Developing Long-Term, Daily Datasets of Evaporative Demand for the Conterminous US

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Abstract:

Operational hydrologists and agriculturalists often seek to predict actual evapotranspiration (*ET*) fluxes. However, as they can seldom characterize actual moisture conditions in the soil and vegetation regimes, they are unable to estimate or forecast *ET* directly. Instead, they first estimate evaporative demand (E_0) (sometimes known as "potential *ET*") as an upper limit to actual *ET* and then apply E_0 to drive hydrologic models or empirical relations that account for soil moisture conditions and vegetative constraints on moisture transfer, and thereby derive *ET*.

There are various formulations of E_0, with a wide variety of data requirements and philosophies, and, consequently, of scientific and operational validity. Here we summarize the ongoing development and uses of two daily time-series of E_0 that are scientifically defensible, long term (30+ years), and CONUS-wide. Ultimately, these time-series will be unbiased with respect to the observations they seek to model and at a fine spatial resolution. These datasets are currently under development with two goals in mind: (i) to improve streamflow forecasting in the NWS River Forecast System, which would be of use to operational hydrologists, and (ii) to provide reference crop *ET* forecasts to NWS end-users, primarily agriculturalists.

Two goals:

1. Improve streamflow forecast skill across the Colorado River Basin at daily and water-supply-season time-scales (April 1 to July 31) by improving the evaporation driver (E_0) in the NWS River Forecast System.

This will entail (i) replacing the current static E_0 (Fig 5) in the Sacramento Soil Moisture Accounting (SAC-SMA) model [Ref 1] with a physically based, temporally dynamic E_0 that reflects ongoing weather-scale variability; (ii) simulating streamflows from the SAC-SMA model across the period 1980 – 2009; (iii) and recalibrating the SAC-SMA model to adapt the evaporation-related parameters to the new data input; in order to (iv) maximize the streamflow forecast skill score.

2. Provide forecast end-users across the NWS Western Region with forecasts of reference crop *ET* (ET_{rc}) at daily to weekly time-scales. This is driven primarily by demand from end-users in agriculture who seek guidance in making decisions regarding near-term water demand.

Our goal here is two-fold: (i) to provide a new *ET*-related forecast system using only currently forecast weather variables; and (ii) to provide a climatological context for these forecasts, as most users would otherwise be unfamiliar with what it represents.

These will be the first large-scale operational ET_{rc} forecasts.

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Model drivers:

We need two sets of drivers:
1. Reanalysis data drive the SAC-SMA simulations in Goal 1 and the ET_{rc} climatology in Goal 2.
2. Forecast data drive the short-term ET_{rc} forecasts in Goal 2.

1. Reanalysis: North American Land Data Assimilation System (NLDAS) [Refs 2, 3]
- Air temperature at 2-m elevation, *T* (K)
- Specific humidity at 2-m elevation, *q* (kg/kg)
- Down-welling short-wave radiation, SW_{dn} (W/m²)
- Down-welling long-wave radiation, LW_{dn} (W/m²)
- Station pressure, P_{atm} (Pa)
- Wind speed at 10-m elevation, U_{10} (m/sec)
- Hourly time-step
- 0.125-deg (~12 km) resolution

2. Forecast: National Digital Forecast Database (NDFD) [Ref 4]
- Air temperature at 2-m elevation, *T* (F)
- Dewpoint temperature at 2-m elevation, T_{dew} (F)
- Wind speed at 2-m elevation, U_2 (m/sec)
- Areal extent of cloud cover, *ECA* (%)
- Hourly, 3-hourly, or 6-hourly time-steps
- 2.5-km or 5-km resolution

Model variables:

Output variables:

E_{pan} = synthetic pan evaporation (in mm/day)
ET_{rc} = reference crop evapotranspiration (in mm/day)

Input variables:

λ = latent heat of vaporization (from NLDAS *T* or NDFD *T*)
Δ = saturated vapor pressure-temperature relation slope (from *T*)
a_P = ratio of the effective surface areas for heat and water-vapor transfer in a pan
γ = psychrometric constant (from *T*, P_{atm})
Q_n = net available energy for evaporation (from NLDAS: SW_{dn}, LW_{dn}; NDFD: *ECA*, *T*)
$f_q(U_2)$ = vapor transfer function (from NLDAS: U_{10}; NDFD: U_2)
e_{sat} = saturated vapor pressure (from *T*)
e_a = actual vapor pressure (from NLDAS: *T*, *q*, P_{atm}; NDFD: T_{dew})
U_2 = wind speed at 2 m (from NLDAS U_{10} NDFD: U_2)

All input variables (SW_{dn}, LW_{dn}, U_{10}, *T*, P_{atm}, and *q*) are available as reanalyses (NLDAS) or forecasts (NDFD).

