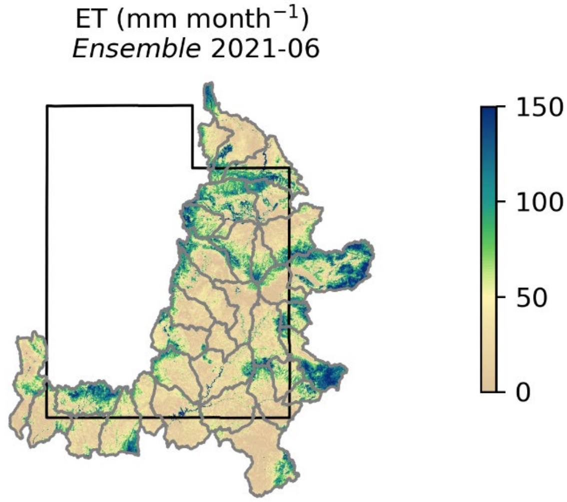
OpenET Historical Review (1990-2023) for the Colorado River Authority of Utah



AJ Purdy[1,9], Rick Allen[5], Garshaw Amidi-Abraham[10], Marth Anderson[11], Will Carrara[1,9], Josh Fisher[2], Christopher Hain[9], Maurice Hall[10], Justin Huntington[5], Gregory Halverson[9], Lee Johnson[1,9], Ayse Kilic[7], Forrest Melton[9], Blake Minor[5], Charles Morton[5], Peter Revelle[5], Anderson Ruhoff[6], Yun Yang[2,3]

With Contributions from Gabriel Senay[12], Gabe Parrish[12] and Mac Friedrichs[12]

September 2024

OpenET Technical Series, No. 002

California State University Monterey Bay[1], Chapman University[2], Cornell University[3], Desert Research Institute[5], Evapotranspiration Plus, LLC[5], Federal University of Rio Grande do Sul[6], GreenBlue ET LLC[7], Mississippi State University[8], National Aeronautics and Space Administration[9], OpenET, Inc.[10], United States Department of Agriculture[11], United States Geological Survey[12]

Prepared for:

Colorado River Authority of Utah

Suggested Citation: *Purdy et al., 2024. "OpenET Historical Review (1990-2023) for the Colorado River Authority of Utah" Prepared by California State University Monterey Bay, Cornell University, Desert Research Institute, Evapotranspiration Plus LLC., Federal University of Rio Grande do Sul, GreenBlue ET LLC, Mississippi State University, National Aeronautics and Space Administration, OpenET Inc., United States Department of Agriculture with contributions from United States Geological Survey. Prepared for Colorado River Authority of Utah.*

1. Overview

The objectives of the historical quality review report were to 1) provide an overview of the OpenET modeling system, 2) review differences between the OpenET ensemble and eeMETRIC, 3) identify geographic anomalies or temporal discontinuities in historic ET data; and 4) discuss limitations and considerations when using OpenET evapotranspiration (ET) data from any model. The appendix to this report includes detailed descriptions of the individual models, their strengths and limitations, and individual reviews by each modeling team. The main findings from the analysis and report are highlighted for the Colorado River Authority of Utah (the Authority) below:

1.1. Key Findings

- Overall, the historical ET data from the OpenET individual models and the ensemble value were found to exhibit relatively accurate performance for regions of the Colorado River Basin in Utah, consistent with previous analyses conducted for the Upper Colorado River Commission and in the OpenET Phase II accuracy assessment and intercomparison study (Volk et al., 2024). The evaluations presented in the report show support for OpenET adoption by the Authority, especially for applications related to quantification of ET from croplands.
- When compared to on-ground cropland observations with similar aridity to Utah, an initial evaluation found the OpenET ensemble value and individual models to exhibit reasonably high accuracy, consistent with findings of the Phase II intercomparison. Over natural lands such as evergreen forests, mixed forests, grasslands, shrublands, and wetlands, the Phase II intercomparison revealed lower agreement between the OpenET ensemble ET value and individual models with ground-based measurements, though mean absolute error values for most land cover types and model are still less than 1 mm/day.
- A basin water balance ET (WBET) evaluation found the OpenET ensemble value showed similar performance relative to prior satellite-based ET evaluations in the Western United States (US). Individual models show more varied performance against WBET for basins in the Colorado River Basin relative to ground-based ET evaluations.
- For agricultural land cover types, an evaluation of the temporal change in the fraction of ET relative to reference ET from an alfalfa surface (ETrF) revealed anticipated responses to water shortages. For example, in the Uinta Basin and the eastern slope of the Abajo Mountains, decreases in ETrF occur in both basins during periods of drought. When evaluating the range of modeled ET relative to the ensemble ET value, strong agreement was found for irrigated croplands. These attributes provide support for applications of OpenET for consumptive use quantification over croplands.
- For non-agricultural lands, the review found a potential high bias in OpenET values for very dry regions. For certain basins in the southern CRB in Utah, long-term mean annual ET was found to be greater than precipitation. For some basins, a high proportion of surface water may at least partially explain greater ET rates. However, this is not the case for all basins, and a high bias in ET is consistent with the Phase II model accuracy assessment for non-agricultural land. The finding may be explained in part by the presence of measurement and interpolation uncertainty in gridded precipitation. The ET values from eeMETRIC and SSEBop are more similar to precipitation over non-

agricultural land, and use of one or both of these models may mitigate this potential bias. Additional on-ground measurements in non-agricultural land cover types would support diagnosing the source of difference between precipitation and ET for this analysis and guide improvements to the OpenET models for natural lands in very arid environments.

- The strongest inter-model agreement, evaluated as the model range divided by the OpenET ensemble value, occurs during summer months over irrigated agricultural lands. This finding implies stronger confidence in OpenET ET values for the growing season over croplands. A wider range was found during winter months and also in very arid landscapes for all seasons, driven in part by very low ET rates. Results from this analysis can be used to guide selection of future on-ground ET measurement sites and improve the OpenET ensemble by identifying a subset of the most accurate models for a given application or use-case.
- At least 24 clear-sky satellite retrievals per year occur for the majority of land area within the Colorado River Basin (CRB) in Utah. Prior to 1999 and during 2012, when only one Landsat satellite was in orbit, fewer clear-sky retrievals occurred, especially in mountainous areas with snow cover. For use of OpenET data prior to 1999 or during 2012, the OpenET team recommends inspecting the number of clear sky observations for each month. For example, if a certain region experiences less than 1 clear sky image for a given month during the growing season, that month's data should not be used to compute long-term consumptive use estimates. An online application to inspect the number of cloud-free images by month will be shared with the Authority.
- When comparing the OpenET ensemble to eeMETRIC version 0.20.26, the review found the OpenET ensemble value demonstrates slightly improved accuracy (lower MAE and RMSE) and greater explanation of variance (higher R squared value) when compared against ground-based observations over croplands. A WBET analysis found the OpenET ensemble and eeMETRIC have slopes similarly close to 1.0, but the OpenET ensemble shows greater explanation of variance. Pixel-wise comparisons over agricultural land for June, July, and August multi-year averages reveals the OpenET ensemble and eeMETRIC to be within +/-10% of each other for irrigated croplands. A larger difference is found in rainfed agriculture (>20%), with eeMETRIC ET values being greater than the OpenET ensemble for these regions. Inter-annual changes in ETrF averaged to a basin also show close agreement for irrigated lands and eeMETRIC values are larger than the OpenET ensemble for rainfed croplands. When evaluating the ratio of ET:P, the eeMETRIC model maintains ratios closer to 1.0 for the driest basins in the CRB, while the OpenET ensemble average ET:P ratio can exceed 1.3. The eeMETRIC ET values may provide a more accurate ET value for very arid conditions, and while eeMETRIC is among the best performing models for the region, the accuracy evaluation supports the adoption of the OpenET ensemble value over agricultural land.
- Additional ground observations and field campaigns to collect measurements of ET, and expansion of ground-based reference ET monitoring networks, would support improved model accuracy and refinement to the OpenET modeling system. The OpenET team looks forward to new ground observations being collected by the Utah Geologic Survey. Additional observations will support creating an improved OpenET ensemble ET value from a subset of the best performing OpenET models, especially over challenging land

cover types. Collection of additional ground-based ET data in regions where inter-model ET values are large and over land cover types with higher uncertainty (e.g. wetlands, open water) will support the greatest advances in satellite-based ET modeling.

2. OpenET Overview

2.1. Modeling system

OpenET provides actual evapotranspiration (ET) data that represents the total amount of water being transferred from the land surface to the atmosphere. OpenET leverages Google Earth Engine to operationally run and store data from six ET models (ALEXI/disALEXI; eeMETRIC; geeSEBAL; PT-JPL; SIMS; and SSEBop) and an ensemble ET value for the 23 westernmost states. OpenET daily and monthly data for the current year and the past 5 years are made available via the Data Explorer. Data from 2013 to present are also available through a public Application Programming Interface (API), and more recently through the Farm And Ranch Management Support (FARMS) user interface. The OpenET modeling system facilitates the creation of a historical ET data record for the Authority.

2.2. Models

Table 1 provides an overview of the 6 models included in the OpenET ensemble. Data from all models and the ensemble were produced retrospectively for the Colorado River Basin of Utah from 1991-present, with the exception of disALEXI which relies on ancillary data sources that began in 2000. A description of the individual models, their strengths and known limitations can be found in Appendix A.

Table 1. Models and versions used in OpenET historical data generated for the Authority.

Model acronym	Model name	Primary references
ALEXI/DisALEXI v 0.0.32	Atmosphere-Land Exchange Inverse/Disaggregation of the Atmosphere-Land Exchange Inverse (ver. 0.0.32)	Anderson et al. (2007, 2018)
eeMETRIC v 0.20.26	Mapping Evapotranspiration at High Resolution with Internalized Calibration (ver. 0.20.26)	Allen et al. (2005, 2007, 2011)
geeSEBAL v 0.2.2	Surface Energy Balance Algorithm for Land using Google Earth Engine (ver. 0.2.2)	Bastiaanssen et al. (1998); Laipelt et al. (2021)
PT-JPL v 0.2.1	Priestley-Taylor Jet Propulsion Laboratory (ver. 0.2.1)	Fisher et al. (2008)
SIMS v 0.1.0	Satellite Irrigation Management Support (ver. 0.1.0)	Melton et al. (2012); Pereira et al. (2020)
SSEBop v 0.2.6	Operational Simplified Surface Energy Balance (ver. 0.2.6)	Senay et al. (2013); Senay (2018); Senay et al., (2023)

2.3. Data inputs

OpenET models rely on multispectral and thermal Landsat observations with additional gridded meteorological data from gridMET and the National Land Data Assimilation System (NLDAS). Table A.1 details the primary and secondary satellite inputs in addition to the sources of gridded meteorological data for each model.

2.4. Temporal frequency / coverage

The historical ET dataset produced for the Authority includes monthly ET assets from 1990 - present covering the geographic extent of the Colorado River Basin areas of Utah and the HUC-8 boundaries that intersect the state's border. Daily data for the historical record are made available through the custom instance of the API set up for the Authority. Daily ET values are produced on demand using the API from the historical Landsat scene assets for each model. In addition to accessing the data through the API, a publicly accessible Google Bucket was shared with the Authority to access monthly ET values from each model and the ensemble as GeoTIFFs. Figure 1 shows the extent of data produced for the Authority.

2.5. Ensemble overview

A key objective of OpenET is to provide a single ET value for a requested location and time step, calculated from an ensemble of six models, while making individual model results available to provide transparency and support assessment and increase understanding of uncertainties. Evaluations to-date show that the ensemble tends to be more accurate than any individual model. The ensemble value is computed at a given time step as the simple arithmetic average after outlier ET model values for the timestep are removed. Outlier ET values are detected and removed using the Median Absolute Deviation (MAD) method. MAD is a measure of scale, or spread of the data, based on the median of the absolute deviations from the median of the distribution. An amendment to this approach, for purposes of this study, involved retaining a minimum of four models to calculate the ensemble value. The use of multiple ET models

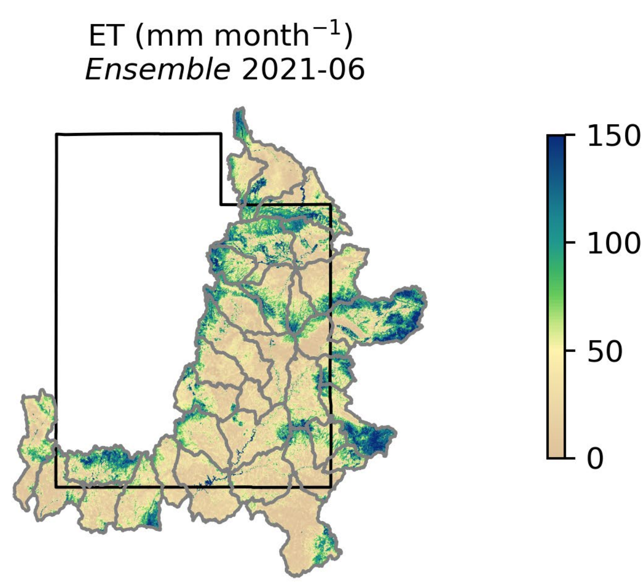


Figure 1. ET from the OpenET ensemble from June, 2021. HUC 8 boundaries shown within the Colorado River Basin.

allows for identification of individual modeled ET outliers by intercomparison. This attribute improves quality in areas with limited to no in-situ monitoring, such as areas of the CRB in Utah. Melton et al., 2022 provides a more detailed description of MAD and ensemble value calculation. Figure 1 shows the monthly ET for the HUC 8 Colorado River Basins in Utah from June 2021.

2.6. Accuracy Assessment

A 2023 intercomparison study evaluated the accuracy of all 6 ET models and the ensemble value for 152 ground-based observations (Volk et al., 2024). Mean Absolute Error (MAE), Mean Bias Error (MBE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) were used to evaluate model accuracy. The intercomparison study found the OpenET ensemble has strong accuracy at monthly time-scales for croplands sites (N=91) with MBE -5.27 mm (-5.8% of measured ET) and MAE = 15.84 mm (17% of measured ET). The intercomparison also evaluated the OpenET ensemble accuracy for individual land cover types including evergreen forests (MBE 27% and MAE 40%), grasslands (MBE -2% and MAE 45%), mixed forests (MBE 29% and MAE 32%), shrublands (MBE 7% and MAE 49%), and wetlands/riparian (MBE 13% and MAE 29%). Table 2 shows the ensemble ET accuracy for both croplands and natural land cover classifications. Improved accuracy is found for longer temporal aggregations (e.g., water year and calendar year). The supplementary information from Volk et al., 2024 provides more details about the ensemble and individual model accuracies for each land cover across different timesteps.

