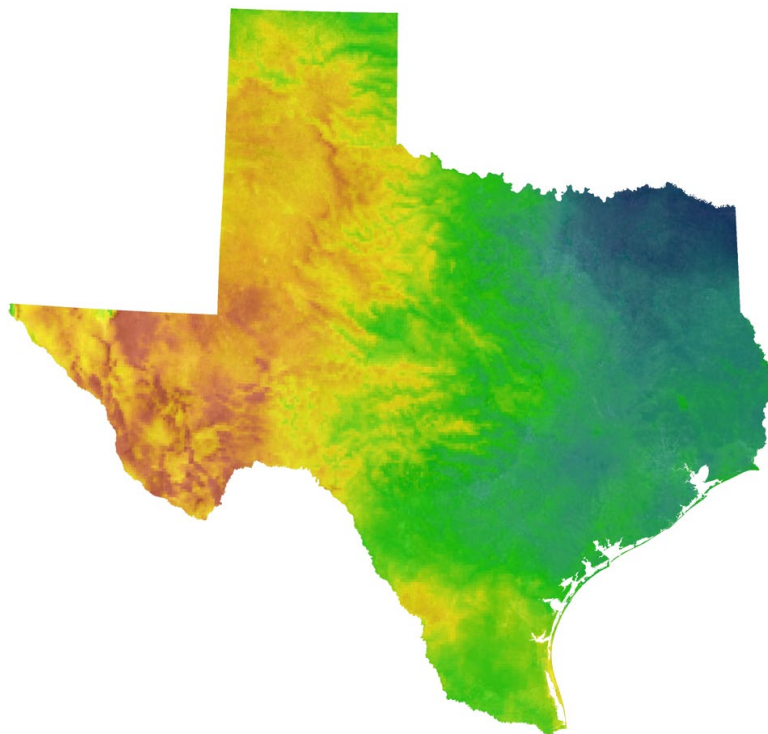


Monitoring daily reservoir evaporation losses for the State of Texas

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(Cover Picture: Map of annual average gridded pond evaporation estimates for the State of Texas produced using Daily Lake Evaporation Model. Color ramp scales from blue to red showing areas of low to high evaporation rates.)

Executive Summary

Reservoir evaporation is a critical component of water budgeting and operations but is often overlooked or simplified due to the difficulty in obtaining consistent, accurate estimates. Historically, reservoir evaporation estimation throughout Texas has relied on pan evaporation methods that are known to have large bias and uncertainty (Friedrich et al., 2018). Recent advancements in hydrometeorological modeling and cloud-based data processing allow for real-time production of high-resolution evaporation estimates capable of informing water management decision making in near-real time. This project developed a daily reservoir evaporation database which can be freely accessed and visualized by water managers and stakeholders in Texas. More specifically, reservoir evaporation estimates were produced from 1980 to present for 188 major water supply reservoirs using the Daily Lake Evaporation Model developed by Zhao and Gao (2019). This database contains historical and near real-time high quality data records of evaporation rates and volumes for major water supply reservoirs throughout Texas. Evaporation estimates incorporate meteorological forcing data and reservoir storage information to provide the best available estimates of reservoir evaporation. In addition to site specific estimates, hypothetical pond evaporation estimates were developed for six different sized pond scenarios using a 4-kilometer resolution climate grid for the entire State of Texas. Reservoir evaporation estimates are accessible directly through interactive web visualization tools as well as an application programming interface. Automated software routines run daily to provide near real-time estimates for up-to-date decision making and support.

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List of Acronyms

API	Application Programming Interface
DLEM	Daily Lake Evaporation Model
DRI	Desert Research Institute
GEE	Google Earth Engine
IDW	Inverse Distance Weighted
NLDAS	North American Land Data Assimilation System
RTMA	Real-time Mesoscale Analysis
QAQC	Quality Assurance and Quality Control
TAMU	Texas A&M University
UI	User Interface

Introduction

Reservoir evaporation is a critical component of water budgeting and operations but is often overlooked or simplified due to the difficulty in obtaining consistent and accurate estimates. Historically, reservoir evaporation estimation throughout Texas has relied on pan evaporation methods that are known to have large bias and uncertainty (Friedrich et al., 2018). Recent advancements in lake evaporation modeling (Zhao and Gao, 2019; Zhao et al., 2022), operational high spatio-temporal meteorological forcings (Abatzoglou, 2013; De Pondeca et al., 2011) and cloud-based data processing (Gorelick, 2017) allow for real-time production of both reservoir specific and high-resolution gridded evaporation estimates capable of informing water management decision making in near-real time.

The primary objective of this project is to develop a daily reservoir evaporation database which can be freely accessed and visualized by water managers and stakeholders in Texas. This database contains historical and near real-time, high quality data records of evaporation rates and volumes for major water supply reservoirs throughout Texas. Evaporation estimates incorporate meteorological forcing data and reservoir depth information to provide best available estimates of reservoir evaporation. In addition to reservoir specific estimates, a gridded product was developed to provide evaporation estimates for six different pond size scenarios throughout the entire State of Texas.

This technical report highlights key data processing and evaporation modeling tasks accomplished throughout the study and details the development and functionality of web and API visualization and analysis tools. Evaporation modeling was performed for a total of 188 major water supply reservoirs throughout Texas (Figure 1). Additional details about the Texas A&M University (TAMU) Daily Lake Evaporation Model (DLEM) and Texas evaporation dataset can be found in the complementary scientific manuscript “Developing a Daily Lake Evaporation Model and Generating a Long-term Daily Reservoir Evaporation Dataset in Texas” (Zhao et al., 2023, In-review). Additional documentation covering the evaporation database and Application Programming Interface (API) can be found here: <https://twdb.dri.edu/>.

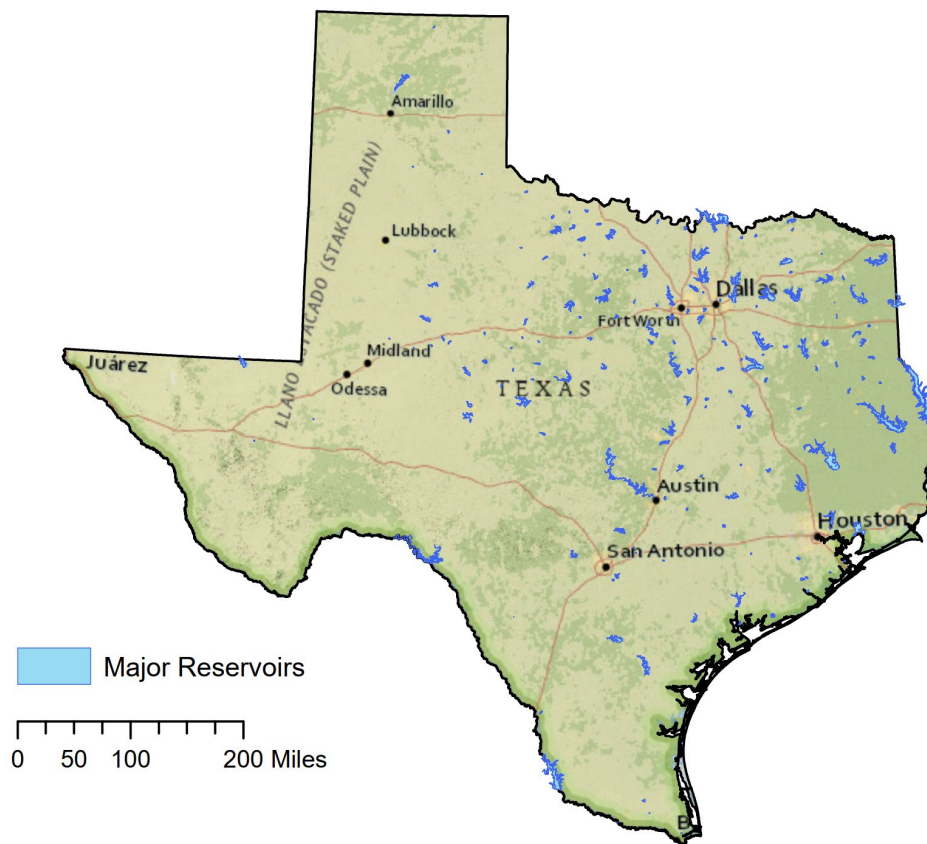


Figure 1: Map of 188 major water supply reservoirs throughout Texas included in the evaporation modeling effort.

