Large-scale evaporative demand: opportunities in reanalyses, forecasting, and projections.

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&

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Background

NOAA's reference *ET* (ET_0) project motivation

Produce first consistently modeled, accurate CONUS-wide ET_0 dataset:

- up-to-date and temporally extensive, dynamic, physically based
- hosted by Integrated Water Resources Science and Services (IWRSS) at National Water Center (Tuscaloosa, AL).
- free to all.

SECURE Water Act, 2009:

Provide stakeholders **technical information** and **tools** to answer two primary questions:

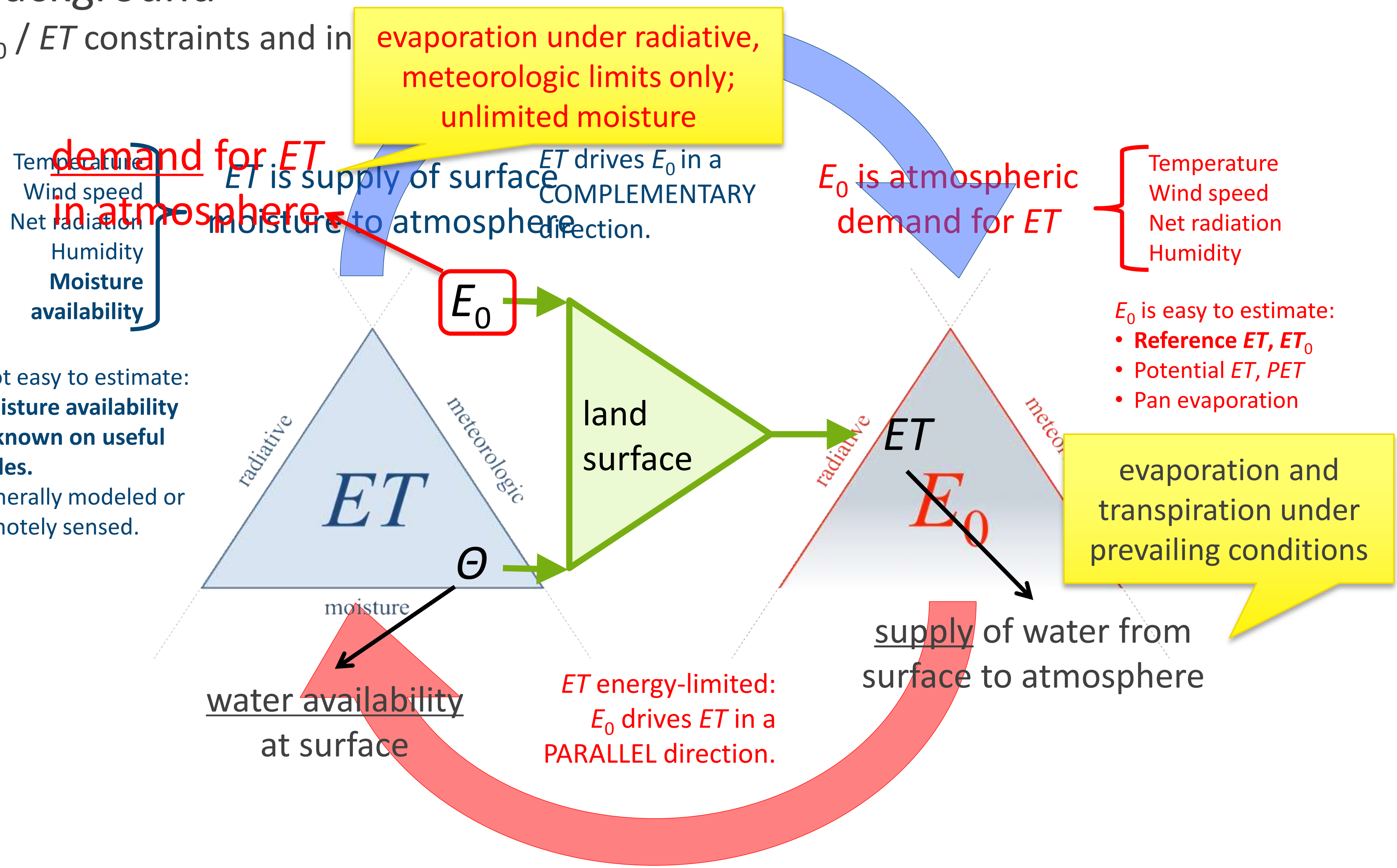
- Does the Nation have enough freshwater for human and ecological needs?
- Will this water be present for future needs?

Provide a consistent input to

- National Water Census (NWC)
- climatology for the new NWS
- drought-related uses:
  - stand-alone drought inde
  - input to US Drought Monitor indices

Background

E_0 / ET constraints and in

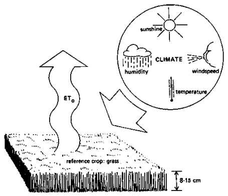


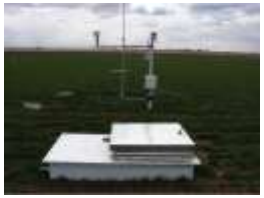
Background

Variety of metrics for E_0

- potential evaporation (*PET*)

- reference crop *ET*, ET_0





- pan evaporation

ESTIMATED: from WX obs, R/S data, or reanalyses

complete physics:
- SW radiation
- LW radiation
- air temperature
- humidity
- wind speed
- atmospheric pressure

temperature-based:
- air temperature
- T_{max}
- T_{min}

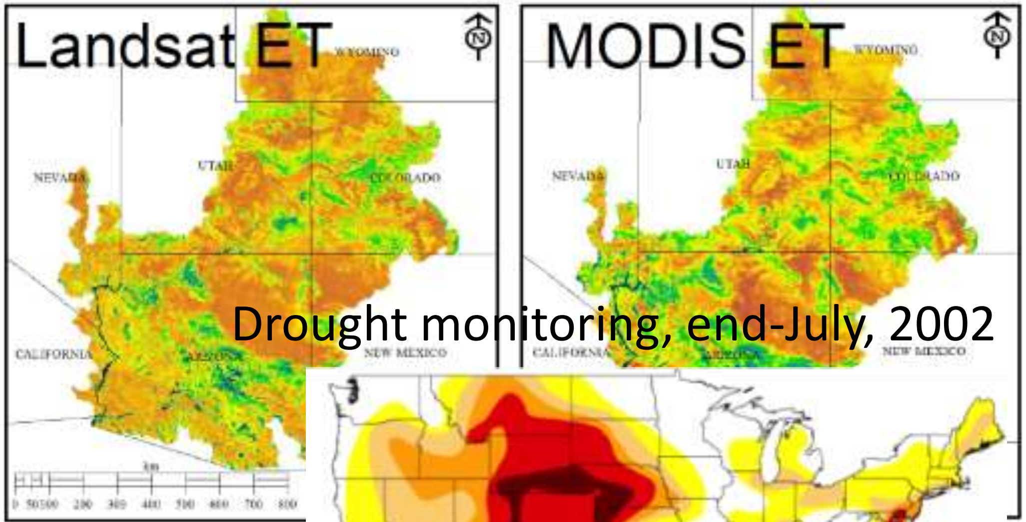
OBSERVED: physically integrates all above drivers

Background

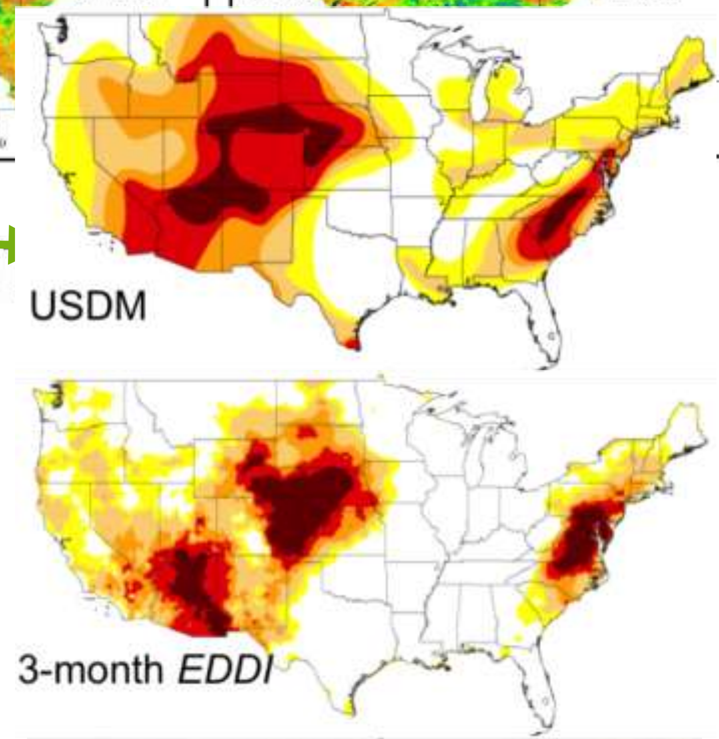
Uses of E_0

Estimating crop *ET:*

- scheduling irrigation (FAO-56)
- short-term forecasting (FRET)



Drought monitoring, end-July, 2002



Θ E

Eagle Fire, Temecula, CA, May, 2004

λ = latent heat of vaporization
R_n = net radiation (SW + LW) at crop surface
G = ground heat flux
U_2 = 2-m wind speed
e_{sat} / e_a = saturated / actual vapor pressure
$\Delta = de_{sat}/dT$ at air temperature T
γ = psychrometric constant
C_n, C_d = constants for crop type and time-step

NOAA's reference *ET* (ET_0) reanalysis

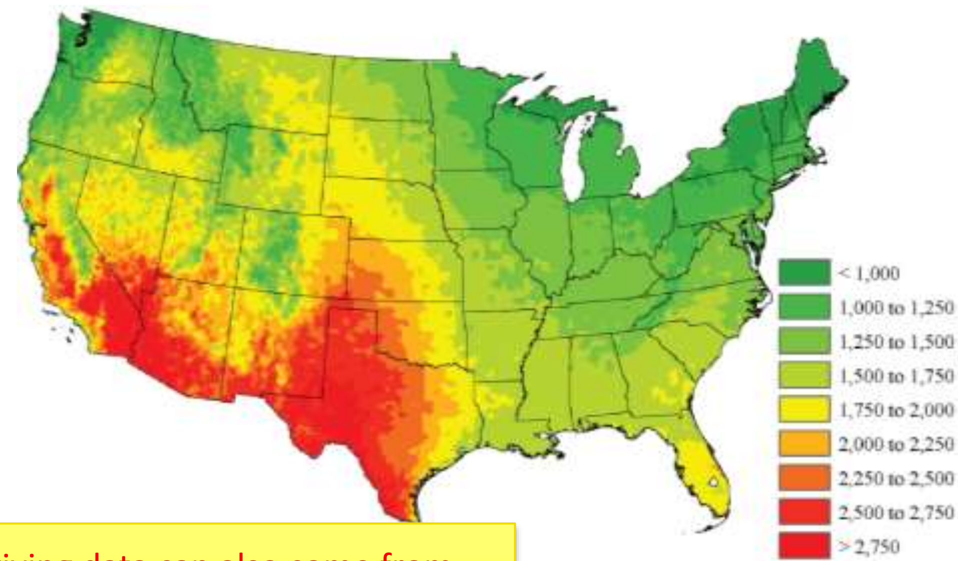
Estimating E_0 from ET_0

Penman-Monteith reference *ET* equation:
ASCE Standardized reference *ET* / FAO-56

$$ET_0 = \underbrace{\frac{0.408\Delta}{\Delta+\gamma(1+C_dU_2)}(R_n - G)\frac{86400}{10^6}}_{\text{Radiative forcing (sunshine, } T\text{)}} + \underbrace{\frac{\gamma\frac{C_n}{T}}{\Delta+\gamma(1+C_dU_2)}U_2\frac{(e_{sat} - e_a)}{10^3}}_{\text{Advective forcing (wind, humidity, } T\text{)}}$$

