OpenET: Filling a Critical Data Gap in Water Management for the Western United States

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Research Impact Statement: OpenET has developed an operational system for satellite mapping of field-scale evapotranspiration across the western United States.

ABSTRACT: The lack of consistent, accurate information on evapotranspiration (ET) and consumptive use of water by irrigated agriculture is one of the most important data gaps for water managers in the western United States (U.S.) and other arid agricultural regions globally. The ability to easily access information on ET is central to improving water budgets across the West, advancing the use of data-driven irrigation management strategies, and expanding incentive-driven conservation programs. Recent advances in remote sensing of ET have led to the development of multiple approaches for field-scale ET mapping that have been used for local and regional water resource management applications by U.S. state and federal agencies. The OpenET project is a community-driven effort that is building upon these advances to develop an operational system for generating and distributing ET data at a field scale using an ensemble of six well-established satellite-based approaches for

mapping ET. Key objectives of OpenET include: Increasing access to remotely sensed ET data through a web-based data explorer and data services; supporting the use of ET data for a range of water resource management applications; and development of use cases and training resources for agricultural producers and water resource managers. Here we describe the OpenET framework, including the models used in the ensemble, the satellite, meteorological, and ancillary data inputs to the system, and the OpenET data visualization and access tools. We also summarize an extensive intercomparison and accuracy assessment conducted using ground measurements of ET from 139 flux tower sites instrumented with open path eddy covariance systems. Results calculated for 24 cropland sites from Phase I of the intercomparison and accuracy assessment demonstrate strong agreement between the satellite-driven ET models and the flux tower ET data. For the six models that have been evaluated to date (ALEXI/DisALEXI, eeMETRIC, geeSEBAL, PT-JPL, SIMS, and SSEBop) and the ensemble mean, the weighted average mean absolute error (MAE) values across all sites range from 13.6 to 21.6 mm/month at a monthly timestep, and 0.74 to 1.07 mm/day at a daily timestep. At seasonal time scales, for all but one of the models the weighted mean total ET is within ±8% of both the ensemble mean and the weighted mean total ET calculated from the flux tower data. Overall, the ensemble mean performs as well as any individual model across nearly all accuracy statistics for croplands, though some individual models may perform better for specific sites and regions. We conclude with three brief use cases to illustrate current applications and benefits of increased access to ET data, and discuss key lessons learned from the development of OpenET.

(KEYWORDS: agriculture; consumptive use; evapotranspiration; field scale; Landsat; open data systems; remote sensing; satellite; water sustainability.)

INTRODUCTION

Drought and water scarcity are becoming perennial challenges across the western United States (U.S.), and recent studies have highlighted the potential for interactions between climate change and natural variability in precipitation to drive acute and prolonged drought events in the region (Diffenbaugh and Swain 2015; Williams et al. 2020). Ensuring adequate water supplies for food production while sustaining water supplies for domestic, industrial, and environmental uses requires careful management of water resources. Challenges in accessing consistent, accurate information on evapotranspiration (ET) and consumptive use of water by irrigated agriculture is one of the most important data gaps for water managers in the western U.S. and other arid agricultural regions globally. While accurate data for all hydrological variables are important to improving both local and regional water balances and information on water supplies, data on ET are particularly important for improving the management of water resources in the western U.S. and High Plains, since ET is the second-largest component of the surface water balance, following precipitation (Arnold et al. 1999). ET is the transfer of water vapor to the atmosphere through the combined processes of evaporation from the Earth's surface (including water bodies) and transpiration through plant tissues. The ET that occurs as a result of application of water to a field is removed from the water supply within a basin. For agricultural fields over unconfined aquifers, ET is often equivalent to the consumptive use, which is a use of water that removes water from available supplies without a return to a water resource (Jensen 1974). In the western U.S., ET from irrigated agricultural lands accounts for the large majority of consumptive water use, and ranges from 59% in Texas to 97% in Idaho, with a West-wide average of approximately 80% of total water use by people (Dieter et al. 2018). ET data can be valuable in guiding irrigation management and scheduling to maximize on-farm water use efficiency and crop yields, supporting water trading programs, developing accurate water budgets, and advancing water management strategies to sustain water supplies for agriculture, people, and ecosystems (Fisher et al. 2017). Developing innovative and effective water management strategies is difficult without accurate, consistent information about ET from agricultural lands. However, at present, there is not a single and universally accepted source of field-scale ET information for the U.S. (Evenson et al. 2018). ET is consistently identified as a high priority data gap or information need in assessments conducted for the U.S. water resources management community (MDNR Technical Workgroup 2010; Jenkins et al. 2018; National Academies of Sciences, Engineering and Medicine, Space Studies Board 2019; WWAO 2020).

While there are a wide range of approaches available for measuring ET (Alfieri and Kustas 2020), it is difficult and expensive to measure accurately on the ground, and current approaches require specialized instrumentation and knowledge (Allen et al. 2011). ET rates vary substantially across the landscape, making it impractical to estimate through

interpolation from sparse networks of ground-based monitoring stations, as is commonly performed for precipitation, runoff, and groundwater elevations (Dunn and Mackay 1995; Hatfield and Prueger 2011). Recent advances in remote sensing of ET have led to the development of multiple approaches for ET mapping across the land surface at a spatial scale of 30×30 m (0.22 acres) per pixel, and many are advancing toward operational use by U.S. state and federal agencies (Anderson et al. 2012; Irmak 2012; Melton et al. 2012; Senay et al. 2013; Fisher et al. 2017). The OpenET project is integrating many of these advances and supporting further improvements in water management by increasing access to remotely sensed ET data. OpenET has developed a platform for data processing and distribution to provide automated and widely accessible ET data at user-defined spatial scales and timeframes across the western U.S. OpenET is a collaborative effort involving six ET modeling teams from the U.S. and Brazil, and (in alphabetical order) California State University Monterey Bay, the Desert Research Institute, Environmental Defense Fund, Google LLC, Habitat Seven, National Aeronautics and Space Administration (NASA), Stanford University, U.S. Department of Agriculture (USDA), U.S. Geological Survey (USGS), Universidade Federal do Rio Grande do Sul, University of Idaho, University of Maryland, University of Nebraska-Lincoln, University of Wisconsin, and key partners from the agriculture, water resource management, and conservation communities. The project is implementing an ensemble of satellite-based ET models on Google Earth Engine (Gorelick et al. 2017), which provides a shared, high performance, cloud-based, computing platform where teams can collaborate on preprocessing of satellite, meteorological, and land cover inputs to increase the consistency of data processing and reduce the range of estimates from the ensemble of models. While OpenET could be implemented on other cloud-based platforms in the future, Earth Engine currently provides automated services for retrieval, storage, and access for all required inputs to the ET models, freeing the modeling teams to focus on improvement of the model implementations and efficient processing of satellite and meteorological inputs.

OPENET MODELS AND DATA INPUTS

The current ensemble of ET models included in OpenET is summarized in Table 1. Models selected for inclusion in the OpenET ensemble have been used by government agencies with responsibility for water

TABLE 1. Models used in OpenET.

Model acronym	Model name	Primary references
ALEXI/ DisALEXI	**A**tmosphere-**L**and **Ex**change **I**nverse/ **Dis**aggregation of the **A**tmosphere-**L**and **Ex**change **I**nverse (ver. 0.0.27)	Anderson et al. (2007, 2018)
eeMETRIC	**M**apping **E**vapo**t**ranspiration at High **R**esolution with **I**nternalized **C**alibration (ver. 0.20.15)	Allen et al. (2005, 2007, 2011)
geeSEBAL	**S**urface **E**nergy **B**alance **A**lgorithm for **L**and using Google Earth Engine (ver. 0.2.1)	Bastiaanssen et al. (1998); Laipelt et al. (2021)
PT-JPL	**P**riestley-**T**aylor **J**et **P**ropulsion **L**aboratory (ver. 0.2.1)	Fisher and Tu (2008)
SIMS	**S**atellite **I**rrigation **M**anagement **S**upport (ver. 0.0.20)	Melton et al. (2012); Pereira et al. (2020)
SSEBop	**Op**erational **S**implified **S**urface **E**nergy **B**alance (ver 0.1.5)	Senay et al. (2013); Senay (2018)

use reporting and management in the western U.S., and some models are widely used internationally. Prior use by a state or federal agency in the western U.S. was a primary requirement for inclusion of a model in OpenET, in addition to participation in OpenET by one or more members of the science team that originally developed each model. OpenET relies entirely on publicly available satellite, meteorology, crop type, topography, land use, and soils data as inputs to the ET models. Landsat is currently the primary satellite dataset used within the OpenET platform, where all models rely on Landsat satellite data to produce data at a spatial resolution of 30×30 m, along with gridded weather variables including solar radiation, air temperature, humidity, and wind speed. The Landsat program, a joint effort of NASA and the USGS, provides the longest continuous space-based record of Earth's land surface in existence, dating back to 1972 for optical data and to 1982 for thermal data. Landsat is currently the only operational satellite that combines thermal and optical data at the spatial resolution needed to calculate surface energy balances at the level of individual agricultural fields, which is often required for assessing water use and managing water rights. Several models implemented within the OpenET framework also integrate data from GOES, Sentinel-2, Suomi NPP, Terra, Aqua, ECOSTRESS, and other satellites

TABLE 2. Primary Model Inputs

Model acronym	Satellite and ancillary inputs	Meteorological inputs
ALEXI/ DisALEXI	*Primary*: Thermal data from GOES (ALEXI) and Landsat (DisALEXI); surface reflectances from MODIS and Landsat TM/ETM+/OLI *Secondary*: NLCD land cover data	Insolation, near-surface wind, air temperature, vapor pressure and atmospheric pressure from the Climate Forecast System Reanalysis (CFSR); ALEXI additionally uses CFSR atmospheric temperature profile data
eeMETRIC	*Primary*: Surface reflectance and thermal radiation from Landsat TM/ETM+/OLI *Secondary*: NLCD land cover data (for USA) and GlobCover for the globe, SRTM DEM, SURGO (USA) and FAO Harmonized World Soil Database v 1.2 (globe)	Insolation, near-surface wind speed, air temperature, and vapor pressure from CIMIS and North American Land Data Assimilation System (NLDAS) for the USA, and from Climate Forecast System Ver. 2 (CFSV2) for the globe; Precipitation from gridMET
geeSEBAL	*Primary*: Surface reflectance and thermal radiation from Landsat TM/ETM+/OLI *Secondary*: Elevation from SRTM; Cropland data layers from USDA NASS	Daily shortwave incident radiation from GRIDMET; Hourly near-surface wind speed, air temperature, specific humidity and atmospheric pressure from NLDAS
PT-JPL	*Primary*: Surface reflectance and thermal radiation from Landsat TM/ETM+/OLI *Secondary*: MODIS maximum fraction of absorbed photosynthetically active radiation (fAPAR)	Insolation, near-surface wind speed, air temperature, and vapor pressure from CIMIS and North American Land Data Assimilation System (NLDAS)
SIMS	*Primary*: Surface reflectances from Landsat TM/ETM+/OLI and Sentinel-2A/2B *Secondary*: USDA Cropland Data Layer and state crop mapping data products; Surface reflectances from Terra/ Aqua MODIS and Suomi NPP VIIRS can be used for gap-filling	ET_o data from Spatial CIMIS (in California); gridMET ET_o and precipitation data for other states
SSEBop	*Primary*: Thermal radiation from Landsat *Secondary*: NDVI from Landsat and SRTM DEM	ET_o data from Spatial CIMIS (in California) and gridMET; Daymet Daily Maximum Air Temperature (long-term average)

to produce ET data at a range of spatial and temporal scales.