Daily Lake Evaporation Model

Reservoir evaporation estimates produced by this project are based on a daily version of Texas A&M Lake Evaporation Model (DLEM) developed by Zhao and Gao (2019). DLEM utilizes a Penman combination equation along with reservoir fetch and heat storage effects represented. DLEM requires input solar radiation, wind speed and direction, air temperature, vapor pressure deficit, and reservoir area and depth data. Meteorological forcing data is adjusted to over water conditions using wind functions developed by McJannet (2012).

Reservoir heat storage within DLEM is simulated using an equilibrium temperature approach where water column temperature at the current timestep is calculated from water temperature at the current timestep, equilibrium temperature, and a lag time. The equilibrium temperature is defined as the water temperature at which there is no heat exchange between air and water. The lag time is a function of reservoir depth. Inclusion of heat storage adjustments improves evaporation estimates in large, deep-water bodies where a significant amount of radiative energy in the spring goes towards warming the water body rather than fueling evaporation. Conversely, in the fall when the water body is warm and air temperatures are cool, heat storage can increase evaporation rates. Daily evaporation rate estimates are combined with reservoir surface area information to estimate volumetric losses.

As part of the Texas-wide modeling effort, additional work was performed to validate and test DLEM performance. DLEM evaporation estimates were compared with eddy covariance-based data from locations both within and outside of Texas including Lake Mead, Lake Mohave, Lake Powell, and Lake Limestone (Figure 2). Results demonstrate the capability of DLEM to capture daily variation and magnitude in evaporation rates from multiple locations and reservoir sizes. Additional details about DLEM validation and performance can be found in Zhao et al., 2023 (In-review).

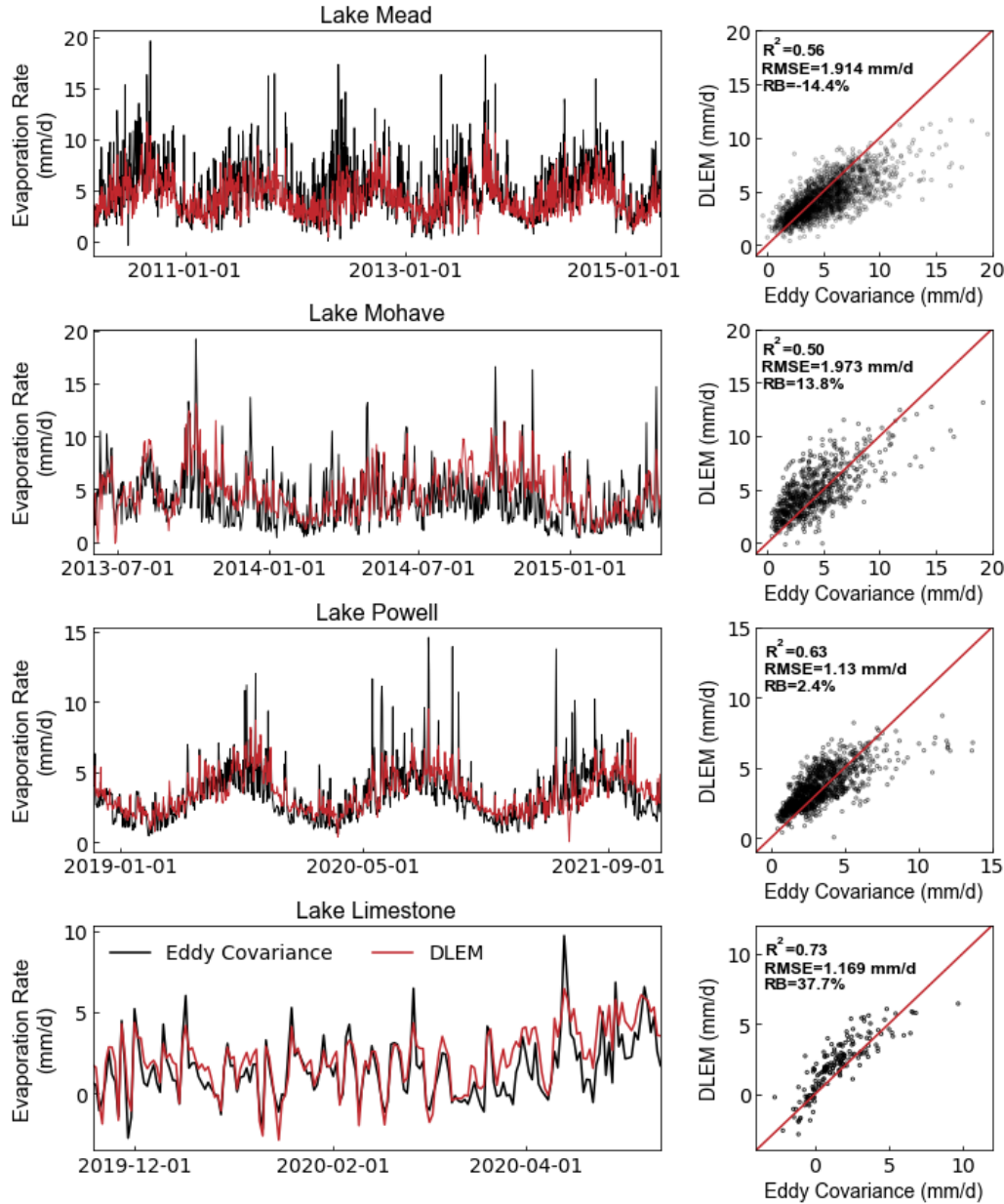


Figure 2: Timeseries (left) and scatterplot (right) comparison of the DLEM estimates and EC observations for Lake Mead from 1 March 2010 to 30 April 2015, Lake Mohave from 1 June 2013 to 20 April 2015, Lake Powell from 8 November 2018 to 15 December 2021, and Lake Limestone from 18 November 2019 to 16 May 2020. The scatter plot 1 to 1 reference line is shown in red. Figure modified from Zhao et al., 2023 (In-review).

Input Data

Reservoir Depth, Area, Volumes

Reservoir area, depth, and storage volume information for major reservoirs, with existing hydrographic and volumetric surveys, was provided by the Texas Water Development Board. Post-processing workflows were used to reconstruct historical timeseries of depth and area using area-elevation-volume curves and interpolation. A detailed description of the QAQC and processing procedure can be found in the supporting manuscript (Zhao et al., 2023; under review). Real-time reservoir depth information is utilized where available. Locations without real-time depth information utilize static depths based on full pool estimates. Evaporation estimates are produced from 1980 to present or for the post-construction period for reservoirs that were built after 1980. Daily real-time updates incorporate automated data retrieval from the [Water Data for Texas](#) data portal.

Pond Area, Depth Relationships

Six different pond size scenarios were selected for evaporation modeling based on typical area, depth relationships for ponds throughout Texas (Table 1). Scenarios represent a wide range of storage conditions including relatively small, shallow ponds as well as larger, deeper systems. Evaporation estimates produced by the pond analysis include daily, monthly, and annual totals from 1980-2022. Data produced by this analysis can be leveraged for historical review and future planning initiatives.

There are two approaches to retrieve evaporation estimates for a specific pond scenario. If the size and depth of the pond of interest are similar to one of the provided scenarios, estimates of that scenario can be used directly as the pond evaporation estimates. However, if the pond size or depth is significantly different from all scenarios, multiple scenarios estimates can be combined using the inverse distance weighted (IDW) interpolation method to calculate the best estimate. Sensitivity tests show the root mean square error is less than 0.01 inch/day applying the IDW method.

Table 1: Table summary of pond evaporation scenarios modeled for all climate grid cells throughout Texas.

Scenario	Depth (ft)	Area (acres)	Volume (acre-ft)
1	5	5	25
2	10	5	50
3	5	25	125
4	10	25	250
5	10	100	1000
6	20	100	2000

Climate Data

Gridded Climate Dataset Evaluation

Multiple gridded climate products exist capable of providing the necessary DLEM forcing data, however, the capability of these datasets to accurately represent overwater conditions is uncertain. For this analysis we evaluated the accuracy of four gridded climate products: real-time mesoscale analysis (RTMA; DePondeca et al., 2011), gridMET (Abatzoglou, 2013), NLDAS (Xia et al., 2012), and TerraClimate (Abatzoglou et al., 2018). Product accuracy was assessed by comparing climate model estimates to station-based weather data collected within close proximity to reservoirs in Texas. A total of 13 TexMesonet station datasets were used during the weather product evaluation. Variables of interest include wind speed, air temperature (minimum and maximum), vapor pressure, solar radiation, and reference evapotranspiration. This evaluation includes raw weather variables such as temperature and windspeed as well as computed values such as reference evapotranspiration that relies on a combination of multiple inputs. Data comparisons were made for three time periods including the growing season (April-October), summer (July-August, JJA), and annual aggregations. Summary results from the station comparison are shown in Table 2. Results for the individual stations comparisons are included in the Supplemental Tables section.

