurance and quality control of model inputs and results. This requires significant expertise devoted to specific methods and the institutional knowledge to maintain and modify estimation methodology to produce realistic results. As computing power increases and self-correcting algorithms are implemented, the demand for such expertise would be expected to decrease along with the complexity on the user-side of the models.

2.3.3.3. Intrusiveness

By definition, most remote sensing-based ET methods are minimally intrusive, as they employ software development, remotely sensed satellite imagery, and technical knowledge rather than field-based infrastructure development. However, remote sensing methods require calibration data collected by field equipment (i.e. CIMIS stations), hence involving some intrusion. As increasing amounts of data become more readily available and modeling groups refine their methodology to better represent actual conditions through studies such as this, the already minimal intrusiveness of modeling methods would be expected to decrease.

2.3.3.4. Resolution

Spatial results datasets for the remote sensing-based ET models (DisALEXI, SIMS, METRICs, and UCD-PT) generated with a 30x30-meter resolution (equal to about 0.22 acres) due to the resolution of Landsat satellite image inputs. CalSIMETAW and DETAW use tabulated data over larger areas, as surveyed by DWR. CalSIMETAW uses Detailed Analysis Unit/County (DAU-CO) boundaries across California employed for planning purposes; the Delta includes portions of six different DAU-COs. DETAW calculates ET for 168 different subareas in the DSA, which are generally mapped to represent a single Delta island per subarea; a map of the DETAW regions appears in Appendix D.

Final results were produced at various time scales for this study: CalSIMETAW, DETAW, and DisALEXI submitted daily results for both water years which were averaged to produce monthly values. ITRC-METRIC submitted monthly averages and daily values on select overpass dates. SIMS submitted monthly averages for the entire two years of study and daily values for water year 2016. UCD-METRIC submitted daily averages on overpass dates which were averaged to monthly values using a proportional mean. UCD-PT provided both monthly average and daily values for both 2015 and 2016.

2.3.3.5. Relative Accuracy

Accuracy ranges for each method are published in their respective peer-reviewed literature, but no specific error analysis was conducted by modeling groups as part of this study. Previous studies of the METRIC method employed by UC Davis and ITRC have reported accuracies for seasonal ET of ±10% relative to measured ET across a range of crops and vegetation types in Idaho, including alfalfa, pasture, and potatoes. Larger errors were reported over shorter time periods (i.e. single overpass days in Idaho) when comparing model estimates to field lysimeter measurements (Allen et al., 2007b). Similarly, the SIMS model's ETcb estimates have been within 10% of measured ET from well-watered crops based on seasonal data. Further information on error analyses and the estimated accuracies of each model are presented in their respective references in Table 2. These accuracy ranges are generally consistent with the average absolute percentage difference from the method ensemble mean (Section 3.2.1), but the basis for the reported accuracy needs further examination. Because ET estimation techniques are constantly being improved through experience including this study, and because greater spatial and temporal resolution data are becoming available on a cost-effective basis, it is likely that overall accuracy in ET estimates for all methods will increase with time.

3 Evapotranspiration Measurements and Estimates

All independent research groups participating in this study estimated ET for the Delta using their respective methods with standard input datasets, as described in Section 2.3 and Appendices C through I. For the initial results of the 2015 season, a "dry run" of all seven models was conducted during the summer of 2016 using land use information from the 2015 Land IQ survey (Figure 1 and Appendix J) and Spatial CIMIS data based on the fourteen original stations in and around the Delta (Section 2.3.2). Datasets were made available to all groups, but models employed their own assumptions regarding if and how each of these datasets were used.

The UC Davis field campaign team collected bare soil ET data in late 2015 and deployed the expanded set of stations to multiple crops during the spring and summer of 2016 (Section 2.2). Model ET estimates and field measurements presented in the Interim Report for the project in late September 2016 (Medellín-Azuara et al., 2016) represented a true blind comparison, where no groups were permitted to see other results or the draft field data prior to its release. The Interim Report, which also includes field-based estimates for bare soil in 2015, is still available on the project website (https://watershed.ucdavis.edu/project/delta-et).

Land IQ's draft 2016 land use data was released to the research groups in late March 2017 and subsequently revised in May 2017. At that time, most groups submitted draft 2016 ET estimates. Following the release of the 2016 field data in May 2017, modeling groups were permitted to submit final updated results for both 2015 and 2016. Some groups chose to use the field data to calibrate their model results for the final reporting, though not all did so. All results presented in this report reflect the final estimates submitted by groups, including estimates for 2015 that may have changed since the Interim Report. All estimates and submissions from the entire project timeline are available upon request.

Each modeling group submitted estimates of daily ET rates (mm/day) averaged over monthly timesteps, along with total monthly ET volume estimates for each of the 24 months of the study (October 2014 to September 2016). Several models also provided daily ET estimates at daily timesteps for satellite overpass dates or the entire study period (Table 2 and Section 2.3.3.4). Results were stored in compartmentalized online repositories to allow standardized blind comparisons during the initial assessment. Full results in raster formats and standardized outputs in spreadsheet format are available for download on the project website.

The seven ET estimation methods employ a range of assumptions and may have spatial limitations based on the extent of land use data, regional bioclimate, and other boundary conditions. Therefore, not all models are capable of estimating ET for the entire Legal Delta and the Delta Service Area (DSA). CalSIMETAW and DETAW provide data only for specific subareas within the DSA which were not extrapolated beyond that region's boundary for this report. DisALEXI, ITRC-METRIC, SIMS, UCD-METRIC, and UCD-PT all cover areas beyond the Legal Delta. Because the results submitted by all methods can be directly summarized based on Land IQ data for the DSA, the majority of results in this section cover only the DSA. Furthermore, not all models are capable of estimating ET for all land cover types surveyed by Land IQ (Figure 1 and Table 1). For example, SIMS does not estimate ET for Floating Vegetation, Riparian, Semi-Agricultural/ROW, Upland Herbaceous, Urban, Open Water, or Wet Herbaceous/Sub-Irrigated Pasture (two of which are considered agricultural land uses). Therefore, the total Delta ET estimates reported in the following sections include only those agricultural land uses noted in Table 1 which could be estimated by the majority of the methods.

This section presents the results of the 2015 and 2016 field campaigns, along with several presentations of ET estimates for the seven groups. Additional group comparisons and discussion are presented in Section 4.1, and the field and model ET results are compared side-by side in Section 4.2.

3.1 Field Evapotranspiration Measurements and Regional Meteorological Modeling

This section presents measurements and field-based estimates of ET from the 2015 and 2016 field campaigns that are described in Section 2.2 and Appendix B. Measurements and estimates include bare soil for the late 2015 water year and ET measurements with eddy covariance and surface renewal stations for alfalfa, corn, and pasture in 14 locations in the Delta for the latter half (primary growing season) of the 2016 water year.

3.1.1 2015 Field Campaign Results over Fallow Fields

The 2015 field-based estimates and measurement of actual evapotranspiration (ETa, Box 1) from bare soil are plotted alongside CIMIS reference evapotranspiration (ETo, averaged between the 47-Brentwood, 70-Manteca, and 71-Modesto stations for the same time period) in Figure 5.

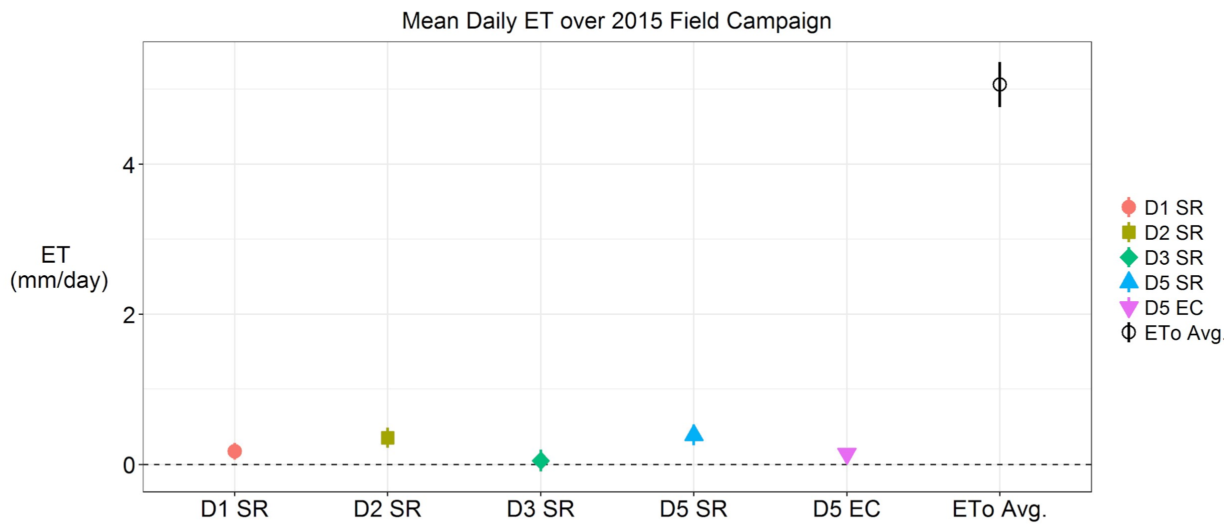


Figure 5. Mean daily ETa from bare soil stations (surface renewal and eddy covariance) and ETo from nearby CIMIS stations for September 2015. Vertical bars represent one standard error of the mean.

As expected, fallow field ET measurements and estimates were significantly lower than nearby ETo values, with the exception of some rainy days at the end of the deployment period. Four stations showed an average ET of 0.22 mm/d, with values ranging from 0.05 to 0.39 mm/d for the limited deployment period (month of September) and for stations of this elevation (between 1.5 m and 17 m above sea level). The higher elevation values were from a field with some sparse weeds, and the other two stations were in a field with a low elevation (1.5 m), which raised the possibility that tidal variations of the water levels surrounding the field or other factors changing the local water tables could enhance the near-surface soil moisture availability for evaporation. The daily fractions of reference ET (EToF = ETa / ETo) were low and close to zero, whereas after a rain event on October 1st they ranged between 0.4 and 0.75.

Fallow fields below sea level were not available for study in this initial field campaign. Station D4, which was deployed outside the Legal Delta boundary (Figure 3), did not yield accurate or precise results in a post-deployment field calibration (see discussion in Appendix B). Therefore Figure 6 and comparisons in Section 4.2 do not include data from station D4. Because of random errors and uncertainty related to the instrumentation (further discussed in Appendix B), the mean values that are slightly above zero in Figure

5 fall within the range of zero ETa for all stations. The project Interim Report contains additional plots of 2015 field-based ET estimates, and full datasets collected during the campaign are available on the project website (https://watershed.ucdavis.edu/project/delta-et).

As highlighted in the Interim Report (Medellín-Azuara et al., 2016), the short period of bare soil field measurements in 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. As a result of uncertainties related to bare soil ET within the Delta, a bare soil pilot study employing field equipment and satellite imagery for selected sites throughout the Delta is will be conducted for the 2018 growing season (additional recommendations appear in Section 5).

3.1.2 2016 Field Campaign Results over Alfalfa, Corn, and Pasture

Field-based estimates of ETa from surface renewal (SR) and eddy covariance (EC) stations in 2016, including direct ET measurements over alfalfa by an IRGASON (IRG) station at site D13, are plotted in Figures 6 through 8. These plots also include a comparison to Spatial CIMIS ETo, averaged across each 2x2-km pixel containing a field station, over the same period. Monthly average fraction of reference ET (EToF = ETa / ETo), which is related to the average crop coefficient (Kc) under ideal conditions, is also plotted in Figures 6 through 8. Observed EToF values were generally consistent with independent field-based estimates of ETa and EToF measured by other research groups in the Delta at the same time and in the recent past. These studies suggest that EToF values in the Delta region are lower than Kc values defined for ideally well-watered, unstressed crops elsewhere in California such as those published by Snyder et al. (2007). This cross-comparison is discussed in detail in Appendix B.

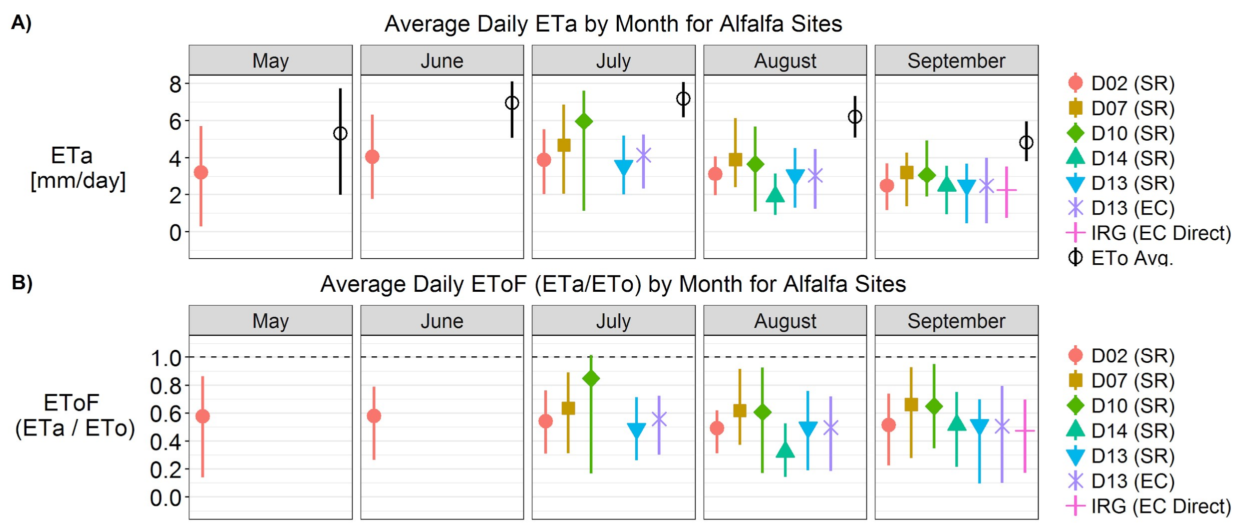


Figure 6. Monthly average daily A) ETa and B) EToF for stations in alfalfa sites. Points represent the mean and the bars represent minimum and maximum daily values. Each station with at least 8 days of measurements in a given month was included in the plots. The average daily Spatial CIMIS ETo across all sites is plotted in A) for reference.

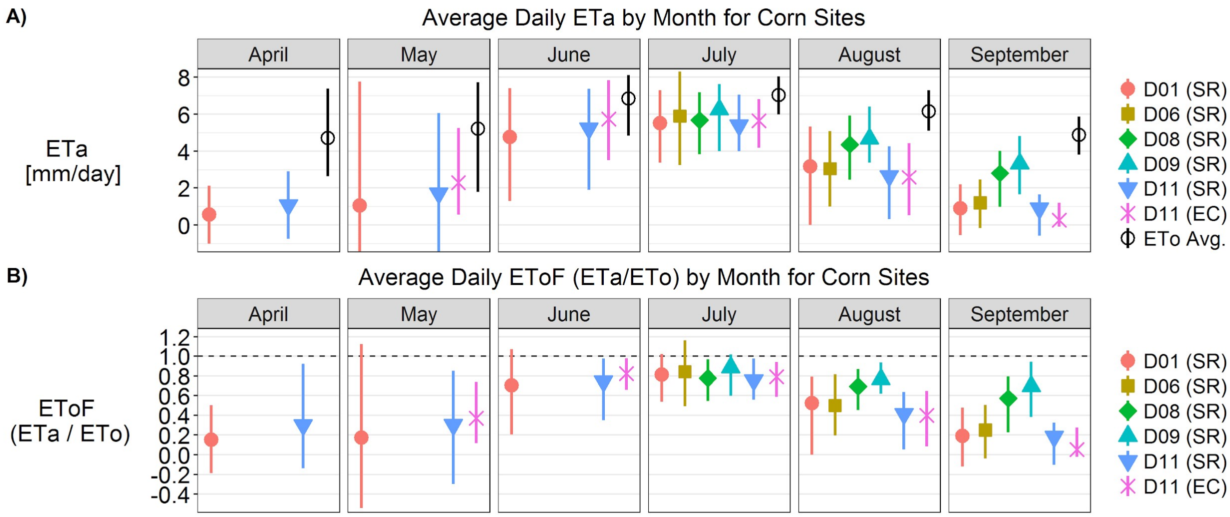


Figure 7. Monthly average daily A) ETa and B) EToF for stations in corn sites. Points represent the mean and the bars represent minimum and maximum daily values. Each station with at least 8 days of measurements in a given month was included in the plots. The average daily Spatial CIMIS ETo across all sites is plotted in A) for reference.

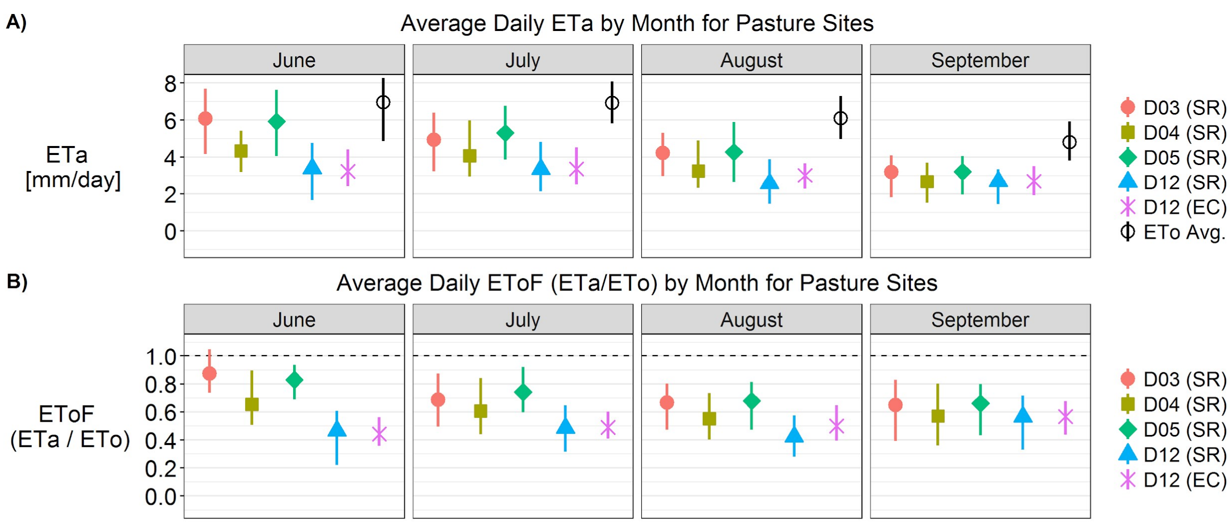


Figure 8. Monthly average daily A) ETa and B) EToF for stations in pasture sites. Points represent the mean and the bars represent minimum and maximum daily values. Each station with at least 8 days of measurements in a given month was included in the plots. The average daily Spatial CIMIS ETo across all sites is plotted in A) for reference.

Alfalfa monthly mean ETa values estimated from field data ranged from 2 to 6 mm/day, while monthly mean EToF values ranged from near 0.33 to 0.85, peaking in July, with some daily values at one site reaching approximately 1.0 (Figure 6). The direct eddy covariance measurements by the IRGASON at site D13 yielded the lowest ETa and EToF values, but when corrected using the Twine et al. (2000) method they were comparable to the energy budget residual methods using eddy covariance and surface renewal. A cross-comparison and individual plots of ETa for each station appear in Appendix B. Field-based EToF values of 0.62 in August 2016 and 0.61 in September 2016 were consistent with simultaneous independent measurements of 0.42 to 0.61 and 0.60 to 0.77, respectively, taken at the

University of California (UC) Berkeley site on Bouldin Island. Twitchell Island values were lower than UC Berkeley's (further discussion appears in Appendix B). UC Berkeley reported additional complete data from 2013-2016 that showed significant interannual variability and monthly average EToF values ranging from 0.5 to 0.98 from May through October (but also varying by month). The highest reported EToF value for all years, 0.98, occurred in July 2013. The lowest EToF, excluding years without available October data, was 0.58 in October 2013. For alfalfa, Allen et al. (1998) and Snyder et al. (2007) report Kc values of 0.40 shortly after cutting and peaking at 1.20 mid-season. The monthly average field-based ET from any given station tended not to vary as much because the extreme values associated with one harvest cycle were averaged out at the monthly scale. When field-based ETa estimates were only available for part of a month, mean values could be greatly affected if the data available 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.

Corn stations showed peak monthly mean field-based EToF estimates of 0.76 to 0.9 in July 2016 (Figure 7), whereas the peak Kc values commonly used for grain and silage corn outside the Delta are 1.00 to 1.05 (Snyder et al., 2007). These results were similar to measurements reported at the UC Berkeley Twitchell Island corn site during July 2012, which had EToF values ranging from 0.62 to 0.85 and slightly higher values in August (depending on measurement method). Caution must be exercised in comparing 2012 data with 2016 data because of the potential for interannual variability, as seen in the UC Berkeley alfalfa data. Further details on the UC Berkeley measurements are included in Appendix B. Historical measurements by Snyder (2010) using the energy budget residual method with eddy covariance and surface renewal reported corn Kc values peaking at approximately 0.8 for Webb Tract in the Delta. Snyder (2010) also reported another researcher had measured a Kc value peaking at 0.9 for corn in the Delta. DWR data reported corn EToF values of 0.96 to 1.01 in July-September 2009 and 0.81 to 0.98 in the same months of 2011 (Section B2 in Appendix B).

For pasture, field-based ETa values at individual stations varied widely from 3.2 to 6 mm/day depending on the measurement method and site (Figure 8). Station D12 generally yielded the lowest values, ranging from 0.28 to 3.3 mm/day, but this site had sparser vegetation inside the measurement enclosure which could have affected the net radiation or ground heat flux measurements. EToF values at site D03 peaked near 0.9, while D12 peaked near 0.55. The mean Kc value for rotated grazing pasture provided by Allen et al. (1998) and Snyder et al. (2007) is 0.95, with a range from 0.5 to 1.15. Snyder et al. (2008) found average EToF ranging from near 0.9 to 1.14 in a pasture on Twitchell Island. The low field-based EToF estimates at some of the stations could be indications of lesser amounts of irrigation and canopy cover variations, as visually observed by UC Davis personnel when visiting the sites periodically for maintenance. Other potential effects, such as the influence of cattle panel fencing necessary to protect the instruments from animal damage, are discussed in Appendix B.

It should be noted that in other areas of California and the U.S, higher peak Kc values for alfalfa, corn, and pasture have been reported (Blaney and Criddle, 1962; Snyder et al., 2007). However, previous research on ETa and Kc note that EToF is dependent on many factors such that crop coefficients developed for a particular crop type, soil, plant water status (such as last rainfall or irrigation date), and climate may not match the actual ETa and EToF values for crops whose locations, soils, plant water status, and climate are different from where the original Kc values were determined (Blaney and Criddle, 1962; Smith et al., 1991; Allen et al., 1998). The regional climate of the Delta differs from much of the rest of California's Central Valley (among other relevant differences). For example, Drexler et al. (2008) found that when the "Delta Breeze" was occurring, wetland EToF dropped from 1.3-1.8 or greater to 0.8-

0.9. This demonstrates the strong influence of weather patterns particular to specific regions in decreasing EToF. Snyder (2010) also noted that the Delta climate resulted in lower EToF values than for other regions. A more detailed analysis and discussion of the 2016 field measurements and related discussions with citations can be found in Appendix B. Full datasets collected from the field campaign are available on the project website (https://watershed.ucdavis.edu/project/delta-et).

3.1.3 Regional-Scale Weather Model Results

The regional-scale weather model WRF-ACASA was run to investigate if it could provide wind field data inputs for the Delta region that are required by some ET models. Though no models chose to use these fields for this study, its validity as compared to wind speeds measured at CIMIS field stations was examined. Figure 9 compares the average wind speed measured at two meters above ground level at four CIMIS stations in the Delta (47-Brentwood, 70-Manteca, 140-Twitchell Island, and 167-Tracy, see Figure 3) to the average wind speed modeled by WRF-ACASA at the same height and locations over a 24-hour period. Hourly confidence intervals computed for the observed values using a 2-tailed Student's t-test and methods outlined by Weisberg (1980) are also plotted.

