Proactive Quality Control based on Ensemble Forecast Sensitivity to Observations

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Outline

1. EFSO (Ensemble Forecast Sensitivity to Observations)
   and "Proactive QC"

2. EFSR (Ensemble Forecast Sensitivity to Observation Error Covariance matrix **R**)
   and tuning of **R**

3. Future Directions: Operational Applications

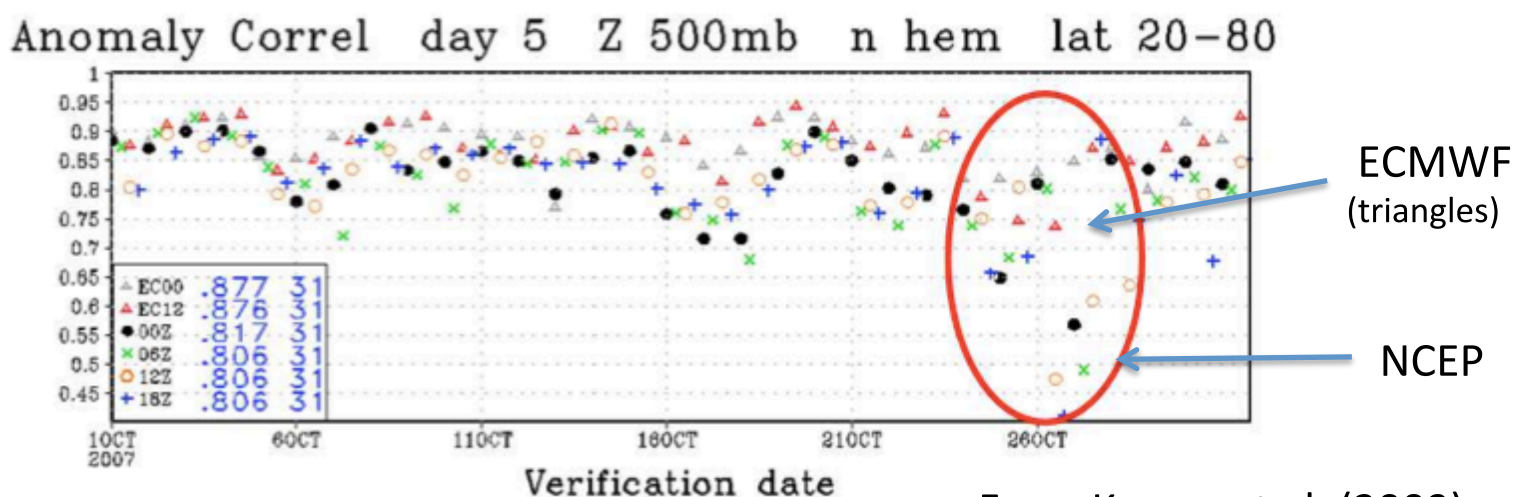
(Appendix: semi-implicit Lorenz *N*-cycle scheme)

Part 1:

EFSO (Ensemble Forecast Sensitivity to Observations)

and "**Proactive QC**"

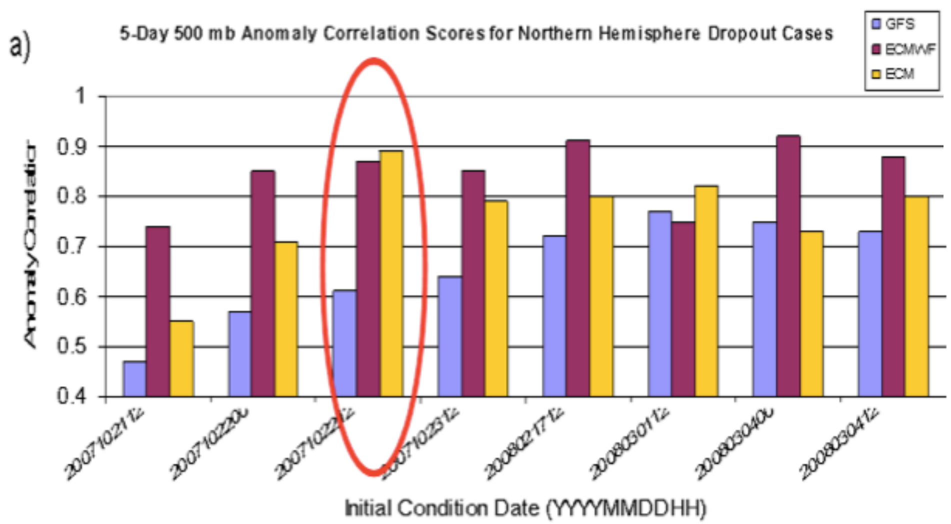
Motivation:
The NCEP “forecast skill dropout” problem



