Development, Validation, and Application of OSSEs at NASA/GMAO

Ronald Errico
Nikki Privé

Goddard Earth Sciences Technology and Research Center
at Morgan State University

and

Global Modeling and Assimilation Office
at NASA Goddard Space Flight Center
Acknowledgements

Runhua Yang
Ricardo Todling
Meta Sienkiewicz
Jing Guo
Will McCarty
Joseph Stassi
Wei Guo
Arlindo Da Silva
Amal El Akkraoui
Joanna Joiner
Ronald Gelaro
Michele Rienecker
ECMWF
Outline:

1. General methodology and requirements
2. Simulation of observations and their errors
3. OSSE validation in terms of DAS statistics
4. OSSE validation in terms of forecast statistics
5. Warnings
6. Problems with latest GMAO experiments
Data Assimilation of Real Data

Real Evolving Atmosphere, with imperfect observations. Truth unknown

Observing System Simulation Experiment

Climate simulation, with simulated imperfect “observations.” Truth known.
Applications of OSSEs

1. Estimate effects of *proposed instruments* (and their competing designs) on analysis skill by exploiting simulated environment.

2. Evaluate present and *proposed techniques* for data assimilation by exploiting known truth.
Requirements for an OSSE

1. A simulation of “truth”, generally produced as a free-running forecast produced by an NWP model (termed the “Nature Run”).

2. A simulation of a complete set of observations, drawn from truth.

3. A simulation of observational instrument plus representativeness errors to be added to the results of step 2.

4. A data assimilation system to ingest the results of step 3.

All these steps must be done well enough to produce believable and useful metrics from step 4.
Choice of a Nature Run

1. A good simulation of nature in all important aspects
2. Ideally, individual realizations of the NR should be indistinguishable from corresponding realizations of nature (e.g., analyses) at the same time of year.
3. Since a state-of-the-art OSSE will require a cycling DAS, the NR should have temporal consistency.
4. For either 4DVAR or FGAT 3DVAR, or for high spatial resolution, NR datasets should have high frequency (i.e., < 6 hours)
5. Since dynamic balance is an important aspect of the atmosphere affecting a DAS, the NR datasets should have realistic balances.
6. For these and other reasons, using a state-of-the-art NWP model having a demonstrated good climatology to produce NR data sets is arguably the best choice.
Simulations of Nature (Nature Runs)

<table>
<thead>
<tr>
<th></th>
<th>ECMWF</th>
<th>GMAO</th>
</tr>
</thead>
<tbody>
<tr>
<td>NR Source</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Availability</td>
<td>now</td>
<td>Summer 2014</td>
</tr>
<tr>
<td>Horizontal Resolution</td>
<td>35 km</td>
<td>7 km</td>
</tr>
<tr>
<td># Vertical levels</td>
<td>91</td>
<td>72</td>
</tr>
<tr>
<td>Full Period</td>
<td>1 year</td>
<td>2 year</td>
</tr>
<tr>
<td>Output Frequency</td>
<td>3 hourly</td>
<td>0.5 hourly</td>
</tr>
<tr>
<td>Other Characteristics</td>
<td>O3</td>
<td>16 aerosols, CO, CO2, O3</td>
</tr>
<tr>
<td>Data set size</td>
<td>2 TB</td>
<td>2500 TB</td>
</tr>
</tbody>
</table>
Simulation of Observations

1. Any observation that can be assimilated can be simulated!

\[ \mathbf{y} = H_z(\mathbf{z}) \]

2. Differences between the H used to assimilate and simulate will be interpreted by the DAS as representativeness errors

\[ \epsilon_R = H(\mathbf{x}_t[\mathbf{z}]) - H_z(\mathbf{z}) \]

3. Therefore, as more realism is modeled for the observation simulation compared to the assimilation, more representativeness error is introduced, including gross errors that must be identified by the DAS quality control.

4. It may be necessary to compensate for deficiencies in the nature run (e.g., unrealistic cloud cover) when simulating observations.
Simulation of Observation Errors

1. When simulating observations, there is no instrument and thus no instrument error. It therefore needs to be explicitly simulated and added, unless it is negligible.

2. An error of representativeness is generally implicitly created:

\[
\epsilon_R = H(x_t[z]) - H(z)
\]

3. The real representativeness error is likely underestimated by the implicit component. Additional representativeness error needs to be simulated.