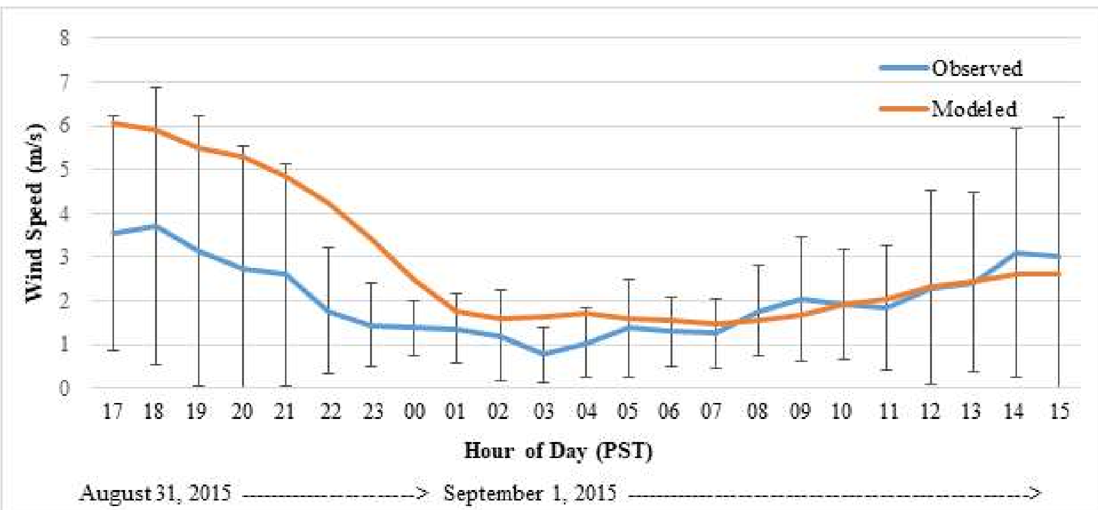


Figure 9. Wind speeds modeled by WRF-ACASA compared to CIMIS station observations, averaged over four stations for 24-hour period. Error bars represent 95% confidence intervals.

As Figure 9 indicates, the WRF-ACASA model's outputs were generally within the confidence interval of the observed wind speeds for the entire 24-hour period starting at 5:00 pm on August 31, 2015. The model was particularly accurate for low wind speeds (less than 2 m/s) observed from 1:00 to 7:00 am. WRF-ACASA tended to overestimate high wind speeds in the evening, while daytime modeled speeds were closer but slightly less than those observed. Following the 24-hour model run plotted in Figure 9, the simulation diverged from the CIMIS-measured wind speeds (see additional figures in Appendix M); it appears that the modeled "Delta Breeze" weakened unrealistically at all four locations. Average linear regression slopes and R^2 values across all four stations for the first 24 hours were 0.75 and 0.9, respectively. These results suggest that the current version of WRF-ACASA may be useful for retrospective analysis of ET and short-term forecasts of less than 24 hours, but longer runs will require additional model improvements to increase the accuracy of results. Further discussion and additional model results appear in Appendix M.

3.2 Crop Evapotranspiration Estimates

This section summarizes the results of the seven ET estimation methods described in Section 2.3 for both the 2015 and 2016 water years. As described in Section 3 above, both years of estimates represent final results submitted by groups following the release of the Interim Report, access to 2015 and 2016 field data from UC Davis, and further refinement of model methodologies and common input datasets during the project. Therefore, the 2015 results presented below are different from those presented in the Interim Report for the project (Medellín-Azuara et al., 2016) and can be considered final for this study. ET estimates are reported in volumes of thousand acre-feet (TAF) per year for regional analysis or average daily rates in millimeters per day (mm/d) for a 30x30-meter pixel (equal to about 0.22 acres) by month; 1 mm/d on a 30x30-meter pixel is equivalent to about 0.02 ft./month, or AF/ac./month. Study results are provided for the entire Legal Delta and the Delta Service Area (DSA) for those agricultural land use classes noted in Table 1; for more complex data analyses only the DSA area is examined. In several cases an ensemble average (mean) of the seven methods is provided, whether by crop, region, or month, in order to provide a baseline estimate of ET magnitude and examine when and where some models may deviate from predominant data trends. A detailed comparison of daily estimates among methods and to the field measurements is presented in Section 4, more detailed comparisons appear in Appendix A, and additional ET figures for other crops and regions appear in Appendix K.

3.2.1 Overall Delta Evapotranspiration from Agricultural Lands

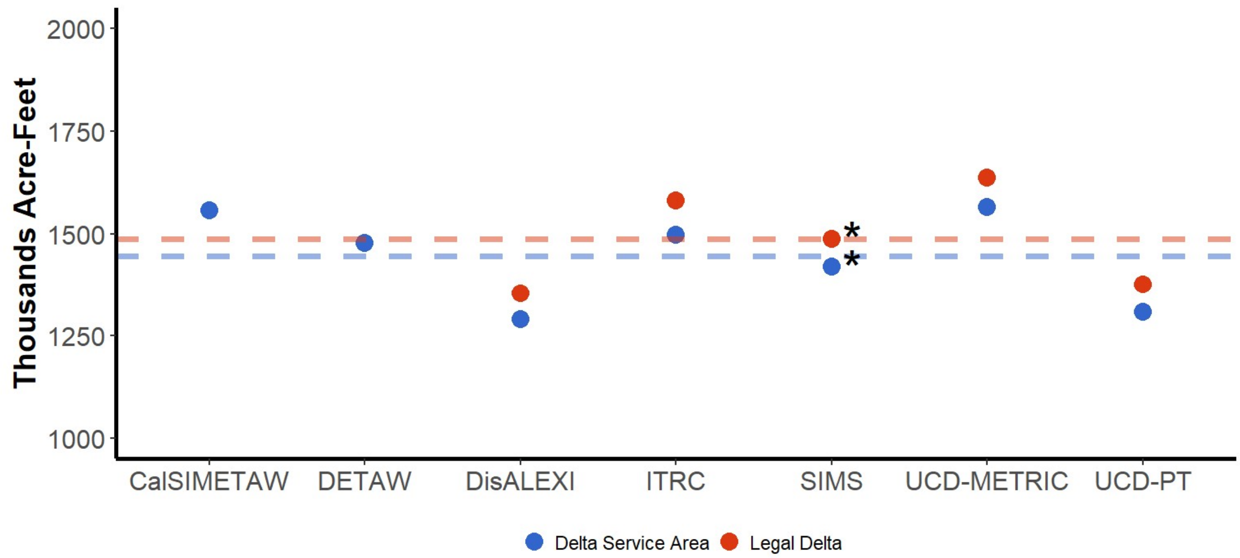
The total crop evapotranspiration volume for agricultural lands in both the Legal Delta and the DSA (including all agricultural crops identified in Table 1) estimated by the seven models in the 2015 and 2016 water years are summarized in Table 3 and Figure 10. CalSIMETAW and DETAW did not produce results outside the DSA for this study. The total consumptive use averaged across the seven estimation methods in 2015 was about 1,445 TAF, with an average absolute difference of ±91 TAF from the ensemble mean, over the 527,603 acres of agricultural land in the DSA. In 2016, this value decreased slightly to 1,379 ± 92 TAF over 521,612 acres of agricultural land. Expanding coverage to the Legal Delta (58,100 acres larger than the DSA, not all of which was agricultural land) estimates from the five available methods averaged about 1,490 ± 95 TAF in 2015 and 1,402 ± 80 TAF in 2016.

Table 3. Total annual evapotranspiration volume estimates in the Legal Delta and the DSA for agricultural lands in 2015 and 2016. Estimates are derived from monthly average daily evapotranspiration for each method.

Method	2015 ET Estimates (TAF)		2016 ET Estimates (TAF)	
	Delta Service Area	Legal Delta	Delta Service Area	Legal Delta
CalSIMETAW	1,556	-	1,513	-
DETAW	1,478	-	1,468	-
DisALEXI	1,290	1,354	1,263	1,325
ITRC-METRIC	1,497	1,581	1,338	1,414
SIMS	1,419* (1,186)	1,488* (1,246)	1,380* (1,160)	1,447* (1,219)
UCD-METRIC	1,565	1,636	1,478	1,544
UCD-PT	1,308	1,377	1,215	1,279
Average	*1,445*	*1,487*	*1,379*	*1,402*
Median	*1,478*	*1,488*	*1,380*	*1,414*

*SIMS does not estimate ET for semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture, so the larger totals include the average ET of the other six models for those land classes. The total in parentheses is the total estimate provided by SIMS without these classes.

A) 2015



B) 2016

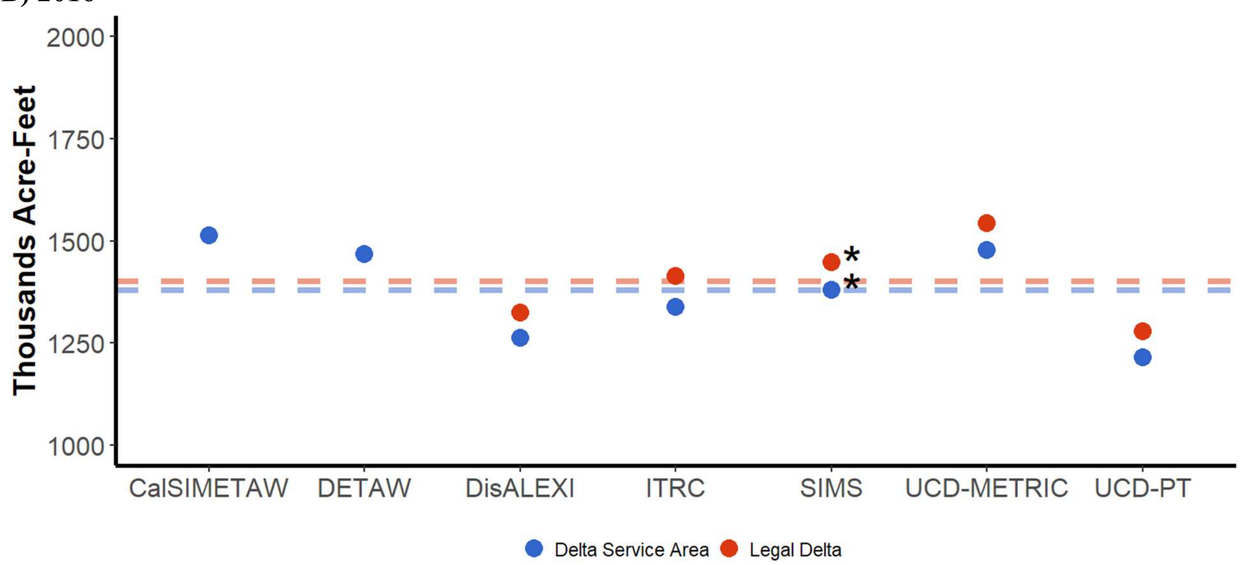


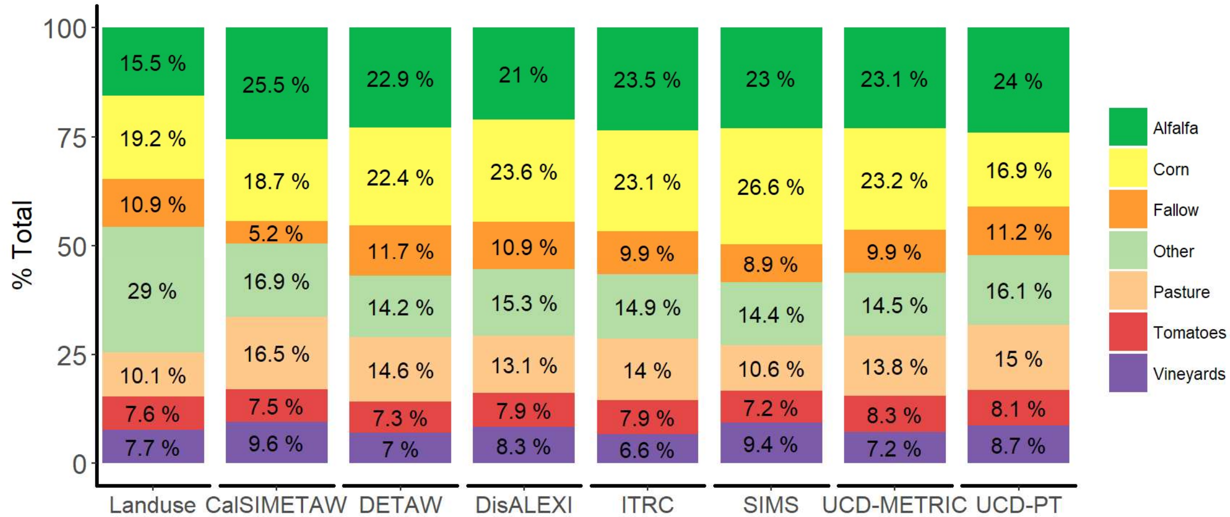
Figure 10. Total evapotranspiration volume for agricultural crops in the Legal Delta and the DSA in water year A) 2015 and B) 2016. The dashed line indicates mean ET across all methods. Estimates are derived from monthly average estimates of daily evapotranspiration for each method.

*SIMS does not estimate ET for semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture, so these points include the average ET from the six other models for those two land classes.

The 2015 estimates for all seven methods across the DSA were within 160 TAF (11% of the mean) of the average estimated ET volume across the seven methods, with an average absolute difference of ±91 TAF (±6.3% of the mean). The largest estimates were produced by UCD-METRIC (+120 TAF or +8.3% of the mean DSA ET) and CalSIMETAW (+111 TAF or +7.7%), while DisALEXI (-155 TAF or -10.7%) and UCD-PT (-137 TAF or -9.5%) were the lowest. DETAW (+33 TAF), ITRC-METRIC (+52 TAF), and SIMS (-26 TAF, with ET for two missing crop categories filled by the average ET of the other models) were all within 4% of the average estimated total crop ET across all methods. Similar data patterns generally held for the five methods capable of estimating ET for the Legal Delta. Methods had even greater agreement on total ET in 2016, with a mean absolute difference of ±92 TAF (±6.7%) from the average estimated ET in the DSA. CalSIMETAW produced the highest estimate (+134 TAF or +9.7%), while ITRC-METRIC (-41 TAF) and SIMS (+1 TAF) were still within 3% of average estimated ET in the DSA. Potential reasons for these differences are discussed in Section 4.

Most of the total ET estimated by all seven methods was from the six crop types with largest acreages identified by Land IQ (Table 1): corn, alfalfa, pasture, fallow, vineyards, and tomatoes. The percent of the total agricultural land area covered by each of these six agricultural land uses in the DSA, as well as the percent of agricultural ET volume in the DSA estimated by each method, are summarized in Figure 11. The "Other" crop category includes all other agricultural land use categories (Table 1) not represented by the other rows, and for SIMS this category does not include ET estimates for semi-agricultural/ROW and wet herbaceous/sub-irrigated pasture land uses.

A) 2015



B) 2016

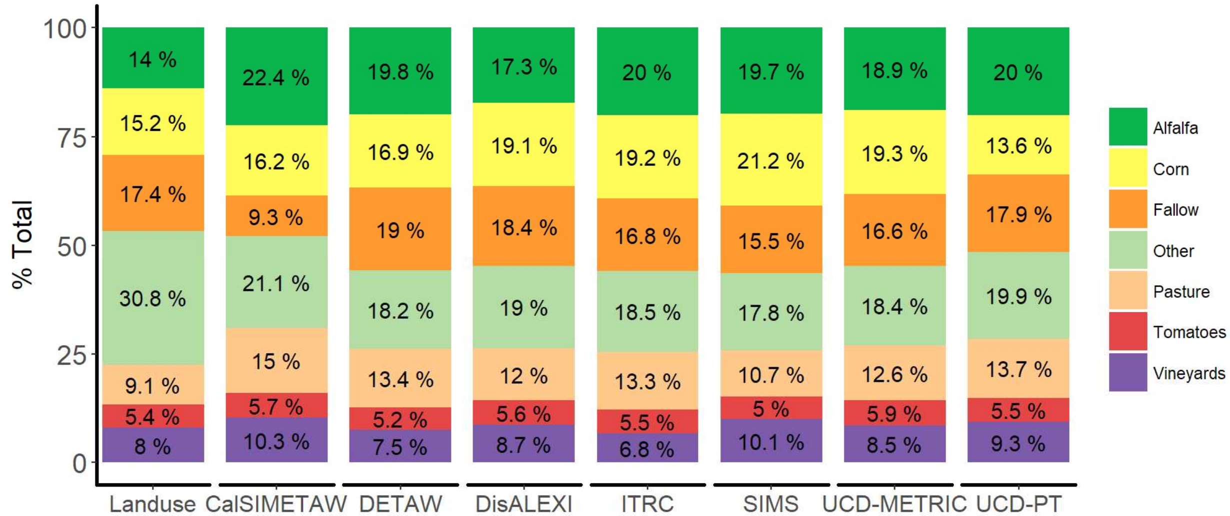


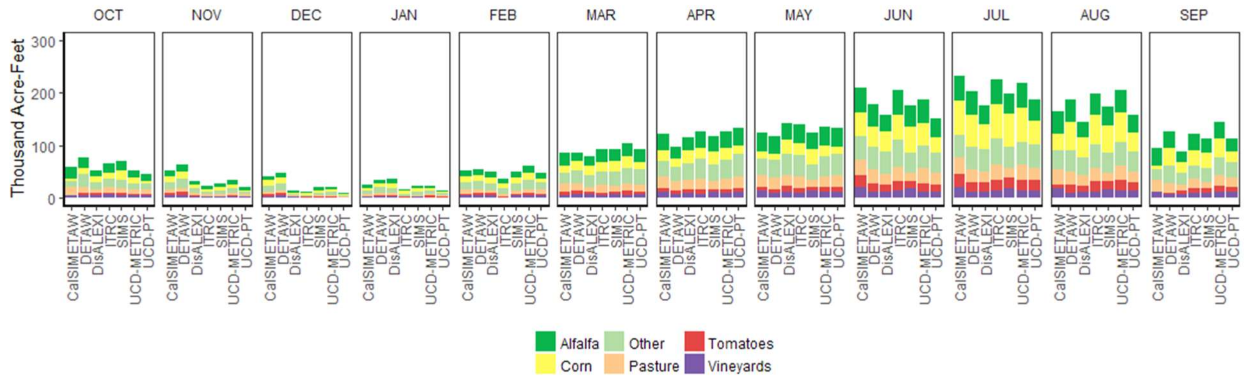
Figure 11. Contribution of major crops to agricultural land use area (far left column) and total agricultural evapotranspiration volume in the DSA, by method, for (A) 2015 and (B) 2016. Stacked bars represent percentage of agricultural land area or annual evapotranspiration volume, by crop.

Alfalfa, corn, and pasture totaled 40% and 45% of the land area analyzed in 2015 and 2016, respectively, and the dominant crop in the Delta changed from corn in 2015 to alfalfa in 2016. These three major crops comprise nearly three-fifths of DSA crop consumptive use estimated by all methods, as shown in Figure 11 above. All methods estimated that alfalfa used the most water of a single crop in both water years, averaging about 22% of the DSA's total estimated ET over about 15% of its agricultural land between both years. All methods also estimated high ET for corn, and pasture was the only single crop which averaged a higher percentage of the DSA's water use than its land use for all methods in both 2015 and 2016. Fallow land 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 major crops, corn and fallow showed the greatest differences between models with absolute differences from the mean of ±2.4% for corn in 2015 and ±2.2% for fallow in 2016.

Among models, CalSIMETAW tended to deviate the most for all the major crops (an average absolute difference of ±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 12 below breaks down ET volume estimates by month and model for major agricultural crop categories (Table 1) for 2015 and 2016. The crop categories in Figure 12 cover only the single annual land use surveyed by Land IQ (Appendix J); annual crops such as corn and tomatoes were likely not being grown from November through February, so during those months those lands were probably fallow.

A) 2015



B) 2016

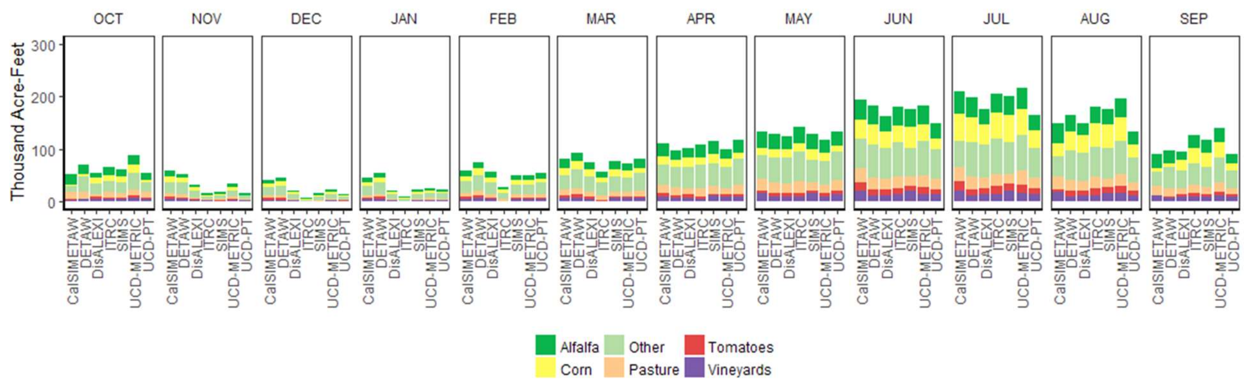


Figure 12. Total monthly estimated evapotranspiration volume of major crops in the DSA, by method, for A) 2015 and B) 2016. Bars represent monthly evapotranspiration volumes.

Figure 12 above shows that all methods reflect similar seasonality patterns in total estimated ET volume estimates for all major crop categories, with most ET occurring during the growing season (roughly March through September). The largest absolute differences between model estimates occur later in the growing season (July through September), while the largest relative differences (as a percent of the mean) occurred in the off-season (generally October through February) when ET is lower (only about 13% of average annual ET).

Because this study was focused on estimating ET for agricultural uses in the Delta, the estimates in this section include only consumptive use for the agricultural crops identified in Table 1. The remaining consumptive uses include ET from floating and native riparian vegetation, upland herbaceous, urban areas, open water, eucalyptus, sudangrass, and nurseries, which covered a total of 201,904 acres in 2015 and 214,852 acres in 2016 (29.7% and 31.6% of the DSA, respectively). Only six of the seven methods compared in this study are capable of estimating ET for these water uses (SIMS currently masks them out before making ET estimates), but estimates available from methods with that capability averaged about 612 TAF in 2015 and increased to 653 TAF in 2016 for these non-agricultural water uses. Of these totals, urban ET estimates averaged about 142 TAF in 2015 and 140 TAF in 2016. If, upon further study, such estimates prove accurate, these non-agricultural water uses are significant: as much as 45% of the average total DSA agricultural ET and nearly one-third of total Delta ET. It should be noted, however, that most remote sensing methods that develop a surface energy balance are not specifically designed for these types of land uses and are typically only calibrated for the vegetation and land characteristics of agricultural crops. Accordingly, future research should focus on the accurate estimation of ET from riparian vegetation and other non-agricultural land uses in order to provide a more complete picture of consumptive water uses in the Delta. The accurate estimation of non-agricultural water uses is likely to become increasingly important in light of efforts toward science-based ecological restoration in the Delta (additional recommendations appear in Section 5).

3.2.2 Average Evapotranspiration by Crop Type

By overlaying ET results provided by each model onto the land use survey data provided by Land IQ (Figure 1), ET estimates for specific crops at various times of the year were examined. The monthly mean daily ET rate, averaged across all DSA pixels under each crop category, is plotted for the eight major non-fallow crop categories by model in Figure 13. For comparison purposes, the corresponding average grass reference evapotranspiration (ETo) over the DSA from Spatial CIMIS (Hart et al., 2009) is also plotted. Similarly, Figure 14 plots the annual cumulative ET per unit area (in both mm and ft., which is AF/ac.) in the DSA by model for the same major crop types in 2015 and 2016. Similar figures plotting ET for all land use classes in the Delta appear in Appendix K.

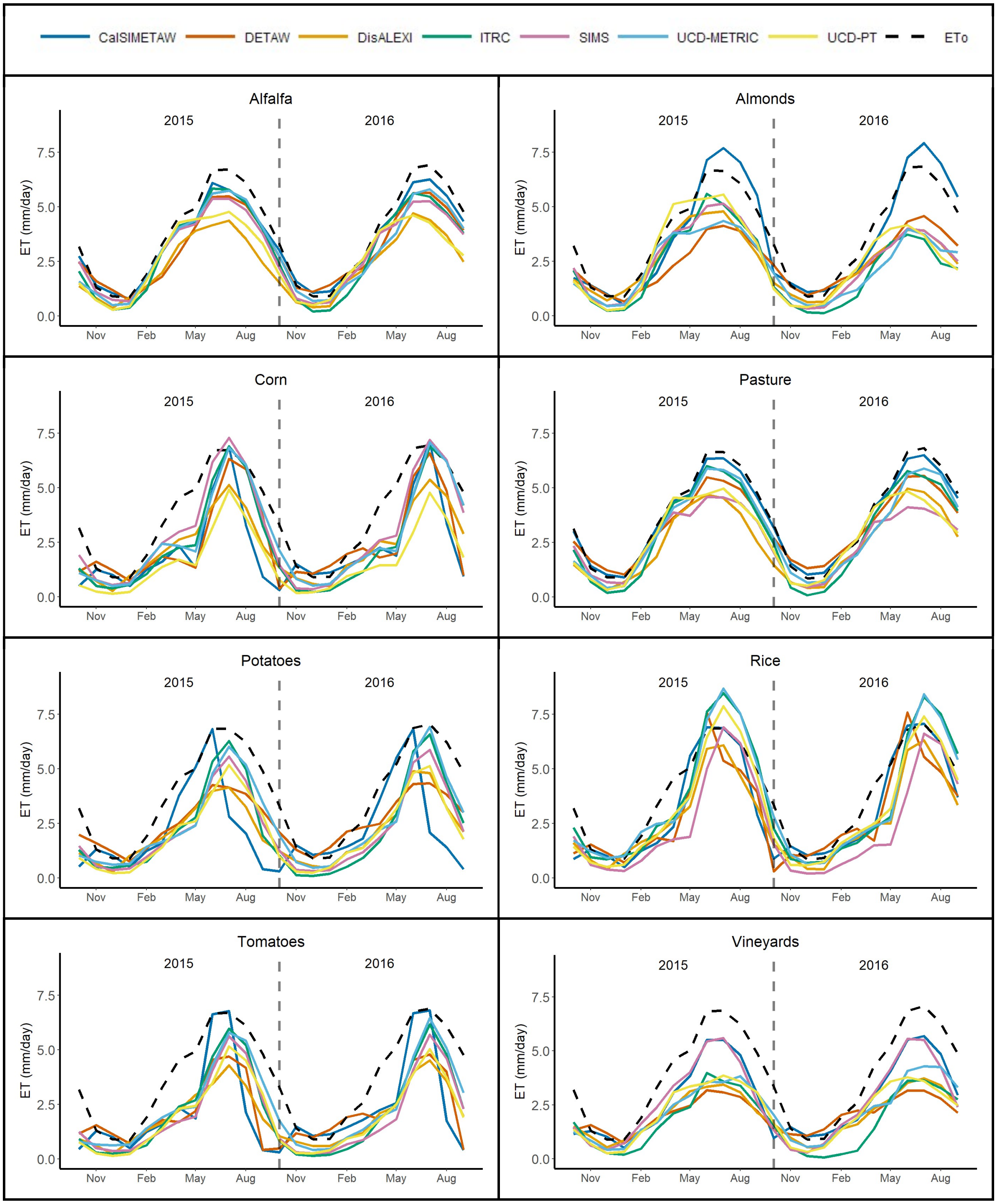


Figure 13. Time series plots of mean monthly average daily evapotranspiration rate, by model, averaged over the DSA for major crop types in 2015 and 2016. Reference Evapotranspiration (ETo) values from Spatial CIMIS, averaged across the DSA, are also included for reference.