"Reference" crop is specified:

- 0.12-m grass or 0.50-m alfalfa
- well-watered , actively growing
- completely shading the ground
- albedo of 0.23



Drivers from NLDAS-2:

- temperature at surface (2 m)
- specific humidity at surface
- downward SW at surface
- wind speed (10 m)

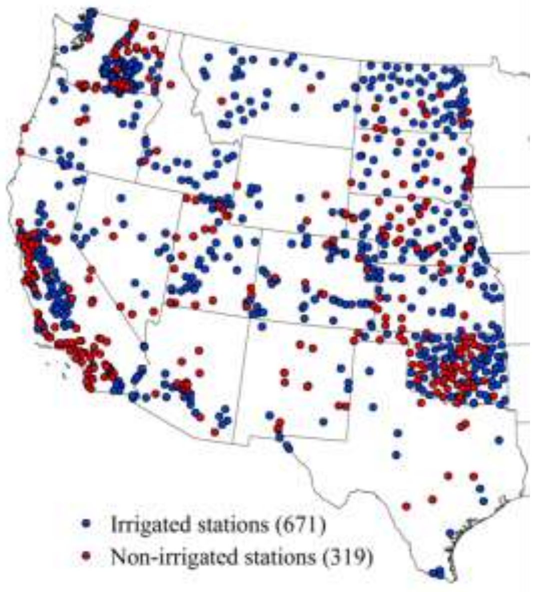
1981-2010
- present
ide

Driving data can also come from

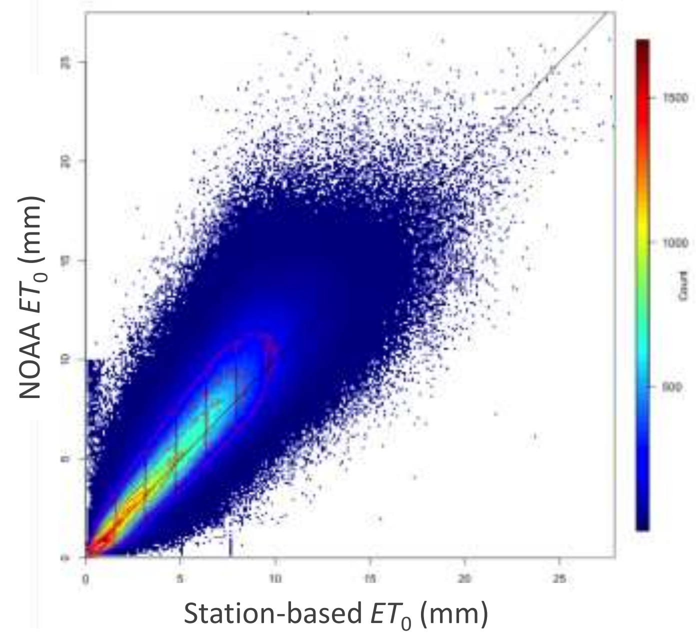
- station observations
- remote sensing
- reanalyses
- Numerical Weather Predictors
- Global Climate Models

NOAA's ET_0 reanalysis

Verification across western US



All stations, all year, daily ET_0



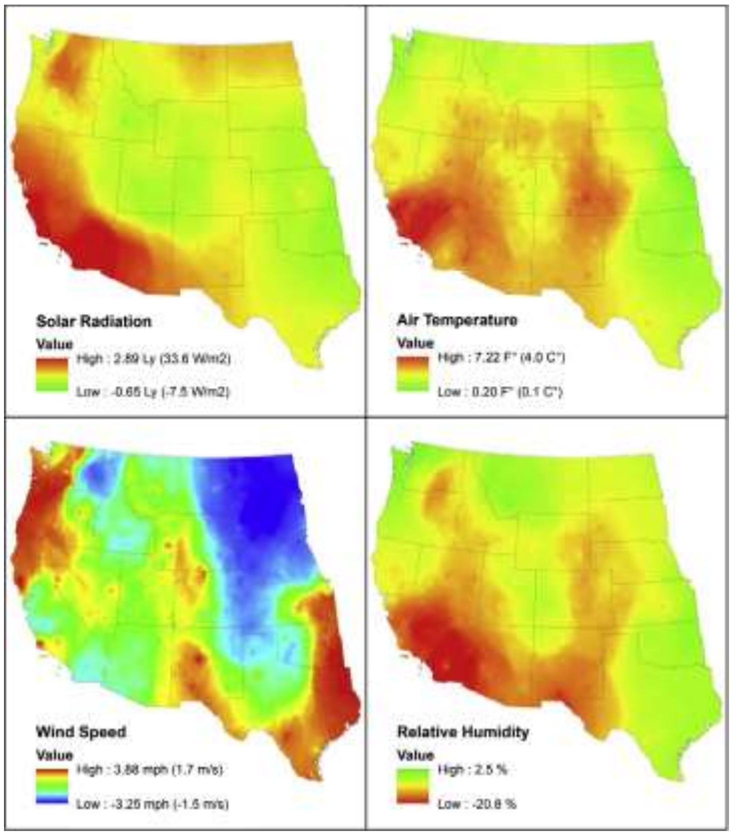
Summary of verification results:

- growing-season daily r^2 ~ 0.64
- July-Sept daily r^2 < 0.6
- warm-season +ve bias
- cool-season –ve bias
- year-round, over-predicts station-based ET_0 by ~11%
- lowest biases in non-irrigated areas

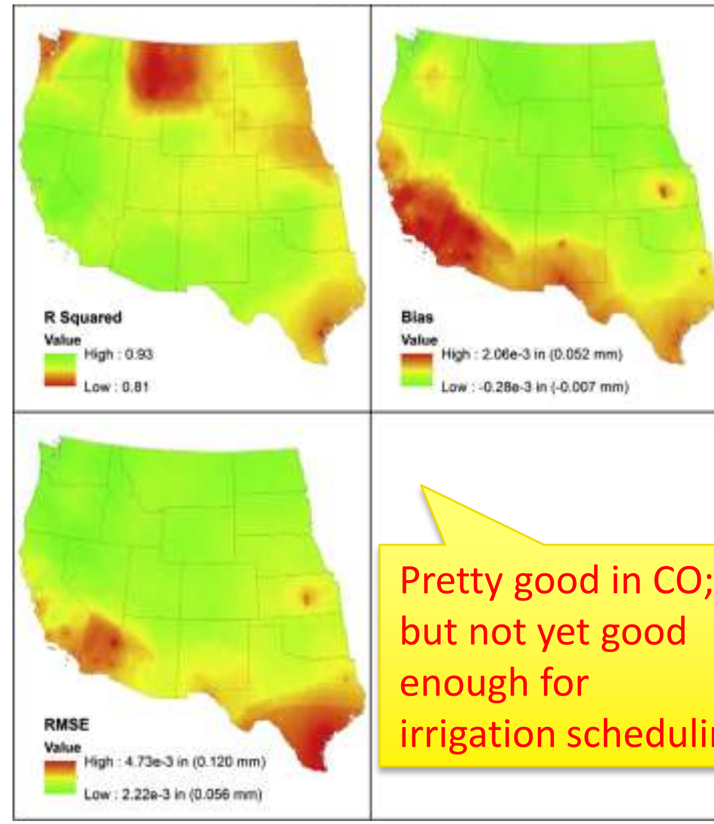
NOAA's ET_0 reanalysis

Data uncertainty across western US

Bias



Reference *ET* (ET_0)

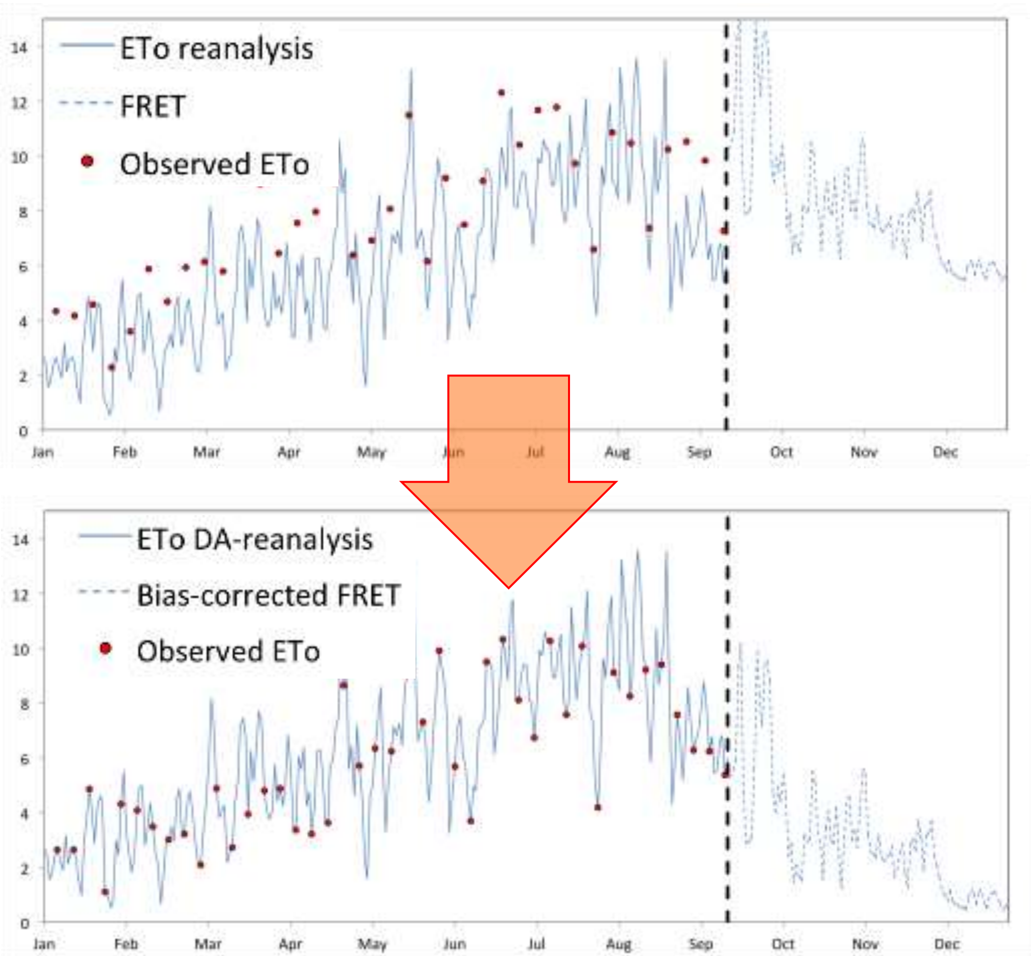


Pretty good in CO; but not yet good enough for irrigation scheduling

[*Lewis et al., J.Hydrology 2014*]

