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  Ronnie Abolafia-Rosenzweig  Aaron Heldmyer  Leah Bensching
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**

SMAP sensing depth = 5 cm
Calculating ESMAP

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

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

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

\[ Q = 0 \]

\[ \Delta S \]

\[ \text{negligible} \]
Valid SMAP Overpass Intervals

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

Water balance calculation over intervals without significant precipitation

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)

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

Constants

NLDAS2 Forcing or LSM
MOD13A2 EVI

Restrict by percent of roots in the surface layer

A linear soil moisture restriction on transpiration

\[ SM_r = \frac{\theta_{\text{SMAP}} - \theta_{\text{WLT}}}{\theta_{\text{REF}} - \theta_{\text{WLT}}} \]

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

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, \( q_{\text{bot}} \)**

- Flux is not measured *in situ*

Darcian velocity for unsaturated zone:

\[
q_{\text{bot}} = K(\psi) \left( \frac{\psi_S - \psi_{RZ}}{Z_S - Z_{RZ}} + 1 \right)
\]

Hydrus

in situ

SMAP

Little Washita OK
SMAP Core Validation Site
ESMAP vs Soil Drying Rate

- In the absence of precipitation
  - ESMAP approximates soil drying rate
  - $q_{\text{bot}}$ approaches zero and can even be upward
- Surface transpiration is relatively small, most transpiration comes from the root zone
ESMAP vs NLDAS2 Noah

**Probability Density vs Soil Drying Rate [cm/day]**

- SMAP (Solid Line)
- Noah (Dashed Line)

**Probability Density vs Soil Evaporation [cm/day]**

- ESMAP (Solid Line)
- Noah (Dashed Line)
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

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

Research question:
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

Synthetic experiment:
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
Simulated 6 AM Soil Water Content for each particle

Different Irrigation Forcing for each particle

Best Estimate Irrigation

Best Estimate Irrigation

Synthetic Truth: Precipitation + Known Irrigation

Simulated SMC

Simulated 6 AM Soil Water Content for each particle

Apply Weight \( i \) to particle irrigation

Truth Soil Moisture Content (SMC)

6 AM Truth SMC = Synthetic “Observation” for DA System

Assimilate

Synthetic DA Experiment Design

 Subtract Obs. Precipitation

D
Surface Soil Moisture (cm$^3$cm$^{-3}$) vs. Precipitation Forcing (mm)

- **Different irrigation “precipitation” forcing for each particle**

**Particle Filter Weights**
- W1 = 0.005
- W2 = 0.480
- W3 = 0.500
- W4 = 0.015

**Particle Smoother Weights**
- W1 = 0.083
- W2 = 0.167
- W3 = 0.150
- W4 = 0.600

**Particle Smoother**

\[ P_{PBS} = P1 \times 0.0025 + P2 \times 0.4871 + P3 \times 0.4557 + P4 \times 0.0547 \]

**Date**
- August 1, 0600
- August 2, 0600
- August 3, 0600

- **Resample**

Different colors and markers represent different particle stages and their respective weights.
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

Demonstration of daily assimilation: Soil moisture

Particle Batch Smoother - Soil Moisture Time Series

Surface Soil Moisture (cm$^3$cm$^{-3}$)

Date

04/23/15 04/27/15 05/01/15 05/05/15 05/09/15 05/13/15

Particles
PBS Best Estimate
Synthetic Obs.
Demonstration of daily irrigation calculation
Demonstration of daily irrigation performance

<table>
<thead>
<tr>
<th>Percent bias</th>
<th>1.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>0.98</td>
</tr>
</tbody>
</table>
Performance for SMAP 1-3 day overpass interval

<table>
<thead>
<tr>
<th>Return Interval</th>
<th>Daily</th>
<th>Overpasses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent bias</td>
<td>1.8</td>
<td>0.46</td>
</tr>
<tr>
<td>R</td>
<td>0.98</td>
<td>0.98</td>
</tr>
</tbody>
</table>

**Irrigation Results**

**SMAP Return Interval**

- IRRG	extsubscript{PBS}
- Truth Irrigation

![Graph showing daily irrigation from 04/15 to 09/15 with two lines representing IRRG	extsubscript{PBS} and Truth Irrigation.]
Performance for larger signal-to-noise