The primary satellite and meteorological inputs to each model are summarized in Table 2. The OpenET ensemble includes both energy balance and reflectance-based approaches to ET mapping, models that were developed for global monitoring applications, and models that were developed for local-scale irrigation management. The ensemble includes models that leverage gridded meteorological reference ET data for time integration between Landsat overpass dates, and models that utilize coarser resolution data from geostationary satellites to derive daily ET values (Table 2). This diversity of approaches helps to overcome the limitations of any particular model, while improving the reliability of data for operational use over the long term.

The approach taken by OpenET of implementing an ensemble of models is designed to better inform practitioners regarding ET model agreement and disagreement, ensure data continuity, and take advantage of the strengths of the different ET mapping methods across different regions and land cover types. In cases where estimates from different methods vary substantially, the differences in estimates can present an important impediment to effective adoption of remotely sensed ET data, as users and developers of the data must resolve questions regarding overall model accuracy and dependability, and identify the "best" model for use for the intended location and application. One key objective of OpenET is to calculate a single, ensemble ET value for each location and timestep, while still making the individual model results available. The OpenET ensemble value used in this study was calculated as the mean of all models, and this approach has performed well during Phase I of the intercomparison and accuracy assessment described below. Other options for calculation of the ensemble value include use of the ensemble median or a weighted mean, outlier filtering based on the median absolute deviation (Leys et al. 2013), or even a single value from the most accurate model for a particular geographic region, season, land cover, or crop type. A strength of the ensemble approach is that providing a single ET value from an ensemble of well-established approaches addresses questions from the practitioner community regarding which model to use while providing transparency about the range of estimates as an indicator of model uncertainty. One disadvantage of the ensemble approach is that the accuracy of any weighted or unweighted mean of multiple models can be negatively influenced by outliers. To address this, the results from Phase II of the intercomparison study will be used to calculate the final ensemble value, where models that consistently perform poorly for particular regions, crops, or land cover types may be filtered out or have lower weighting.

OpenET uses weather station measurements across the U.S. that are integrated into assimilation systems to produce spatially distributed or gridded weather datasets including gridMET (Abatzoglou 2013) for calculation of grass reference ET (ET_o) and precipitation, Spatial CIMIS (Hart et al. 2009) for calculation of ET_o in California, and the North American Land Data Assimilation System (NLDAS; Mitchell et al. 2004; Xia et al. 2012; Zhang et al. 2020) for calculation of instantaneous ET on the dates of satellite overpass. These datasets are used within the OpenET platform for various model parameters and variables, such as atmospheric stability, net radiation, wind speed, precipitation, and surface air temperature gradients. One of the primary variables derived from gridded weather data is grass reference ET (ET_o), which is calculated using the American Society of Civil Engineers (ASCE) Standardized Penman-Monteith equation (Walter et al. 2000; ASCE-EWRI 2005). With the exception of ALEXI-DisALEXI, ET_o data are used to support the calculation of daily actual ET between Landsat satellite overpasses, which currently occur every eight days. First, the fraction of grass reference ET (ET_oF) for each satellite overpass date and for each 30 m pixel is calculated by dividing the satellite-derived ET by the ET_o. The ET_oF values, which are relatively stable over time (Allen and Tasumi 2007; Chávez et al. 2008), are then linearly interpolated on a daily timestep for all days between cloud-free satellite overpass dates. Next, each ET_oF value is multiplied by the corresponding daily ET_o value to produce a daily time series of actual ET for every pixel. These per-pixel, daily time series of actual ET are then aggregated to monthly and annual time periods. To ensure that gridded ET_o data are representative of agricultural weather conditions, hundreds of weather stations located in agricultural areas were filtered, quality controlled and then used by OpenET for bias correction of gridded ET_o. Weather station data were passed through rigorous quality assurance and quality control (QAQC) procedures following Allen (1996) and ASCE and FAO guidelines (Allen et al., 1998; ASCE-EWRI 2005).

One exception to the ET_o approach to time integration is the ALEXI/DisALEXI model. ALEXI/DisALEXI uses the coarser resolution ET information derived from the ALEXI model (Anderson et al. 2007) driven with GOES satellite data to provide the daily ET, and applies the DisALEXI algorithm to disaggregate the coarser resolution ET data to 30 m using the Landsat thermal and multispectral data (Cammalleri et al. 2013). DisALEXI uses daily solar insolation to interpolate ET for days between Landsat overpass dates. The ALEXI/DisALEXI ET modeling system also uses meteorological inputs from the Climate Forecast System Reanalysis (CFSR) (Saha et al. 2010, 2014).

Following the production of daily and monthly ET by individual models and production of ensemble ET values, OpenET relies upon a number of publicly available datasets related to land cover and agricultural field boundaries to compute data summaries for millions of agricultural fields. Ancillary data used by OpenET include crop type information from the USDA Cropland Data Layer (CDL) (Boryan et al. 2011) as well as state agencies, USDA soils data, the USGS National Elevation Dataset (NED) (Gesch et al. 2002), USGS land use classifications from the National Land Cover Database (NLCD) (Homer et al. 2015), irrigation status datasets (Ketchum et al. 2020), and manually digitized agricultural field boundaries from USDA, state agencies, and research groups. The USDA CDL data product is updated annually, and crop type data from states including California, Idaho, Washington and others are updated by state agencies on intervals of one to three years. OpenET updates crop type information for all fields on an annual basis, giving priority to state-level data products, and using the USDA CDL for all locations for which state-level data are not available. OpenET plans to compile and update field boundaries from publicly available data sources every five years. These ancillary datasets are used to support data exploration, calculation of summaries of ET and other variables for individual fields, and for aggregation of data by crop type and land cover classification. In cases where the user has more accurate local information on field boundaries, crop type, irrigation status, land cover type or other ancillary information, the OpenET Application Programming Interface (API) can be used to extract data summaries for these user-defined regions of interest using a raster mask, shapefile, or other geometry.

MODEL INTERCOMPARISON AND ACCURACY ASSESSMENT

Recently, Foster and Mieno (2020) highlighted the importance of conducting rigorous analyses of remotely sensed ET and estimates of agricultural water use prior to application of the data for water resource management applications. A rigorous analysis of the accuracy of the satellite-based ET models in the OpenET ensemble is central to decisions by agricultural producers and water managers to use data from OpenET for applications at field to basin scales. The OpenET team is currently conducting one of the largest model intercomparison and accuracy

assessments to date for the field-scale ET modeling systems included in the OpenET ensemble. The primary dataset for the intercomparison and accuracy assessment study has been collected from eddy covariance (EC) networks that measure the exchanges of water vapor, carbon dioxide, and energy between the land surface and the atmosphere. These stations are important because they provide in situ estimates of ET for specific locations with known land use and vegetation types. The current ground-based ET dataset includes more than 139 flux tower sites across the U.S., including data collected at Ameriflux sites and included in the FLUXNET2015 dataset (Baldocchi et al. 2001; Pastorello et al. 2017, 2020), as well as additional flux towers deployed on agricultural fields by collaborators at USDA, USGS, the University of California Agriculture and Natural Resources (UCANR) Institute and other university partners (Anderson et al. 2017; Alfieri et al. 2019; French et al. 2020; Pereira et al. 2020). Nearly all flux tower sites in the dataset are instrumented with open path EC instrumentation systems (Baldocchi 2014). While the exact instrumentation varies by site, all sites include a four-way net radiometer to measure net radiation, an infrared gas analyzer and 3D ultrasonic anemometer to measure latent and sensible heat fluxes, and heat flux plates and soil thermocouple probes to measure the ground heat flux. Additional information about the typical instrumentation deployed at the Ameriflux sites is provided in Baldocchi et al. (2001).

The OpenET team developed and applied a rigorous and automated screening process to review the EC data, identify outliers, fill gaps in the instrument measurement record, and perform daily energy balance closure following an adaptation of data processing procedures established by the FLUXNET2015 dataset (Pastorello et al. 2017, 2020). Flux tower datasets were extensively screened using automated procedures, followed by visual inspection to identify outliers and gaps in instrument measurement records (Volk et al., 2021). Data gaps in the flux tower ET datasets of up to two hours during the daytime, as defined by periods of positive net radiation, and up to four hours during periods of negative net radiation, were gap-filled using linear interpolation. Days having longer time gaps were excluded. Site data records were filtered to exclude months having more than five missing days of in situ ET estimates per month. For months with fewer than five missing days, missing days were gap-filled through linear interpolation of daily ET_oF values calculated from the flux tower ET data record to estimate ET_oF values for the missing days. The daily ET_oF value on each missing day was then multiplied by the corresponding bias-corrected gridMET ET_o value to provide an estimate

of ET. Daily energy balance closure ratios were calculated at each site for non-gap filled daily data as the ratio of turbulent to radiative fluxes. Only sites having a minimum average daily energy balance closure ratio of 0.75 during the growing season, and 0.6 during the winter, were included in the intercomparison study. For all sites included in the analysis, we performed an energy balance closure adjustment at daily timesteps using the energy balance ratio approach (Wilson et al. 2002; Pastorello et al. 2020). We used the average daily energy balance closure ratio and the difference between the closed and unclosed data record as indicators of the uncertainty and measurement error in the flux tower datasets. As a final step, sites were reviewed using aerial imagery from the USDA National Agricultural Imagery Program (NAIP) and wind speed and direction data from the site to ensure that the flux tower location was representative of the surrounding field or land cover type to be sampled from the remote sensing models, and that the vegetation condition was relatively homogenous in the direction of the predominant winds. A Landsat-based normalized difference vegetation index (NDVI) analysis was used to assess and confirm the uniformity of vegetation surrounding the flux sites. Two static footprints were analyzed for each site: a 90×90 m footprint and a 210×210 m footprint. By default, these footprints were centered on the flux tower, but were shifted by 30–90 m if required based on the analysis of wind direction and conditions surrounding the tower location to avoid inclusion of roads, buildings, adjacent fields, ponds, or other nonrepresentative surfaces in the upwind tower footprint. In addition, a dynamic footprint analysis was conducted based on the two-dimensional Flux Footprint Prediction approach outlined in Kljun et al. (2015) to identify sites where a static footprint may not sufficiently capture the effects of variable wind directions on the measurement footprint of each tower (e.g., large differences in wind direction and speed between the morning and afternoon or seasonally). No sites were removed as a result of this analysis, but the static footprints were adjusted at 115 sites, including 18 of the 24 Phase I cropland sites, to account for prevailing wind direction or the presence of nonrepresentative surfaces in the tower footprint. A table summarizing the site ID, site name, crop type, location, and energy balance closure for each of the 24 Phase I cropland sites is provided in the Supporting Information.