3. Difference in eeMETRIC UCRB vs OpenET provisional historic data set

The version of eeMETRIC (v0.20.26**)** reflected in the historical data shared with the Authority differs from the eeMETRIC version (v0.20.33) that was used in the Upper Colorado River Basin (UCRB) Consumptive Use Study (eeMETRIC sensitivity study). The main differences between the two eeMETRIC model versions include updates to: 1) the LST correction procedure, 2) sensible heat computation over steep slopes areas outside of mountainous terrain, and 3) crop type representation within eeMETRIC. The change to the OpenET crop type represented in eeMETRIC will drive larger differences between the two model versions for grass/pasture and wetland designations in the current OpenET crop type data layer. These changes were found to reduce ET values after conversion to other hay/non-alfalfa designations.

Table 2. Monthly accuracy metrics relative to tower monthly ET for sites grouped by their general land cover type. (Reproduced from Volk et al., 2024 Supplementary Information Table 3)

Land cover type	Statistic	Ensemble	DisALEXI	eeMETRIC	geeSEBAL	PT-JPL	SIMS	SSEBop
Croplands Mean station ET = 91 (mm/month)	Slope	0.92	0.92	0.95	0.85	0.91	0.99	0.95
	MBE (mm)	-5.27 (-5.8%)	-7.72 (-8.4%)	-2.44 (-2.7%)	-12.18 (-13.3%)	-2.9 (-3.2%)	4.32 (4.7%)	-6.08 (-6.7%)
	MAE (mm)	15.84 (17.3%)	19.91 (21.8%)	21.23 (23.2%)	22.69 (24.8%)	18.12 (19.8%)	17.93 (19.6%)	22.4 (24.5%)
	RMSE (mm)	20.44 (22.4%)	25.35 (27.7%)	26.97 (29.5%)	29.05 (31.8%)	23.67 (25.9%)	23.1 (25.3%)	27.72 (30.3%)

	R-squared	0.9	0.86	0.83	0.83	0.87	0.86	0.85
Evergreen Forests Mean station ET = 62 (mm/month)	**Slope**	1.24	1.3	1.17	1.34	1.17	NA	1.23
	MBE (mm)	16.8 (27.3%)	18.83 (30.6%)	10.78 (17.5%)	22.93 (37.3%)	16.22 (26.4%)	NA	16.71 (27.2%)
	MAE (mm)	24.68 (40.1%)	29.06 (47.2%)	25.94 (42.2%)	31.27 (50.8%)	25.11 (40.8%)	NA	26.84 (43.6%)
	RMSE (mm)	29.96 (48.7%)	34.75 (56.5%)	31.76 (51.6%)	38.2 (62.1%)	29.88 (48.6%)	NA	32.63 (53.0%)
	R-squared	0.62	0.55	0.55	0.59	0.58	NA	0.52
Grasslands Mean station ET = 40 (mm/month)	**Slope**	0.87	0.88	0.89	0.89	1.02	NA	0.78
	MBE (mm)	-0.88 (-2.2%)	2.4 (6.0%)	-1.77 (-4.4%)	2.96 (7.4%)	6.68 (16.7%)	NA	-6.2 (-15.5%)
	MAE (mm)	18.02 (45.1%)	20.33 (50.9%)	19.65 (49.2%)	27.15 (67.9%)	19.84 (49.6%)	NA	17.99 (45.0%)
	RMSE (mm)	22.72 (56.9%)	25.67 (64.2%)	25.21 (63.1%)	35.57 (89.0%)	24.22 (60.6%)	NA	22.45 (56.2%)
	R-squared	0.54	0.48	0.56	0.22	0.56	NA	0.53
Mixed Forests Mean station ET = 62 (mm/month)	**Slope**	1.19	1.14	1.06	1.3	1.2	NA	1.22
	MBE (mm)	17.72 (28.8%)	13.51 (21.9%)	6.55 (10.6%)	27.32 (44.4%)	22.35 (36.3%)	NA	18.93 (30.8%)
	MAE (mm)	19.76 (32.1%)	19.37 (31.5%)	18.55 (30.1%)	30.32 (49.3%)	23.79 (38.7%)	NA	22.03 (35.8%)
	RMSE (mm)	24.73 (40.2%)	24.12 (39.2%)	25.12 (40.8%)	36.0 (58.5%)	28.61 (46.5%)	NA	27.59 (44.8%)
	R-squared	0.87	0.85	0.79	0.81	0.85	NA	0.83
Shrublands Mean station ET = 31 (mm/month)	**Slope**	0.98	0.98	0.91	1.18	1.12	NA	0.78
	MBE (mm)	2.27 (7.4%)	2.64 (8.6%)	-1.84 (-6.0%)	11.38 (37.0%)	8.57 (27.9%)	NA	-6.17 (-20.1%)
	MAE (mm)	15.28 (49.7%)	16.84 (54.7%)	19.09 (62.0%)	22.07 (71.7%)	17.38 (56.5%)	NA	14.5 (47.1%)
	RMSE (mm)	19.27 (62.6%)	20.92 (68.0%)	23.64 (76.8%)	28.55 (92.8%)	20.8 (67.6%)	NA	17.98 (58.4%)
	R-squared	0.48	0.46	0.4	0.36	0.47	NA	0.57
Wetland/Riparian Mean station ET = 88 (mm/month)	**Slope**	1.06	1.14	1.11	1.06	0.99	NA	1.02
	MBE (mm)	11.9 (13.5%)	20.88 (23.7%)	14.52 (16.5%)	14.45 (16.4%)	8.84 (10.0%)	NA	5.29 (6.0%)

	MAE (mm)	25.94 (29.5%)	31.38 (35.7%)	31.75 (36.1%)	32.88 (37.4%)	28.69 (32.6%)	NA	21.61 (24.6%)
	RMSE (mm)	31.31 (35.6%)	37.85 (43.0%)	37.04 (42.1%)	41.01 (46.6%)	36.14 (41.1%)	NA	27.01 (30.7%)
	R-squared	0.75	0.69	0.68	0.61	0.65	NA	0.8

Table 3. Monthly mean statistics for 18 cropland stations with similar aridity to Utah. Reproduced from Table 1 of the preliminary OpenET intercomparison report for Utah (Volk 2024).

Statistic \ Model	Ensemble	DisALEXI	eeMETRIC	geeSEBAL	PT-JPL	SIMS	SSEBop
Slope	0.92	0.78	1.03	0.82	0.85	1.0	1.02
MBE (mm)	-4.36 (-3.6%)	-19.79 (-16.2%)	10.62 (8.7%)	-16.47 (-13.5%)	-10.42 (-8.5%)	5.63 (4.6%)	5.84 (4.8%)
MAE (mm)	18.73 (15.3%)	31.71 (25.9%)	21.13 (17.3%)	28.78 (23.5%)	25.56 (20.9%)	19.7 (16.1%)	24.73 (20.2%)
RMSE (mm)	23.4 (19.1%)	39.73 (32.5%)	26.97 (22.1%)	35.42 (29.0%)	31.13 (25.5%)	24.31 (19.9%)	29.72 (24.3%)
R^2	0.89	0.7	0.87	0.76	0.81	0.86	0.82

A review of the sensitivity found area-weighted ETa rates are on average 1.45% greater for eeMETRIC v0.20.33 relative to eeMETRIC v0.20.66 from 1991-2023 for Utah. The largest deviation was found to be 5.45% in 2012. Model updates to the OpenET modeling system are currently scheduled for January of 2025. After 2025, the OpenET team plans to synchronize eeMETRIC data versions to be consistent with eeMETRIC v0.20.33.

4. Quality evaluation metrics

4.1. Intercomparison accuracy statistics

None of the 152 sites included in the Phase II model intercomparison and accuracy assessment were located in Utah. A separate report to the Authority has identified a subset of the 152 benchmark sites based on the similarity of the aridity index at each site with the mean aridity index for Utah (AI = 0.3) (Volk 2024). Table 3 shows the ET accuracy for the OpenET ensemble and the six OpenET models. The ensemble value shows the best performance relative to the individual models with respect to MBE, MAE, RMSE, and R^2.

4.2. Water balance closure using OpenET

Evaluating the total ET values by water balance closure for HUC 8 basins provides a top-down mechanism to evaluate model fidelity across larger geographic domains. Here, we use water balance ET (WBET) values computed at the level-8 Hydrologic Unit Code (HUC 8) sub-basins from Senay et al., 2023 in the Colorado River Basin to evaluate the OpenET models.

$$WBET = P - Q - \Delta S \tag{1}$$

where *P* is annual precipitation, *Q* is annual runoff, and ΔS represents annual water storage change. The WBET data includes precipitation sourced from PRISM, and runoff sourced from USGS stream gauges. The change in storage was assumed to be 0 for each year and would explain some of the deviation. The OpenET ensemble was found to have a slope of 1.04 and a mean bias error of less than 8% for 5 water years and 123 unique basins (322 basin-water years) (Figure 2). The OpenET team will work to expand this analysis to better diagnose drivers of disagreement to guide adoption.

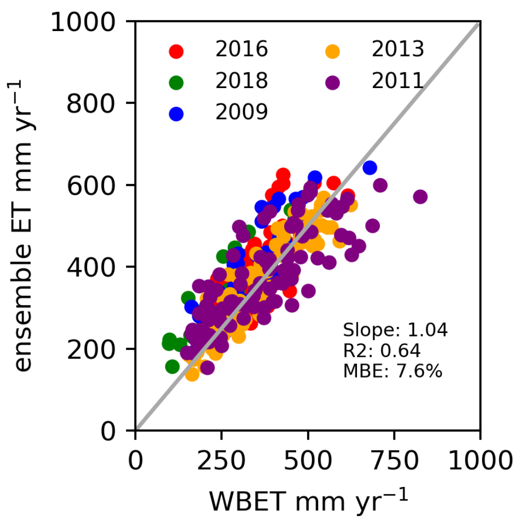


Figure 2. Scatter plot comparing WBET (x axis) with the OpenET ensemble (y-axis) for HUC 8 basins within the CRB. Each color represents a different water year. 1:1 line shown for reference.

4.3. Temporal anomalies for select basins

To identify temporal anomalies or geographic discontinuities in historic data generated from 1991 to 2023 for the Authority, we evaluated spatial patterns and temporal changes in the ratio of ET to reference ET (ETrF), the ratio of ET to precipitation (P), MAD/ET ratio, and the number of clear-sky retrievals. Spatial patterns in ETrF averaged for agricultural lands reveal which HUC 8 watersheds have larger fractions of irrigated lands. Temporal changes in ETrF averaged for agricultural lands at the HUC 8 scale indicate which areas are resilient to deficits in precipitation or impacted by changes in land use. Comparing ET to precipitation (ET/P) for non-agricultural lands facilitates evaluation of whether any HUC 8 watersheds exhibit bias relative to one measure of potential available water. Seasonal maps of the range of ET models divided by the ensemble ET value can be used to infer which regions exhibit more, or less, uncertainty in the ensemble ET value. The MAD/ET ratio is a measure of model agreement that can inform confidence for given locations and seasons. Additionally, the number of clear sky retrievals help evaluate confidence for certain periods of record. Together, these evaluation metrics are used to identify inconsistencies or deviations from the anticipated model behavior for the OpenET historical record.

5. Evidence of anomalies or discontinuities

5.1. EToF for agricultural areas by HUC 8

Evaluating changes in ETrF for agricultural lands at the HUC 8 resolution provides assurance that the OpenET models are capturing potential changes in land use, irrigation reliance, or the response of rainfed farmlands to inter-annual variations in water availability. The inspection of ETrF for agricultural lands within the CRB HUC 8 basins within Utah revealed patterns consistent with higher and lower fractions of irrigated croplands (Figure 3). Cooler tones likely indicate a higher fraction of irrigated cropland relative to dryland cropland for each basin or basins that receive greater rainfall for dryland crops. The individual model analyses in the Appendix reveal similar geographic patterns.

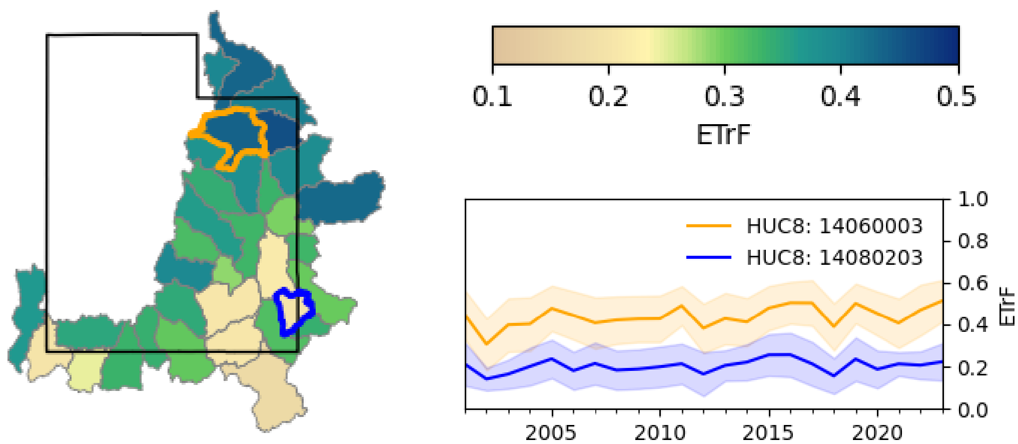


Figure 3. Left: Map of the mean OpenET ensemble ETrF for only agricultural lands from 2001-2023. Right: Time series of ETrF by year for the ensemble and eeMETRIC within the Duchesne HUC 8 14060003 (orange) and Montezuma 14080203 (blue) basins.

5.2. Non-ag areas ET/P by HUC 8

In Utah, like many water-limited regions, ET is often limited by the availability of water in natural systems. We evaluate the fidelity of ET models across natural lands (non-agricultural lands) by evaluating geographic patterns and temporal changes in the ratio of ensemble ET value to precipitation (P) from gridMET (Abatzoglou 2013). For very dry regions where runoff approaches 0, the ET:P ratio should be close to 1.0. Values less than 1.0 are explained by more surface water runoff from a basin and possibly sub-rootzone vertical drainage. Values greater than 1.0 can result from a higher fraction of surface water (e.g. Lake Powell), contributions by spring-fed water sources, or known high bias in ET models for non-agricultural lands. Figure 4 shows the geographic distribution of average ET:P for the CRB within Utah. Larger ratios of ET:P are found in the southern CRB in Utah and coincide with very low precipitation and high fractions of surface water. A time series of ET:P is presented for two representative basins identified by the Authority for detailed analysis, the Duchesne and Montezuma basins. The Duchesne contains a higher proportion of irrigated agricultural lands, while the Montezuma is characterized more by rainfed agricultural lands. Basins with ET:P values greater than 1, such as Montezuma, are primarily located in the southern CRB in Utah. Review of these figures should bear in mind the presence of uncertainty in the precipitation data due to measurement and interpolation errors. However, these errors would be expected to be random and cancel out over extended time periods absent any known persistent bias. Also, there can be year-to-year carryover of precipitation as soil storage and snowpack that could cause some year-to-year variation. On balance, however, it is likely that the observed results are caused by positive bias of the ET models for non-agricultural classes except grassland (Table 2).

