Introduction

- Assistant Professor at University of Colorado
- Research group interests:
  - Quantifying the impacts of climate and land-cover changes on water resources
  - Remote sensing applications
  - Land surface modeling

Andrew Badger

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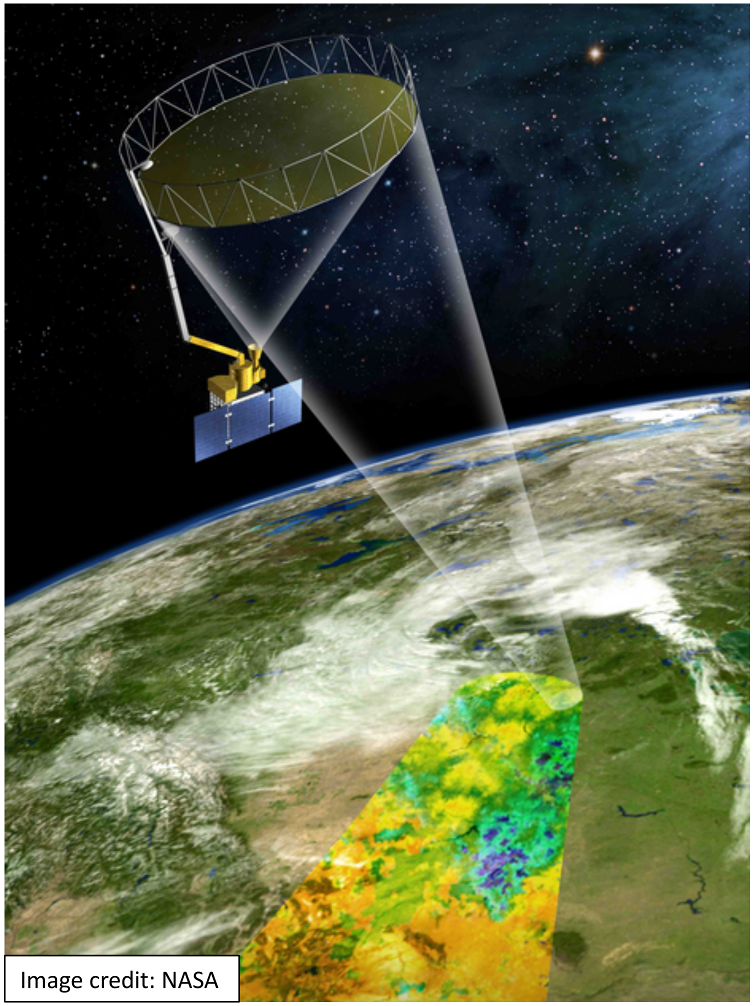
Overview

1. Applications of soil moisture variability
   - Applying remotely sensed (SMAP) soil moisture to estimate surface evaporation
   - Developing a DA framework to predict irrigation magnitude applicable to remotely sensed soil moisture
2. Evaluating the changing importance of snowpack in water supply prediction
   - Implications of projected future snow conditions for streamflow forecasting

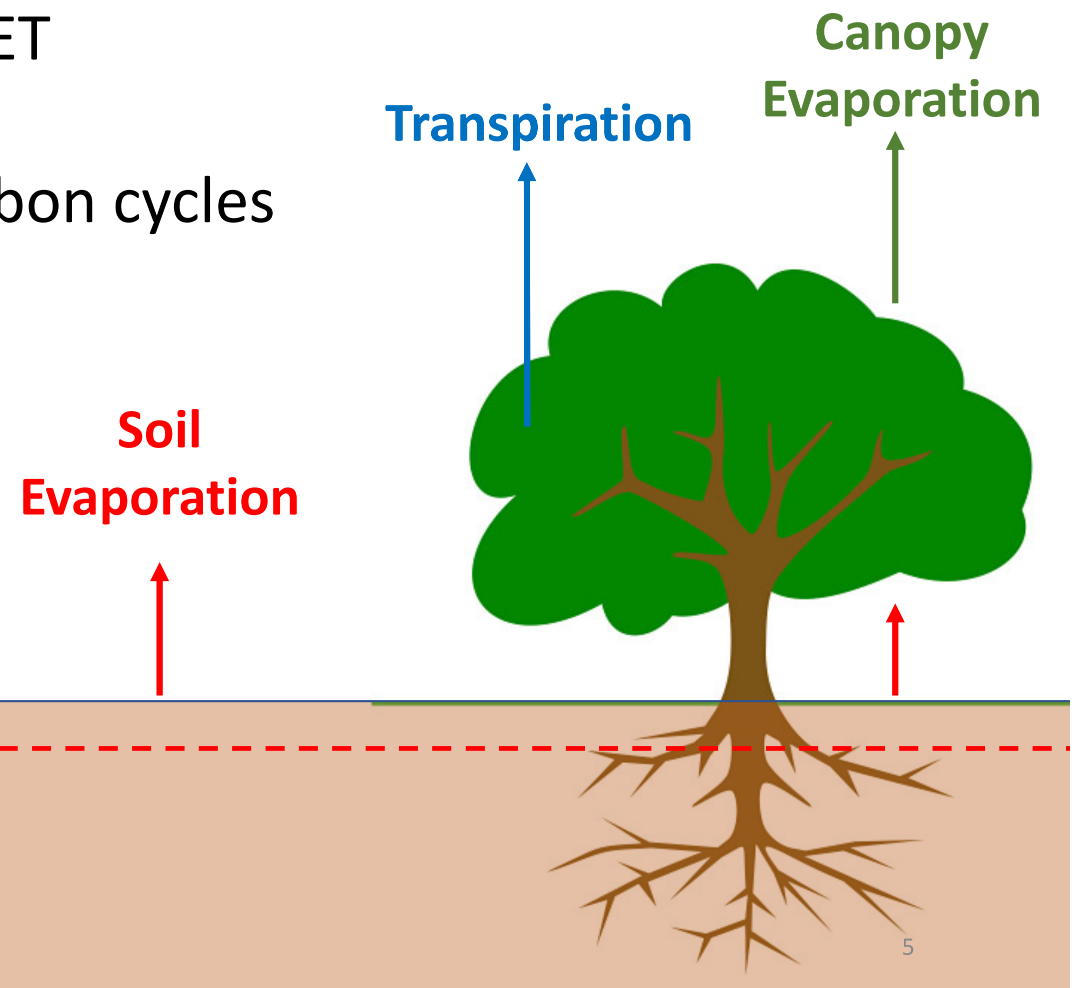


Using SMAP Satellite Observations to Estimate Terrestrial Evaporation Rates

Why focus on soil evaporation?

1. Guide development of models, ET algorithms, and partitioning
2. Understanding of water and carbon cycles

Using SMAP soil drying in a multi-platform framework allows us to produce a unique estimate of soil evaporation: **ESMAP**



Calculating ESMAP

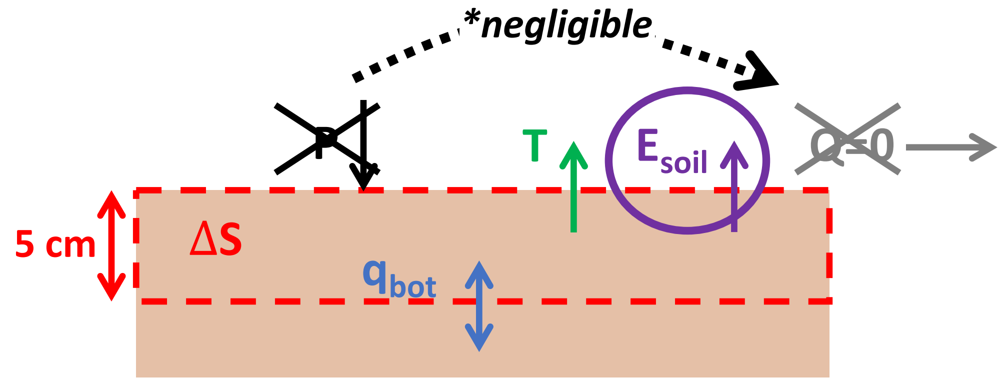
Time interval of SMAP overpasses

$$\sum_{t}^{t+1} P = \sum_{t}^{t+1} \left(E_{soil} + T + q_{bot} + \Delta S\right)$$

- P = Precipitation between SMAP observations – **from NLDAS forcing**
- T = Transpiration from surface layer – **from a variation of the Penman-Monteith (MOD16 algorithm)**
- q_{bot} = flux across bottom of surface layer – **from Hydrus-1D**
- ΔS = Change in surface layer soil moisture between **SMAP observation**

Residual will be loss due to soil evaporation - **ESMAP**

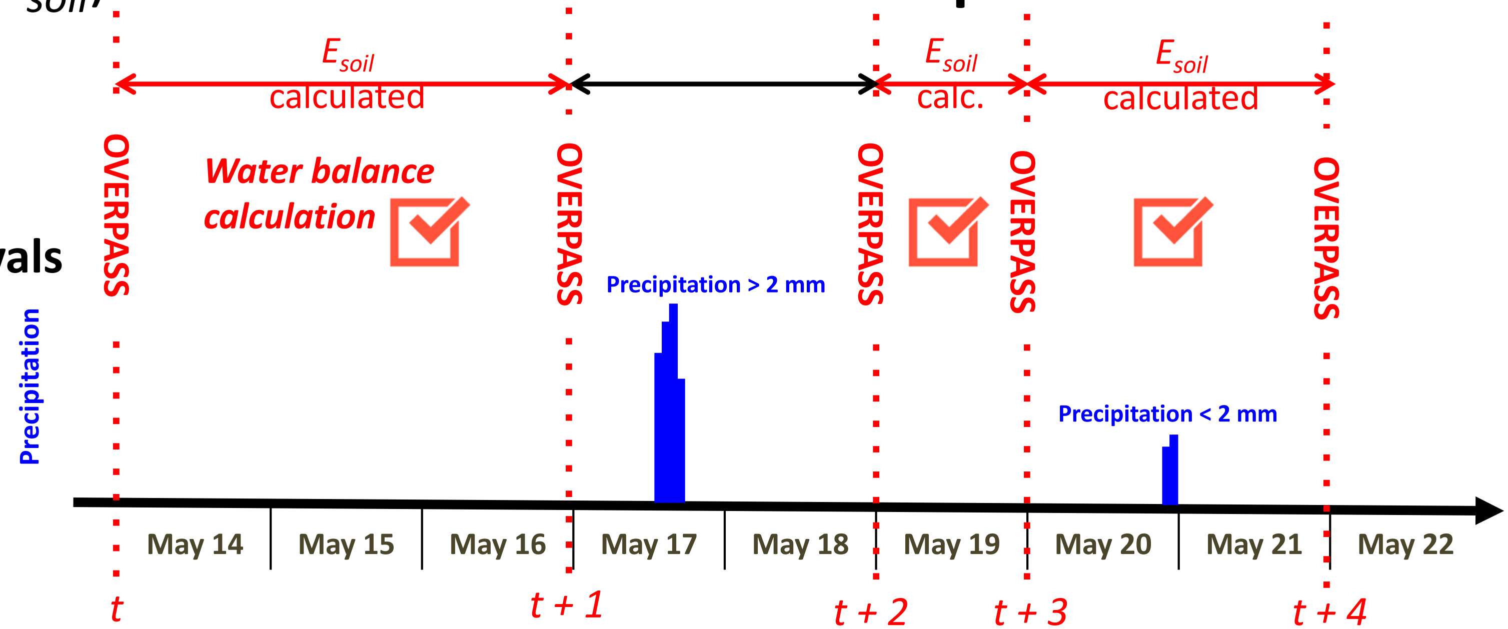
Calculating ESMAP



Valid SMAP Overpass Intervals

Soil evaporation (E_{soil}) calculated between **valid overpass intervals**.

Water balance calculation over intervals without *significant precipitation*

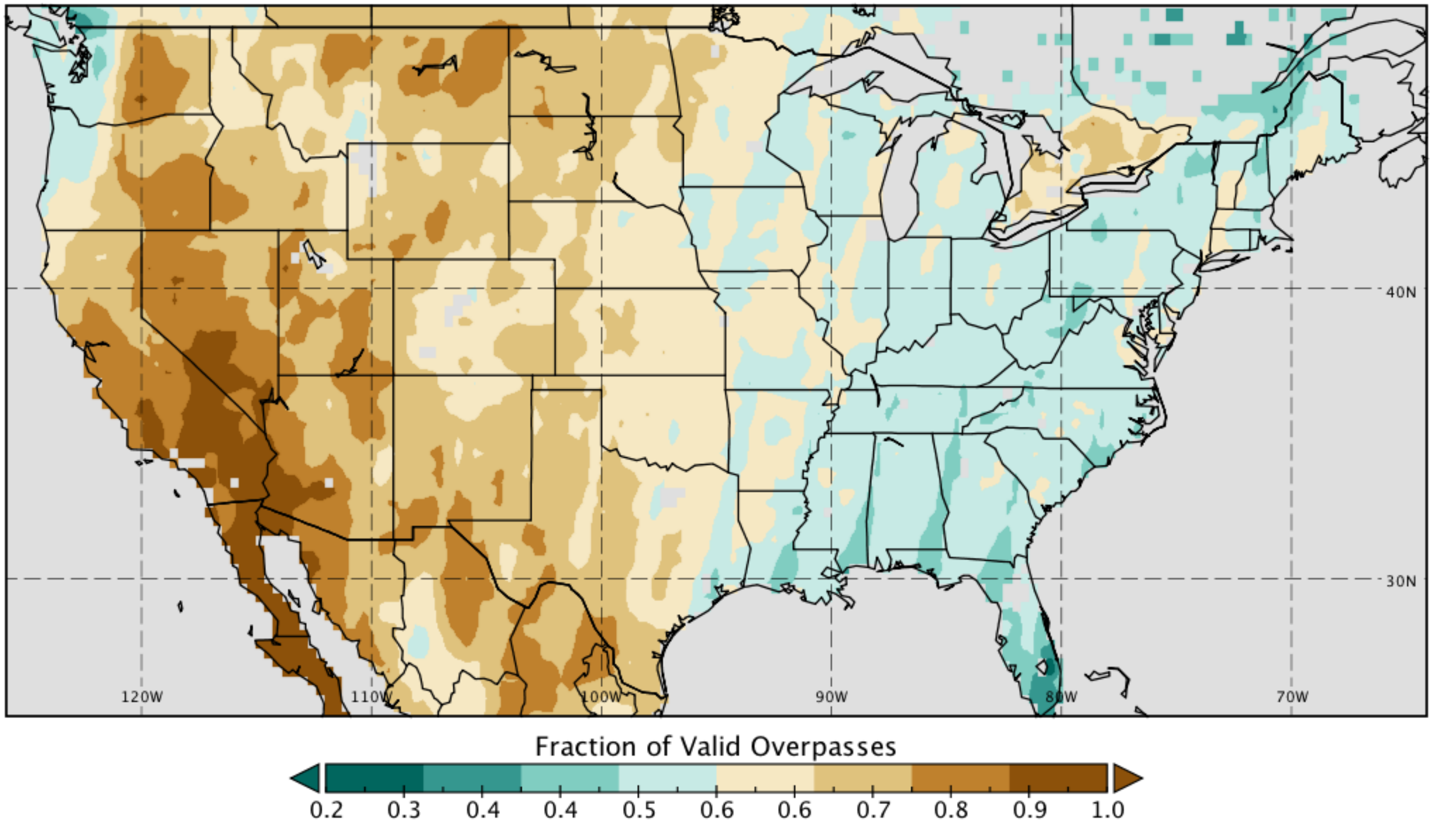


NLDAS | Estimated | Estimated | **Observed via SMAP**

$$\sum_{t}^{t+1} P = \sum_{t}^{t+1} (E_{soil} + T + q_{bot} + \Delta S)$$

Excluding intervals with infiltration,
evaporation is primarily due to soil drying