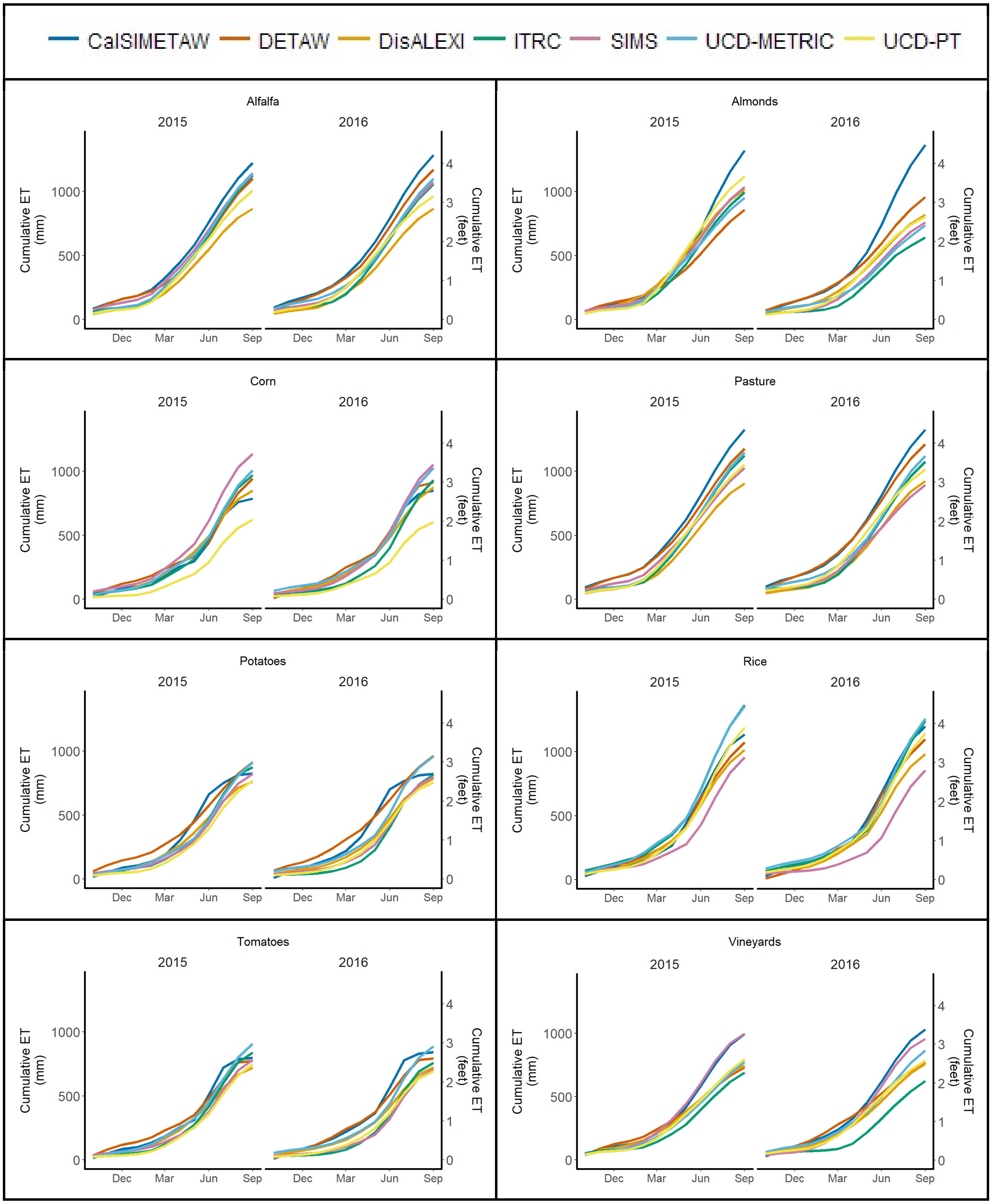


Figure 14. Cumulative evapotranspiration per unit area in the DSA, by method, for major crop types in 2015 and 2016.

Figure 13 shows that monthly ET estimates across all seven methods under comparison are generally less than reference ET, with the exception of rice during the growing season for most models and almonds during the summer for CalSIMETAW (discussion related to this issue appears in Appendix C). All methods tracked similar seasonal variation, except for potatoes and tomatoes where CalSIMETAW's higher ET estimates were shifted about a month earlier than other models (it should be noted that CalSIMETAW estimates potential ET, ETc, which may be higher than the actual ET, ETa, estimated by most other methods). 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). As previously discussed, absolute ET discrepancies between methods are more significant for summer months when ET is the highest, but relative differences between methods increasingly occur during late fall and winter months for most crops.

In general, Figure 14 shows that most models estimated alfalfa, pasture, and rice to have the highest water uses per unit area (cumulative mm or AF/ac. per-pixel) among the major crops, while almonds, potatoes, and tomatoes generally had the lowest estimates. All seven models are generally in agreement about seasonal changes in ET rate, with the majority of ET volume occurring during the growing season (March through September). However, some small anomalies between methods can be observed: DETAW estimated the lowest ET volume for alfalfa (possibly due to crop coefficient assumptions discussed in Appendix D), CalSIMETAW estimated the highest ET volume for almonds (likely due to its assumption that all trees were mature, Appendix C) and pasture (likely because it estimates ETc rather than ET, Box 1 and Appendix C), UCD-PT estimated the lowest ET volume for corn (likely due to its calibration to the field data, Section 4.2.3), whereas SIMS estimated higher ET for corn and lower ET for rice (potentially due to its ETcb estimates not including evaporation from open water, Appendix G), and ITRC-METRIC was on the low end for vineyards (potentially due to canopy cover or assumptions about similar roughness to orchards, Appendix F).

Because it shows the average ET rate across the DSA, Figure 13 does not indicate the spatial variation of ET estimates for a given crop in different areas of the Delta. These variations appear in Figure 15, which plots monthly average ET (in mm/d) for July 2015 and 2016. The box-and-whisker plots represent all pixels of each crop in the DSA (as surveyed by Land IQ), showing the median, first and third quartiles, and 9th and 91st percentiles. Similar figures plotting monthly ET variation for a given land use class and model for all land uses classes in the Delta appear in Appendix K.

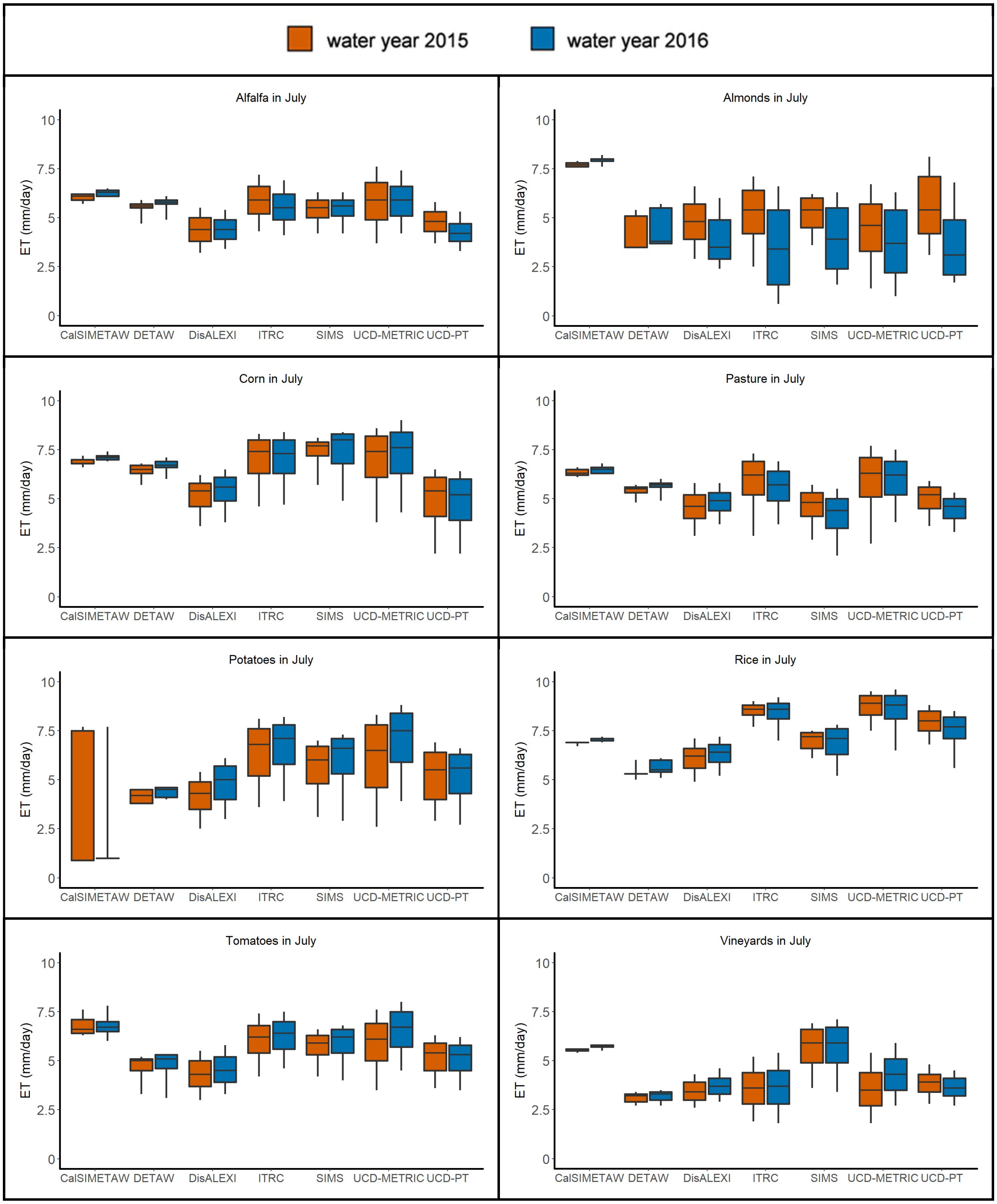


Figure 15. Dispersion of monthly average daily evapotranspiration rates in the DSA, by model, for selected crops in July 2015 and 2016. Center line represents the median, boxes represent the first and third quartiles, and whiskers represent the 9th and 91st percentiles.

The remote sensing-based ET methods generally captured larger spatial variation in ET estimates (Figure 15) than CalSIMETAW and DETAW, which estimate ET at coarser resolutions (Section 2.3.3.4). CalSIMETAW provides estimates by Detailed Analysis Unit/County (DAU-CO), only six of which fall within the DSA; thus, for any given month, CalSIMETAW provides a maximum of six different ET values. This is why its boxes and whiskers appear either very large (i.e. potatoes) or very small (i.e. vineyards) depending on the crop. CalSIMETAW's assumed crop coefficients, planting dates, and irrigation schedules are based on publications and communications from DWR's regional farm advisors, so they may vary significantly by region for select crops. DETAW has a slightly higher resolution, with each month having 168 possible values for each of the DSA subareas, but its results are still fairly consistent across the DSA and show less variation than other methods that output 30x30-meter resolution. These remote sensing-based models capture wider variation in ET within each crop type that likely better reflects localized conditions within the Delta. The remote sensing methods all found that the largest within-crop variation is found in almonds and potatoes, while alfalfa, rice, and vineyards show less variation (at least in July, at the peak of the growing season).

Additional statistical analyses of model results were conducted for the three major crops in the DSA (alfalfa, corn, and pasture). Assuming a normal distribution of ET values across all pixels of a given crop, two-tailed t-tests were performed using the mean and standard deviation of monthly-averaged daily ET rates (Figures 13 and 15) for each model and the ensemble mean of all seven models. Though t-tests typically would not be performed when both populations include the same results (i.e. the estimates from each individual model are included within the ensemble mean), the test was performed in this manner because the ensemble mean is a commonly used metric in this report which provides a good benchmark for overall ET in the Delta. Furthermore, the inclusion of seven models should provide sufficient information to demonstrate when deviations by a single model are significant. Results of these tests indicate that each model's monthly average ET for alfalfa, corn, and pasture is generally statistically similar to the ensemble mean ET for the same crop within a 95% confidence interval. In addition, t-tests resulted in the following notable observations:

- For alfalfa, all models are consistent with the ensemble mean across all months of both 2015 and 2016.
- For corn, only DETAW demonstrated short-term deviations from the ensemble mean ET values during the non-growing season in November 2014 and January 2016.
- For pasture, more methods were in disagreement with the ensemble mean ET in months outside the growing season; CalSIMETAW in November and December 2015, DETAW in December 2014 and November 2015 through January 2016, and ITRC-METRIC in December and January 2016.

Plots of standard deviation values and t-test results for each model and month appear in Appendix A.

3.2.3 Reference Evapotranspiration

Reference evapotranspiration (ETo) in California is the evapotranspiration from a standard grass reference surface of uniform height, which completely shades the soil surface and is adequately watered in the soil profile. ETo is not affected by crop or soil conditions, so it is considered a climatic parameter that can be computed from weather data to represent the evaporative demand of the atmosphere at a specific location and time of the year (Allen et al., 1998 and 2005). The two-step crop-coefficient based ET models (CalSIMETAW, DETAW, and SIMS) rely heavily on daily ETo values, while ITRC-METRIC and UCD-PT use ETo for temporal interpolation of satellite data. DisALEXI is a pure energy balance method and does not utilize ETo to develop ETa estimates. Of the seven ET estimation methods in this study, five utilize Spatial CIMIS grass ETo values (CalSIMETAW, ITRC-METRIC, SIMS, UCD-METRIC, and UCD-PT), while DETAW and DisALEXI generate their own internal ETo estimates. While UCD-METRIC's direct estimates at satellite overpass times use an alfalfa reference crop (ETr), Spatial CIMIS ETo values are used for temporal interpolation and can still be considered the reference ET dataset for the model. ITRC-METRIC typically modifies ETo values using a weather correction model; however, in an effort to standardize inputs, the ETa data compared in this study are based on uncorrected Spatial CIMIS ETo values.

Spatial CIMIS datasets are developed by DWR by interpolating data from established CIMIS stations over well-watered grass (though some site conditions may vary) into daily rasters of various weather components at a statewide 2x2-km resolution (Hart et al., 2009). ETo values are computed from these components using the ASCE version of the Penman-Monteith equation (EWRI-ASCE, 2005). There were fifteen CIMIS stations in the vicinity of the Delta in 2015, four of which (47-Brentwood, 140-Twitchell Island, 167-Tracy, and 212-Hastings Tract East) are within the DSA boundary, and five additional stations (242-Staten Island, 243-Ryde (on Grand Island), 247-Jersey Island, 248-Holt (on Roberts Island), and 249-Ripon) were deployed to areas of the Delta in 2016 to help improve Spatial CIMIS accuracy as part of this project. Daily average 'CIMIS ETo' measurements at these nine CIMIS stations, calculated using the modified CIMIS Penman equation (Temesgen and Eching, 2013), are compared to daily Spatial CIMIS ETo values (both in mm/d) at the corresponding pixels for 2015 and 2016 in Figure 16. Additional information about Spatial CIMIS and CIMIS stations can be provided by DWR's CIMIS branch.

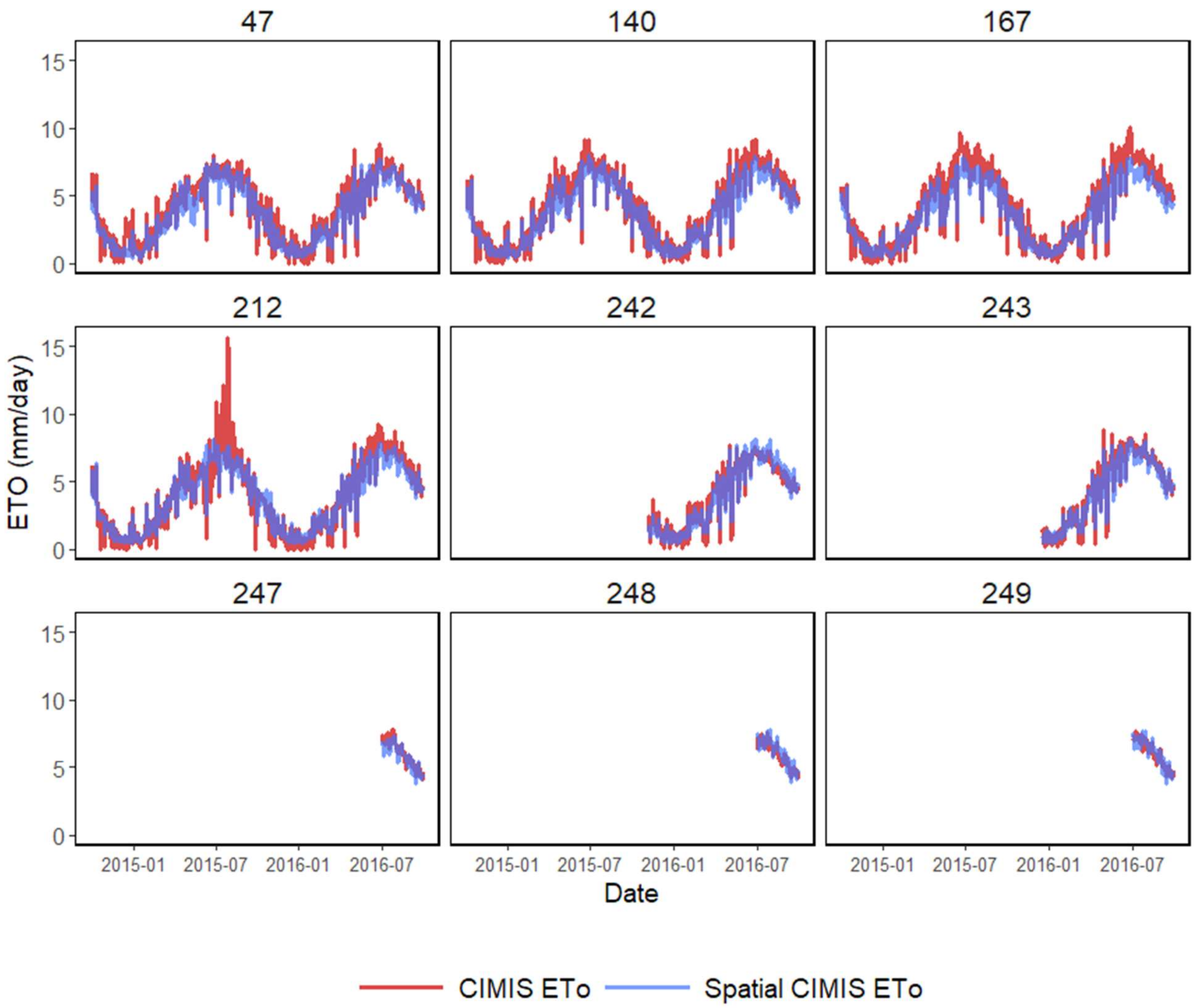


Figure 16. Time series comparison of CIMIS station reference evapotranspiration (ETo) measurements to Spatial CIMIS ETo values at the corresponding pixels in 2015 and 2016.

Five of the CIMIS stations in Figure 16 have limited data because they were deployed by DWR in 2016 as a part of this project. While Spatial CIMIS does have ETo values for these dates and locations, those values were interpolated using data from other CIMIS stations that are farther away. Therefore, Spatial CIMIS data prior to the deployment of the new CIMIS stations were not included in the plots above. Figure 16 shows that CIMIS station observations and Spatial CIMIS values generally followed similar trends for all nine stations in the Delta, though there were occasional short-term deviations where one value (typically the station) was several mm/d larger than the other. At station 167-Tracy, ETo values observed at the CIMIS station were roughly 1 mm/d higher than Spatial CIMIS values for the peak growing season of 2015 and 2016. Station 212- Hastings Tract East measured short-term ETo spikes that were nearly 10 mm/d greater than Spatial CIMIS for the peak 2015 growing season, presumably due to malfunction of CIMIS station sensors during that short time period. Other differences may have been caused by differences in incoming solar radiation (CIMIS stations use pyranometer measurements, while Spatial CIMIS uses GOES satellite measurements) or the spatial interpolation of wind speed, air temperature, and relative humidity. This comparison and the use of Spatial CIMIS by several models suggest that there may be times during both water years when ET estimation models that use Spatial

CIMIS data may differ from field-based estimates (Section 4.2). Additional discussion and comparisons between UC Davis field data, CIMIS stations, and Spatial CIMIS appear in Section 3.1.2 and Appendix B.

DETAW calculates unique ETo values for each of its 168 subareas in the DSA by modifying the Lodi/Stockton CIMIS station's daily ETo values using isolines determined by other CIMIS field stations (a more detailed description of this methodology appears in Appendix D). As a full energy balance method, DisALEXI does not explicitly utilize ETo values but does generate them as a data residual in preprocessing. With the exception of DisALEXI and SIMS, remote sensing-based methods use Spatial CIMIS ETo values to calculate fraction of reference evapotranspiration (EToF, Section 3.2.4) values on satellite overpass dates. These values are multiplied by daily ETo values to interpolate ET estimates between overpasses and in cloudy areas of satellite images. A time series plot of monthly average daily ETo values across the DSA for Spatial CIMIS, DETAW, and DisALEXI appears in Figure 17. Monthly box plots and maps of ETo values for these three sources in July 2016 appear in Appendix K.

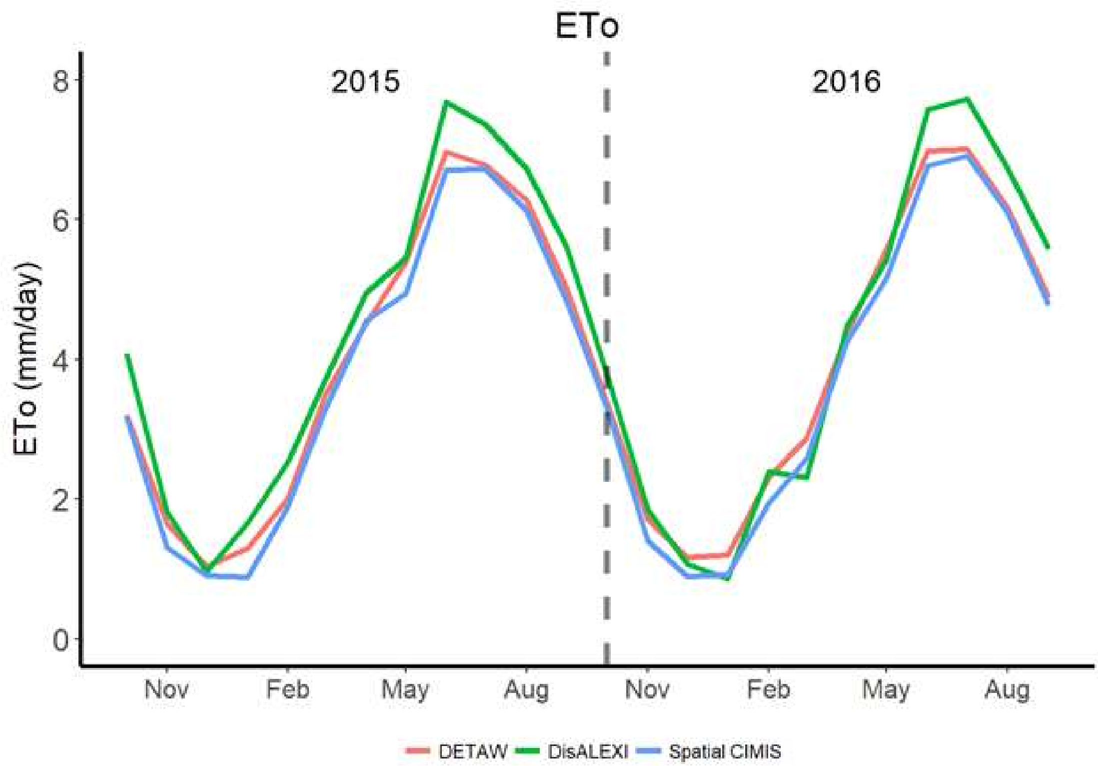


Figure 17. Time series of monthly reference evapotranspiration (ETo) averaged over the DSA for DETAW, DisALEXI, and Spatial CIMIS.