The OpenET model intercomparison and accuracy assessment is being conducted in two phases. In Phase I, data from each model have been extracted over the footprints of 70 flux tower sites, including 24 cropland sites across the U.S. All models were run in

a fully automated mode and the flux tower data were not shared with the modeling teams until the comparisons were complete. For many of the models, this is the first time they have been run on a cloud-based platform in a fully automated framework over a geographic region the size of the western U.S. As such, the results from Phase I summarized in the following section were shared with the teams to evaluate model performance and make improvements to account for errors in the model implementation or to address systematic errors for regions, seasons or land cover types. For Phase II, an additional 69 sites (~50%) have been held back for a blind intercomparison that will be used to assess the final accuracy of each model and make a determination regarding which method to use to calculate the ensemble ET value. Data from an additional 33 sites not included in Phase I or Phase II have also been reserved for future accuracy assessments. Phase I results for croplands are summarized in the following section to illustrate the performance of the individual models and the ensemble value.

MODEL INTERCOMPARISON AND ACCURACY ASSESSMENT: PHASE I RESULTS

The overall results for the comparisons between the flux tower ET and the ET from the OpenET ensemble average and individual models are summarized in Table 3 for monthly data, and in Table 4 for daily data on satellite overpass dates . Results are shown for the ensemble mean as well as the range across the ensemble of models. Key metrics summarized in Tables 3 and 4 include the slope of the best fit line through the origin, the mean absolute error (MAE), mean bias error (MBE) and root mean squared error (RMSE) in mm/month or mm/day, and the coefficient of determination (r^2). The r^2 values were calculated as the square of the Pearson's product-moment correlation coefficient. Acknowledging its limitations as a measure of goodness of fit for model evaluation (Legates and McCabe 1999), we include r^2 as an easily interpreted indicator of the proportion of total variance in the flux tower data that can be explained by the satellite-driven ET models. ET values for the 24 cropland flux sites were calculated using the closed energy balance. ET values for the satellite-driven models are shown for the 90×90 m footprints for each site; results from the 210×210 m footprints were very similar. Site UA2_KN20 was a short-season leaf lettuce crop, and after QAQC filtering, it did not have one complete month of data and was removed from the monthly

TABLE 3. Summary of monthly accuracy assessment metrics for Phase I of the intercomparison for 23 cropland sites for the weighted monthly mean ET. The dataset included 1,307 total months and the mean monthly station ET across all 23 sites was 82.62 mm/month. Results are shown for the ensemble mean ET and the range across individual models included in the ensemble.

	Ensemble mean	Range across individual models
Slope (though origin)	0.95	0.86 to 1.02
MBE (mm/month)	−2.3	−12.9 to 3.8
MAE (mm/month)	13.6	15.5 to 21.6
RMSE (mm/month)	17.4	20.9 to 27.4
r^2	0.96	0.89 to 0.94

Notes: ET, evapotranspiration; MAE; mean absolute error; MBE, mean bias error; r^2, coefficient of determination; RMSE, root mean squared error.

TABLE 4. Summary of daily accuracy assessment metrics for Phase I of the intercomparison for 24 cropland sites for the weighted daily mean ET. The dataset included 3,203 days and the mean daily station ET across all 24 sites was 3.39 mm/day. Results are shown for the ensemble mean ET and the range across individual models included in the ensemble.

	Ensemble mean	Range across individual models
Slope (though origin)	0.90	0.81 to 0.96
MBE (mm/day)	−0.20	−0.57 to 0.02
MAE (mm/day)	0.74	0.85 to 1.07
RMSE (mm/day)	0.96	1.12 to 1.39
r^2	0.84	0.69 to 0.78

statistics. The 23 remaining sites had a combined total of 1,307 complete monthly data records, and daily comparisons were conducted for all dates for which satellite data were available over each flux tower site ($n = 3,203$ days).

To calculate the overall summary statistics in Tables 3 and 4 for slope, MBE, MAE, and RMSE, we calculated a weighted mean value for each statistic from the 23 (monthly) or 24 (daily) flux tower sites using the square roots of sample size ($\sqrt{n}$) of each site following Obrecht (2019). This weighting was applied to reduce the greater influence of sites that had longer periods of record, and to ensure that model performance at all sites contributed to the overall result summaries. Since a weighted mean of r^2 values is difficult to interpret, we calculated the overall r^2 value by pooling data from all sites and applying a weighting to each data point based on the ratio $\sqrt{n}/n$, and then calculating the r^2 value from the pooled data. Statistical summaries of the results for each of the individual sites are also provided in the Supporting Information. All statistics were calculated using the NumPy 1.17.2 (Harris et al. 2020)

and SciPy 1.3.2 (Virtanen et al. 2020) Python libraries.

The results summarized in Table 3 show strong overall agreement with the flux tower ET for all models and the ensemble mean. The slopes of the best fit lines through the origin range from 0.86 to 1.02, with a slope of 0.95 for the ensemble mean, and the MBE for the ensemble mean is only −2.3 mm/month overall. The MAE for the ensemble mean is 13.6 mm/month (equivalent to an average of 0.45 mm/day), and results for individual models range from 15.5 to 21.6 mm/month (equivalent to 0.51–0.72 mm/day). RMSE values, which are more strongly influenced by outlier values from each model, are 17.4 mm/month (equivalent to 0.58 mm/day) for the ensemble mean and range from 20.9 to 27.4 mm/month (equivalent to 0.70–0.91 mm/day). r^2 values show good correlation with the flux tower ET for all models and range from 0.89 to 0.94 for the individual models, with a value of 0.96 for the ensemble mean. These summary statistics indicate low bias errors overall, strong correlation with the flux tower ET, and accuracies that are within 13–30 mm/month of the flux tower ET data at a monthly timestep.

Results for the daily data are summarized in Table 4 and are similar to the monthly results. The slopes of the best fit lines range from 0.81 to 0.96 for the individual models, with a slope of 0.90 for the ensemble mean. MBE values range from −0.57 to 0.02 mm/day, with a value of −0.20 mm/day for the ensemble mean. MAE values range from 0.85 to 1.07 mm/day for the individual models, with a value of 0.74 for the ensemble mean. RMSE values range from 1.12 to 1.39 mm/day for the individual models, with a value of 0.96 mm/day for the ensemble mean. r^2 values also show a good correlation with the flux tower ET for all models and range from 0.69 to 0.78 for the individual models, with a value of 0.84 for the ensemble mean. As expected with linear interpolation of ET_oF between image dates, MAE and RMSE values increase slightly at a daily timestep, the r^2 values decrease, and the slopes of the best-fit lines move away from the 1:1 line. However, taken together, these summary statistics indicate low bias errors overall, strong correlation with the flux tower ET at both daily and monthly timesteps, and accuracies that are within the range of 13–30 mm/month, and 0.7–1.4 mm/day.

Overall, the OpenET ensemble mean performs as well or better than any individual model across most accuracy metrics, with the lowest MAE and RMSE values and the highest r^2 at both daily and monthly timesteps. The MAE for the mean of the model ensemble as a percent of the monthly n-weighted flux tower ET is 16.4% at a monthly timestep, and 21.8%

at a daily timestep. For reference, members of the OpenET user working groups (described below) specified an error of ±10%–20% as the accuracy target for ET data at a monthly timestep, and ±15%–25% as the accuracy target for daily ET data. It is noteworthy that the MAE and RMSE values for the ensemble mean are noticeably lower than the range of values across the individual models. One reason for the strong overall performance of the model ensemble is that individual models may occasionally "miss" and provide ET values that differ substantially from the flux tower ET or other reference dataset. This can be due to data quality issues in input data or physical conditions that depart from the model assumptions. However, since the ensemble value is currently calculated as the mean of all models, and due to the different designs of the models, errors from any one model are dampened in the ensemble mean, resulting in fewer large "misses" and lower MAE and RMSE values for the ensemble mean.

Of the 24 cropland sites included in Phase I, 15 sites had sufficient data to calculate ET for one or more complete growing seasons and 10 sites had sufficient data to calculate ET for one or more complete water years. Results for the total growing season ET are summarized in Figure 1, and results for the water year are summarized in Figure 2. For this analysis, we used gridMET climate data (Abatzoglou 2013) from 1980 to 2020 to define the mean annual start and end dates of the growing season at each ground-based ET station. We used 300°C cumulative degree days to define the start date of the growing season, and the first −2°C killing frost to determine the end date. Degree days used daily average temperature, and minimum daily temperatures were used to define the killing frost date (Huntington and Allen 2010). Monthly ET was used to sum annual growing season totals by rounding growing season start and end dates to the nearest month, and only years without any monthly gaps for the full growing season were included. Results were weighted by the square root of the sample size (in total growing seasons or years) for each site.

Figure 1 illustrates two important findings from Phase I of the OpenET intercomparison. First, the ensemble square root of n-weighted mean growing season ET is within 3 mm (0.5%) of the flux tower ET (601 mm/growing season). Second, all but one of the models are within ±8% of both the ensemble mean and the flux tower ET, and all models are within ±15%, illustrating good overall agreement across the ensemble of models, and very good agreement with flux tower measurements at seasonal timesteps. In addition, the range between the ET calculated from the closed and unclosed energy balance provides one measure of the uncertainty in the ET calculated from
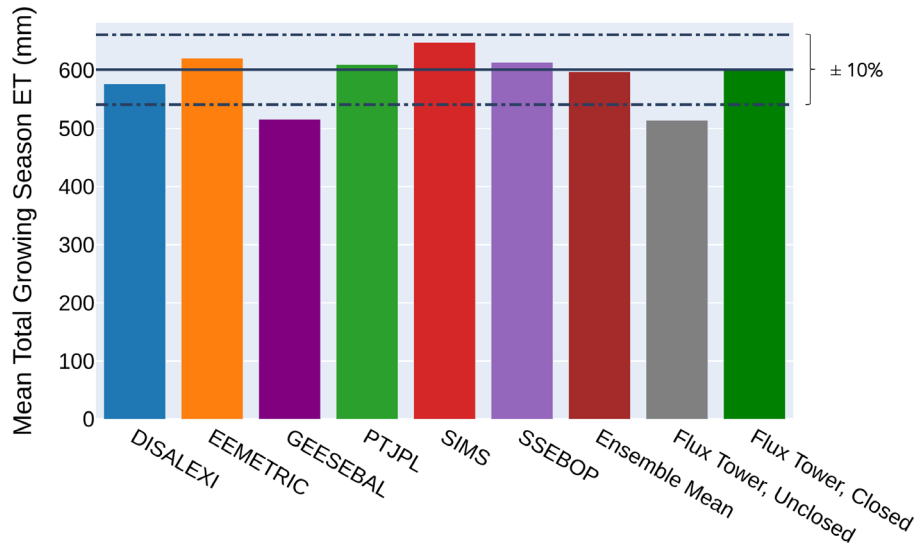
FIGURE 1. Total growing season weighted mean ET ($n = 15$ sites with 40 total growing seasons) for six satellite-driven ET models, the ensemble mean ET, and ET calculated from the closed and unclosed energy balances at each flux tower site.
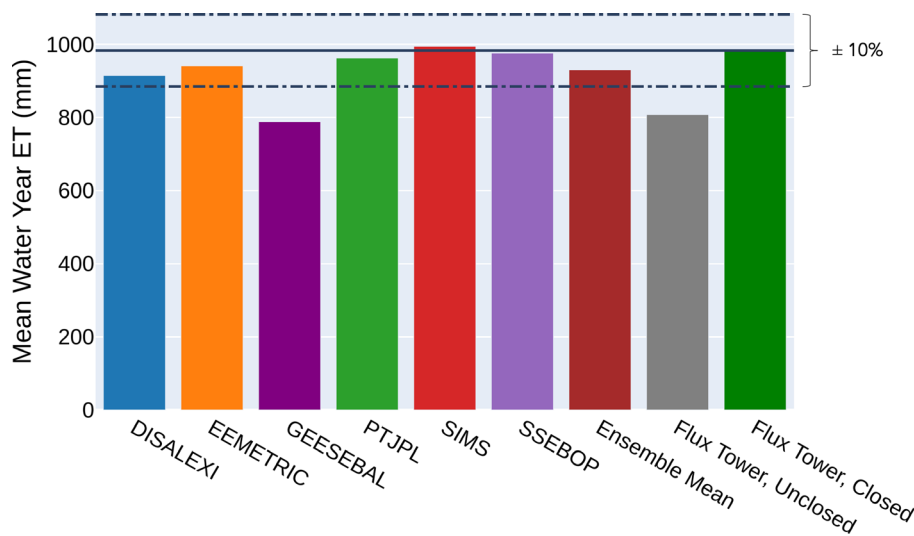
FIGURE 2. Total annual water year n-weighted mean ET for cropland sites ($n = 10$ with 23 total site-years) for six satellite-driven ET models, the ensemble mean ET, and ET calculated from the closed and unclosed energy balances at each flux tower site.

the flux tower measurements (Stoy et al. 2013). No models from the OpenET ensemble fall below the weighted mean ET calculated from the unclosed energy balance. DisALEXI, geeSEBAL, and the ensemble mean fall within the range between the closed and unclosed energy balance models. eeMETRIC, PT-JPL, SIMS, and SSEBop are greater than the closed energy balance ET but within 8% (47 mm) of the closed flux tower ET.