From Kumar et al. (2009)

- NCEP’s 5-day Forecast skill is generally very high (~ 0.9 level)
- However, it occasionally drops to a low level (= “dropout”)
- In some cases, all NWP centers suffer.
- But in some cases, NCEP does suffer while ECMWF does not.

Motivation:
The NCEP "forecast skill dropout" problem



GFS-GSI (Operational)

ECMWF

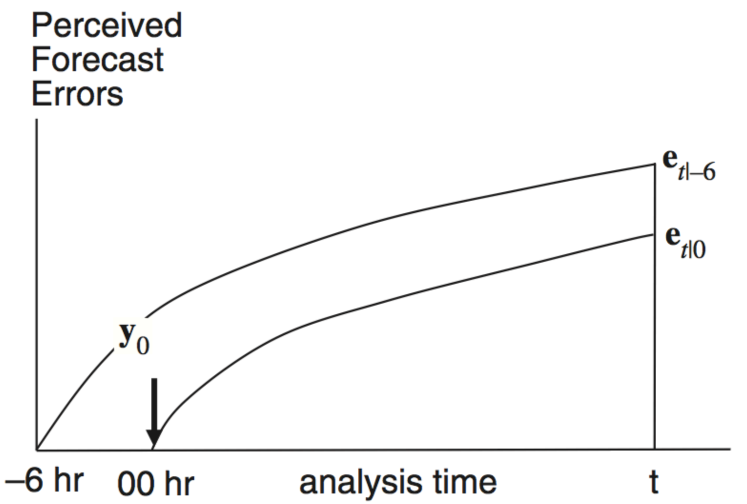
GFS-GSI which assimilates "Pseudo-Obs" generated from ECMWF analysis

From Kumar et al. (2009)

- "Culprit" is not the model but "bad observations" (or inability of DA system to properly assimilate them)

→ **How can we detect those "flawed" observations?**

EFSO: Ensemble Forecast Sensitivity to Observations



From Kalnay et al (2012)

$$\overbrace{\Delta e^2}^{\text{Reduction of forecast error by the assimilation of obs.}} = \mathbf{e}_{t|0}^T C \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T C \mathbf{e}_{t|-6}$$

$$\approx \frac{1}{K-1} \delta \mathbf{y}_0^T \mathbf{R}^{-1} \mathbf{Y}_0^a \mathbf{X}_{t|0}^{fT} C \left(\mathbf{e}_{t|0} + \mathbf{e}_{t|-6} \right)$$

O-B of the ens. mean

forecast spread

analysis spread in obs. space

- Quantifies **how much *each* observation improved/degraded the forecast**
- First invented for a variational DA-system using the ***adjoint method*** by Langland and Baker (2004)
- Liu and Kalnay (2008) adapted it to LETKF (***no adjoint***)
- Kalnay et. al (2012) gave an improved, simpler formulation
- The new formulation is
  - more accurate
  - simpler and easier to implement
  - applicable to any formulation of EnKF
- Ota et al. (2013) successfully implemented the new EFSO into the NCEP's operational GFS system

Ota et al. (2013): Identification of "flawed" observations by 24-hour EFSO

Table 3. List of local 24-hour forecast failure cases (initial time from 00 UTC, 8 January 2012, to 18 UTC 7 February 2012)

