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

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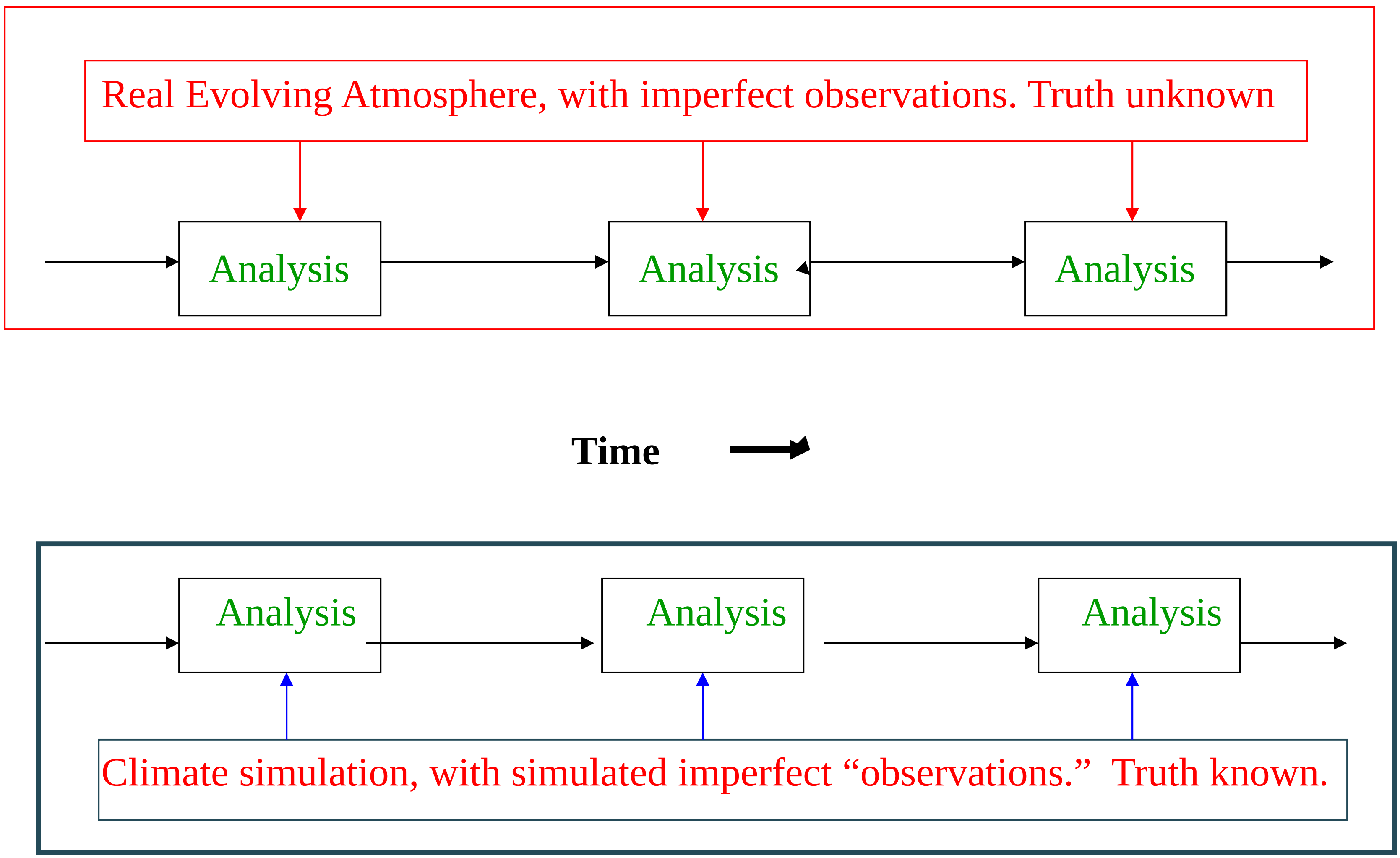
Outline:

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



Observing System Simulation Experiment

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)

NR Source	ECMWF	GMAO
Availability	now	Summer 2014
Horizontal Resolution	35 km	7 km
# Vertical levels	91	72
Full Period	1 year	2 year
Output Frequency	3 hourly	0.5 hourly
Other Characteristics	O3	16 aerosols, CO, CO2, O3
Data set size	2 TB	2500 TB

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:

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

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

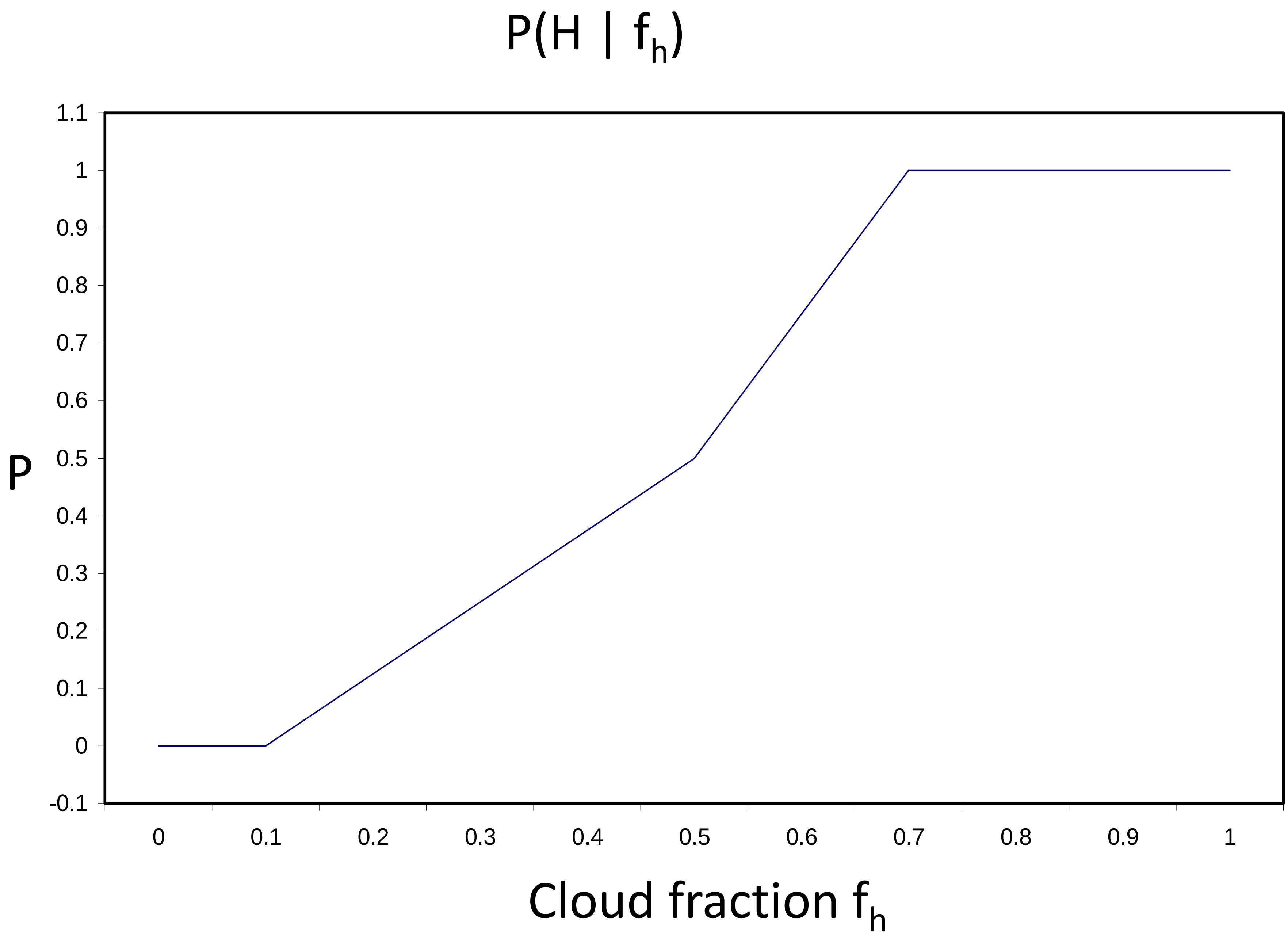
$$P_H = \int_{F_h} P(H|f_h)P(f_h)\; df_h$$