NOAA's ET_0 reanalysis

Multi-generational ET_0 product



Gen-0:

- ET_0 reanalysis biased wrt obs
- FRET biased wrt ET_0 reanalysis

Gen-1:

- ET_0 obs assimilated into reanalysis
- FRET bias-corrected against ET_0 DA-reanalysis

Gen-X:

- finer-scale NLDAS-3 forcing

NOAA's ET_0 reanalysis
Ideal features

- Accuracy quantified, QA/QC
- Institutional support for drivers
- Consistency of assimilation of observations
- Large spatio-temporal extents, high resolutions
- Capture long-term climatology
- Provide probabilistic context for events
- Forecastable at various time-scales

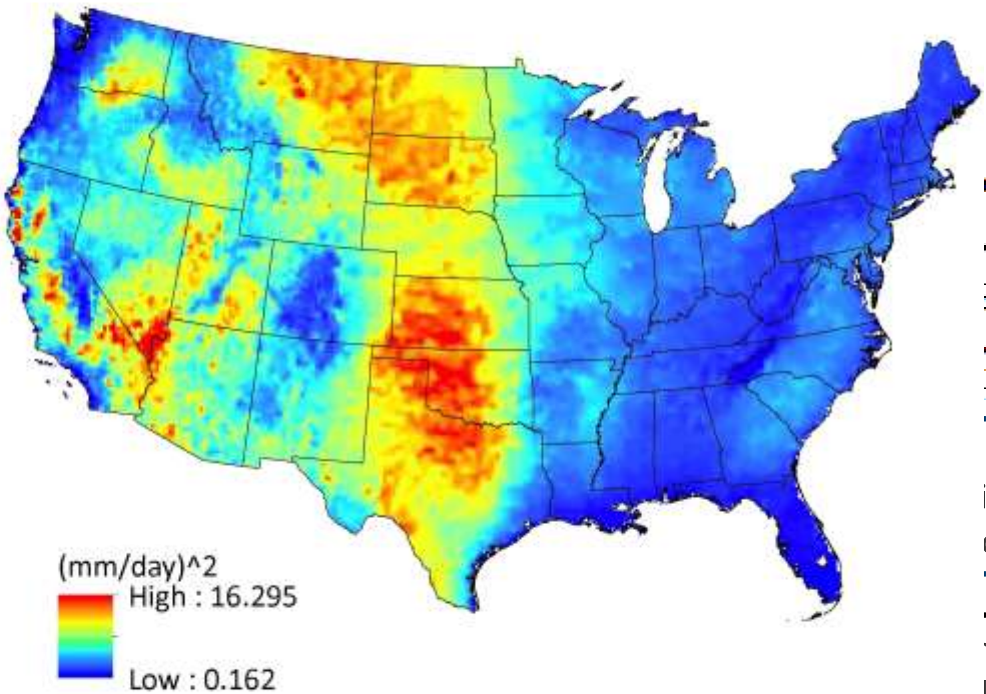
Decomposition and attribution

Uncertainty analysis of ET_0

$$ET_0 = \frac{0.408D}{D + g(1 + C_d U_2)}(R_n - G)\frac{86400}{10^6} + \frac{g\frac{C_n}{T}}{D + g(1 + C_d U_2)}U_2\frac{(e_{sat} - e_a)}{10^3} = \boxed{g(T, q, U_{10}, R_d)}$$

(1) Variability analysis

$$\sigma^2_{ET_0} = F_T + F_q + F_{U_{10}} + F_{R_d} =$$



σ_{T,R_d}

σ_{q,R_d}

T_0 ... R_d σ_{U_{10},R_d}

T_0 ... $\sigma_{R_d,U_{10}}$

s in (1) and
ions in (2)
om dataset

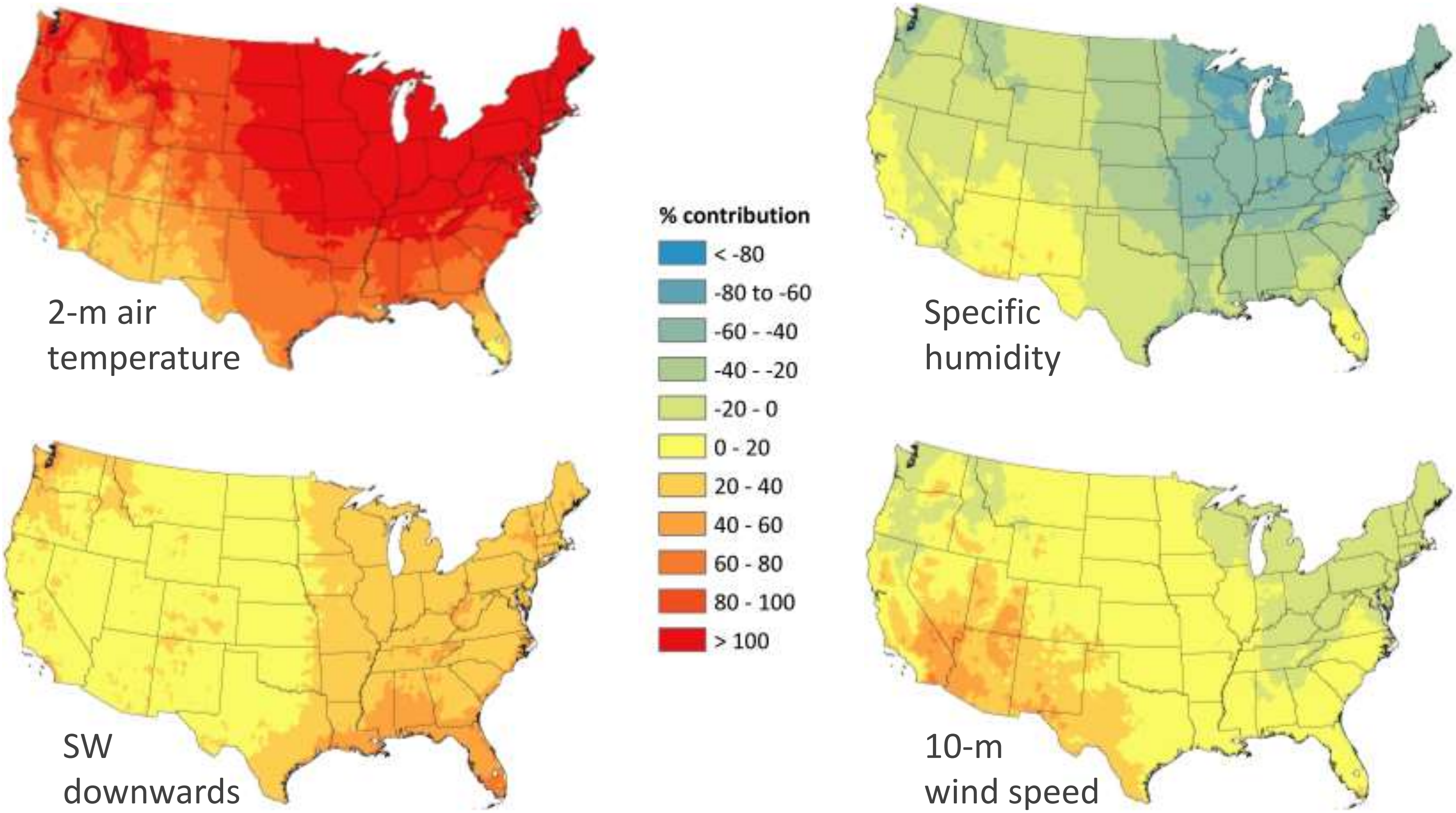
(2) Change attribution

$$\Delta ET_0 = \frac{\partial ET_0}{\partial T}\Delta T + \frac{\partial ET_0}{\partial q}$$

d (2) derived
del formulation
[*Hobbins et al., Trans. ASABE 2016*]

Decomposition and attribution

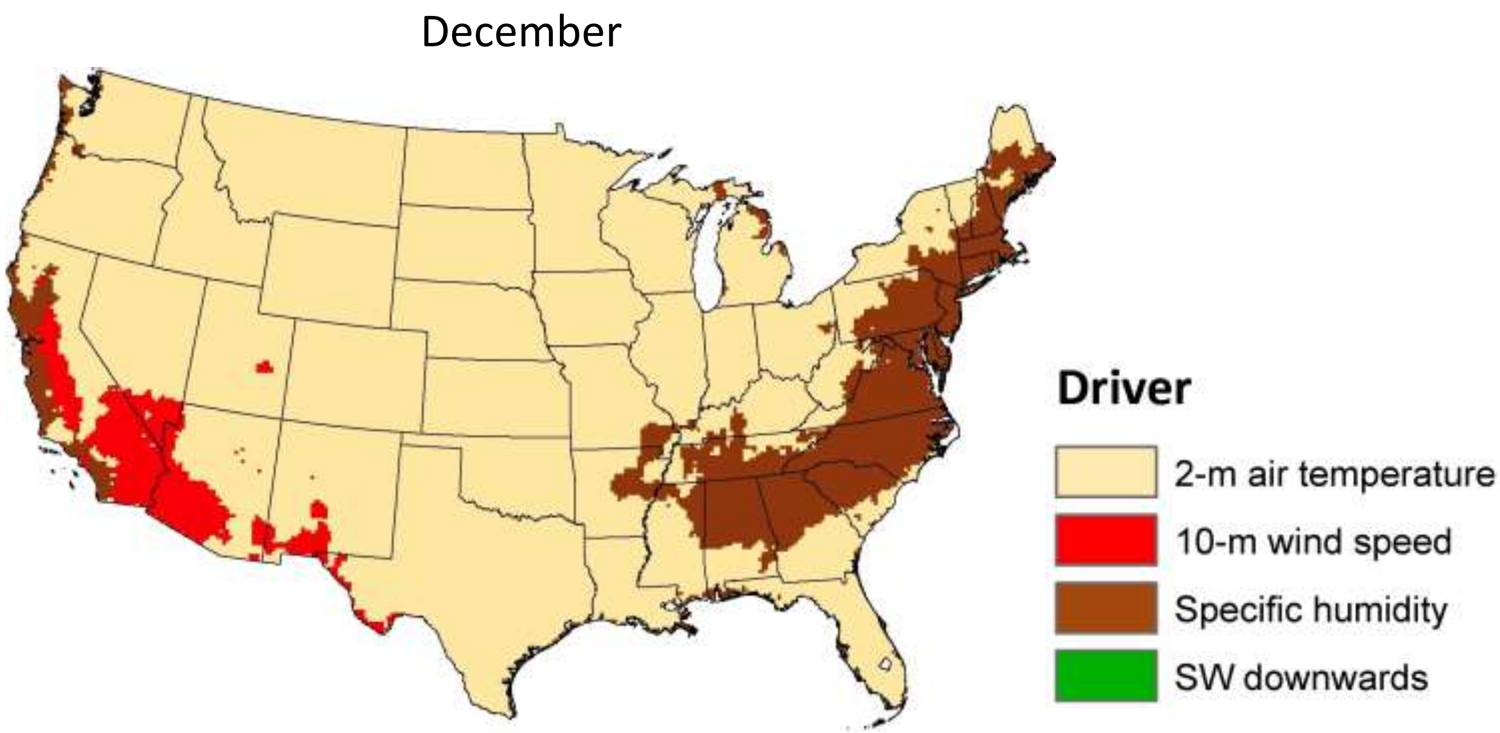
MJJASO variability contributions, daily ET_0, by driver