Table 2: Summary table of average bias statistics for station, gridded climate comparisons between alfalfa reference ET (ET_r), vapor pressure, wind speed, solar radiation, and air temperature.

		ET _r			Vapor Pressure			Wind Speed, 2m		
		gs	summer	annual	gs	summer	annual	gs	summer	annual
RTMA	mean	1.00	0.98	1.02	1.00	0.98	1.02	0.88	0.88	0.88
	min	0.90	0.86	0.93	0.90	0.86	0.93	0.48	0.47	0.50
	max	1.07	1.06	1.09	1.07	1.06	1.09	1.10	1.11	1.11
	stddev	0.05	0.05	0.05	0.12	0.12	0.12	0.19	0.20	0.18
gridMET	mean	0.86	0.86	0.86	0.86	0.86	0.86	0.68	0.67	0.70
	min	0.74	0.72	0.69	0.74	0.72	0.69	0.26	0.25	0.28
	max	0.94	0.94	0.95	0.94	0.94	0.95	0.88	0.89	0.92
	stddev	0.06	0.06	0.07	0.13	0.13	0.13	0.20	0.20	0.19
NLDAS	mean	0.80	0.78	0.83	0.80	0.78	0.83	0.68	0.67	0.70
	min	0.67	0.65	0.66	0.67	0.65	0.66	0.26	0.25	0.28
	max	0.89	0.86	0.92	0.89	0.86	0.92	0.88	0.88	0.92
	stddev	0.06	0.07	0.07	0.13	0.14	0.13	0.20	0.20	0.19
TerraClimate	mean	0.73	0.71	0.73	0.74	0.73	0.74	0.80	0.80	0.79
	min	0.05	0.05	0.05	0.12	0.12	0.12	0.34	0.32	0.36
	max	1.07	1.06	1.09	1.07	1.06	1.09	1.09	1.09	1.07
	stddev	0.12	0.12	0.13	0.12	0.12	0.12	0.31	0.31	0.32
		Solar Radiation			Minimum Air Temperature*			Maximum Air Temperature*		
		gs	summer	annual	gs	summer	annual	gs	summer	annual
RTMA	mean	0.93	0.93	0.94	-0.06	-0.15	0.00	1.26	1.16	1.26
	min	0.89	0.89	0.90	-0.90	-0.87	-0.99	0.35	0.20	0.43
	max	1.00	0.99	1.04	0.65	0.48	0.78	3.04	3.32	2.95
	stddev	0.03	0.03	0.04	0.48	0.42	0.57	0.82	0.91	0.71
gridMET	mean	0.93	0.93	0.94	1.12	0.71	1.42	0.51	0.33	0.68
	min	0.89	0.89	0.89	0.40	-0.13	0.79	0.10	-0.05	0.21
	max	1.00	0.99	1.05	1.96	1.47	2.28	1.21	1.02	1.32
	stddev	0.03	0.03	0.04	0.42	0.46	0.43	0.31	0.31	0.32
NLDAS	mean	0.93	0.93	0.94	-0.57	-0.97	-0.48	-0.78	-1.11	-0.26
	min	0.89	0.89	0.89	-1.61	-1.95	-1.62	-1.97	-2.83	-1.22
	max	1.00	0.99	1.04	1.12	0.78	1.16	0.53	0.90	0.82
	stddev	0.03	0.03	0.04	0.77	0.75	0.80	0.76	1.05	0.63
TerraClimate	mean	1.00	0.99	1.01	0.97	0.75	1.18	0.17	-0.02	0.35
	min	0.96	0.96	0.97	0.23	-0.04	0.26	-0.77	-1.06	-0.51
	max	1.08	1.08	1.13	1.78	1.48	2.13	1.49	1.52	1.60
	stddev	0.04	0.03	0.05	0.50	0.54	0.54	0.75	0.87	0.69

*Temperature bias values are expressed as an absolute bias (station-gridded product). All others are expressed as a ratio (station/gridded product).

Compared to other climate products, the RTMA dataset consistently better captured weather conditions at the 13 comparison stations. Importantly, RTMA showed the best estimate capability for reference ET which utilizes a similar approach to the Penman equation utilized by the DLEM model. Notably, RTMA outperformed all other models for vapor pressure estimates due to its incorporation of buoy-based datasets and a land/water mask. TerraClimate outperformed the other models when estimating solar radiation but performed poorly when estimating both vapor pressure and reference ET. RTMA does not currently provide estimates of incoming solar radiation, so NLDAS solar radiation was utilized in the RTMA collection (it should be noted the gridMET solar is based on NLDAS as well). Differences between the

gridMET and RTMA solar radiation occur during the resampling process from the original 12-km resolution NLDAS product to 4 km and 2.5 km resolution grid cells for gridMET and RTMA, respectively. Based on its holistic performance and ability to capture near reservoir vapor pressure and reference ET, RTMA was selected as the key forcing datasets for DLEM application in Texas.

Real-time Mesoscale Analysis

Daily near surface weather conditions were extracted from the RTMA dataset stored within [Google's Earth Engine Data Catalog](#). RTMA provides hourly estimates of near surface windspeed and direction, temperature, specific humidity, and pressure at 2.5 km resolution (De Pondeca et., al. 2011). Hourly data were aggregated to daily timesteps prior to extraction. Daily RTMA data aggregation start and end at 6 UTC to represent central standard time midnight to midnight day. Data extraction workflows utilized the RTMA water mask combined with reservoir maximum areal extent information to extract meteorological data most representative of average over water conditions for each reservoir (Figure 3). Cell selection for smaller reservoirs with no water masked values was based on minimum cell elevation for all cells intersecting the reservoir's maximum extent.

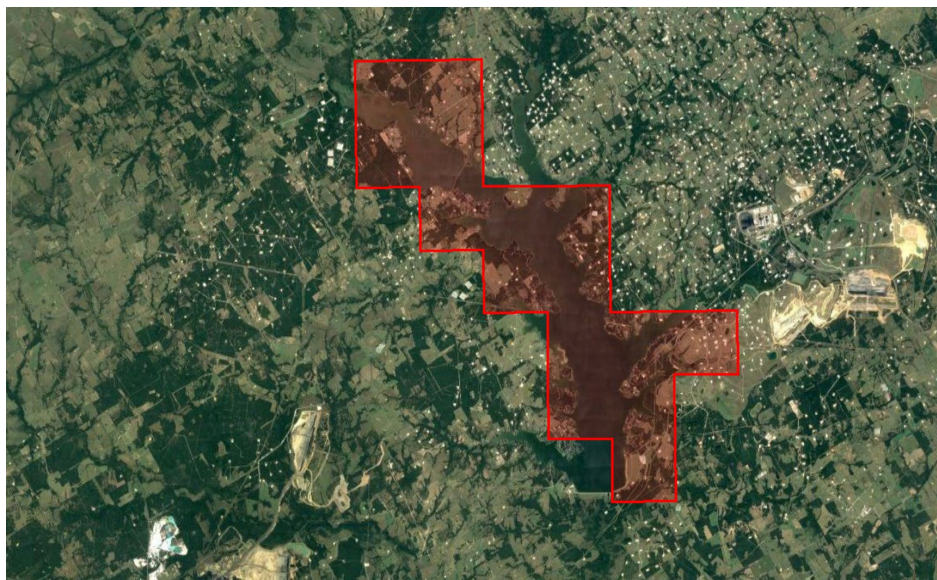


Figure 3: Example figure of RTMA water mask (shown in red) and base map reservoir extent for Lake Limestone in Texas.

Pre-2016 Climate Data

The Google Earth Engine RTMA dataset begins in 2011, however, data coverage prior to 2016 includes numerous gaps and missing values. To extend the evaporation estimate record back to 1980 we incorporated information from the gridMET climate dataset (Abatzoglou, 2013). All evaporation estimates from 2016 forward use RTMA directly, however, estimates prior to 2016 utilize a hybrid meteorological dataset based on direct comparisons of RTMA with gridMET. gridMET provides near surface meteorological estimates at 4km resolution from 1979–present, however, gridMET does not incorporate buoy-based station data or conditioning for overwater conditions and can overestimate aridity in irrigated and, or wet environments (Huntington, 2011; Abatzoglou, 2013).