Results for the total ET for the water year are summarized in Figure 2. Values for each site were again weighted by the square root of the sample size

(i.e., the number of years) for each site to account for variability in the length of the data records. Results follow similar patterns to the results shown in Figure 1. All but one of the models are within ±7% (68 mm/year) of both the ensemble mean ET (930 mm) and the closed flux tower n-weighted mean annual ET (983 mm/year). The ensemble mean, eeMETRIC, PT-JPL, SIMS, and SSEBop are all within 5% (53 mm/year) of the closed flux tower ET. Four of the models and the ensemble mean fall between the ET values calculated from the closed and unclosed energy balance, and SIMS is slightly higher

FIGURE 3. Comparisons between the monthly ET from the OpenET ensemble of models and the flux tower ET for a nonirrigated, rainfed field in Mead, Nebraska with a maize-soybean rotation (Suyker 2001), shown as a scatter plot (a) and a time series graph (b). The average daily energy balance closure at this site was 0.87, and the shaded area between the dashed lines in (b) represents the range between the ET calculated from the unclosed energy balance (gray dashed line) and the closed energy balance (black dashed line) from the flux tower measurements.
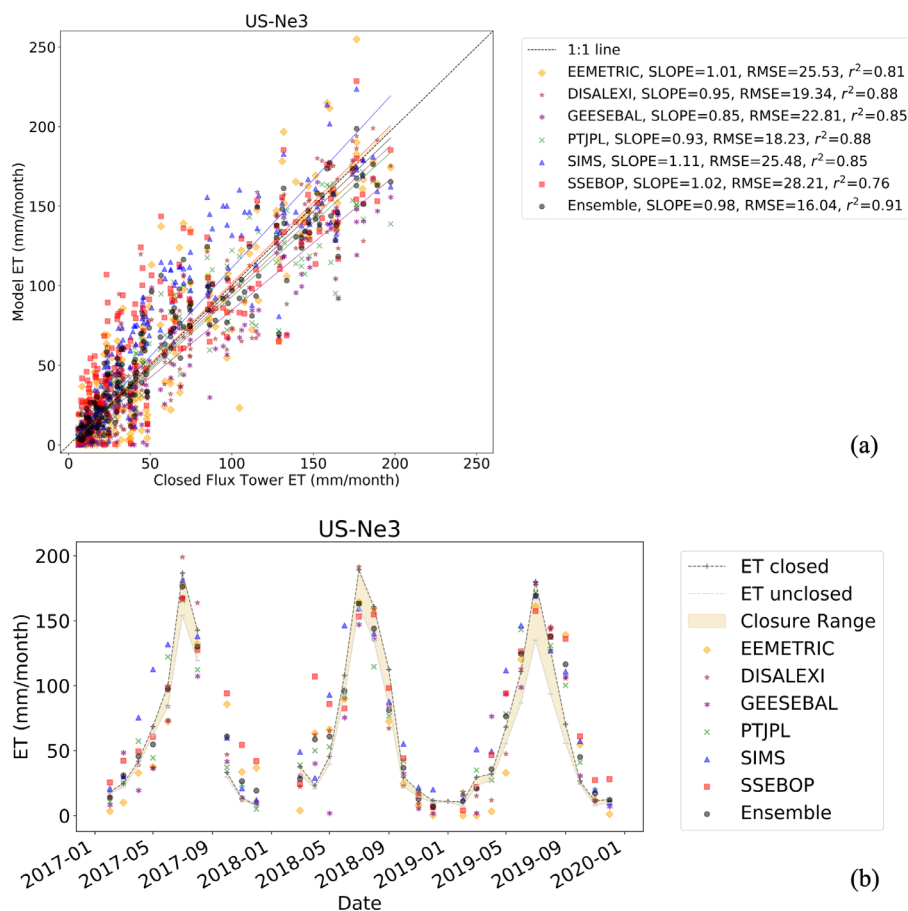
but within 1% (12 mm) of the ET calculated from the closed energy balance.

To illustrate the performance of the individual models and the model ensemble over specific sites, Figures 3–5 provide scatter plots and time series graphs for representative crops including a rainfed maize-soybean rotation (Ameriflux site US-Ne3, Nebraska), a flood-irrigated alfalfa (Ameriflux site US-Tw3, California) and an almond orchard irrigated with dripline emitters (Ameriflux site US-ASH USSL, California).

Results shown in the example Figures 3–5 provide evidence of good agreement across the model ensemble and generally close agreement of the individual models with the closed flux tower ET. For the rainfed maize-soybean rotation in Nebraska (Suyker 2001), the slopes of the best fit lines for each model range from 0.85 to 1.11, r^2 values range from 0.76 to 0.88, and RMSE values range from 18.2 to 28.2 mm/month. The ensemble mean monthly ET calculated from the

six models has a slope of 0.98, r^2 value of 0.91 and the lowest overall RMSE of 16.0 mm/month. All models follow the seasonal time series of flux tower ET closely, although some models overestimate monthly ET values in July in some years (Figure 3).

Figure 4 illustrates similar results from the irrigated alfalfa site in the San Francisco Bay-Delta (Chamberlain et al. 2013–2018), although with a wider range across the model ensemble. The slopes of the best fit lines range from 0.69 to 1.12, r^2 values range from 0.85 to 0.96, and RMSE values range from 15.4 to 36.6 mm/month. Despite the wider range in ET estimates from individual models, the ensemble mean again shows good agreement with the flux tower ET, with a slope of the best fit line of 0.92, RMSE value of 13.5 mm/month, and an r^2 value of 0.96. Despite the overall good agreement, this site illustrates how a negative bias in one or more models in the ensemble can also impact the ensemble ET value. In addition, the ability to compare ET models
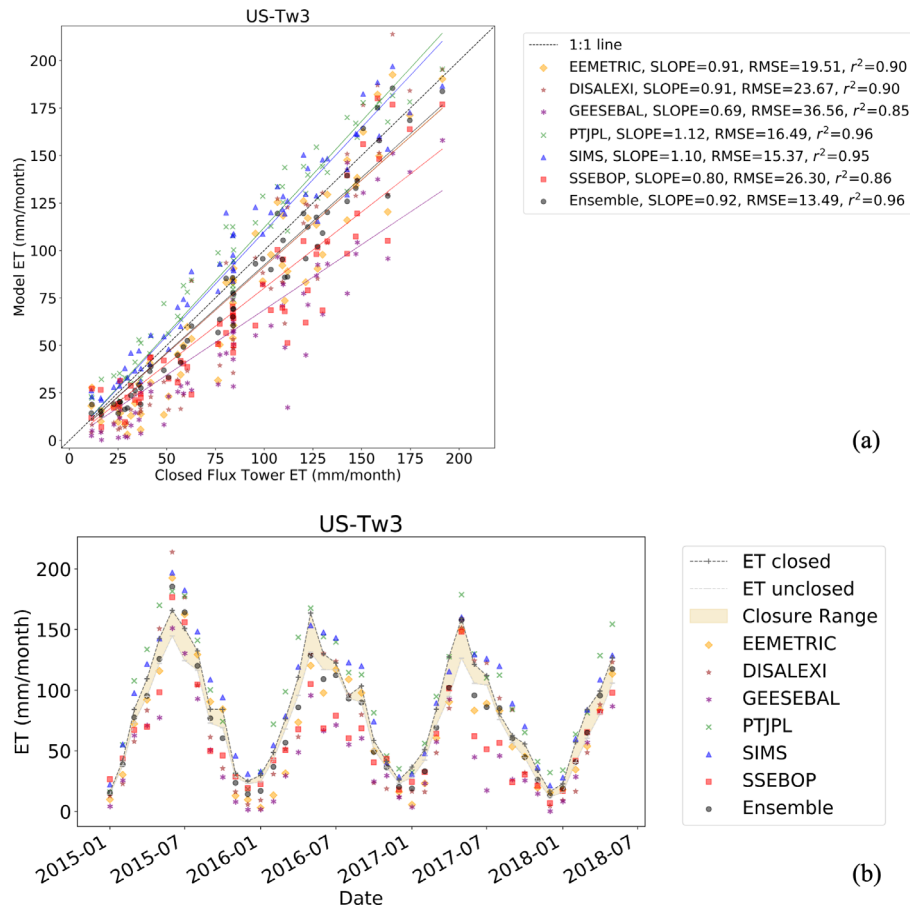
FIGURE 4. Comparisons between the ET from the OpenET ensemble of models and the flux tower ET for an irrigated alfalfa field in the San Francisco Bay-Delta, California (Chamberlain et al. 2013–2018), shown as a scatter plot (a) and a time series graph (b). The average daily energy balance closure at this site was 0.85, and the shaded area between the dashed lines in (b) represents the range between the ET calculated from the unclosed energy balance (gray dashed line) and the closed energy balance (black dashed line) from the flux tower measurements.

across a wide range of sites has allowed the team to identify the strengths of each model, as well as situations in which each model may have consistent biases. Phase II of the accuracy assessment will explore techniques for identifying and removing outliers to reduce bias in the ensemble ET value, but when the range of ET values across the ensemble is large, it may be difficult to fully eliminate positive or negative biases introduced by one or more models in the ensemble.

Results from the almond orchard site in the southern San Joaquin Valley are shown in Figure 5, demonstrating very good agreement between the ET values from all the satellite-driven models and the flux tower ET. For the individual models, the slopes of the best fit lines range from 0.87 to 0.97, r^2 values range from 0.89 to 0.92, and RMSE values range from 22.9 to 28.6 mm/month. The ensemble mean ET also performs very well at this site, with a slope of the best fit line of 0.93, RMSE of 24.0 mm/month, and r^2 value of 0.91. The time series graph shown in

Figure 5b also illustrates how well the satellite-based ET tracks the flux tower ET at this site overall.