Initial	Area	Size	Rate	N	Denied observation (denied number/total number)	Change (estimate)
06 UTC JAN 12	50N–80N 145E–175W	1.99	1.36	5	AMSUA ch4, 5, 6 (2735/125 063)	−8.7% (−19.5%)
00 UTC JAN 16	30N–60N 20W–0	2.71	1.35	6	GPSRO 600–950 hPa (50/4918)	−0.6% (−4.3%)
18 UTC JAN 27	30S–0 105E–120E	2.40	1.21	1	AIRS (19 908/670 041)	−0.2% (−6.0%)
00 UTC JAN 30	70S–40S 165E–165W	2.00	1.25	6	AMSUA ch1, 3, 4, 5, 15 (3822/164 934)	−4.7% (−12.8%)
06 UTC FEB 2	50N–80N 150W–110W	3.01	1.22	5	GPSRO 250–400 hPa, 600–850 hPa (407/13 092)	−11.7% (−8.7%)
06 UTC FEB 4	30N–60N 150W–130W	1.81	1.26	3	IASI (57 950/1 177 256), HIRS ch3, 4, 9, 11, 12, 14, 15 (785/73 419), Aircraft 950 hPa ∼, 125–600 hPa (5794/100 896)	−25.5% (−81.6%)
18 UTC FEB 6	**60N–90N 40E–100E**	**1.71**	**1.38**	**2**	**MODIS_Wind (10 970/43 452)**	**−28.4% (−47.7%)**

- Identified 7 cases of potential "regional forecast skill dropouts"
- Rerun the analyses and forecasts without using "flawed" obs. identified by 24-hour EFSO
- The forecast errors were substantially reduced.

“Proactive QC”: Proposed Algorithm

Suppose we wish to identify and delete “flawed” obs. at 00h.

① Run regular DA cycle from -06h to 00h.

② Run regular DA cycle from 00h to 06h.

③ Detect “regional dropouts” using the information available from ① and ②.

④ Perform **6-hour EFSO** to identify “flawed” obs. at 00h.

⑤ If “flawed” obs. are identified, repeat 00h analysis without using the detected “flawed” obs.

Key questions to be addressed in order for the Proactive QC to work

- **Are 6 hours long enough for detecting “flawed observations”?**
  - Forecast errors are computed as Forecast-minus-Analysis
  - When compared to the errors of very short-term forecast, analysis errors might not be small.

  → Estimation of forecast errors becomes more difficult.
- **What is the best criterion for rejection of observations?**

  Rejecting too many observations might lead to forecast degradation, but too few would make little difference.

  → How to strike the best balance?
- **Does rejection of those observations really improve analysis and forecast?**

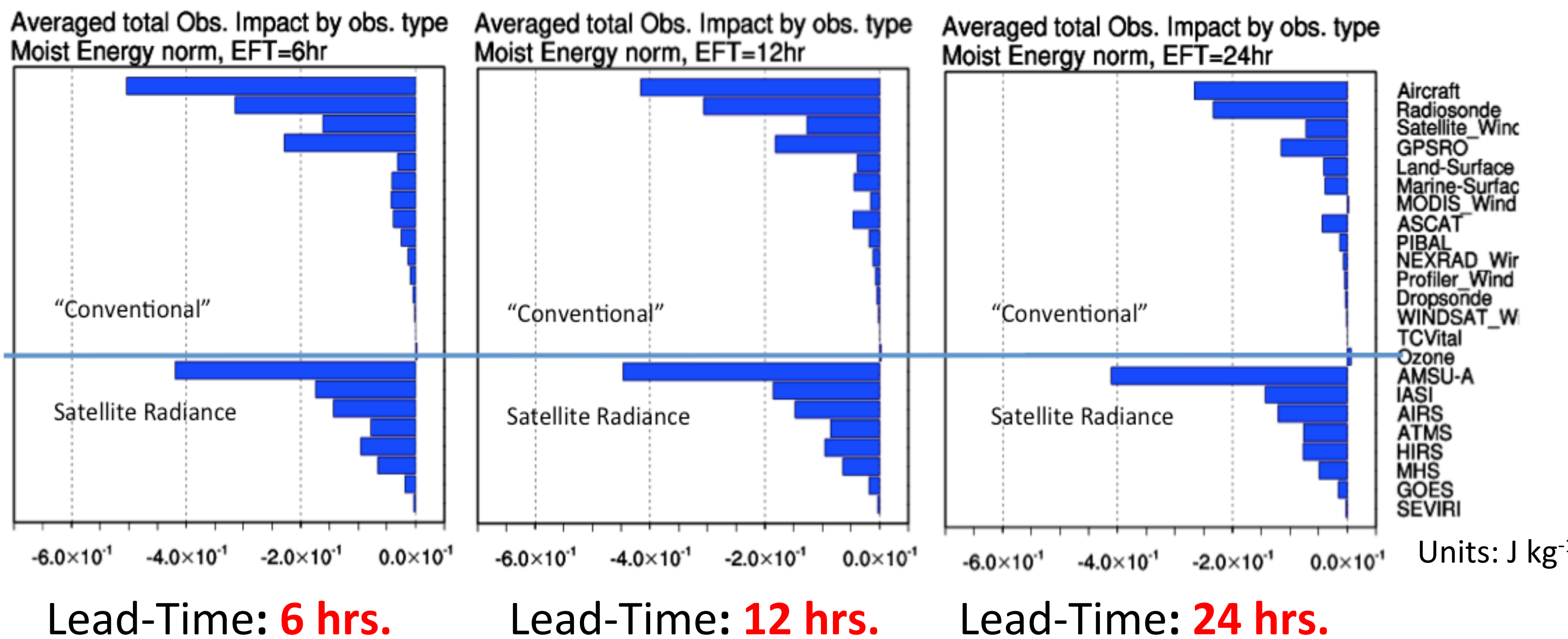
Experiments with quasi-operational NCEP's GFS/GSI system
Experimental Set-up