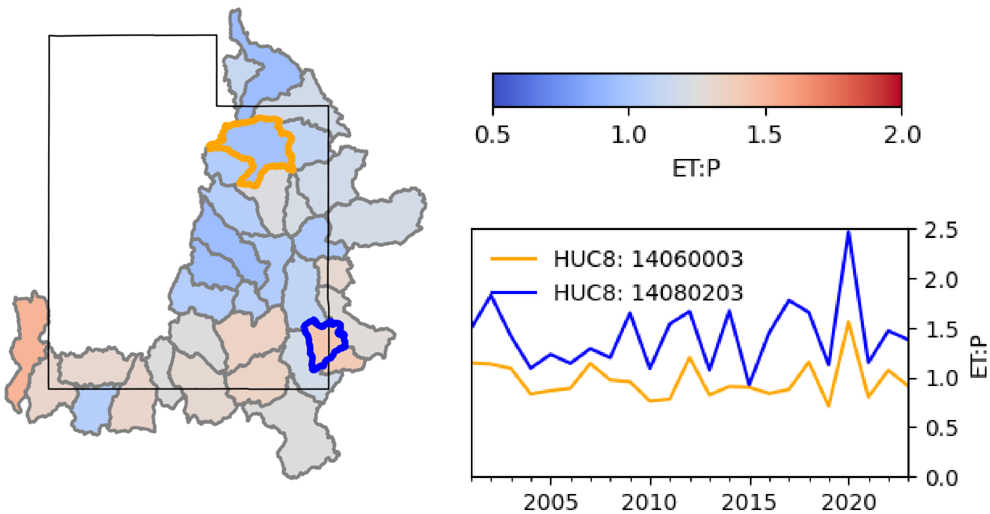


Figure 4. Left: Map of the mean OpenET ensemble ET:P for only non-agricultural lands within HUC 8 basins from 2001-2023. Cooler tones are where P exceeds ET. Warmer tones indicate regions where ET exceeds P. Right: Time series of ensemble mean ET:P by year for the Duchesne HUC 14060003 (orange) and Montezuma HUC 14080203 (blue) basins.

5.3. MAD / ET ensemble value

The range (maximum-minimum) of modeled ET used in the ensemble MAD calculation relative to the ensemble ET value can be used to indicate variability around the ensemble ET value for specific geographic regions and seasons. Stronger agreement is found over agricultural lands and during summer months (Figure 5). Moderate to strong agreement is found in the forested regions of the mountains during summer months. Lower inter-model agreement relative to the ensemble value is found during winter months and in the desert. These findings are consistent with prior intercomparisons and accuracy evaluation studies (Volk et al., 2024). Collection of additional ground-based ET data in regions with lower inter-model agreement would be valuable in identifying the best performing models within the OpenET ensemble, and in making improvements to all models.

Figure 6 shows strong inter-model agreement for annual ET over agricultural lands that are irrigated or have sufficient precipitation in the Uinta Basin, and moderate to strong agreement for rainfed rangelands on the eastern slope of the Abajo Mountain Range. Evaluations focusing on agricultural regions in the Duchesne and Montezuma basins found strong agreement for irrigated lands, and strong-to-moderate agreement in rainfed agricultural lands along the eastern side of the Abajo Mountains (Figure 6).

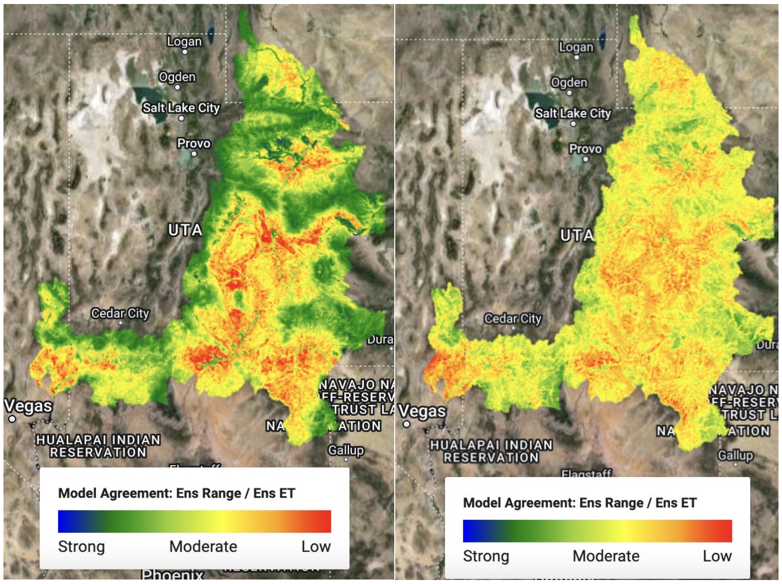


Figure 5. Multi-annual mean ensemble range divided by the ensemble value for the CRB of Utah. Left) For summer months June, July, and August. Right) For winter months December, January, and February.

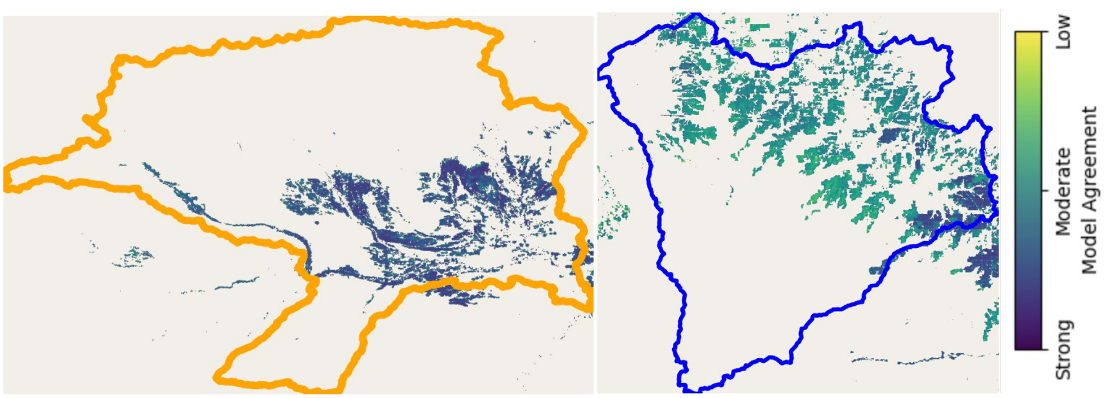


Figure 6. Ensemble range divided by the ensemble value for agricultural lands for the Duchesne Basin (left) and Montezuma Basin (right). Cooler tones indicate strong model agreement..

5.4 Number of cloud free observations

Confidence in an ET value for a particular location and time can be inferred from the associated number of successful (clear sky) satellite observations. Each OpenET model applies a cloud screening procedure on individual Landsat retrievals. Time integration techniques support filling each pixel across a scene. Figure 7 presents the average number of cloud-free observations per year for the region as represented by the eeMETRIC masking procedure. While each model applies a slightly different masking procedure, the number of cloud-free pixels is largely the same. Two distinct periods of record are shown, where the retrieval frequency is impacted by the number of satellites in orbit. Before 1999 only one satellite, Landsat 5, was operating. After 1999, two Landsat satellites were in orbit, with the exception of 2012. The period from 2012 to 2020 is representative of the entire 2000-present period of record. More than 12 successful observations were available annually for much of the region, indicating reasonable probability of realizing one retrieval per month. The SW-NE striping pattern is due to zones of Landsat path overlap, where increased viewing opportunities exist. It is important to consider that the overlap zones contain some image acquisitions that are only one day apart, so the additional observations do not necessarily correspond to vegetation information that is equally distributed in time.

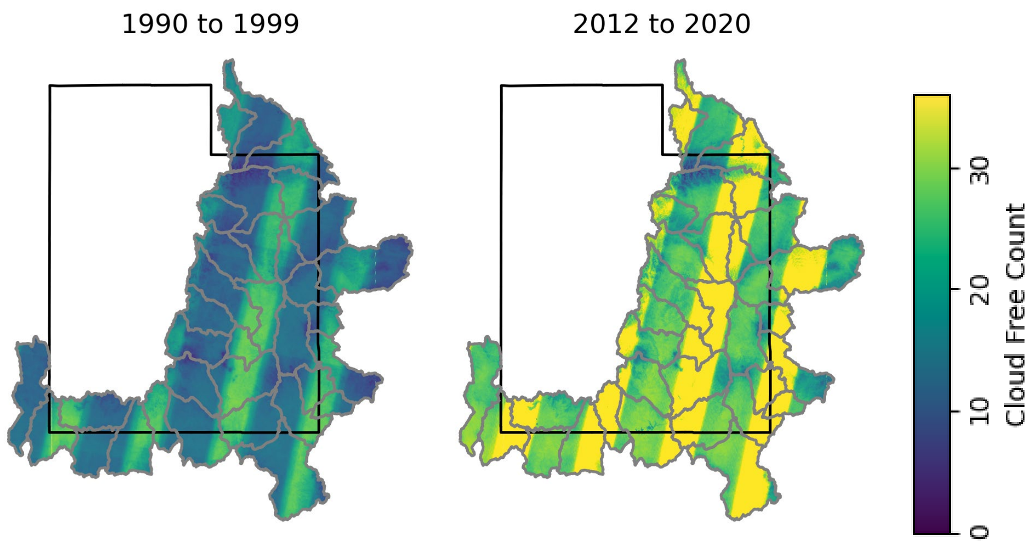


Figure 7. Left: Annual average count of clear sky Landsat retrievals from 1990-1999 when only one satellite was in orbit. Right: Annual average count from 2012-2020 whentwo satellites were in orbit.

A minimum of one clear sky observation per month should be adequate in describing the evolution of ET as a fraction of reference ET from month to month (Allen et al. 2007). The current review finds that the monthly observation counts are likely adequate post-2000, while confidence might be reduced for pre-1999 analyses involving monthly timesteps, due to extended interpolation periods. Lowest confidence, from an observational standpoint, might apply to pre-1999 data in non-overlap zones during months with more prevalent cloud cover. The OpenET team is actively working to develop tools and interpretable metadata to facilitate end-user evaluation of locations and months of interest.

Differences between eeMETRIC and the OpenET ensemble ET value

Differences between the OpenET ensemble ET value and eeMETRIC version 0.20.26 are presented to document potential differences between the two ET data sources, in particular to place any decisions based on the OpenET ensemble in context with the eeMETRIC v0.20.33 data being used in the UCRB. The following sections visualize differences in geographic patterns and temporal changes in both ETrF for agricultural lands and the ET:P ratio for non-agricultural lands at the HUC 8 basin unit. Additionally, pixel-wise mean seasonal differences from eeMETRIC and the OpenET ensemble are presented.

To evaluate potential differences between the OpenET ensemble ET value and eeMETRIC, we evaluate mean total ET across all CRB HUC 8 basins in Utah, and the fraction of reference ET (ETrF) and the ratio of ET:P for the Duchesne and Montezuma Basins. Figure 9 shows timeseries of multi-annual mean ET by HUC 8, as well as timeseries of inter-annual average ETrF for the OpenET ensemble (dashed line) and eeMETRIC (solid line) for two basins. The ETrF mean values track closely for the Duchesne Basin (HUC 8: 14060003), while eeMETRIC is greater than the OpenET ensemble for the majority of years in the Montezuma Basin (HUC 8: 14080203). The ET:P ratio tracks very closely for the Duchesne Basin (eeMETRIC average ET:P = 0.91 and OpenET ensemble ET:P = 0.97), while larger deviation is seen in the Montezuma Basin with the ensemble ET:P ratio exceeds 1.5 more frequently (eeMETRIC average ET:P = 1.09 and OpenET ensemble ET:P = 1.42). Figure 10 shows the average percent difference in ET for June, July, and August between the OpenET ensemble and eeMETRIC for each agricultural pixel. Closer agreement is seen in the Duchesne Basin where more irrigated agriculture exists. One can infer from these figures the largest areas of disagreement between the OpenET ensemble are for non-irrigated agriculture and natural lands.

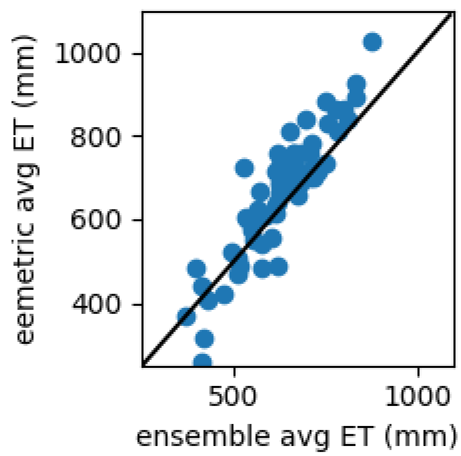


Figure 8. Average ET for agricultural lands comparing eeMETRIC (y-axis) to the OpenET ensemble (x-axis).

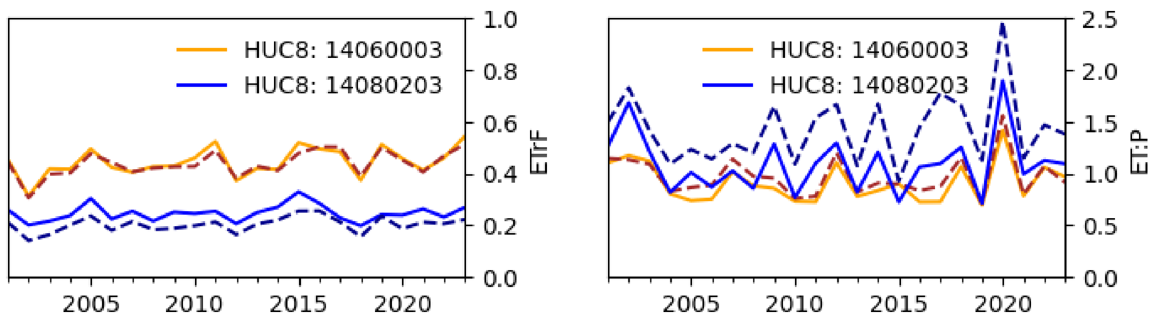


Figure 9. Comparison of the OpenET ensemble (dashed lines) to eeMETRIC (solid lines) for the Duchesne (orange) and Montezuma (blue) basins. Left: Average ETrF for only agricultural lands. Right: Average ET:P for non-agricultural lands.

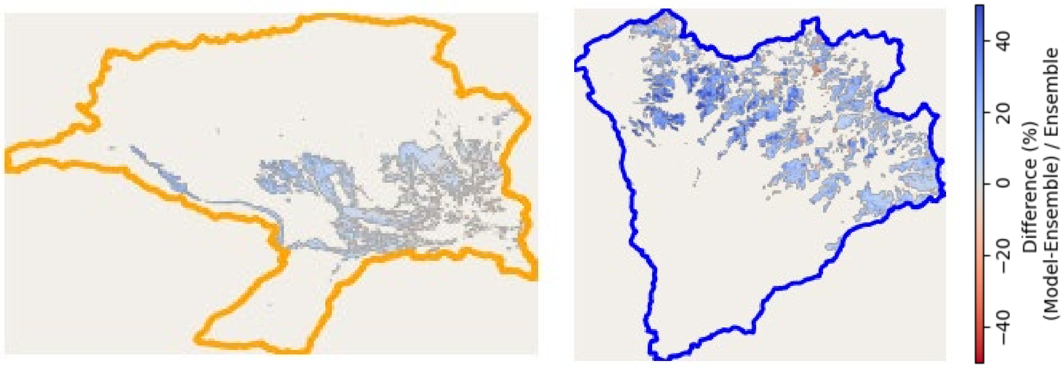


Figure 10. Multi-annual mean eeMETRIC ET relative to ensemble ET for June, July, and August (JJA). Blue tones indicate eeMETRIC is greater than the ensemble value and red tones indicate eeMETRIC is less than the ensemble value for JJA. Left) Duchesne (orange), HUC 8 14060003 basin, irrigated agriculture shows eeMETRIC and the ensemble are within 20 percent for the majority of agriculture areas. Right: Montezuma (blue), HUC 14080203 basin, shows larger deviations over dryland farms.