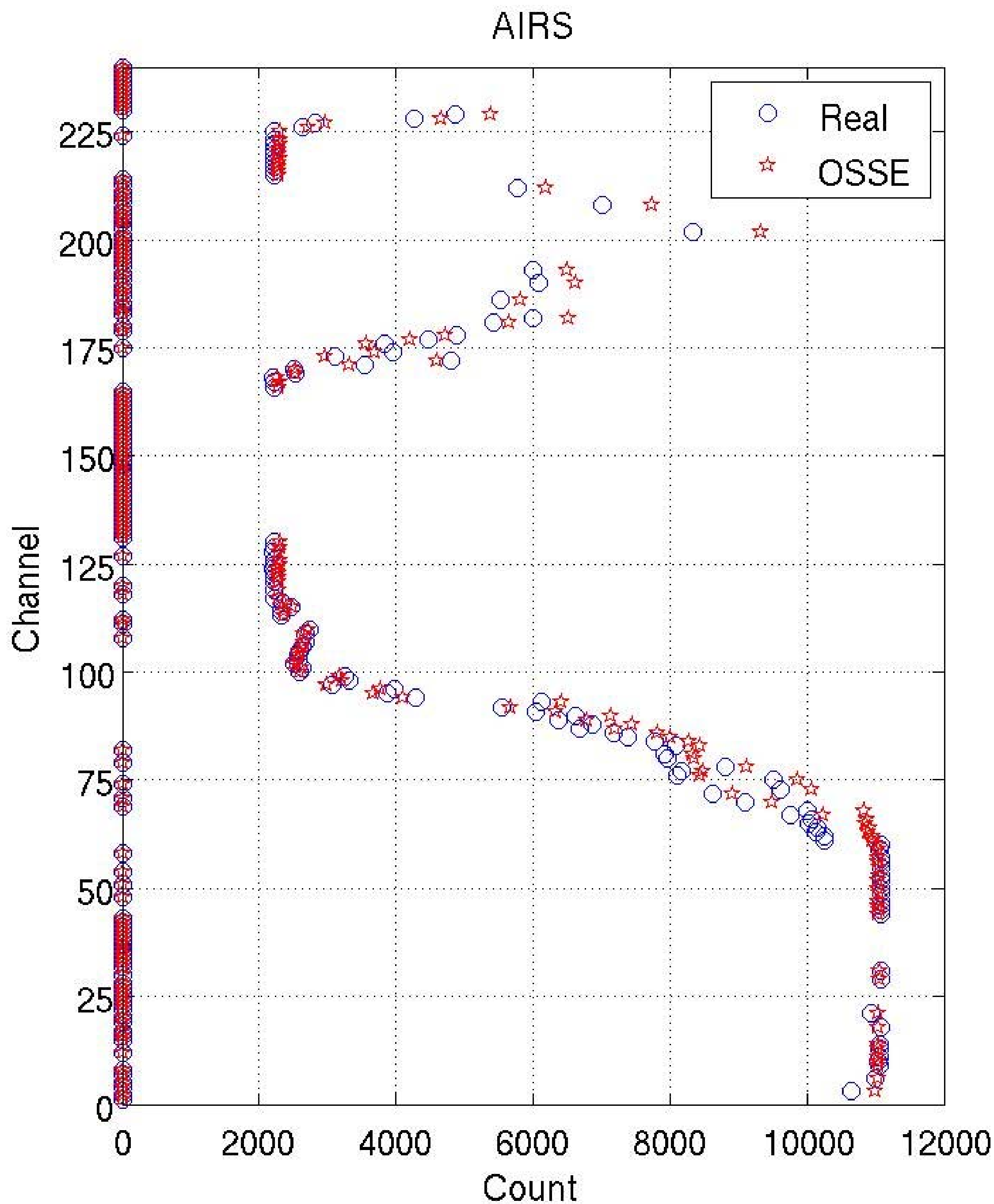
Effective radiative surface is a medium-level cloud

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

Effective radiative surface is a low-level cloud

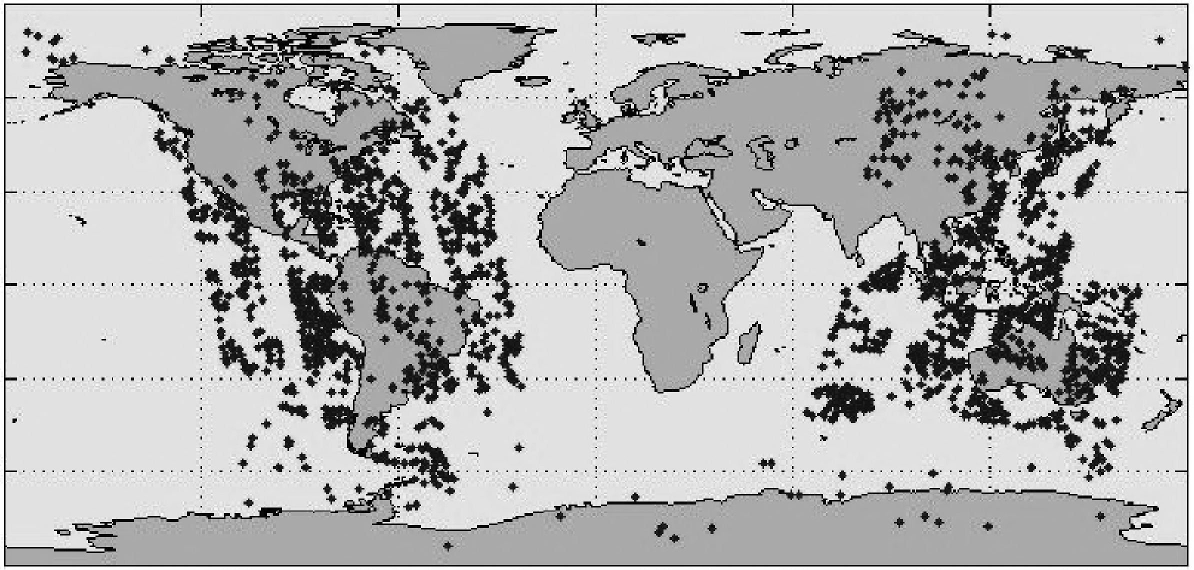
$$P_L = \int_{F_h}\int_{F_m}\int_{F_l} P([L|\overline{H}\cap\overline{M}]|f_l)\; [1 - P(H|f_h) - P(M|f_m, f_h)]\; P(f_l, f_m, f_h)\; df_l\; df_m\; df_h$$


P(H | f_h)
1.1
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
P
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Cloud fraction f_h

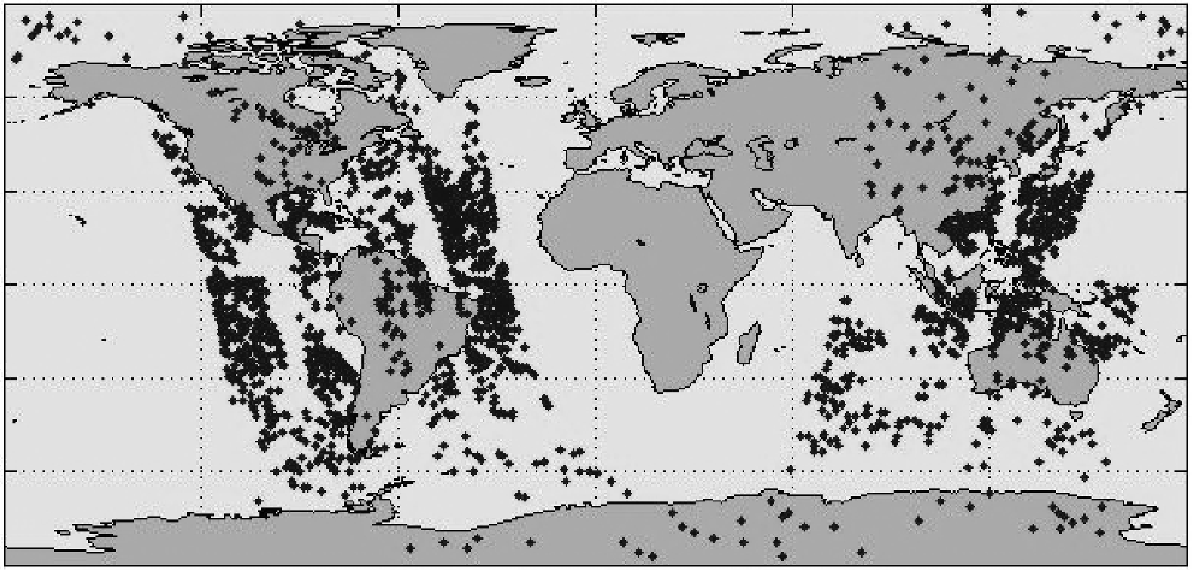

AIRS
Real
OSSE
Channel
Count
0
25
50
75
100
125
150
175
200
225
0
2000
4000
6000
8000
10000
12000

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

$$\tilde{\mathbf{A}} = \tilde{\mathbf{A}}(\mathbf{B}, \tilde{\mathbf{B}}, \mathbf{R}, \tilde{\mathbf{R}}, \mathbf{Q})$$