Compared to Spatial CIMIS and DisALEXI, DETAW exhibits considerable spatial and temporal variation in ETo values that is likely due to its modification of ETo calculated using the Hargreaves-Samani Equation at the Lodi/Stockton CIMIS station. This value is increased up to 15% in the west Delta and decreased by 20% in the east Delta (Appendix D and maps in Appendix K). These ETo values averaged higher than Spatial CIMIS during the winter and growing seasons, while values were similar during transitional months. Prospects for incorporating Spatial CIMIS ETo values into DETAW to improve data consistency are discussed in Section 4.1.1 below. DisALEXI's ETo values are consistently higher than Spatial CIMIS for the entire study period, especially during the peak growing season, with an average difference of about 1 mm/d. DisALEXI's ETo values are computed as a function of Climate Forecast System Reanalysis (CFSR) data, so these differences are likely a result of entirely different inputs. However, as DisALEXI does not actually use ETo values for computing ETa estimates, these differences may merely suggest trends in ETa rather than critical differences from other models.

3.2.4 Fractions of Reference Evapotranspiration by Crop Type

Fraction of reference evapotranspiration (EToF) is the ratio of actual crop evapotranspiration (ETa) to reference evapotranspiration (ETo). Under optimal conditions or for models that estimate potential ET (ETc, i.e. CalSIMETAW), EToF will approach the crop coefficient (Kc) value. Kc represents corrections made to reference ET to account for the impacts of varying crop, water, and soil conditions at a particular place and time on ET (Allen et al., 1998). Though not all methods evaluated in this study use a crop coefficient approach to calculate ETa or ETc, EToF serves as a diagnostic for comparing methods for specific crops, particularly during the growing season. Since CalSIMETAW estimates potential evapotranspiration (ETc), its calculated EToF values would be expected to match its Kc values; similarly, SIMS's calculated EToF and basal crop coefficient (Kcb) values are equivalent. For all other methods which estimate actual ET (ETa), EToF values would be less than theoretical Kc values but would approach them under ideal conditions. Since UCD-METRIC uses an alfalfa reference ET (ETr) for direct estimation (Appendix H), its calculated EToF values would not necessarily match assumed alfalfa reference-based Kc values. However, because they are used for temporal interpolation (Section 3.2.3), grass-based EToF values are still relevant for analysis of model results.

Monthly EToF values for each method were calculated by dividing monthly ET estimates by the monthly ETo value (Spatial CIMIS for most methods and ETo-comparable values for DETAW and DisALEXI, Section 3.2.3) for the same pixel. These values were then averaged across the DSA for each Land IQ-identified crop category to produce two-year plots of monthly EToF across the DSA for each crop and model. Results appear in Figure 18 for the eight major crops in the Delta and in Appendix K for all land use classes in the Delta.

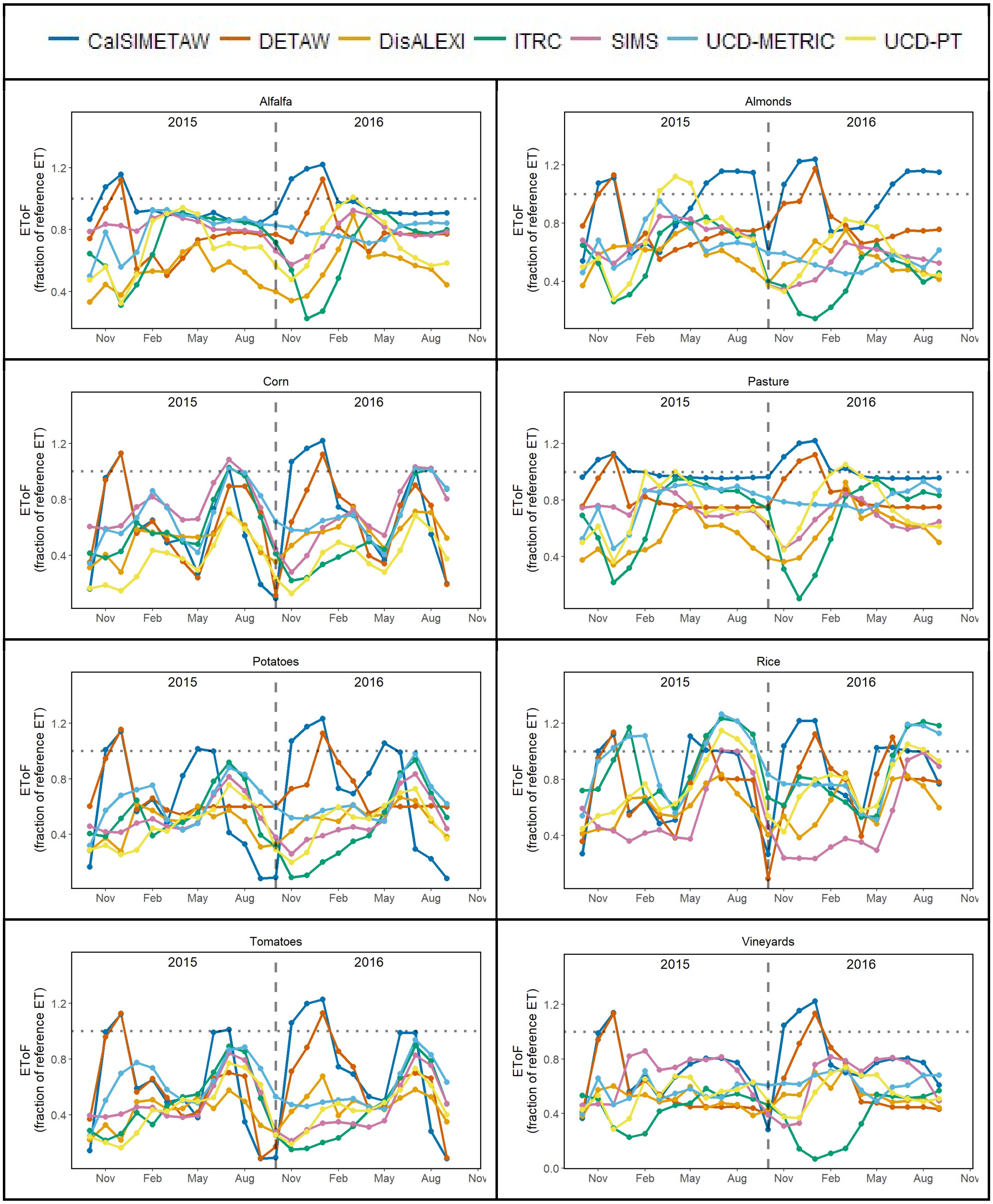


Figure 18. Time series of calculated monthly fraction of reference evapotranspiration (ETOF) averaged over the DSA for major crop types in 2015 and 2016.

Though EToF values deviated between models at times, they are generally in agreement and followed similar trends during the growing season for most crops. Almonds and vineyards exhibited some larger differences between models during the early and late growing season, potentially pointing to uncertainties in remotely estimating ET from tree and vine crops during seasonal transitions. At these times of the year ETo and ET values are higher and Landsat images are more typically cloud-free, whereas cloudier images during the winter require interpolation strategies unique to each model. When dividing the low winter ET estimates (Section 3.2.2) by similarly low reference ET values (Section 3.2.3), even small differences between models may result in largely different EToF values. This is particularly true for pasture, alfalfa, and corn, following differences in ETa or ETc estimates (Figure 13). Few crops are likely to be planted at this time of the year, suggesting uncertainties in estimating ET from bare soil in the Delta. EToF values for CalSIMETAW and DETAW deviate significantly from the other models for many crops, often reaching peak values during the winter. DWR has indicated that this occurs because both models use a two-stage evaporation model to adjust crop coefficients as a function of ETo and wetting frequency. During the rainy and early irrigation seasons, both models assume higher Kc values (with a maximum of 1.2) to account for higher soil wetting frequencies. These high values occur at a time when ETo values are low, so they have less of an impact on the magnitude of ET estimates than a high EToF value during the peak growing season would. Unless insufficient clear sky satellite imagery was available, remote sensing models would still be expected to detect intermittent wetting events and bare soil evaporation at these same times.

Though DisALEXI uses strictly the energy balance methodology to estimate ET, its residually-calculated EToF values generally agree with those estimated by the other remote sensing methods, especially the METRIC models. For crops with low growth heights even during the peak growing season (i.e. alfalfa, pasture, and potatoes), ITRC-METRIC produced lower EToF values than other methods. This may be due to the unique treatment of bare soils in each model that change how the residual evaporation from bare soils is estimated and assigned. Mean monthly EToF values derived from SIMS and UCD-PT follow similar seasonality, though SIMS values are generally higher for corn and vineyards during the growing season. SIMS exhibits low EToF values for rice during the growing season, likely due to issues with evaporation from open water on flooded fields. UCD-PT also shows seasonally low EToF values for corn, which may have been related to its field data calibration (Section 4.1.3).

3.2.5 Evapotranspiration Estimate Variation

As demonstrated above, the ET estimates made by the seven participating groups vary by crop, month, and water year. These differences were evaluated by calculating both the coefficients of variation (unitless) and the absolute variation (in mm/d) between methods for each month of the study for the eight major crops in the Delta. The coefficient of variation was calculated on a per-pixel level for each month by dividing the standard deviation of model ET estimates by the ensemble mean of estimates, then averaging across the DSA for each crop type. This metric demonstrates the differences between models relative to the magnitude of ET estimated to be occurring at the given time. The absolute variation was calculated on a monthly per-pixel basis by averaging the monthly absolute difference of each ET estimate from the ensemble mean of the seven models, again averaged across the DSA. This metric shows where the largest numerical differences in ET estimates occur between methods. Plots of both variation metrics appear in Figure 19.

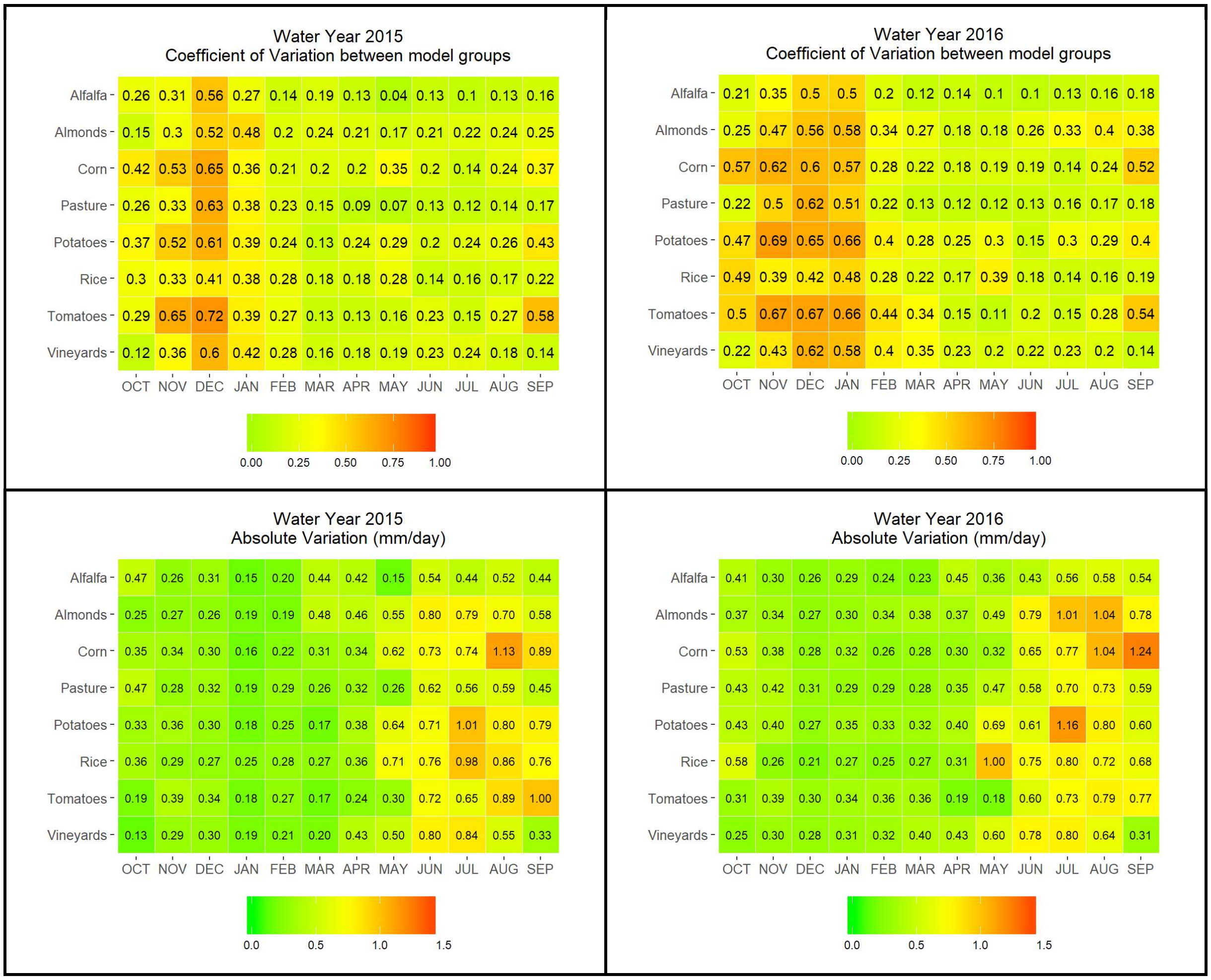


Figure 19. Coefficients of variation (top) and absolute variation (bottom) among methods for major crop types in the DSA in 2015 (left) and 2016 (right). Higher numbers represent greater discrepancies among models for the given crop and month.

As Figure 19 indicates, coefficients of variation among models were generally higher from September through January for most crops (especially corn, potatoes, tomatoes, and vineyards). ET estimates in these months represent about 23% of annual ET volumes, so these relative differences are more prominent during months with considerably less ET. Furthermore, the primarily annual crops of the Delta are not typically grown in these months. Even year-round crops such as almonds, pasture, and vineyards are typically dormant during the winter and would be expected to have considerably lower ET as well. The Land IQ dataset used to mask ET results represents only a "snapshot" of crop planting patterns during peak growing season (July 2015 and May-July 2016) that does not factor in planting or harvesting dates. This may result in different estimates for the DWR methods that use pre-calibrated crop coefficients (CalSIMETAW and DETAW) with assumed growing schedules. The masking of remote sensing methods to a single crop each year may also inaccurately show wintertime ET that occurred from what was observed as bare soil in satellite images. For year round-crops, the inherently lower energy fluxes observed by satellites in the cooler months could also cause uncertainty in residual energy balances calculated by remote sensing-based methods. The masking of clouds common in wintertime images, or the use of fewer images during these months (lists of Landsat overpass dates used are provided in Appendix A) due to cloud presence would also cause variations among these methods, as their spatial and temporal interpolation methods were not standardized for this study.

The absolute variation plots in Figure 19 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). For these months there are certain crops which have greater absolute differences among models: almonds, corn, potatoes, rice, and tomatoes, primarily late in the growing season (July through September). Most of these crops also showed higher coefficients of variation at other points in the season, suggesting there is 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, leafy crops like corn and orchards causing shadows in satellite images, and open water on rice fields. As with the coefficient of variation, the limited "snapshot" of annual land uses could cause disagreement between methods because the assumed planting/harvest schedules in the crop coefficient-based methods (CalSIMETAW and DETAW) may not always align with bare soils observed in satellite images after harvest.

3.2.6 Spatial Distribution of Evapotranspiration

It is important to examine the extent and variation of study results across the Delta, as localized weather patterns and geographic land use trends may affect ET estimates. The variations in temporal and crop-specific ET discussed above result from spatially varying ET estimates based on the land uses surveyed by Land IQ that were used to estimate ET and mask the results of remote sensing methods. Excluding non-agricultural land uses (Table 1), annual spatial datasets were assembled by multiplying each model's monthly estimates of average daily ET by the number of days in each month, then summing to get an annual total ET volume. The average and standard deviation of total annual ETa estimates for all seven methods were then calculated for each agricultural 30x30-meter pixel (as previously discussed, Semi-Agricultural/ROW and Wet Herbaceous/Sub-Irrigated Pasture pixels had no estimates from SIMS).

The average annual ET (in mm) across all seven methods for each pixel is mapped for 2015 and 2016 in the upper portion of Figure 20. The low range of 150 mm is equal to about 0.5 AF/ac. or ft. annually, while the high range of 1,500 mm is about 5 ft. annually. The coefficient of variation among the seven methods (Section 3.2.5) was also computed for each pixel and appears in the lower portion of Figure 20 below. These values represent annual coefficients of variation rather than the monthly values in Figure 19 above. The maps in Figure 20 also delineate the five major regions of the Delta (Section 3.2.7) and provide their mean annual ET and coefficient of variation (CV) values across the seven methods.

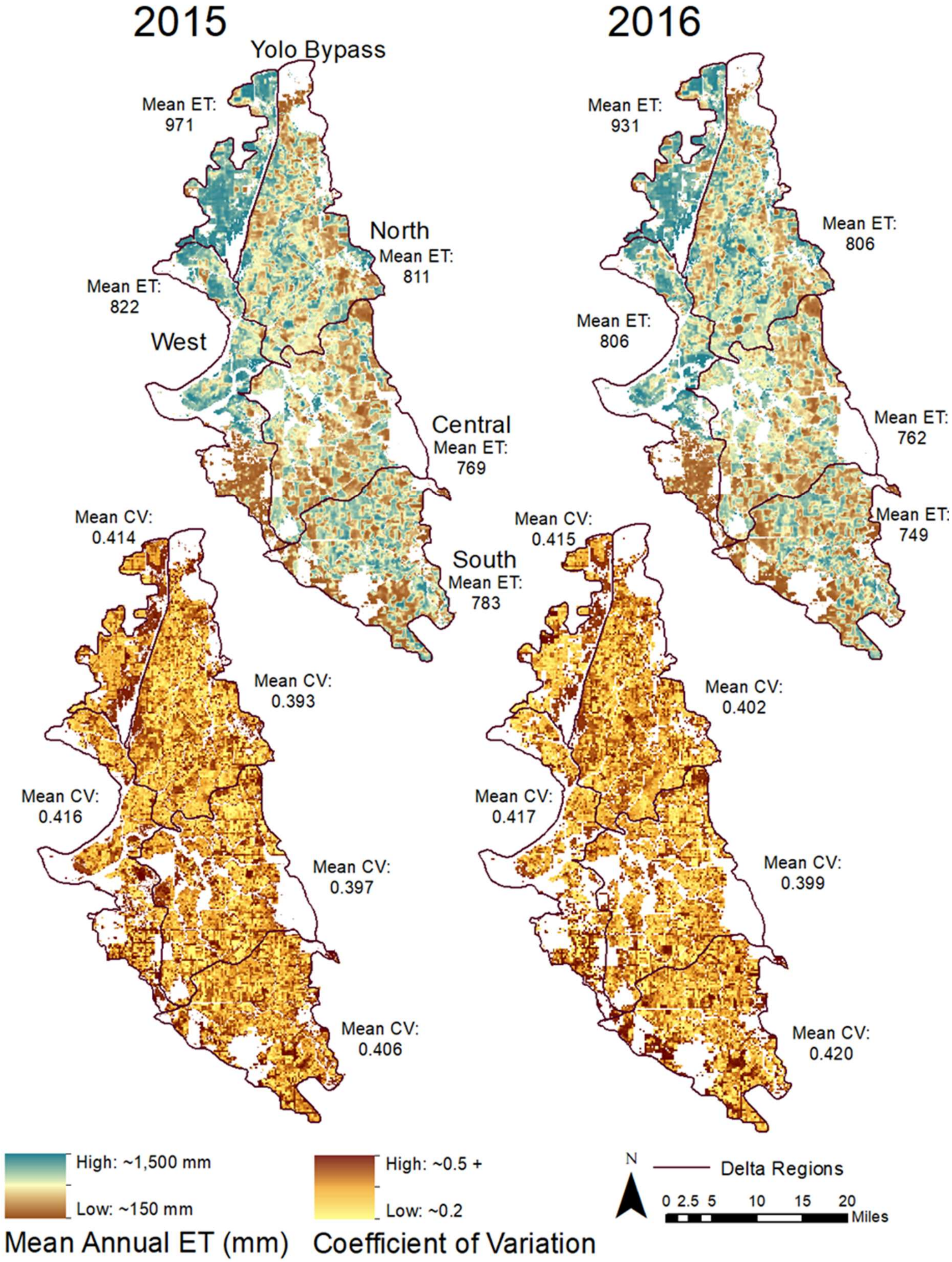


Figure 20. Map of average annual evapotranspiration (top) and coefficient of variation (bottom) among all seven methods in the DSA in 2015 (left) and 2016 (right). White areas represent non-agricultural land uses surveyed by Land IQ (Table 1).

Average ET estimates in Figure 20 are an indication of the spatial distribution of ET estimates among methods and their discrepancies by regions, given that some methods lie on the extremes. Average ET values in Figure 20 show the northwest and west-central Delta have clusters of agricultural areas with higher ET (light and dark blue), where the dominant land uses are pasture and alfalfa (Figure 1). Some areas close to Walnut Grove with a diverse crop mix also show high ET. The southern Delta has scattered areas with high ET, primarily corresponding with alfalfa. The central Delta and agricultural areas close to urban centers in the southwest edge of the Delta are among areas with the lowest annual ET (yellow and brown).

The coefficient of variation maps in Figure 20 show that variation among the model estimates does not always correlate with ET; the southwest Delta east of Tracy has low ET with high variation, clusters in the central-eastern and central-southern Delta have both low variation and low ET, and north of the Yolo Bypass and Sherman Island have high ET with wide degrees of variation in small clusters. Generally, there is higher variation 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 or Franks Tract.

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 estimated rates 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. 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. When compared to Figure 19, Figure 20 shows that coefficients of variation generally decrease as ET results are averaged over the entire year rather than a single month.

3.2.7 Evapotranspiration in Regions of the Delta

Because evapotranspiration estimates change across the Delta based on varying land uses and regional weather patterns, the Delta was subdivided into several large regions to examine patterns in total ET volume estimates in 2015 and 2016. This analysis may also inform regional water management and administration efforts by aligning with jurisdictional boundaries for several water agencies. Five major areas within the DSA were delineated based on the DETAW subareas mapped by DWR (Appendix D) and the service boundaries of the North, Central, and South Delta Water Agencies. These five areas include the Central Delta, North Delta, South Delta, West Delta, and the Yolo Bypass; a map of these regions appears in Figure 21 and these regions are also overlaid in Figure 20.

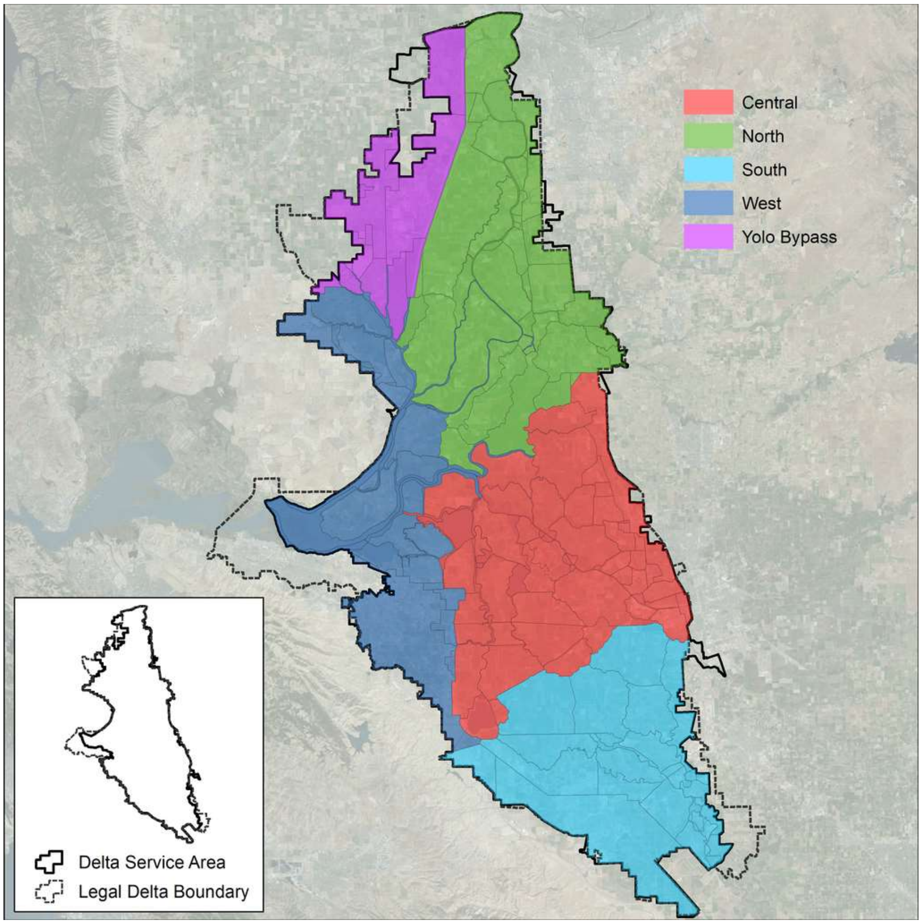


Figure 21. Map of regions within the DSA chosen for further analysis.