6. Conclusions and recommendations to the Authority

The review of the OpenET ensemble of models and ensemble ET value over CRB HUC 8 basins in Utah revealed accuracy consistent with prior intercomparisons and behavior consistent with known geographic patterns in irrigation. To evaluate the models, this report used a combination of on-ground evaluations, basin evaluations, inspection of temporal and spatial anomalies, evaluation of ET relative to ETo and P, inspection of the model range over the ensemble value, and quantification of the number of cloud-free retrievals by pixel.

When compared to on-ground observations and WBET, the OpenET ensemble ET showed strong accuracy. For a subset of benchmark cropland sites based on the similarity of the aridity index with the mean aridity index for Utah (AI = 0.3), the ensemble value shows the best performance relative to the individual models with respect to MBE, MAE, RMSE, and R2. The accuracy of the OpenET ensemble in this subset is similar to the Phase II OpenET accuracy assessment for croplands (Volk et al., 2024). Additionally, the OpenET ensemble value demonstrated low bias (<10%) and high explanation of variance when compared WBET for 5 water years. While these results demonstrate confidence in the application of the OpenET ensemble, on-ground observations within Utah remain valuable to support adoption, use, and diagnosis of potential sources of disagreement between OpenET and other measures of consumptive use. The OpenET consortium looks forward to continuing to support the work led by the Utah Geologic Survey to collect ground observations to assess OpenET's accuracy for key regions and crops in Utah.

Spatial patterns of multi-annual mean ETrF for croplands and the ratio of ET:P for non-agricultural lands averaged to the HUC 8 basin-scale revealed spatial patterns that reflect basins with more and less rainfall. An in depth evaluation of these variables for the Duchesne and Montezuma basins also showed greater ET rates in the Duchesne basin relative to the Montezuma for cropland areas. For the Duchesne basin, where more irrigated agriculture exists, closer agreement across the OpenET models relative to the ensemble value is observed, indicating increased confidence in the ET values. Additionally, closer agreement is seen between the OpenET ensemble and eeMETRIC, the model adopted by the UCRC. For the Montezuma basin, where more rainfed agriculture exists, we find moderate to strong agreement across the OpenET models relative to the ensemble. Temporal changes in ET:P found that for most years the ensemble ET value was within a reasonable range of total annual precipitation values, with an E:P ratio of less than 1.5, especially when considering the arid environment and basins with large open surface water bodies. One exception is a spike in ET:P found in 2020 that coincides with snow and soil water carrying over from a normal year into an extremely dry and hot year.

When compared to eeMETRIC, the OpenET ensemble value is moderated at the high and low end of the range in ET; i.e., the OpenET ensemble value is lower than eeMETRIC for higher ET values, and greater than eeMETRIC for very low ET values. The multi-year average ETrF maps follow similar geographic patterns. The ratio of ET:P shows that the OpenET ensemble value accounts for a greater fraction of P than eeMETRIC on average. For June, July and August mean conditions, eeMETRIC was found to be greater than the ensemble ET value for rainfed agriculture. These findings are consistent with prior analyses of model behavior across irrigated and non-irrigated croplands.

Across the CRB in Utah, the number of cloud free observations on average exceeds 12 per year for many areas. However, before 1999 or during 2012, when only one Landsat was in orbit, fewer clear-sky Landsat observations are available. Ideally, at least one clear-sky observation per month should be available to support adoption and use of OpenET data during this period. Monthly ET values made using a single Landsat can still be used with confidence, as long as the user considers the number of images that are actually being used for the interpolation for a given month. A GEE application to be shared with the Authority and other partners will provide this capability for known periods of time with less frequent satellite observations.

Opportunities remain to continue to improve theOpenET ensemble ET value

Iterative improvement to the OpenET modeling system and analyses requires a combination of additional ground observations to evaluate ET and ETo, and refinement of the irrigated extent within Utah. Ground based observations of ET being led by the Utah Geologic Survey provide an opportunity to evaluate OpenET accuracy for croplands in key regions of the CRB. The expansion of ET data collection also supports working towards improved ET values over wetlands and natural systems. The analysis presented in Figure 5, specifically areas where a wider range in inter-model ET values exists, may be useful in identifying priority sites for future flux tower deployments. Ground-based ET observations can help identify which of the models are most accurately capturing ET rates for that particular region and support calculation of an improved ensemble ET value. Installation of additional agricultural weather stations to monitor ETo will support the development of improved bias correction surface for the ETo data used by OpenET, and will provide another avenue to refine ET accuracy for regions of Utah where topographic complexity may currently limit the representativeness of ETo data. As additional ETo observations become available, the OpenET team has the tools to support production of updated bias correction surfaces across the CRB.

Supplemental data layers important to the application of OpenET, such as maps of irrigated fields by year, can directly impact the success of water conservation programs being managed by the Authority. A report led by DRI and OpenET comparing irrigation status methods in the UCRB found that two commonly used methods to map irrigated acreage can differ by more than 90,000 acres in a given year within Utah (DRI and OpenET 2024). Additionally, relative to a recently applied method using harmonized inputs from Landsat and Sentinel, irrigated acreage may be underestimated by as much as 100,000 acres for regions of Utah in the UCRB. The report found that identifying irrigated lands using EToF in excess of 0.5 for a minimum 3 months between May and October compared favorably to the new approach as a way to support retrospective irrigation status mapping. Future research to refine methods to map field boundaries and irrigation status is needed and would benefit from comparison to field-level irrigation management information. A consistent and accurate field boundary and irrigation status dataset would also help to support effective management of any future voluntary conservation program administered by the Authority.

References

Abatzoglou, J. T. (2013), Development of gridded surface meteorological data for ecological applications and modeling. Int. J. Climatol., 33: 121–131. https://doi.org/10.1002/joc.3413

Allen et al. 2007. Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC)—Model. Journal of Irrigation and Drainage Engineering 133 (4): 380–94. https://doi.org/10.1061/(ASCE)0733-9437(2007)133:4(380)

Allen, R.G., Pereira, L.S. Estimating crop coefficients from fraction of ground cover and height. *Irrig. Sci.* **2009**, 28, 17-34. https://doi.org/10.1007/s00271-009-0182-z

DRI + OpenET (2024) Intercomparison of Irrigation Status Mapping Methods and Irrigated Acreage Results for Upper Colorado River Basin

Melton et al., 2022. OpenET: Filling a Critical Data Gap in Water Management for the Western United States. Paper No. JAWR-20-0084-P of the Journal of the American Water Resources Association (JAWR). https://doi.org/10.1111/1752-1688.12956

Pereira, L., P. Paredes, F. Melton, L., Johnson, T. Wang, R. López-Urrea, J. Cancela, R. Allen, 2020. Prediction of crop coefficients from fraction of ground cover and height. Background and validation using ground and remote sensing data. Special issue: Updates & Advances to the FAO56 Crop Water Requirements Methods, *Agricultural Water Management* 241, 106197. https://doi.org/10.1016/j.agwat.2020.106197

Senay et al., 2022. Improving the Operational Simplified Surface Energy Balance Evapotranspiration Model Using the Forcing and Normalizing Operation. Remote Sens. 2023, 15(1), 260; https://doi.org/10.3390/rs15010260

Volk et al., 2024. Assessing the accuracy of OpenET satellite-based evapotranspiration data to support water resource and land management applications. Nature Water https://doi.org/10.1038/s44221-023-00181-7

Volk, J., 2024. Intercomparison and accuracy assessment of OpenET for Utah: a preliminary report. Prepared for the Colorado River Authority of Utah

7. Appendix

7.1. Individual Model Overview

Individual model evaluations and reviews provide information to guide adoptions and use of ET data from an individual model. The reviews were completed to ensure each model does not experience anomalous behavior.

7.1.1. ALEXI/DisALEXI

7.1.1.1. Model overview

DisALEXI is a disaggregation algorithm associated with the regional Atmosphere-Land Exchange Inverse Model (ALEXI, Anderson et al., 1997, 2004, 2007). Both ALEXI and DisALEXI are based on the Two-Source Energy Balance (TSEB) land surface representation developed by Norman et al. (1995). At regional scale, ALEXI model uses time-differential measurements of morning land surface temperature (LST) rise from geostationary satellites to estimate daily flux, in this application at 4 km resolution. Using higher-resolution LST information obtained from Landsat (sharpened from native to 30-m resolution), DisALEXI uses Landsat LST to downscale ALEXI fluxes to 30-m field scale, a scale that is more useful for water management applications. Currently, DisALEXI ET data are limited to the MODIS/VIIRS era (2001-present),since ALEXI uses MODIS LAI as a key input.

7.1.1.2. Accuracy strengths

DisALEXI has been successfully applied in many regions with various land cover and climate types. DisALEXI works well for regions with large fractional vegetated areas, while having relatively higher uncertainty for small irrigated fields isolated from the dry background. This also explains why DisALEXI performs well in the CONUS scale monthly ET evaluation in Volk et al., 2024, but shows a lower performance in the preliminary Utah evaluation (Table 7.1.1.1).

Table 7.1.1.1) Mean monthly statistics between modeled-measured ET for cropland stations. Statistics from Volk et al., 2024 & Volk 2024.

Evaluation Data	MBE mm/month (%)	MAE mm/month (%)	RMSE mm/month (%)	R^2	N
Phase II Assessment	-7.72 (-8.4%)	19.91 (21.8%)	25.35 (27.7%)	0.86	44
Preliminary Utah Evaluation	-19.79 (-16.2%)	31.71 (25.9%)	39.73 (32.5%)	0.7	18

The scatter plot between annual DisALEXI ET and water balance ET shows that DisALEXI ET is generally higher than WBET (Figure 7.1.1.1). This is consistent with the comparison between Ensemble ET and WBET. There is a higher bias for 2011, which is a wet year based on the U.S. Drought Monitor data. This suggests that there might be a larger annual water storage change in 2011 and assuming zero storage change in the water balance method could overestimate ET in wet years.

Figure 7.1.1.2 illustrates the average ETrF for agricultural lands from 2001 to 2023, which shows a similar spatial pattern as other models. The timeseries of average ETrF of the two HUC 8 watersheds are also similar as the values from other models, indicating different irrigation management practices and different responses to drought conditions.

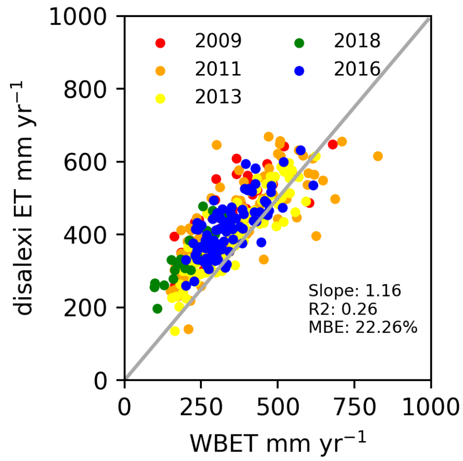


Figure 7.1.1.1) Scatter plot comparing water balance ET (x axis) with DisALEXI ET (y axis).

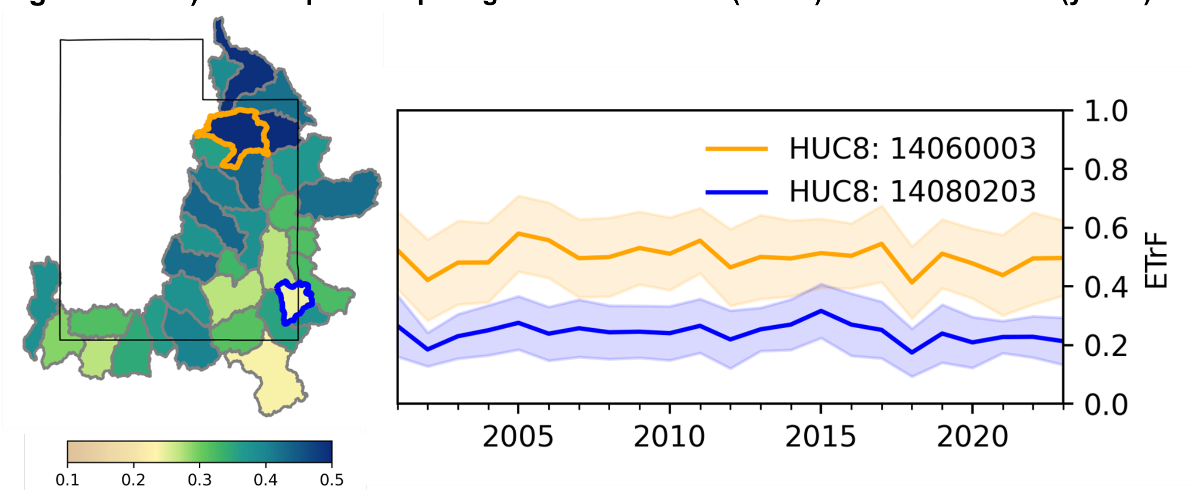


Figure 7.1.1.2) Left: Map of DisALEXI mean ETrF for only agricultural lands from 2001-2023. Cooler tones indicate a higher fraction of irrigated lands relative to rainfed agriculture for each basin. Right: Time series of ETrF by year for DisALEXI within the Duchesne HUC 8 14060003 (orange) and Montezuma 14080203 (blue) basins.