SMAP Overpasses



Number of SMAP overpasses

April 1, 2015 to April 16, 2018

A Variation of the Penman-Monteith (MOD16)

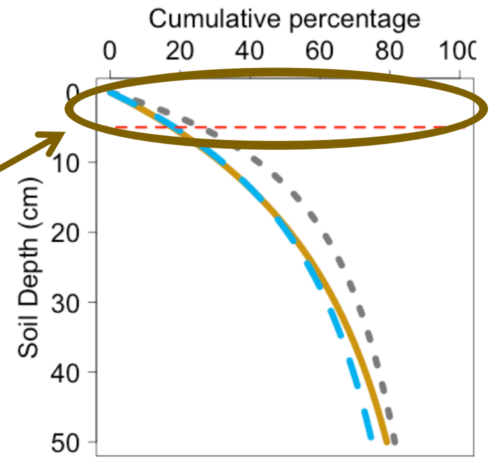
$$\lambda E_{Trans} = \frac{(s \times A_C \times F_C + \rho \times C_p \times (e_{sat} - e) \times F_C / r_a) \times (1 - F_{wet})}{s + \gamma \times (1 + r_s / r_a)}$$

Constants

NLDAS2 Forcing or LSM

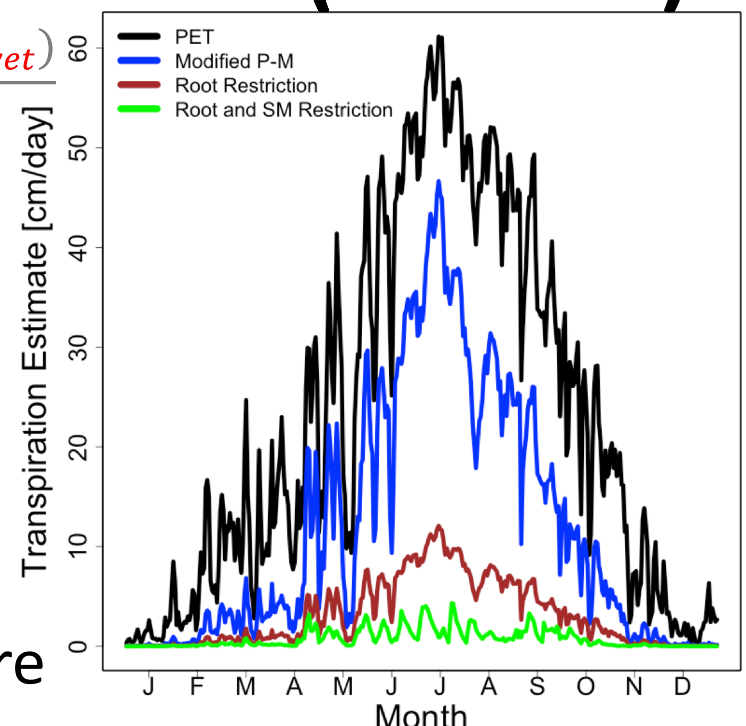
MOD13A2 EVI

Restrict by percent of roots in the surface layer



A linear soil moisture restriction on transpiration

$$SM_r = \frac{\boldsymbol{\theta_{SMAP}} - \theta_{WLT}}{\theta_{REF} - \theta_{WLT}}$$



Now we have an estimate for transpiration from the surface layer!

$$\sum_{t}^{t+1} \overset{\text{NLDAS}}{P} = \sum_{t}^{t+1} (E_{soil} + \overset{\textbf{Estimated}}{\mathbf{T}} + \overset{\text{Estimated}}{q_{bot}} + \overset{\text{Observed via SMAP}}{\Delta S})$$

Eq. 2, 15 and 22 from Mu et al. (2011)

Hydrus 1-D Simulations

- Soil hydraulic properties from NLDAS
- Meteorological forcing from NLDAS

How to constrain the bottom flux, q_{bot}

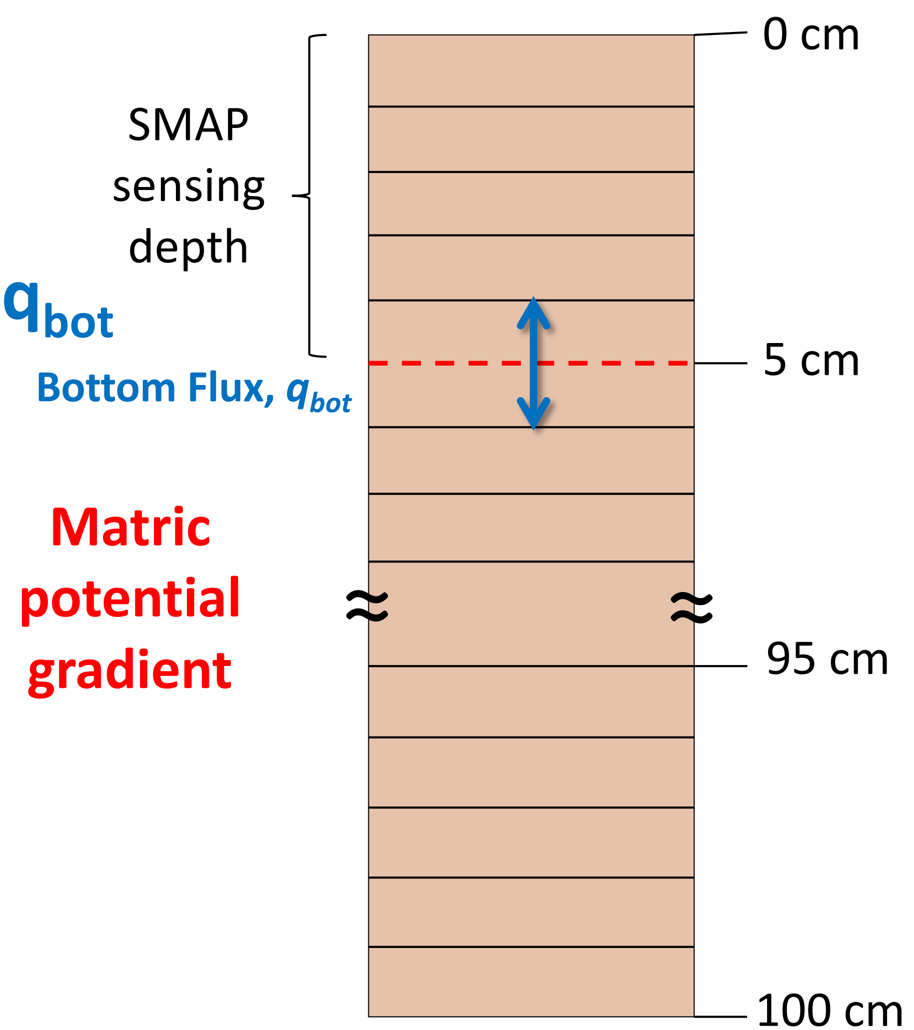
- Flux is not measured *in situ*

Darcian velocity for unsaturated zone:

$$\boldsymbol{q_{bot}} = K(\psi)\left(\frac{\psi_S - \psi_{RZ}}{z_S - z_{RZ}} + 1\right)$$

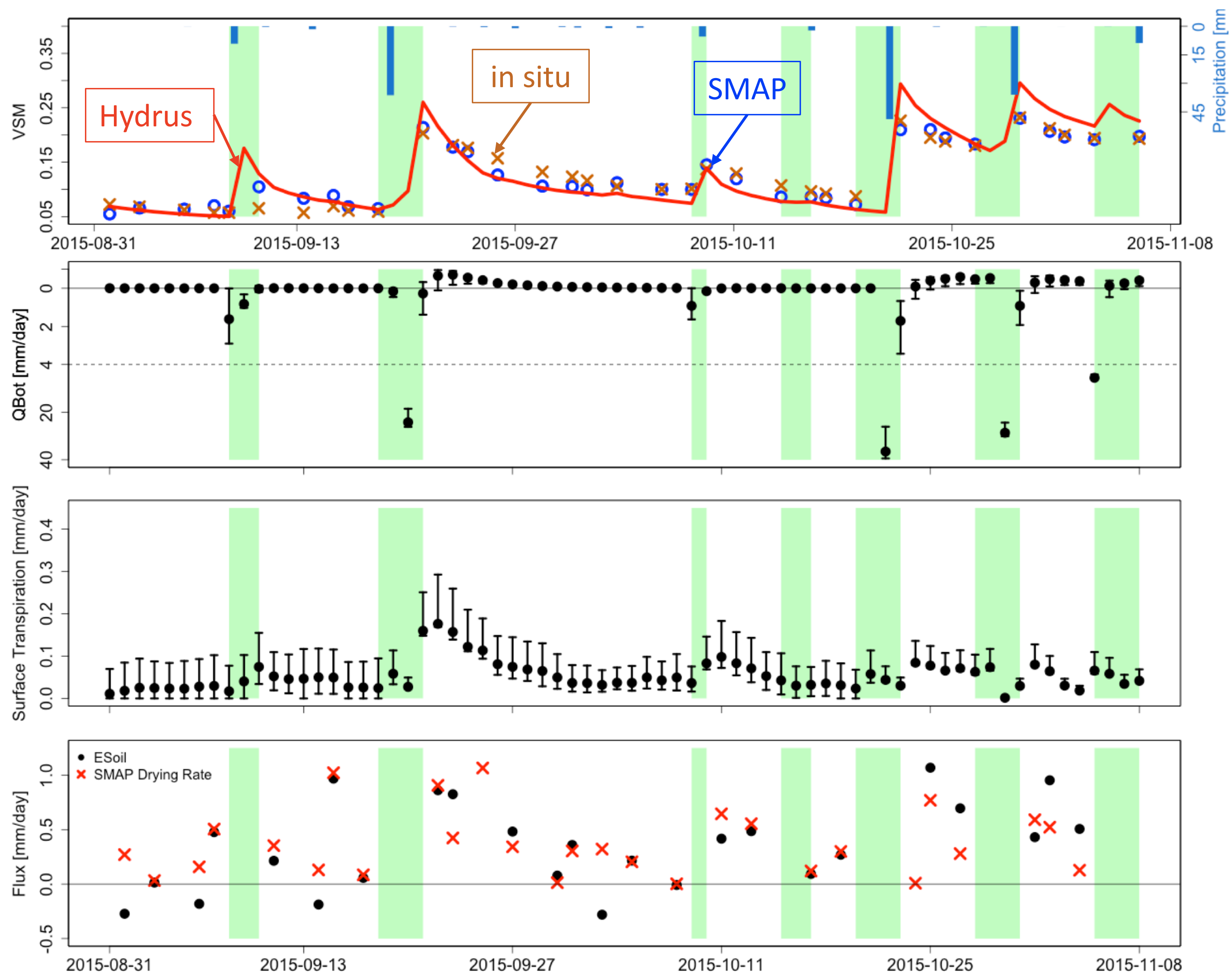
Matric potential gradient

$$\sum_{t}^{t+1} \underbrace{P}_{\text{NLDAS}} = \sum_{t}^{t+1} (\underbrace{E_{soil} + T}_{\text{Estimated}} + \underbrace{\boldsymbol{q_{bot}}}_{\textbf{Estimated}} + \underbrace{\Delta S}_{\text{Observed via SMAP}})$$



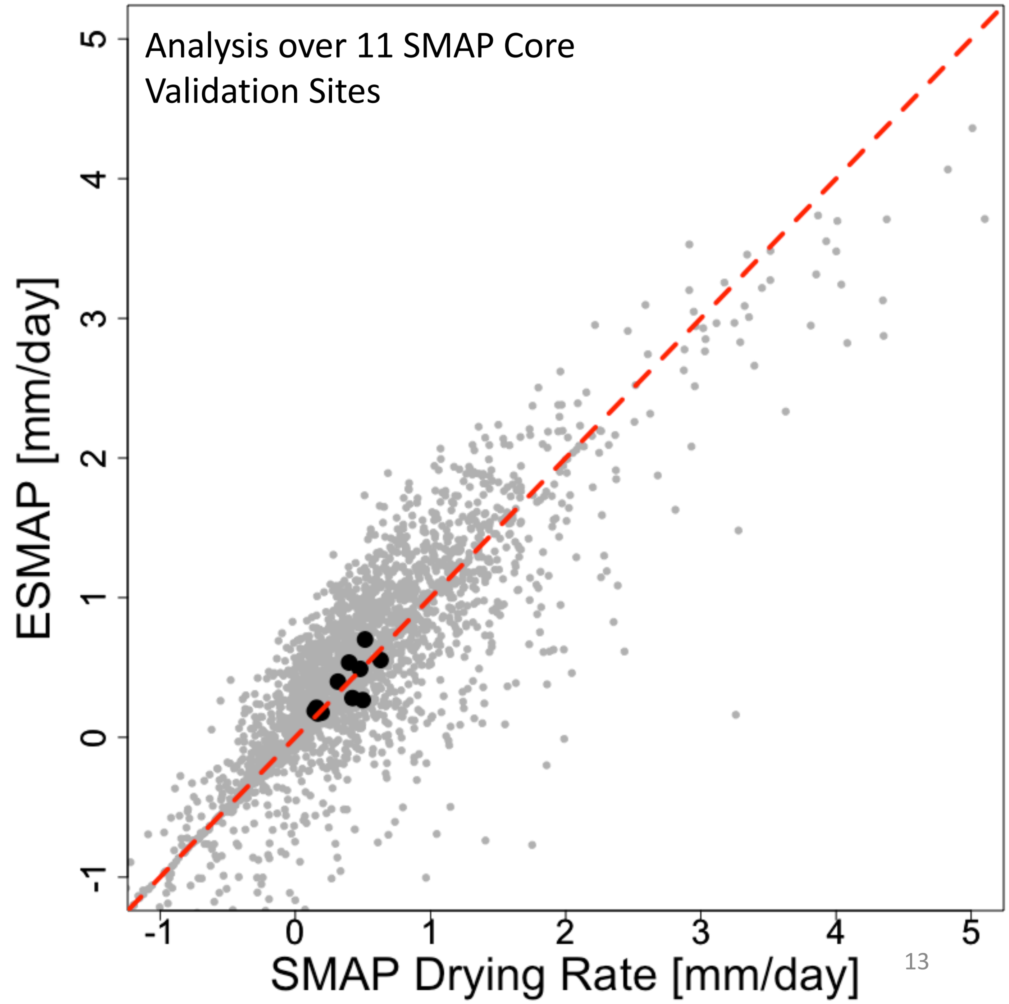
Simunek, J., et al. "HYDRUS-1D.", version 4.17 (2003).