Bias correction factors were developed by comparing average monthly conditions from RTMA with gridMET for each 4km gridMET grid cell. Prior to comparison RTMA was resampled to the 4 km gridMET grid using a mean reducer. Monthly ratios of RTMA to gridMET were developed based on 2016-2021 data for windspeed, specific humidity, and solar radiation. Temperature correction factors were developed by subtracting gridMET monthly average minimum and maximum temperature from RTMA. Bias correction factors were then applied to each individual forcing variable on a monthly basis prior to model input. Similar bias correction workflows have been utilized to estimate reference evapotranspiration from gridMET based on comparisons between agricultural weather stations and gridMET (Melton et al., 2021, Volk et al., 2021).

Evaporation Modeling Results

Modeling efforts produced daily estimates of reservoir evaporation for 188 major water supply reservoirs throughout the state from 1980–present. Evaporation estimates highlight spatial and temporal patterns related to climate and storage conditions. Evaporation averaged 58.5 inches/year across all sites and years. The highest average evaporation rates were observed at Casa Blanca Lake averaging 73.7 inches/year, while the lowest rates were observed at Lake Palestine, averaging 49.7 inches/year (Figure 4). Lake Palestine showed the highest interannual variability with a standard deviation of 6.4 inches/year ($n=43$, 1980–2022). Lake Balmorhea showed the lowest interannual variability with a standard deviation of 1.8 inches/year. The highest single year evaporation rate occurred at Casa Blanca Lake in 2011 (81.5 inches/year). More detailed discussion and analysis of reservoir evaporation estimates can be found in the supporting manuscript (Zhao et al., 2023, In-review).

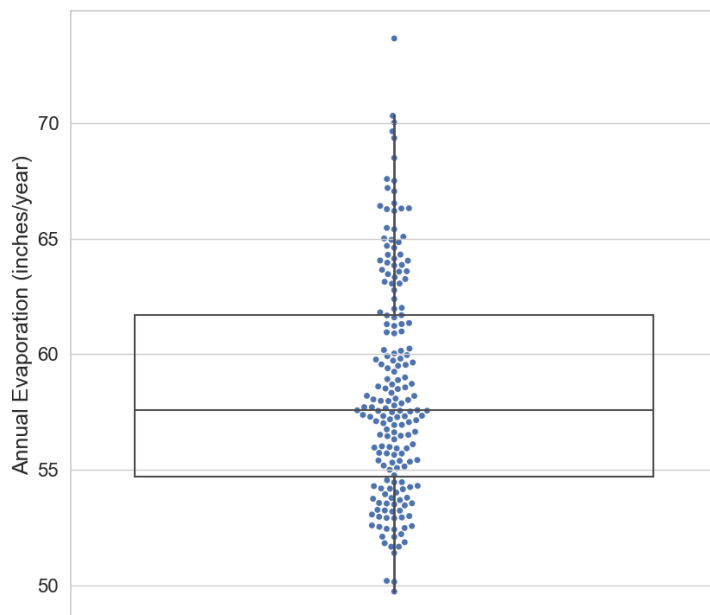


Figure 4: Boxplot summary of average annual evaporation estimates for all reservoirs. Each point represents the average evaporation rate for a single reservoir from 1980–2022 ($n=188$). Blue dots show the density of values at each rate within the dataset.

Gridded pond evaporation estimates produced for the entire State of Texas follow distinct climatic patterns related to atmospheric evaporative demand (Figure 5). More arid regions throughout southern and western Texas experience increased pond evaporation rates relative to the more temperate, humid areas of central and eastern Texas. Smaller, shallow pond simulations show increased evaporation rates relative to larger, deeper systems (Figure 5).

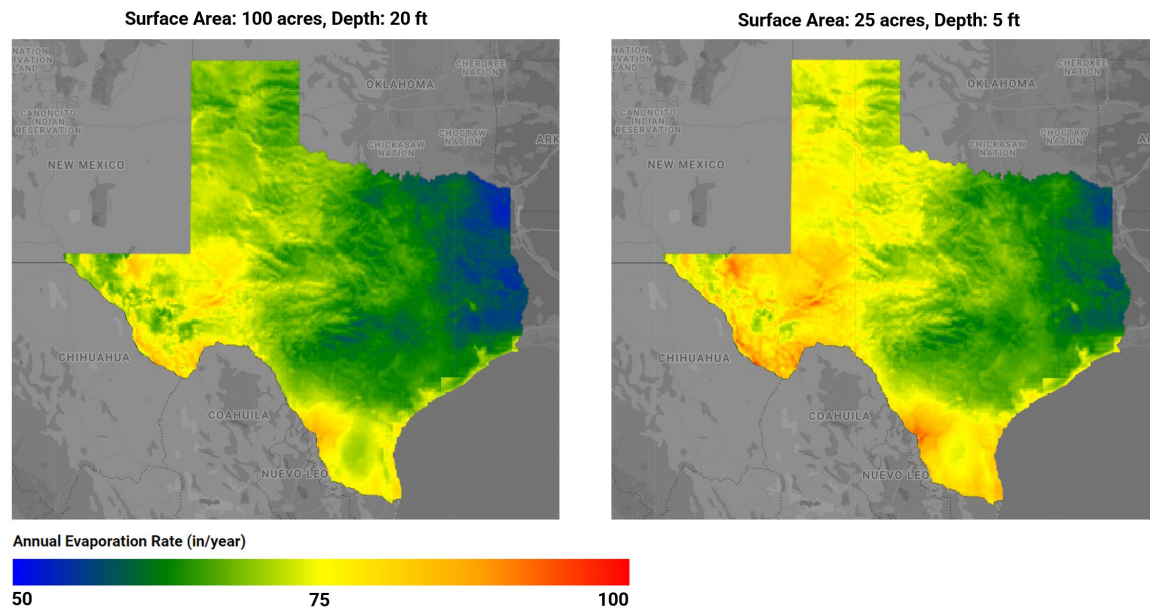


Figure 5: Map of gridded pond evaporation estimates throughout Texas for two different scenarios. Left) 100 acres, 20 ft deep; Right) 25 acres, 5 ft deep.

Reservoir Evaporation Database and Application Programming Interface

To provide wide-scale data access, DRI set up a virtual machine server that hosts the geodatabase, a postgresSQL database with a Postgis extension, as well as the geodatabase fastAPI, a python web framework.

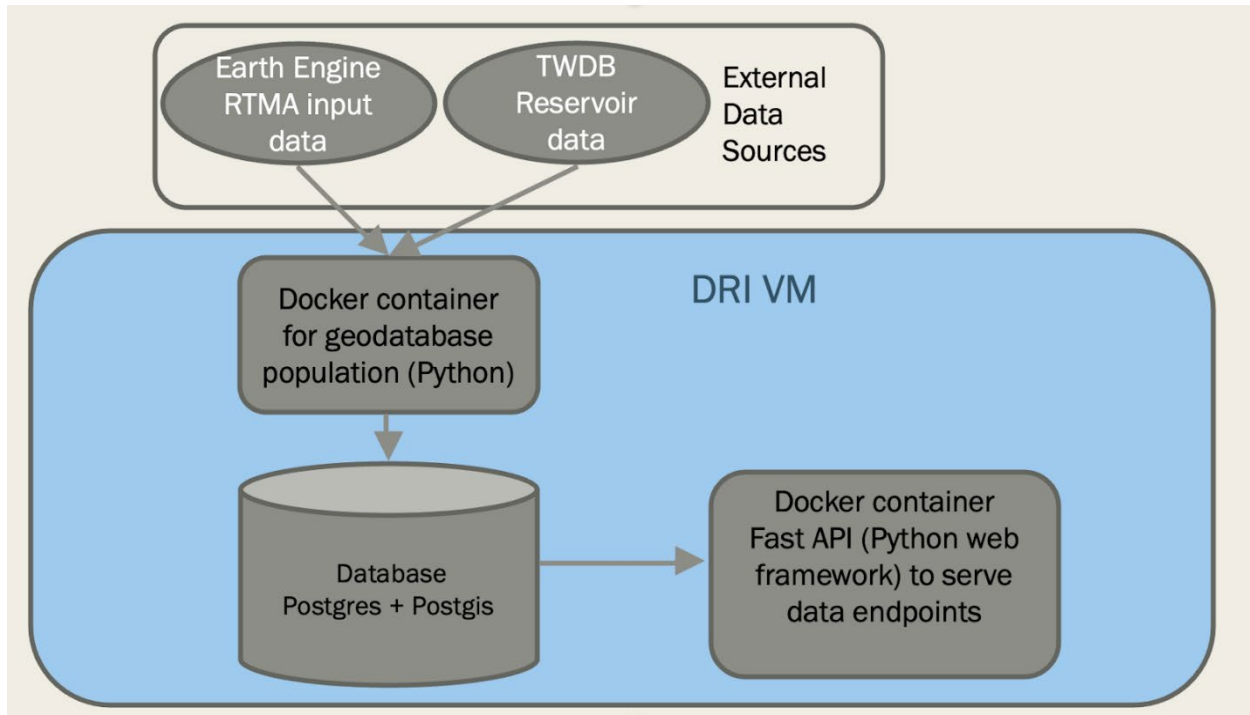


Figure 6: Conceptual diagram of reservoir evaporation software system hosted on virtual servers at DRI.

