## The Design, Validation, and Applications of Observing System Simulation Experiments

By

Ronald M. Errico

Goddard Earth Sciences and Technology Center (UMBC) Global Modeling and Assimilation Office (NASA)

## Outline

- 1. OSSE basics
- 2. The OSSE project at GMAO
- 3. Validation metrics
- 4. Use of an OSSE to evaluate a DAS
- 5. Warnings

### **Data Assimilation of Real Data**



## **Observing System Simulation Experiment**

## Applications of OSSEs

- 1. Be able to estimate the effect of proposed instruments on analysis and forecast skill by "flying" them in a simulated environment.
- 2. Be able to evaluate present and proposed data assimilation techniques in a simulation where "truth" is known perfectly.

## Requirements for an OSSE system

- 1. A self-consistent and realistic simulation of nature.
- 2. Simulation of all presently-utilized observations, derived from the "nature run" and having simulated instrument plus representativeness errors characteristic of real observations.
- 3. A validated baseline assimilation of the simulated data that, for various relevant statistics, produces values similar to corresponding ones in a real DAS.

## 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, 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.

#### Results using a Kalman Filter

*Applied to a linear model with white noise error, etc.* Analysis

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{B}\mathbf{H}^{\mathrm{T}} \left[\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^{\mathrm{T}}\right]^{-1} \left[\mathbf{y} - \mathbf{H}\mathbf{x}_b\right]$$

Analysis error covariance

$$\mathbf{A} = \left(\mathbf{B}^{-1} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\right)^{-1}$$

Forecast Error

$$\mathbf{B} \;=\; \mathbf{M} \mathbf{A}^{(n-1)} \mathbf{M}^{\mathrm{T}} \;+\; \mathbf{Q}$$

 ${f R}$  includes instrument plus representativeness error

$$\mathbf{R} = \mathbf{E} + \mathbf{F}$$

Therefore  $\mathbf{A} = \mathbf{A}(\mathbf{E}, \mathbf{F}, \mathbf{Q}, \mathbf{M})$  Daley and Menard 1993 MWR

### Characteristics of Real 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)

## The GMAO OSSE Project

NASA Personnel: Ronald Errico, Runhua Yang, Will McCarty, Meta Sienkiewicz, Emily Liu, Ricardo Todling, Ronald Gelaro, Jing Guo, Arlindo da Silva, Ravi Govindaraju Michele Reinecker, Joanna Joiner (200+ years of expertise, mostly in data assimilation)

Consultations with JCSDA, NCEP, NESDIS, ECMWF

Some support from NSF

## **Immediate Goal**

Quickly generate a prototype baseline set of simulated observations that is significantly "more realistic" than the set of baseline observations used for the previous NCEP/ECMWF OSSE.

Account for:

- Resources are somewhat limited
- The Nature Run may be unrealistic in some important ways Some issues are not very important compared to others Some important issues may still have many unknown aspects

Two Ways of Generating Observations

- Create observations as realistically as possible Most complete way of incorporating realism Less prone to erroneous pre-judgements about importance Many obs not used due to data thinning Must incorporate gross errors (need statistics model) Some obs characteristics may be irrelevant (e.g., cloudy IR) May need to adjust due to NR deficiencies (e.g., precip)
- 2. Create observations with realistic distributions and error statistics Minimal but necessary requirement for simulating observations Must decide and consider what is important Can ignore some aspects of obs (e.g., many details of gross errors) Can ignore details of some portions of DAS algorithm (e.g, QC) Can design with flexibility to account for NR unrealism

# The OSSE problem: DAS: $x_a - x_b = K [y - H(x_b)]$ OSSE obs: $y = H'(x_{NR})$

- 1. The information provided to the DAS by the observations are the *innovations*  $y-H(x_b)$ .
- 2. Differences between the operators H and H' contribute to the innovations in a way that is interpreted by the DAS as a contribution to the *representativeness* error.
- 3. Making H' more realistic but concurrently more unlike H acts to make the representativeness error more realistic rather than to increase the observation information content unusable by the DAS.
- 4. A valid OSSE requires that the characteristics of rep. + instrument errors, including their non-Gaussian aspects, are sufficiently considered and adequately simulated.

## Validation Metrics

- 1. Data assimilation is a fundamentally statistical problem, and an observing system therefore can only be reliably evaluated statistically.
- 2. For a NR given by a free-running NWP model solution, there is no correspondence between realizations of "weather" in it and in the real world on any specific date.

#### Validation of numbers of assimilated obs

### Example from GMAO OSSE test for HIRS-3, NOAA-17, Jan 2006



#### Validation of spatial distribution of assimilated obs



Locations of Brightness Temperature accepted by the Quality-Control for NOAA-17 channel 7 HIRS-3 on 15 Jan 2006 at 0 UTC +/- 3hrs

Ignore colors

OSSE Data



### Validation of analysis increment $(x_a - x_b)$ statistics



OSSE

Standard deviations of analysis increments u field, 500 mb



#### Validation of analysis increment $(x_a - x_b)$ statistics



OSSE

mean values of analysis increments u field, 500 mb

Real

#### Validation of O-F and O-A statistics

### Example from GMAO OSSE test for HIRS-3, NOAA-17, Jan 2006



#### **Reference DAS**



### Validation of O-F distribution



OSSE Data

Real Data

Distribution of Innovations (O-F) of Brightness Temperature accepted by the Quality-Control for NOAA-17 channel 7 HIRS-3 on 15 Jan 2006 at 0 UTC +/- 3hrs Ignore colors



#### Validation of Obs Impacts

## Adjoint-derived estimates of observation impacts J=2\*KE+APE of 24-hour forecast error



Validation of Forecast Skill

Use of an OSSE to evaluate a DAS

Errico, R.M., R. Yang, M. Masutani, M., and J. Woollen, 2007: Estimation of some characteristics of analysis error inferred from an observation system simulation experiment. Meteorologische Zeitschrift, **16**, 695-708.

Nature Run: ECMWF 1993 model T213L31, 5-week simulation

DAS: NCEP SSI system from 2005 at T170L42 resolution

Standard Deviation of the analysis increment for the u-wind in the former NCEP/ECMWF OSSE

> T170L42 resolution Feb. 1993 obs network



stdv Ainc\_U at 494mb



#### Analysis error standard deviations: u on eta=0.5 surface



Measured Gain at 12Z ~500 mb

$$gain = \frac{\sigma_b^2 - \sigma_a^2}{\sigma_b^2}$$



#### Horizontal 2-D Spectra of Transient Fields at ~716 mb 12Z, T170

Solid=Nature Run

Dotted = Analysis Error



# Warnings

## Past problems with some OSSEs

- 1. Some OSSEs use "no obs" as control
- 2. Some OSSEs have no validation of their control DAS
- 3. Some OSSEs are based on very limited "case studies"
- 4. Some OSSEs use unrealistic obs errors (e.g., no rep. error)
- 5. Some OSSEs use a very 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 more thoughtfully.
- 2. Validate OSSEs more carefully.
- 3. Specify reasonable obs error statistics.
- 4. Avoid conflicts of interest.
- 5. Avoid over-selling results.
- 6. Only attempt to answer appropriate questions
- 7. Consider possible effects of any approximations
- 8. Be critical of your own work
- 9. Be skeptical of others' works
- 10. Expose poor work.