Little Washita
OK
SMAP Core
Validation
Site

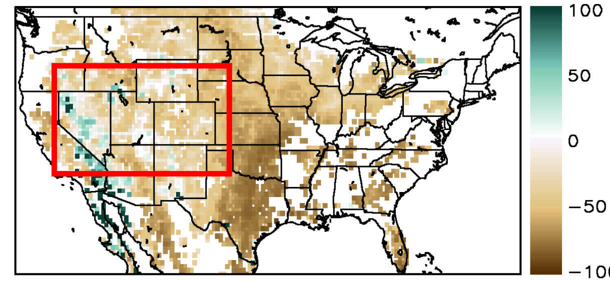


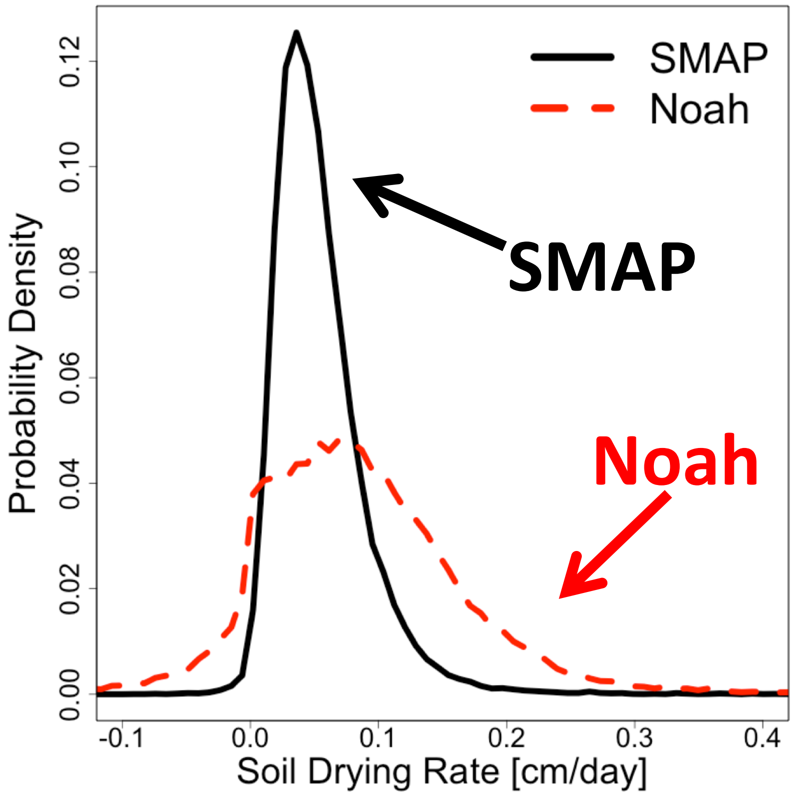
ESMAP vs Soil Drying Rate

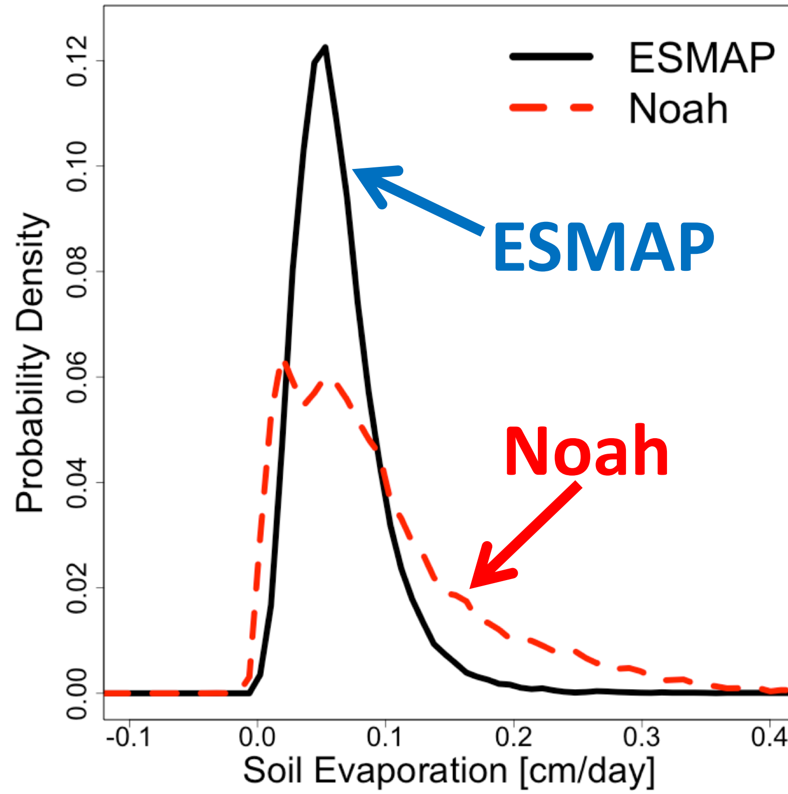
- In the absence of precipitation
  - ESMAP approximates soil drying rate
  - q_{bot} approaches zero and can even be upward
  - Surface transpiration is relatively small, most transpiration comes from the root zone



ESMAP vs NLDAS2 Noah







ESMAP Summary

- ESMAP is a unique approach to measure one component of ET
- The ***alpha*** version of ESMAP is on the same scale as Noah soil evaporation

Moving forward…

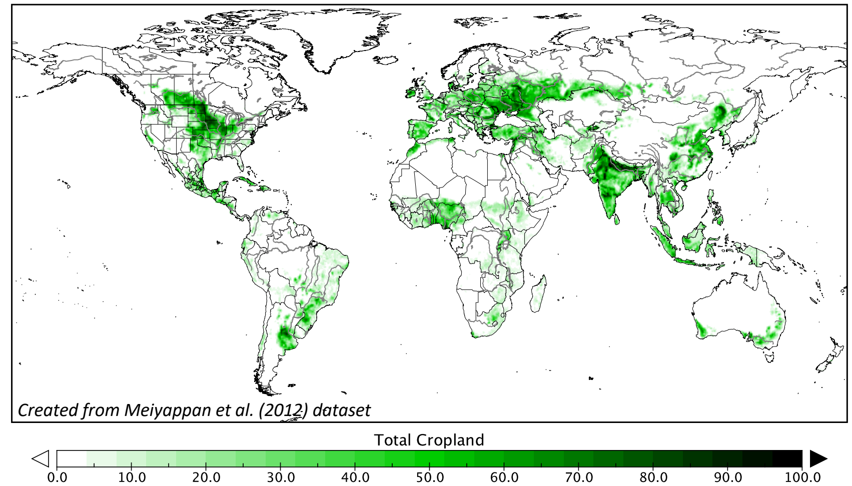
- Data assimilation is underway within a LSM to fill gaps
- Understand uncertainties:
  - Soil hydraulic properties
  - PET and transpiration estimates
- Validate ESMAP against observed and modeled estimates
- Expand time and spatial domain

E.S. Small, B. Livneh, Abolafia-Rosenzweig, R., and A.M. Badger, 2018: Estimating soil evaporation using satellite-based soil moisture drying rates (*in prep*).

Developing a *Data Assimilation* framework to predict irrigation

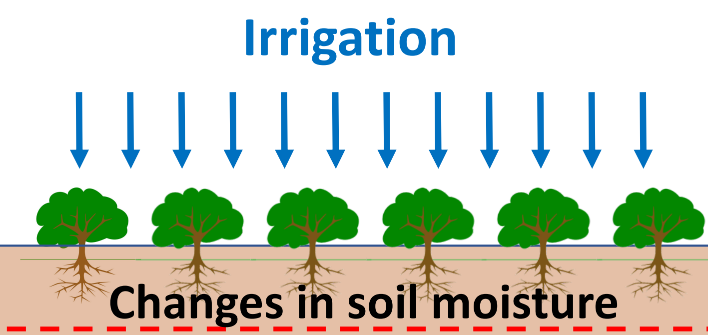
Why focus on irrigation?

1. Represents among the largest global consumptive water uses
2. Alters the water and energy balances
3. Poorly observed



<u>Research question:</u>

Can observed **changes in soil moisture** guide estimates of irrigation through **data assimilation?**



Experiment overview

- The long-term goal is to apply the method to remotely sensed soil moisture, e.g. SMAP
- First test the approach using simulated soil moisture from a land surface model (LSM) to understand the impacts of key uncertainties.
- Apply a Particle Batch Smoother data assimilation scheme; relies on as few as possible external parameterizations