[*Hobbins et al., Trans. ASABE 2016*]

Decomposition and attribution

Top driver of daily variability, by month



[*Hobbins et al., Trans. ASABE 2016*]

Decomposition and attribution

Attribution of drought dynamics

We can know which drivers are most affecting changes in E_0 – and therefore in drought.

$$E_0 = f\left(T, R_d, q, U_2\right), \text{ so}$$

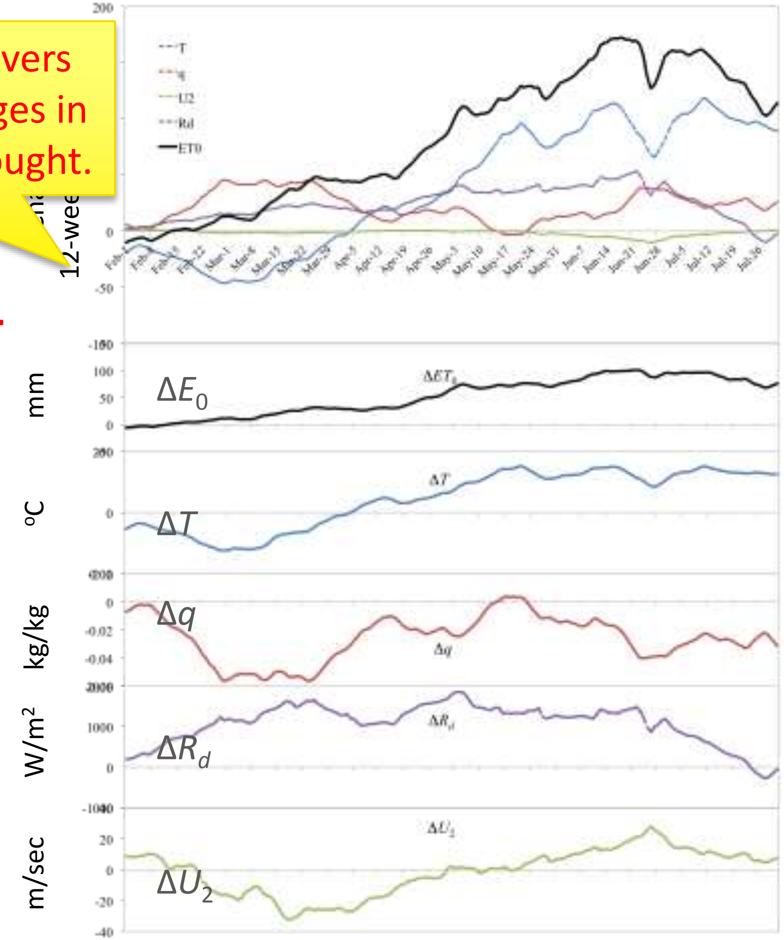
$$DE_0 = \frac{\partial E_0}{\partial T} DT + \frac{\partial E_0}{\partial R_d} DR_d + \frac{\partial E_0}{\partial q} Dq + \frac{\partial E_0}{\partial U_2} DU_2$$

anomalies observed in reanalyses

derived analytically [Hobbins, 2016]

Drought intensification (increasing E_0) forced by

- first, below-normal q (while T falling)
- then, increasing T and, to a lesser degree, R_d
- U_2 plays little role



E_0 in Sacramento River basin: Feb-Jul, 2014

T = air temperature
q = specific humidity
R_d = downwelling SW
U_2 = wind speed

[*Hobbins et al.*, JHM 2016]

Dangers of *T*-based E_0 parameterizations

Regional long-term trends in drought

IPCC has concluded that warming results in:

- globally, d
- droughts e

PDSI hydrology model forced by E_0 based on *T* alone.

ected to grow,

ore extensive.

BUT, comparing physically based E_0 vs. *T*-based E_0:

- E_0 trends (30-year, observed) driven by wind, not *T*

  – Australia [*Roderick et al., GRL 2007*]

- PD

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Causal link in *T*-based drought analyses is often reversed: increased *T* often results from drought, doesn't force it.

  - bal dimming; stilling; *VPD* changes
  - differences in signs of PDSI trend signs (*T*-based +ve over 7x physical-based area)

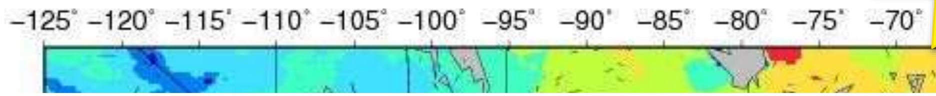
  – global [*Sheffield et al., Nature 2012*]

Debunking the T-driven E_0 paradigm

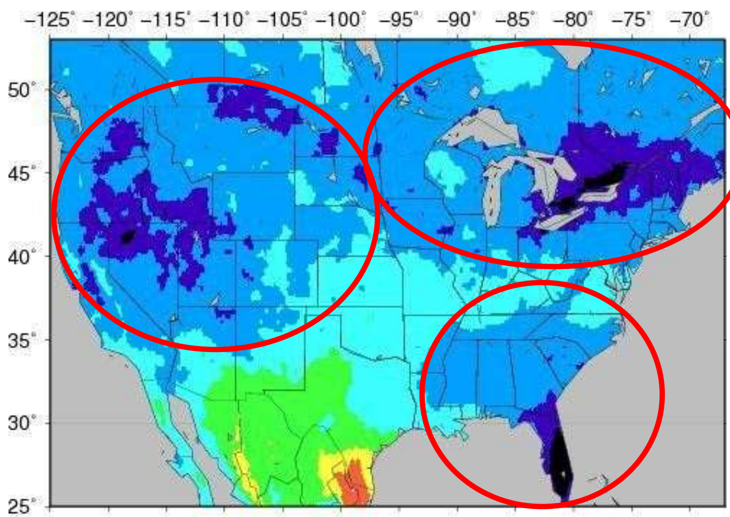
How do T and R_d co-vary?

Although widely available, T is an unnecessarily poor proxy for radiative forcing

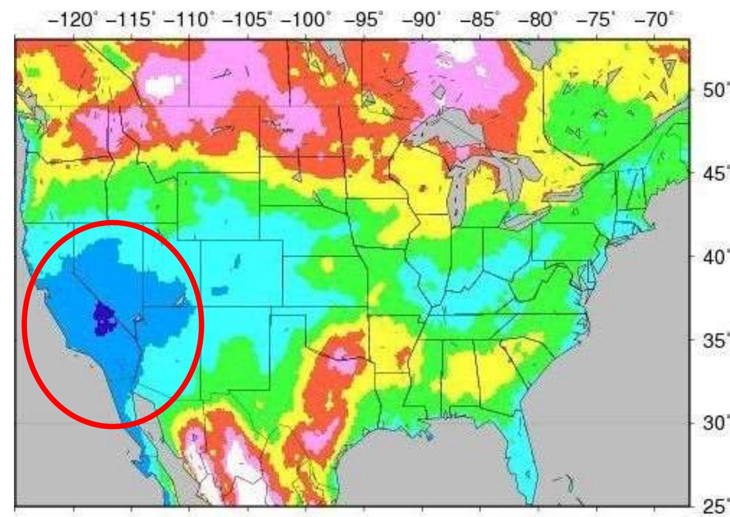
Annual covariance, $\sigma_{Rd,T}$

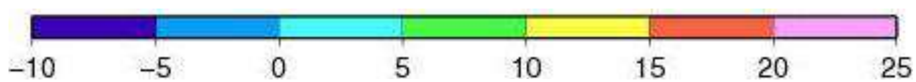


January covariance



July covariance





(°C.W/m^2)

[*Hobbins et al., JHM 2012*]

Scenario planning with E_0
Meeting SLC's freshwater needs

SLC Dept. of Public Utilities water-supply scenario planning:

- Δclimate
- drought scenarios
- operational scenarios

- *Runoff* reduction – -3.8% / °F
- seasonal reductions – largest in May-Sept
- earlier, reduced volume
- greatest threat – meeting late-summer water demands

Runoff modeling:

analytical expression

climatological monthly $\bar{E}_0$

$\Delta E_0 = \Delta T \dfrac{\partial E_0}{\partial T}$

$\Delta\bar{E}_{0_i}$

ΔT = 1–6 ˚F by 2035–64

calibrated to sub-basin

SAC-SMA model

$\Delta ET \rightarrow \Delta Runoff$

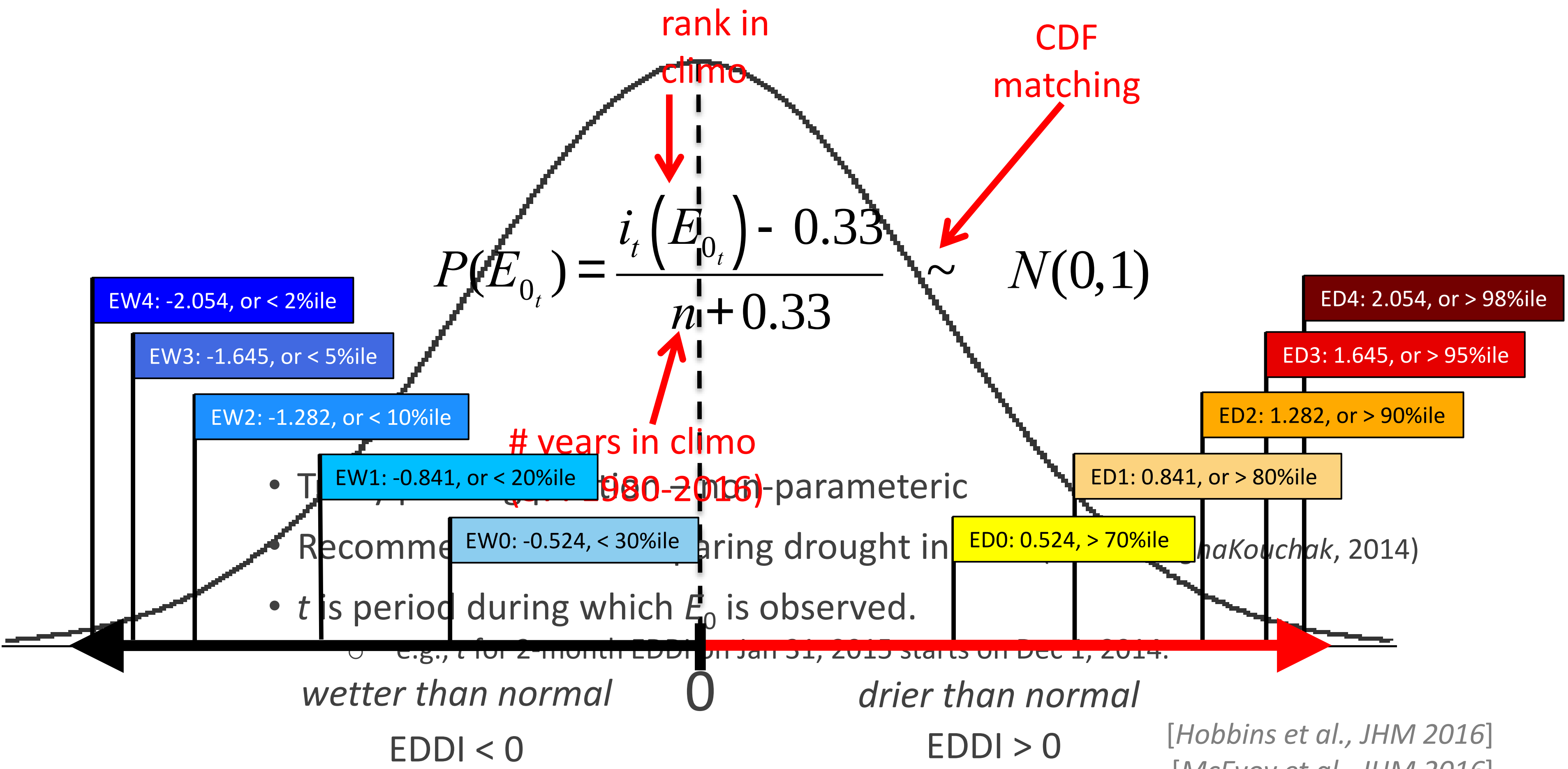
$\Delta Prcp_t, \Delta T_t$

dynamic *Prcp*, *T*

[*Bardsley et al., Earth Interactions 2013*]

