Assimilation of AMSR-E data and application to the initialization of soil moisture reservoirs in a seasonal forecasting system

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4 – USDA
5 – George Mason University
A simple view of land-atmosphere feedback

Precipitation wets the surface...

...causing soil moisture to increase...

...which causes evaporation to increase during subsequent days and weeks...

...which affects the overlying atmosphere (the boundary layer structure, humidity, etc.)...

...thereby (maybe) inducing additional precipitation

Perhaps such feedback contributes to predictability?

Two things must happen:
1. A soil moisture anomaly must be “remembered” into the forecast period.
2. The atmosphere must respond predictably to soil moisture anomalies.

e.g. Koster et al., *J. Hydromet.*, 2004; Koster et al., *Science*, 2004
NASA seasonal forecast initialization

Operational system (since April 2004)

- Observed precipitation, radiation
- Land model
- Model soil moisture
- GCM initialization
- "Optimal" atmosphere
- Seasonal climate prediction
- Atmos. data assimilation
- Conventional and satellite observations of atmosphere
Future system: AMSR-E assimilation merges information from model and observations.
Soil moisture assimilation

**Remainder of talk: Soil moisture data assimilation**

*Optimal* merging: Consider relative uncertainties in modeled and observed soil moisture. NEED ERROR BARS FOR AMSR-E PRODUCT!
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Results from SMMR

ASSIMILATE

1. SMMR (1978-87)
Satellite retrievals (Owe et al.)
(upper 1.25cm, ~140km, ~3 days)

2. Catchment Model (CLSM) (1979-93)
Model results with observation-corrected
meteorological forcing (Berg, Famiglietti,
et al.)
(upper 2cm, ~40…150km, 6h)

3. Ground data
Global Soil Moisture Data Bank (GSMDB;
Robock et al)
(upper 5…10cm, point scale, ~10 days)
~200 stations total
~70 included in analysis

VALIDATE

AVG. # OF SMRR DATA PER MONTH (79-87)
Global soil moisture climatology?

Bias between model and SMMR soil moisture

1. Strong global and regional biases in all moments.
2. Satellite and model agree equally well (or poorly…) with ground observations ⇒ no agreed climatology.
3. For seasonal forecasts, need only normalized anomalies.
⇒ Scale satellite data before assimilation into a model.

Reichle et al., *J. Hydromet*, 2004
Soil moisture scaling for data assimilation

1. At every location, find percentile of a given satellite measurement on the satellite’s climatological cumulative distribution function (CDF).

2. Find soil moisture that produces the same CDF value on the corresponding model CDF ⇒ “scaled” satellite measurement for assimilation.

In short: Assimilate percentiles.
Soil moisture scaling for data assimilation

**ORIGINAL 9-year data sets**
(model & SMMR soil moisture)

**SCALED 9-year data sets**
(model & SMMR soil moisture)

CDF scaling based on 1 year of satellite data

Reichle et al., *J. Hydromet*, 2004
Reichle & Koster, *GRL* 2004

1 year of satellite data sufficient for considerable reduction in long-term bias.
Results from SMMR

ASSIMILATE

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   (upper 1.25cm, ~140km, ~3 days)

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VALIDATE

Not available under dense vegetation, close to water surfaces, in frozen soil.
## Validation against in situ data

<table>
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<tr>
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<th>Time series correlation coeff. with in situ data [-] (with 95% confidence interval)</th>
<th>Confidence levels: Improvement of assimilation over</th>
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<tr>
<td></td>
<td></td>
<td>SMMR</td>
</tr>
<tr>
<td>Surface soil moisture</td>
<td></td>
<td>.44±.03</td>
</tr>
<tr>
<td>Surface anomalies</td>
<td></td>
<td>.32±.03</td>
</tr>
<tr>
<td>Root zone soil moisture</td>
<td></td>
<td>n/a</td>
</tr>
<tr>
<td>Root zone anomalies</td>
<td></td>
<td>n/a</td>
</tr>
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Assimilation product agrees better with ground data than SMMR or model alone. Modest increase may be close to maximum possible with imperfect in situ data. Modern satellite (AMSR-E), forcing, and validation data should increase skill.