Background or Forecast error error

$$\tilde{\mathbf{B}} = \tilde{\mathbf{B}}(\tilde{\mathbf{A}}, \mathbf{Q}, M)$$

Observation error

$$\tilde{\mathbf{R}} = \tilde{\mathbf{R}}(\tilde{\mathbf{E}}, \tilde{\mathbf{F}})$$

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

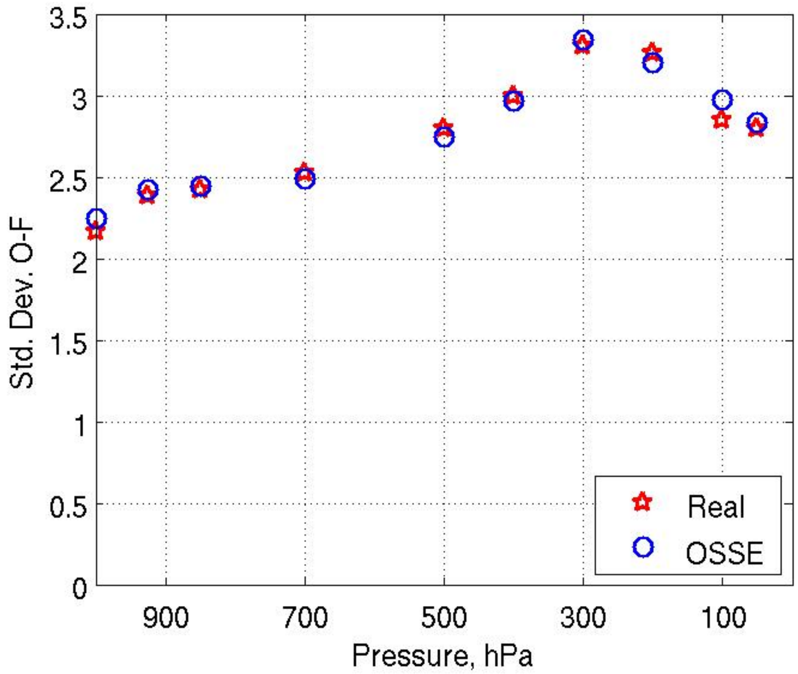
As for any simulation, OSSE results apply to the assimilation of real data only to the degree the OSSE for such an application validates well with regard to relevant metrics.

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

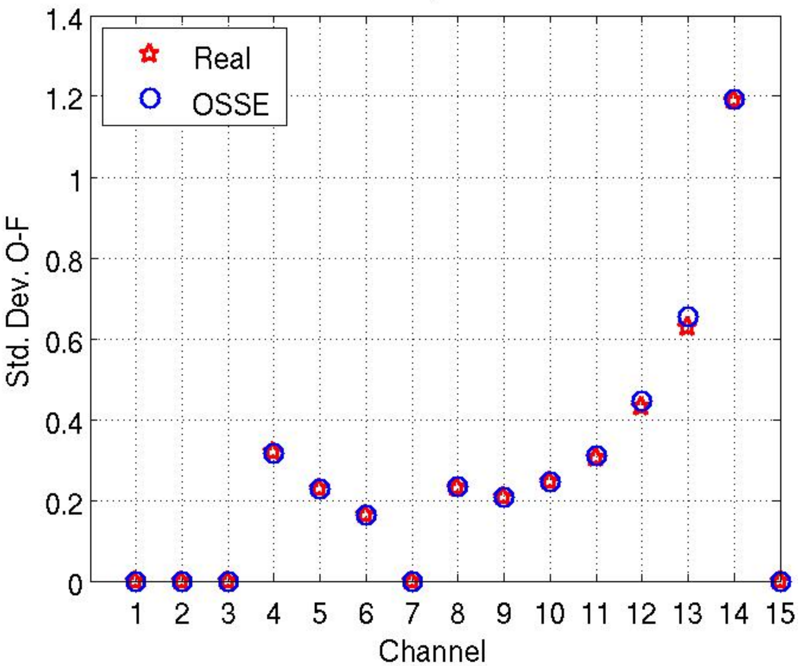
Since data assimilation is a fundamentally statistical problem, OSSE validation and application must generally be statistical.

Standard deviations of QC-accepted y-H(xb) values (Real vs. OSSE)

RAOB U Wind

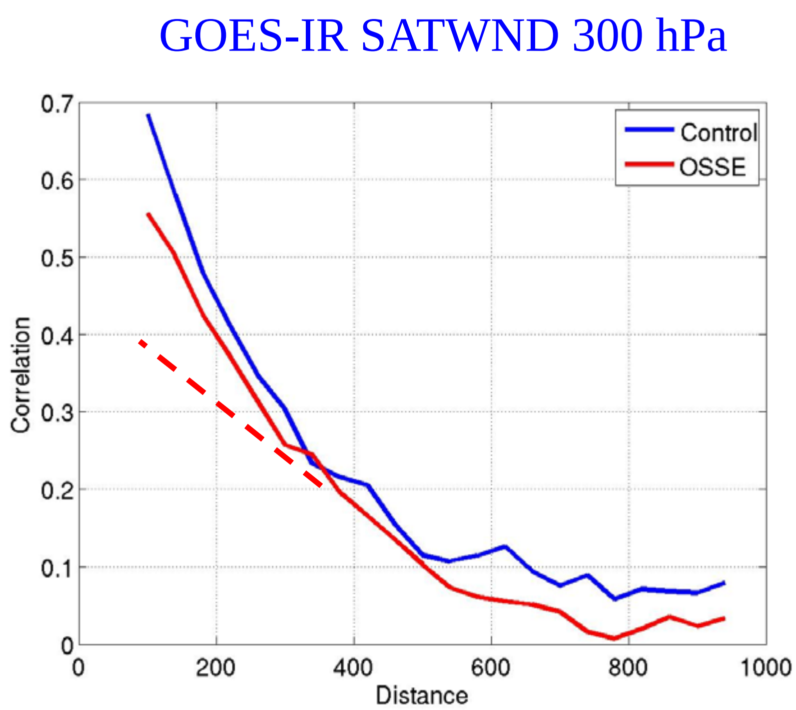


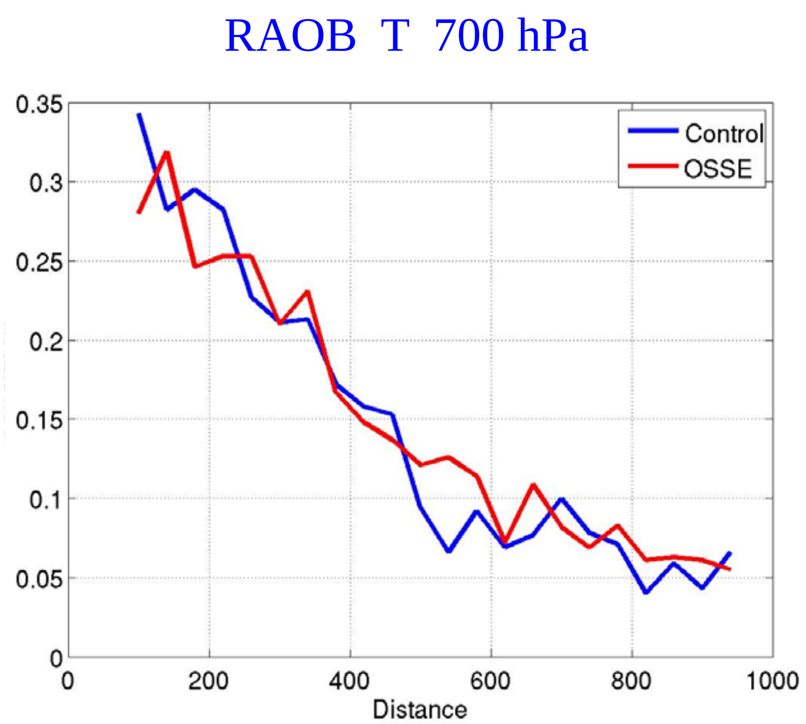
AMSU-A METOP-A



Horizontal correlations of y-H(xb)