ET_0 reanalysis in drought monitoring

Evaporative Demand Drought Index (EDDI)

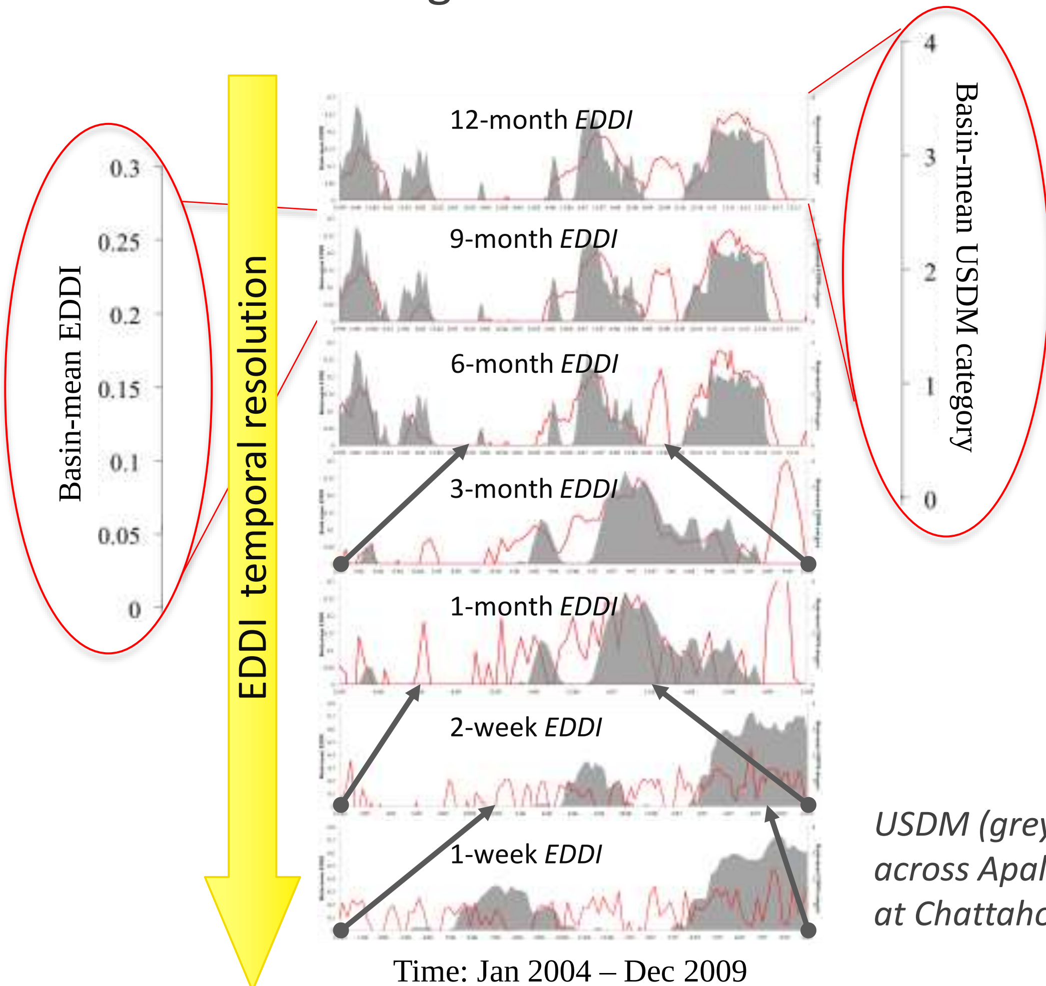


[*Hobbins et al., JHM 2016*]
[*McEvoy et al., JHM 2016*]

What does EDDI offer?

A multi-scalar drought estimator

USDM = United States Drought Monitor



Signals of different drying dynamics are evident at different time-scales

USDM (grey) and EDDI (red) across Apalachicola River basin at Chattahoochee, FL.

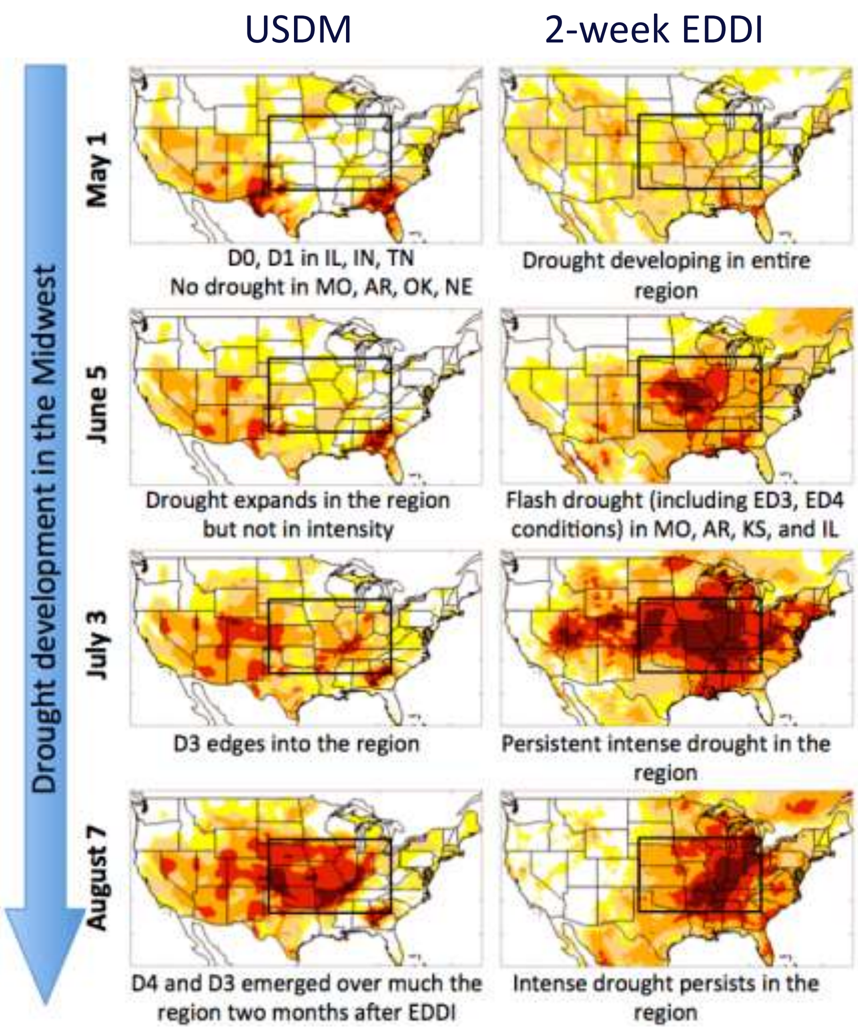
[*Hobbins et al., JHM 2016*]
[*McEvoy et al., JHM 2016*]
[*McEvoy et al., GRL 2016*]

What does EDDI offer?

Leading indication of drought

2-week EDDI captures
severe drought conditions
~2 months before USDM

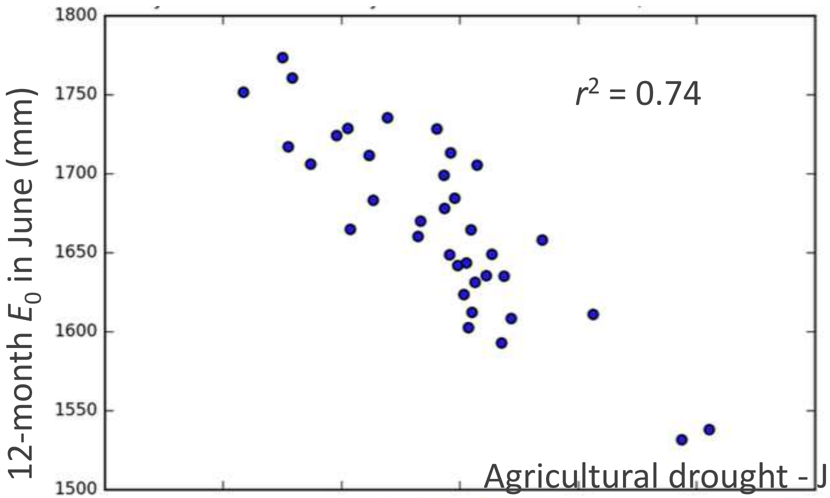
"Flash drought" in the US Midwest, 2012



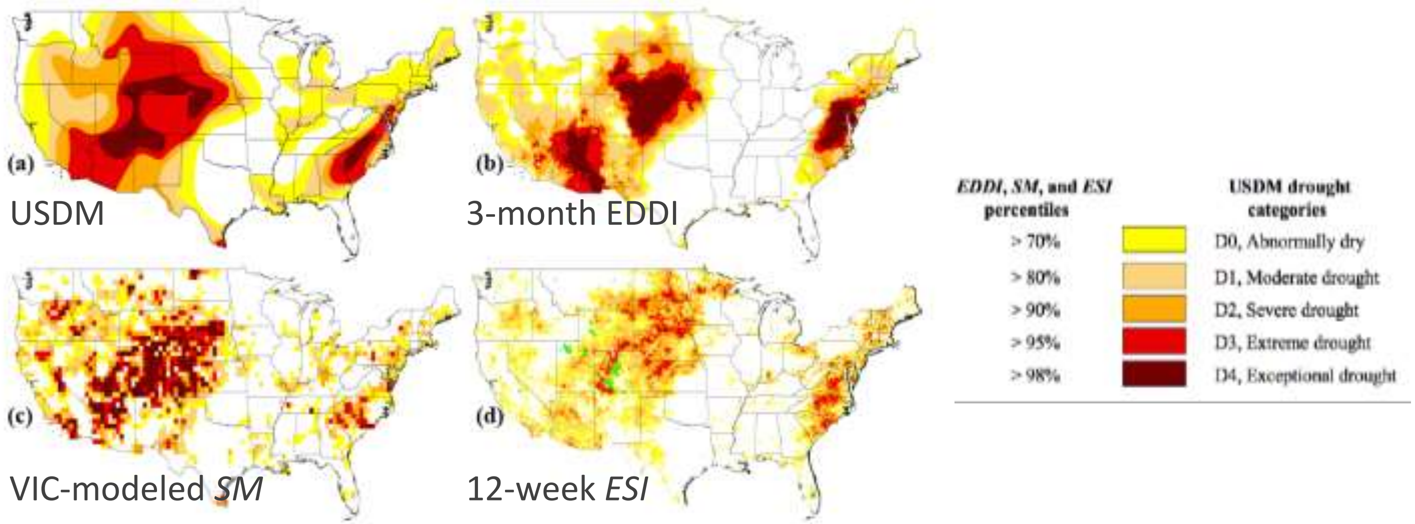
What does EDDI offer?