Goal 1: Improving streamflow forecast skill across the CBRFC

E_{pan} from the PenPan model of Linacre [Ref 5] modifies the familiar Penman equation [Ref 6] to replicate the enhanced characterization of radiative and advective dynamics of evaporation pans, as follows:

$$\lambda E_{pan} = \frac{\Delta}{\Delta + a_P\gamma} Q_n + \frac{a_P\gamma}{\Delta + a_P\gamma} f_q(U_2)(e_{sat} - e_a)$$

The formulation consists of a weighted combination of an radiative driver and an advective driver. It has been shown to synthesize monthly E_{pan} observations well [Ref 7].

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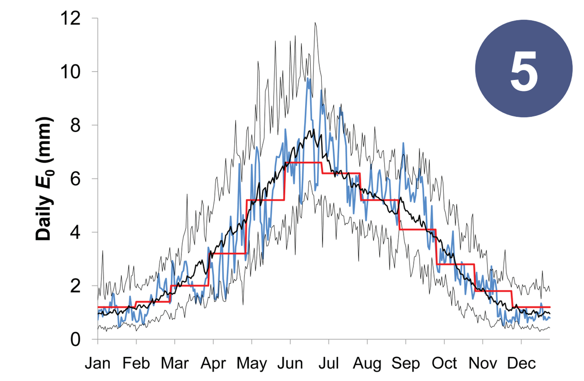
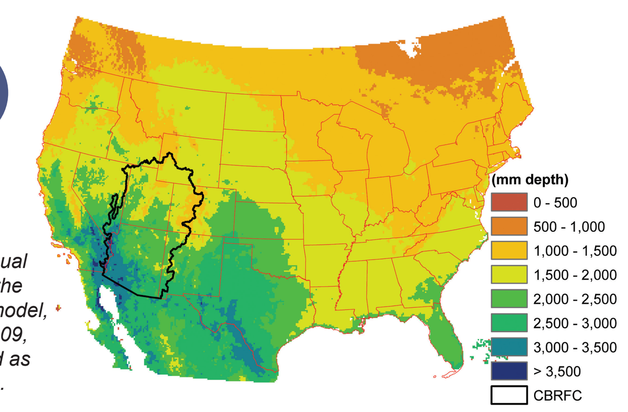
A US class-A evaporation pan.

5



Daily evaporation driver across DRGC2. The red stepped line shows the current E_0 driver, with no inter-annual variability; black lines show the inter-annual range of the new dynamic driver (daily E_{pan}) across 1980—2009, as the mean (bold black), maximum (upper black) and minimum (lower black). Also shown in blue is daily E_{pan} for an example year (1983).

1



Mean annual E_{pan} from the PenPan model, 1980 – 2009, expressed as mm depth.

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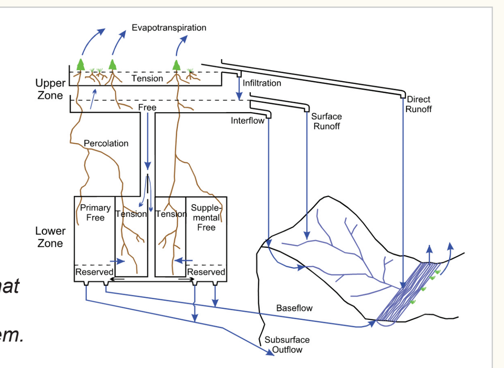
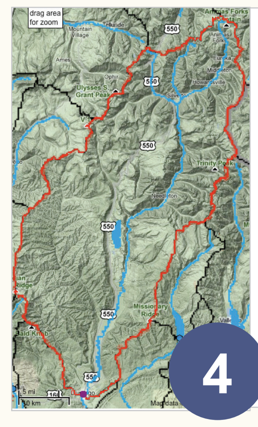


The concept of the Sacramento Soil Moisture Accounting (SAC-SMA) model that underpins the NWS River Forecast System.