A summary of each Delta region's attributes appears in Table 4, including the average elevation (based on the USGS National Elevation Dataset at 30-meter resolution), total land area, percent of agricultural land use (based on classes in Table 1), average total agricultural ET volume in 2015 and 2016 across all seven models (in thousand acre-feet, TAF), and average ET per unit area on agricultural lands (in acre-feet per-acre, AF/ac. or ft.). The ensemble mean of the seven models was used in this case in order to provide insights into regional trends in consumptive use that may aid in Delta water management. Regional variations in ET estimates across the seven methods were not considered since they are addressed in Section 3.2.6 and Figure 20.

Table 4. Attributes of Delta Regions and average evapotranspiration estimates across all seven methods for agricultural lands.

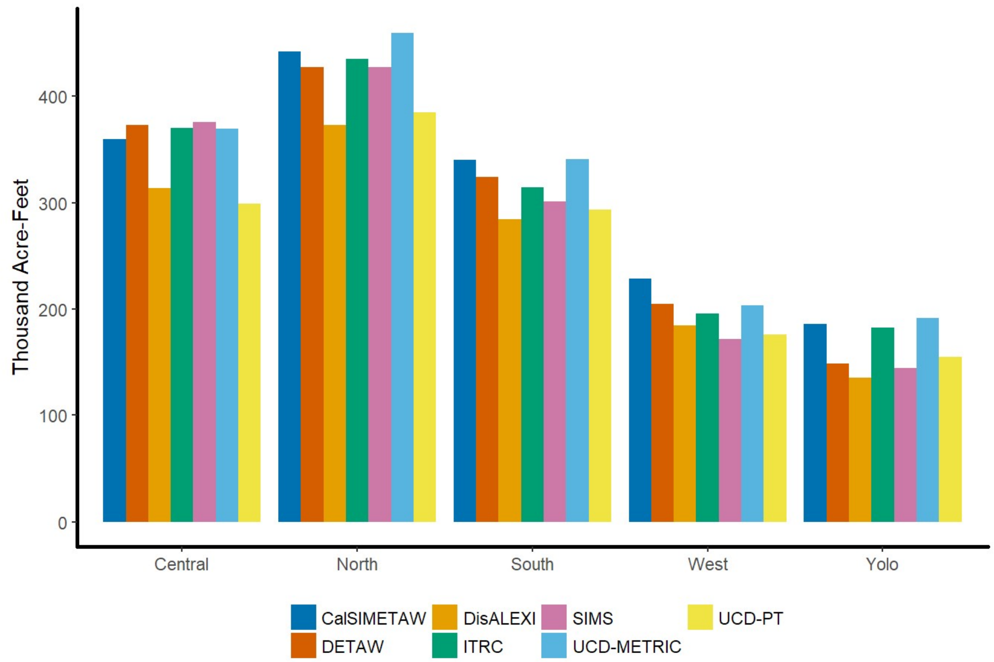
Delta Region	Avg. Elevation (ft.)	Total Area (ac.)	Percent Agricultural Land Uses		Ensemble Avg. Total Agricultural ET (TAF)		Ensemble Avg. Unit Agricultural ET (AF/ac.)	
			2015	**2016**	**2015**	**2016**	**2015**	**2016**
Central Delta	0.35	176,718	68.6%	66.8%	351	341	2.89	2.89
North Delta	4.98	175,269	78.9%	77.7%	421	410	3.04	3.01
South Delta	29.5	142,807	76.2%	75.5%	314	301	2.89	2.79
West Delta	16.2	122,321	52.6%	48.9%	195	179	3.03	2.99
Yolo Bypass	13.3	63,119	71.5%	68.2%	163	149	3.61	3.46
Delta Service Area	*11.7*	*679,594*	*70.2%*	*68.3%*	*1,445*	*1,379*	*3.02*	*2.97*

The attributes in Table 4 indicate that the North Delta had the largest average estimated consumptive water use in the Delta, with the highest annual ET of 421 TAF in 2015 and 410 TAF in 2016. However, the large-scale pasture and patches of rice grown in the Yolo Bypass (Figure 1) are the most water-intensive since it had the highest unit agricultural ET (average total ET for agricultural land uses divided by agricultural area) of 3.61 AF/ac. in 2015 and 3.46 AF/ac. in 2016. The South Delta had the lowest unit ET in both 2015 and 2016 (2.89 AF/ac. and 2.79 AF/ac., respectively). Though only about half of its area is used for agriculture, the West Delta's standardized ET was very close to the average for the entire Delta Study Area.

Agricultural areas decreased in all regions of the Delta from 2015 to 2016, causing net reductions in total ET for all regions and the DSA overall (-4.6%). 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 (-8.6%), which appears to have been caused by large-scale fallowing in the area from 2015 to 2016 (Figure 2). The South Delta experienced modest decreases in ET (-4.2% in total), and the Central and North Delta had the lowest decreases in total ET (-2.8% and -2.6%, respectively). Unit ET was similar in both years in the Central, North, and West Delta, though the South Delta and the Yolo Bypass showed more substantial reductions (-3.5% and -4.2%, respectively) and the DSA's overall unit ET decreased slightly (-1.7%) from 2015 to 2016. This suggests that large-scale land fallowing (discussion below Table 1) decreased unit ET and may also indicate changes in irrigation practices on existing crops which resulted in lower consumptive use.

The total ET volume, in thousand acre-feet, estimated for the major Delta regions by each model in 2015 and 2016 is plotted in Figure 22.

A) 2015



B) 2016

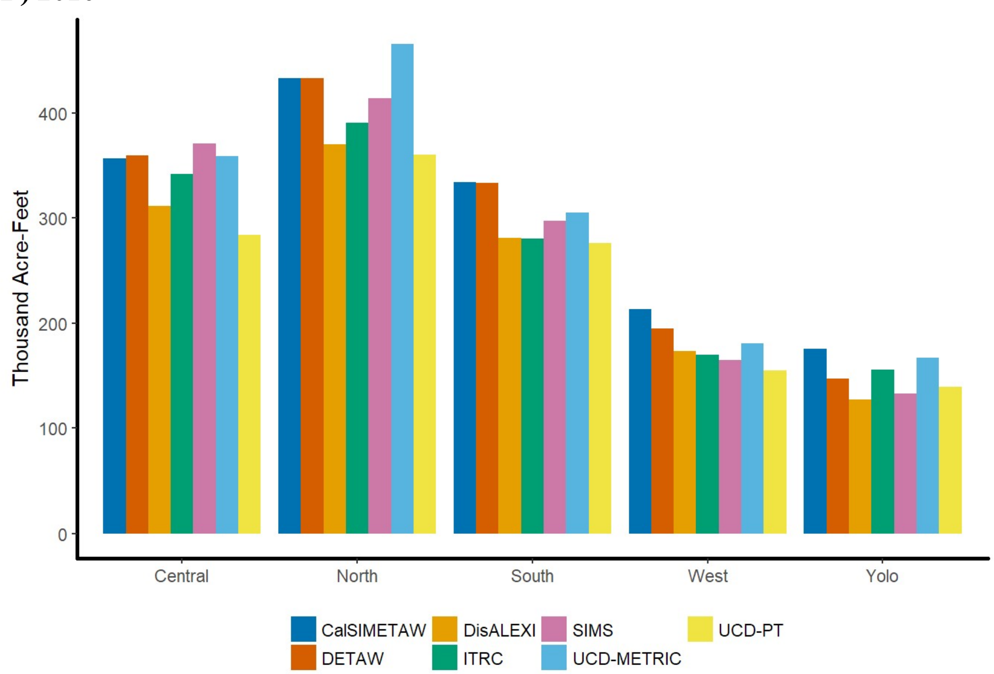


Figure 22. Total annual evapotranspiration volume for agricultural land uses in regions of the DSA in A) 2015 and B) 2016.

Figure 22 indicates that all models estimated within about 500 TAF of each other for each of the Delta regions in 2015 and 2016, though the North Delta and the Yolo Bypass had the greatest variation between estimates. UCD-METRIC estimated the highest ET for all regions in both years, CalSIMETAW and DETAW were often in close agreement near or slightly higher than the mean ET, ITRC-METRIC was in-line with the average ET for most regions, and DisALEXI, SIMS, and UCD-PT were often in agreement and near the lowest ET for all regions. The reasons for these similarities and differences are discussed further in Section 4.1 below.

4 Technical Comparative Discussion

This report examines and compares consumptive use estimates from multiple methods and field stations for a selection of crops grown in the Delta over the course of the 2015 and 2016 water years (October 2014 to September 2015 and October 2015 to September 2016, respectively). Model estimates provide an overview of how consumptive use by crops is likely to be distributed spatially and temporally in the Delta. Field-based ET values, while limited to only parts of the water year and select crops in specific locations, demonstrate the impact of microclimates on ET and offer data on much finer timescales. Correlation and variation between field measurements and model estimates provide valuable insights into the accuracy and usefulness of both methods for ET estimation on multiple scales.

In both 2015 and 2016, the total average estimates of consumptive use from all methods are roughly consistent with the California Water Plan Update 2013 and other studies (Siegfried et al. 2014). However, methods differ in their ET estimates for specific crops at specific times of the year (Section 3.2). This is to be expected as the seven ET estimation methods compared in this study all have differences in input datasets, analysis algorithms, and assumptions. Though inputs were standardized where possible for this study, remaining differences between models include selections of satellite overpass dates, estimate interpolation between overpasses, masking procedure for cloudy images, different land cover interpretations, thermal corrections, and different meteorological inputs such as reference evapotranspiration (ETo). The final updated 2015 and 2016 ET estimates presented show some increased convergence between models since the Interim Report for the project, with most final estimates being roughly within 10% of the mean ET across all methods. Only final model estimates are presented in this report, as an incremental analysis of estimate changes since the Interim Report is beyond the scope of this report. A daily comparison of daily ET results between paired methods is presented in Section 4.1 below, with independent information from each group about methodological differences that may cause discrepancies in ET estimates. Further information on this comparison appears in Appendix A.

A comparison of model ET estimates to the field-based ET estimates and measurements developed by UC Davis was also done. While the 2015 field campaign results in the Interim Report were limited to roughly a month of bare soil ET estimates at four stations (Medellín-Azuara et al., 2016), field measurements in 2016 were significantly expanded to cover the three major crops in the Delta at fourteen different field stations. An intercomparison of model estimates with field campaign results is presented in Section 4.2, including both 2015 bare soil and 2016 alfalfa, corn, and pasture results. Independent information from the UC Davis field campaign team and each modeling group regarding the potential causes of differences is also provided. An additional discussion and comparison of ET measurements with Unmanned Aerial Vehicles (UAVs) is presented in Section 4.4, and further information about that study appears in Appendix L.

Comparison figures were produced using model results at specific locations on specific dates (an explanation of which appears in the Section 4.1 introduction below), along with field-based ET estimates when available (Section 3.1). Comparisons were primarily presented in scatter plots, with ET estimates from a given model or the field campaign on each axis and a single point representing ET estimates from each on a single date at a single location. Linear regressions of these points for a given crop show the correlation and bias of the two models or between a given model and the field-based estimates. R^2 values represent the strength of the correlation, so a R^2 value of one would indicate perfect correlation but not necessarily agreement in estimates. 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 or field-based estimate 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). Time series plots were also prepared for individual locations to present all available data. Comparison statistics were computed for each set of paired datasets, both between models and for model-to-field comparisons. Mean bias, which is the average of the differences between two sets of estimates, quantifies which was higher on average than the other (in mm/d) for a single crop or across all three. Root-mean-square error (RMSE, also in mm/d), the square root of the average square of the absolute differences between estimate datasets, quantifies the overall absolute deviation (in mm/d) between the two. The comparison protocol and key comparisons are presented in the sections below; additional figures and data appear in Appendix A.

4.1 Paired Method Comparison for Specific Dates and Sites

Though the seven models compared in this study are in fair agreement regarding total evapotranspiration volumes in the Delta (Section 3.2.1), results of comparisons indicate some differences between model estimates depending on specific crops, times of the year, and regions of the Delta (Sections 3.2.2 through 3.2.7). Due to many unique assumptions and procedures employed by each model, the reasons for each of these differences are numerous. To isolate multiple factors and facilitate a detailed identification of methodological differences that may have caused discrepancies in ET estimates, the methods were clustered into three groups based on similar methodologies: 1) CalSIMETAW and DETAW (non-remote sensing-based two-step approaches), 2) ITRC-METRIC and UCD-METRIC (remote sensing based on the METRIC method), and 3) DisALEXI, SIMS, and UCD-PT (remote sensing-based with some shared features). For each of the method groups, comparisons of daily ET estimates were made for specific dates at specific locations in the Delta.

Comparison dates were chosen based on the overpass dates that each remote sensing model selected to make estimates using satellite data (Section 2.3.2); the dates used by each model are listed in Appendix A. These estimates are referred to hereinafter as “direct” estimates, though they are technically extrapolated from instantaneous satellite measurements to the entire day on which they took place. To reduce uncertainties in continuous or monthly ET estimates due to temporal interpolation outside of overpassing times and days, daily ET results (in mm/d) estimated on Landsat overpass days were evaluated. This was also the smallest time scale on which results were consistently received from modeling groups. 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 contain clouds. Some remote sensing models further provided continuous daily data for one or both years of the study (Table 2 and Section 2.3.3.4); CalSIMETAW and DETAW, which do not use satellite data, provided continuous daily estimates for the entire study period. Methods were compared directly only for those overpass dates which paired models both used for direct ET estimation.

The locations for comparison were chosen based on the 14 field stations deployed by UC Davis in 2016 (Section 2.2.3), as they represent the three primary crops in the Delta and provided additional data for comparison purposes (Section 4.2). Intercomparisons between models were not limited to days with available 2016 field data, however. To eliminate small local ET variations, results from each model were averaged across a 3-by-3-pixel grid (8,100 m^2 or about two acres) around each field station, and it was verified that none of these pixels contained atypical vegetation growth or non-crop areas such as farmstead or roads. Estimates were also averaged over the entire farm field ("parcel," as surveyed by Land IQ) where stations were located. The grid and parcel-level datasets were compared by model, crop/station, and year/season, and statistical tests revealed that differences between the two datasets were not significant within a 95% confidence interval. CalSIMETAW and DETAW would not be affected by these spatial comparisons since their output resolution is much more coarse than remote sensing-based models. Therefore, all comparisons in the following sections use the 3-by-3 grid-averaged data. Maps of field parcels and grids, comparative scatter and time series plots, and statistical test results for these comparisons appear in Appendix A.

The comparative scatter plots, time series, and statistics (Section 4 introduction) for each key model pairing, along with specific questions tailored to each model, were sent to each of the seven groups with the goal of identifying key methodological differences between paired models and the prospects for ET estimates converging in the future. Individual meetings were conducted with each group, and the following sections summarize these findings. The paired method scatter plots and statistics are reproduced in the sections below; scatter plots for all possible model pairs, time series plots for all fourteen station locations, tables of comparative statistics, and full minutes from meetings with groups appear in Appendix A.

4.1.1 CalSIMETAW and DETAW

CalSIMETAW and DETAW were selected for direct comparison because they are both utilized by DWR for planning and management purposes. Both models are two-step crop coefficient-based and do not use satellite imagery, so their results were compared for all 58 satellite overpass dates used by the other remote sensing groups in 2015 and 2016 (Appendix A). These dates were spread throughout the study period but largely occurred from February through October. A scatter plot comparing CalSIMETAW and DETAW's results for each day and field station, separated by crop type, appears in Figure 23. Linear regression lines, equations, and R^2 values for each crop are also shown.

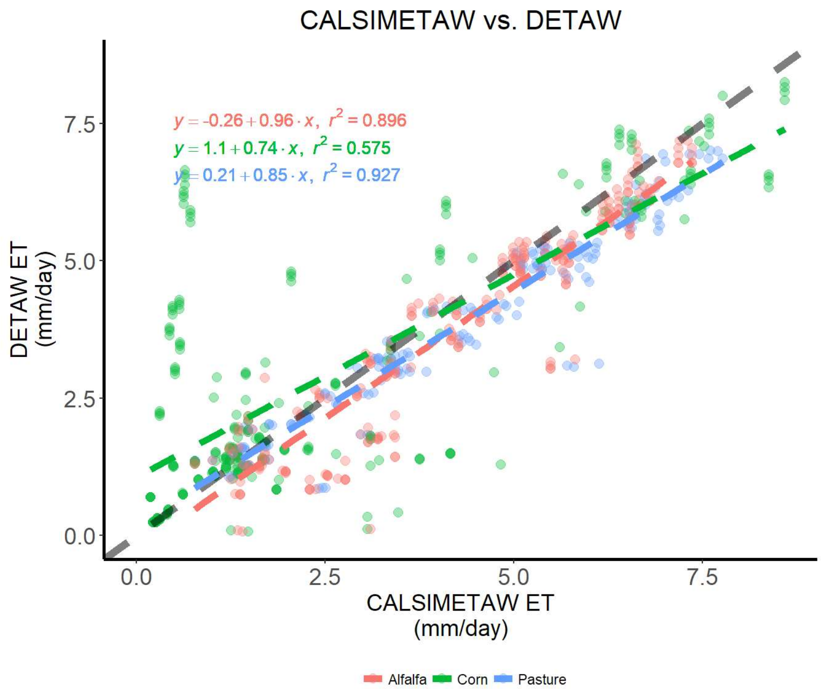


Figure 23. Comparison of daily estimated evapotranspiration by CalSIMETAW and DETAW for selected dates in 2015 and 2016. Each point represents a single daily estimate at a single field station, colored dashed lines and equations represent linear regressions for each model, and the gray dashed line represents the 1:1 ratio.

CalSIMETAW and DETAW are in very good agreement for most data points, with a RMSE of 1.14 mm/d for select dates and fields containing the three major crops in the Delta. CalSIMETAW's results were higher on average than DETAW's, with a positive mean bias of +0.07 mm/d (the lowest among all model pairs) across all three crops, +0.39 mm/d for alfalfa, and +0.3 mm/d for pasture. CalSIMETAW did have a negative mean bias of -0.43 mm/d for corn when compared to DETAW, including several outlying estimates where DETAW estimated much higher ET. Time series plots for single locations (Appendix A) indicate that these discrepancies occurred at four of the five corn stations in late August through mid-September of 2015 and 2016. These specific differences are caused by different assumptions of harvest dates between models, wherein CalSIMETAW assumed that crops were harvested earlier than DETAW, causing a drop in ET 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.

CALSIMETAW and DETAW are based on the same principles, so they would be expected to produce similar results if used on the spatial scale with the same inputs, including reference ET (ETo), crop coefficients (Kc), irrigation periods, and temperature. However, the fundamental difference between the two is that CalSIMETAW estimates potential ET (ETc), while DETAW estimates actual ET (ETa). This modification was made following DETAW's development by Snyder et al. (2006) and Kadir (2006) through calibration and validation with SEBAL-estimated ETa in the 2007 and 2008 growing seasons. CalSIMETAW's ETc results would be expected to exceed ETa results due to plant stress caused by lack of water (see Box 1); agreement of results for a given time and location indicate that DETAW modeled minimal plant stress. The two models are also used on different spatial scales, since CalSIMETAW is used for statewide water planning and DETAW is focused on water accounting in the Delta. These spatial differences alone may also drive discrepancies between the models and in comparisons to other estimates with finer spatial variability. Further regional and systematic differences may also be caused by DETAW's unique ETo values (Section 3.2.3), and other built-in differences that have developed between the models based on modeler judgement. Though CalSIMETAW and DETAW cover different land use categories (DETAW has 11, compared to CalSIMETAW's 26), this would not impact the above comparisons as alfalfa, corn (classified as a field crop), and pasture are present in both models.

Although ETc tends to be higher than ETa, convergence between CalSIMETAW and DETAW could be improved through common spatial scales, ETo values, temperatures, crop coefficients, and planting/irrigation/harvest schedules. CalSIMETAW is undergoing additional improvements to account for immature orchard crops (Appendix C) and will be adapted for groundwater planning under the Sustainable Groundwater Management Act (SGMA), while DETAW's inputs and methods are being recalibrated using the 2016 UC Davis field data and other information obtained from this study. Active communication and cooperation between modeling groups at DWR has already been fostered as a direct result of this study.

4.1.2 ITRC-METRIC and UCD-METRIC

ITRC-METRIC and UCD-METRIC were selected for direct comparison because they represent different implementations of the METRIC remote sensing approach first developed by Allen et al. (2007a and 2007b). While UCD's approach is essentially the default METRIC model (Appendix H), ITRC has made significant modifications to develop its own custom METRIC model (Appendix F). The two methods had 18 common satellite overpass dates in water years 2015 and 2016; ITRC provided data for 15 of these dates. Common dates between the models were spread throughout the study period but occurred primarily during May, July, August, and October. A scatter plot comparing ITRC-METRIC and UCD-METRIC's results for each common overpass and field station, separated by crop type, appears in Figure 24. Linear regression lines, equations and R^2 values for each crop are also shown.

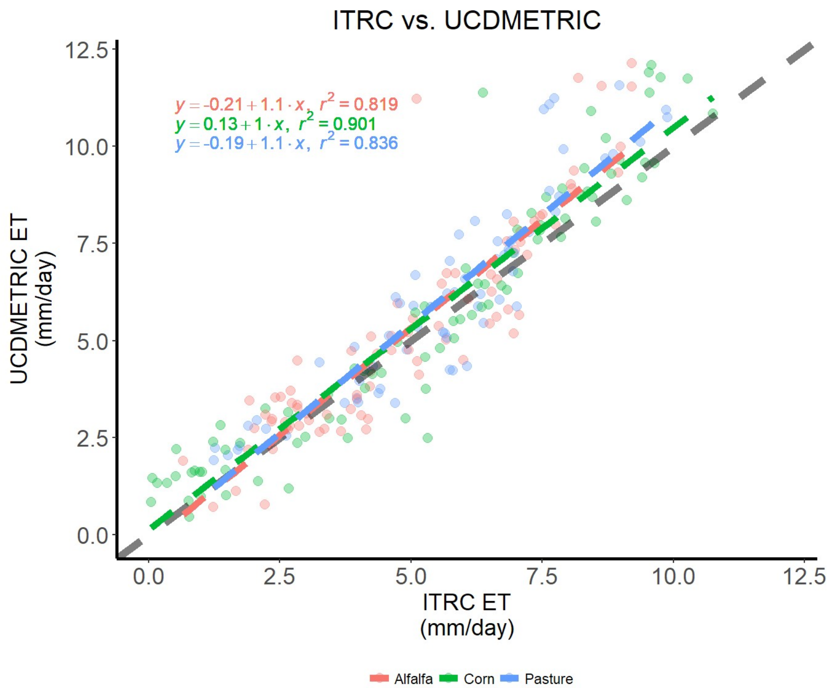


Figure 24. Comparison of daily estimated evapotranspiration by ITRC and UCD-METRIC for common overpass dates in 2015 and 2016. Each point represents a single daily estimate by each model at a single field station, colored dashed lines and equations represent linear regressions for each model, and the gray dashed line represents the 1:1 ratio.

ITRC-METRIC and UCD-METRIC are in good agreement for most data points, with an RMSE of 0.89 mm/d (the lowest among all model pairs) for common overpasses over select fields of the three major crops in the Delta. Individual crop RMSE values were among the lowest of model pairs: 0.84 mm/d for alfalfa, 0.89 mm/d for corn, and 0.95 mm/d for pasture. UCD-METRIC generally estimated slightly higher ET, with a mean bias of +0.25 mm/d over ITRC-METRIC for all three crops overall, +0.18 mm/d for alfalfa, +0.21 mmd for corn, and +0.39 mm/d for pasture. UCD was especially higher on days with high ET. These systematic differences are likely caused by several methodological and version differences between approaches, as well as the modeler judgement that is inherently required as part of the METRIC model.

METRIC model operation is largely dependent on its internal calibration procedure, which requires the selection of a ‘hot’ bare soil and ‘cold’ well-irrigated reference crop pixel 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 may be affected by 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 ET 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 (ETrF for UCD, EToF for ITRC) 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 (further discussion appears in Appendix H).