(Implemented on top of GFS/hybrid GSI ***ported to JCSDA's S4 by Dr. Jim Jung****)*

- **Forecast Model**: NCEP's GFS model
- **Resolution**: ***half*** of the operational:
  – T254L64 (deterministic), T126L64 (ensemble)
- **DA system:** hybrid GSI (as in the operational), but EnKF part replaced by LETKF
- **Observations**: same as the NCEP operational system
- **Period**: 34 days (Jan – Feb, 2012)
- **LETKF:** Covariance localization and inflation (same as the operational)
- **EFSO:**
  - **Localization**: same as LETKF + moving localization of Ota et al. (2013)
  - **Error norm**: Moist total energy norm

EFSO's sensitivity to forecast lead time
(1) Time average

Average net observation impact for each observation type



- EFSO results are not very sensitive to the choice of evaluation lead time.

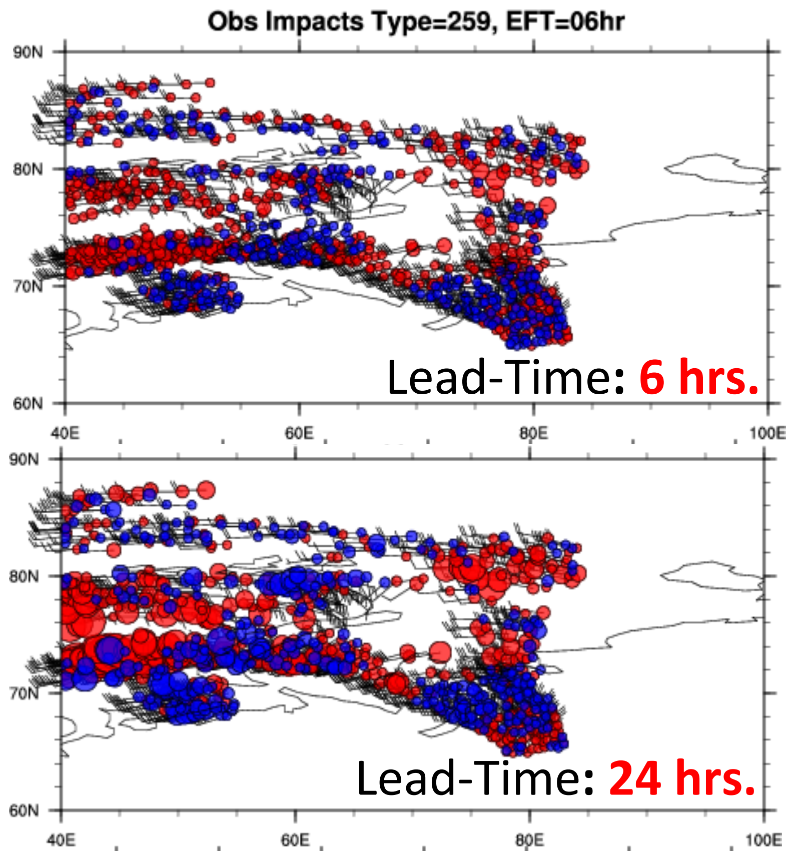
EFSO’s sensitivity to forecast lead time
(2) Individual Cases

Example: MODIS wind near the North Pole on Feb 06 18UTC, 2012

Geographical distribution of EFSO from each. obs.