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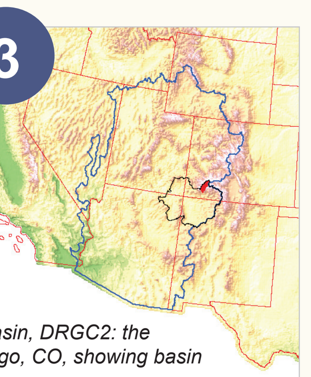

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Right: Location of test-basin DRGC2 (red) in the San Juan river basin (small black outline) in the Colorado Basin River Forecast Center forecast region (large blue outline).

Left: Map of the test-basin, DRGC2: the Animas River at Durango, CO, showing basin relief and rivers.

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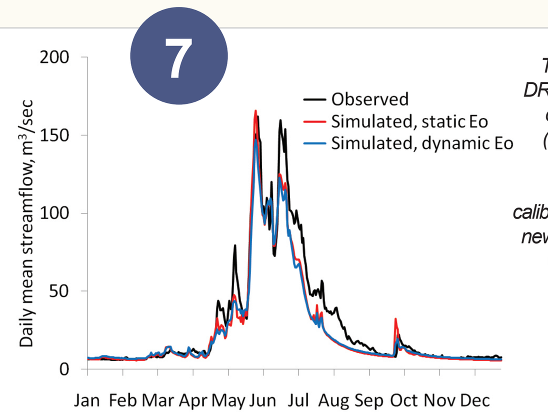

Three hydrographs at DRGC2 for 1983: (i) the observed streamflow (black); (ii) the current static E_0 driver with current operational calibration (blue); and the new dynamic E_{pan} driver with the evaporation-relevant parameters optimized (red).

The Root Mean Square Error Skill Score (RMSE-SS) can be used to assess the performance, or skill, of the SAC-SMA model in simulating (Q_{sim}) the observed daily streamflow (Q_{obs}). Here we compare the RMSE-SS for the current static E_0 driver (shown in red in Fig 5) and the new dynamic E_0 driver (shown in black in Figure 5), both with and without recalibration of the SAC-SMA model. The RMSE-SS derives as follows:

$$RMSE_{sim} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{sim_i} - Q_{obs_i})^2} \qquad RMSE\text{-}SS = 1 - \frac{RMSE_{sim}}{RMSE_{ref}}$$

A perfect simulation ($Q_{sim} = Q_{obs}$) yields an RMSE-SS of 1. A zero RMSE-SS indicates no change in skill as compared to the existing, or reference, simulation. A more skillful simulation yields a positive RMSE-SS, a less skillful simulation yields a negative RMSE-SS. The table below indicates the skill of each run, using the current RMSE from the static E_0 driver run (the top-left entry in the table) as a reference ($RMSE_{ref}$). The most cogent comparison in this framework is that indicated in bold in the bottom-right entry.

RSME-SS compared		E_0 type	
		current (static)	dynamic
SAC-SMA recalibration	none	(0.000)	-0.109
	SCE-UA optimization	-0.102	**-0.079**

- For the current static E_0 driver, recalibrating the SAC-SMA model with the objective Shuffled Complex Evolution (SCE-UA) optimization method [Ref 10] reduces the skill when compared to the manual calibration used in current operations.
- For the new dynamic E_0 driver, the objective SCE-UA method increases the skill.
- The system works. No operational or calibration issues were raised.
- These preliminary results suggest a way forward to improve the daily and seasonal streamflow forecast skills of the dynamic E_{pan} driver: an objective recalibration (e.g., the SCE-UA method) followed by subjective refinements by experienced CBRFC forecasters.

Goal 2: Forecasting ET_{rc} across the West

The reference crop *ET* (ET_{rc}) formulation from the FAO-56 [Ref 8] international standard, the Penman-Monteith [Ref 9] equation is:

$$\lambda ET_{rc} = \frac{\Delta}{\Delta + \gamma(1 + 0.34U_2)} Q_n + \frac{\gamma}{\Delta + \gamma(1 + 0.34U_2)} \frac{0.9}{T} \frac{\lambda}{86400} U_2 (e_{sat} - e_a)$$

It consists of a weighted combination of a radiative driver and an advective driver.

The reference crop is specified:
- well-watered grass,
- actively growing,
- 0.12 m in height,
- completely shading the ground,
- albedo of 0.23.