While the results of the Phase I intercomparison and accuracy assessment demonstrate that the models are already performing well for cropland sites, following the completion of additional model improvements, there may be further increases in model accuracy metrics. Results for the other individual cropland sites included in Phase I are consistent with the three examples above, and tables listing daily and monthly summary statistics for individual sites are provided in the Supporting Information. Generally, there is good agreement across models, and the majority of models compare well with the flux tower ET. Phase II of the accuracy assessment will extend the findings of the intercomparison and accuracy assessment to include other land cover types. In addition, results from Phase II will be used to evaluate and select methods for outlier detection and removal, and calculation of the ensemble ET value. Results will also inform decisions about the
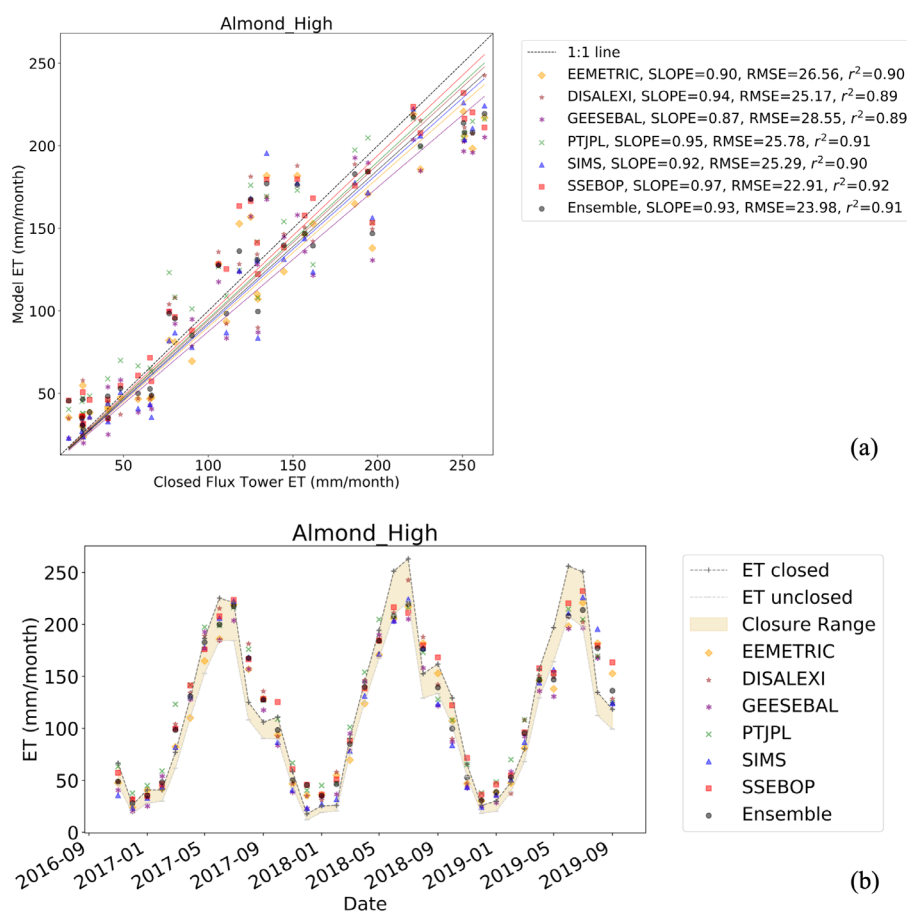
FIGURE 5. Comparisons between the ET from the OpenET ensemble of models and the flux tower ET for an irrigated almond orchard in the San Joaquin Valley, California (Anderson 2016), shown as a scatter plot (a) and a time series graph (b). The average daily energy balance closure at this site was 0.83, and the shaded area between the dashed lines in (b) represents the range between the ET calculated from the unclosed energy balance (gray dashed line) and the closed energy balance (black dashed line) from the flux tower measurements.

use of a subset of models, or even a single model, for particular regions or land cover types to minimize the influence of persistent biases in one or more models on the ensemble ET value.

OPENET ARCHITECTURE

OpenET builds upon decades of investment by NASA, USGS, NOAA, and the European Space Agency (ESA) to develop, launch, and operate a constellation of Earth observing satellites and to develop the ground data systems required to capture, process, store, and distribute satellite data freely to the public. The project is leveraging past work to develop gridded meteorological datasets used to calculate reference ET and produce and distribute these data operationally (Hart et al. 2009; Abatzoglou 2013). OpenET uses the Google Earth Engine platform

(Gorelick et al. 2017) as a shared cloud-computing platform that allows teams from multiple federal agencies and university research institutions to collaborate on the development of the OpenET software architecture. An overview of the major components of the OpenET architecture is provided in Figure 6. OpenET models use satellite, meteorological, climate, and land use data stored in the Earth Engine data catalog, which increases the consistency of preprocessing of data inputs that are common across multiple models and facilitates intercomparison of model results. This allows the OpenET team to reduce differences in ET estimates across the model ensemble that are due solely to differences in gap-filling algorithms or approaches used for time integration between satellite overpasses. Model outputs from individual Landsat scenes for each model are stored on Earth Engine as raster assets, as are the time-integrated data for monthly and annual total ET datasets.

User

- Custom Data Reports
- OpenET Data Explorer
- Integration with other Applications

Delivery Layer

- GeoServer
- PostgreSQL (Geodatabase)
- API
- Raster Images (GeoTIFF, EE assets)
- Data Summaries and Timeseries (geojson, csv)

Data, Models, and Processing

Cloud Platform (currently Google Earth Engine)

Satellite Data
Landsat, Sentinel 2, GOES, Suomi-NPP, Terra, Aqua

Meteorological Data
gridMET, Spatial CIMIS, NLDAS, CFSR, Daymet

Agricultural, Land Cover, Elevation, Boundaries
USDA, CDL, USGS, NLCD, SRTM, publicly available field boundaries, political and hydrologic boundaries

Models
ALEXI/DisALEXI
eeMETRIC
geeSEBAL
PT-JPL
SEBAL
SIMS
SSEBop

Cloud-based Processing
Earth Engine, Google Cloud Platform

Outputs
Intermediate data products and daily, monthly, annual gridded ET, ETo, ETr, ETof, ETrf, irrigation statuts

Primary Data Sources

USGS EROS Data Center
NASA LP DAAC
NASA GES DISC
ESA Copernicus
CA DWR CIMIS
gridMET Data Services
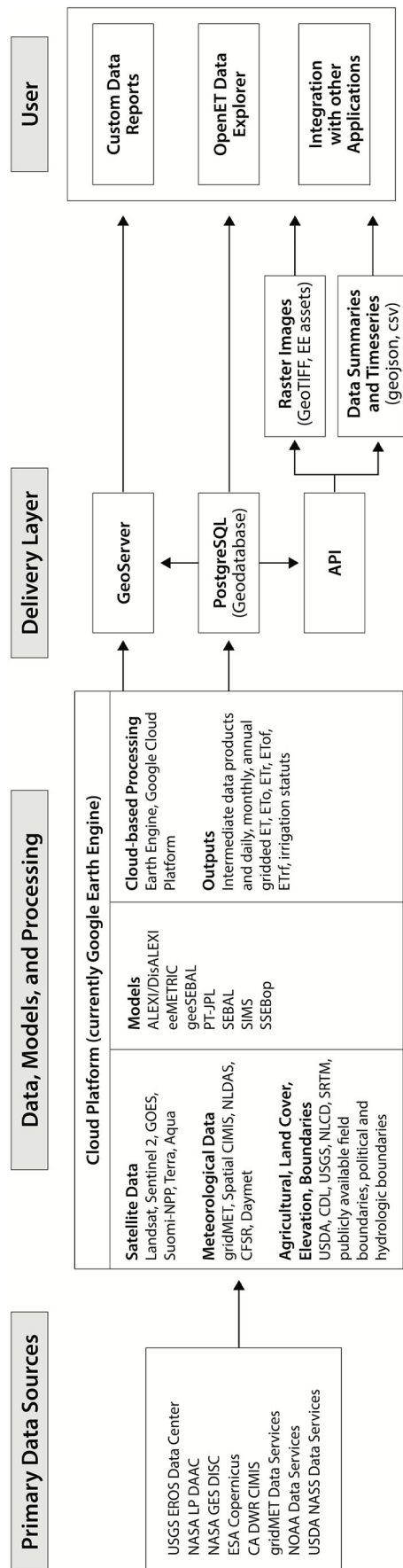NOAA Data Services
USDA NASS Data Services

FIGURE 6. Overview of the OpenET system architecture.

In addition to gridded, raster data archives, OpenET includes a PostGIS database (Obe and Hsu 2011) to store time series of ET data for individual polygons. The database is designed to include field boundaries, watersheds, irrigation district boundaries, locations for riparian vegetation or invasive species, and other geometries. Publicly available field boundary datasets have been compiled from state agencies as well as from the 2008 USDA Common Land Unit (CLU) database. Priority is given to more recent field boundary datasets produced by each state, and the CLU data are used only in cases where no state or local level datasets are publicly available. These datasets have been filtered to remove overlapping and redundant polygons, as well as very small slivers (<0.25 acres) and very large polygons associated with grazing on nonirrigated rangelands and shrublands. Using Earth Engine, time series of ET are calculated from the gridded, 30 m datasets for each model and for each polygon and stored in the geodatabase, facilitating rapid retrieval and analysis. Crop type information for each year is calculated for each field boundary from the USDA CDL (Boryan et al. 2011) based on the mode and is stored in the geodatabase.

OpenET includes a Data Explorer (Figure 7) that provides a web-based graphical user interface (UI) allowing users to easily explore and query ET data across the western U.S. for any field or location of interest. The web UI is based on Leaflet for mapping functionality, JQuery (Severance 2015) for front-end interactive features, and HighCharts (Kuan 2012) for interactive generation of graphs. OpenET provides access to both spatially continuous gridded datasets and choropleth maps that summarize data to individual field boundaries. The web UI displays monthly time series of data for each field (Figure 9). Clicking on the field opens an interface that allows the user to plot monthly and cumulative annual time series for the past five years and the current year, and to plot the data for the ensemble ET value or for individual models (Figure 9). The UI also allows the user to plot reference ET, fraction of reference ET, and NDVI as complementary and diagnostic datasets to assist in evaluating the ET time series. The UI allows the user to view and download graphs, along with the data used to generate the graphs.