Some METRIC input datasets varied between the models based on operator judgement and may have introduced additional systematic differences. 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 USGS; though it has developed a more advanced sharpening process, it was not employed for this study (Appendix F). UCD-METRIC developed a custom process for the Delta to mask out open water and riparian areas before sharpening the thermal data. 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. While UCD-METRIC used the Land IQ dataset provided by DWR for this study (Section 2.1 and Appendix J), due to time constraints associated with adapting that dataset, ITRC chose to use a quality-controlled version of the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) (USDA, 2017). More information regarding this dataset appears in Section 4.2.1 below and Appendix F.

UCD-METRIC is still in the development stage and is being refined with additional iterations, analysis software tools, and analyst experience. The generic METRIC model is also continually being updated by the University of Idaho with respect to individual energy balance components and in specific 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). It is likely that both the METRIC software versions and further modifications by ITRC may produce different results even with the same inputs. As further changes are made to either model, this may result in results diverging to some degree rather than converging. However, close model versions, similar operator experience, internal sensitivity analysis and model iterations, and consistent input datasets, would all be expected to improve convergence between the two METRIC models.

4.1.3 DisALEXI, SIMS, and UCD-PT

DisALEXI, SIMS, and UCD-PT were selected as the third group of paired comparisons, though they are each unique methods with less obvious similarities than the other paired methods. DisALEXI and SIMS had 19 common satellite overpass dates, all in water year 2016 and primarily during May, July, and August; a scatter plot comparing results for each overpass day and field station appears in Figure 25. DisALEXI and UCD-PT had nine common dates, mostly during July and August 2016; their comparison plot appears in Figure 26. Finally, SIMS and UCD-PT had 20 common dates in 2015 and 2016; their comparison plot appears in Figure 27. These dates were spread throughout the study period but occurred primarily from August through October. Each of the below plots is separated by crop type, with linear regression lines, equations, and R^2 values provided for each of the three major crops in the Delta.

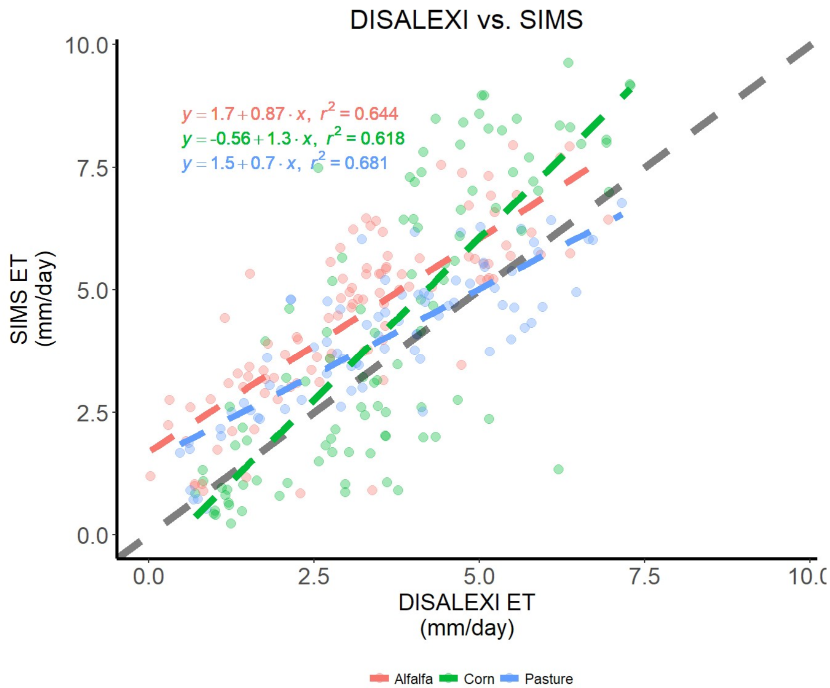


Figure 25. Comparison of daily estimated evapotranspiration by DisALEXI and SIMS for common overpass dates in 2016. Each point represents a single daily estimate by each model at a single field station, colored dashed lines and equations represent linear regressions for each crop, and the gray dashed line represents the 1:1 ratio.

Figure 25 shows that, compared to the other plots in this section, DisALEXI and SIMS are in poor agreement, with an RMSE of 1.64 mm/d (the highest among all model pairs) for common overpasses over selected fields of the three major crops in the Delta. These discrepancies are higher for alfalfa and corn (RMSE values of 1.70 and 1.96 mm/d, respectively), while the models are in fair agreement for pasture (RMSE of 1.04 mm/d). SIMS generally estimated higher ET for all three crops, with an overall mean bias of +0.87 mm/d over DisALEXI and a high mean bias of +1.25 mm/d for alfalfa. Time series plots for single locations (Appendix A) suggest that these large discrepancies occurred over relatively short periods during the peak growing season. This is likely due to a variety of assumptions and methodological differences that result from the two models being built for considerably different scales and approaches to ET estimation.

DisALEXI strives to estimate ET at a very large extent (up to globally) for research purposes, whereas SIMS is targeted towards field-level water management and irrigation scheduling. SIMS estimates basal crop ET (ETcb), which assumes unstressed crop conditions and dry soil surfaces. DisALEXI, on the other hand, attempts to capture stressed crop conditions using satellite thermal data and includes an evaporation component. Therefore, SIMS would be expected to estimate higher ET than other models during water-stressed conditions. Conversely, dates where DisALEXI or other models estimated higher ET than SIMS may have been caused by early season irrigation or precipitation events which resulted in evaporation from exposed topsoil. DisALEXI utilizes a large amount of satellite data compared to SIMS, including Geostationary Operational Environmental Satellite (GOES) sensible heat flux measurements at a 1x1 km resolution; depending on the heterogeneity of the study area, sharpening of this data could potentially bias DisALEXI's estimates in comparison to models using different datasets. DisALEXI also uses coarse insolation inputs from the University Corporation for Atmospheric Research (UCAR) Climate Forecast

System Reanalysis (CFSR) at a global scale, rather than local-scale meteorological measurements from a system like CIMIS, causing potential systematic differences as a result of data sharpening. DisALEXI used coarse-resolution National Land Cover Database (NLCD) information from the Multi-Resolution Land Consortium (MRLC) rather than the fine-resolution Land IQ data used by other methods; however, because it is a strict energy balance approach to ET estimation this would not be expected to bias estimates significantly.

When averaging ET results over larger spatial scales such as parcels or regions of the Delta and temporal scales like month or water year, variations in both models tend to smooth out; SIMS grid-level results for all three crops showed a +0.05 mm/d mean bias over the parcel scale (Appendix A), and monthly comparisons for the overall Delta (Sections 3.2.1 through 3.2.7) show greater relative agreement between SIMS's and other models as a whole. DisALEXI and SIMS estimates may not be expected to converge 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 to improve prospects for convergence.

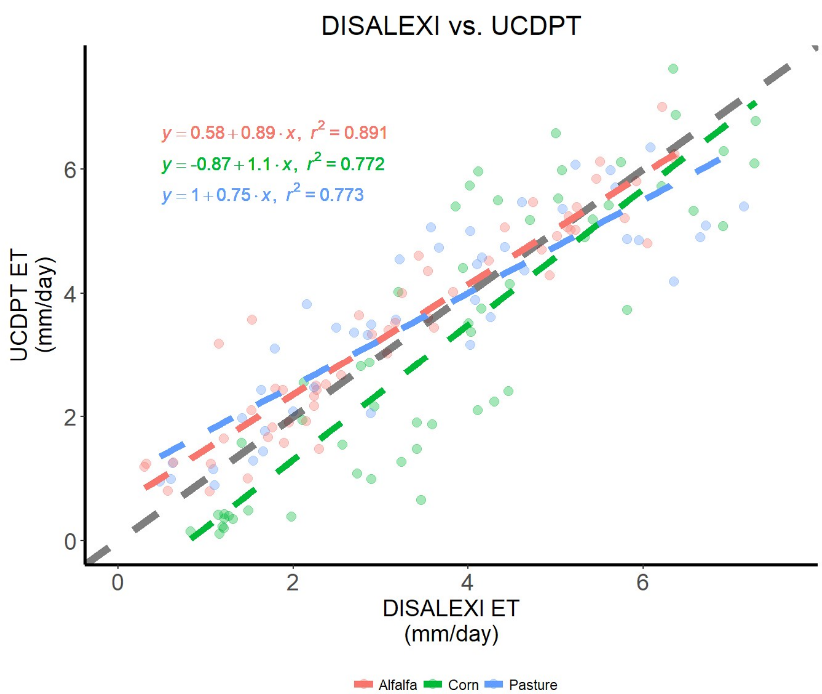


Figure 26. Comparison of daily estimated evapotranspiration by DisALEXI and UCD-PT for common overpass dates in 2016. Each point represents a single daily estimate by each model at a single field station, colored dashed lines and equations represent linear regressions for each crop, and the gray dashed line represents the 1:1 ratio.

DisALEXI and UCD-PT are in good agreement, with an overall RMSE of 1.11 mm/d during common overpasses over selected fields of the three major crops in the Delta. The biggest discrepancies between these two models were found over corn fields (RMSE of 1.43 mm/d), where DisALEXI had a mean bias of +0.63 mm/d over UCD-PT. Estimates were higher from UCD-PT for alfalfa and pasture, with respective mean biases of +0.21 and +0.12 mm/d over DisALEXI. As with SIMS, DisALEXI and UCD-PT have fundamental methodological differences, hence many of the sources of discrepancy discussed for SIMS above would also apply to this comparison. Estimates made by UCD-PT rely on field data for parameter optimization, so its use of the 2016 UC Davis field data (Section 3.1.2) for calibration and validation of alfalfa, corn, and pasture ETa values would also tend to bias its results against other models which may not agree with the field data (Section 4.2 below). While UCD-PT can produce ETa estimates without field data calibration (Appendix I), its modeling team believes that calibration to additional field data increases its model accuracy and makes it more robust and optimized. Ideally additional field data should be gathered for the full growing season for crops to which the model is not yet calibrated.

DisALEXI uses a Priestley-Taylor component to make an initial estimate of transpiration based on net radiation divergence within the canopy, so DisALEXI and UCD-PT results would be expected to agree in times of full vegetation cover and minimal water stress. DisALEXI's use of higher temporal resolution data such as GOES and MODIS could cause outliers in comparison to UCD-PT, since UCD-PT uses net radiation at a daily scale. UCD-PT inherently requires field data for validation, whereas DisALEXI does not explicitly use any input ET measurements. These data would only be used to correct the physical process assumptions made by the model. Thus DisALEXI and UCD-PT estimates would not be expected to converge further unless significant process changes and input datasets changes are made to both models.

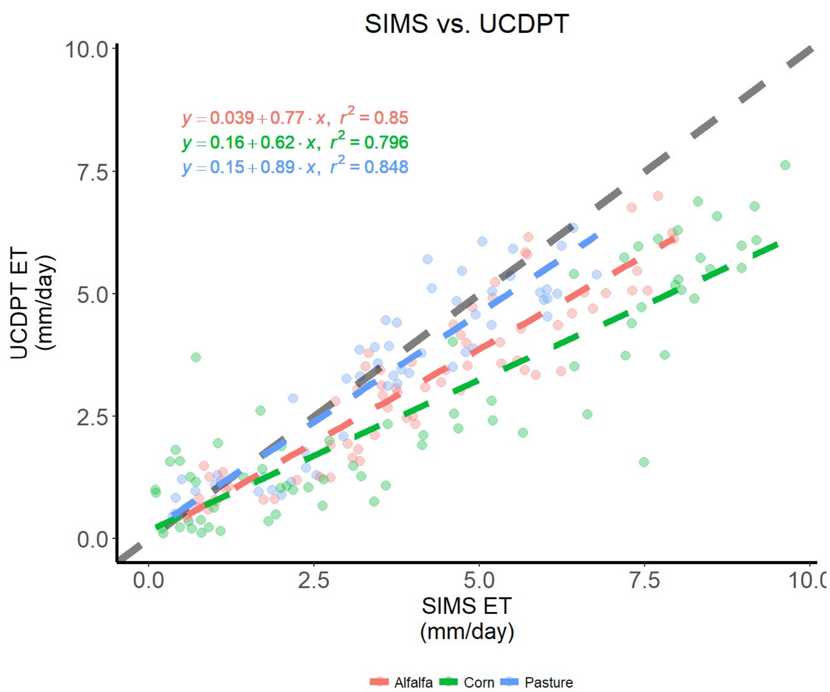


Figure 27. Comparison of daily estimated evapotranspiration by SIMS and UCD-PT for common overpass dates in 2015 and 2016. Each point represents a single daily estimate by each model at a single field station, colored dashed lines and equations represent linear regressions for each crop, and the gray dashed line represents the 1:1 ratio.

Figure 27 shows that SIMS and UCD-PT are in somewhat poor agreement in ET estimates, with a RMSE of 1.44 mm/d for common overpasses over the three major crops in the Delta and a corn RMSE of 1.98 mm/d (the highest of any model pairing for an individual crop). SIMS generally estimated higher ET for all three crops, particularly corn (mean bias of +1.27 mm/d over UCD-PT) and alfalfa (mean bias of +0.88 mm/d). ET estimates by SIMS and UCD-PT were highly correlated, however, with R^2 values ranging from 0.80 to 0.85. This suggests that both models likely capture similar spatial and temporal variability. As SIMS and UCD-PT are substantially different in their methods, many of the differences discussed between DisALEXI and SIMS above (i.e. SIMS's basal crop ET possibly being greater than actual ET and short-term precipitation causing lower estimates for SIMS) would also apply for the comparison between SIMS and UCD-PT. Furthermore, UCD-PT's calibration to the 2016 UC Davis field data (Section 3.1.2) would cause differences if SIMS's estimates did not align with field-based estimates (Section 4.2 below). This is especially true for corn, for which less than a full season of data was available from the UC Davis field campaign for calibration.

While the SIMS team would expect that its ETcb results would be representative for much of the crop acreage in the Delta, the field team noted that some of the fields where stations were installed were irrigated only sporadically (further discussion appears in Appendix B). If farmers were to delay irrigation to aid with harvest (i.e. mid-season alfalfa cutting) or to adjust for inadequate water supplies, then SIMS estimates would be higher than other models. This would also be the case if there were residual biomass left in the field after harvest (i.e. corn). Intentionally stressed crops (i.e. fruit orchards, or wine grape vineyards) would also have different results between SIMS and other models during specific times of the year. SIMS is sensitive to estimated canopy height variations, to the empirical relationship between crop coefficient and fractional crop cover, and does not use thermal input data. UCD-PT is also undergoing refinements to use additional satellite data, and the accuracy of its estimates may be expected to increase further.

4.1.4 Additional Model Differences

Estimation of different types of ET (potential ET by CalSIMETAW, basal crop ET by SIMS, actual ET by other methods) would cause differences between models for crops in the Delta which are maintained in less than optimal condition. Though input datasets for the seven ET estimation models were standardized where possible for this study (i.e. use of Spatial CIMIS ETo by five of the methods), some input data differed between models due to modeler judgement (i.e. DisALEXI and ITRC-METRIC using different land use data, and UCD-METRIC using custom thermal sharpening methods). Furthermore, the assumptions of some methods are hardcoded and would take significant time to modify to encourage agreement between models (i.e. crop coefficients, irrigation scheduling, and harvest calendars between CalSIMETAW and DETAW).

A common data source among the five remote sensing-based methods (DisALEXI, ITRC-METRIC, SIMS, UCD-METRIC, and UCD-PT) is satellite overpass data from NASA's Landsat satellites, one of which passes over the Delta site every eight days. At the discretion of each model operator, each team utilized a different set of scenes from both Landsat 7 and 8 to develop ET estimates (Appendix A); the daily estimate comparisons above used only common dates between paired methods. UCD-PT used the most images (43) across all water years, with cloudy observations filtered out at the pixel level, while UCD-METRIC used the fewest images (21). UCD-METRIC did not use any images for water years 2014 or 2017, which may have led to poor interpolation during the early part of water year 2015 and late part of water year 2016. Total annual ET estimates for the Delta would be expected to converge among methods if all models were able to use the same overpass images to develop estimates. However, even then the models differ in the method for masking clouds visible in these images and in the procedure used to interpolate daily ET estimates between overpasses. This contributes to discrepancies among methods on non-overpass dates. These differences can be seen in the monthly estimate variations described in Section 3.2; due to the complexity of masking and interpolation methods and the numerous differences they could cause, daily estimates on non-overpass dates were not compared for this study but do appear in time series plots in Appendix A.

Most remote sensing methods used to estimate ET rely on the optimization of some key parameters, often using ground data for verification and calibration. For example, METRIC, one of the energy budget residual-based approaches, assumes that the ET of the well-watered 'cold' pixels is equal to an alfalfa reference ET multiplied by a constant. Thus, discrepancies between METRIC ET estimates can be introduced both by the operator's selection of the reference ET site and by adjusting the constant to account for region-by-region differences. Due to the unique characteristics in the Delta, with its many channels and wind corridors, regional differences may be significant even over modest distances. The crop coefficients for SIMS are derived empirically as a function of crop canopy cover based on the normalized difference vegetation index (NDVI), combined with associated estimates of crop height and stomatal control. Similarly, the partitioning of available energy to latent heat in the UCD-PT approach is dependent on calibrated empirical relationships with leaf area index and moisture index. Before applying the method for ET mapping, these empirical coefficients are usually optimized for each plant functional type or crop type with available field measurements. The objective is to minimize the differences between field-measured and estimated ET, and thus increase the accuracy of ET estimation. Each of the seven methods compared in this study was developed and tested with various field datasets collected over various time periods and locations, usually outside the Delta study area, chosen at the discretion of each model's operator. For this project, only UCD-PT chose to use a subset of the field data collected by UC Davis for model calibration and parameter optimization and to use the remaining field data for independent validation (Section 4.2.3 and Appendix I).

4.2 Comparison to Field-Measured Evapotranspiration

The following sections compare the results of 2015 and 2016 field-based ET estimates to model-based ET estimates made by the seven research groups at the corresponding locations in the Delta. Ground-truthed crop identification at the field stations is also compared to Land IQ's land use dataset and NASS Cropland Data Layer for both water years. Model results were averaged over a 3-by-3-pixel grid (8,100 m^2 or about two acres) around each of the stations in order to smooth out small regional variations; a more thorough explanation of this procedure appears in the introduction to Section 4.1, and supplemental figures appear in Appendix A. Though a fetch analysis was not conducted as part of the UC Davis field campaign for this study (references appear in Appendix B), these pixel grids are likely similar to the average measurement distance of the equipment at field stations during the time of satellite overpasses.

4.2.1 Assessment of Land Use Data at Field Campaign Sites

Land use datasets were used to assign ET estimates by the two DWR crop coefficient models (CalSIMETAW and DETAW) compared in this study. Though remote sensing-based models do not explicitly use land use data to estimate ET, those data do play a role in the intermediate steps of several models (Section 4.1). Furthermore, land use datasets were used to mask ET results to present them by crop in this study (Sections 3.2.1 through 3.2.5). To evaluate errors in land use surveys which may have affected model estimates to some degree when compared to field-based ET estimates, the observed crop type growing at the field stations was compared to land use classification datasets. The field station deployment locations (Section 2.2 and Figure 3) were compared to their corresponding pixels in the Land IQ dataset (Section 2.1 and Appendix J) and the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL). The CDL is a national 30x30-meter-resolution land cover dataset (USDA, 2017) that was used by ITRC-METRIC to develop its ET estimates (Section 4.1.2 and Appendix F). These land use comparisons are summarized for both 2015 and 2016 in Table 5. Though DisALEXI used National Land Cover Database information instead of the Land IQ, since it is a strict energy balance model this would not be expected to bias ET estimates significantly.

Table 5. Land use comparison between field campaign stations and corresponding Land IQ and NASS CDL 30x30-m pixels for 2015 and 2016.

Water Year	Station ID	Field Station Crop	Land IQ Classification	CDL Classification
2015	D1	Fallow (entire year)	Tomatoes	Other Hay/Non-Alfalfa
	D2	Fallow (entire year)	Tomatoes	Other Hay/Non-Alfalfa
	D3*	Fallow (Corn in growing season)	-	Safflower
	D5	Fallow (Alfalfa/Oats in growing season)	Fallow	Sweet Corn
2016	D02	Alfalfa	Alfalfa	Alfalfa
	D07	Alfalfa	Alfalfa	Alfalfa
	D10	Alfalfa	Alfalfa	Alfalfa
	D13	Alfalfa	Alfalfa	Alfalfa
	D14	Alfalfa	Alfalfa	Alfalfa
	D01	Corn	Corn	Corn
	D06	Corn	Corn	Corn
	D08	Corn	Corn	Corn
	D09	Corn	Fallow	Corn
	D11	Corn	Corn	Corn
	D03	Pasture	Pasture	Alfalfa
	D04	Pasture	Pasture	Alfalfa
	D05	Pasture	Pasture	Alfalfa
	D12	Pasture	Pasture	Fallow/Idle Cropland

*2015 Station D3 was outside the Legal Delta, so no Land IQ classification information was available at the point.

For the 2015 irrigation season, field-based ET estimates were developed only for fallow fields (though the crop previously grown in each field during 2015 was noted) above sea level. Fallow fields were cleaned to remove 2015 season crop planting material and weeds prior to field equipment deployment, though stations D1 and D2 had sparse weeds. Land IQ's classifications for stations D1 to D5 (station D4 was excluded due to an uncertain calibration of a radiometer) apply to crops being grown during the prime irrigation season (roughly March through September). However, the crops surveyed by Land IQ do not correspond with the crops known to be grown during the irrigation season for any of the three stations with available data (though Land IQ's fallow classification for D5 does match the condition under which field measurements were taken). Depending on when they assumed that final harvests took place in the regions where stations D1 and D2 were located, CalSIMETAW and DETAW may have estimated ET from tomatoes rather than fallow land when field measurements were taking place in September 2015. Remote sensing ET estimates would not be expected to be impacted by misclassifications, as they would observe bare soil in satellite images regardless, but ET estimates from fields D1 and D2 were reported under tomatoes (Sections 3.2.1 through 3.2.5) rather than fallow lands. The increased accuracy of Land IQ's 2016 classifications may point to improvements in identification techniques over time (Appendix J).

The crop classifications in the NASS CDL dataset also do not match any of the crops known to be grown at the 2015 field stations, though this would not be expected to bias ITRC-METRIC's results unless substantial aerodynamic resistance adjustments were made for these crops compared to bare soil.

For the 2016 irrigation season, the Land IQ classification matches the crops known to be grown at all field stations except for D09, which was surveyed as fallow even though corn was planted at the field site. This may have been caused by Land IQ surveying at a time after the crop was harvested, or due to improper identification at a time when the crops were still young. Any inconsistencies should be addressed directly with Land IQ since its work (Section 2.1 and Appendix J) was outside the direct scope of this study. This misclassification caused CalSIMETAW and DETAW to estimate ET for fallow land at D09, likely biasing estimates lower than they would have been from corn and making them lower than field-based corn ET estimates. Other remote sensing results for field D09 would have been reported under fallow rather than corn (Sections 3.2.1 through 3.2.5) due to masking procedures. UCD-METRIC's results would only be biased by this misclassification in the very unlikely event that field D09 was selected as a 'hot' bare soil pixel; surface roughness is not adjusted for corn, and satellite images would still have captured vegetation attributes in the pixel. The CDL dataset matched the field stations for all alfalfa and corn sites, but all pasture stations (D03, D04, D05, and D12) were misclassified at the corresponding pixel as either alfalfa or idle land; surrounding pixels in the same parcels were a mix of alfalfa, fallow/idle, and grassland/pasture. This points to the difficulty of differentiating among similar-looking short crops in satellite images, though it should not have affected ITRC's results since alfalfa and idle land would not be adjusted for aerodynamic resistance compared to pasture (it is highly unlikely that the single field station was selected as a 'cold' well-watered reference alfalfa pixel for the entire Delta). Large spatial scale and remotely sensed land use datasets such as CDL have inherent uncertainties, but the impact of pixel-level misclassifications would be anticipated to decrease significantly at the scale of the Delta. Nevertheless, certainty in local or field-scale crop classifications may help improve the accuracy of ET estimation models and help with validation of remotely-sensed data.

4.2.2 Fallow Fields Comparison in 2015

Estimates of evapotranspiration from each of the seven methods under study were compared to field-based ET estimates at four fallow fields for the period from September 7, 2015 through October 5, 2015. Because less than a complete month of field data were available, the monthly average of field-based estimates for September 2015, in mm/d, was compared to monthly average estimates reported by models. Model estimates were averaged across a 3-by-3-pixel grid (8,100 m^2 or about two acres) around each of the field stations. As mapped in Figure 3, Stations D1 and D2 were located near Byron Highway (West Delta), Station D3 was by Kasson Road (outside the South Delta), and Station D5 was near Crocker Road (South Delta). Because station D3 was located just outside the DSA, CalSIMETAW and DETAW did not produce ET estimates that could be compared to field data at that location.