ET_{rc} is then multiplied by various soil moisture, stress, and phenology factors known to the end-user, to yield an actual *ET* estimate, e.g.:

$$ET = k_s k_c(t) ET_{rc} \text{ or } (k_s k_{cb} + k_e)(t) ET_{rc}$$

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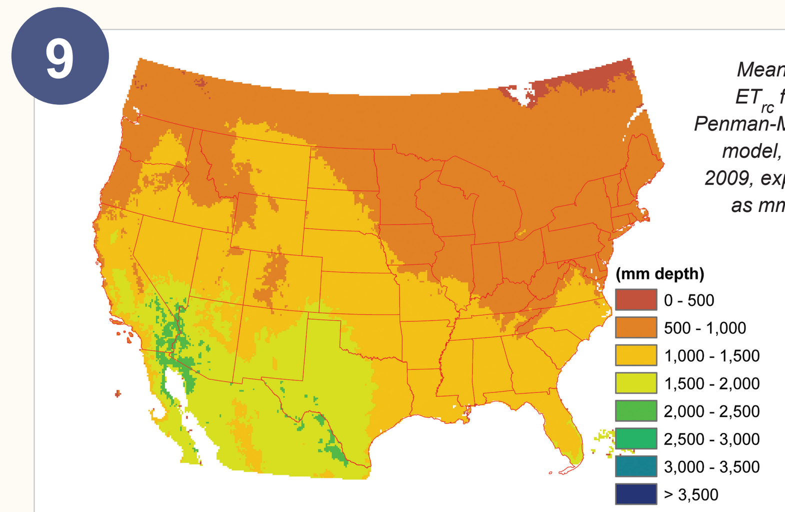
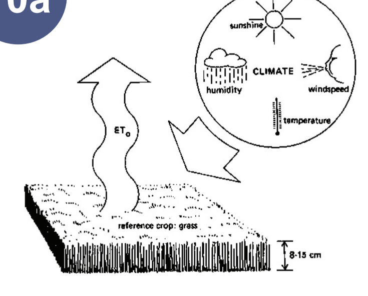
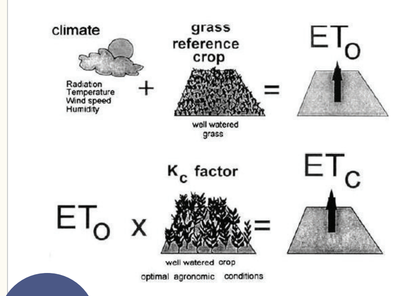


Mean annual ET_{rc} from the Penman-Monteith model, 1980—2009, expressed as mm depth.

10a



ET_{rc} concept: a standard crop under standard conditions is specified.



10b

ET_{rc} concept: ET_{rc} is multplied by a series of factors that reflect (in this example) different crops, phenology, soil stress, etc.

Crop	$K_{c\ initial}$	$K_{c\ mid\text{-}season}$	$K_{c\ end\text{-}of\text{-}season}$
Barley	0.30	1.15	0.25
Chickpea	0.40	1.00	0.35
Cotton	0.35	1.15-1.20	0.70-0.50
Maize	0.30	1.20	0.35
Navy bean	0.40	1.15	0.35
Peanut	0.40	1.15	0.60
Sorghum	0.30	1.00-1.10	0.55
Soybeans	0.40	1.15	0.50
Sunflower	0.35	1.15	0.35
Wheat	0.30	1.15	0.25

10c

ET_{rc} concept: examples of crop coefficients K_c for various crops at various stages of growth.

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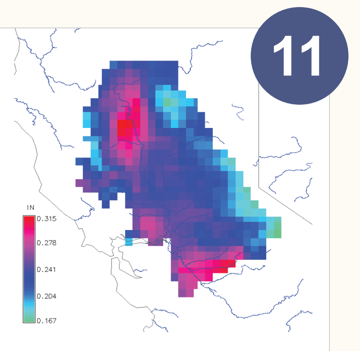

Climatological ET_{rc} for a day in mid-August. Climatologies are NLDAS-derived for 1980—2009.