Monitoring across sectors

VIC = Variable Infiltration Capacity model
ESI = Evaporative Stress Index

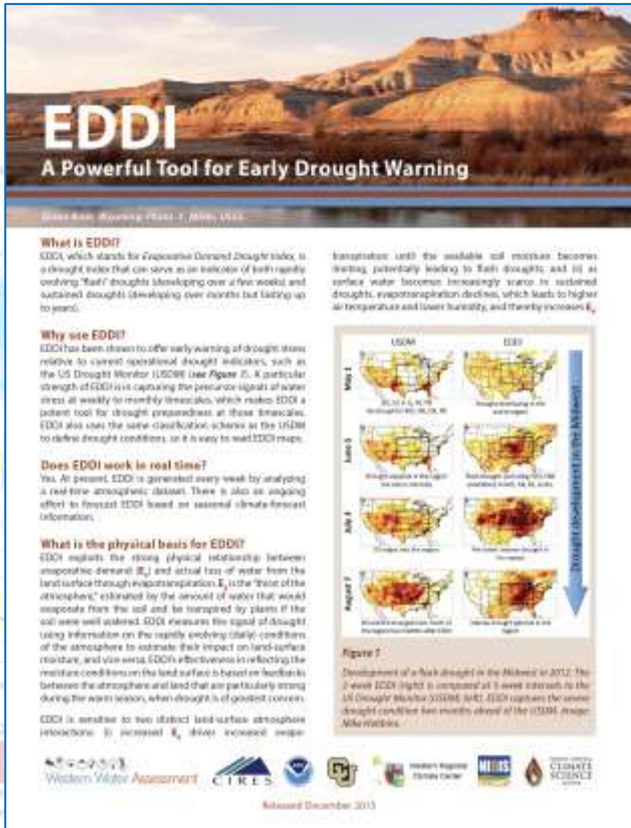


Agricultural drought - July 31, 2002

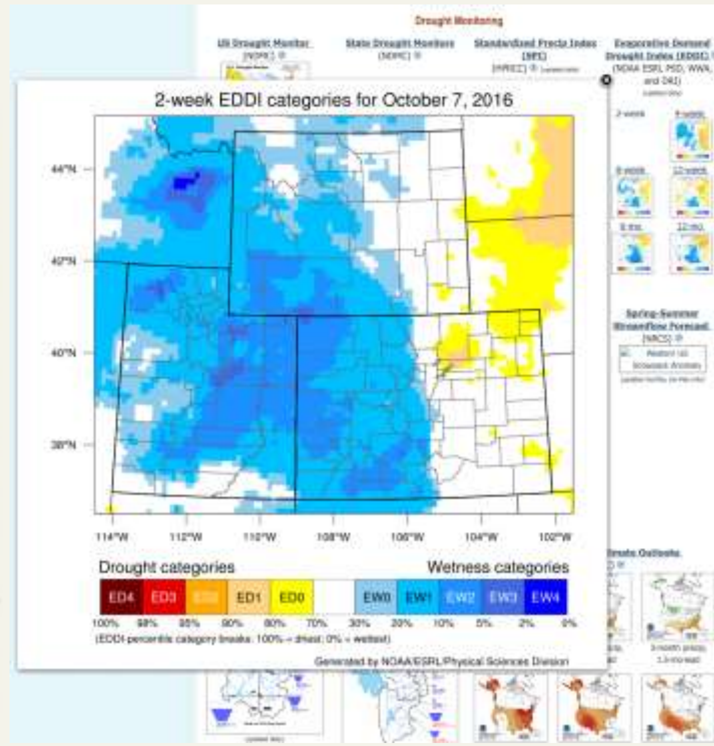


What does EDDI offer?

Near-real-time monitoring



Western Water Assessment's
Intermountain West Climate Dashboard



Live EDDI maps available:

- http://wwa.colorado.edu/climate/dashboard.html
- ftp://ftp.cdc.noaa.gov/Public/mhobbins/EDDI/IMW_DEWS/

Short-term forecasting of ET_0
NOAA's motivations

Stakeholder-led demand

No widely available public- or private-sector ET_0 forecasts

Permit more-informed water management, conservation decisions

Potential users and uses:

- Agricultural users, especially irrigators – plan daily to weekly irrigation
- Academic / agricultural outreach community
- Water resource managers of sophisticated supply systems – forecast demand at weekly or longer time-scales
- USBR – plan reservoir releases, especially a week or two out
- USFS – nation's water supply
- NIDIS – support near-future analysis in drought conditions

Short-term forecasting of ET_0

NWS 1- to 7- day forecast ET_0 (FRET) product

Forecast estimate of ET_0 for 24-hour period:

Deterministic forecast:

- no ensemble forecasts

Time-and space specs:

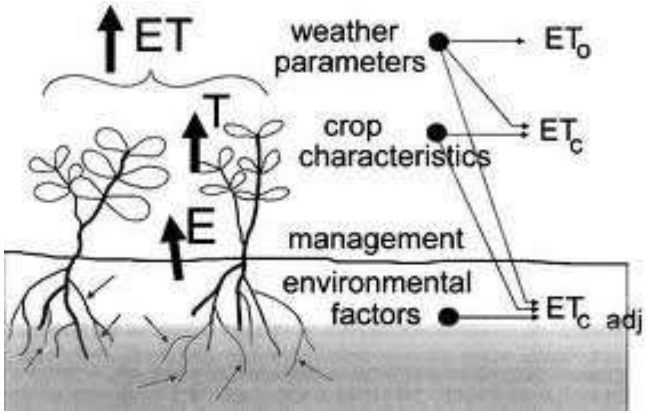
- 1- to 7-day lead time
- 24-hour periods run 6z to 6z
- HRAP grid (~2.5 kms)

Penman-Monteith (ASCE):

- 12-cm grass reference crop

Drivers:

- sensible weather elements from coupled NWPs
  - T_{max}, T_{min}
  - RH_{max}, RH_{min}
  - *10-m wind speed*
  - *Sky* (cloud cover %)

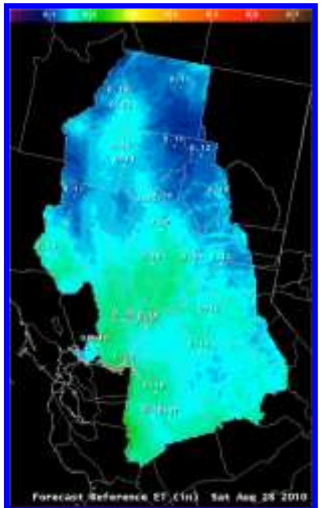


drivers forecasted by loading data from a model (or blend of models), expertly tweaked for consistency with neighboring WFOs / specific local conditions,
- e.g., for wind: may load local WRF data and then increase areas in the Delta for Delta breeze.

Short-term forecasting of ET_0

FRET product

Forecast surface, generated from NWP



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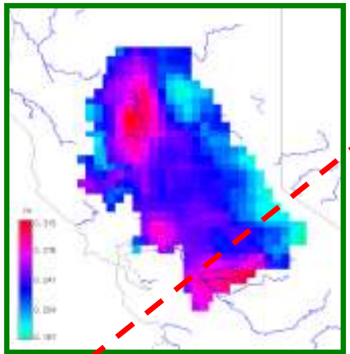
NLDAS climatology, specific to 2-wk period



Penman-Monteith algorithm

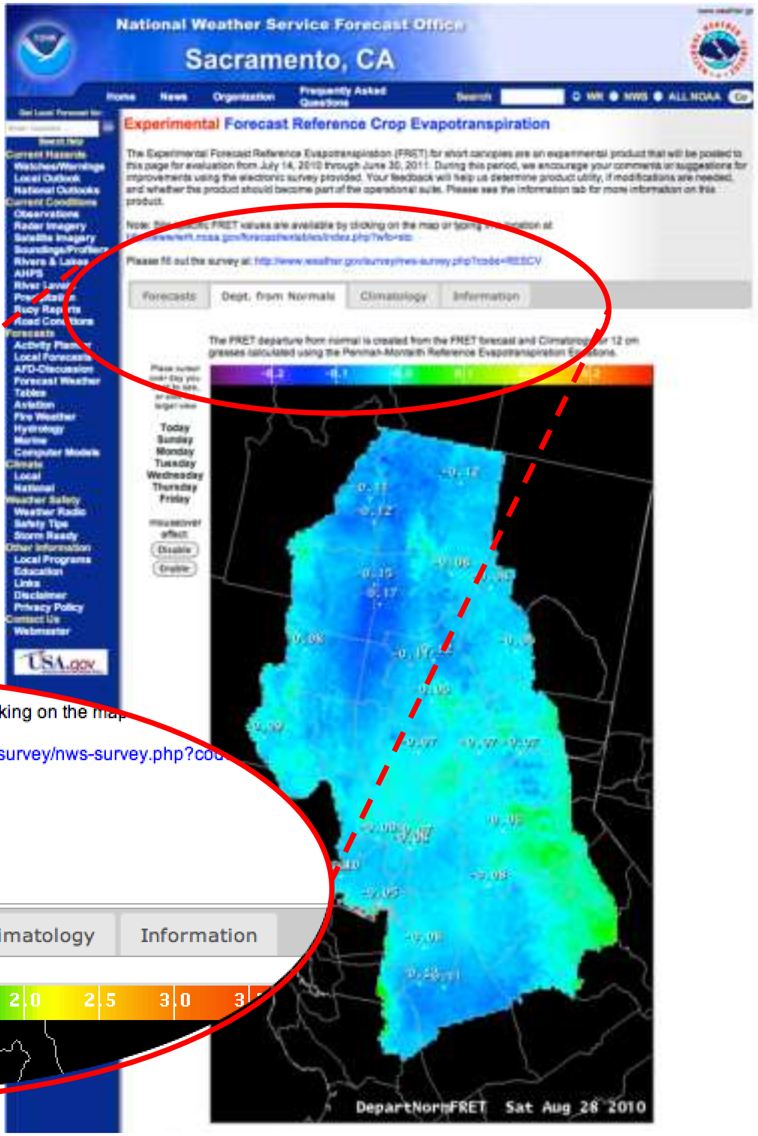
Forecast grids:

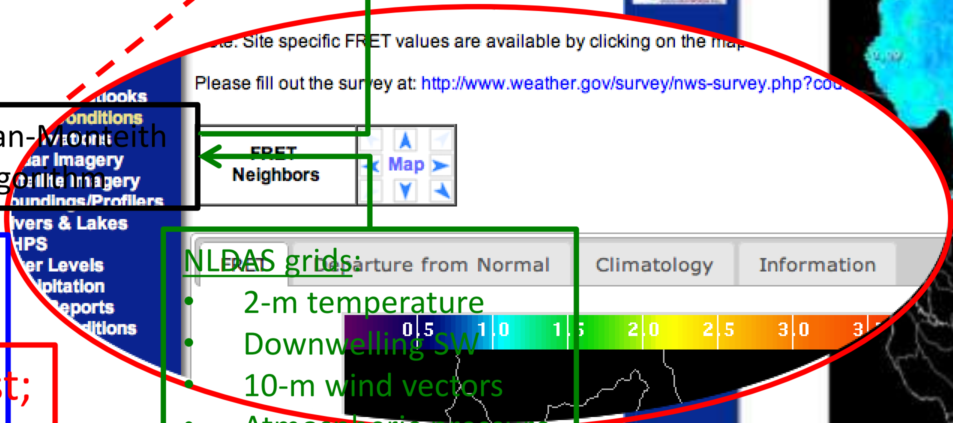
- Temperature
- Sky cover
- Wind speed
- Relative humidity

Deterministic forecast; no ensemble.