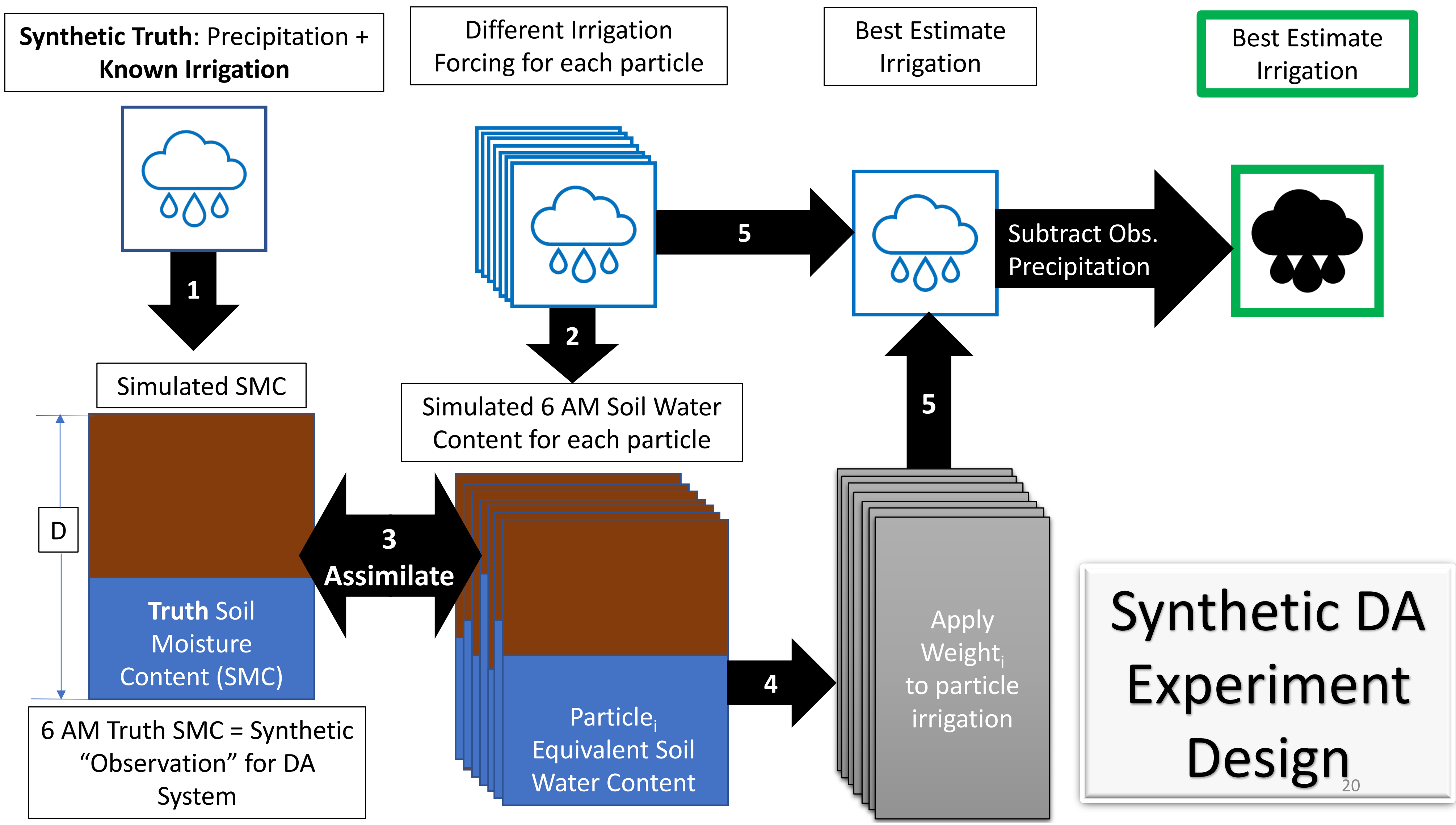
Experiment overview

<u>Synthetic experiment:</u>

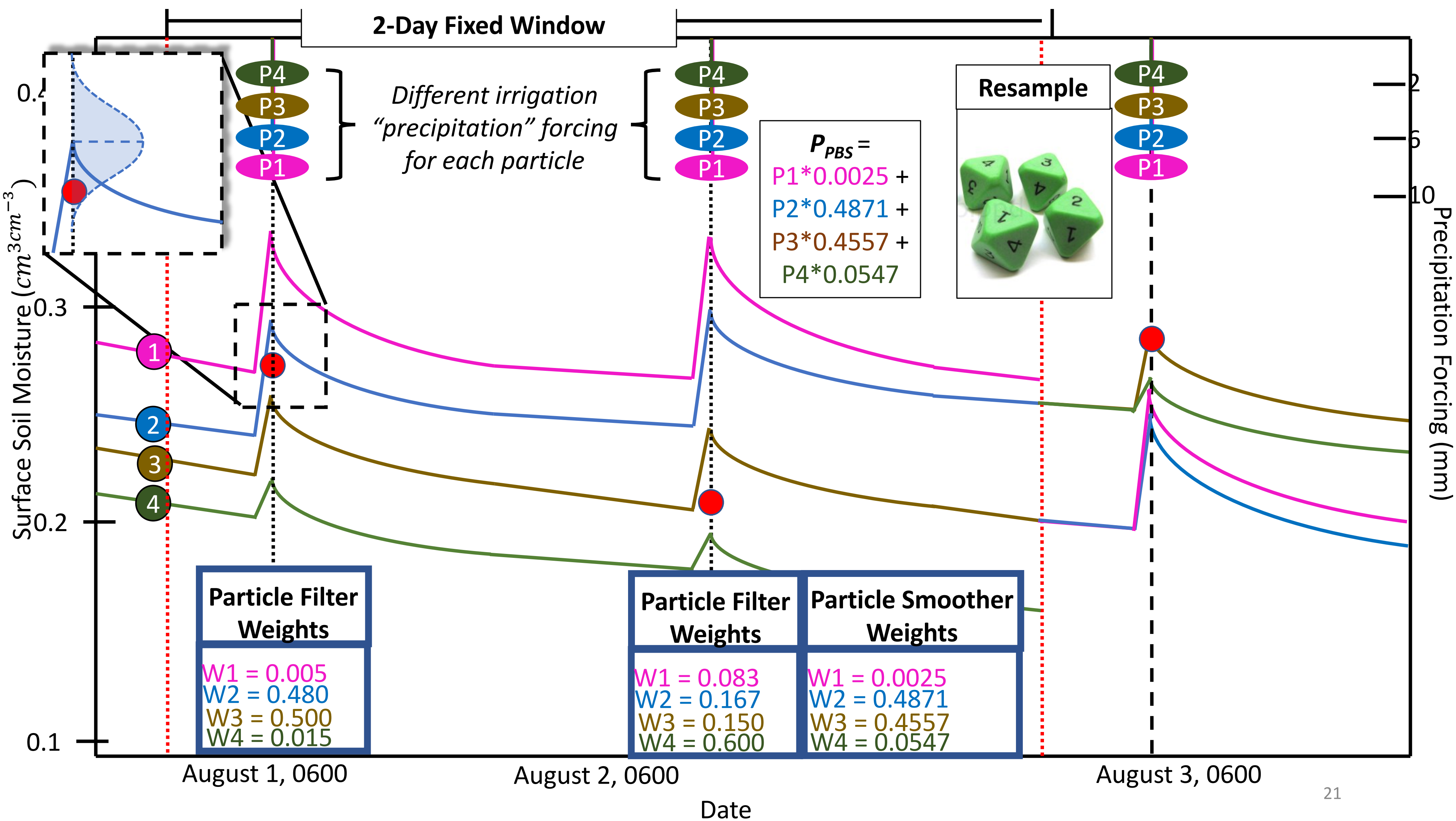
1. Apply known irrigation to a land surface model simulation = **Synthetic Truth Irrigation**

The soil moisture from the synthetic truth simulation represents remotely sensed soil moisture

2. Apply the Particle Batch Smoother (data assimilation) to identify the irrigation forcing that produces the closest match in soil moisture



Synthetic Truth: Precipitation + Known Irrigation
Different Irrigation Forcing for each particle
Best Estimate Irrigation
Best Estimate Irrigation
1
2
5
5
Subtract Obs. Precipitation
Simulated SMC
Simulated 6 AM Soil Water Content for each particle
D
Truth Soil Moisture Content (SMC)
3 Assimilate
4
Particle$_i$ Equivalent Soil Water Content
Apply Weight$_i$ to particle irrigation
6 AM Truth SMC = Synthetic "Observation" for DA System
Synthetic DA Experiment Design



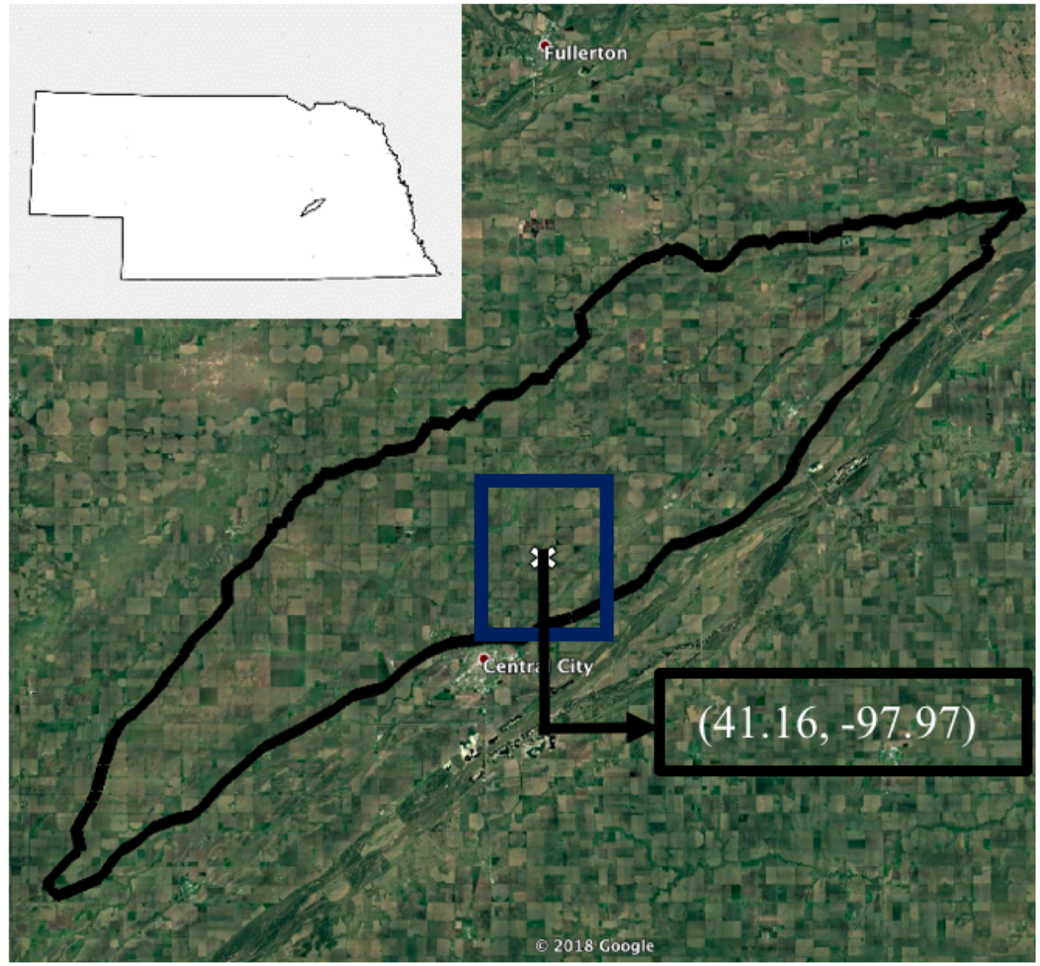
2-Day Fixed Window
Different irrigation "precipitation" forcing for each particle
P4
P3
P2
P1
1
2
3
4
P_{PBS} =
P1*0.0025 +
P2*0.4871 +
P3*0.4557 +
P4*0.0547
Resample
Particle Filter Weights
W1 = 0.005
W2 = 0.480
W3 = 0.500
W4 = 0.015
Particle Filter Weights
W1 = 0.083
W2 = 0.167
W3 = 0.150
W4 = 0.600
Particle Smoother Weights
W1 = 0.0025
W2 = 0.4871
W3 = 0.4557
W4 = 0.0547
Surface Soil Moisture (cm^3cm^{-3})
0.4
0.3
0.2
0.1
Precipitation Forcing (mm)
2
6
10
August 1, 0600
August 2, 0600
August 3, 0600
Date

Case study:

VIC LSM model grid-box (Silver Creek NE, 06772898) 692 mm irrigation applied*

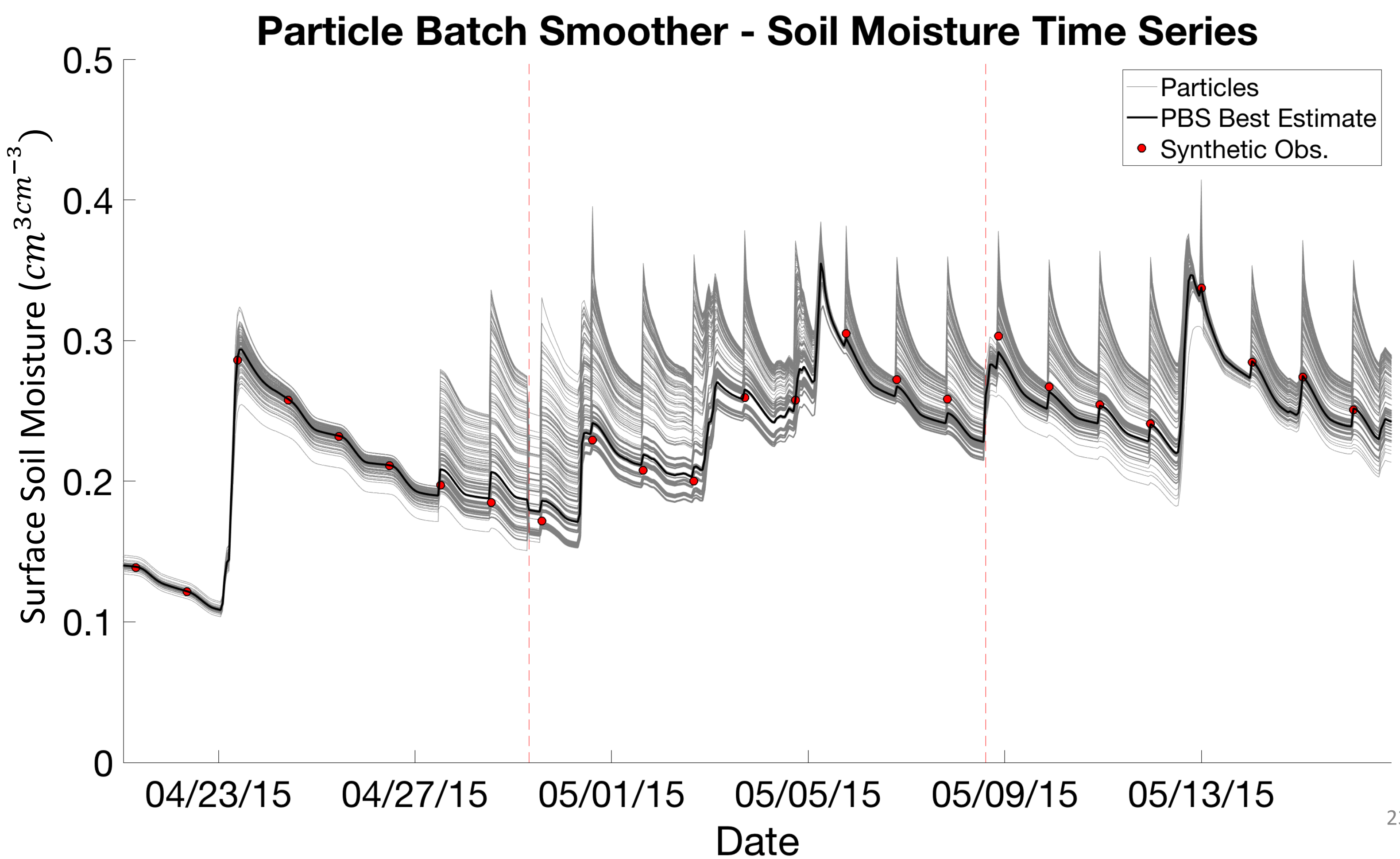
Examine performance for:

1. Daily ‘Observation’
2. 1-3 day SMAP overpasses
3. Enhanced signal-to-noise
4. Unknown irrigation time
5. Model uncertainty

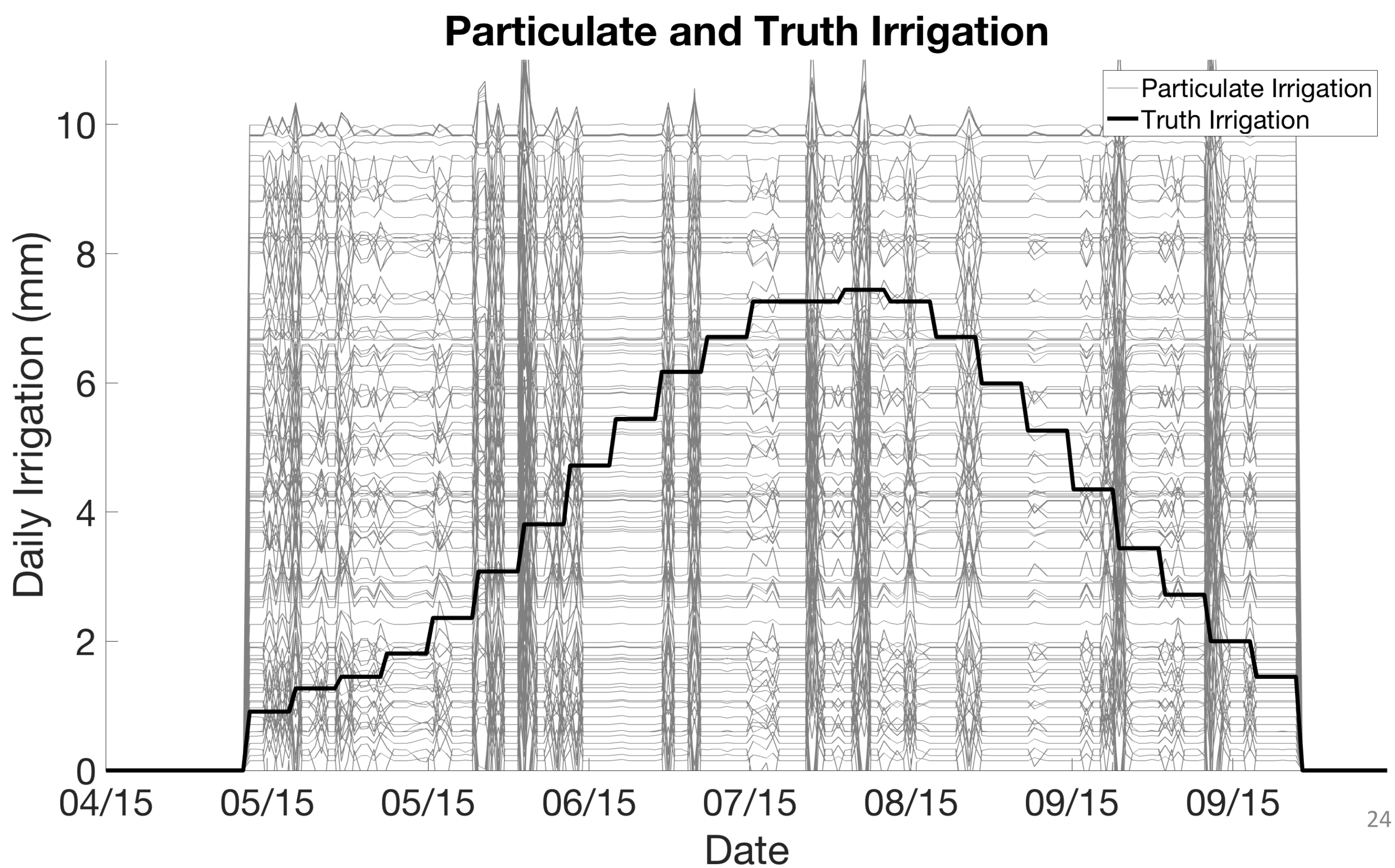


*Yonts, C. D. (2002). *Crop water use in western Nebraska*. Cooperative Extension, Institute of Agriculture and Natural Resources, University of Nebraska-Lincoln.