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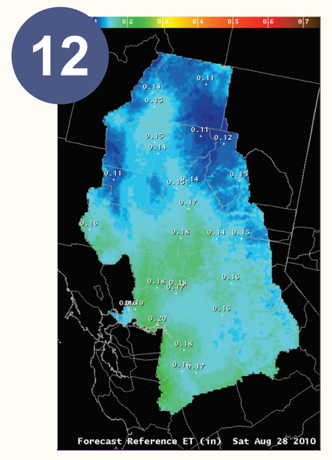

Forecast ET_{rc} for a day in mid-August, 2010. Forecasts are NDFD-derived.

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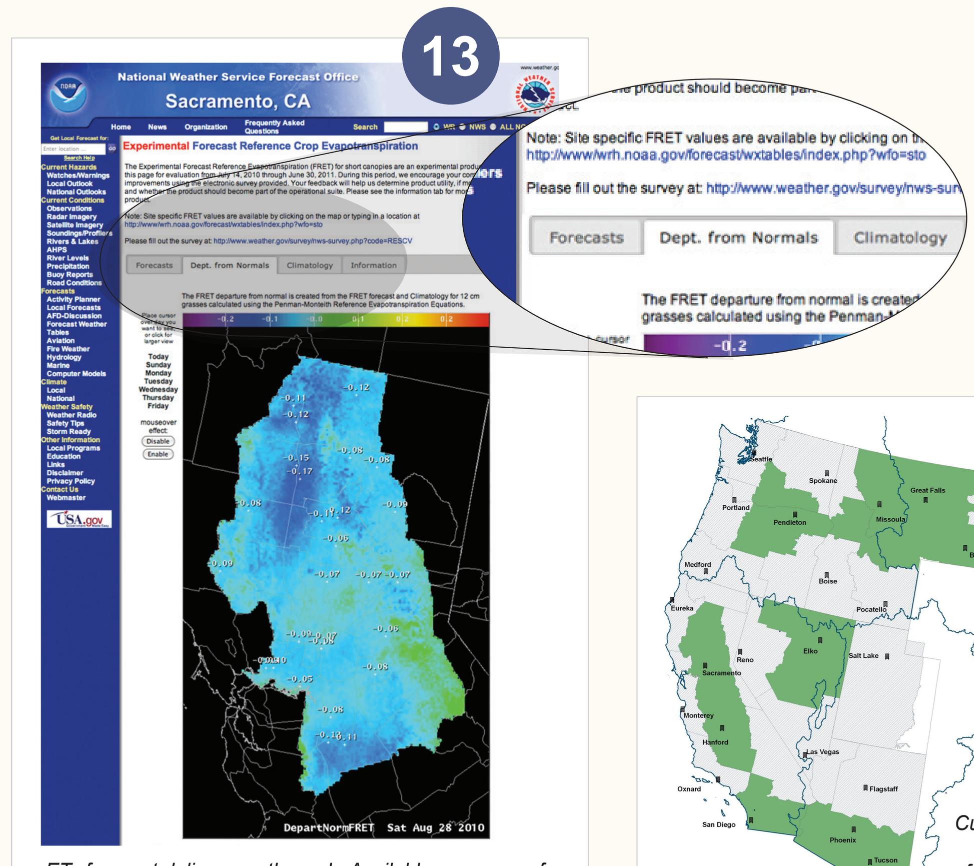
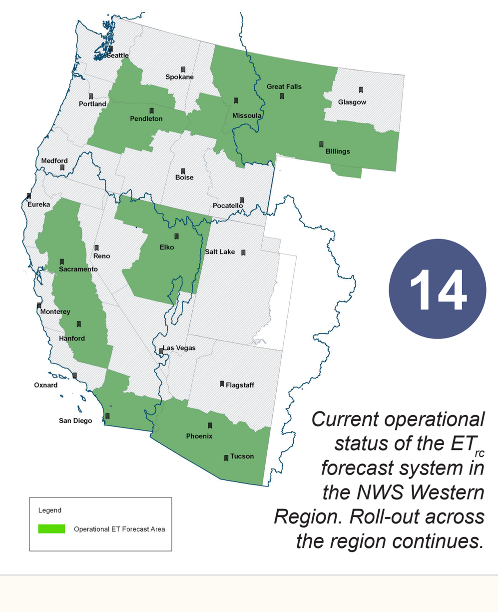


ET_{rc} forecast delivery on the web. Available are maps of the NDFD-derived forecast, the NLDAS-climatology, and the forecast departure from normal (shown above), and a brief explanation of the ET_{rc} concept.