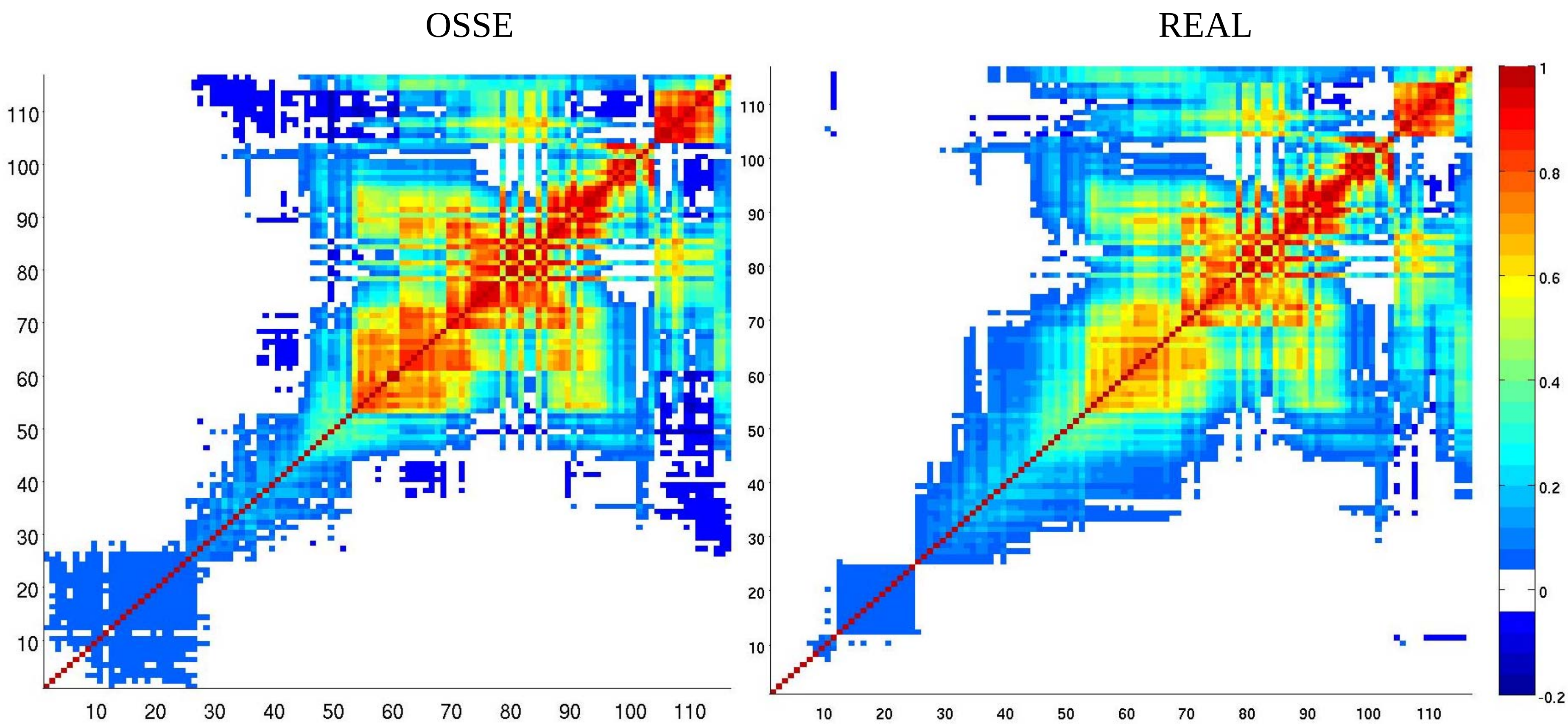
Evaluations for 20-90 N





= = = is OSSE without correlated observation errors

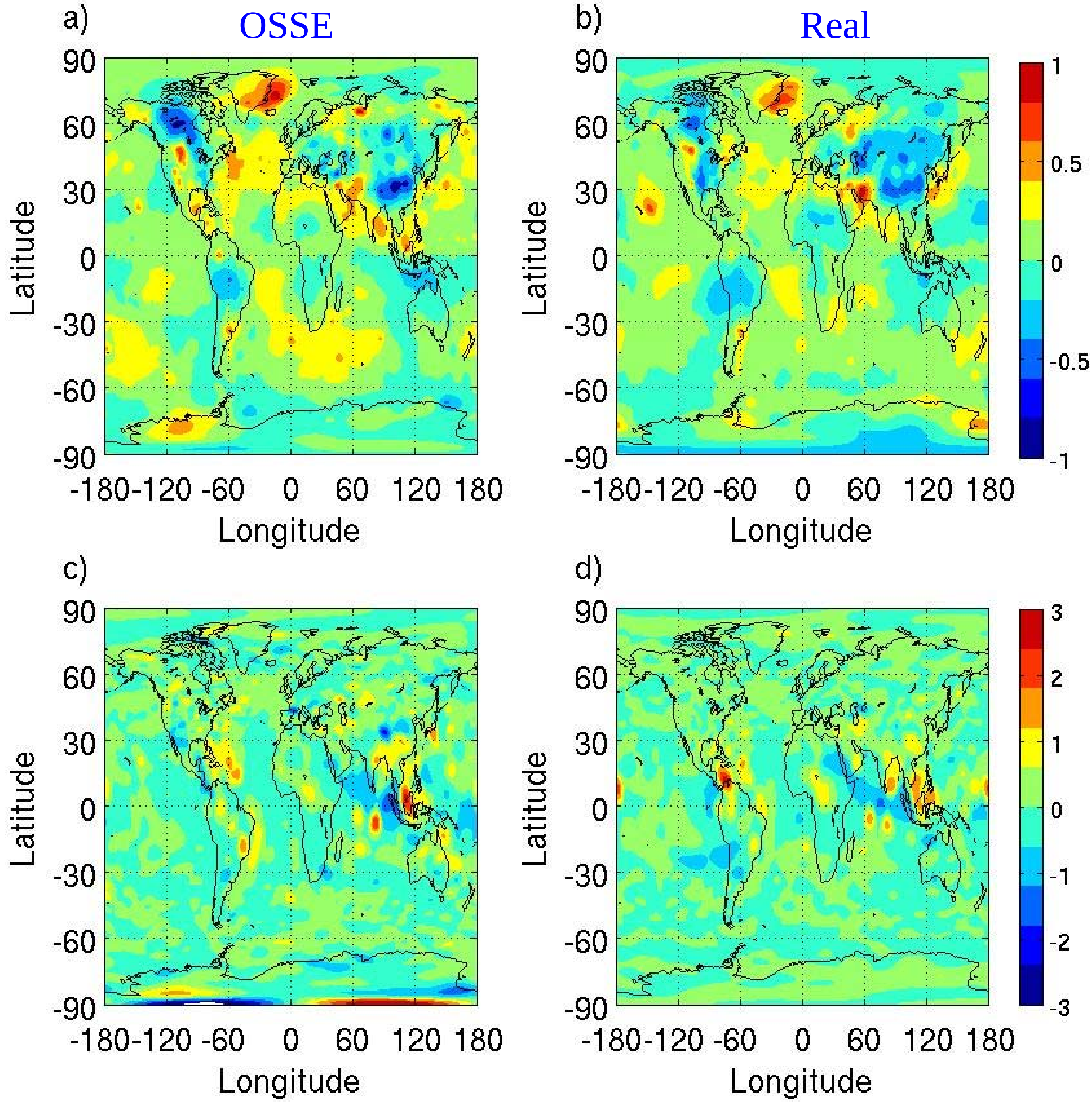
Correlations Between Channels of AIRS Innovations