Reservoir evaporation for 188 major water supply reservoirs throughout Texas is produced using a workflow surrounding the TAMU DLEM model. Each day, cron jobs running python scripts retrieve the latest available RTMA forcing data from Earth Engine along with reservoir storage information from the Water Data for Texas web portal needed to run the TAMU DLEM model. RTMA forcing data is provided with a 2-day lag time allowing for evaporation estimation three days prior to today's date. Forcing data is processed and combined with the previous day's DLEM estimate of water temperature for input to the DLEM model. In addition to DLEM model output DRI produces Net Evaporation, Evaporation Volume and Net Evaporation Volume. All data including both forcing and model output is then ingested into a PostgreSQL database for storage and API access. The reservoir evaporation codebase including database population code, the API framework and the web application is housed within a private GitHub repository for easy management and consistent tracking of historical changes. The data can be accessed via the geodatabase API (<https://twdb.dri.edu/>). DRI has set up a Swagger UI for easy access via a web browser. Data can also be accessed directly from the command line via curl or programmatically. Additional information regarding API set-up and use can be found in the API Quick Start Guide appendix.

Web Interface

In support of data access and visualization, web-based user interfaces were developed for both the reservoir evaporation and pond evaporation products. These web portals utilize [Google's Earth Engine Apps](#) (eeApp) framework to support map-based data visualization and time series access. Google's Earth Engine App provides a simple, low-cost option for visualization and delivery of dynamic spatial data via a web-based user interface.

Reservoir Evaporation Web Application

After DLEM application and database ingestion, data is also converted to Earth Engine image format and uploaded to Earth Engine storage buckets for web-based display. Reservoir image collections include both daily and monthly evaporation totals along with the input forcing data and reservoir depth and area information. This image collection can then be automatically queried through the eeApp interface for customized data visualization and downloading. All map and time series visualizations are generated in real-time allowing for flexible plotting (Figure 7).

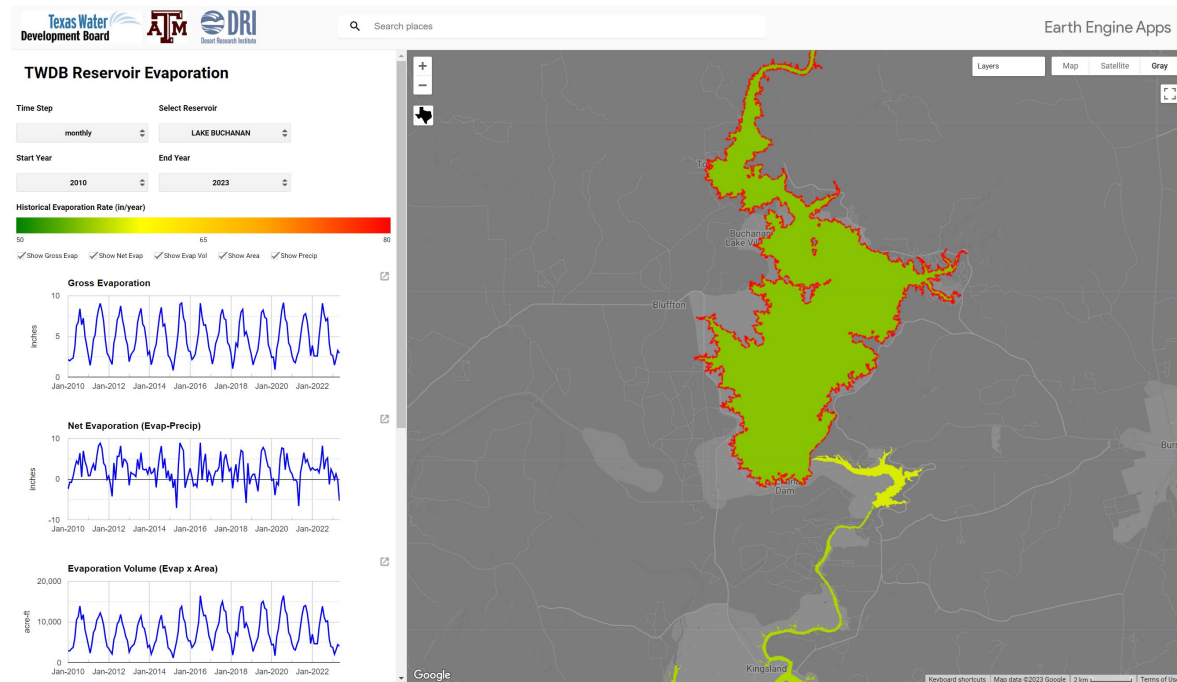


Figure 7: Screenshot of Texas reservoir evaporation web application located at: <https://dri-apps.earthengine.app/view/twdb-reservoir-evaporation>

Pond Evaporation Web Application

In addition to reservoir specific estimates, gridded estimates of pond evaporation for six different pond scenarios were produced using the Earth Engine processing platform. Direct use of Earth Engine's data collections and parallel processing environment allows for streamline production of evaporation estimates through all of Texas. DRI translated the TAMU DLEM codebase to python-based Earth Engine code syntax for direct application in the Earth Engine framework. Estimates produced by the original TAMU DLEM code and Earth Engine version produced identical output.

Both spatial and time series estimates are accessible via a web-based user interface (UI) (Figure 8). The web interface supports automated charting for quick visualization as well as download options for follow-up analyses and post processing. Spatial maps capture general climate patterns throughout Texas, showing higher evaporation rates in the west and southwestern areas of the state. Lower evaporative demand areas in the east and northeast show reduced pond evaporation rates.

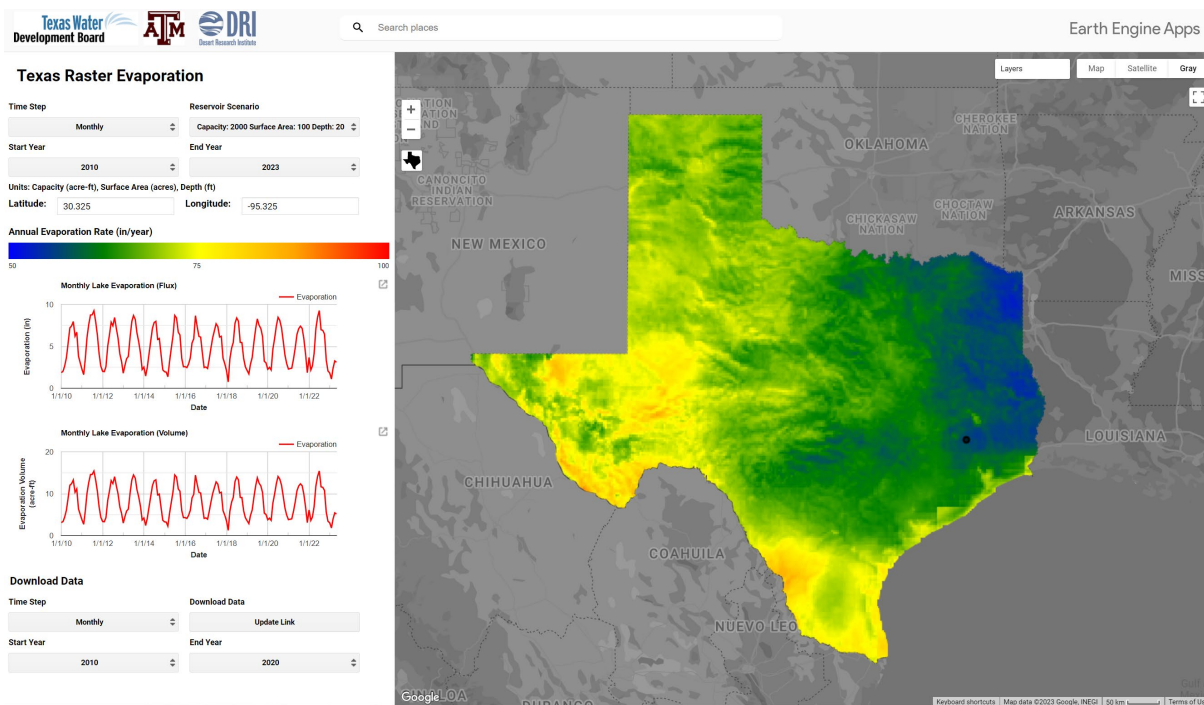


Figure 8: Screenshot of Texas gridded pond evaporation web application located at: <https://dri-apps.earthengine.app/view/twdb-raster-lake-evaporation>