14



Current operational status of the ET_{rc} forecast system in the NWS Western Region. Roll-out across the region continues.

Conclusions & Current Accomplishments

We have created the first E_0 reanalysis at an RFC-operational scale and resolution. A new forecast system for ET_{rc} is now operational and rolling out across the NWS Western Region. The ongoing reanalysis effort is yielding ET_{rc} estimates with a five-day latency, a short time-lag that renders it a potentially powerful new tool for real-time drought monitoring.

Goal 1: Improving streamflow forecast skill across the CBRFC: Thus far, we have proved the concept: the new dynamic E_{pan} driver of the SAC-SMA model can be seamlessly integrated into the NWS River Forecast System and there affects streamflow simulation skill. While first results over a single basin indicate a small decrease in simulation skill, a standard manual recalibration of the basin is most likely to result in significant skill improvement. Such a manual recalibration, while subjective, can balance various goals: forecasting on a daily basis (e.g., for low flows, peak-flow estimates and timings) versus water supply seasonal-volume forecasting.

Goal 2: Forecasting ET_{rc} across the western US: We have created a system to forecast daily-to-weekly ET_{rc}. While the project was initiated primarily with agricultural users in mind, it has generated significant interest from decision-makers at the state and regional levels. A verified, high-resolution, reanalyzed, and/or forecast ET_{rc} would be useful in short-term decision-making, drought analyses across time scales, and, in the longer term, demand-planning:

- The primary use of ET_{rc} is to assist farmers in making decisions regarding irrigation scheduling up to a week into the future.
- The US Drought Monitor currently has no physically based metric of evaporative demand. Instead, its PDSI input has a flawed *T*-based E_0 driving its bucket model [Ref 11]. Incorporating near-real-time ET_{rc} reanalyses and forecast ET_{rc} directly into the Monitor would enhance its capabilities with respect to monitoring recent, ongoing, and future drought development. At longer time-scales, the analyses of long-term drought trends, such as using the popular Palmer Drought Severity Index (PDSI), have heretofore been stymied by the lack of long-term reanalyses of E_0.
- The increasingly uncertain hydrologic environment presents utility districts and operators of reservoirs and trans-mountain diversions with thorny strategic capital decisions. As a result, they are becoming increasingly interested in demand-planning and particularly in long-term forecasts of E_0.

Ongoing & Future work:

Operationally, the dynamic E_0-driven streamflow forecasting system (i.e., Goal 1) is still some time away from an active transition from research to operations at NWS River Forecast Centers. However, the ET_{rc} forecast system (i.e., Goal 2) is spreading across the NWS Western Region, with plans for CONUS-wide adoption.

We are expanding the dynamic E_0 study to other models of evaporative demand, both physically based (e.g., the Penman, Penman-Monteith, and Kimberly Penman formulations) and temperature-based (e.g., the Hargreaves, Hamon, Thornthwaite, Blaney-Criddle formulations).

We are improving the reanalyses and forecasts by verifying both the drivers (particularly the derivation of SW_{dn} from *ECA*) and E_0 (against observations of E_{pan} and ET_{rc} at CIMIS stations), and generating finer-scale, longer-term reanalyses of evaporative demand that incorporate the 4-km spatial resolution of the Real-Time Mesoscale Analysis dataset and the over 30-year extent of the NLDAS dataset.

Future work on varied time-scales will include the incorporation of seasonal drivers (e.g., from the Climate Forecast System at NCEP) in order to provide better seasonal-scale water demand estimates, and on climate scales, incorporation of IPCC scenarios for climate-scale forecasts and strategic decision-making.

Scientific Contributions:

The new E_0 datasets, when verified and at a finer resolution, suggest various scientific contributions. An ongoing study of the temporal and spatial variability of E_0 should answer various questions: which drivers dominate the spatial and temporal variability of E_0? which E_0 is best for hydrologic operations across CONUS? are temperature-based E_0-models ever preferred over physically based E_0 models?

The rigorous, long-term reanalyses of streamflow and ET_{rc} should permit analyses of long-term trends in streamflow and drought across CONUS, identifying which physical driver dominates such trends, and make a significant contribution to the vexed issue of the effects of climate change and variability on hydrology across the Colorado Basin, thereby furthering the goals of the Colorado River Reconciliation project.