Demonstration of daily assimilation: Soil moisture

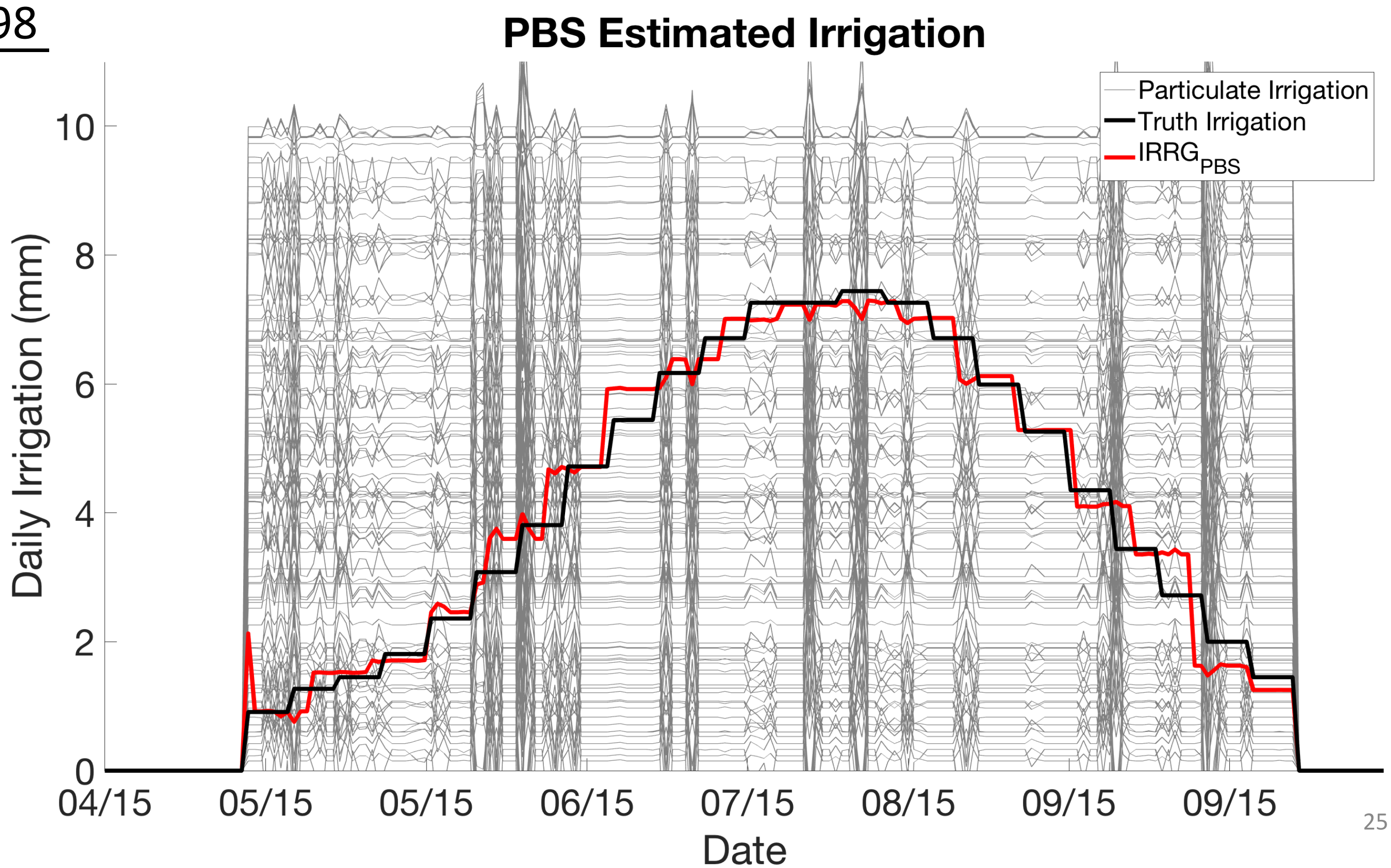


Demonstration of daily irrigation calculation



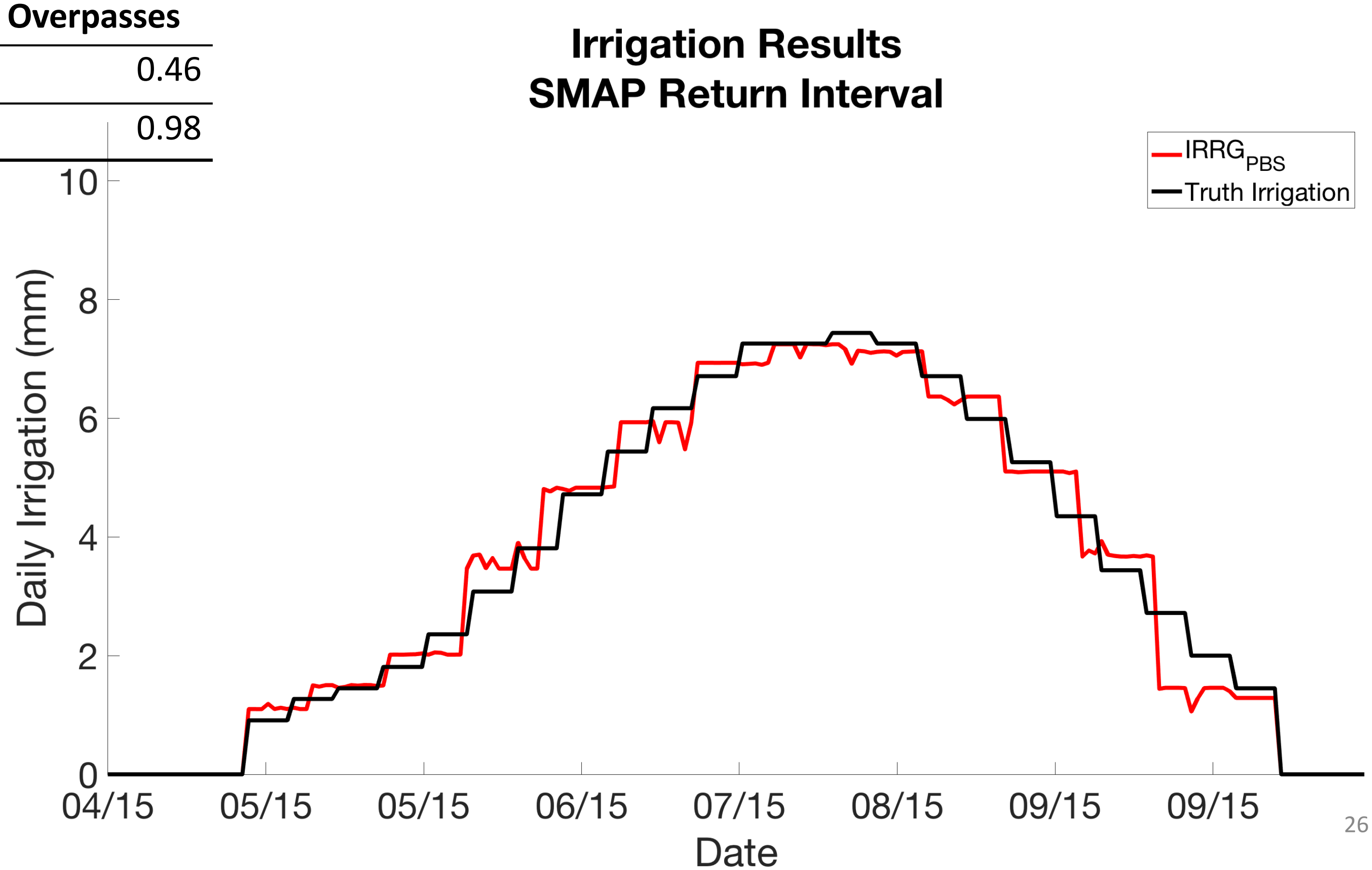
Demonstration of daily irrigation performance

Percent bias	1.8
R	0.98



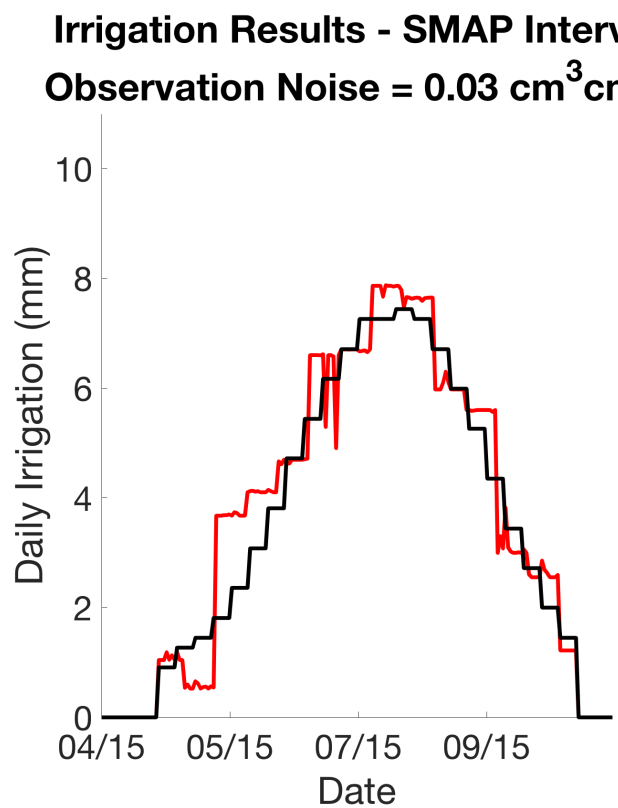
Performance for SMAP 1-3 day overpass interval

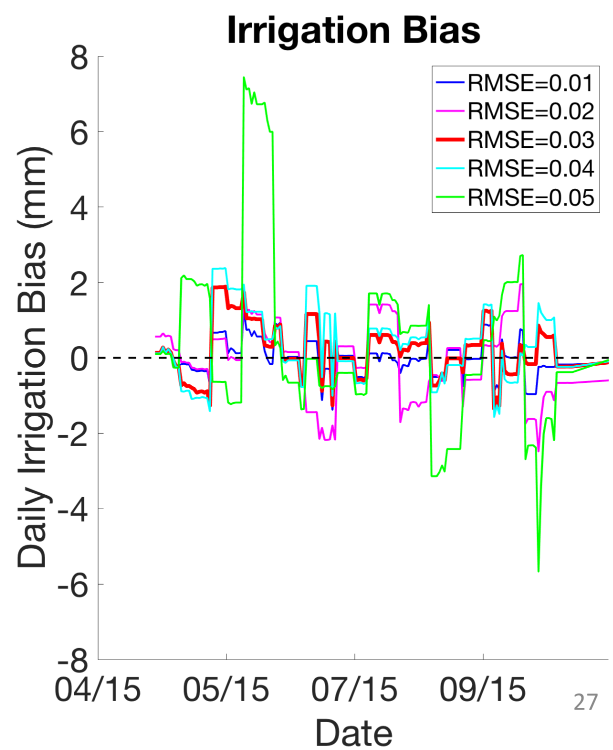
	Return Interval	
	Daily	Overpasses
Percent bias	1.8	0.46
R	0.98	0.98



