Recent Advances in Land Surface Data Assimilation

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Water Cycle Research Making a Difference

http://crew.iges.org
Land Surface Prediction: Accurate land model prediction is essential to enable data assimilation methods to propagate or extend scarce observations in time and space. Based on water and energy balance.

\[
\text{Input - Output} = \Delta S \\
P + \text{Gin} - (\text{Q} + \text{ET} + \text{Gout}) = \Delta S \\
Rn - G = \text{Le} + H
\]

Dominant land surface horizontal processes:
- Groundwater movement
- Horizontal temperature/water diffusion/advection
- Runoff

Assume 1-D Physics at mesoscales (greater than 100m)
- Gravity and gradient driven water & energy movement
- Horizontal processes very weak
- Observed horizontal correlations related to forcing
- Perturbation in state will not change neighbor

Ramifications of 1-D assumption:
- 1-D (vertical) assimilation very cheap
- No account for horizontal correlation in observation/model
- No “advection” of observation information horizontally

Land observations mostly at surface
- Surface skin temperature, soil moisture
- Snow cover
- Want to retrieve full root-zone profile; longer memory states

Nonlinear Processes
- Freeze/Thaw, Infiltration, Interception, Snow Cover, Leaf Fall
- Difficult to linearize, derive adjoint, etc.
Data Assimilation merges observations & model predictions to provide a superior state estimate.

Remotely-sensed hydrologic state or storage observations (temperature, snow, soil moisture) are integrated into a hydrologic model to improve prediction, produce research-quality data sets, and to enhance understanding.

Soil Moisture Assimilation

Snow Cover Assimilation

Theory Development

Also: Runoff, Evapotranspiration, groundwater (gravity), and Carbon Assimilation
Soil Moisture Observation Error and Resolution Sensitivity:

NOTE:
Assimilation of near-surface soil moisture can degrade profile soil moisture if errors are not known perfectly.

- Observation Error (% v/v)
- Spatial Resolution (minutes of arc)
- Temporal Resolution (days)
- Moisture RMS Error (% v/v)
- Soil Moisture Error (% v/v)
- Surface (assimilation)
- Root zone (assimilation)
- Profile (assimilation)
- Surface (no assimilation)
- Root zone (no assimilation)
- Profile (no assimilation)
State and bias filtering: which frequency is optimal?

State and bias filtering extracts more info from observations

⇒ less frequent updating required

State + bias estimation

CLM2.0 + OPE3 data


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Soil Moisture Data Assimilation

Adaptive filtering: retrieval of off-diagonal error covar elements

Training period

Application period

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Soil Moisture Data Assimilation

Adaptive filtering: result when assimilating only 1 profile

Averaged soil moisture plot from 17 sites (SMEX03-Georgia) over AMSR-E 1/4 degree grid. Noah (10 cm and 5 cm layer SM), CLM (4.5 cm layer, layer 1+ layer 2), SCAN (just one station, 5 cm), AMSR-E (2 cm layer), SMEX03 (6 cm layer).
Assimilation of AMSR-E Land Products into the NOAH LSM

Paul Houser, Yan Luo, Xiwu Zhan, Alok Sahoo, Kristi Arsenault, Brian Cosgrove

**GOAL:** Implement Kalman Filter to assimilate land satellite data products into the Noah land surface model installed in the Land Information System (LIS)

**PROGRESS:** Three data assimilation algorithms (DI, EKF, EnKF) have been implemented in LIS and has been tested with various soil moisture observations

**FUTURE:**
- Expand validation of assimilation results.
- Optimize ensemble perturbation procedures
- Finalize AMSR-E scaling philosophy
- Explore brightness temperature assimilation (CRTM)
- Expand to snow cover assimilation

**Quandary:** Official AMSR-E soil moisture product has very low variability, which produces an assimilated product with low variability

**CDF Matching:** Scales AMSR-E to model climatology, erasing any real variability in AMSR-E

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Estimating Bias:

\[
\begin{align*}
    b_t^f &= \mu b_{t-1}^a \\
    b^a &= b^f - L[y^o - (Hx^f - Hb^f)] \\
    L &= P^{bias_b} H^T (HP^{bias_b} H^T + HP^f H^T + R)^{-1}
\end{align*}
\]

Correcting Bias:

\[
\begin{align*}
    \tilde{y}^o &= y^o + Hb^a \\
    x^a &= x^f + K[\tilde{y}^o - Hx^f] \\
    K &= P^f H^T (HP^f H^T + R)^{-1}
\end{align*}
\]

a. Full Scheme

\[ P^{bias_b} = \gamma \ast P^f \]

b. Approximate Scheme

\[ L = \alpha \ast K \]

0 < \mu, \gamma, \alpha \leq 1  

tunable bias correction parameters

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EnKF data assimilation with model climatology key

Top Layer Soil Moisture

- AMSR_E
- Noah Forecast
- Corrected AMSR_E
- "Observation bias"

Bias Estimates

- 0
- 1
- 2
- 3
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v/V

16JUN 2005
1JUL
16JUL
1AUG
16AUG
1SEP
16SEP
(a) Time series plot of the in-situ, AMSR-E and LSMEM SM at 130 hr along with daily average precipitation and irrigation for 2003.

Scatter plot of the corresponding (b) in-situ and AMSR-E soil moisture, (c) in-situ and LSMEM soil moisture data.
Daily top layer soil moisture time series plots from Noah (10 cm layer) open loop and EnKF simulations, in-situ measurements (5 cm layer) and LSMEM retrieval (~ 1 cm).
SMMR Snow Retrieval Error & Assimilation Impact

Error due to signal saturation

Error due to snowpack liquid

Error due to water body contamination

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Land Surface Data Assimilation: Summary

Progress:
- Soil moisture, skin temperature, and snow assimilation have been demonstrated.
- Evapotranspiration, runoff, groundwater (gravity), and carbon assimilation are underway.

Lessons Learned:
- We need to pay attention to the consequences of assimilation, not just the optimum assimilation technique. i.e. does the model do silly things as a result of assimilation, as in snow assimilation example.
- Land model physics can be biased, leading to incorrect fluxes, given correct states.
- Most land observations are only available at the surface, meaning that biased differences in surface observations and predictions can be improperly propagated to depth.
- Assimilation does not always make everything in the model better. In the case of skin temperature assimilation into an uncoupled model, biased air temperatures caused unreasonable near surface gradients to occur using assimilation that lead to questionable surface fluxes.

Near Future Directions:
- Methods to address simultaneous model and observation bias.
- New observations (SMOS, Aquarius, SMAP, etc.).
- Coupled Assimilation (to avoid uncoupled biases).
- Mass/Energy conserving data assimilation techniques?