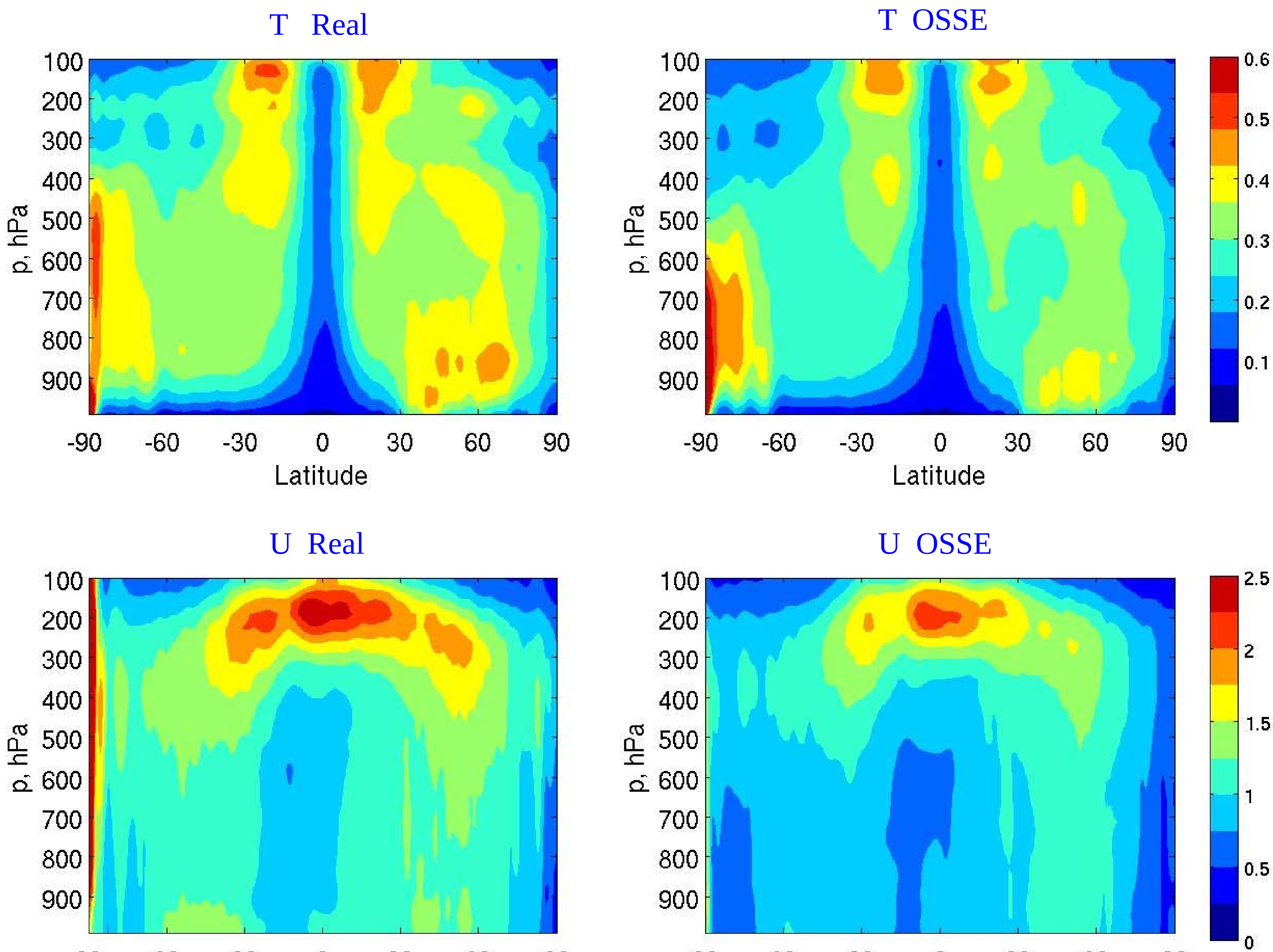
T 850 hPa

Time mean
Analysis increments

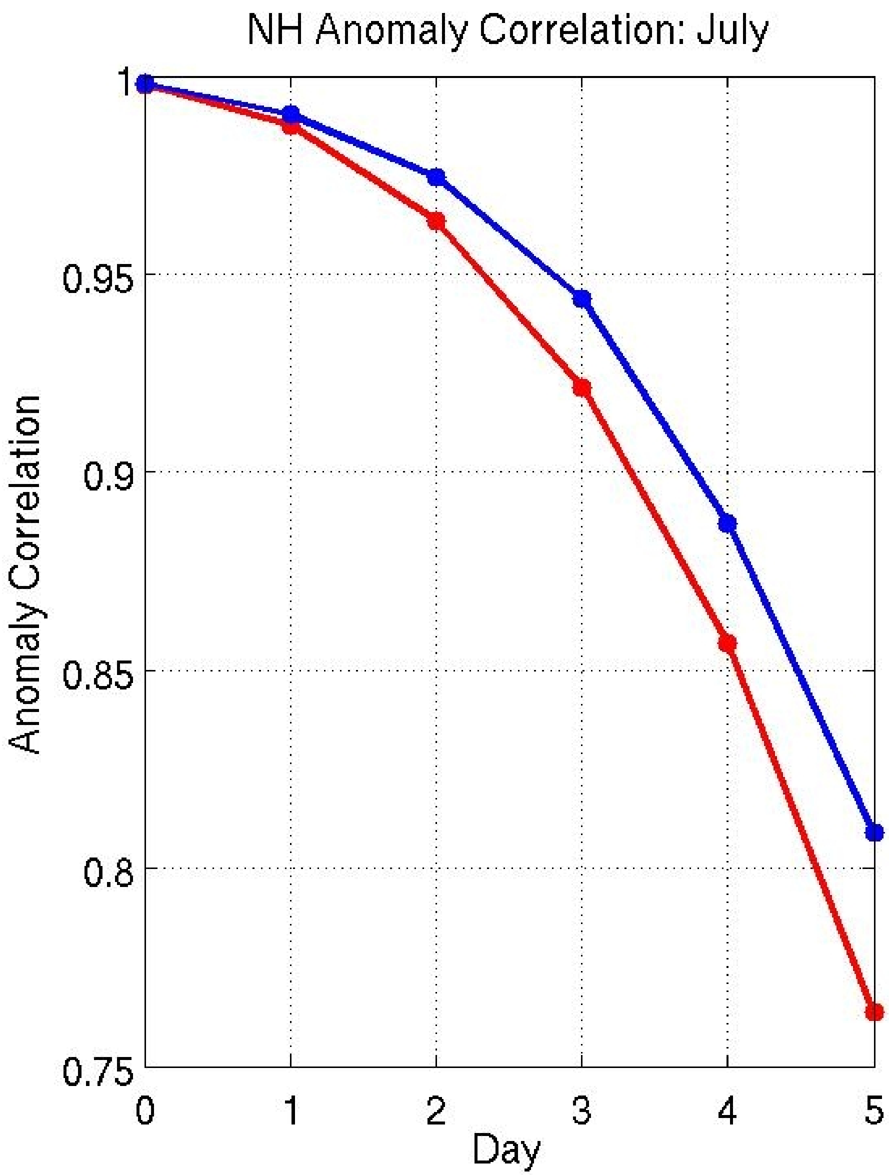
U 500 hPa

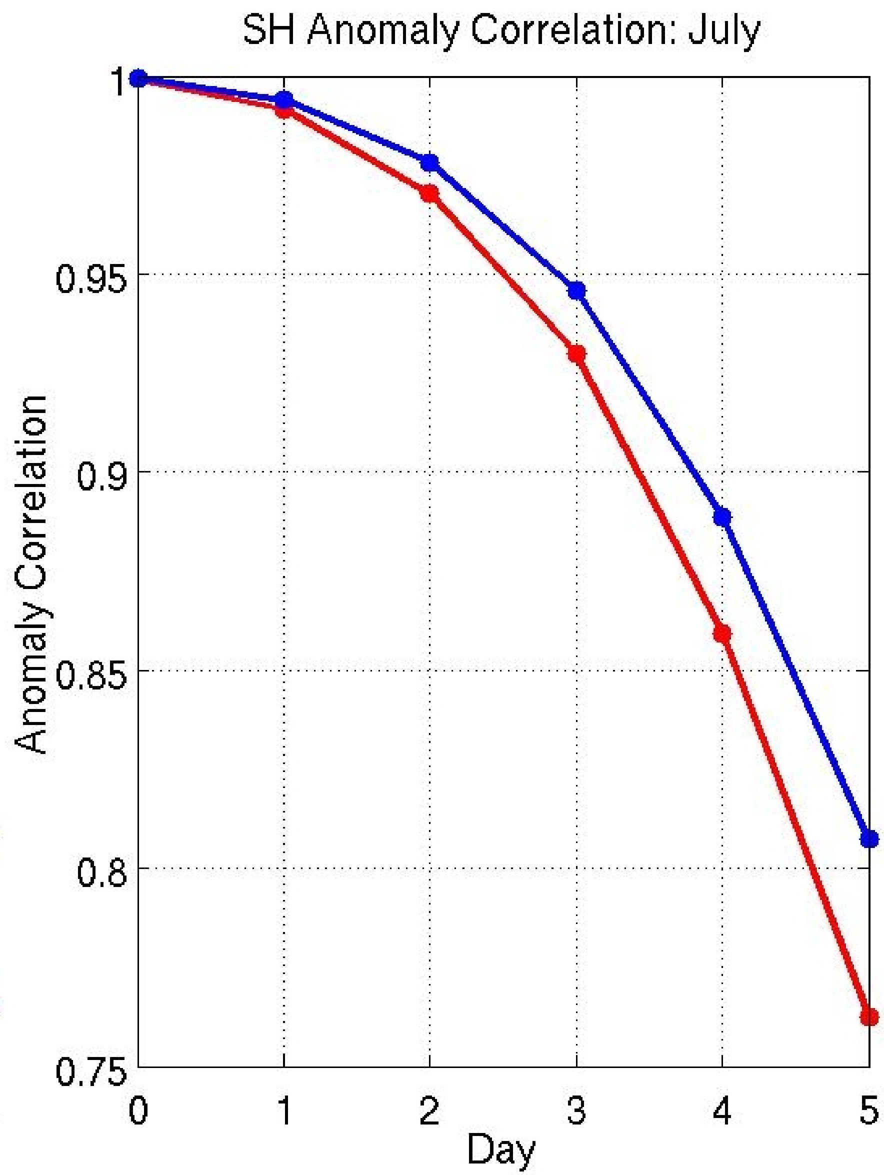


Square roots of zonal means of temporal variances of analysis increments

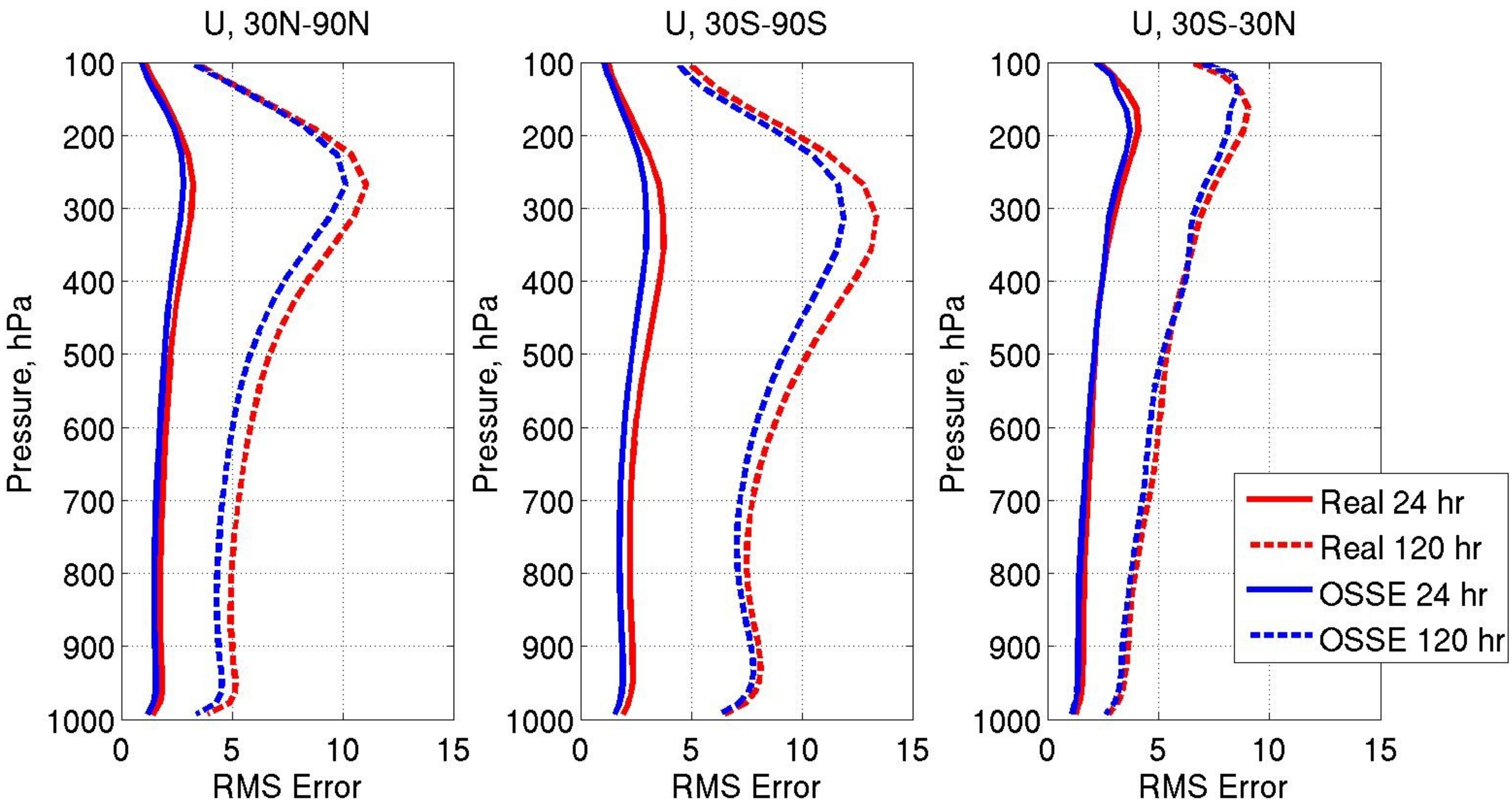


OSSE vs Real Data: Forecasts