Summary

This project developed automated workflows to produce reservoir evaporation estimates for the State of Texas using the TAMU DLEM. Estimates rely on gridded climate data from RTMA and real-time storage information (depth, area, capacity) from the Water Data for Texas data portal. Reservoir specific estimates from 1980–present were produced for 188 major water supply reservoirs throughout Texas. Real-time updates (~3-day latency) are provided daily to support operational decision making and water resource planning. In addition to reservoir specific estimates, a gridded product was developed to provide estimates throughout the entire state for six different pond scenarios.

Data produced by this project will be used to inform water resources planning and conservation initiatives throughout Texas. Importantly, this product provides a consistent dataset for local, state, and federal agencies to share and utilize. Next steps will focus on continued data production as well as data application and integration within existing planning and management processes.

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API Quick Start Guide

The Texas Reservoir Evaporation API provides access to evaporation data for water reservoirs located across the state of Texas.

Project Summary:

Reservoir evaporation is a critical component of water budgeting and operations but is often overlooked or simplified due to the difficulty in obtaining consistent, accurate estimates. Historically, reservoir evaporation estimation throughout Texas has relied on pan evaporation methods that are known to have large bias and uncertainty (Friedrich et al., 2018). Recent advancements in hydrometeorological modeling and cloud-based data processing allow for real-time production of high-resolution evaporation estimates capable of informing water management decision making in near-real time. This project developed a daily reservoir evaporation database which can be freely accessed and visualized by water managers and stakeholders in Texas. This database contains historical and near real-time high quality data records of evaporation rates and volumes for major reservoirs throughout Texas. Evaporation estimates incorporate meteorological forcing data and reservoir storage information to provide best available estimates of reservoir evaporation.

Relevant Links

- TX A&M Lake Evaporation Model:
<https://www.sciencedirect.com/science/article/abs/pii/S0034425719301063>
- Web-based Visualization Tool:
<https://dri-apps.earthengine.app/view/twdb-reservoir-evaporation>
- Python API example:
https://drive.google.com/drive/folders/1CpKPuRl31s94hYiyJEJipce9cSU_McQ4?usp=sharing

How to use the API

1. Go to <https://twdb.dri.edu/>
2. Request API key
 1. Click on “/auth/request_key”
 2. Click on “Try it out”
 3. Fill out the Form
 4. Click on “Execute”
 5. Your API key should arrive via email within the next 24 hours.

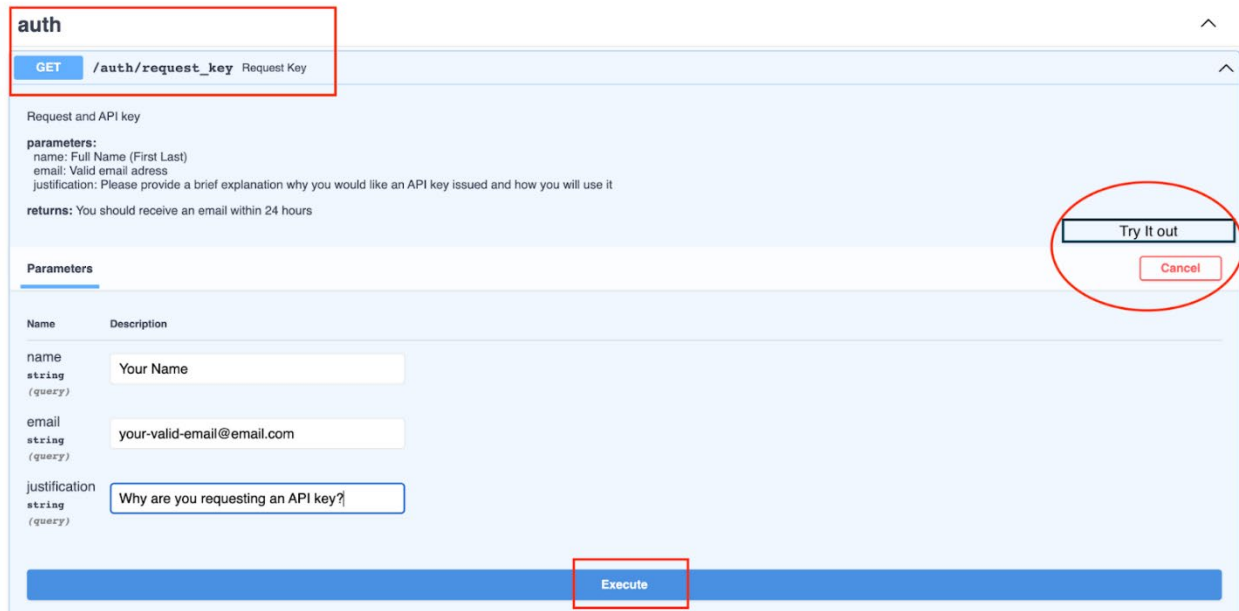


Figure A-1: Screenshot of swagger page API authorization request end point.

3. Authorize with your API key

1. Click on “Authorize”
2. Enter your API Key in the “Value” field.
3. Click on “Authorize”
4. “Close” the window

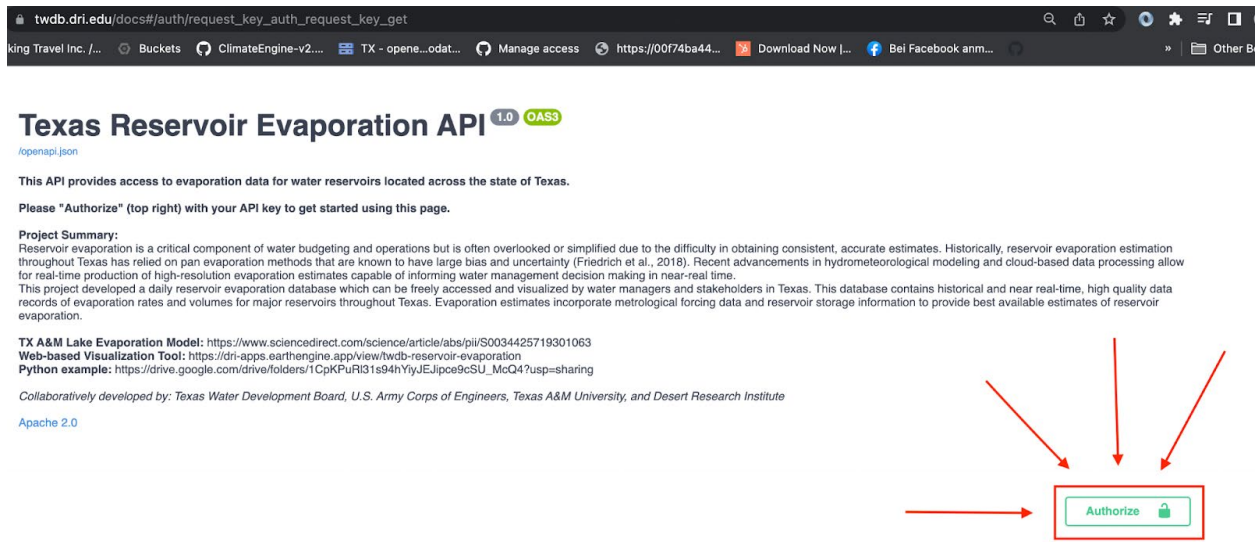


Figure A-2: Screen shot of swagger page API authorization key link.

4. Start using the API
 1. Use the “help” section to obtain information on parameters to use with requests.
 2. Use the timeseries section to obtain data.