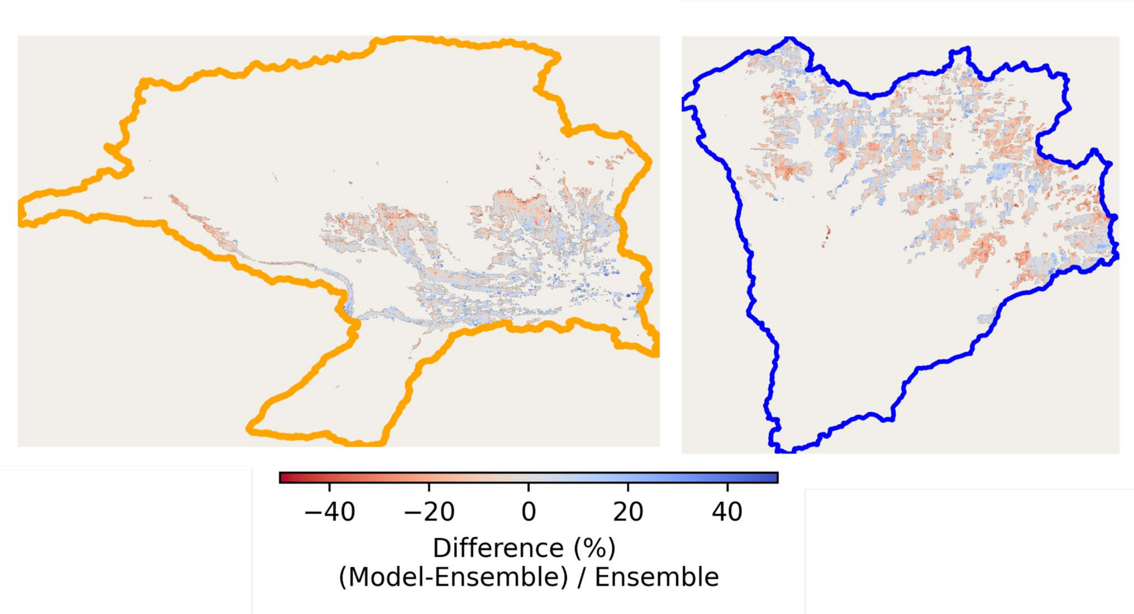


Figure 7.1.1.3) Multi-annual mean percent ET difference between DisALEXI and the OpenET Ensemble for agricultural lands for the Duchesne Basin (Orange) Left and the Montezuma Basin (Blue) right.

Across the agricultural lands for the Duchesne Basin and the Montezuma Basin, the difference between DisALEXI and ensemble exhibits both positive and negative values, with most areas showing a difference within +/- 20% (Figure 7.1.1.3).

7.1.1.3. Known limitations

For the known issues, terrain effects (primarily, slope and aspect impacts to net radiation) are not currently considered in DisALEXI, which has been identified as the next step for improvement. Due to the disaggregation approach used, ET in small isolated irrigated fields sitting within a predominantly dry background may have higher uncertainty (e.g., low fractional vegetated area within the 4km ALEXI pixel). Accuracy improves for regions with larger fractional vegetated area. An advantage of the TSEB modeling approach is that it does not rely on identification of within-scene dry and wet pixel end-members, which may be advantageous over scenes lacking these extreme conditions.

DisALEXI applications are currently limited to the MODIS/VIIRS era (2001-present). This is because ALEXI uses MODIS LAI as a key input. Work is underway to extend ALEXI (and therefore DisALEXI) applications back to the 1980s by using AVHRR-derived LAI in ALEXI. Another difference compared to other OpenET models is that DisALEXI currently uses meteorological inputs from the Climate System Forecast (CFSR) - Reanalysis to be consistent with ALEXI inputs. ETrF time series shown are computed with respect to reference ET from GridMet, which is used in other OpenET models but may be somewhat different from CFSR. This may introduce some discrepancy between DisALEXI and other models in terms of ETrF related to differences in ETr used as the normalization flux.

7.1.2. eeMETRIC

The eeMETRIC modeling team provided an initial report review of eeMETRIC v0.20.26 to the UCRC that captured an artifact resulting from the OpenET crop type data layer potentially mis-categorizing grass/herbaceous as grass/pasture and agriculture as wetland. An updated analysis is being prepared for the UCRC focused on eeMETRIC v0.20.33 to reflect the changes documented in Section 3. The eeMETRIC modeling team will complete a focused evaluation for the Authority at a later date and an updated version of this report will be provided once complete. For any near-term questions regarding anticipated changes in eeMETRIC, please contact Rick Allen and Ayse Kilic.

7.1.3. geeSEBAL

7.1.3.1. Model overview

The Google Earth Engine implementation of the Surface Energy Balance Algorithm for Land (geeSEBAL) estimates evapotranspiration (ET) through the surface energy balance by combining thermal and multispectral remote sensing data and reanalysis meteorology (Kayser et al., 2022; Laipelt et al., 2021;Bastiaanssen et al., 1998). geeSEBAL algorithm is based on the estimation of latent heat (LE) as a residual of the instantaneous surface energy balance equation, based on net radiation (Rn), ground heat flux (G) and sensible heat (H). The automated statistical algorithm to select the hot and cold endmembers is based on a simplified version of the Calibration using Inverse Modeling at Extreme Conditions (CIMEC) algorithm proposed by Allen et al. (2013), where quantiles of LST and the normalized difference vegetation index (NDVI) values are used to select endmember candidates in the Landsat domain area. The cold and wet endmember candidates are selected in well vegetated areas, while the hot and dry endmember candidates are selected in the least vegetated cropland areas. Based on the selected endmembers, geeSEBAL assumes that in the cold and wet endmember all available energy is converted to latent heat (with high rates of transpiration), while in the hot and dry endmember all available energy is converted to sensible heat. Finally, estimates of daily evapotranspiration are upscaled from instantaneous estimates based on the evaporative fraction, assuming it is constant during the daytime without significant changes in soil moisture and advection.

7.1.3.2. Accuracy strengths

geeSEBAL performance is dependent on topographic, climate, and meteorological conditions, with higher sensitivity and uncertainty related to hot and cold endmember selections for the CIMEC automated calibration, and lower sensitivity and uncertainty related to meteorological inputs (Laipelt et al., 2021 and Kayser et al., 2022). Based on these sensitivity assessments, one of the key strengths of geeSEBAL is its consistent accuracy for regional scale assessments in data scarce areas, with lower sensitivity to meteorological forcing data and lower dependency to model parameterization, making the model useful for large-scale applications. Specifically over irrigated cropland, geeSEBAL has a significant potential for assessment of ETa for irrigation monitoring and management (Gonçalves et al., 2022). The use of geeSEBAL based on an automated calibration algorithm (as the simplified CIMEC) can provide new opportunities to improve our understanding of hydrological and energy changes at regional to continental scales at high spatial resolution over long-term time series.

geeSEBAL has been successfully applied in many regions worldwide, over multiple land cover and climate conditions, usually showing consistent accuracy for agricultural water management, even without ground measurements. Table 7.1.3.1 shows the comparison of monthly geeSEBAL estimates compared to ground measurements over cropland areas from the OpenET Phase II assessment report for Utah.

Table 7.1.3.1 Mean monthly statistics between modeled-measured ET for cropland stations. Statistics from Volk et al., 2024 & Volk 2024.

Evaluation Data	MBE mm/month (%)	MAE mm/month (%)	RMSE mm/month (%)	R^2	N
Phase II Assessment	-12.18 (13.3%)	22.69 (24.8%)	29.05 (31.8%)	0.83	44
Preliminary Utah Evaluation	-16.47 (-13.5%)	28.78 (23.5%)	35.42 (29.0%)	0.78	18

Overall, geeSEBAL yielded a similar estimate of the OpenET ensemble in both low and high ends of the ET spectrum, when compared to the average ET for agricultural lands when averaged to HUC 8 basins in Utah. Figure 7.1.3.1 supports geeSEBAL ET estimates consistency when compared to the OpenET ensemble, presenting a consistent accuracy over the long-term time series.

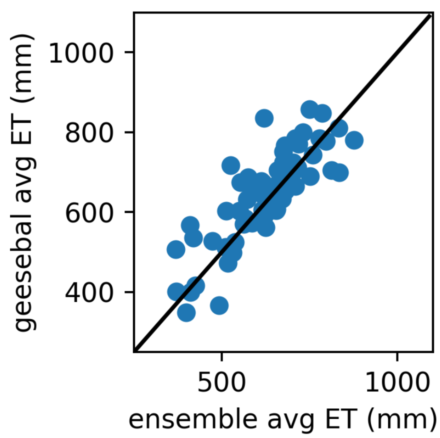


Figure 7.1.3.1. Multi-annual average ET for agricultural lands summarized by CRB HUC 8 boundaries in Utah.

The scatterplot between annual geeSEBAL ET estimates and the water balance ET shows that geeSEBAL model estimates are slightly higher than the water balance estimates (Figure 7.1.3.2), with a MBE by 20.5%. The spatial and temporal assessment of the water-balance indicated a moderate hydrological consistency in the annual time scale average. Due to the hydrological imbalance found for geeSEBAL more improvements are needed to achieve lower uncertainties and higher accuracy of ET estimates when assessing single models. However, the use of an ET ensemble can reduce these uncertainties significantly (i.e., for the ET ensemble we found a MBE of 7.6% and R2 of 0.64). Thus, ET estimates based on multiple model ensembles can enhance spatial refinements and yield a higher accuracy when compared to the water-balance approach (Ruhoff et al., 2022).

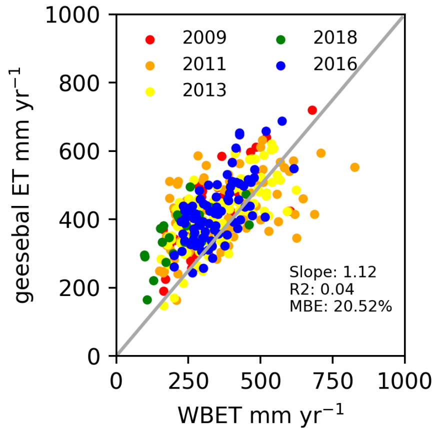


Figure 7.1.3.2. Scatter plot comparing evapotranspiration estimates from the water balance approach (x-axis) and geeSEBAL estimates (y-axis).

Figure 7.1.3.3 illustrates the average ETrF for agricultural areas from 2001 to 2023, based on geeSEBAL (solid lines) and the OpenET ensemble (dashed lines) estimates for the Duchesne (orange) and the Montezuma (blue) HUC 8 basins. Overall, we found consistent estimates of the ETrF between geeSEBAL and the OpenET ensemble for both HUC 8 basins, with similar values, indicating geeSEBAL yielded a similar behavior of the OpenET ensemble ET. However we also found a slight underestimation of geeSEBAL at the HUC 8 Montezuma basin after 2014, over a predominant rainfed area. For the Duchesne basin, where more irrigation exists, geeSEBAL presented a similar behavior than the OpenET ensemble for the whole time series.

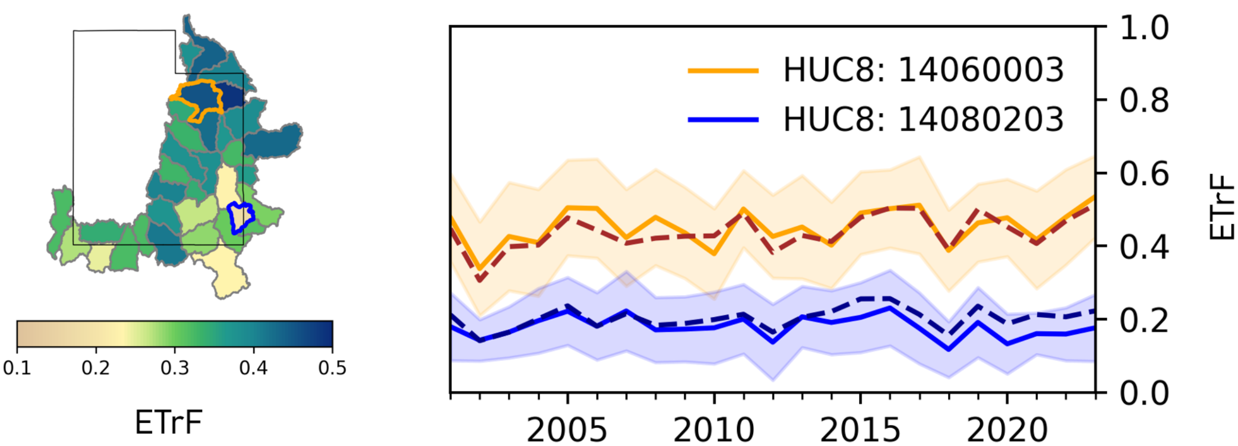


Figure 7.1.3.3. Left: Map of geeSEBAL average ETrF for agricultural areas from the 2001-2023 time series. Greener tones indicate a higher fraction of irrigated lands relative to rainfed agriculture for each basin (golden tones). Right: Time series of ETrF by year for geeSEBAL within the Duchesne HUC 8 14060003 (orange) and Montezuma 14080203 (blue) basins.

By comparing the spatial pattern the annual average ET estimates based on geeSEBAL and the OpenET ensemble over agricultural areas in the Duchesne (HUC 8 14060003; left) and the Montezuma (HUC 8 14080203, right) basins (Figure 7.1.3.4), we found similar (slightly overestimated, with differences usually lower than 20%) results between both estimates at the Duchesne HUC 8 basin, where irrigations is predominant, while at the Montezuma basin geeSEBAL underestimated ET when compared to the OpenET ensemble (with overall differences higher than 20%). This results allowed us to conclude that geeSEBAL is able to detect irrigation management practices over time (as in the Duchesne basin), while over non-irrigated areas ETrF was slightly underestimated, especially during recent years (2014-2023), indicating more research and assessment to understand the reasons geeSEBAL has a higher uncertainty over rainfed cropland. The geeSEBAL team is investigating these issues especially over arid climates.

Across the agricultural lands for the Duchesne Basin and the Montezuma Basin, the difference between geeSEBAL and the OpenET ensemble exhibits both slightly negative and positive values, respectively, with most areas showing a difference within ±20%.

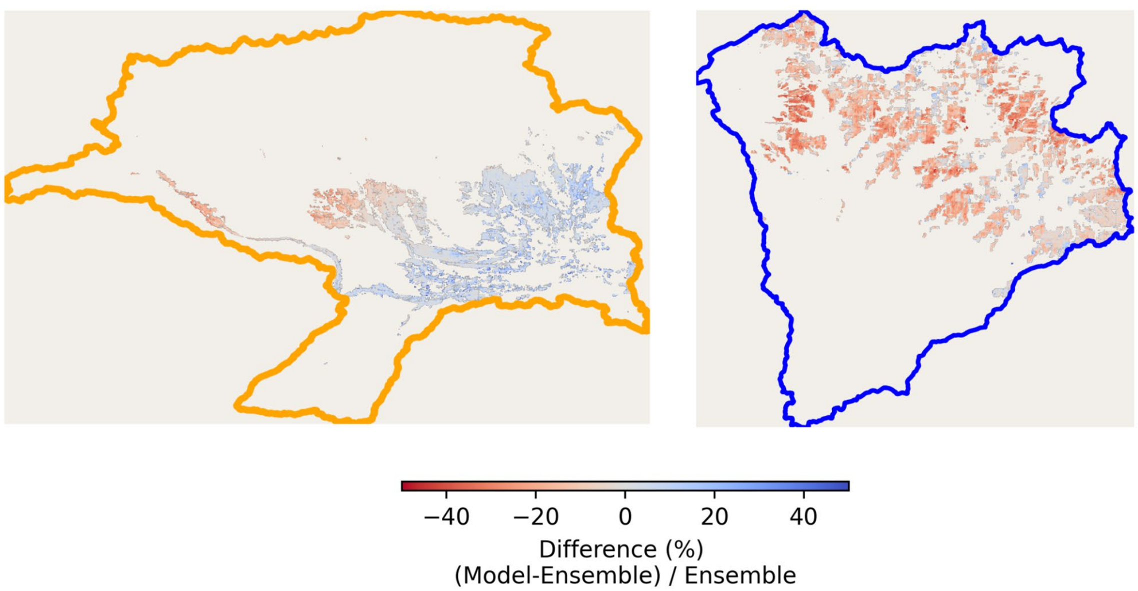


Figure 7.1.3.4. Multi-annual mean percent ET difference between geeSEBAL and the OpenET Ensemble for agricultural lands for the Duchesne Basin (Orange) Left and the Montezuma Basin (Blue) right.