NLDAS grids:

- 2-m temperature
- Downwelling SW
- 10-m wind vectors
- Atmospheric pressure
- Specific humidity





Short-term forecasting of ET_0

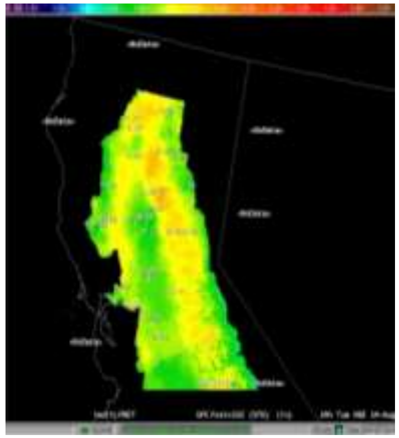
Example forecasts, 1-day FRET

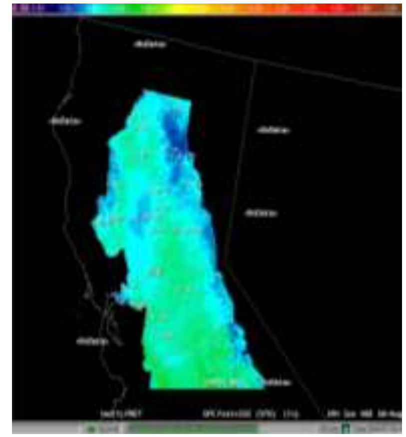
Aug 24, 2013 - hot

Aug 29, 2013 - cool

Forecast:

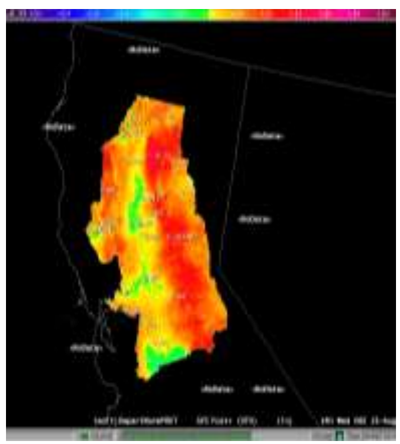
1-day FRET

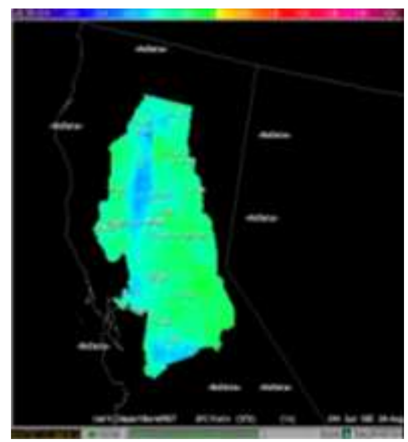




Anomaly:

$\mathrm{FRET}_{1d} - \overline{ET_0}$

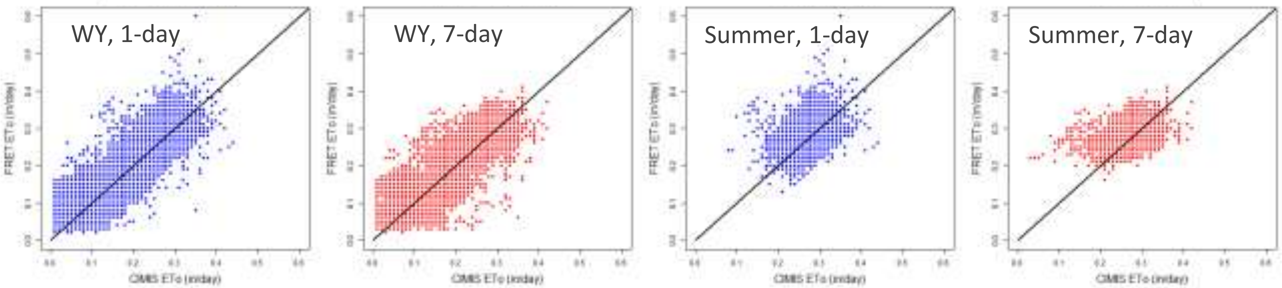




Short-term forecasting of ET_0

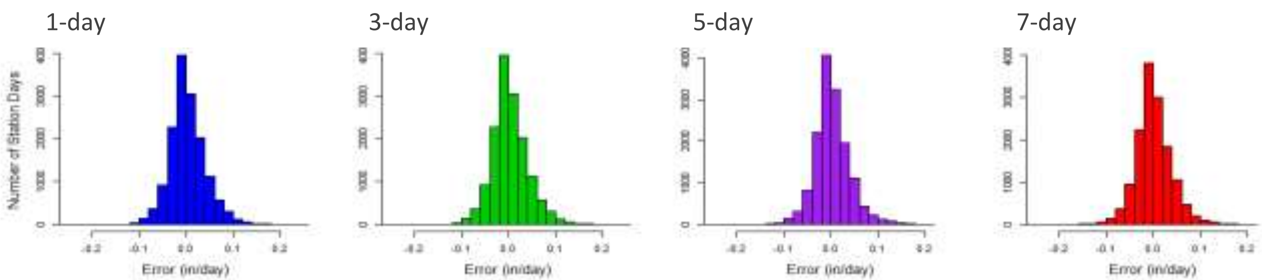
FRET verification

Water year (WY) and summer FRET ET_0 vs. CIMIS observations



> 80% of FRET values within 0.05 in/day of observed ET_0 for all forecast periods.

FRET – CIMIS observation for 48 stations

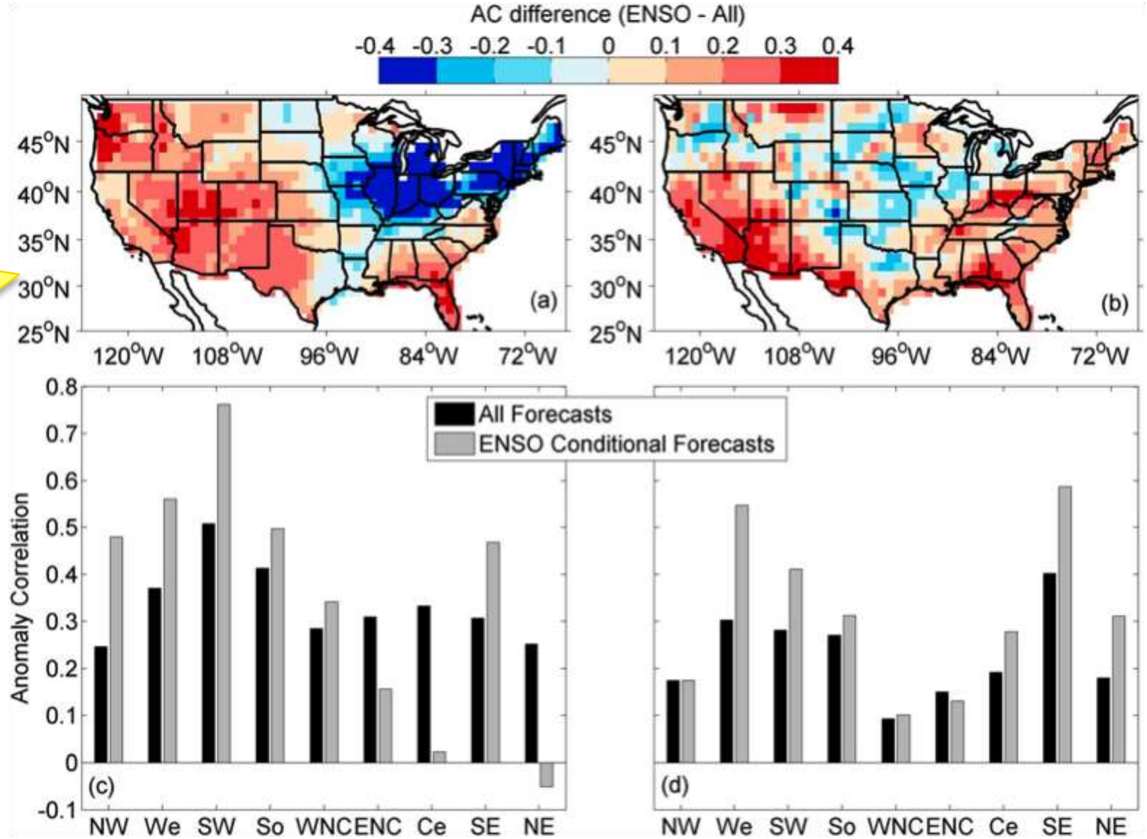


FRET has slight +ve bias wrt observed ET_0, increased bias in summer.

