Assimilation of Multiresolution Radiation Products into a Downwelling Surface Radiation Model

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GMAO Seminar Series
October 12, 2010
“Water. It’s about water.”

Response by former Professor and Pulitzer-winning author Wallace E. Stegner when asked what a newcomer should know about California
Hydrologic Cycle
I. Project Motivation
II. Satellite-based Downwelling Radiation Model
III. Ensemble-based Data Assimilation Scheme
IV. Summary of Recent Research
V. Future Work
Project Motivation

- Improve **distributed estimates** of hydrologic states / fluxes (and uncertainty)
  - **Physically-consistent**, cloud-coupled forcing
  - Utilize **satellite-borne** instruments
  - Lead to improved characterization of the **key modes of variability** in land surface states
  - Applicable in physically-based, distributed **hydrologic model** and/or **land surface model** applications
Project Approach

Satellite Measurements
- Clouds
  - Atmosphere
  - Land Surface

Prior Forcing
- Radiation
- Precipitation

Existing Measurement Products, Z

Data Assimilation Framework
\[ y(x, t) \Rightarrow y(x, t | Z) \]
- Information Exchange
- Improve Accuracy
- Reduce Uncertainty
- Spatial Downscaling
- Added Value

Distributed Hydrologic Model
- Radiation
- Precipitation
I. Project Motivation
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Brief Overview

- **Question**: Can a relatively simple model capture space-time patterns in radiative flux?
- Satellite-derived, cloud-coupled estimates of total downwelling radiation
  - Merger of VISST, AIRS, and MODIS products
  - High-resolution (~4 km, ~hourly)
  - Compares well to ground-based radiometer network observations
- Computationally efficient; intended use in ensemble data assimilation scheme
# Satellite-based Inputs

<table>
<thead>
<tr>
<th>Product Name</th>
<th>Required State/Parameter</th>
<th>Orbit Type</th>
<th>Spectral Range</th>
<th>Approximate Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIRS</td>
<td>Near-surface air temperature and humidity</td>
<td>P</td>
<td>IR, MW, NIR, VIS</td>
<td>~50 km, ~1/2 day</td>
</tr>
<tr>
<td>MODIS</td>
<td>Black-sky albedo</td>
<td>P</td>
<td>VIS</td>
<td>~1 km, 16 days</td>
</tr>
<tr>
<td>MODIS</td>
<td>White-sky albedo</td>
<td>P</td>
<td>VIS</td>
<td>~1 km, 16 days</td>
</tr>
<tr>
<td>MODIS</td>
<td>Total precipitable water</td>
<td>P</td>
<td>IR</td>
<td>~5 km, ~1/2 day</td>
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<tr>
<td>MODIS</td>
<td>Near-surface air temperature and humidity</td>
<td>P</td>
<td>IR, NIR</td>
<td>~5 km, ~1/4 day</td>
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<tr>
<td>VISST</td>
<td>Effective cloud height</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
</tr>
<tr>
<td>VISST</td>
<td>Effective cloud temperature</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
</tr>
<tr>
<td>VISST</td>
<td>Effective cloud pressure</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
</tr>
<tr>
<td>VISST</td>
<td>Cloud base height</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
</tr>
<tr>
<td>VISST</td>
<td>Cloud base pressure</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
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<tr>
<td>VISST</td>
<td>Liquid/ice cloud phase</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
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<tr>
<td>VISST</td>
<td>Liquid/ice water path</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
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<tr>
<td>VISST</td>
<td>Effective hydrometeor size</td>
<td>G</td>
<td>IR, VIS</td>
<td>~4 km, ~1/48 day</td>
</tr>
</tbody>
</table>

G=Geostationary; IR=Infrared; LW=Longwave; MW=Microwave; NIR=Near Infrared; P=Polar; SW=Shortwave; VIS=Visible

*Forman and Margulis [2009]*
Shortwave Conceptual Model

\[ R_{\text{SW}}(x, t) = R_{\text{SW}_0} \tau_{\text{SW}} (1 + A \alpha_{\text{diff}}) \frac{1 - r_c - a_c}{1 - r_c a_c} \]

\( \approx 1 \) (clear-sky)