<table>
<thead>
<tr>
<th>Observation Noise - RMSE (m³m⁻³)</th>
<th>0.01</th>
<th>0.02</th>
<th>0.03</th>
<th>0.04</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent bias</td>
<td>0.12</td>
<td>0.43</td>
<td>2.38</td>
<td>3.51</td>
<td>9.45</td>
</tr>
<tr>
<td>R</td>
<td>0.97</td>
<td>0.93</td>
<td>0.91</td>
<td>0.86</td>
<td>0.73</td>
</tr>
</tbody>
</table>

**Irrigation Results - SMAP Interval**

Observation Noise = 0.03 cm³cm⁻³

**Irrigation Bias**

Date: 04/15 05/15 07/15 09/15

Daily Irrigation (mm)

Daily Irrigation Bias (mm)
The issue of unknown irrigation time

Daily Irrigation Signal

Timing of satellite overpasses and DA

Irrigation applied after the satellite overpass

Irrigation Timing
- 2-3 AM
- 4-5 AM
- 5-6 AM (Truth)
- 6-7 AM
- 8-9 AM

Surface Soil Moisture (cm$^3$ cm$^{-3}$)

Date

08/01/00 08/01/06 08/01/12 08/01/18 08/02/00 08/02/06 08/02/12
Performance for unknown irrigation times

<table>
<thead>
<tr>
<th>Particulate Irrigation Timing</th>
<th>2-3 AM</th>
<th>4-5 AM</th>
<th>6-7 AM</th>
<th>8-9 AM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent bias</td>
<td>16.87</td>
<td>8.91</td>
<td>57.94</td>
<td>15.9</td>
</tr>
<tr>
<td>R</td>
<td>0.95</td>
<td>0.98</td>
<td>0.85</td>
<td>0.36</td>
</tr>
</tbody>
</table>

**Irrigation Results - SMAP Interval**

- **2-3 AM Particulate Irrigation**
- **4-5 AM Particulate Irrigation**
- **6-7 AM Particulate Irrigation**
- **8-9 AM Particulate Irrigation**
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:
  o 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

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)

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.
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:

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

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

NRCS Visual Interactive Prediction and Estimation Routines (VIPER) supports linear, Z-score, and principal components regression
Baseline: Example for a Colorado River tributary

Predictive flow model

\[ Q = a(SWE_i) + b \]
Are higher elevation predictors more robust under climate warming?

**Predictive flow model**

\[ Q = a_i(SWE_i) + b \]
What about under future climate?

Based on 29 CMIP5 predictions, hydrologically downscaled*

Historical simulated April 1 SWE compares favorably with station observations (n=133; R=0.93)

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

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

Predictive flow model

\[ Q = a_i(SWE) + b \]

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

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Drought</td>
</tr>
<tr>
<td>Drought</td>
<td>Hits (YY)</td>
</tr>
<tr>
<td>No Drought</td>
<td>Misses (NY)</td>
</tr>
</tbody>
</table>

\[
ETS = \frac{\text{Hits} - \text{Hits}_{\text{random}}}{\text{Hits}+\text{Misses}+\text{FalseAlarms} - \text{Hits}_{\text{random}}} \\
1 \text{ – Perfect; } -1/3 \text{ – No skill}
\]
Build a new prediction model every 5 years (as is done in practice) until the year 2100

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

30 year calibration period

5 year application
The Upper Colorado River Basin appears uniquely resilient to warming in a drought prediction context.

**Drought Equitable Threat Score (ETS)**

\[
ETS = \frac{\text{Hits} - \text{Hits}_{\text{random}}}{\text{Hits} + \text{Misses} + \text{False Alarms} - \text{Hits}_{\text{random}}} \\
1 - \text{Perfect; 0 - No skill}
\]
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.

\[ Q = a_i(SWE) + b \]  

Predictive flow model

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**

Acknowledgements

Contributors: Ronnie Abolafia-Rosenzweig, Andrew Badger, Eric Small, Lisa Dilling, Rebecca Page, Jeff Lukas

NASA SUSMAP Grant, NNX16AQ46G, PI-Livneh: Monitoring soil evaporation using SMAP surface soil moisture in a water balance framework

NOAA Sectoral Applications Research Program Grant, NA16OAR4310132, PI-Livneh: “Advancing the Use of Drought Early Warning Systems in the Upper Colorado River Basin”;