	2012 Water Year			2012 Summer		
FRET forecast period	**BIAS** (in/day)	**MBE** (-)	**MAE** (in/day)	**BIAS** (in/day)	**MBE** (-)	**MAE** (in/day)
1-day	0.006	0.18	0.029	0.015	0.07	0.036
3-day	0.006	0.18	0.028	0.015	0.08	0.034
5-day	0.006	0.18	0.028	0.013	0.08	0.032
7-day	0.004	0.17	0.028	0.012	0.07	0.032

Seasonal forecasting of ET_0

ET_0 forecast seasonally with greater skill than Prcp



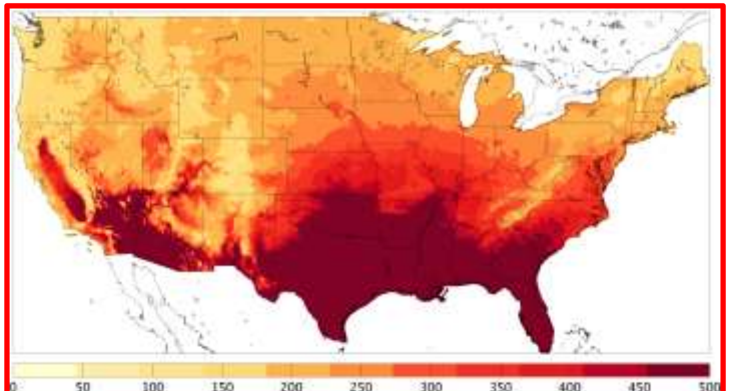
[*McEvoy et al., GRL 2016*]

Climate-scale projections of E_0

Model uncertainty: physically based vs. T-based E_0

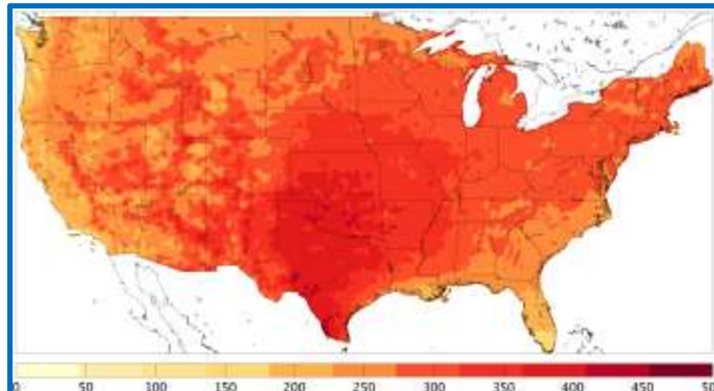
20-model mean results for RCP85 E_0, 2070-2099 minus 1950-2005

Δ Thornthwaite (mm/year)



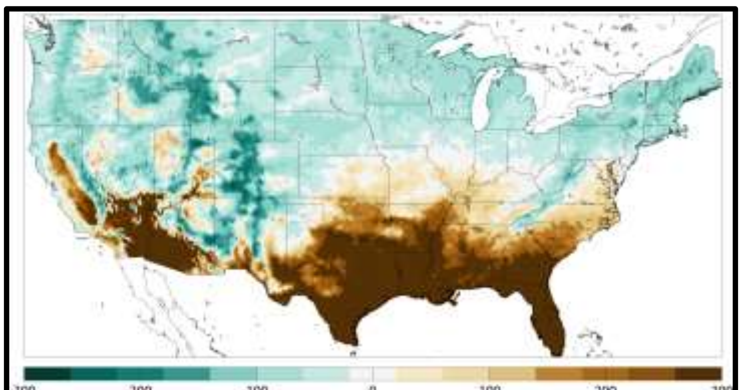
$$\Delta E_p(T) = f\left(\left.\frac{\partial E_p}{\partial T}\right|_{\bar{T}}, \Delta T \right)$$

Δ Penman-Monteith (mm/year)



$$\Delta E_p(T, SW, SH, U) = f\left(\begin{array}{l} \left.\frac{\partial E_p}{\partial T}\right|_{\bar{T}}, \Delta T, \\ \left.\frac{\partial E_p}{\partial SW}\right|_{\overline{SW}}, \Delta SW, \\ \left.\frac{\partial E_p}{\partial SH}\right|_{\overline{SH}}, \Delta SH, \\ \left.\frac{\partial E_p}{\partial U}\right|_{\bar{U}}, \Delta U \end{array} \right)$$

Δ Thornthwaite – Δ Penman-Monteith



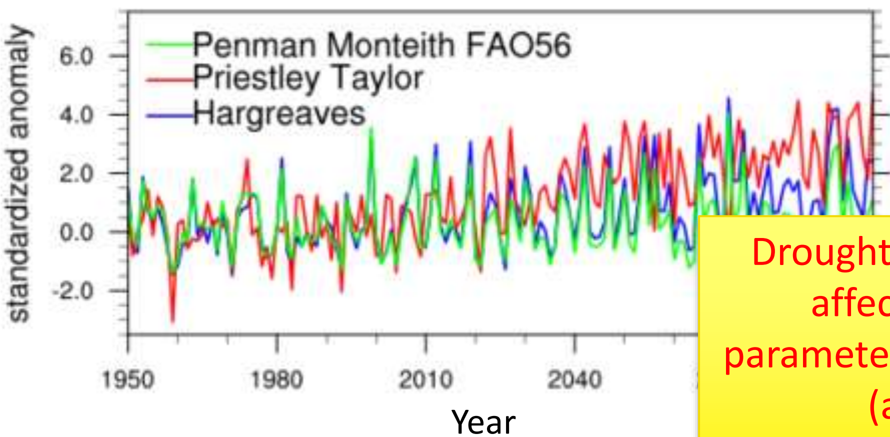
T-based ΔE_0:

- overestimated in hotter regions;
- underestimated in colder regions.

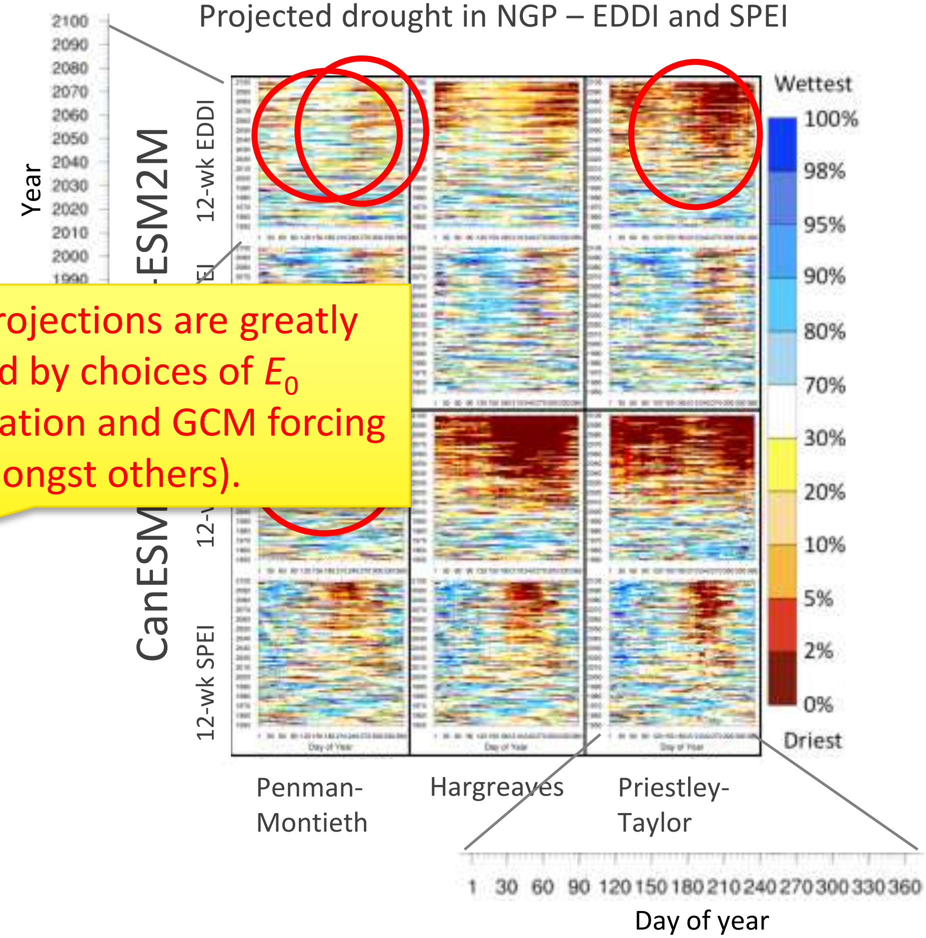
Climate-scale projections of E_0

How to estimate regional drought risk under climate change ?

Projected evaporative demand – Northern Great Plains



Projected drought in NGP – EDDI and SPEI



Drought projections are greatly affected by choices of E_0 parameterization and GCM forcing (amongst others).

For drought-risk projections, users often use what is available (and easiest to use).

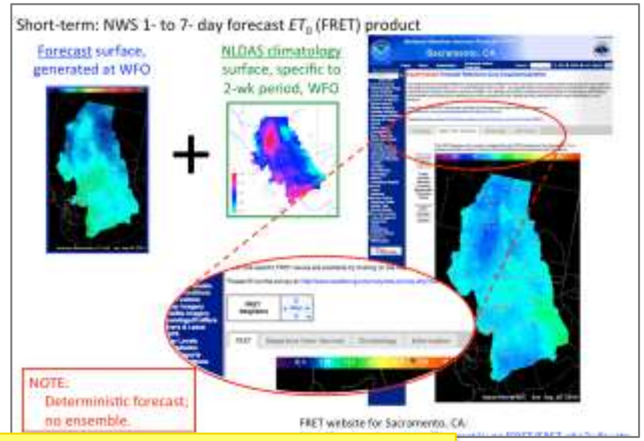
[*Dewes et al.*, submitted to PLoS ONE, 2016]

Forecasting ET_0

Across time-scales

Short-term:

- 1- to 7-day forecasts
- Drivers: Numerical Weather Prediction
- CONUS



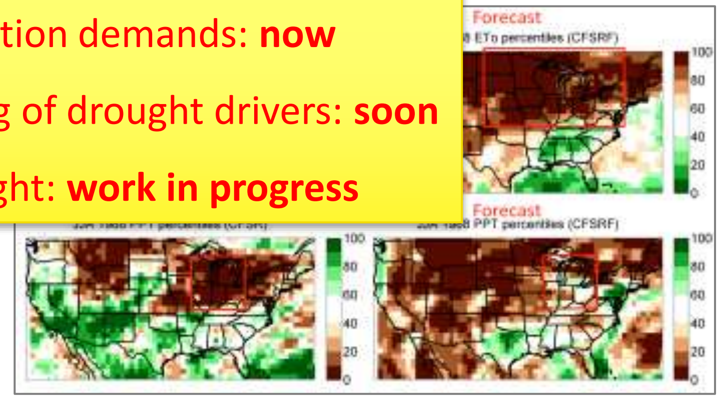
Forecasting of irrigation demands: **now**

Seasonal forecasting of drought drivers: **soon**

Projections of drought: **work in progress**

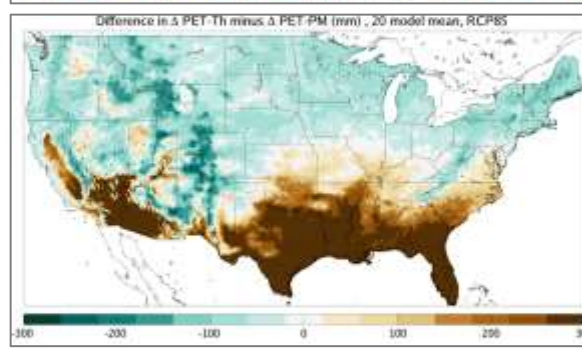
Seasonal scale:

- 90-day forecasts
- Drivers: NMME-2
- CONUS



Climate scale:

- Multi-decadal climate projections
- Drivers: CMIP5 GCM runs
- Global



Take-home thoughts on E_0

- Must be physically based
- Often more readily available than *ET* (than *Prcp*, often)
    - latency can be significant.
- Many uses:
    - crop water requirements – original conceit
    - conversion via R/S to *ET* – various space-scales
    - land-surface modeling for *ET*
    - drought monitoring – e.g., EDDI
        - driver in high-res. *ET* estimation
        - drought metric in itself
        - near-real-time monitoring
        - early warning of drought
        - tracks fast-moving droughts
        - attribution of evaporative drought drivers
- ET_0 reanalysis provides probabilistic context for droughts
- Forecastable at various time-scales