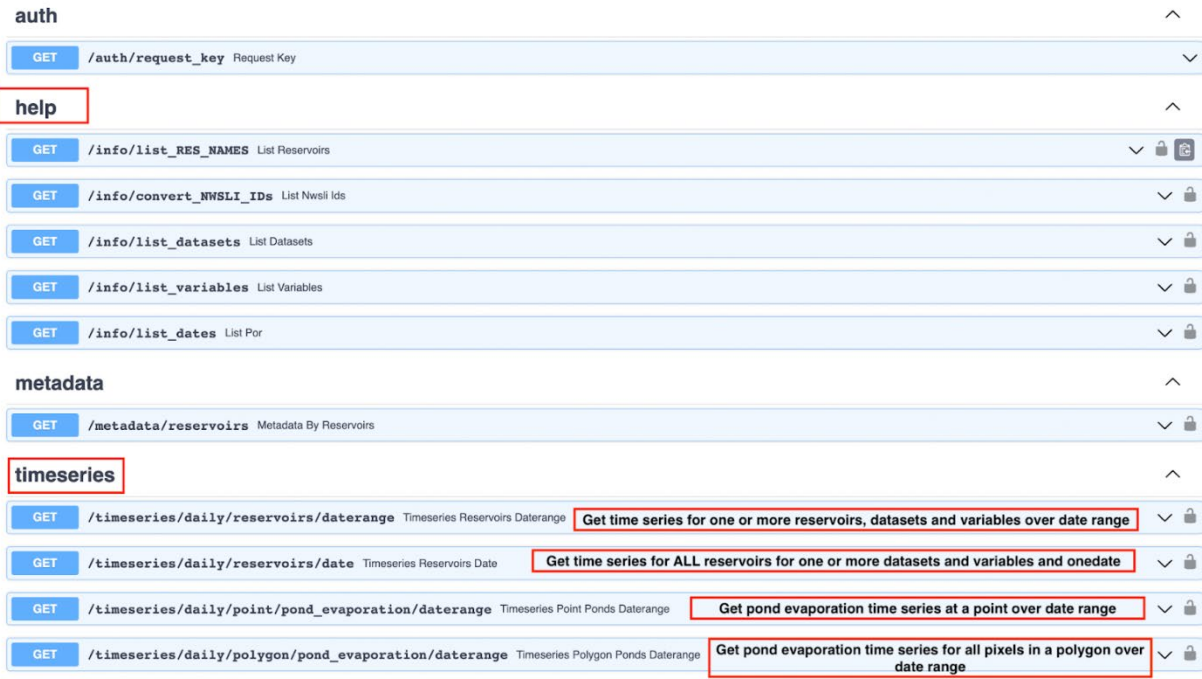


Figure A-3: Screenshot of swagger page API end point options.

Supplemental Tables

Table S1: Summary table of TexMesonet weather station included in gridded climate comparison analysis.

STATION ID	Elevation (ft)	Elevation (m)	Latitude	Longitude	Record Start	Record End
Miller_Creek	1335	406.9	33.414	-99.401	9/3/2003	2/23/2022
Cedar_Hill_SP	520	158.5	32.609	-96.993	12/17/2003	2/23/2022
Cedar	3052	930.2	35.690	-101.568	4/18/2002	2/23/2022
Falcon_Lake	219	66.8	26.555	-99.136	11/15/2002	4/7/2022
Coleman	1509	459.9	31.515	-99.651	4/8/2003	2/28/2022
Paint_Creek	1854	565.1	31.906	-100.582	12/11/2006	2/28/2022
Possum_Kingdom	925	281.9	32.867	-98.562	2/6/2003	2/23/2022
Athens	470	143.3	32.221	-95.766	7/12/2002	2/23/2022
Doc_Curb_Pump_Station	732	223.1	30.992	-97.545	9/27/2018	2/28/2022
Corsicana_Pump_Station	430	131.1	31.957	-96.687	12/1/2019	2/28/2022
Aquilla_Water_Supply_District	532	162.2	31.921	-97.179	8/21/2019	2/28/2022
Lake_Murvaul_Panola	198	60.4	32.027	-94.414	4/27/2020	2/23/2022
Lake_Striker_Rusk	328	100.0	31.934	-94.975	12/17/2019	2/28/2022

Table S2: Summary table of bias ratios and adjustment factors (temperature) between Terra Climate and 13 TexMesonet weather station datasets in Texas. Comparison statistics show relative bias for alfalfa reference ET (ET_r), vapor pressure (E_a), wind speed at 2 meters (u₂), minimum temperature (T_{min}), maximum temperature (T_{max}) and incoming solar radiation (S_{rad}).

Terra Climate	ET _r			E _a			u ₂			T _{min}			T _{max}			S _{rad}		
Station ID	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average
Miller_Creek	1.370	1.335	1.413	1.029	1.012	1.034	0.915	0.944	0.909	1.206	1.041	1.231	0.194	-0.136	0.311	0.975	0.972	0.984
Cedar_Hill_SP	1.238	1.220	1.279	1.000	0.974	1.020	0.777	0.788	0.772	0.767	0.577	1.121	0.926	0.889	0.900	0.969	0.966	0.975
Cedar	1.380	1.351	1.462	1.032	1.028	1.024	0.793	0.815	0.797	1.545	1.472	1.648	1.492	1.519	1.565	0.986	0.983	0.995
Falcon_Lake	1.378	1.406	1.410	1.048	1.003	1.064	0.956	1.030	0.926	0.744	0.585	1.038	1.337	1.161	1.598	1.036	1.027	1.027
Coleman	1.344	1.304	1.402	1.019	0.995	1.032	0.928	0.910	0.928	1.670	1.462	2.006	0.339	0.312	0.512	0.966	0.961	0.977
Paint_Creek	1.252	1.217	1.317	1.022	0.994	1.031	0.717	0.701	0.742	1.036	0.724	1.461	0.624	0.491	0.828	0.990	0.992	0.995
Possum_Kingdom	1.320	1.292	1.361	1.009	0.978	1.019	0.810	0.815	0.795	1.783	1.478	2.133	0.600	0.589	0.545	0.965	0.961	0.974
Athens	1.187	1.174	1.213	1.035	1.021	1.053	0.851	0.888	0.826	1.419	1.397	1.556	-0.209	-0.395	-0.088	0.978	0.975	0.984
Doc_Curb_Pump_Station	1.258	1.266	1.279	1.022	0.988	1.046	1.015	1.057	0.964	0.393	0.158	0.650	-0.389	-0.725	-0.146	0.962	0.981	0.973
Corsicana_Pump_Station	1.130	1.099	1.154	1.020	1.008	1.048	0.731	0.701	0.732	0.375	0.165	0.700	-0.687	-1.065	-0.243	0.979	0.984	0.989
Aquilla_Water_Supply_District	1.272	1.253	1.293	1.065	1.041	1.094	1.094	1.087	1.074	0.557	0.193	0.729	-0.541	-1.065	-0.271	1.000	1.017	1.011
Lake_Murvaul_Panola	1.085	1.046	1.135	0.577	0.566	0.588	0.344	0.323	0.360	0.892	0.570	0.848	-0.770	-0.855	-0.508	1.083	1.078	1.130
Lake_Striker_Rusk	0.986	0.955	0.985	1.080	1.072	1.101	0.412	0.365	0.458	0.234	-0.038	0.258	-0.671	-0.979	-0.473	1.047	1.017	1.102

Table S3: Summary table of bias ratios and adjustment factors (temperature) between NLDAS and 13 TexMesonet weather station datasets in Texas. Comparison statistics show relative bias for alfalfa reference ET (ETr), vapor pressure (Ea), wind speed at 2 meters (u2), minimum temperature (Tmin), maximum temperature (Tmax) and incoming solar radiation (Srad).