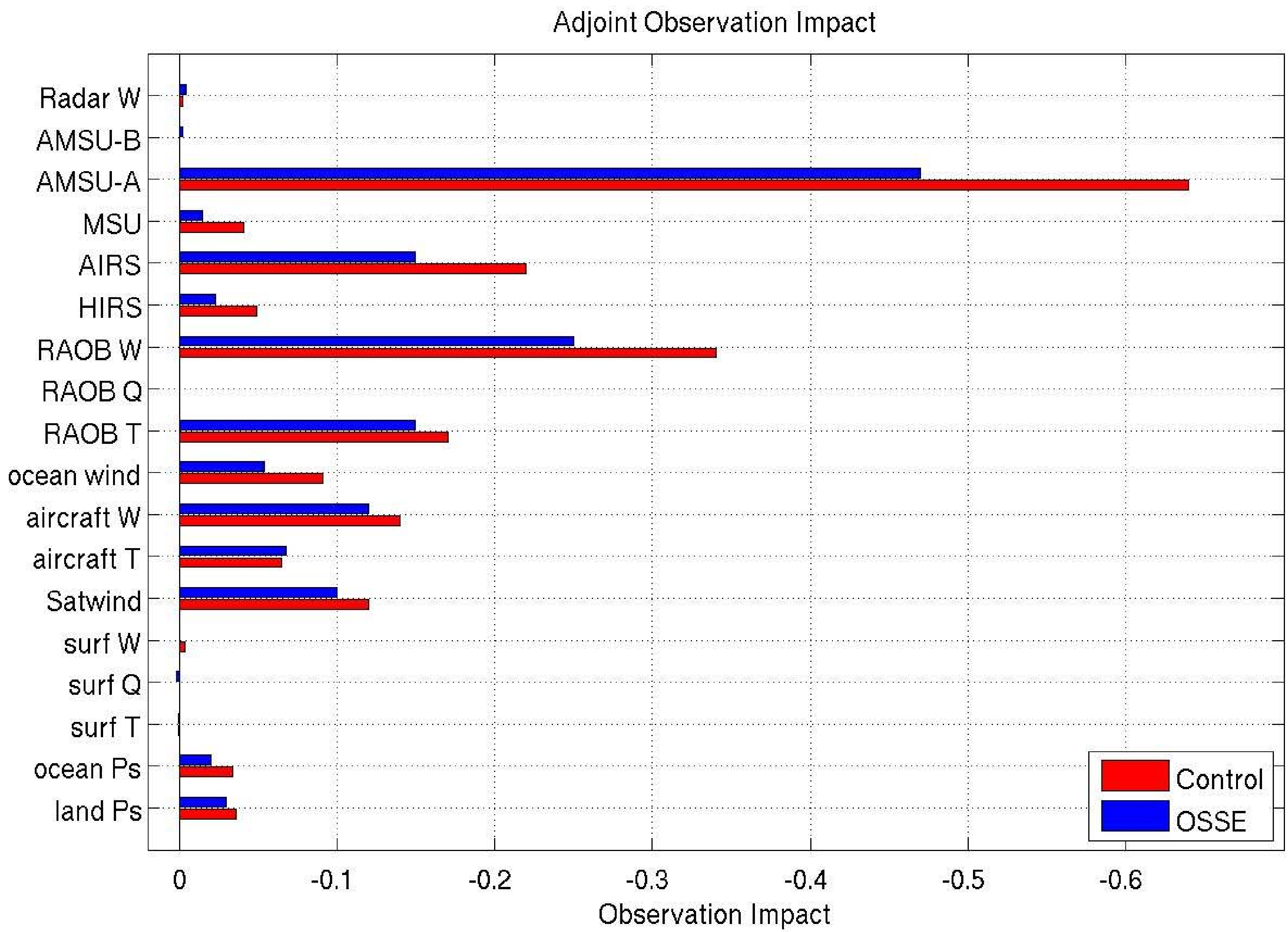
U-Wind RMS error: July



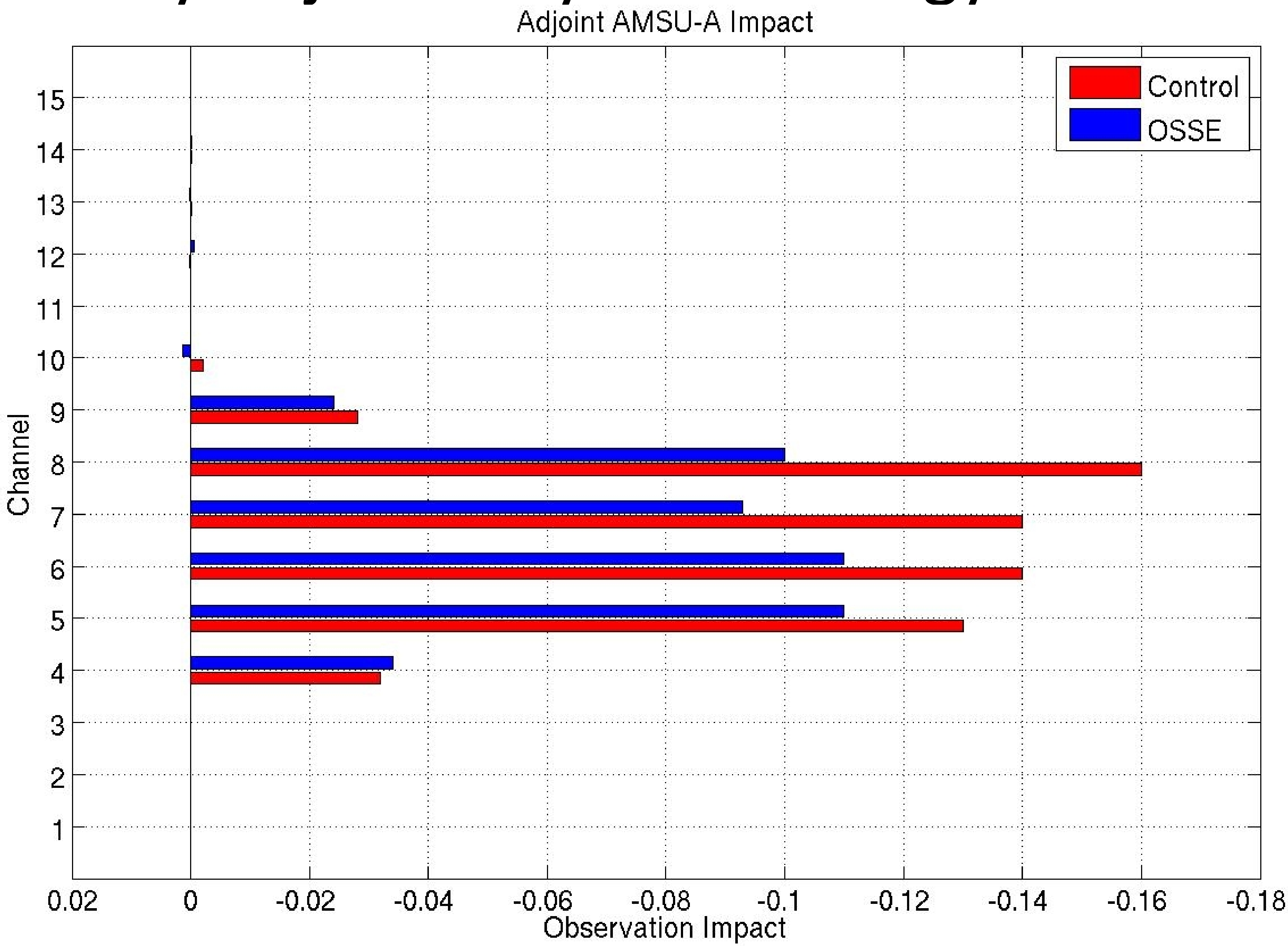
Solid lines: 24 hour RMS error vs analysis

Dashed lines: 120 hr forecast RMS error vs analysis

July Adjoint: dry error energy norm



July Adjoint: dry error energy norm