OpenET also allows users to view and query the data as raster maps at the original satellite resolution (30 × 30 m) and draw geometries on the data to define and query regions of interest. Using the OpenET Reporting UI, users will also be able to upload shapefiles to define regions of interest, and specify the models, variables, and time periods of interest and generate custom reports for locations in the western U.S. using secure, private accounts that
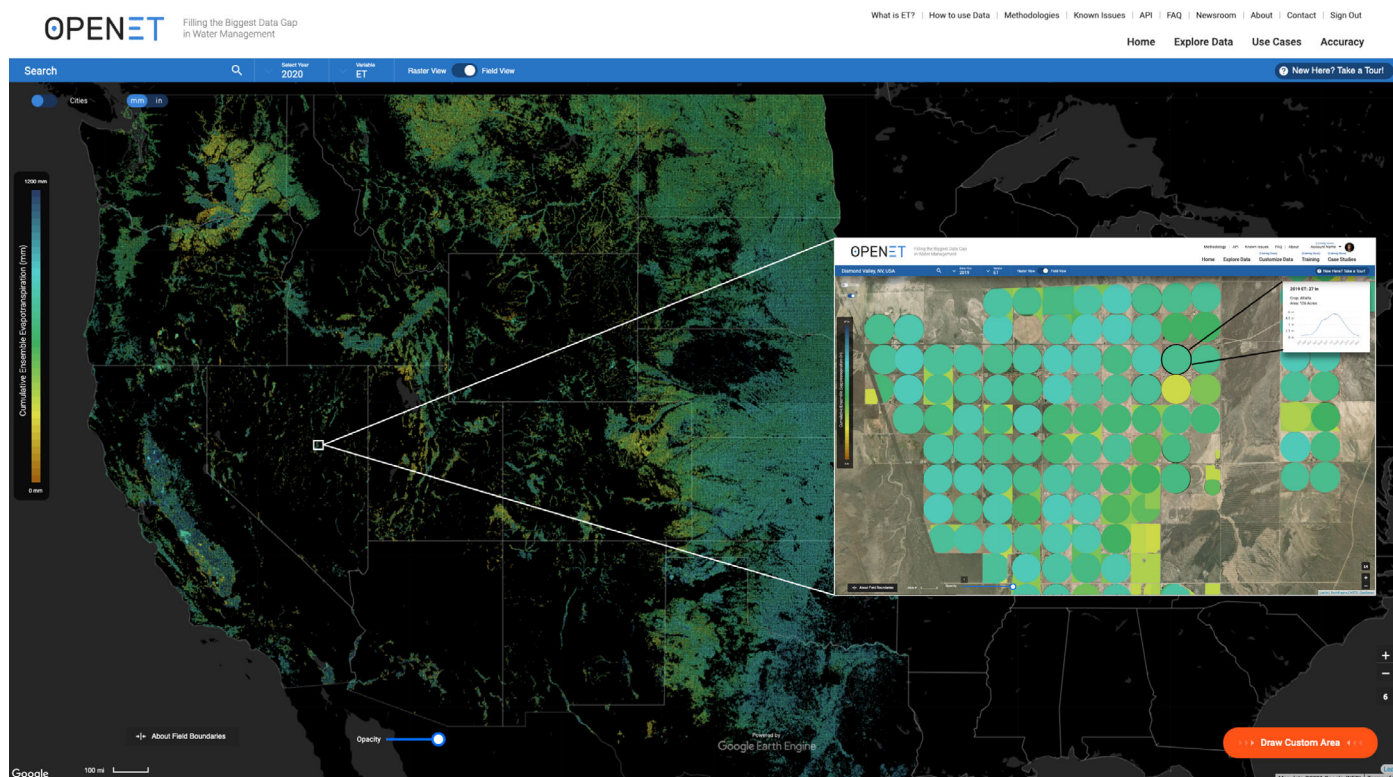
FIGURE 7. The OpenET Data Explorer showing data for fields across the western United States (U.S.), and a close-up view for individual fields near Diamond Valley, Nevada.

are protected from access by other users. Finally, OpenET provides an API that enables access to data services via scripted, automated machine-to-machine queries to facilitate the integration of data from OpenET within applications for irrigation scheduling, farm management, or water resources reporting, administration and management. The API follows the OpenAPI standard and currently uses SWAGGER.IO for API documentation and to provide a graphical UI for the API.

USER-DRIVEN DESIGN AND USE CASES

The design and development of OpenET has been user-driven from the outset to ensure that the platform meets a range of user requirements and provides utility for a broad range of water users and decision-makers. To define user requirements and demonstrate the value of OpenET for supporting sustainable land and water management practices, the team has developed a set of Use Case partnerships that represent a diversity of potential users and applications. The Use Case partnerships include growers and agricultural interest groups making irrigation management and other decisions at the field scale, water district managers building water accounting and trading platforms, and even broader drought and supply and demand assessments by state and federal agencies at larger scales. OpenET has convened representatives from state and federal agencies, policymakers, NGOs, farmers and agricultural companies, and other practitioners into geographically focused Working Groups to ensure that the team receives input from a broad range of perspectives. Through semi-structured interviews, quarterly webinars, and annual workshops, the team solicits feedback on topics including the UI design; spatial, temporal, and accuracy requirements; and outreach opportunities.

In total, OpenET developed more than a dozen use cases to inform the design of the platform, UI, and the data services available through the API. The following use cases from California and Colorado provide examples that illustrate a common need for transparent, credible, and easily accessible ET data across a variety of purposes (Figure 8). First, the Rosedale-Rio Bravo Water Storage District (Rosedale)

Sacramento-San Joaquin Delta

Helping the State Water Board and Delta landowners simplify regulatory compliance and more cost effectively **track and report water use** in the Delta

Bureau of Reclamation

Helping the Bureau of Reclamation improve **accuracy and trust in consumptive use** reporting for the Upper Colorado River Basin, and paving the way for creative demand management programs that increase drought resilience across the basin

Rosedale-Rio Bravo

Developing a **healthy water trading program** in the critically overdrafted Kern Groundwater Basin in California

Diamond Valley, NV

Helping farmers in Diamond Valley, NV estimate historical groundwater use and document reductions in groundwater use through **reduced pumping and improved irrigation efficiencies** in order to meet requirements to reduce water use by as much as 50% over the next 30 years

LEGEND

- Groundwater Management
- Irrigation and Crop Management
- Rangeland Management
- Regulatory Compliance
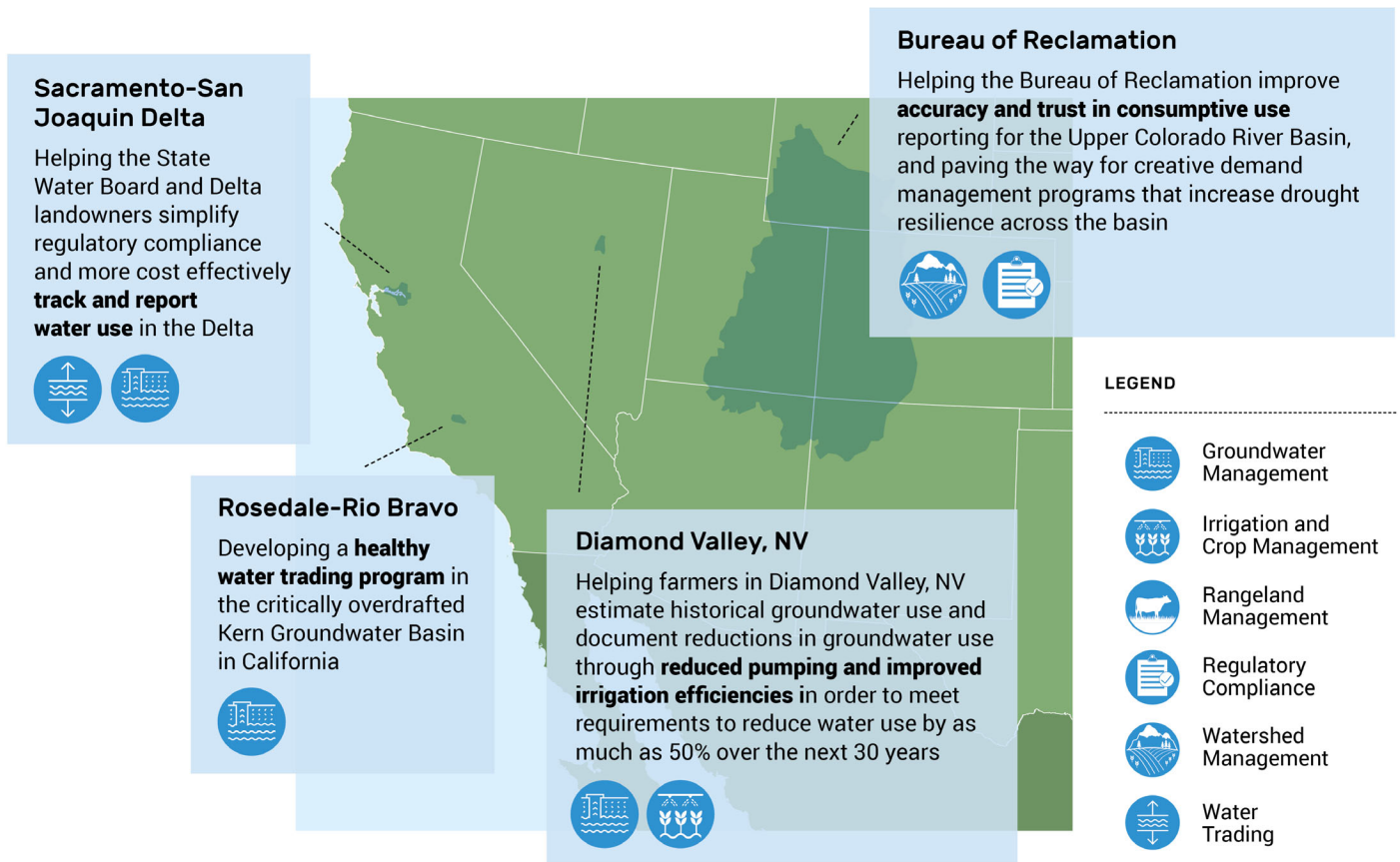- Watershed Management
- Water Trading

FIGURE 8. Examples of use cases and partners that are currently testing data from OpenET across the West.

serves landowners on 17,800 ha (44,000 acres) in the critically overdrafted Kern Basin in California. Unlike many other districts in the area, nearly all of Rosedale's water supplies are used to recharge the groundwater aquifer (Christian-Smith 2013). Under California's Sustainable Groundwater Management Act, Rosedale has developed a Groundwater Sustainability Plan (GSP) to balance its supply and demand within 20 years. Data from OpenET and other sources are important for Rosedale at both the parcel level for irrigation and crop management, and at the subbasin scale for implementation of their open-source water accounting platform. The platform, launched in Spring 2020, allows growers to more accurately track their agricultural water usage and consumption, and serves as a foundation to launch a regional water trading program. The ability of growers to buy and sell water from one another can accelerate the adoption of a wide range of innovative water management practices and reduce the economic impacts of drought on agricultural producers (Connell 2015). Currently, the Rosedale-Rio Bravo Water Accounting Platform uses the OpenET API to retrieve monthly total ensemble ET data for every

parcel in the district via automated queries to the API. The information is stored within the Water Accounting Platform and distributed to growers and landowners in the district via a web dashboard, allowing them to track water usage against their annual allocation. In the future, these data will also serve as the basis for supporting water trades within the district during times of water shortage, allowing growers to sustain crop production while meeting the goals of the GSP.