NLDAS	ETr			Ea			u2			Tmin			Tmax			Srad		
Station ID	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average
Miller_Creek	0.839	0.837	0.865	1.074	1.102	1.049	0.858	0.877	0.866	-1.611	-1.950	-1.623	-0.773	-1.292	-0.140	0.932	0.934	0.938
Cedar_Hill_SP	0.774	0.753	0.823	1.050	1.076	1.025	0.642	0.633	0.670	0.538	-0.093	0.859	-0.668	-1.119	0.063	0.910	0.919	0.917
Cedar	0.889	0.865	0.918	1.099	1.127	1.075	0.877	0.878	0.879	-1.423	-1.840	-1.382	0.211	-0.284	0.820	0.959	0.955	0.969
Falcon_Lake	0.811	0.830	0.834	1.062	1.054	1.055	0.722	0.708	0.778	-0.825	-0.726	-1.005	0.531	0.898	0.527	0.891	0.908	0.889
Coleman	0.866	0.852	0.892	1.009	1.025	0.995	0.856	0.852	0.862	-0.979	-1.317	-0.795	-0.636	-0.907	-0.137	0.923	0.922	0.934
Paint_Creek	0.855	0.847	0.890	1.030	1.042	1.014	0.763	0.760	0.791	-1.198	-1.311	-1.152	-0.049	-0.259	0.531	0.946	0.947	0.952
Possum_Kingdom	0.820	0.808	0.853	1.037	1.058	1.016	0.714	0.717	0.720	-0.108	-0.618	0.081	-0.546	-0.950	0.026	0.916	0.928	0.926
Athens	0.763	0.749	0.789	1.059	1.083	1.034	0.654	0.662	0.666	1.125	0.776	1.155	-1.118	-1.438	-0.674	0.891	0.887	0.899
Doc_Curb_Pump_Station	0.772	0.743	0.812	0.990	1.027	0.965	0.749	0.744	0.751	-1.081	-1.541	-0.857	-1.891	-2.519	-1.117	0.891	0.900	0.896
Corsicana_Pump_Station	0.694	0.650	0.730	1.009	1.048	0.986	0.536	0.496	0.570	-0.890	-1.399	-0.673	-1.946	-2.831	-1.037	0.912	0.920	0.914
Aquilla_Water_Supply_District	0.798	0.761	0.841	1.053	1.094	1.031	0.884	0.853	0.917	-0.896	-1.605	-0.677	-1.968	-2.763	-1.215	0.942	0.958	0.944
Lake_Murvaul_Panola	0.822	0.837	0.814	0.555	0.554	0.560	0.258	0.252	0.278	0.012	-0.402	-0.015	-0.462	-0.233	-0.414	1.002	0.988	1.044
Lake_Striker_Rusk	0.675	0.663	0.664	1.033	1.049	1.015	0.291	0.268	0.334	-0.103	-0.554	-0.163	-0.770	-0.772	-0.610	0.948	0.905	0.995

Table S4: Summary table of bias ratios and adjustment factors (temperature) between RTMA and 13 TexMesonet weather station datasets in Texas. Comparison statistics show relative bias for alfalfa reference ET (ETr), vapor pressure (Ea), wind speed at 2 meters (u2), minimum temperature (Tmin), maximum temperature (Tmax) and incoming solar radiation (Srad).

RTMA	ETr			Ea			u2			Tmin			Tmax			Srad		
Station ID	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average
Miller_Creek	0.976	0.964	0.991	1.045	1.050	1.041	0.956	0.962	0.957	0.310	0.302	0.356	0.911	0.811	0.947	0.929	0.928	0.935
Cedar_Hill_SP	0.920	0.910	0.926	0.985	0.991	0.981	0.661	0.667	0.657	-0.162	-0.129	-0.117	1.876	1.845	1.739	0.919	0.920	0.924
Cedar	1.065	1.062	1.055	0.946	0.957	0.935	0.826	0.851	0.807	-0.242	0.008	-0.516	3.044	3.316	2.494	0.958	0.952	0.968
Falcon_Lake	0.968	0.968	0.995	0.983	0.985	0.982	0.750	0.759	0.765	-0.885	-0.651	-0.969	2.816	2.677	2.954	0.904	0.929	0.903
Coleman	1.066	1.035	1.091	0.986	0.993	0.984	1.102	1.109	1.101	0.573	0.266	0.778	0.938	0.630	1.030	0.926	0.923	0.935
Paint_Creek	1.051	1.032	1.071	0.985	0.987	0.984	1.030	1.023	1.037	0.475	0.354	0.532	1.197	0.913	1.303	0.947	0.952	0.948
Possum_Kingdom	1.039	1.019	1.060	1.011	1.016	1.006	1.060	1.056	1.050	0.227	0.068	0.402	1.251	1.121	1.241	0.924	0.932	0.928
Athens	0.977	0.960	0.992	1.006	1.001	1.007	1.006	1.029	0.975	0.651	0.478	0.772	0.801	0.588	0.975	0.897	0.887	0.900
Doc_Curb_Pump_Station	1.049	1.034	1.064	0.930	0.933	0.928	0.980	1.002	0.951	-0.904	-0.868	-0.985	1.369	1.471	1.243	0.891	0.901	0.897
Corsicana_Pump_Station	0.961	0.939	0.987	0.968	0.970	0.963	0.859	0.835	0.859	-0.156	-0.381	-0.003	0.466	0.245	0.672	0.912	0.920	0.914
Aquilla_Water_Supply_District	1.012	0.993	1.051	1.020	1.021	1.014	1.087	1.074	1.109	0.068	-0.220	0.265	0.346	0.200	0.435	0.942	0.958	0.944
Lake_Murvaul_Panola	0.995	0.950	1.035	0.547	0.544	0.556	0.481	0.473	0.503	-0.415	-0.595	-0.367	0.751	0.845	0.709	1.002	0.988	1.042
Lake_Striker_Rusk	0.903	0.864	0.934	0.995	0.997	0.988	0.637	0.596	0.712	-0.266	-0.526	-0.112	0.570	0.382	0.622	0.948	0.905	0.994

Table S5: Summary table of bias ratios and adjustment factors (temperature) between gridMET and 13 TexMesonet weather station datasets in Texas. Comparison statistics show relative bias for alfalfa reference ET (ETr), vapor pressure (Ea), wind speed at 2 meters (u2), minimum temperature (Tmin), maximum temperature (Tmax) and incoming solar radiation (Srad).

GridMET	ETr			Ea			u2			Tmin			Tmax			Srad		
Station ID	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average	Apr-Oct Average	JJA Average	Annual Average
Miller_Creek	0.933	0.941	0.941	1.041	1.025	1.046	0.874	0.892	0.883	1.175	0.919	1.276	0.372	0.093	0.565	0.932	0.935	0.939
Cedar_Hill_SP	0.814	0.817	0.822	1.060	1.043	1.080	0.635	0.627	0.663	1.211	0.765	1.638	0.433	0.275	0.715	0.911	0.921	0.917
Cedar	0.940	0.933	0.951	1.144	1.140	1.137	0.877	0.878	0.879	1.569	1.453	1.666	1.215	1.021	1.319	0.959	0.955	0.969
Falcon_Lake	0.850	0.841	0.872	1.030	1.026	1.052	0.715	0.705	0.764	0.833	0.655	1.086	0.576	0.354	0.845	0.890	0.906	0.889
Coleman	0.929	0.917	0.945	1.030	1.015	1.045	0.863	0.856	0.869	1.405	0.824	1.899	0.473	0.211	0.877	0.922	0.922	0.934
Paint_Creek	0.909	0.900	0.927	1.039	1.015	1.052	0.749	0.744	0.776	1.501	1.027	1.886	0.982	0.662	1.221	0.943	0.945	0.949
Possum_Kingdom	0.868	0.874	0.876	1.075	1.058	1.079	0.713	0.716	0.718	1.958	1.472	2.283	0.759	0.669	0.814	0.916	0.927	0.926
Athens	0.836	0.835	0.835	1.029	1.024	1.041	0.659	0.668	0.670	1.349	1.048	1.613	0.157	-0.022	0.341	0.889	0.885	0.897
Doc_Curb_Pump_Station	0.854	0.852	0.846	1.043	1.035	1.064	0.743	0.739	0.746	0.778	0.353	1.118	0.303	0.080	0.417	0.891	0.901	0.898
Corsicana_Pump_Station	0.795	0.770	0.776	1.044	1.041	1.069	0.536	0.496	0.572	0.711	0.214	1.018	0.339	0.109	0.556	0.912	0.920	0.914
Aquilla_Water_Supply_District	0.902	0.884	0.891	1.094	1.087	1.118	0.884	0.853	0.920	0.869	0.337	1.220	0.098	-0.054	0.206	0.942	0.958	0.947
Lake_Murvaul_Panola	0.842	0.849	0.793	0.579	0.566	0.605	0.259	0.253	0.283	0.404	-0.134	0.791	0.248	0.328	0.306	1.003	0.988	1.045
Lake_Striker_Rusk	0.737	0.724	0.693	1.062	1.052	1.085	0.292	0.268	0.340	0.784	0.292	0.970	0.677	0.600	0.636	0.948	0.904	0.998