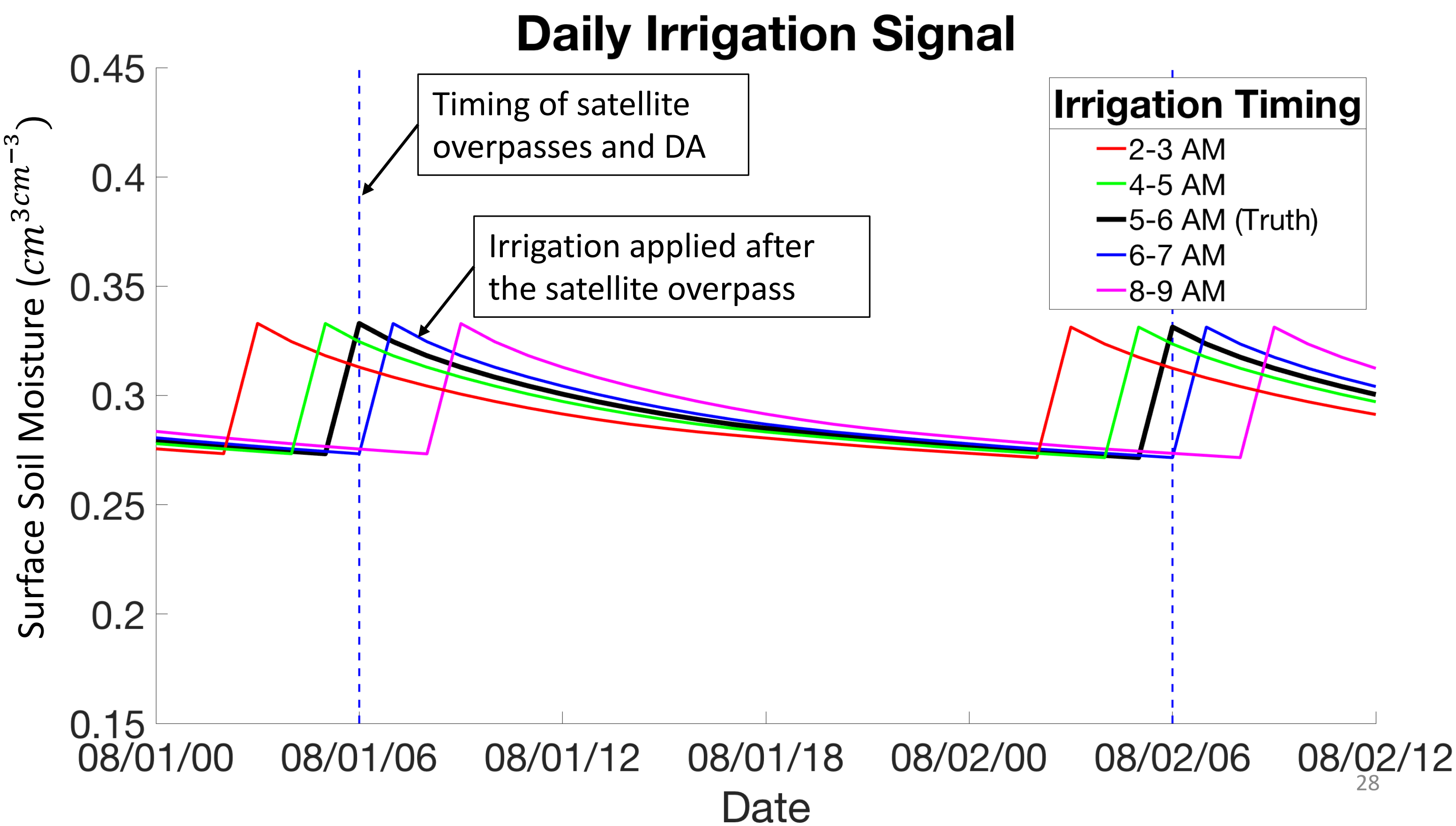
Performance for larger signal-to-noise

	Observation Noise - RMSE (m^3m^{-3})				
	0.01	**0.02**	**0.03**	**0.04**	**0.05**
Percent bias	0.12	0.43	2.38	3.51	9.45
R	0.97	0.93	0.91	0.86	0.73



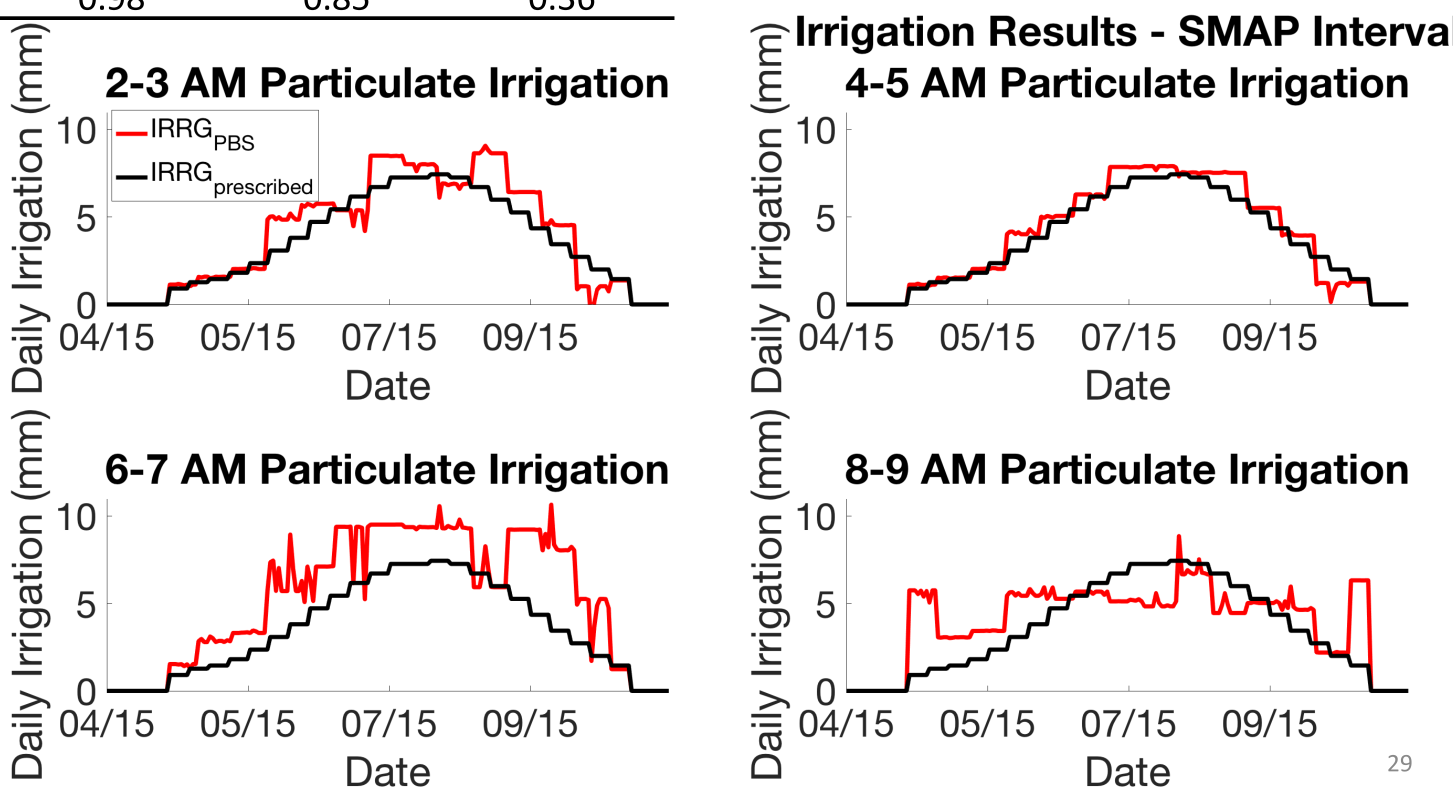


The issue of unknown irrigation time



Performance for unknown irrigation times

	Particulate Irrigation Timing			
	2-3 AM	**4-5 AM**	**6-7 AM**	**8-9 AM**
Percent bias	16.87	8.91	57.94	15.9
R	0.95	0.98	0.85	0.36



Irrigation summary

- The particle filter is a unique approach to estimate irrigation
- The synthetic experiment shows promise, yet highlights key uncertainties

Moving forward…

- Uncertainty of irrigation time is perhaps the most significant:
  - A two-stage approach that first estimates the time of irrigation, then the magnitude
- Exploring model uncertainty, e.g. unknown parameters to represent differences between remote sensing and LSMs

Abolafia-Rosenzweig, R., et. al., 2018: A method for estimating irrigation with a particle batch smoother (*in prep*).

How will changes in projected snowpack affect our ability to predict seasonal streamflow

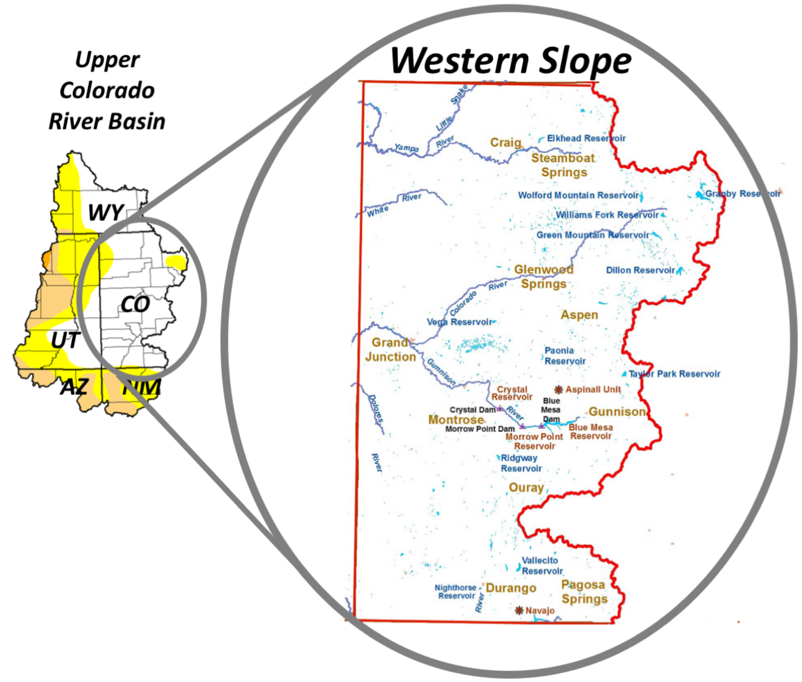
Overview

- Managing for drought in the Upper Colorado River Basin (UCRB)
  - Interviews with regional water managers
- Snowpack as a key predictor of streamflow
  - Future snow projections and changes in streamflow predictability

Are snowpack sensitivities in the UCRB unique relative to the western U.S?

Motivation for this research

- Concerns over drought risk throughout the UCRB—*Western Slope* systems are understudied
- Growing awareness: Increased investments in drought information systems
- Need to better understand how water managers manage for drought and use information now, in order to support them in the future
- Uncertainty around future indicator robustness

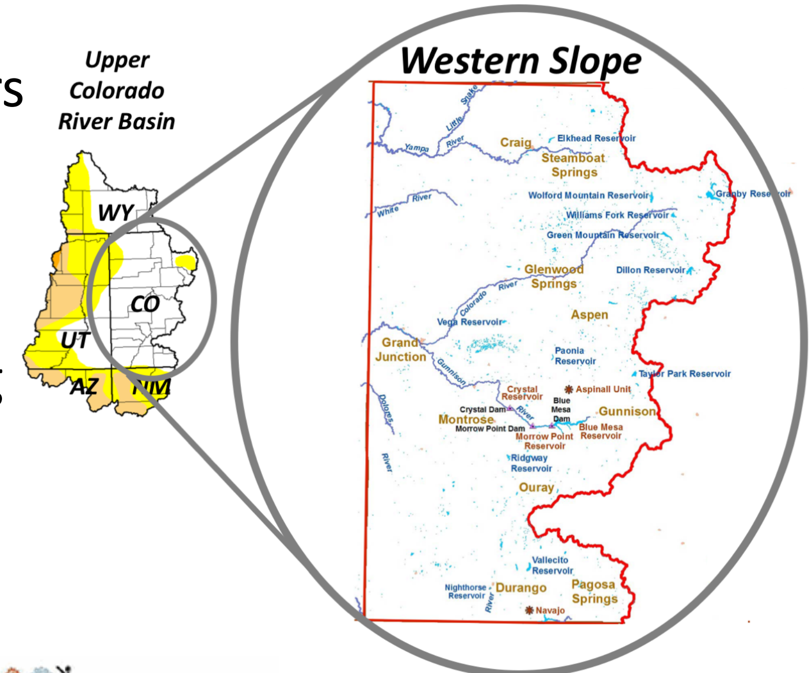


Research led by Rebecca Page and Lisa Dilling

Methods

- Five water systems across the Western Slope
- 17 in-person interviews with key decision-makers
- Reviewed internal documents
- Observed decision-making meetings
- Analyzed interview transcripts, documents, and observation notes using *nVivo* qualitative coding software

Research led by Rebecca Page and Lisa Dilling



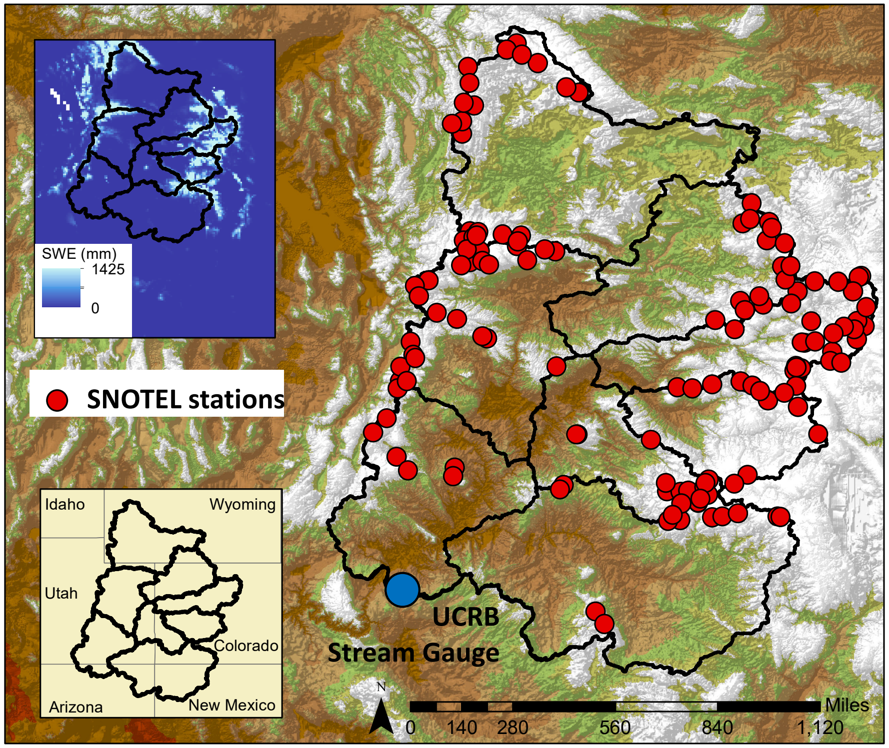
Snow Water Equivalent **(SWE) was identified as the most reliable** for water supply forecasting here (consistent with 112 UCRB stakeholders, *McNie, 2014*)

McNie, E. 2014. Evaluation of the NIDIS Upper Colorado River Basin Drought Early Warning System. Available at: http://wwa.colorado.edu/publications/reports/NIDIS_report.pdf

How will the predictive value of snow information change under a warmer climate?

Step 1 Baseline: Evaluate the predictive power of historical snow observations to forecast warm season streamflow, through statistical and physics-based models.