In the Upper Colorado River Basin, OpenET is currently being used to address several priority questions related to demand management, including evaluating the potential water conservation and agronomic viability for reducing irrigation on high-altitude irrigated pasture. This use case brings together expertise from OpenET, American Rivers, Trout Unlimited, Colorado State University, Utah State University, The Nature Conservancy, and agricultural producers in the region around Kremmling, Colorado. Data from OpenET are currently being used to compare water savings on parcels with zero or partial irrigation relative to reference parcels with normal irrigation. Through this use case, the team is
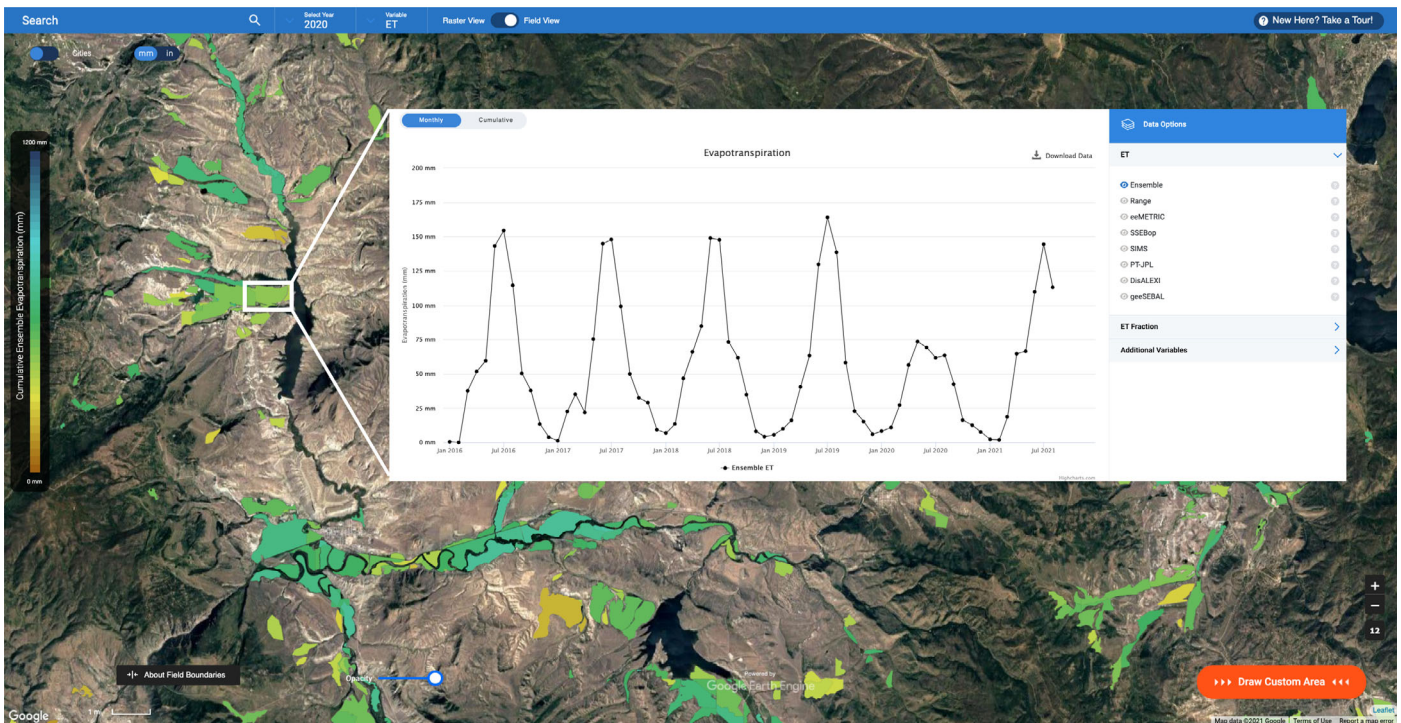
FIGURE 9. Time series of monthly ET data are easily accessible and viewable for agricultural fields across the western U.S. An example is shown for a field (white box) in Kremmling, Colorado based on the ensemble mean of all OpenET methods, illustrating reduced ET in 2020 as a result of participation by the grower in a demand management trial.

working to answer questions regarding how variations in forage species, soil, and groundwater conditions might affect consumptive use. Data from OpenET are valuable because they provide a consistent reference across the study area and can provide historic data to characterize baseline conditions over a range of time periods. In addition, OpenET is able to measure the change in consumptive use for each parcel, which is especially important for sites that are adjacent to riparian corridors where pasture grasses may have access to shallow groundwater. In these situations, it is possible for fields to have moderate levels of ET even without irrigation, limiting the value of metering applied irrigation water for evaluating the effects of different irrigation treatments on consumptive use. As stakeholders in the Upper Basin explore the feasibility of demand management programs, this use case provides information to address important questions about measuring and verifying water conservation, understanding agronomic impacts of reduced irrigation, integrating compensation for reduced water use with existing agricultural operations, and evaluating environmental aspects and tradeoffs associated with alternative strategies. An example is shown in Figures 9 and 10 for a field in Kremmling, Colorado. Monthly and

annual ET rates for this grass pasture (and adjacent irrigated pastures) were consistent from 2016 to 2019 (Figure 9), with peak monthly ET rates of 148–164 mm/month (5.8–6.5 in./month) and annual ET rates of 667–696 mm/year (26.3–27.4 in./year) (Figure 10). In 2020, the grower participated in a pilot demand management program and heavily reduced irrigation on this pasture, and as shown in Figure 10, there was a substantial reduction in ET to 449 mm/year (17.7 in./year). In contrast, ET for adjacent fields and reference fields in 2020 remained within the range observed for 2016–2019. The ability for both agricultural producers and program administrators to quickly and easily evaluate changes in ET associated with the implementation of demand management programs is an important prerequisite for expanded use of demand management across the Upper Colorado River Basin under the Drought Contingency Plans for the Basin.

A third use case is in the Sacramento-San Joaquin Delta, where significant portions of the agricultural acreage lie below the external surface water level, so that irrigation water is diverted out of the surrounding channels and onto agricultural lands in the Delta, primarily with siphons. Like other diverters across California, Delta landowners are faced with the
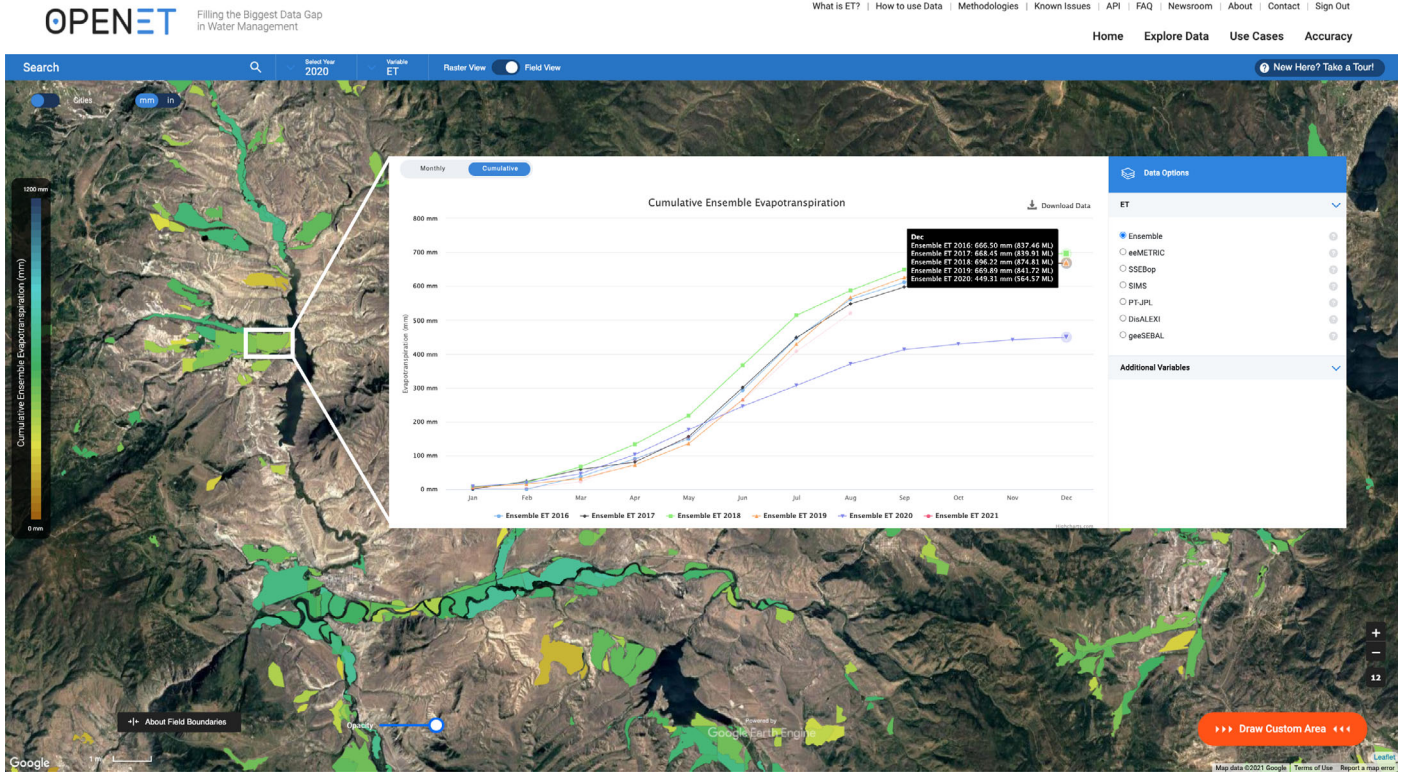
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FIGURE 10. Cumulative total ET data can also be easily accessed and displayed facilitating evaluation of changes in annual ET and consumptive use. Example shown for a field (white box) in Kremmling, Colorado, illustrating a reduction in ET in 2020 when the field was enrolled in a pilot demand management program.

difficult task of finding a cost-effective way to comply with California's Senate Bill 88, a regulation that requires monitoring and reporting of all diversions exceeding 12,335 m^3 (10 acre-feet) per year. OpenET is providing growers in the Delta with a consistent, dependable way to accurately estimate and report consumptive water use. This is viewed as a significant improvement over the high cost of installing meters at every point of diversion and return flow, as is currently required by the regulations implementing SB88. For this use case, a key strength of OpenET is the ability to provide a single value from the ensemble of ET models that represents a consensus estimate from the scientific community. At the same time, users can assess agreement across the full ensemble as an indicator of expected uncertainty in the ET data. An example time series for a single field in the Delta is shown in Figure 11, with data shown for the ensemble ET value and all individual models.

The Delta Measurement Consortium, which includes water contractors, farmers, conservation groups and representatives from the California State Water Resources Control Board, has reviewed data from OpenET and selected OpenET data as the basis for a Delta-wide alternative compliance plan for SB88, as allowed for under the original legislation.

Under the alternative plan of compliance, data from OpenET would be used as a "rebuttable presumption," allowing the grower or landowner to accept the ET data from OpenET or submit documentation from flow meters if preferred.

Through these use cases and others, partners have recommended features and functionality for the OpenET Data Explorer and API, identified concerns from agricultural producers about data privacy and worked with the team to resolve these concerns, and clearly communicated the advantage of providing a single ET value from the ensemble of models. The insights and recommendations provided through these partnerships are integral to the success of OpenET.