Gautier et al., 1980;
Diak and Gautier, 1983;
Frouin et al., 1988;
Slingo et al., 1989; Liou, 1992;
Gautier and Landsfeld, 1997;
Lee and Margulis, 2007a
Forman and Margulis, 2009
Stefan-Boltzmann Law [c. 1889];
Idso, 1980;
Satterlund, 1979;
Forman and Margulis, 2009

\[
R_{LW}(x, t) = \sigma \left( \varepsilon_a T_a^4 + (1 - \varepsilon_a) \varepsilon_c T_c^4 \right)
\]
Model Application and "Verification"
Cloud States via VISST

Cloud Bottom Height

Effective Cloud Temperature

Cloud Water Path

Cloud Particle Size

29-Sep-2003 [UTC]

Cloud States via VISST

Cloud Bottom Height

Effective Cloud Temperature

Cloud Water Path

Cloud Particle Size

29-Sep-2003 [UTC]
Nominal Radiation Results

Cloud Base Temperature

Nominal Longwave

Cosgrove et al., 2003

Cloud Hydrometeor Size

Nominal Shortwave

Pinker et al., 2003

Forman and Margulis [2009]
Clear-sky Example (22 stations)

Forman and Margulis [2009]
Cloudy-sky Example (21 stations)

Forman and Margulis [2009]
Summary of Findings

• Development of satellite-derived, cloud-coupled downwelling radiative fluxes
  o Requires no ground-based inputs
• High-resolution (space and time)
• Computational efficiency lends itself to ensemble-based framework
• Comparable (or reduced) error to advanced, readily-available products
I. Project Motivation
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**Brief Overview**

- **Question**: Can an ensemble data assimilation scheme capture (and **reduce**) radiative flux uncertainty?
  - **Perturb** atmospheric, land surface, and cloud states (**satellite inputs**)
  - **Spatially-correlated, cross-correlated**
  - **Prior** (unconditioned) ensemble
- Condition prior estimate using a Bayesian conditioning scheme
  - **Merge** model with measurements
- **Reduce uncertainty** while adding value
Uncertainty Characterization

Nominal Simulation

\[ y(x, t) = \begin{bmatrix} R_{LW}^1(x, t) \\ R_{SW}^1(x, t) \end{bmatrix} = \mathcal{A} [u(x, t), t] \]

Prior Replicate

\[ y_j(x, t) = \begin{bmatrix} R_{LW, j}^1(x, t) \\ R_{SW, j}^1(x, t) \end{bmatrix} = \mathcal{A} [u_j(x, t), t] \text{ for } j \in [1, N] \]

Input Uncertainty

\[ u \sim p_u(u); \quad u_j \leftarrow p_u(u) \]

Multiplicative Perturbations

\[ \gamma(x, L) \sim LN(1, C_\gamma(x)) \]

\[ u_j(x, t) = u(x, t) \cdot \gamma_j(x, L) \]

Data-derived Covariance

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>AS</th>
<th>q_\alpha</th>
<th>RS</th>
<th>T_a</th>
<th>WV</th>
<th>HS</th>
<th>T_e</th>
<th>WP</th>
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<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
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<tr>
<td>AS</td>
<td>0</td>
<td>1</td>
<td>-0.24</td>
<td>0.8</td>
<td>-0.44</td>
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<td>q_\alpha</td>
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<td>-0.24</td>
<td>-0.18</td>
<td>0.18</td>
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<td>0.16</td>
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<td>-0.18</td>
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<td>1</td>
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<tr>
<td>WV</td>
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<td>-0.4</td>
<td>0.24</td>
<td>1</td>
<td>0</td>
<td>0</td>
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<tr>
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<td>T_e</td>
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<td>0</td>
<td>0.35</td>
<td>0.35</td>
<td>1</td>
</tr>
</tbody>
</table>

* A: Albedo; AS: Aerosol scattering coefficient; q_\alpha: Air specific humidity; RS: Rayleigh scattering coefficient; T_a: Air temperature; WV: Column-integrated water vapor; HS: Cloud hydrometeor size; T_e: Cloud-base temperature; WP: Cloud water path
Cross-correlated, Spatially-correlated