Reichle & Koster, *GRL* 2005
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Time series stats of AMSR-E and SMMR retrievals

AMSR-E mean [m$^3$m$^{-3}$] (06/02-05/05)

SMMR mean [m$^3$m$^{-3}$] (01/79-08/87)
Time series stats of AMSR-E and SMMR retrievals

AMSR-E std \([m^3 m^{-3}]\) (06/02-05/05)

SMMR std \([m^3 m^{-3}]\) (01/79-08/87)
Time series stats of AMSR-E and SMMR retrievals

AMSRE mean \([\text{m}^3\text{m}^{-3}]\) (06/02-05/05)

AMSRE std \([\text{m}^3\text{m}^{-3}]\) (06/02-05/05)

SMMR mean \([\text{m}^3\text{m}^{-3}]\) (01/79-08/87)

SMMR std \([\text{m}^3\text{m}^{-3}]\) (01/79-08/87)

Skukuza site (01/79-08/87)
Comparison of AMSR-E and model soil moisture

AMSR-E and model soil moisture show large differences in mean, variability, and dynamic range. Time series are uncorrelated ($R^2 = .02$).
Assimilation of AMSR-E soil moisture

Skukuza (25.0 S, 31.5 E)

- model
- assimilation
- scaled AMSR-E
- in situ (smA05)
- AMSR-E

surface soil moisture

2003/12/01 2004/01/01 2004/02/01 2004/03/01
Assimilation of AMSR-E soil moisture

Skukuza (25.0 S, 31.5 E)

- Model
- Assimilation
- In situ (smA15)
- In situ (smA30)
- AMSR-E

(root zone soil moisture)

2003/12/01 2004/01/01 2004/02/01 2004/03/01
Validation against in situ data

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<th>Time series correlation coeff. with in situ data [-] (Jun 02 – Apr 05, monthly average)</th>
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<tr>
<td></td>
<td>N</td>
</tr>
<tr>
<td>Surface soil moisture</td>
<td>1</td>
</tr>
<tr>
<td>Root zone soil moisture</td>
<td>1</td>
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For this site, the assimilation product does NOT agree better with ground data than model alone.

Biggest concern are AMSR-E retrievals.
Conclusions

Results:

Improved land initialization enhances sub-seasonal prediction skill.

SMMR assimilation improves land initialization.

AMSR-E assimilation system implemented.

AMSR-E assimilation results undergoing validation.

Biggest concern at this time are AMSR-E soil moisture retrievals.

Outlook:

Continue assessment of soil moisture estimates.

Impact of SMMR and AMSR-E assimilation on seasonal predictions.
THE END.
**Work Plan**

**TASK I – Preparation of input data sets.**

**TASK II – Assimilation and analysis of soil moisture data**
Prepare four different soil moisture datasets: Integrate land model with
1. GCM-produced precip./radiation (GCM forced with observed SST)
2. observed precip./radiation
3. GCM-produced precip./radiation + assimilation of AMSR-E soil moisture
4. observed precip./radiation + assimilation of AMSR-E soil moisture
Assess impact of AMSR-E data on soil moisture estimation.

**TASK III – Experimental prediction**
Ensemble seasonal forecast experiments with initial conditions from TASK II.
Assess impact of observed precip./radiation and AMSR-E assimilation on seasonal forecasts.
Establish routine AMSR-E land assimilation in operational GMAO seasonal forecasting system.
Sample NASA forecast – August 2004

Validation (CAMS)

CAMS Precipitation  Aug. 2004

Forecast 1st month

Aug. 2004 Precipitation init:2004/08/01

Forecast 2nd month

Aug. 2004 Precipitation init:2004/07/01

AMIP ensemble (uses only SST information)

AMIP Aug. 2004 Precipitation

Precipitation

Temperature

CAMS Surface Temperature  Aug. 2004

Aug. 2004 Temperature init:2004/08/01

Aug. 2004 Temperature init:2004/07/01

AMIP Aug. 2004 Temperature

-16 -8 -4 -2 -1 -.5 1 2 4 8 16 mm/day

-5 -4 -3 -2 -1 -.5 .5 1 2 3 4 5 °C
Soil moisture assimilation


Propagation $t_{k-1}$ to $t_k$:

$$x_k^{i+} = f(x_{k-1}^{i-}) + w_k^i$$

$w =$ model error

Update at $t_k$:

$$x_k^{i+} = x_k^{i-} + K_k(y_k^i - x_k^{i-})$$

for each ensemble member $i=1\ldots N$

$$K_k = P_k (P_k + R_k)^{-1}$$

with $P_k$ computed from ensemble spread
Soil moisture scaling for data assimilation

Solution:
Ergodic substitution of variability in space for variability in time.
Soil moisture scaling for data assimilation

Ideally, compute local CDF from long time series at point of interest.

Approximate CDF from many 1-year time series at grid points within 2º from point of interest.

A single year of satellite data is sufficient for a good approximation of the ideal CDF.
Illinois (89.5W, 38.6N)

Validation against in situ data

SMMR assimilation product has improved phase of annual cycle.

Reichle & Koster, GRL 2005