On average, the majority of land area for the CRB in Utah has sufficient clear-sky image retrievals to generate monthly ET values (higher than 20 images per year after 2012, and higher than 12 images per year before 2000) (Figure 7.1.3.5). Areas in the north eastern section of the state with high elevation and more frequent cloud cover show fewer than 10 clear sky images per year, especially before 2000. Similar to all other models, limited clear-sky satellite retrievals can impact accuracy of monthly ET values and further inspection on a month-by-month basis for these basins prior to use. These findings are consistent with other OpenET models.

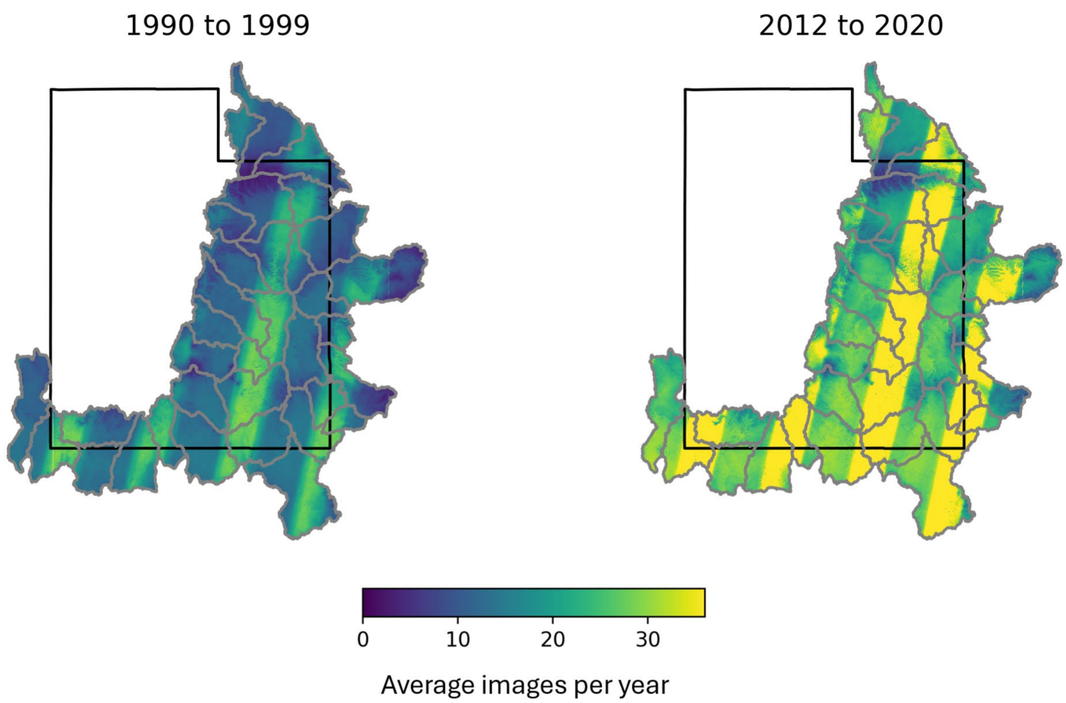


Figure 7.1.3.5. Number of cloud-free observations for areas where the geeSEBAL model provides data within the CRB in Utah.

7.1.3.3. Known limitations

Known limitations of geeSEBAL are related to the selection of the hot and cold endmembers for internal calibration. In the case of geeSEBAL, a main challenge in developing a large-scale and long-term time series is the endmember selection for internal calibration. Since the algorithm is highly sensitive to the spatial domain, which can significantly change ET accuracy, especially over heterogeneous landscapes. To reduce uncertainties related to complex terrain, we included some improvements to correct LST and global radiation on the surface to represent the effects of topographic features on the model's endmember selection algorithm and ET estimates. However, improvements to the hot and cold endmembers selection to estimate the near surface and air temperature difference (dT) in arid and temperate climates, where uncertainties in ET estimates are related to elevated LST in bare soil and sparsely vegetated areas, are still under assessment. We are also investigating separate solutions for open water evaporation, including an improved representation of the heat transferred to the water column.

7.1.3.4. geeSEBAL conclusions

For the Authority data review, geeSEBAL accuracy assessment showed a consistent overall agreement with the OpenET ensemble, and monthly ET estimates exhibited satisfactory performance relative to flux tower ET, in a similar range of other OpenET models. The geeSEBAL team is currently working to improve model uncertainties, specially for issues related to the automated selection of cold and hot endmembers. However, current geeSEBAL ET estimates are within the model's uncertainty range. geeSEBAL is a reliable model to provide ET estimates for the Authority, on a long term temporal scale over large areas. FInally, we highlight that when geeSEBAL and the OpenET ensemble ET are compared to the water balance approach, our results provided important information about the ET dynamics at basin scale, supporting the optimized ET based on the combination of multiple models for the western part of the US and Utah.

7.1.4. PT-JPL

Model overview

The original PT-JPL model formulation provides consistent and accurate ET data across all land covers (Fisher et al., 2008). Compared to the other ET models, the PT-JPL original formulation was intended to provide global-scale ET values free of calibration. In OpenET, updates to model inputs, and time integration of meteorological variables for PT-JPL were made to take advantage of contemporary gridded weather datasets, provide consistency with other models, improve open water evaporation estimates, and account for advection over crop and wetland areas in semiarid and arid environments (Melton et al., 2022).

Accuracy strengths

The PT-JPL model performs well over irrigated agricultural areas and shows strong agreement with the ground-based ET datasets. Overall, the PT-JPL has a very low MBE relative to other models for croplands, and a high explanation of variance and low error relative to other models for many natural land covers including evergreen and mixed forests (Table 2). A slightly negative mean bias error was found in the cropland accuracy assessment from the Phase II intercomparison and the preliminary evaluation done for Utah (Table 7.1.4.1; Volk et al., 2024; Volk 2024). Figure 7.1.4.1 shows that PT-JPL has a high bias relative to WBET for lower WBET values (<500 mm/yr). The high bias found in arid regions over non-agricultural land cover is consistent with prior evaluations of PT-JPL.

Table 7.1.4.1) Mean monthly statistics between modeled-measured ET for cropland stations. Statistics from Volk et al., 2024 & Volk 2024.

Evaluation Data	MBE mm/month (%)	MAE mm/month (%)	RMSE mm/month (%)	R^2	N
Phase II Assessment	-2.9 (-3.2%)	18.12 (19.8%)	23.67 (25.9%)	0.87	44
Preliminary Utah Evaluation	-10.42 (-8.5%)	25.56 (20.9%)	31.13 (25.5%)	0.81	18

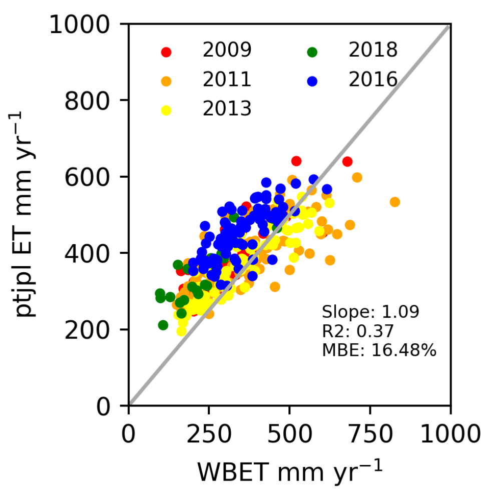


Figure 7.1.4.1) Scatter plot comparing water balance ET (x axis) with the PT-JPL ET

Similar to other models, the majority of land area for the CRB in Utah has sufficient clear-sky retrievals to generate monthly ET values (>12) (Figure 7.1.4.2).

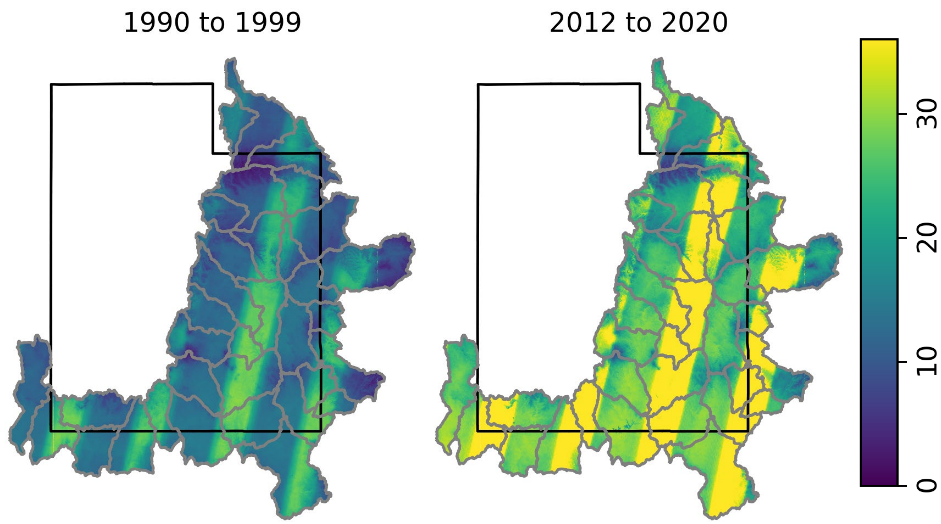


Figure 7.1.4.2) Number of cloud-free observations for areas where the PT-JPL model provides data within the CRB.

Factors affecting PT-JPL relative to other models

The PT-JPL model can exhibit a high bias in very arid regions where ETw is much larger than ETo and/or atmospheric moisture content as represented by relative humidity and vapor pressure deficit does not represent changes in moisture content across landscape. Therefore, when PT-JPL is high and the ensemble ET values are low, the absolute difference between the two can still be small, but the relative percentage difference can be high. This is the reason for larger differences in regions where fields do not irrigate (Figure 7.1.4.3 and Figure 7.1.4.4). Differences may also be explained by mis-calibrated ecophysiological stress functions related to temperature or water availability not being appropriately constrained.

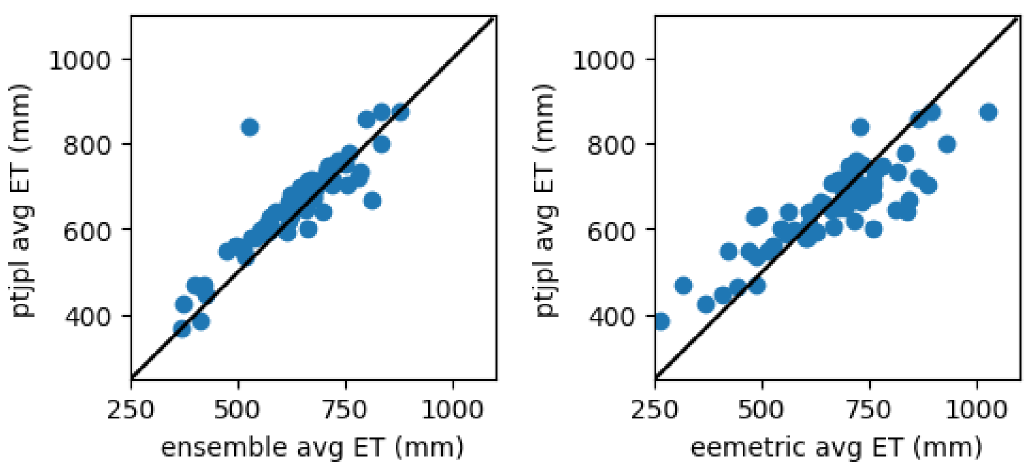


Figure 7.1.4.3) Multi-annual mean ET for agricultural lands summarized by CRB HUC 8 boundaries in Utah. Left: PT-JPL ET vs Ensemble ET. Right: PT-JPL ET vs eeMETRIC ET.

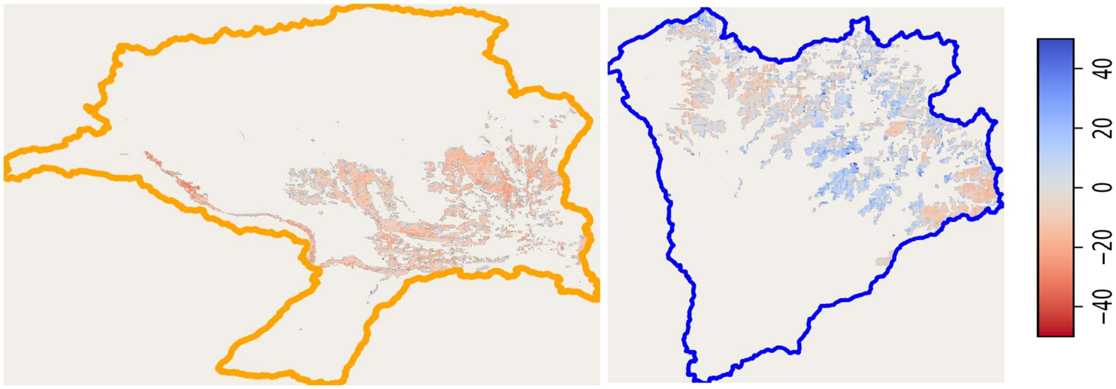


Figure 7.1.4.4) Multi-annual mean percent ET difference between PT-JPL and the OpenET Ensemble for agricultural lands for the Duchesne Basin (Orange) Left and the Montezuma Basin (Blue) right.

Patterns of ETrF for the regions of the CRB within Utah reflect known differences in PT-JPL values relative to the ensemble value over irrigated and non-irrigated lands. Figure 7.1.4.4 shows the relative difference to the ensemble value, which includes ET data from many surface energy balance models. For basins with greater fractions of irrigated lands, such as the Duchesne, PT-JPL average ET is lower than the ensemble ET value. For regions with greater fractions of rainfed agriculture, PT-JPL average ETrF is greater than the ensemble value (Figure 7.1.4.5). Despite the differences to the ensemble value, PT-JPL ET values demonstrate similar inter-annual changes in ETrF relative to the ensemble value.

Patterns of ET:P for the regions of the CRB within Utah reveal PT-JPL to be within close proximity to P for the majority of non-irrigated lands (Figure 7.1.4.6). Lower fractions of PT-JPL ET:P are found for northern and western basins. Larger ET:P ratios are seen in the driest basins. Additionally, a time series analysis reveals that a very large ET:P ratio is seen in 2020 that coincides with a severe regional drought.