Due to seepage, evaporation from bare soil can be increased if stations are located in areas below sea level. Recent precipitation can also enhance evaporation, though all 2015 field stations were located above sea level (1.5 to 17 meters) and precipitation had not occurred for well over a month before the start of the field measurements. Precipitation did occur on September 30 and October 1, 2015, and the topsoil was wet until the end of the deployment period on October 5 (Medellín-Azuara et al., 2016). Comparisons between field-based and model ET estimates, as well as reference ET (ETo) data from Spatial CIMIS (Hart et al., 2009) at corresponding locations, are presented in Figure 28 below.

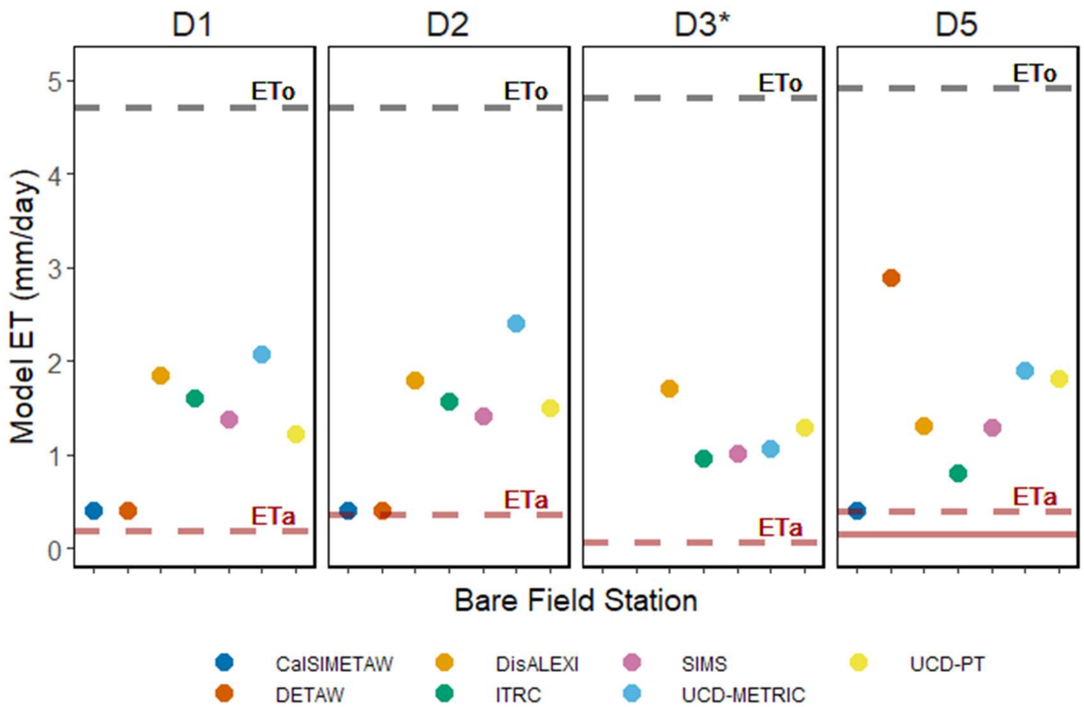


Figure 28. Comparison of average daily evapotranspiration estimates between models and 2015 field-based measurements for September 2015. The red dashed line represents surface renewal estimates, the solid red line for D5 represents eddy covariance measurements, and the black dashed line presents average Spatial CIMIS reference evapotranspiration (ETo).

*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.

As expected, all model and field-based estimates of bare soil ET in September 2015 were well below Spatial CIMIS ETo values for the same time and location. Computed ETo estimates for the sites using field data (Appendix B) had interquartile ranges from 4 to 6 mm/d across all four sites in September. The ensemble average estimate by models 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-based estimates. The bias of models over the field estimates range 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 ETa values closest to those reported at field stations, and DETAW's ETa values for all but station D5 were also very close to those measured. It appears that both models assumed that tomatoes had been harvested from D1 and D2 by September (Section 4.2.1), so these low values were likely produced by DWR's two-stage evaporation model developed to account for ET from fields during the non-growing season (Appendix C). UCD-METRIC generally estimated the greatest ET for the period, which was likely a result of its 'hot' pixel calibration (Section 4.1.2 and Appendix H).

A total of 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 during the month (Appendix A). 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.

Satellite overpasses would be expected to capture satellite-acquired data (i.e. radiation and thermal) that corresponded with the actually bare fields as long as the images employed were within the field equipment deployment time period. 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 ETo was likely declining throughout the month at the sites (Section 3.2.3). Other occurrences of bare soil estimates being greater than field-based may have been caused by limitation in model parameterizations for bare soil. For example, UCD-PT used a generalized parameterization of the PT coefficient because there were insufficient bare soil field measurements available to calibrate its coefficients. Though SIMS does not estimate evaporation from bare soil (Section 2.3.1 and Appendix G), it sets basal crop coefficient (Kcb) values to 0.15 for agricultural bare soil following ASCE (2016). Any residual vegetation left in fields D3 (corn) or D5 (alfalfa/oats) following harvest would further elevate Kcb values, however. Other discrepancies 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.

As discussed in Section 3.1.1, the short period of bare soil field measurements and other uncertainties around measurements limit the ability to draw definite conclusions about bare soil ET measurements and modeling from this study alone (additional recommendations appear in Section 5). Because of the foregoing limitations, a specific study of ET over bare fields is planned for the 2018 growing season.

4.2.3 Alfalfa, Corn, and Pasture Comparison in 2016

Daily evapotranspiration estimates from each of the seven models were obtained for satellite overpass dates on which imagery was used to directly estimate ET (Section 4.1 and Appendix A). This methodology allowed for the most detailed comparison and minimized the discrepancies in monthly ETa estimates among models (Section 3.2) that may have been caused by interpolation between satellite images. Model estimates were extracted at the locations of the 14 field stations over alfalfa, corn, and pasture (the three predominant crops in the Delta) fields in 2016 (Figure 3), averaging estimates over a 3-by-3 grid of pixels around each field station to average out small regional differences. For every overpass date with available field measurements, these daily ET estimates (in mm/d) were compared to the daily average field-based ET estimation (including direct ET measurements over alfalfa by an IRGASON station at site D13) at each of the fourteen field stations (Section 3.1). Though deployment timelines for the field stations varied (Figure 4), a total of 20 Landsat overpass dates had at least one station with available measurements for comparison (Appendix A). Results from CalSIMETAW and DETAW, which do not utilize satellite data, were compared for all 20 overpass dates during deployment. Comparison scatter plots between the field data and each model are plotted by crop, including linear regression lines, equations, and R^2 values, in Figure 29. Comparative statistics (Section 4 introduction) were also computed, and additional comparison plots and statistics appear in Appendix A.

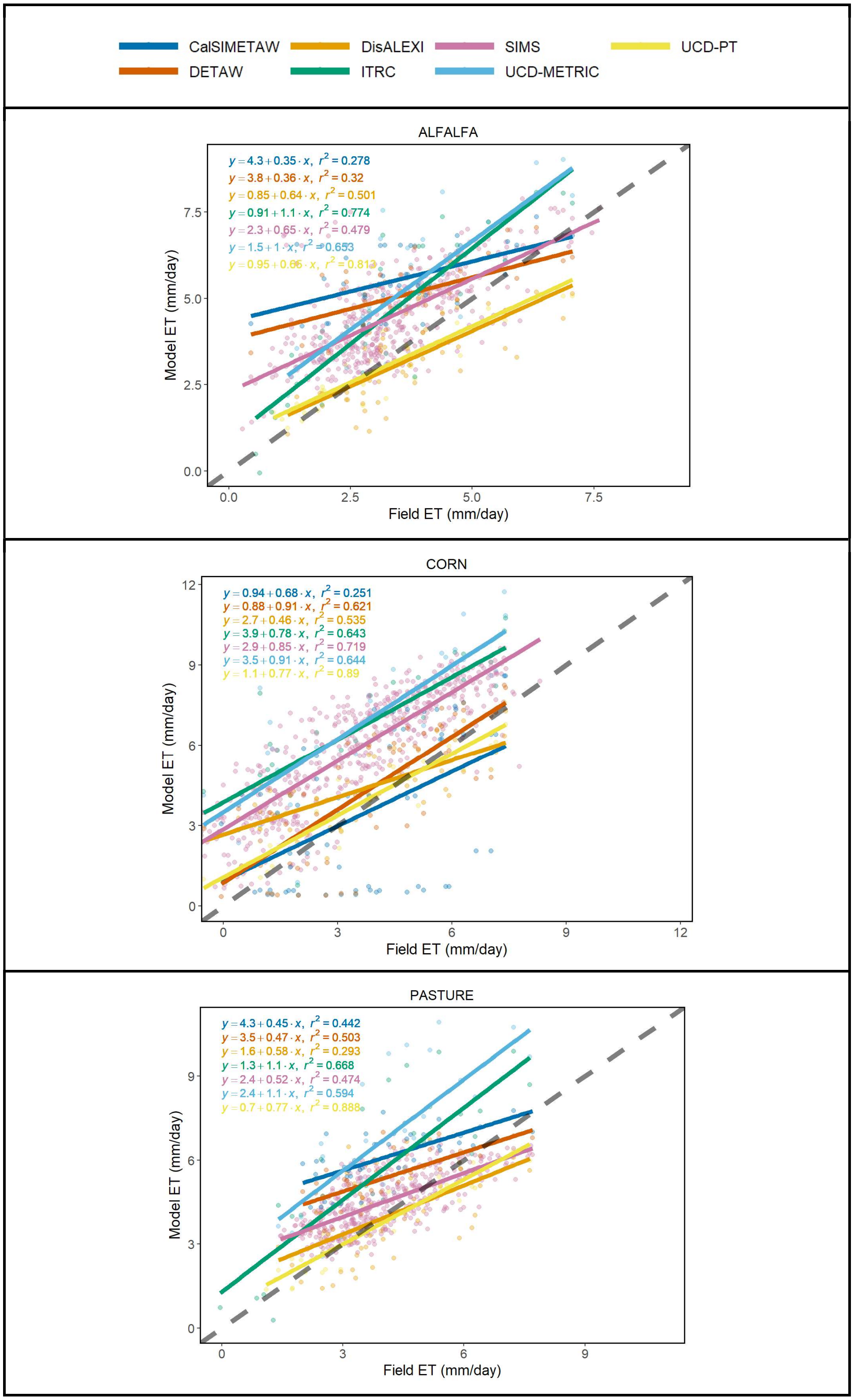


Figure 29. Comparison of daily average evapotranspiration estimates in alfalfa, corn, and pasture to 2016 field-based estimates and measurements. Each point represents a single daily estimate and daily average measurement at a single field station, solid lines represent linear regressions for each model with respective R^2 values, and the gray dashed line represents the 1:1 ratio.

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 (Appendix I). This is likely the reason that UCD-PT ET estimates had the lowest RMSE values (0.94 mm/d for alfalfa, 0.76 mm/d for corn, 0.78 mm/d for pasture, and 0.82 mm/d overall) when compared to the field-based estimates, as well as the lowest mean biases (-0.39 mm/d for alfalfa, +0.09 mm/d for corn, -0.33 mm/d for pasture, and -0.19 mm/d overall) over the field data on its overpass dates.

Field-based ET estimates and measurements in 2016 ranged from 0-8 mm/d across all stations (the horizontal axis in Figure 29), while the model-estimated ET range on overpass dates (the vertical axis in Figure 29) varied from 0-12 mm/d depending on the crop. In general, the estimated ET values from all methods match similar trends to field-based values, capturing much of the temporal and spatial variation between stations. However, many estimation models showed a systematic positive bias with respect to field data for all three crops. In contrast, in the high ET range (> 6 mm/d) for alfalfa and pasture, a negative bias with respect to field-based measurements and estimates appears more common among methods. For alfalfa and corn, the y-intercepts of linear regression lines for the METRIC models and SIMS were similar to the mean bias of a few mm/day seen for the 2015 fallow field data (Figure 28).

For overpass dates with available field data over the three major crops in the Delta (excluding UCD-PT since it was calibrated to part of the data), DisALEXI was the closest to field data with an RMSE of 1.43 mm/d and a mean bias of +0.13 over the field data for all three crops combined. DisALEXI was closest compared to alfalfa (1.14 mm/d RMSE and -0.34 mm/d mean bias compared to the field data) and pasture (1.41 mm/d RMSE and +0.04 mm/d mean bias over field), though SIMS had a lower RMSE (1.03 mm/d) compared to field measurements. UCD-METRIC had both the highest RMSE and the highest mean bias for the three crops combined (3.08 mm/d and +2.62 mm/d, respectively) and for most of the individual crops (Appendix A). ITRC-METRIC showed a similar slope for each crop but with less upward bias (2.55 mm/d RMSE and +2.06 mm/d mean bias over field for all three crops combined). While CalSIMETAW and DETAW had relatively low overall mean bias compared to the field data (+0.60 mm/d and +0.56 mm/d over all field data, respectively) and DETAW estimated closest to the corn field measurements (1.53 mm/d RMSE and +0.53 mm/d mean bias over field), their high overall RMSE values (2.69 mm/d for CalSIMETAW and 2.16 mm/d for DETAW) and skew from the 1:1 line in Figure 29 indicate considerable outliers in the upper and lower end of ET estimates, especially for alfalfa (where CalSIMETAW had the largest discrepancies, 2.28 mm/d RMSE and +1.96 mm/d mean bias over field data). As a whole, RMSE values between models and field-based estimates were lowest for alfalfa (1.63 mm/d average, compared to 2.22 mm/d for corn and 2.16 mm/d for pasture), while model mean biases compared to the field data were generally lowest for pasture (+0.73 mm/d over the field data on average, compared to +0.99 mm/d over field for alfalfa and +1.29 mm/d over field for corn).

Several modeling groups were concerned that field-based ET estimates and measurements were much lower than expected for well-irrigated crops. It was suggested 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. Additional field data collection, including soil-water content and plant-water stress as well as a full season of crop ET measurements, were also requested by modeling groups in the future in order to determine if fields are deficit irrigated, to support the results in this report, and increase knowledge of particular conditions in the Delta. Based on its knowledge of micrometeorological techniques and extensive post-deployment cross-comparisons, the UC Davis field team believes that the field-based ETa estimates developed from the collected data are supported by other literature and data for the Delta. Low EToF values estimated from field data in the Delta region may be due to deficit irrigation or unique conditions in the Delta potentially associated with particular soil and nutrient conditions, water availability, depth to the water table, 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 more than adequate fetch was obtained by careful sensor placement height and location. Discrepancies between field-based and model-based ET estimates appear to be greater than the field measurement error bands developed from literature comparisons (Appendix B). Discrepancies are similar to the random differences of 20-30% and slope differences of approximately 10-20% observed by Allen, et al. (2007a) when comparing estimates from an early version of the METRIC model (not the UCD or ITRC versions compared herein) to field lysimeter data for overpass days in Idaho. A detailed discussion of the field results, error analyses, and comparisons to other ET measurements appear in Appendix B.

There are a variety of reasons that research groups proposed to explain the discrepancy between model estimates and the field-based estimates and measurements, which vary by both the crop type and the specific field station (additional time series plots appear in Appendix A). The higher bias of CalSIMETAW and DETAW for low ET values might be due to field-estimated EToF values for dry end-of-season conditions (Section 3.1.2) being lower than the published Kc values for initial and final cropping periods (typically around 0.15) which are built into those models. Furthermore, due to misclassification by Land IQ both models were technically estimating ET for fallow land instead of corn at site D09 (Section 4.2.1); this may have caused some of their negative bias at the higher end of ET values for corn. At other times of the season, the assumed growth, irrigation, and cutting schedules within these models may have differed from actual field conditions. An actual 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. Finally, the coarse spatial resolution of CalSIMETAW and DETAW alone may have caused discrepancies compared to field-scale data which captured finer regional ET variations and on-farm irrigation schedules. Irrigation schedules 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 that are not captured in the large-scale model. METRIC models require the correction of leaf shadows to prevent underestimation of albedo, which introduces uncertainty in the corn ET estimates from ITRC and UCD-METRIC. Systematic differences between models and the field data are unlikely to be caused by the 'hot/cold' pixel selection (Section 4.1.2); 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 estimates would be expected to have a high bias over field-based 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.

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 EToF values in the Delta suggested by the field-based estimates could cause differences between them and model estimates if they assumed spatial homogeneity 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). Remote sensing models which extrapolate instantaneous satellite overpass data to develop daily estimates (including the two METRIC models) could bias ET 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 methodology for masking out clouds. Depending on model use of absolute temperature measurements, horizontal differences in the vertical atmospheric profiles of major greenhouse gases (i.e. water vapor and carbon dioxide) could differ compared to the profiles assumed by thermal data (for those models that use it). Vegetation canopy radiative/turbulence transfer simplification assumptions could also be inconsistent with actual surface conditions in the field. Other methods and assumptions inherent to remote sensing and ET modeling, including the methodological differences among models discussed in Section 4.1, may also be responsible for observed differences between model and field-based ET measurements and estimates.

Existing differences between model estimates and field data collected by UC Davis could be further investigated and potentially reduced through the collection of additional field data such as irrigation timing, crop condition, and soil properties. Field data collection over homogeneous, well-irrigated sites would also be expected to converge with some modeled ET estimates which assume more ideal crop conditions. Comparisons to field-collected data, examination 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.

4.3 Summary of Model and Field Comparative Attributes

Generalized characteristics for three categories of estimation methods were determined based on the models evaluated in this study and the comparisons above. Based on their applications in the California Delta, this information may provide insight for farmers, water managers, or the public in determining the relative strengths of various estimation methods for certain applications. Table 6 below provides brief qualitative summaries of the benefits of each model type (remote and non-remote sensing-based) and field data compared to each other, as demonstrated by the comparisons performed as part of this study.

Table 6. Qualitative strengths of each evapotranspiration estimation method.

Compared to...	Strengths of Non-Remote Sensing-Based	Strengths of Remote Sensing-Based	Strengths of Field Data
Non-Remote Sensing-Based		Finer spatial resolution and larger scale, geospatial rather than tabular output, less required crop literature, spatial land use data not required for direct estimation, captures crop water stress and other actual field conditions.	Required to develop crop literature, finer temporal and spatial resolution, captures local weather and soil variations, fewer assumptions about heterogeneity, can provide calibration and validation data.
Remote Sensing-Based	Calibrated to regional crop literature, simplified tabular outputs, doesn't require large amounts of satellite data, doesn't require extensive extrapolation between overpasses, no masking (i.e. clouds) or sharpening (i.e. thermal data) required.		Provides calibration and validation data, finer temporal resolution, captures microclimates and water stresses, requires fewer assumptions about energy transport.
Field Data	Larger spatial scale, less intrusive and labor-intensive, already calibrated to crop literature and extension outreach.	Larger spatial scale, adaptable to different regions, less intrusive, requires computation rather than equipment, can be calibrated and verified in real-time.	

4.4 Use of Unmanned Aerial Vehicles to Estimate Evapotranspiration

A preliminary side-study, sponsored by UC Water, was conducted by UC Davis to estimate ET in alfalfa, corn, and pasture fields on Staten Island using Unmanned Aerial Vehicles (UAVs) and to compare to remote sensing-based estimates from an established model. Flights were conducted over three fields also used during the field campaign (D02 in alfalfa, D11 in corn, and D03 in pasture, Figure 3), so field-based ET estimates from surface renewal stations installed by UC Davis in those fields were also compared. Nine UAV flight missions were made, five of them concurrent with Landsat 8 overpasses (path 44, row 33) on July 29, August 30, September 15, and October 1, 2016. High spatial resolution thermal and five-band multispectral (red, green, blue, red-edge, and near-infrared) cameras were used to collect data with path widths of about 25 meters and 80% overlap, yielding data maps of about nine acres (35,000 m^2) for each of the three fields. Resulting thermal (1-meter resolution) and multispectral (0.05-meter resolution) maps were analyzed and processed in METRIC software (Allen, et al. 2007a and 2007b) to produce ETa estimates at 1-meter resolution.

One UAV-based approach utilized thermal and multispectral data to replace all typical Landsat inputs (METRIC-UAV-thermal), and a hybrid approach using red and near-infrared data to develop normalized difference vegetation index (NDVI) inputs (METRIC-UAV-NDVI) was also compared. UAV-developed

NDVI values were used to bias-correct fractions of alfalfa reference evapotranspiration (ETrF) values within the METRIC-L8 results; this approach could be considered a fusion of Landsat and UAV inputs to produce high spatial resolution results. Preliminary high-resolution results from both UAV approaches were compared to the results from the original METRIC method developed by Allen et al (2007a and 2007b) using Landsat 8 data at a 30-meter resolution (METRIC-L8, which is different from the ITRC and UCD approaches discussed elsewhere in this report) for the same fields and overpass dates. Full results and a more detailed explanation of the side study's methodology appear in Appendix L. Results for the METRIC-L8, METRIC-UAV-NDVI, and METRIC-UAV-thermal approaches are summarized and compared in Table 7.

Table 7. Comparison of ET estimates for the conventional METRIC model and two UAV-based methods.

Date	Crop	Method	Mean ET (mm/d)	vs. METRIC-L8
July 29, 2016	Alfalfa	METRIC-L8	6.01	-
		METRIC-UAV-NDVI	6.19	+3.0%
August 30, 2016	Alfalfa	METRIC-L8	5.69	-
		METRIC-UAV-NDVI	5.61	-1.4%
		METRIC-UAV-thermal	5.11	-10.2%
	Corn	METRIC-L8	7.39	-
		METRIC-UAV-NDVI	7.28	-1.6%
	Pasture	METRIC-L8	6.53	-
		METRIC-UAV-NDVI	6.23	-4.5%
September 15, 2016	Alfalfa	METRIC-L8	2.61	-
		METRIC-UAV-thermal	2.48	-4.8%
	Corn	METRIC-L8	4.56	-
		METRIC-UAV-NDVI	4.49	-1.6%
	Pasture	METRIC-L8	4.31	-
		METRIC-UAV-NDVI	4.56	+5.8%
October 1, 2016	Alfalfa	METRIC-L8	4.27	-
		METRIC-UAV-thermal	3.59	-15.8%
	Corn	METRIC-L8	4.52	-
		METRIC-UAV-NDVI	4.47	-1.0%

The low ET rates estimated over alfalfa on September 15 were likely caused by a cutting that took place the previous week. Corn was measured during its last maturity stages prior to harvest, showing very low difference in daily ET while the crop was standing (-1.6%) and after harvest (-1.0%) when compared to METRIC-L8. Mean daily ET estimates from the METRIC-UAV-NDVI approach were reasonably consistent with METRIC-L8 estimates on the whole, averaging an absolute difference of 2.5% across all three crops (corn had the lowest average difference, while pasture had the highest). METRIC-UAV-thermal estimates showed greater differences, averaging 10.3% deviation for alfalfa.

Instantaneous ET estimates, in millimeters per hour (mm/hr), by both UAV-based approaches were also compared to the field-based surface renewal half-hourly estimates (also converted to mm/hr) developed at the same locations and times. In these cases, UAV-based estimates were predominantly lower than the ground-based estimates for all three crops. Results showed average absolute differences of 19% in alfalfa, 3% in pasture, and 26% in corn for UAV-based estimates compared to ground-based estimates. Alfalfa and pasture crops yielded both positive and negative differences between the methods, whereas corn UAV-based estimates were consistently lower than field-based estimates. A further comparison of UAV-based estimates to the seven models compared in this study is under development. UAV technology shows promise for estimating ET at a field-scale, but appropriate protocols need to be developed for increasing consistency in measurements and estimation using the multispectral and thermal images obtained. Further information on the UAV side-study appears in Appendix L.

5 Conclusions and Policy Recommendations

Evapotranspiration is one of the largest and most important quantities in local and regional water balances. However, ET is one of the most uncertain water balance components as it is invisible, hard to estimate, and subject to substantially varying quantitative estimation methods and data. Remote sensing methods are better suited for large regional ET estimates, where field measurements cannot practically provide broad areal coverage cost-effectively. Crop coefficient approaches such as CalSIMETAW and DETAW offer similar results in a simplified format but may fail to capture particular field responses to local conditions on fine spatial scales. Advantages of remote sensing methods include consistency in image acquisition time at a relatively low cost 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 30 below. These biophysical processes are included in different ET methods at various levels of complexity. For example, a 30x30-meter resolution pixel may encompass soil and crops with a variety of root and canopy systems in vertical layers, affecting the accuracy of energy balance calculations for ET estimation that rely on single or two-layer turbulent transfer approximations and horizontal homogeneity. Optical remote sensing approaches such as SIMS largely avoid such complexities but are relatively insensitive to the influences of crop water stress or bare-soil evaporation on ET. Cloud masking and removal of cloud shadows pose challenges to remote sensing-based ET estimations, especially if these occur for a sequence of satellite overpasses. For methods using satellite-acquired thermal data, short-term irrigation or precipitation and the presence of some atmospheric gases and aerosols may influence thermal signals from the land surface, especially when they occur in localized areas that may be different from calibration sites.

State agencies and other stakeholders currently support a wide range of methods for measuring and estimating ET from crops and other ecosystems. Crop ET measurement and estimation methods also continue to evolve and improve with new capabilities from field equipment, unmanned aerial vehicle (UAV) and satellite sensors, and newer computational methods and platforms. However, few efforts (Kite and Droogers 2000, Lange et al. 2017) have been made to compare these methods, particularly for applied 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.