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.

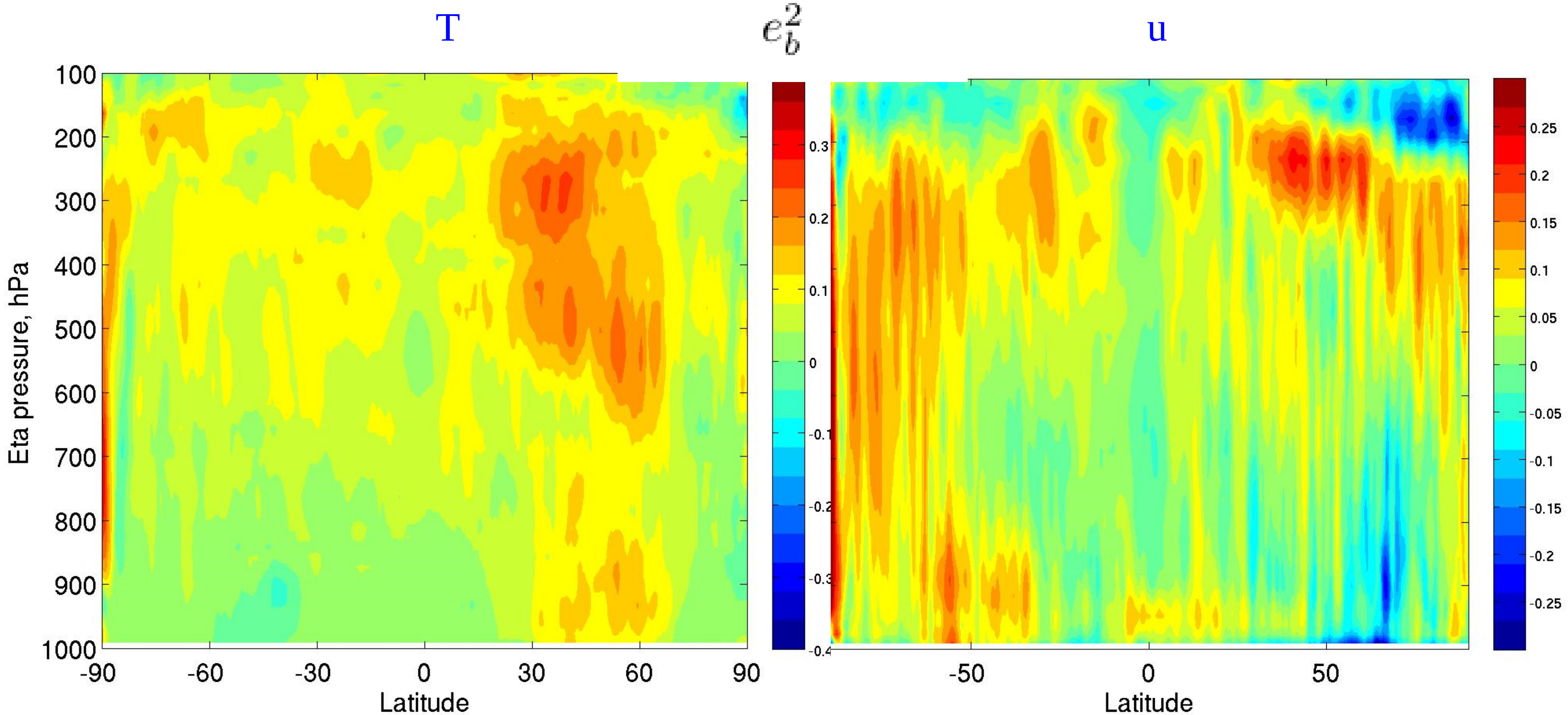
3. OSSEs are just bad science!

Response to Warnings

1. Design OSSEs thoughtfully.
2. Consider implications of all assumptions.
3. Validate OSSEs carefully.
4. Beware of quick shortcuts.
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