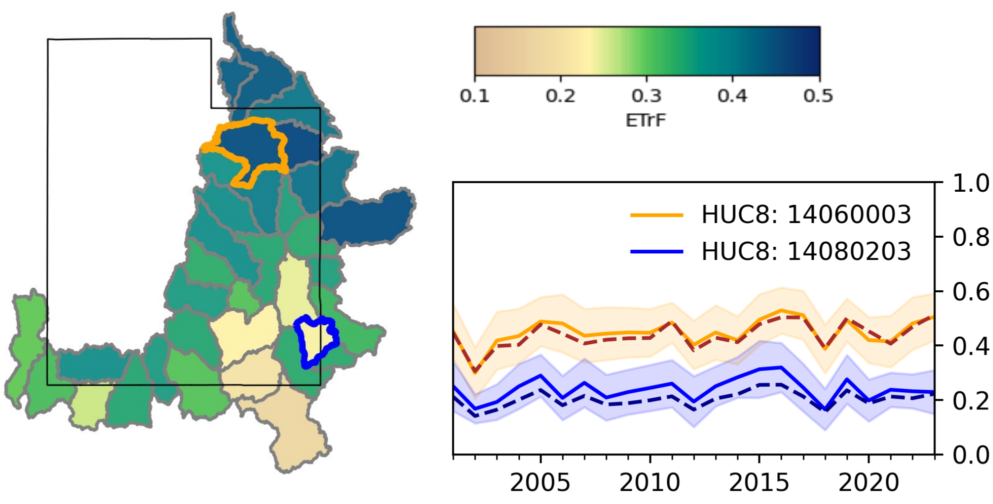


Figure 7.1.4.5) Left: Map of the PT-JPL mean ETrF for only agricultural lands from 2001-2023. Cooler tones would indicate a higher fraction of irrigated lands relative to rainfed agriculture for each basin.

Right: Time series of ETrF by year for the PT-JPL model (solid line and shaded region) compared to the ensemble (dashed line) for the Duchesne (orange) and Montezuma (blue) sub-basins.

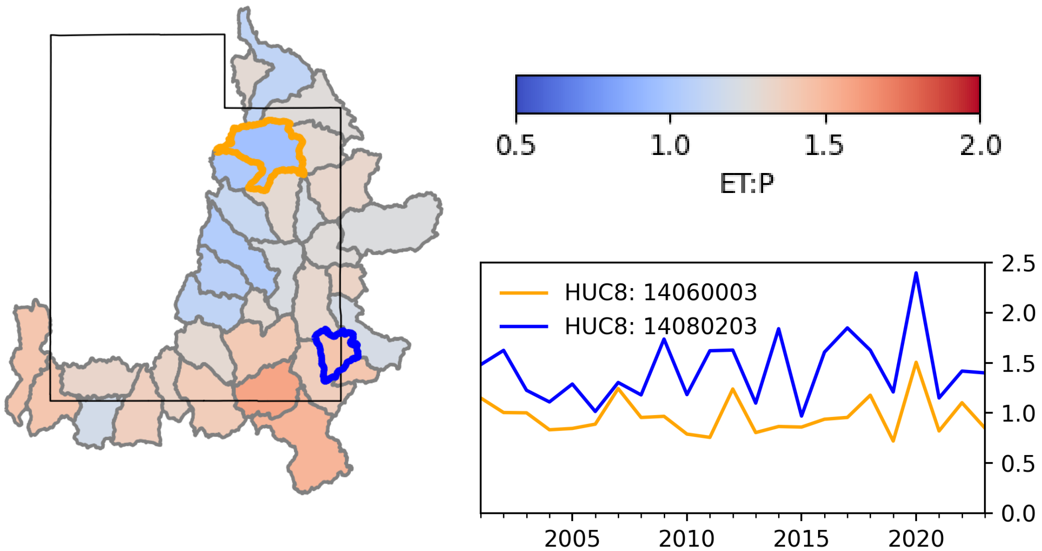


Figure 7.1.4.6) Left: Map of the PT-JPL mean ET:P for only non-agricultural lands from 2001-2023. Cooler tones would indicate regions with more runoff. Warmer tones indicate regions where more P goes to ET. Right: Time series of ET:P by year for the ensemble value and for PT-JPL within the Duchesne (orange), HUC 8 14060003, and Montezuma (blue), HUC 14080203, basins.

Conclusions

The review of the PT-JPL model found that the implementation for the Authority demonstrates the performance consistent with prior basin evaluations and model inter-comparison studies. The review found that PT-JPL exhibits a positive bias for non-irrigated agricultural lands, and lower ET values relative to the ensemble ET value for irrigated lands. Specifically, for certain regions such as the Montezuma basin PT-JPL can be greater than the ensemble value. However, lower ET values relative to the ensemble value are seen for irrigated lands in the Duchesne Basin (Figure 7.1.4.5). When averaged to the HUC 8 basin, PT-JPL was found to be consistent with the OpenET ensemble value (Figure 7.1.4.3). The preliminary accuracy for the Authority shows PT-JPL performed better in the OpenET Phase II accuracy assessment for croplands than for CRAU. Similar performance is seen when evaluating PT-JPL relative to the WBET values where PT-JPL is greater than WBET for lower WBET values and lower than WBET for higher WBET values. When compared to precipitation, PT-JPL ET values exceed 1.5 for many years in the Montezuma Basin. A known bias exists in PT-JPL for natural lands in very arid regions. Despite these differences, the PT-JPL model follows similar inter-annual changes in ET and ETrF relative to the ensemble value, to support use cases that depend on tracking changes in ET rates.

7.1.5. SIMS

Model overview

The Satellite Information Management Support (Melton et al., 2022) provides ET data over agricultural lands. A reflectance-based approach incorporates a density coefficient based largely on fractional ground cover (Allen and Pereira, 2009; Pereira et al., 2020) to compute basal crop coefficients per pixel. The crop coefficients combined with gridded reference ET, precipitation data and a gridded soil water balance model support ET mapping for agricultural lands at various time steps. SIMS assumes well-watered conditions sufficient to meet the water requirements for the satellite-observed vegetation condition and density. A gridded soil water balance model serves to improve representation of evaporation from bare soil and identify periods when available soil water in the root zone may limit ET rates for non-irrigated lands.

Accuracy strengths

A preliminary accuracy assessment involving ground-based observations at 18 sites with similar aridity to Utah was used to assess the OpenET models for the Authority (Volk, 2024). SIMS performed relatively well over cropland areas and showed strong agreement with ground-based ET (MBE 5.63 mm/month, 4.6%; MAE 19.7 mm/month, 16.1%; RMSE 24.31 mm/month, 19.9%; R2 0.86). Consistency was strong between the Authority metrics and the Phase II accuracy assessment (Table 7.1.5.1).

Table 7.1.5.1) Mean monthly statistics between modeled-measured ET for cropland stations (reproduced from Volk et al., 2024 & Volk 2024).

Evaluation Data	MBE mm/month (%)	MAE mm/month (%)	RMSE mm/month (%)	R^2	N
Phase II Assessment	4.3 (4.7%)	17.9 (19.6%)	23.1 (25.3%)	0.85	44-53
Preliminary Utah Evaluation	5.63 (4.6%)	19.7 (16.1%)	24.31 (19.9%)	0.86	18-21

Evidence of anomalies or discontinuities

The evaluation focused on the identification of discontinuities, anomalies, or artifacts in the historical ET record. We evaluated the ratio of ET to EToF relative to NDVI. The analysis captured changes in ET from water availability, and changes in NDVI corresponding to changes in EToF. The SIMS team evaluated these metrics for each of the HUC 8 basins. For the temporal evaluation of EToF relative to NDVI, again the team found values to vary within a reasonable range considering sensitivity of the SIMS model to changes in NDVI (not shown). Changes in EToF independent of NDVI would indicate greater contributions of soil evaporation.

SIMS, like the other models in OpenET, relies on observations from Landsat 5, 7, 8, and 9 across the data record. For the Authority, Figure 7.1.5.1 shows annual average cloud free retrievals for the two distinct periods of record from the SIMS cloud screening procedure. Dark blue areas are locations where the full version of SIMS does not apply (ie, non-ag pixels).An initial inspection by year for each of the HUC 8 basins found that for certain basins, clear sky observations were very low for agricultural areas for 1990 and 1991.

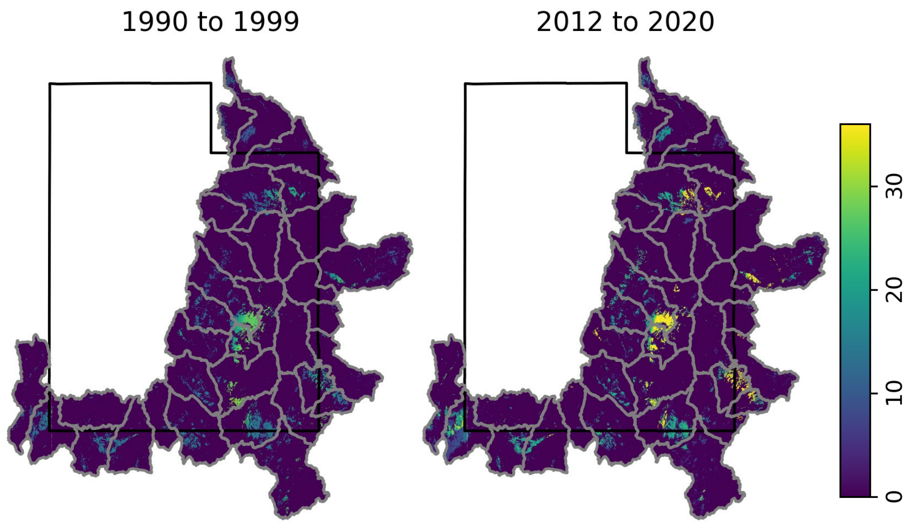


Figure 7.1.5.1) Number of cloud-free observations for areas where the SIMS model provides data within the CRB (ie, agricultural areas).

Factors affecting SIMS ET values relative to other OpenET models

SIMS was originally developed to support irrigation management over agricultural lands. For the purposes of providing continuous ET data across the western U.S. a simple reflectance-based model was implemented for non-agricultural land cover types. This approach was based on a linear transformation of NDVI and does not incorporate the full density-coefficient reflectance-based approach used by SIMS for agricultural lands. This simplified variant of SIMS may frequently produce ET values with a (high) positive bias for non-irrigated agricultural land cover. In these situations, the high ET data are typically detected and removed from the OpenET ensemble calculation on the basis of Mean Absolute Deviation as described above. However, these data remain in the SIMS archive and are accessible via Data Explorer queries in 'raster view' or the OpenET API. For non-agricultural areas, ET data from the simplified version of SIMS should be regarded as a measure of potential ET, and interpreted as an upper limit that would occur under full water supply,

Figure 7.1.5.2 shows that SIMS ET is greater on-average than the OpenET ensemble and eeMETRIC for agricultural lands averaged to HUC 8 basins for Utah. Points closer to the 1-to-1 line indicate basins that likely have a greater fraction of irrigated agriculture, while larger deviations above the line suggest a greater fraction of deficit irrigated or dryland farms for a given basin.

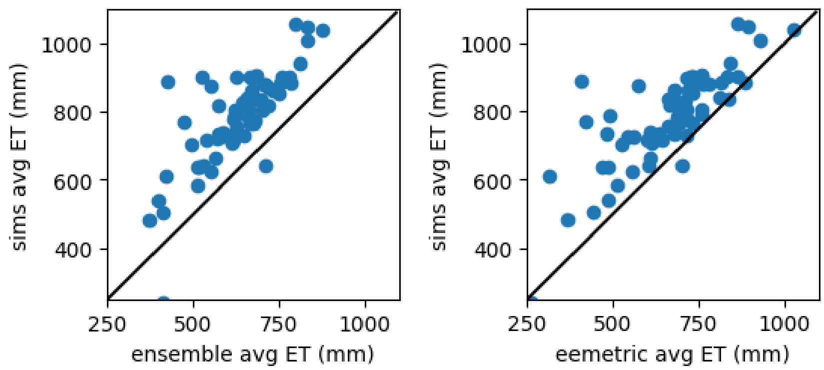


Figure 7.1.5.2) Multi-annual mean ET for agricultural lands summarized by CRB HUC 8 boundaries in Utah. Left: SIMS vs ensemble. Right: SIMS vs eeMETRIC.

The percent differences when averaged across multiple peak growing season months (June, July, and August) for agricultural lands shows that the bias is minimal for irrigated fields (Duchesne) and greater for rainfed fields (Montezuma) (Figure 7.1.5.3).

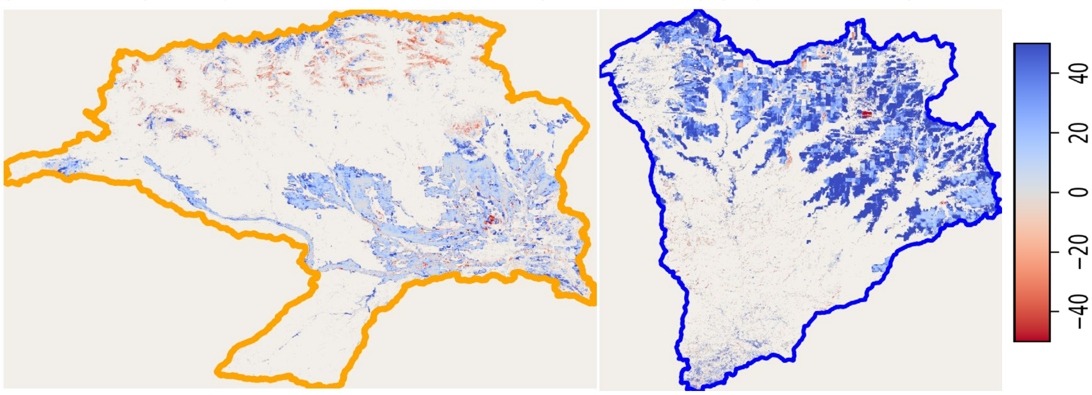


Figure 7.1.5.3) Multi-annual mean percent ET difference between SIMS and the OpenET Ensemble during the growing season for agricultural lands in the Duchesne (left) and Montezuma (right) basins.

SIMS ETrF values capture geographic patterns and inter-annual variations similar to the ensemble. Figure 7.1.5.4 shows average ETrF by HUC 8 subbasin and differences in ETrF between SIMS and ensemble for the Duchesne and Montezuma basins. Both these attributes provide support for the utility of SIMS for tracking differences in ETrF in both spatially and temporally in agricultural lands, where SIMS can complement energy balance models by providing a basis for inferring water stress.