Cloud Hydrometeor Size

Nominal

Replicate #8

Replicate #9

Cloud Base Temperature

d)

e)

f)
Prior (Unconditioned) Results

Forman and Margulis [Part 1, In Press]
Realistic Uncertainty Structure

Forman and Margulis, Part 1, In Press

e.g. Carpenter and Georgakakos, 2004

Lee and Margulis, 2007

Durand et al., 2008

Spatially-correlated, cross-correlated

\[ \gamma(x, L) \sim \text{LN}(1, C_\gamma(x)) \]

Lumped, mutually independent:

\[ \gamma \sim \text{LN}(1, \sigma^2) \]

Ensemble Mean

Ensemble Standard Deviation
Data Assimilation Scheme

Prior Replicate:

\[ y_j^- (x, t) = A [u_j(x, t), t] \text{ for } j \in [1, N] \]

Bayesian Merging Scheme:

\[ y_j^+ (x, t | Z) = y_j^- (x, t) + K \left[ Z + v_j - M (y_j^- (x, t), t) \right] \]

Where

Gain Matrix:

\[ K = C_{yz} [C_{zz} + C_v]^{-1} \]

Measurement (plus error):

\[ Z + v_j \]

Measurement Model:

\[ M (y_j^- (x, t), t) \]
Products for Assimilation

Prior SW

Pinker SW

GEWEX-SRB SW

Prior LW

NLDAS LW

GEWEX-SRB LW

19-Aug-2004 13:15:00 [UTC]
Measurement Error Models

(a) Assimilated measurement RMSE [W m$^{-2}$] for SRB-LW

(b) Assimilated measurement RMSE [W m$^{-2}$] for SRB-SW

(c) Assimilated measurement RMSE [W m$^{-2}$] for NLDAS-LW

(d) Assimilated measurement RMSE [W m$^{-2}$] for Pinker-SW
Conditioned Shortwave Example

Prior Ensemble Mean

Prior Standard Deviation

Posterior Ensemble Mean

Posterior Standard Deviation

19-Aug-2004 06:00:00 [LST]
Prior vs. Posterior Uncertainty

**Shortwave**

- **Prior Ensemble**
  - SW Prior [W m$^{-2}$]
  - Hour of Day [LST]

- **Posterior Ensemble**
  - SW Posterior [W m$^{-2}$]

- **Ground-based Observation**
  - ○

- **Ensemble Mean**
  - -

- **Individual Replicate**
  - =

**Longwave**

- **Prior Ensemble**
  - LW Prior [W m$^{-2}$]

- **Posterior Ensemble**
  - LW Posterior [W m$^{-2}$]

- **Ground-based Observation**
  - ○

- **Ensemble Mean**
  - -

- **Individual Replicate**
  - =

_Forman and Margulis [Part 2, In Press]_
Ensemble Comparisons

Forman and Margulis [Part 2, In Press]
Prior Uncertainty Matters

Forman and Margulis [Part 2, In Press]
Summary of Findings

• **Ensemble** formulation implicitly contains the uncertainty

• Data assimilation framework **adds utility**
  o **Increased accuracy** relative to SIRS
  o **Reduced uncertainty** in posterior ensemble
  o Effectively **downscales measurements**
    - Interpolates in time (smoother only)
    - **Adds value** to existing measurements
  o **Not site specific** and **flexible** with non-Gaussian statistics and non-linear models
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Summary of Recent Research

- **Satellite-based** Assimilation Framework
  - Global framework
  - Uncertainty implicit within ensemble
    - Cross-correlated, spatially-correlated
    - Capture complex spatiotemporal structure
  - Improved accuracy and reduced uncertainty
- Captures key modes (1\textsuperscript{st} and 2\textsuperscript{nd} moments)
- Applications include:
  - Hydrology and earth system science (rad. & ppt.)
  - Water resources management (ppt.)
  - Agriculture (broadband longwave rad.)
  - Renewable energy (broadband shortwave rad.)
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Ensemble Radiation and Precipitation

Cloud Water Path

Precipitation

Shortwave

Longwave

19-Aug-2004 08:00:00 [LST]
Horizontal Correlations in “2D” Filter

\[ \mathcal{L} = 1^\circ \]

\[ \mathcal{L} = 3^\circ \]

\[ \mathcal{L} = 4.6^\circ \]
GRACE DA and SWE Estimation
Acknowledgements

- Professor **Steven Margulis**, Advisor
- **NASA Earth System Science Fellowship**
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- Oklahoma Mesonet Program