CHALLENGES AND LIMITATIONS OF OPENET

Operational production of ET data across the western U.S. at a spatial resolution of 30 m requires processing of tens of thousands of satellite scenes per year. This inherently requires full automation of both the models and the preprocessing of satellite and
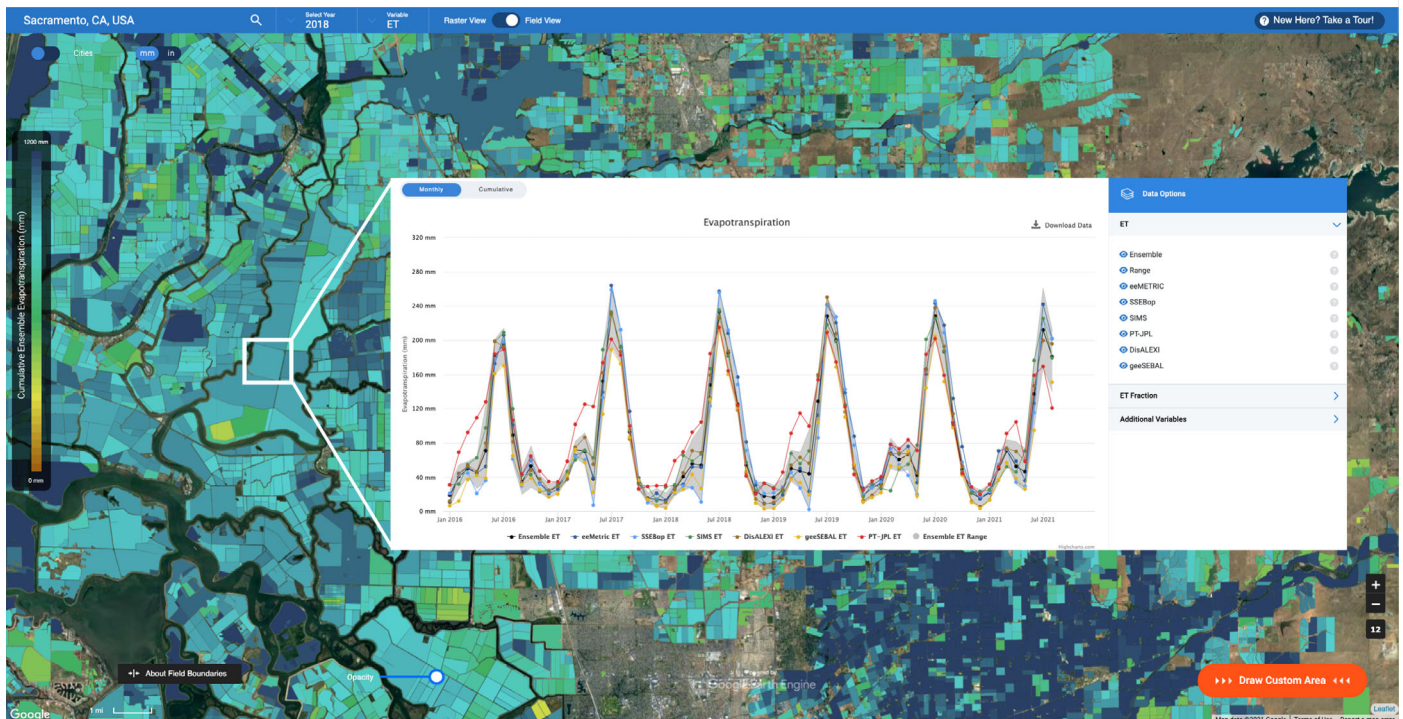
FIGURE 11. OpenET allows users to access data for the ensemble mean (black line), model range after excluding outliers (shaded area), and results from individual models (red, green, light blue, brown, yellow and dark blue lines). An example is shown for a corn field (white box) in the San Francisco Bay Delta where the ability to provide a single ensemble value for ET is a key requirement for operational use.

meteorological data inputs. While OpenET includes automated QAQC procedures, and each model contains its own internal automated calibration and QAQC routines, it is not possible for OpenET to provide the same level of data review and adjustment as may typically be done by a qualified expert analyzing data over a limited region using a supervised modeling approach. An important strength of the ensemble approach is that the full ensemble can be used to identify outlier values and compensate for some of the occasional errors that may occur from a single model. In addition, OpenET is developing a Best Practices Manual to guide users in understanding the strengths and limitations of data produced by OpenET and identifying appropriate applications of the data. However, as with all satellite-derived ET data, careful review by users prior to incorporation into water management applications is recommended, especially in applications that pertain to administration of water rights.

An important challenge for OpenET is the reliance upon daily reference ET information derived from gridded weather data and networks of agricultural weather stations. Daily weather data from the gridMET dataset are bias-corrected for aridity impacts

(ASCE-EWRI 2005) and for wind speed bias using hundreds of agricultural weather stations as a basis. Many of the agricultural weather networks in the western U.S. are operated by small teams of dedicated staff or by agricultural organizations on a voluntary basis in partnership with state and federal agencies. As such, these networks and data products are subject to their own errors and biases (Allen 1996; ASCE-EWRI 2005; ASCE 2016) that can affect the appropriateness of the gridMET bias corrections and, ultimately, the final ET data produced by OpenET. The OpenET framework includes QAQC procedures to identify and flag errors and biases, but the reliance on reference ET datasets and an understanding of the limitations of these datasets in some parts of the western U.S. are important to acknowledge. Future investments in additional agricultural weather stations, and financial support for maintenance of the stations and data systems, is a high priority for further improvements to the overall accuracy of ET data in the western U.S.

Finally, it is important to recognize that while the OpenET team is undertaking one of the largest and most rigorous ET intercomparison efforts conducted to date, the analyses will use 139 stations to assess

988

the overall accuracy of ET data representing millions of acres of land in the western U.S. Fortunately, the stations span a diverse range of crop types and natural ecosystems, providing a robust assessment of model accuracy. However, while potential errors in the flux tower datasets were accounted for by closing the energy balance, uncertainties in ground-based ET estimates remain. Allen et al. (2011) suggested an expected accuracy for EC systems of 10-30% depending on the experience of the operator and frequency of maintenance of the instruments. The assessment of the overall accuracy of the ET data from OpenET at daily and monthly timesteps is limited, in part, by the accuracy and availability of ground-based ET datasets. Collection of additional ground-based ET datasets using carefully maintained and well-calibrated instruments for a wide range of agricultural crops and natural ecosystems will be important in the future to assessing and improving the accuracy of remotely sensed ET data from OpenET and other efforts.

DATA AVAILABILITY AND TIMELINE

OpenET has released the OpenET Data Explorer for use by the public, and the API is currently being evaluated and tested by use-case partners. The Data Explorer and API provide access to 30 m resolution data for the 17 western states within the contiguous U.S. for the period from 2016 to present. In the near future, OpenET will also release the Reporting Interface, along with the API and OpenET Best Practices manual, and will make data from the OpenET gridded raster data archives available in the Earth Engine data catalog. OpenET is currently working to produce retrospective data from 2006 to 2015, with the potential to extend the data record back to 1984 — the start of the Landsat 5 data record.

THE VALUE OF A COMMUNITY EFFORT

As previously described, a key objective of the OpenET effort is to enhance ready access to spatial ET data and to accelerate use of ET data in water management by public and private entities at local, state, and federal levels. Additional important objectives of OpenET are to increase transparency and understanding of the strengths and weaknesses of remotely sensed ET data, increase understanding of the different approaches to ET mapping, and to identify and minimize errors and biases in all ET mapping approaches used within the OpenET framework. Participation of a sizable community of scientists working collaboratively has been essential to achieving these goals. The development of an ensemble value that is endorsed by a community of scientists is difficult to achieve without collaboration and a shared commitment to the common goal of making field-scale ET data operationally available and readily usable for a wide range of applications. In addition, a community effort should build confidence in the data by identifying and potentially reducing the range in ET estimates across the ensemble, identifying and explaining differences between models, and working toward a jointly conducted intercomparison and accuracy assessment. A manual of Best Practices for Application of Remotely Sensed ET Data that has been reviewed and endorsed by the research community is expected to gain widespread adoption and use.

OpenET makes it possible to readily compare ET models at scale, allowing the identification of consistent differences between the various models and approaches. In some cases, modeling teams can take steps to evolve individual models and resolve differences. In other cases, the discrepancies in ET estimates may be due to inherent differences in the ways the models represent physical processes and determine most probable values for ET. However, comparisons at scale allow the teams to identify, document, and explain these differences. Working together, the OpenET team is comparing preprocessing routines, gap-filling techniques, and time integration strategies. Driving all models with the community-selected best available inputs and community-reviewed preprocessing algorithms increases consistency in the ET data and reduces the range of ET values across the full ensemble. It is important to acknowledge that this community effort was made possible through support from the funding partners. The intentional programmatic effort on the part of these funders to encourage collaboration and support a community effort to build OpenET is central to the progress achieved by OpenET to date.

TRANSITION TO LONG-TERM OPERATIONS

OpenET initiated work on planning for transition to long-term operations in the second year of the project, in recognition of the lead-times required to ensure funding support and operational continuity for an effort involving dozens of scientists and

software engineers. The development team worked closely with a diverse range of advisors and use case partners to develop a transition plan that will be implemented over a two-year period. OpenET is currently exploring a strategy that involves both a non-profit organization and a public-benefit corporation or commercial entity. The nonprofit would host and manage the core datasets, software repositories and API, and provide training and support for OpenET users. The public-benefit corporation or commercial entity would scale as needed to provide custom software development, data analysis, and consulting services for the integration of the data with commercial applications.

A key goal of the transition strategy is to ensure that OpenET will be able to technically and financially sustain the availability of the datasets, UIs, and web data services for the foreseeable future. OpenET will need to maintain the models and documentation, and work with the science community to identify potential improvements to the models, test and vet these proposed improvements, and integrate them into the operational versions that are running on the OpenET platform. New models and technological advances in remote sensing of ET will need to be evaluated and incorporated into OpenET in the future. The OpenET team hopes to attract future funding support from agencies, organizations, and foundations who benefit from the ET data directly, or who benefit from the improvements in water management that stem from access to the ET data.

CONCLUSIONS

As farmers and water managers across the western U.S. are working to respond to growing constraints and increasing interannual variability in water supplies, the lack of accurate, consistent, and easily accessible information on ET and consumptive use has emerged as one of the biggest data gaps in the U.S. and around the globe. OpenET has employed a user-driven design approach to develop an operational system for field-scale ET mapping across the western U.S. OpenET is built upon the Google Earth Engine platform using open source software tools to increase transparency and facilitate collaboration across three federal agencies, six ET modeling teams, and a wide range of public and private entities collaborating with OpenET as use case partners and advisors. The use of Google Earth Engine facilitates scaling of the OpenET geographic domain to other regions in the future.

The collaborative, community-driven effort has accelerated progress on the alignment of model inputs and preprocessing routines, and initiation of a joint model intercomparison and accuracy assessment. The ability to easily compare model results at scale has accelerated the ability of the ET modeling community to identify and understand differences across the ensemble of approaches used by OpenET. Results from Phase I of the intercomparison and accuracy assessment demonstrate strong agreement between the satellite-driven ET models and the flux tower ET data across all accuracy statistics evaluated. Overall, the ensemble mean performs as well as any individual model across nearly all accuracy statistics, and the MAE for the ensemble mean is 16.4% (13.6 mm/month) at a monthly timestep and 21.8% (0.74 mm/day) at a daily timestep. The results from Phase II of the ongoing intercomparison study will inform the procedures used to calculate the final model ensemble value, as well as the recommendations in the Best Practices Manual that will accompany the OpenET documentation. The collaborative, user-driven approach adopted by OpenET may also serve as a reference in the future for teams working to develop analogous systems for remotely sensed measures of soil moisture and groundwater, or to implement and test new approaches to sub-seasonal to seasonal forecasts of precipitation.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: The Supporting Information includes tables that provide details for each flux measurement site, along with daily and monthly summary statistics for each site.

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