Step 2 Future Change: Quantify how predictive power will change on the basis of CMIP5 downscaled hydrology simulations for mid-century



Courtesy: Jenna Stewart

Predictive power of historical snowpack

SWE has been used to predict warm-season (Apr-Jul) streamflow in two ways:

- Initializing numerical models
- As a predictor in statistical equations that relate historical April 1 SWE* with April-May-June-July (AMJJ) streamflow

Official regression equations (**VIPER**) relate multiple SWE and precipitation stations to streamflow:

$$\boxed{Q = \sum_{i=1}^{n} a_i SWE_i} + \sum_{j=1}^{m} b_j P_j + \epsilon$$

AMJJ streamflow

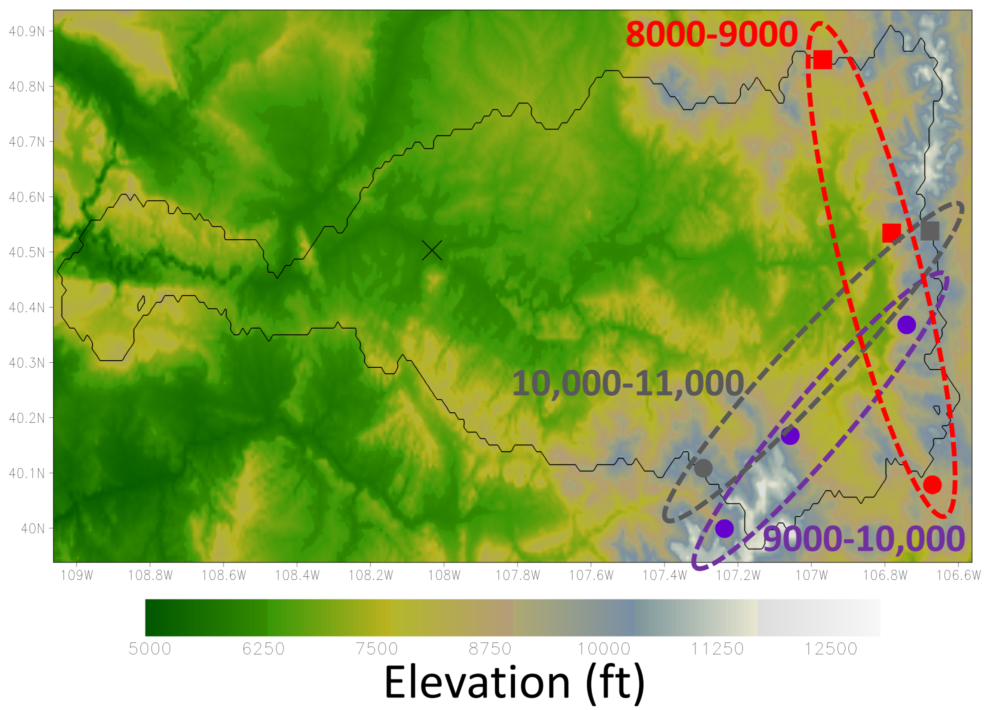
Station data

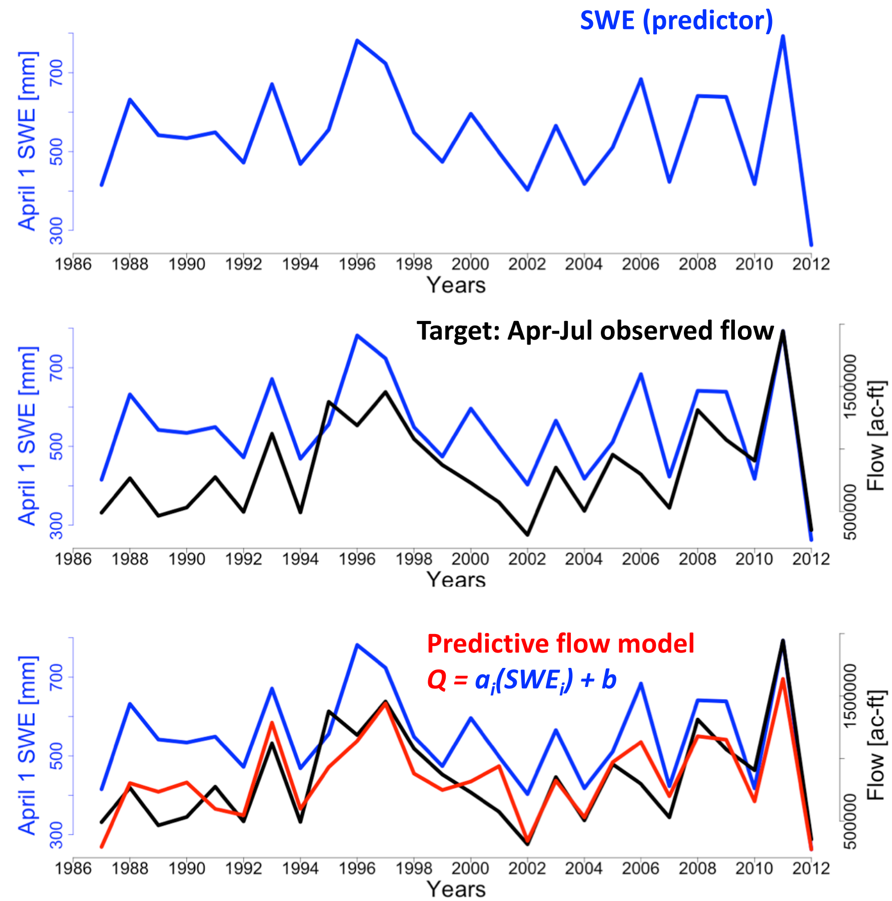
Coefficients

NRCS Visual Interactive Prediction and Estimation Routines (**VIPER**) supports linear, Z-score, and principal components regression

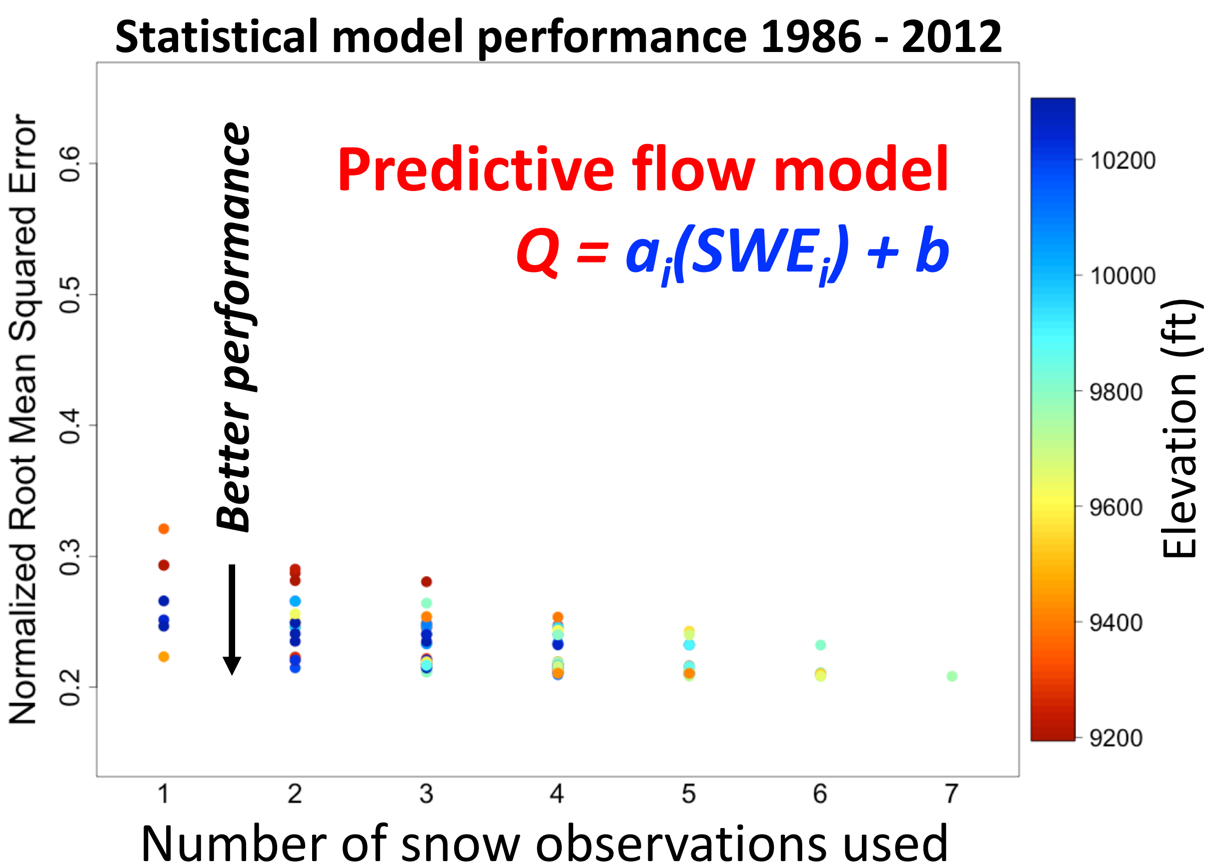
*Other forecast dates include 1 Jan, Feb, Mar, May
Accumulated precipitation is commonly used together with SWE

Baseline: Example for a Colorado River tributary



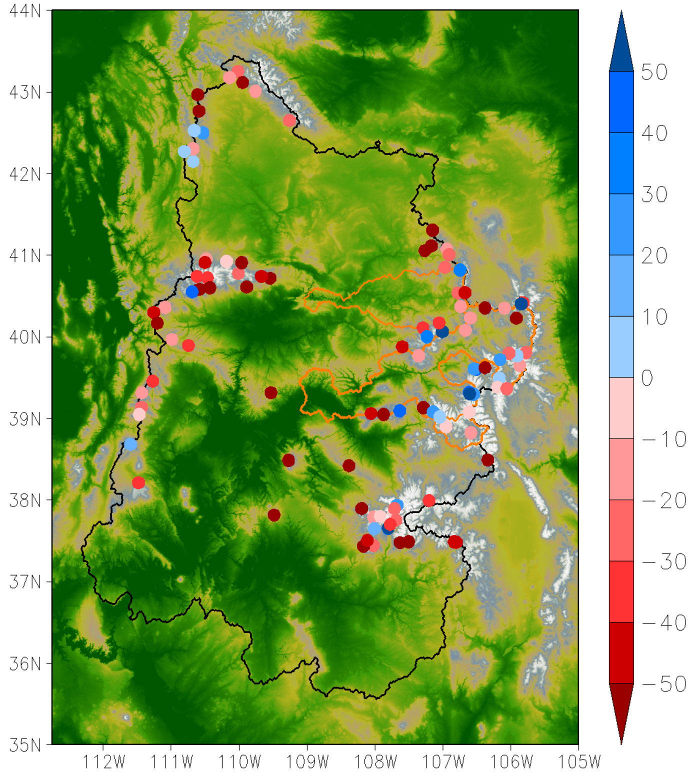


Are higher elevation predictors more robust under climate warming?



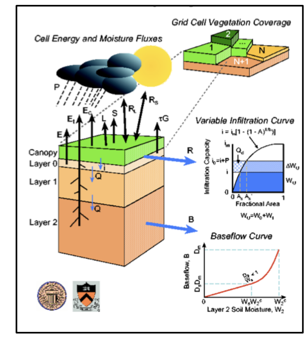
What about under future climate?

Future SWE change



Based on 29 CMIP5 predictions, hydrologically downscaled* Historical simulated April 1 SWE compares favorably with station observations (n=133; *R*=0.93)

VIC model



April 1 SWE bias (mm) for mid century 2036-2065, relative to historical period*:

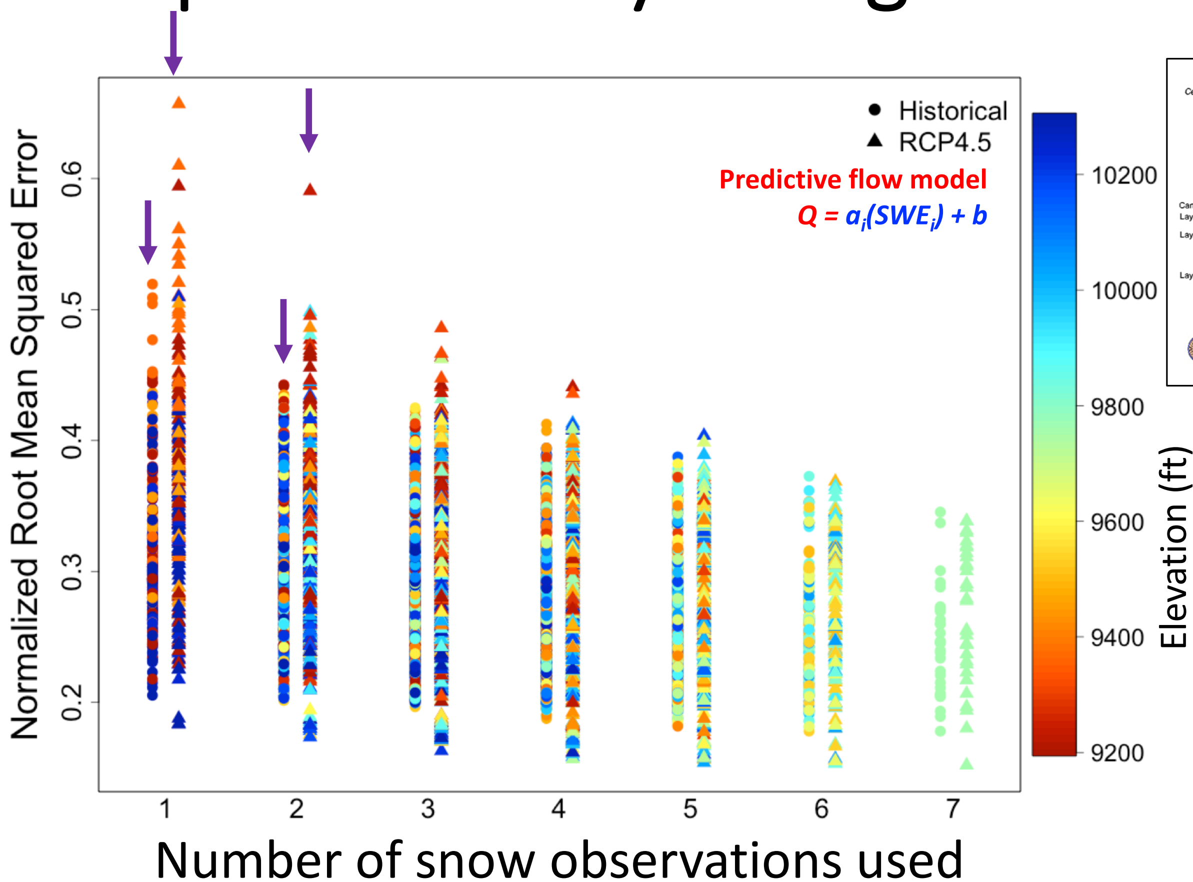
- SWE reductions in most places
- Increases particularly in W. Colorado headwaters

*Brekke, L., Thrasher, B. L., Maurer, E. P., and Pruitt, T. (2013). Downscaled CMIP3 and CMIP5 climate projections: Release of downscaled CMIP5 climate projections, comparison with preceding information, and summary of user needs. Technical Service Center, Bureau of Reclamation, US Department of the Interior, Denver, CO.