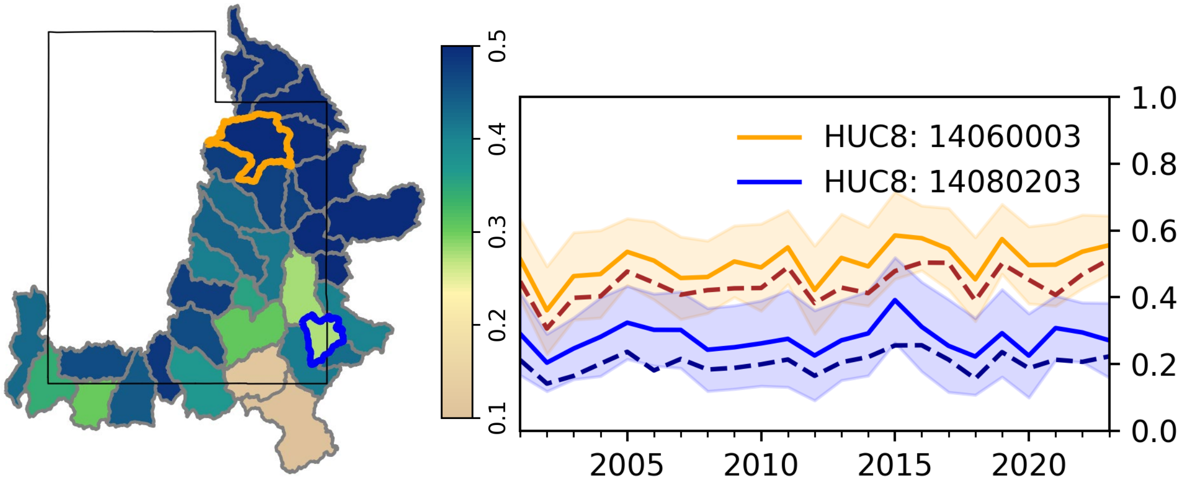


Figure 7.1.5.4) Left: Map of the OpenET SIMS mean ETrF for only agricultural lands from 2001-2023. Cooler tones (higher values) would generally indicate a higher fraction of irrigated lands relative to rainfed agriculture per basin. Right: Time series of ETrF by year for SIMS (solid line and shaded region) compared to the ensemble (dashed line) for agricultural lands of the Duchesne (orange) and Montezuma (blue) basins.

Conclusions

The review of the SIMS model implementation for the Authority generally demonstrates model performance that is consistent with previous evaluations. Metrics were consistent with the Phase II assessment, which found that SIMS was among the most accurate models for cropland (Table 7.1.5.1). Known limitations, due to the model's dependence on vegetation development, were found to be more obvious in basins with greater fractions of deficit-irrigated agricultural lands or dryland farms. Inter-annual trends in ET and EToF were similar between SIMS and the ensemble, and should support agricultural use cases that depend on relative change in ET rates. SIMS could also complement energy balance models for agricultural use cases requiring or benefitting from derivation of ET under well-watered conditions. Special caution should be exercised in use of SIMS in non-ag areas due to use of a simplified framework.

7.1.6. SSEBop

7.1.6.1. Model overview

The Operational Simplified Surface Energy Balance (SSEBop) model by Senay et al. (2013, 2023) is a thermal-based simplified surface energy model for estimating actual ET based on the principles of satellite psychrometry (Senay, 2018). Unlike the other SEB models, SSEBop does not solve for sensible heat and ground heat flux, but instead directly solves for actual ET by applying a coefficient (ET fraction) to the maximum ET. The ET fraction is calculated using remotely sensed surface temperature and two model parameters:(1) a surface psychrometric constant which is determined from gray-sky radiation balance over dry bare surface, and 2) a wet-bulb reference limit (cold/wet limit) which is determined as function of large-area averages of surface temperature, NDVI, and the temperature difference (dT), i.e., the inverse of the surface psychrometric constant using the Forcing and Normalizing Operation (FANO) algorithm (Senay et al., 2023).

7.1.6.2. Accuracy strengths

The performance of the SSEBop model has been evaluated in diverse hydro-climatic zones to provide reasonable accuracy at seasonal, monthly and daily scales with decreasing levels of accuracy. The monthly comparison between a CONUS-wide and an Utah-target analysis focused on cropland measurements shows a relatively consistent performance (Table 7.1.6.1). While percent RMSE is slightly improved (24.3% vs 30.3) the R2 is slightly weakened (0.82 vs 0.85), with an overall good performance.

Table 7.1.6.1) Mean monthly statistics between modeled-measured ET for cropland stations. Statistics from Volk et al., 2024 & Volk 2024.

Evaluation Data	MBE mm/month (%)	MAE mm/month (%)	RMSE mm/month (%)	R^2	N
Phase II Assessment	-6.08 (-6.7%)	22.4 (24.50%)	27.72 (30.3%)	0.85	44
Preliminary Utah Evaluation	5.84 (4.8%)	24.73 (20.2%)	29.72 (24.3%)	0.82	18

The CONUS-wide HUC 8 level water balance ET (WBET)-based evaluation showed an overall good performance (r = 0.94, RMSE = 14%, Bias = -1%) at the national scale with directional regional differences, particularly positive bias in the Northeast (4%) and negative bias in the West (-5%)(Senay et al., 2023). The comparison of the same WBET in the Colorado River Basin (a subset of the West region in Senay et al (2023)) shows a similar negative bias, but at a higher level (-12.7%), indicating a potential underestimation (Figure 7.1.6.1). However, caution should be taken in such interpretations for two reasons: (1) the flux tower comparison does not indicate a similar underestimation and (2) uncertainties as to the level and extent of irrigation in the basin may undermine the assumptions of the basin analysis, making for a more difficult comparison with the model.

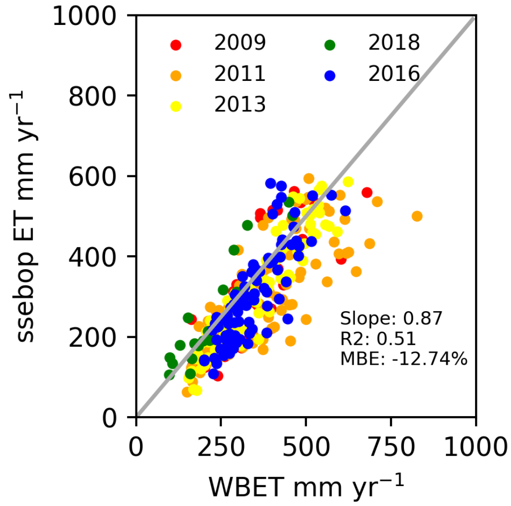


Figure 7.1.6.1. Scatter plot comparing water balance ET (x axis) with SSEBop ET (y axis).

Another way of qualitatively evaluating the performance of the SSEBop model is to compare it to the Ensemble ET. The Figure 7.1.6.2 below shows SSEBop to be generally lower than the Ensemble on the map and on the timeseries for the two sub-basins. This agrees with the WBET in terms of direction of bias, but the magnitude of difference with the Ensemble appears to be much larger, especially for the drier basin (Montezuma).

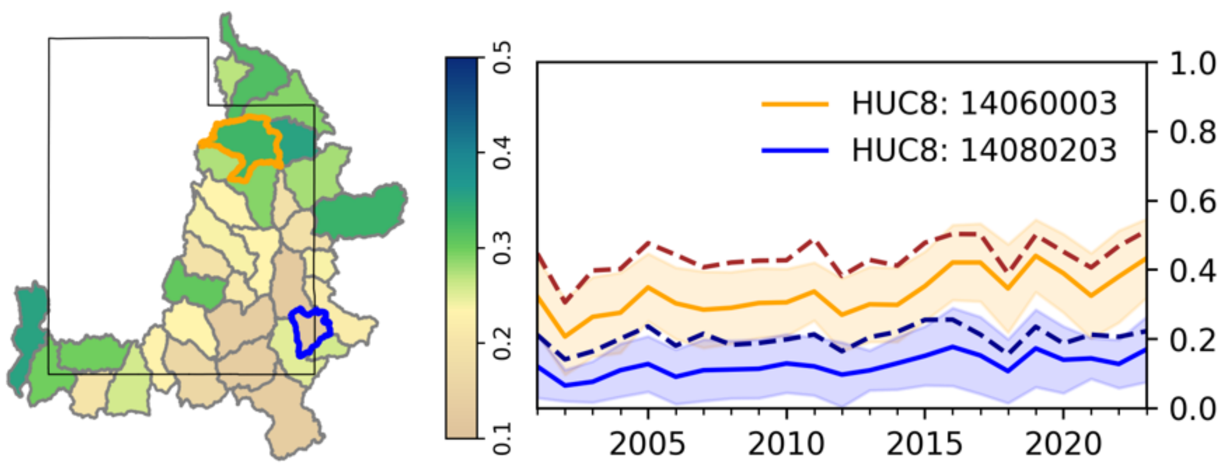


Figure 7.1.6.2) Left: Map of the SSEBop mean ETrF for only agricultural lands from 2001-2023. Cooler tones (higher values) would indicate a higher fraction of irrigated lands relative to rainfed agriculture for each basin. Right: Time series of ETrF by year for the SSEBop model (solid line and shaded region) compared to the ensemble (dashed line) for the Duchesne (orange) and Montezuma (blue) sub-basins.

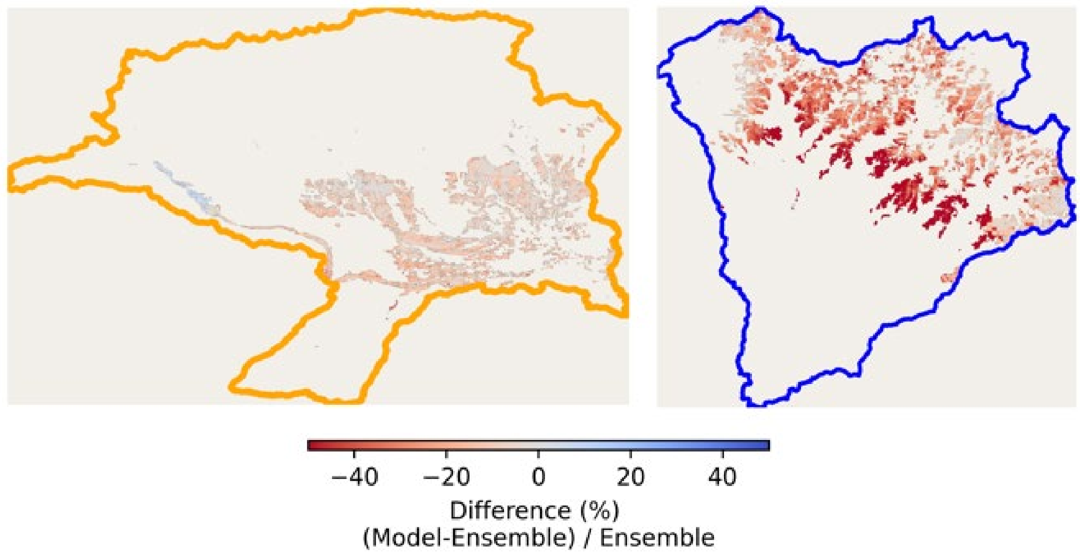


Figure 7.1.6.3) Multi-annual mean percent ET difference between SSEBop and the OpenET Ensemble for agricultural lands for the Duchesne Basin (Orange) Left and the Montezuma Basin (Blue) right.

The percent differences between SSEBop and the ensemble when averaged across multiple peak growing season months (June, July, and August) for agricultural lands shows small negative bias (+/-10%) for irrigated fields (Duchesne) and increased negative bias (more than -20%) for rainfed fields (Montezuma) (Figure 7.1.6.3). However, a look at the performance of the Ensemble ET:P suggests the Ensemble could be overestimating the ET in these two basins. For Montezuma, the ratio is much larger than 1.0 (>~1.3) for most of the years while that of SSEBop averages close to 1.0. Therefore, the negative bias of the SSEBop ET may be correct in direction (agreeing with the WBET), and the relatively large negative bias could simply be because the Ensemble is on the high side on these two basins.

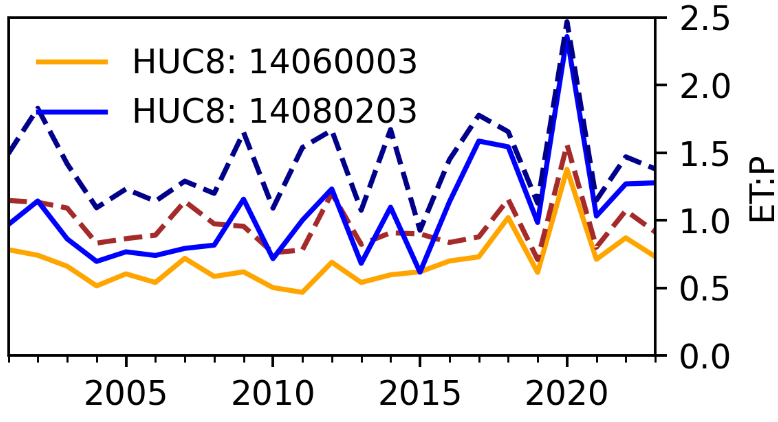


Figure 7.1.6.4 compares the OpenET ensemble (dashed lines) to SSEBop (solid lines) for the Duchesne (orange) and Montezuma (blue) basins. Average ET:P for non-agricultural lands.

7.1.6.3. Known limitations

The relative accuracy of SSEBop ET is lower in highly reflective surfaces like dried playas/gypsum sands as well as mountain shadows, deep water bodies and cloud contaminated surfaces. The SSEBop model uses Landsat Collection 2 (C2) source QA_PIXEL flags for masking unusable pixels (cloud, cloud shadow, snow, etc.) during image processing. SSEBop does not currently apply additional cloud screening or cloud/shadow-buffering techniques during processing. In some instances, model estimates may result in outlier ET values due to cloud mask errors. Similarly, valid pixels for mountain shadows in complex terrain have potential to create abnormal (low) land surface temperature (ST) values, leading to ET overestimation bias on shaded hillslopes. Efforts are underway to mask and fill these areas with reasonable ET estimates or to model them more accurately.

Additionally, the reduced ET signal in low ET times of year and in dry regions decreases relative accuracy of SSEBop ET estimates which is also tied to a higher uncertainty with the land surface temperature input. In general, ongoing developments to support various ST datasets within the model are currently being investigated and implemented.

A known visual model error near shallow water bodies in warm/desert regions has been found to cause erroneous high ET pixel values around the water body. This issue arising from modeling water temperatures has been fixed in recent versions of SSEBop beginning in v0.4.4.

Lastly, future updates for the SSEBop model may include boundary limit parameterization (Tc determination) improvements from a 5km grid (Senay, 2023) to an increased resolution scale. This increase takes into account intermediate layer processing cost and optimization effects with better calibration for more accurate ET model results across all landscapes.

Conclusions

The review of the SSEBop model found that the implementation for the Authority demonstrates performance of the SSEBop model consistent with prior CONUS and regional applications. While the flux tower analysis shows little bias for SSEBop, the Water Balance ET (WBET) and Ensemble analysis shows a general negative bias for SSEBop. The negative WBET is consistent with the negative WBET in Senay et al. (2024) for a larger region (West) that includes the study region in UCRB. The overall good R2 based on flux tower and WBET analyses shows consistency in space and time, and the absolute accuracy of the SSEBop ET model could be improved using a one-time bias correcting calibration procedure.

7.2. Data Inputs

Table A.1) Model Primary Inputs (reproduced from Table 2 in Melton et al., 2022)

Model	Satellite / 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	ET_o data from Spatial CIMIS (in California); gridMET ET_o and precipitation data for other states

	mapping data products; Surface reflectances from Terra/Aqua MODIS and Suomi NPP VIIRS can be used for gap-filling	
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)