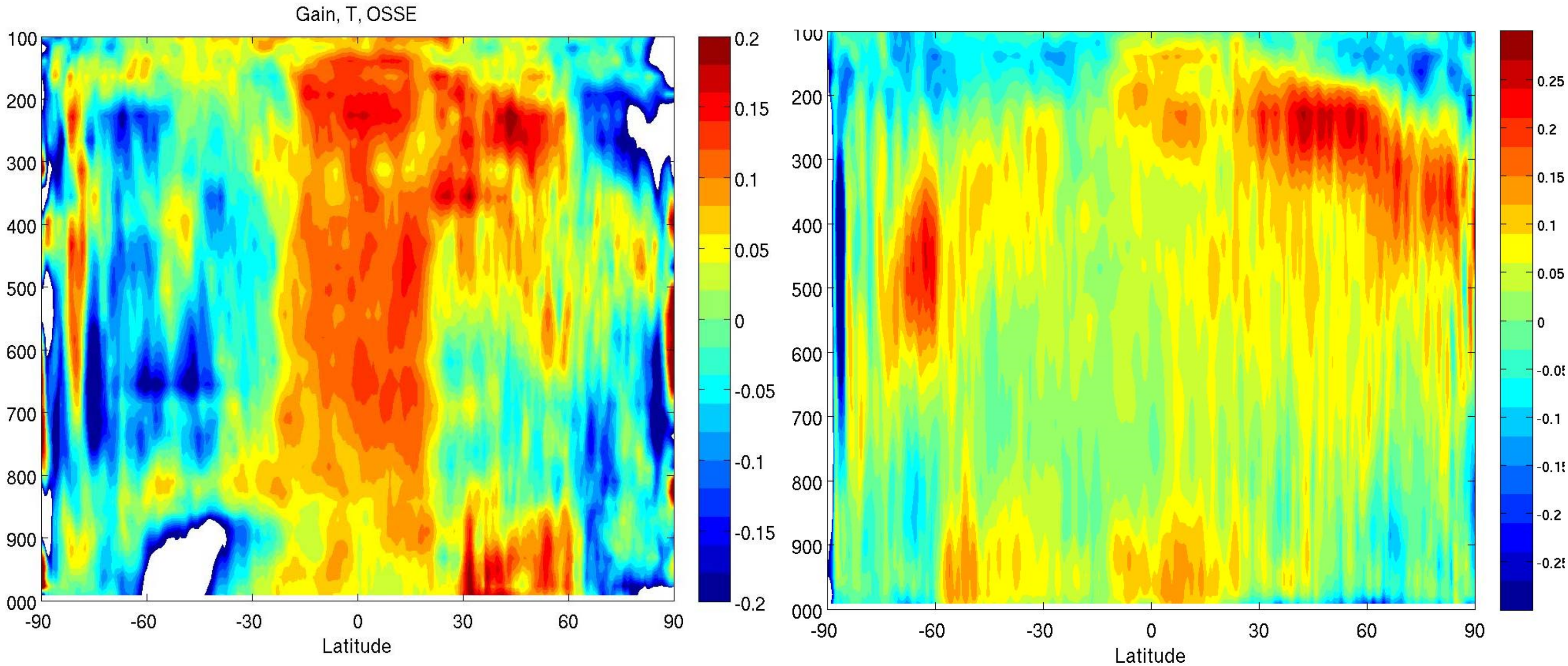
$$\frac{\overline{e_b^2} - \overline{e_a^2}}{\overline{e_b^2}}$$



From validation experiment reported last year

Fractional reduction of zonal means of temporal variances of analysis errors compared with background errors

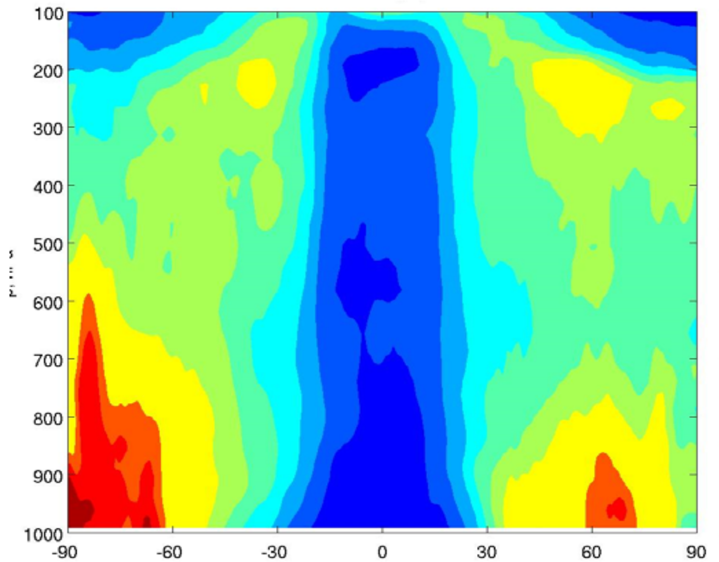
T $\qquad \dfrac{\overline{e_b^2} - \overline{e_a^2}}{\overline{e_b^2}} \qquad$ u



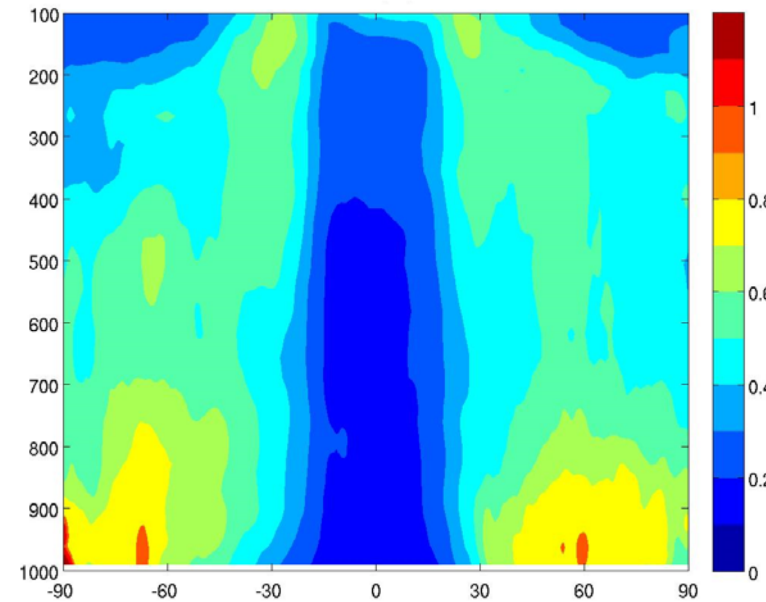
From latest validation experiment

Square roots of zonal means of temporal variances of analysis increments

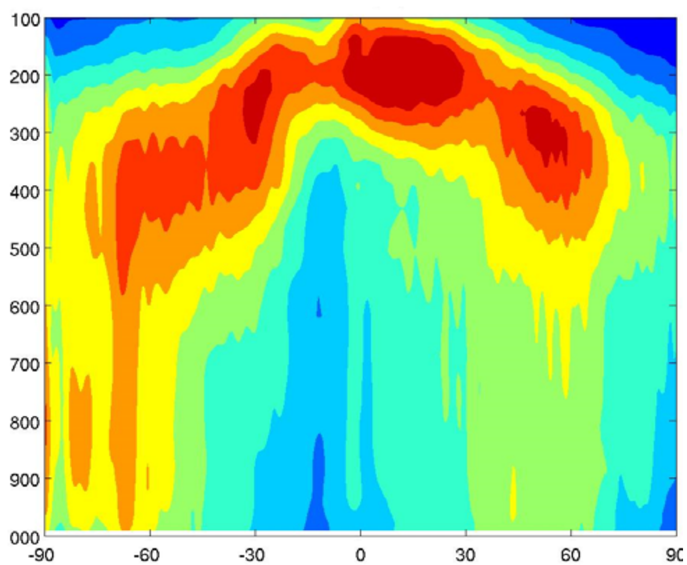
T Real



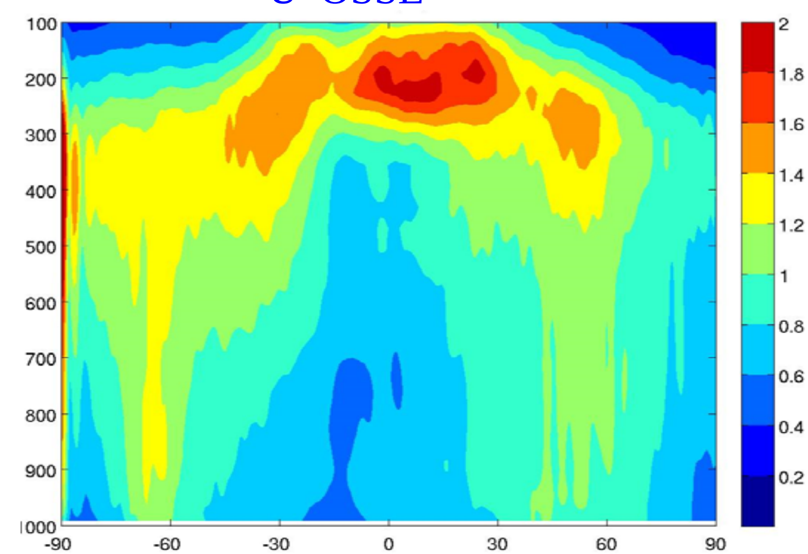
T OSSE



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)

GMAO OSSE Validation Publications

Errico, R. M., R. Yang, N. C. Privé, K.-S. Tai, R. Todling, M. E. Sienkiewicz, J. Guo, 2013: Development and validation of observing system simulation experiments at NASA's Global Modeling and Assimilation Office. *Quart. J. Roy. Meter. Soc.*, **139,** 1162-1178.

Privé, N. C., R. M. Errico, K.-S. Tai, 2013: Validation of forecast skill of the Global Modeling and Assimilation Office observing system simulation experiment. *Quart. J. Roy. Meteorol. Soc.*, **139,** 1354-1363.