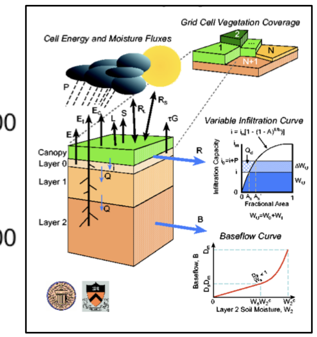
How does future predictability change?

Significant rank correlation between prediction error and elevation (p<0.01)

If we isolate drought years errors get larger in this context



VIC model



*Brekke, L., Thrasher, B. L., Maurer, E. P., and Pruitt, T. (2013). Downscaled CMIP3 and CMIP5 climate projections: Release of downscaled CMIP5 climate projections, comparison with preceding information, and summary of user needs. Technical Service Center, Bureau of Reclamation, US Department of the Interior, Denver, CO.

Drought: Prediction errors in drought years largely depend on the evaluation protocol

Use an *Equitable Threat Score (ETS)* to evaluate the categorical prediction of drought

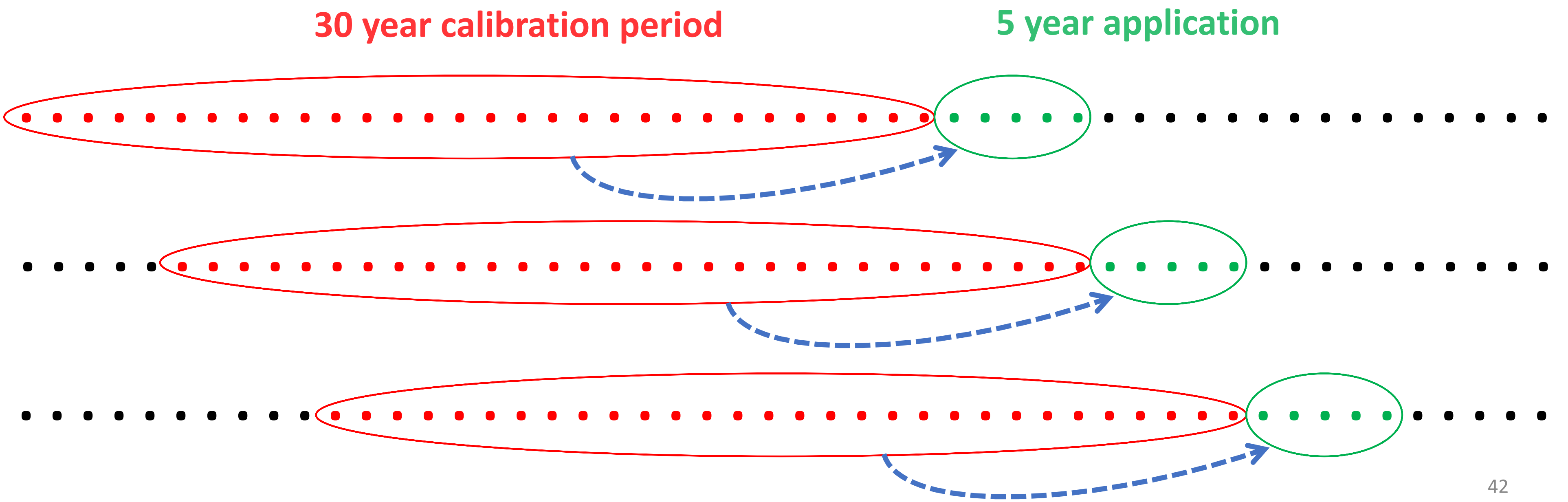
Forecast	**Observation**	
	Drought	No Drought
Drought	Hits (YY)	False alarms (YN)
No Drought	Misses (NY)	Correct rejections (NN)

$$ETS = \frac{Hits - Hits_{random}}{Hits+Misses+FalseAlarms - Hits_{random}}$$

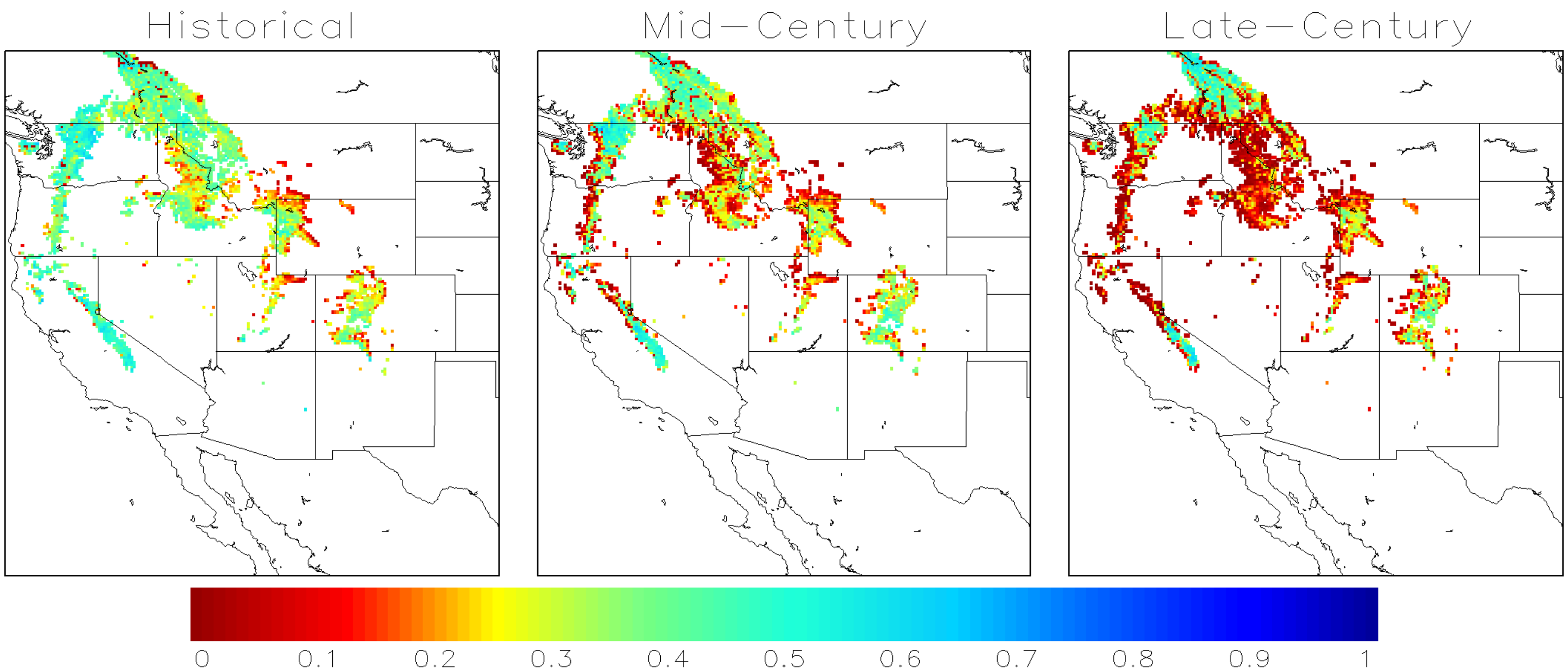
1 – Perfect; -1/3 – No skill

Build a new prediction model every 5 years (as is done in practice) until the year 2100

$$Q = \sum_{i=1}^{n} a_i SWE_i + \epsilon$$



The Upper Colorado River Basin appears uniquely resilient to warming in a drought prediction context

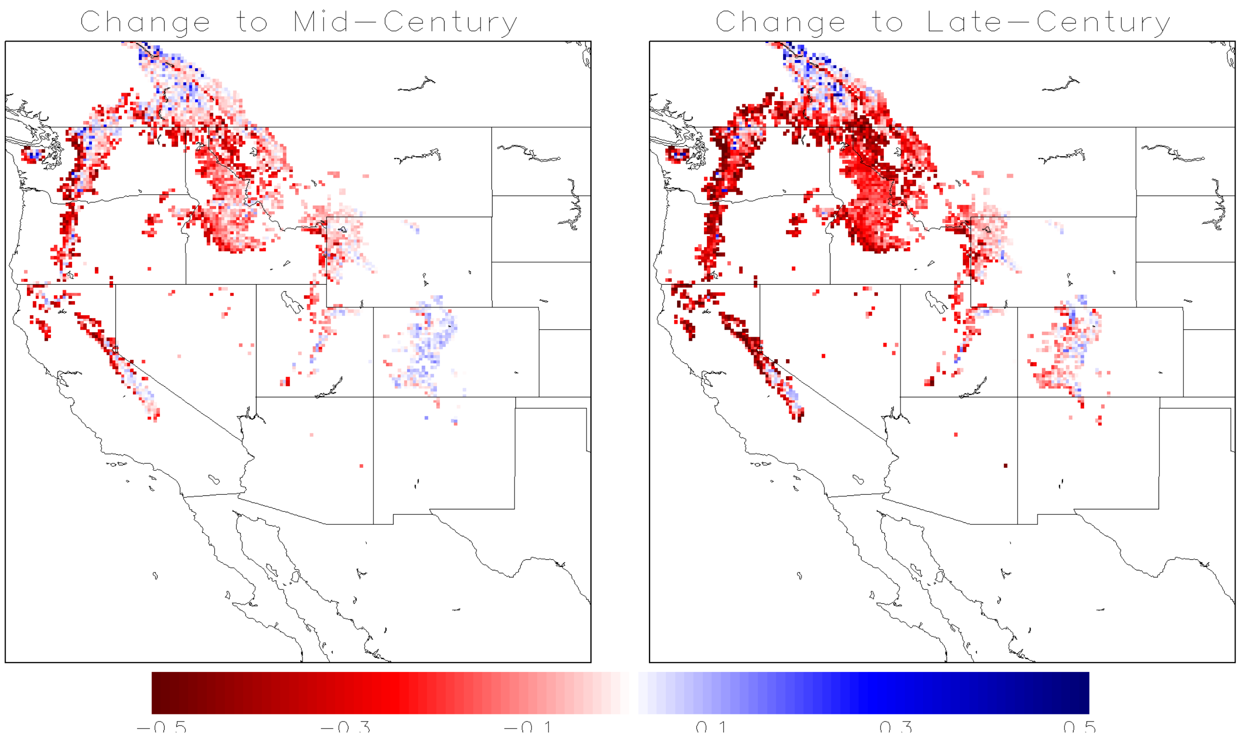


Drought Equitable Threat Score (ETS)

$$ETS = \frac{Hits - Hits_{random}}{Hits + Misses + FalseAlarms - Hits_{random}}$$

1 – Perfect; 0 – No skill

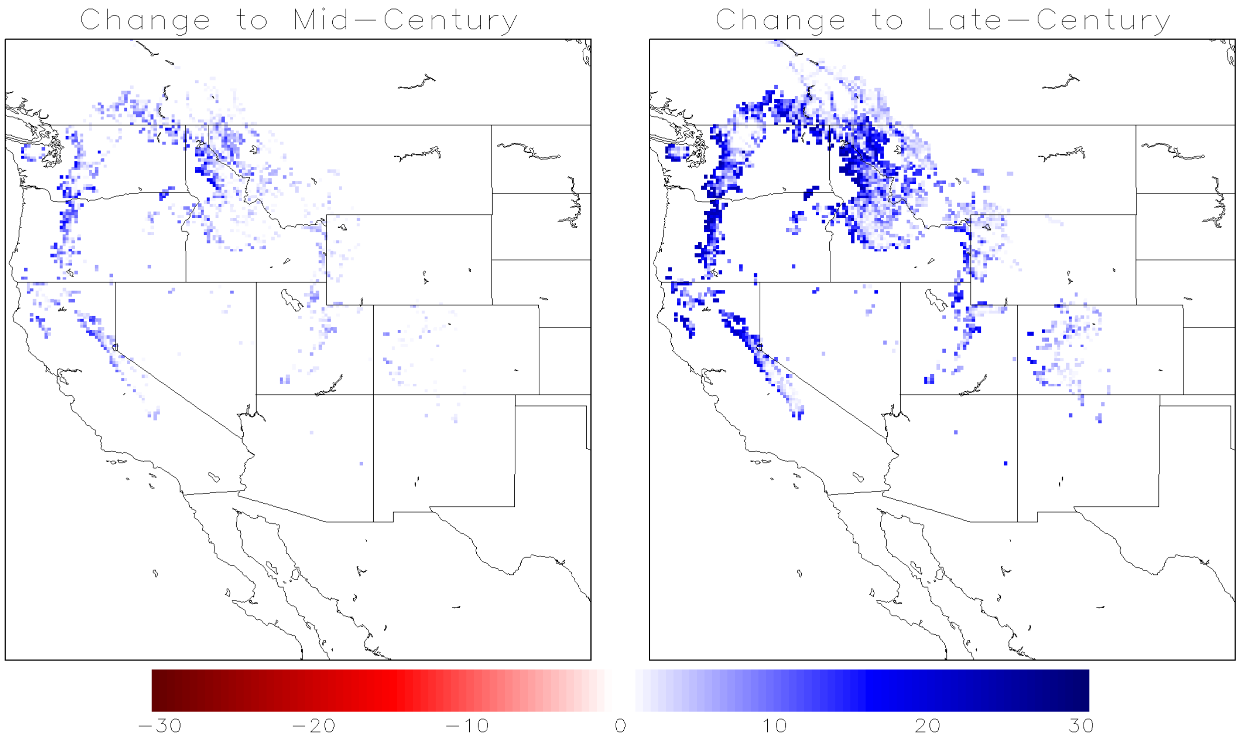
The Upper Colorado River Basin appears uniquely resilient to warming in a drought prediction context



Change in Drought Equitable Threat Score (ETS)

This can be understood through the relative retention of April 1 SWE compared with other regions

Predictive flow model
$Q = a_i(SWE_i) + b$



Change in number of April 1 days without snow

Conclusions and next steps

Drought risk management

- **Drought risk management landscape** (decision context for drought early warning) is **complex**, even for small systems
- **Entrenched reliance** on observed local snowpack suggests that changing information use behavior in the future may be **challenging**

Future hydrology

- Streamflow predictability is **elevation dependent** upon snowpack observations
- Future snowpack/streamflow prediction in the UCRB appears to be **uniquely resilient**

B. Livneh, A.M. Badger, J.J. Lukas, and A. W. Wood, 2018: On the changing role of snowpack in future water prediction (*in prep*).

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