4. If real observation errors are correlated, the simulated ones must also be if the OSSE is to verify.

5. Errors effectively removed by the DAS may not require careful simulation!
Probabilities of radiances being affected by clouds

Effective radiative surface is a high-level cloud

\[ P_H = \int_{F_h} P(H|f_h) P(f_h) \, df_h \]

Effective radiative surface is a medium-level cloud

\[ P_M = \int_{F_h} \int_{F_m} P([M|\overline{H}]|f_m) \left[ 1 - P(H|f_h) \right] P(f_m, f_h) \, df_m \, df_h \]

Effective radiative surface is a low-level cloud

\[ P_L = \int_{F_h} \int_{F_m} \int_{F_l} P([L|\overline{H} \cap \overline{M}]|f_l) \left[ 1 - P(H|f_h) - P(M|f_m, f_h) \right] P(f_l, f_m, f_h) \, df_l \, df_m \, df_h \]
$P(H \mid f_h)$

Cloud fraction $f_h$

$P$
Locations of QC-accepted observations for AIRS channel 295 at 18 UTC 12 July

Simulated

Real
Simulation of observations

RAOB observation lunch time and final pressure determined by a corresponding real observation

RAOB trajectory determined from NR wind fields

RAOB significant levels determined from NR sounding

SATWINDS determined from locations with NR clouds or moisture gradients
All relevant metrics depend on system errors

Analysis error

\[ \tilde{A} = \tilde{A}(B, \tilde{B}, R, \tilde{R}, Q) \]

Background or Forecast error

\[ \tilde{B} = \tilde{B}(\tilde{A}, Q, M) \]

Observation error

\[ \tilde{R} = \tilde{R}(\tilde{E}, \tilde{F}) \]

Daley and Menard 1993 MWR
Observational Error Simulation

All observations have added random error with tuned variances

Portions of added errors for:

- RAOB soundings are vertically correlated
- AMSUA, MHS are horizontally correlated
- SATWINDS vertically and horizontally correlated
- AIRS and IASI channel correlated

No mean errors added

No gross errors added
Assimilation System

GEOS-5 (GMAO) DAS/Model

NCEP/GMAO GSI (3DVAR) scheme

Resolution: 55km, 72 levels

Evaluation for 1-31 July 2005, with 2 week, accelerated spin up in June.

Observations include all “conventional” observations available in 2011 (except for precipitation rates) and all radiance available from AMSU-A, MHS, HIRS-4, AIRS, IASI instruments, plus GPSRO.
Validation of OSSEs

As for any simulation, OSSE results apply to the assimilation of real data only to the degree the OSSE for such an application validates well with regard to relevant metrics.

OSSE validity is first determined by carefully comparing a variety of statistics that can be computed in both the real assimilation and OSSE contexts.

Since data assimilation is a fundamentally statistical problem, OSSE validation and application must generally be statistical.
Standard deviations of QC-accepted y-H(xb) values (Real vs. OSSE)

RAOB U Wind

AMSU-A METOP-A
Horizontal correlations of y-H(xb)

Evaluations for 20-90 N

GOES-IR SATWND 300 hPa

RAOB T 700 hPa

--- is OSSE without correlated observation errors
Correlations Between Channels of AIRS Innovations

OSSE

REAL
Time mean Analysis increments

T 850 hPa

U  500 hPa

OSSE Real
Square roots of zonal means of temporal variances of analysis increments

- **T Real**
- **T OSSE**
- **U Real**
- **U OSSE**
OSSE vs Real Data: Forecasts

NH Anomaly Correlation: July

SH Anomaly Correlation: July
U-Wind RMS error: July

Solid lines: 24 hour RMS error vs analysis
Dashed lines: 120 hr forecast RMS error vs analysis
July Adjoint: dry error energy norm
July Adjoint: dry error energy norm

Adjoint AMSU-A Impact

Control
OSSE
Warnings
Past problems with some OSSEs

1. Some OSSEs use a very reduced observation set of as a control
2. Some OSSEs have very limited validation
3. Some OSSEs are based on very limited “case studies”
4. Some OSSEs use unrealistic observation errors (e.g., no rep. error)
5. Some OSSEs use a deficient NR
Warnings
General criticisms of OSSEs

1. In OSSEs, the NR and DAS models are generally too alike, therefore underestimating model error and yielding overly-optimistic results.

2. When future specific components of the observing systems are deployed, the system in general will be different as will the DAS techniques, and therefore the specific OSSE results will not apply.

3. OSSEs are just bad science!
Response to Warnings

1. Design OSSEs thoughtfully.
2. Consider implications of all assumptions.
3. Validate OSSEs carefully.
5. Specify reasonable observation error statistics.
6. Avoid conflicts of interest.
7. Avoid over-selling results.
8. Only attempt to answer appropriate questions.
9. Be skeptical of others’ works.
10. Be critical of your own work (This is science!).
Fractional reduction of zonal means of temporal variances of analysis errors compared with background errors

\[ \frac{\overline{e_b^2} - \overline{e_a^2}}{\overline{e_b^2}} \]

From validation experiment reported last year
Fractional reduction of zonal means of temporal variances of analysis errors compared with background errors

\[
\frac{\overline{e_b^2} - \overline{e_a^2}}{\overline{e_b^2}}
\]

From latest validation experiment
Square roots of zonal means of temporal variances of analysis increments

T  Real

T  OSSE

U  Real

U  OSSE
Characteristics of Real Observation Errors

1. Generally unknown
2. Even statistics not well known
3. Often biased
4. Correlated (maybe even with background error)
5. Include gross errors
6. Generally non-Gaussian
   (a result of 5 or some basic physics; e.g. nonlinearity)