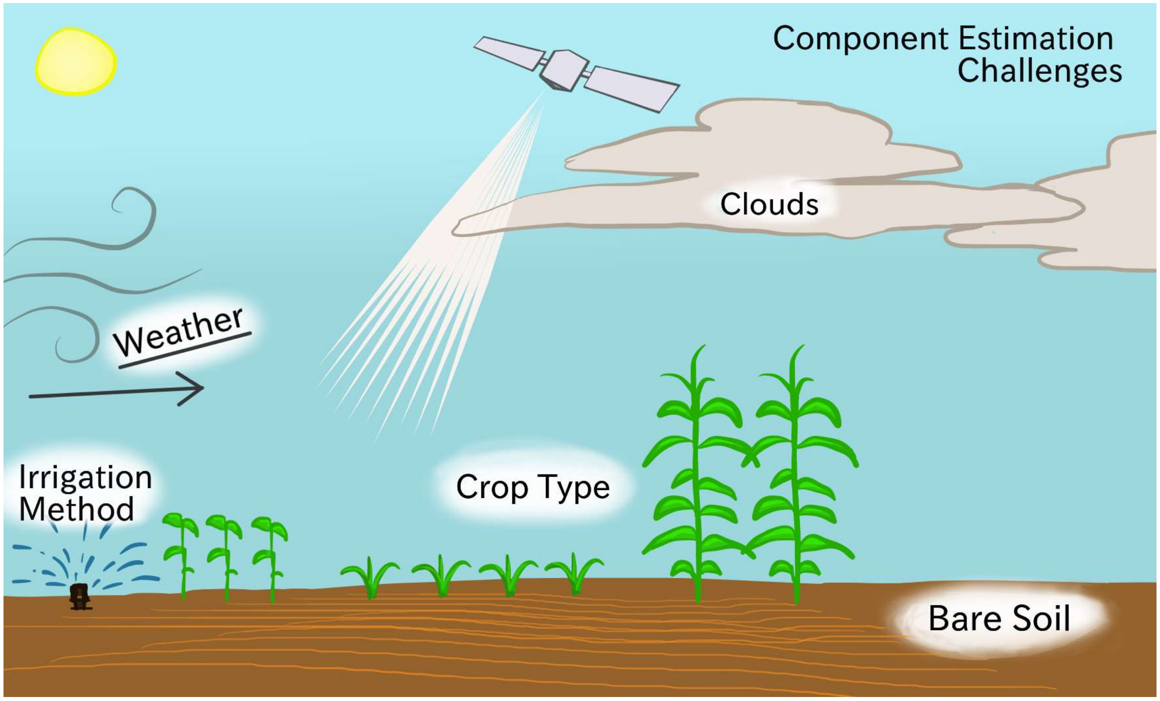


Figure 30. Illustration of some of the challenges in estimating consumptive use.

In the sections that follow, conclusions from field and model-based ET estimation in the Sacramento-San Joaquin Delta for the 2015 and 2016 water years are presented. The report is closed with policy recommendations to improve ET estimation and measurement in the future.

5.1 Field-Based and Model Estimates of Evapotranspiration

This section provides general findings and recommendations regarding ET estimates and field measurements done during this study.

5.1.1 Field-Based Estimates of Evapotranspiration

- **Bare soil field ET.** Field-based estimates of actual evapotranspiration (ETa) from upland fallow fields sampled during the late 2015 summer are nearly zero. These values are lower than those modeled, which range from 1 to 2 mm/day of ET for the same time period and location. Additional measurements for other months and locations are needed to better support these findings. A pilot study of ET over bare fields in the Delta is being planned for the 2018 growing season.
- **Crop ET estimation from field measurements versus models.** ETa from alfalfa, corn, and pasture was estimated and measured directly using field equipment over several months of the 2016 irrigation season and afterwards. The maximum observed monthly average daily ETa was roughly 6 mm/d in summer for all three crops; monthly mean fractions of reference ET (EToF) peaked at 0.9 for corn sites and 0.85 for alfalfa sites. The largest variation in peak EToF values was at corn sites, ranging from 0.55 to 0.9. When comparing the distribution of field-based monthly average daily ET for these locations to average estimates across the Delta by individual models and their ensemble mean, the following findings are supported by statistical tests:
    - Comparing monthly average 2016 field-based ET estimates and measurements to model-

based ensemble mean ET estimates across the Delta provides some useful findings. No significant differences in ET were found between alfalfa field-based estimates and the ensemble mean of ET estimates for any month with field data available. However, significant differences were found for corn and pasture between the ensemble ET estimates and field-based ET for August and September.
    - Monthly mean ET estimates of individual models differ statistically from the field ET over all three crops for most months with field data for CalSIMETAW and DETAW and for August and September for UCD-METRIC. The rest of the models' monthly ET estimates do not differ significantly from the field-estimated ET for the three crops in any given month.
- **Field ET measurements and estimates from different instruments.** Measurements and estimates from all stations and multiple field instrument types and methods such as surface renewal, eddy covariance, and water vapor flux generally agreed. These were also mostly in agreement with independent concurrent and historical measurements from UC Davis, UC Berkeley, and DWR, and some trends were observed. The more complex and expensive direct eddy covariance stations reported lower ETa than the simpler and less expensive eddy covariance energy budget residual stations and surface renewal energy budget residual stations. This difference could be reduced by additional adjustments to the expensive direct eddy covariance method. Random measurement uncertainty was somewhat greater for the surface renewal energy budget residual stations than the eddy covariance stations. Measurement of net radiation is a major driver of ETa and reference evapotranspiration (ETo) field-based estimates, hence the need to measure it accurately. Trade-offs between cost of equipment, apparent accuracy, and correlation of measurement deserve further investigation.
- **Field ET measurement value.** Field measurements and estimates are critical in assessing the field-scale uncertainties and accuracy of ETa estimates made by larger-scale models. Variations in ET measurements and estimates for different specific locations in the Delta were substantiated, and interannual variability was gleaned using data obtained from other sources. Expanding a field campaign to other major crops and natural lands during the entire water year could be useful to assess ETa values across the Delta and enhance model performance under a wider set of land uses.

5.1.2 Model and Field Evapotranspiration Comparison at the Parcel-Scale

Parcel-scale estimates of ET are useful in water accounting for water rights and water transfer administration and transactions. For alfalfa, corn, and pasture, comparisons among models and field-based ET estimates were undertaken using 3-by-3 30-meter pixel grids (8,100 m^2 or about two acres total) around the location of field stations. The following conclusions are supported from these model and field-based ET estimate comparisons:

- **Model comparison to field data.** Model-estimated daily ET values were compared with concurrent field-estimated ETa data during the 2016 growing season for alfalfa, corn, and pasture. Remote sensing-based daily estimates were correlated with field-based estimates on satellite overpass dates but generally estimated higher ET for the three primary crops in the Delta. Biases for the ensemble of methods are about 2 mm/day on average with respect to the field values. Differences are smaller at the higher end of the range (during the summer) for alfalfa and corn, while the lower end (1-3 mm/d during the winter, when skies are typically cloudier) showed a higher bias of models compared to the field data. Improvements to satellite-based ET estimation methods could include increasing temporal resolution, validating interpolation methods, and error assessment of model assumptions, radiation estimates, and vegetation coefficient proxies.

- **Model intercomparison.** Paired intercomparisons were done between similar models on common overpass dates at the locations of the 14 field stations in the Delta over alfalfa, corn, and pasture. These comparisons showed that the two DWR models (CalSIMETAW and DETAW) were in very good agreement with each other, with a root-mean-square error (RMSE) of 1.14 mm/d and the lowest mean bias of CalSIMETAW +0.07 mm/d over DETAW for all three crops. The two versions of the METRIC model (ITRC and UCD) were also in good agreement with each other, with the lowest RMSE of 0.89 mm/d and a mean bias of UCD +0.25 mm/d over ITRC. DisALEXI's estimates agreed well with UCD-PT results, with a RMSE of 1.11 mm/d and mean bias of +0.11 mm/d over UCD-PT. SIMS shows the highest RMSE (1.64 mm/d) and mean bias (+0.9 mm/d) when compared to DisALEXI, whereas compared to UCD-PT it has an RMSE of 1.44 mm/d and a mean bias of +0.85 mm/d. Higher bias by SIMS can be attributed in part to the estimation of basal crop ET versus actual ET. Future comparisons could be conducted between SIMS and CalSIMETAW and DETAW, since all three include crop coefficients at their core. Though standardization of input datasets for models was pursued in this study, modeler-selected input data (e.g. land use data and METRIC 'hot/cold' pixel selection), flexibility in estimation step adjustment, and model-specific parameters calibrated to datasets over time and in areas out of the Delta may greatly influence model differences.
- **ET estimation by UAVs.** Unmanned Aerial Vehicle (UAV) technology provides a high-resolution approach to estimate crop ET and improve in-field water management. Using basic equations from the traditional METRIC model, a daily comparison between satellite and UAV-based estimates over alfalfa placed the two approaches within 10% of each other for alfalfa, corn, and pasture.

5.1.3 Model Evapotranspiration Comparison by Crop

- **Model comparison for primary Delta crops.** The total ET estimated in the Delta differs among methods, but differences in monthly average rates are not statistically significant within 95% confidence for alfalfa, corn, and most months of irrigated pasture. For corn only, DETAW was significantly higher than the ensemble mean for November 2015 and January of 2016. For pasture, statistically significant differences from the ensemble mean occurred from November through January of 2016 for CalSIMETAW, DETAW and ITRC-METRIC. However, even non-statistically different consumptive water uses represent substantial economic differences, based on the market value of water, in the use of different ET estimates for water rights or Delta export management. This is particularly true in dry years.
- **Paired model comparisons.** Intercomparisons of methodologically similar methods' daily estimated ET over small areas in 2015 and 2016 generally indicate good agreement, with mean biases ranging from 0.07 mm/day to 0.87 mm/day for the three major crops in the Delta. Differences in input data, model assumptions, model-specific parameter calibration, hard-coded internal estimation steps, and modeler judgment are likely the major sources of discrepancy among models.
- **Seasonal patterns in ET estimate variation.** The greatest relative cross-method differences in crop ET estimates were found from October to January, when only about 12.5% of annual consumptive water use occurs for the analyzed agricultural land uses. These larger relative differences between methods were seen in corn, potatoes, tomatoes (though these crops would likely not be grown late in the season, indicating the differences likely occur for post-harvest fallow fields), and vineyards. During those cloudy or rainy months there are fewer clear sky

satellite images available, so more temporal interpolation is required than in other months. The largest differences in absolute ET values among methods are during the summer, when the largest ET values occur. This occurred more frequently for almonds, corn, potatoes, rice, and tomatoes.

- **Spatial variation in ET estimates.** Due to their broader coverage and finer spatial resolution, the five remote sensing-based methods captured larger spatial variability in ET estimates within each crop type than the non-remote sensing methods. Amongst these methods, almonds and potatoes had the largest variability in monthly ET estimates.
- **Prospects for model convergence.** Methodologically similar methods produced similar ET estimates when compared at small scales for specific crops on overpass dates and larger spatial scales applied to specific crops, sub-regions, and the entire Delta. Inherent differences in the ET calculated by models result from the fact that some models estimate actual ET and others potential or basal ET, which may limit convergence. So far, results indicate good agreement among methods on the magnitude of consumptive water use in the Delta. Differences in input data, analysis assumptions, operator judgment, and complex processes likely caused some differences in estimates compared for this study. Improved communication among modeling groups and standardization of input datasets such as land use, satellite overpass dates, and coarse data sharpening procedures should improve convergence in ET estimations. However, the differences in ET estimates and the unique approaches, assumptions, and parameterizations used by some models show a range of values and uncertainty inherent in estimates developed by remote sensing.

5.2 Evapotranspiration Estimates for Regions of the Delta

Different areas of the Delta commonly have varying dominant crops 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 hydrodynamic and water quality models that inform Delta water operations and planning. Such regional differences also might be important for water right and transfer administration purposes. Methods employed in this study show some potential to substitute remote estimates for self-reporting of water use by water right holders. Information on irrigation methods (type and frequency) would greatly benefit estimates of water diversions and return flows in the Delta.

Five larger regions within the Delta were identified: from north to south, the Yolo Bypass, North, West, Central, and South Delta. The region with the smallest proportional agricultural uses is the West Delta, given urbanization around Brentwood, public ownership of western islands, and higher salt concentrations in Delta channels (Medellín-Azuara et al., 2014). On the other end, nearly 80% of the North Delta and just above three fourths of the South Delta are devoted to agriculture. Land use classes in the Yolo Bypass include a large proportion of native vegetation and rice because of more frequent flood inundation. Consumptive water use estimates in the entire Delta Service Area averaged 3.02 AF/acre in 2015 and 2.97 AF/acre in 2016. The North Delta region had the highest volume of estimated ET, as well as greater agreement among ET estimates, while the Yolo Bypass had the lowest estimated ET volume and the highest estimated ET per unit area.

5.3 Evapotranspiration Estimates for the Entire Delta

ET estimates for the entire Delta provide useful information for regional and statewide water policy, planning, and accounting. The following conclusions arise from this research on Delta-wide consumptive use:

- **Overall evapotranspiration.** Using the average of the seven model estimates, total annual evapotranspiration from agricultural lands in the Delta Service Area was estimated at 1,445 TAF in 2015 and 1,379 TAF in 2016. These values are broadly consistent with previously published estimates in the 2013 California Water Plan Update water balances for the Delta. Average absolute departure of individual models from these means are about 91 TAF for the Delta Service Area in both years, representing roughly 6.3% and 6.7% of the ensemble means for 2015 and 2016, respectively.
- **Crops with higher consumptive use.** The three major crops in the Delta, alfalfa, corn, and pasture, averaged nearly half of all agricultural consumptive water use in the Delta (588 TAF) across all models. Among these three, alfalfa is the crop with the highest annual average consumptive use per unit area (3.5 AF/acre), accounting for 39.3% of agricultural consumptive use (or 16.6% of all consumptive use) volume in 2016. Corn uses 2.9 AF/acre and pasture uses 3.5 AF/acre on average across models.
- **Changes in land use.** Changes in land use from 2015 to 2016 included increased idle land, decreases in the three major field crops (alfalfa, corn, and pasture), and increased young orchards, based on surveys conducted by Land IQ. This reduced the consumptive use estimated from crops and slightly decreased overall estimated ET between these years. The ensemble average ET per unit of agricultural area was 3.02 AF/acre in 2015 and 2.97 AF/acre in 2016. Differences in ET for fallow lands and young orchards may partially explain the variation in total ET volume between methods.
- **Non-agricultural land uses.** Riparian native, upland herbaceous, and floating vegetation covered almost 80,000 acres (13% of the Delta Service Area) in 2016. Not counting SIMS, the ensemble mean estimated ET from these lands among methods was about 247 TAF/year. Floating vegetation averaged 4.4 AF/acre and riparian vegetation 4.0 AF/acre over the same period, which both exceeded the average 3.0 AF/acre estimated consumptive use from agricultural lands. Open water (4.2 AF/acre) and urban (2.2 AF/acre) land use classes added another 406 TAF/year in estimated consumptive use. When agricultural and the above non-agricultural land use classes are added, the non-agricultural portion of ET represents just above 30% of all consumptive use in the Delta in 2016 (roughly 2.0 MAF). However, not all methods are suited to estimate ET for these land use classes, particularly wetlands. This study was primarily focused on agricultural lands, so the field campaign was confined to those land use types. The adaptation of methods to better quantify ET may be increased with new field-based data, and 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.

5.4 Policy Insights and Future Directions

Crop ET estimates in the Delta have a range of potential uses by state agencies, stakeholders, researchers, and other water professionals. For agencies like the State Water Resources Control Board, some uses include idle land water transfers quantification, water rights permitting and administration, large-scale management of Delta water project inflows and exports, and as part of water flow balances used in water quality estimates.

State agencies, stakeholders, and water professionals also have a variety of interests in the accurate estimation of crop ET statewide to improve water accounting for the implementation of the Sustainable Groundwater Management Act (SGMA). The State of Idaho has used remote sensing-based estimates of ET for a variety of water management, accounting, and water right purposes. Its platform (https://maps.idwr.idaho.gov/ET/) allows users to interactively obtain crop irrigation requirements and other information, improving reporting and transparency and reducing conflict.

High-resolution estimation of ET using remote sensing or UAVs may aid on-farm water management decisions by improving data on water requirements for leaching, enhancement of ditch banks or off-season habitat, and mitigation of different soil conditions for irrigation distribution uniformity.

In light of these needs, some policy insights arise from this work:

- **Pursuit of better technical information.** This study sets an example on how to improve the quality, transparency, and ease-of-access to technical information on ET for the Delta. The approach employed for this study was inclusive and collaborative, involving major research groups and agencies estimating ET across California and elsewhere. Collaborative approaches allow early discussion of research findings, data and method gaps, and the uncertainties involved, and also improve coordination of technical efforts in quantifying ET.
- **Reliability of technical information.** This study also helps establish the current range of uncertainty and challenges in ET measurements and estimation for consideration in water management and policymaking. This two-year effort allowed improvement of models and coordination in estimating and comparing crop ET. The effort also was useful to identify research and data gaps to be addressed in future studies.
- **Evapotranspiration from an ensemble of models and over a year.** This study's results highlight the broad range of estimation results for daily ET from individual models. Despite larger discrepancies at small time and spatial scales, the study results also show some convergence of model estimates for longer time periods and areas such as Delta-wide averages over the water year. Ensemble averages are an avenue to explore in a long-term ET estimation program for the Delta and the state; however, some effort would be needed to integrate the different estimation approaches. The practicality and cost-effectiveness of such efforts need further examination.
- **Bare soil ET.** Idle field ET quantification is critical, as it represents the amount of water potentially saved in comparison to a fully-irrigated crop during the growing season. This amount helps establish net consumptive use in crops and is useful in estimating the amount of water that can be transferred to other uses or saved in voluntary fallowing programs. Preliminary field-based estimates from this study indicate idled field ET for a selection of areas above sea level in late 2015 summer are low, substantially less than reference ET. However, the model-based ensemble ET results show idled land may represent upwards of 15% of Delta agricultural consumptive water use. Limited sampling for idle land ET field measurement during the 2015 season presents high uncertainties for quantification of potential water savings with respect to fully irrigated agriculture. This calls for a more rigorous field-based study over more fields in the Delta, particularly on subsided land watered by seepage. Such a study is currently under development for the 2018 growing season.
- **Non-agricultural consumptive use.** Estimates of ET from non-agricultural land use classes including floating, riparian, and native classes indicate their consumptive use rates may potentially be higher than those of irrigated crops in the Delta. Because most methods are primarily developed for agricultural land uses, however, these estimates require more examination. Refinement of land use information for non-agricultural land use classes could also be done through collaboration with other state agencies and research groups to better differentiate between specific natural vegetative types and potentially invasive species. This area is important for including restored landscapes and programs in regional water balances.

- **Land use survey program.** An accurate, consistent, and long-term land use and crop type mapping survey program for the Delta would substantially improve the basis for accounting and management for water balances at all scales. Such a program will benefit from including winter crop data (multi-cropping) and irrigation method and frequency information. This will potentially extend the quantification of elements in the water balance beyond consumptive use.
- **Unmanned aerial vehicles.** There is promise for using UAV technology in conjunction with field measurements and remote sensing data to increase accuracy in estimations of ET, applied water, and identification of crop water stress at a fine spatial and temporal scale. At present, proper protocols for using this emerging technology for ET estimation have yet to be established, with most applications limited to localized areas rather than regional assessments.
- **CIMIS station density.** As part of this study, five additional CIMIS stations were deployed within the Delta to measure meteorological data and provide ETo values. This greater density decreases the interpolation distance required to produce weather variables which are used by many remote sensing methods. Any resulting increase in accuracy in estimating reference evapotranspiration spatially with Spatial CIMIS remains to be assessed.
- **Use of remotely-sensed estimates to complement or substitute for diversion self-reporting.** Water right holder reporting requirements have increased, imposing significant costs and labor requirements on water users. Remote sensing-based ET estimation methods could provide a cost-effective way to help reduce self-reporting burdens, increase transparency, accuracy, and consistency; such methods have been used successfully in other states such as Idaho. Extrapolating accurate ET estimates to quantify diversions requires additional data acquisition on particular localized conditions such as irrigation infrastructure, soil and drainage, and periodic comparison with field-based ET measurements. A consortium approach involving stakeholders, water and other government agencies, and academic institutions may help establish such a long-term consumptive use estimation program. 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.
- **Implications for groundwater management.** The Sustainable Groundwater Management Act (SGMA) requires basins to reach long-term sustainability. Accurate estimates and measurements of ET, particularly in but not limited to crops, facilitate planning and management at the basin scale. Underestimation of ET may overstate sustainability and overestimation may risk water balance integrity in water transfer, exchange, and net metering accounting as well as overall management. Additional information on local conditions may help refine estimates on recharge fraction and runoff, but ET from irrigated crops represents the largest component in agricultural areas.
- **Promise of new ET estimation improvements.** Enhancements in regional-scale weather modeling, soil-plant-atmosphere land surface models, and remote sensing technologies will substantially improve the precision of ET estimation and potentially allow for forecasting of future water use. Higher spatiotemporal resolution in satellite-based data can help overcome limitations in current platforms, such as those caused by cloudy winter days during infrequent overpasses. UAV technology, with increases in payload-carrying capacity, range, mission durations, and ease of use, may provide precise parcel-level ETa estimates to supplement the wider-area estimates made with satellites. Lastly, field measurement sensors are becoming simpler to use and more affordable, which could translate to the ability to have direct ETa measurements in networked stations, such as an enhanced CIMIS network coupled with direct ETa measurements over well-watered pasture (ETo) and other crops and non-agricultural lands.
- **Cooperation between field campaign and models.** Given the diversity in expert participation

and the broad technical scope of the study, unresolved issues are expected. This report presents 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 this difference between field and model results. Some strategies to reduce these unresolved differences include:

  - Have a field campaign which focuses on detailed paired comparisons with a few modeled estimates, with uncertainty analyses of measurements and modeled ET estimates.
  - Involve multiple water experts in the field campaign, including independent networks such as FLUXNET-AmeriFlux, the Department of Water Resources, and other organizations and expert groups.
  - Explore the use of additional field-obtained data in modeling ET estimates, and compare the outcomes of additional field calibration and validation efforts.
  - Establish an ET program with some minimal base funding to maintain collaboration and advancement of ET quantification in the Delta.

- **Organizing the State's ET estimation efforts.** A consortium involving agencies, educational institutions, research centers, stakeholders, and consultants 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 enhances transparency, access to technical information, and collaboration among research groups, agencies, and stakeholders. This requires some pooled minimum funding to maintain ET estimation program elements, including accurate annual land use surveys (accounting for irrigation technology), data curation and storage, documentation, and organization of data to serve various uses and facilitate research and synthesis.

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Table of Acronyms

ACASA	Advanced Canopy Atmosphere Soil Algorithm
CalSIMETAW	California Simulation of Evapotranspiration of Applied Water
CIMIS	California Irrigation Management Information System
CSUMB	California State University Monterey Bay
CU	Consumptive Use
DAU	Detailed Analysis Unit
DAU-CO	Detailed Analysis Unit area within a County
DETAW	Delta Evapotranspiration of Applied Water
DisALEXI	Disaggregated Atmosphere-Land Exchange Inverse
DWR	California Department of Water Resources
ETa,o,c,aw,rF	Evapotranspiration, various forms (Box 1)
ITRC	California Polytechnic Institute San Luis Obispo Irrigation Training and Research Center
Ka,c,cb	Crop Coefficient (Box 1)
Land IQ	Land IQ, Inc. (Section 2.1 and Appendix J)
LIDAR	Light Detection and Ranging
METRIC	Mapping Evapotranspiration at High Resolution with Internalized Calibration
mm/d	Evapotranspiration rate used in this study. 1 mm/d on a 30x30-meter pixel is equivalent to about 0.02 ft./month (acre-feet/acre/month).
MODIS	Moderate-Resolution Imaging Spectroradiometer
NASA-ARC	National Aeronautics and Space Administration Ames Research Center
NASS-CDL	National Agricultural Statistics Service Crop Data Layer program
NCDC	National Climatic Data Center
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanographic and Atmospheric Administration
PRISM	Precipitation-Elevation Regressions on Independent Slopes Model
PT	Priestley-Taylor approach
SEBAL	Surface Energy Balance Algorithm for Land
SEBS	Surface Energy Balance System
SIMS	NASA Satellite Irrigation Management Support System
SLC	Satellite Overpass Scan Line Corrector
SSURGO	Soil Survey Geographic Database
TAF	Thousand Acre-Foot
UAV	Unmanned Aerial Vehicles
UCD	University of California Davis
USDA-ARS	United States Department of Agriculture-Agricultural Research Service
WRF	Weather Research and Forecasting model
WRF-ACASA	Weather Research and Forecasting model linked to the Advanced Canopy Atmosphere Soil Algorithm

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