Red: negative impact ; Blue: positive impact

the size proportional to the magnitude



- Again, EFSO results are not very sensitive to the choice of evaluation lead time, ***even for individual cases.***

- **→ 6 hours are long enough for detection of “flawed” observations.**

Key questions to be answered

- Are 6 hours long enough for detecting “flawed observations”?

  → **Yes. 6-hr EFSO is equally capable of detecting “flawed” obs. as 24-hr EFSO.**

- What is the best criterion for rejection of observations?

- Does rejection of those observations really improve analysis and forecast?

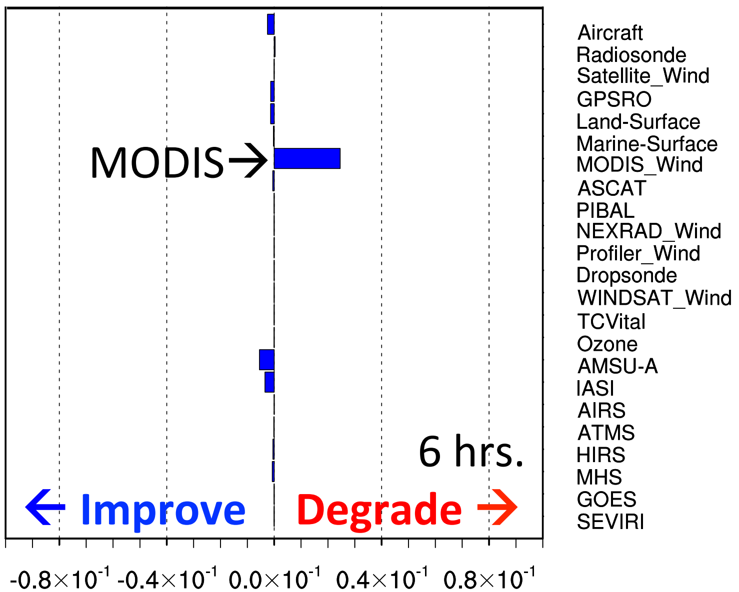
Data Denial Experiments

Case study (1): MODIS case

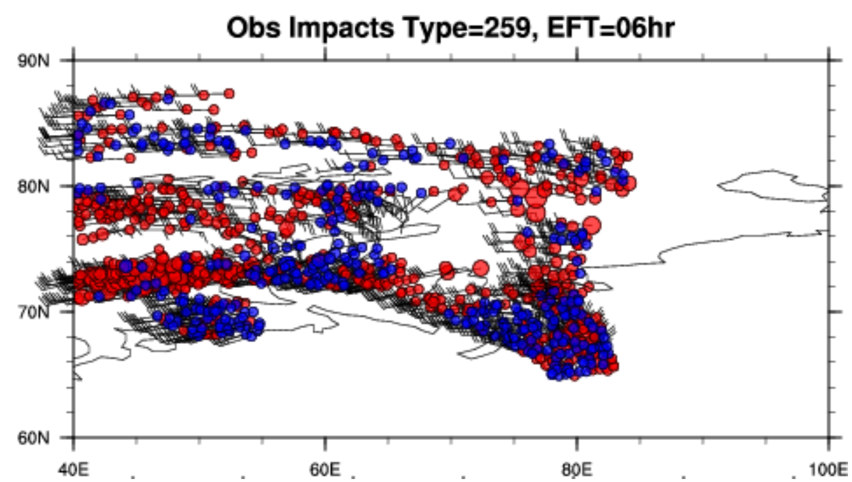
2012-Feb-06-18Z, [60ºN—90ºN] x [40ºE—100ºE]

Net EFSO Impact by obs. types
measured with moist total energy norm

Units: J kg^{-1}



EFSO impact from
each MODIS wind observation



- MODIS wind identified as “flawed” (i.e., with net negative impact).
- There are both **helpful** and **harmful** observations.
- **How can we decide which / how many obs. should be denied?**

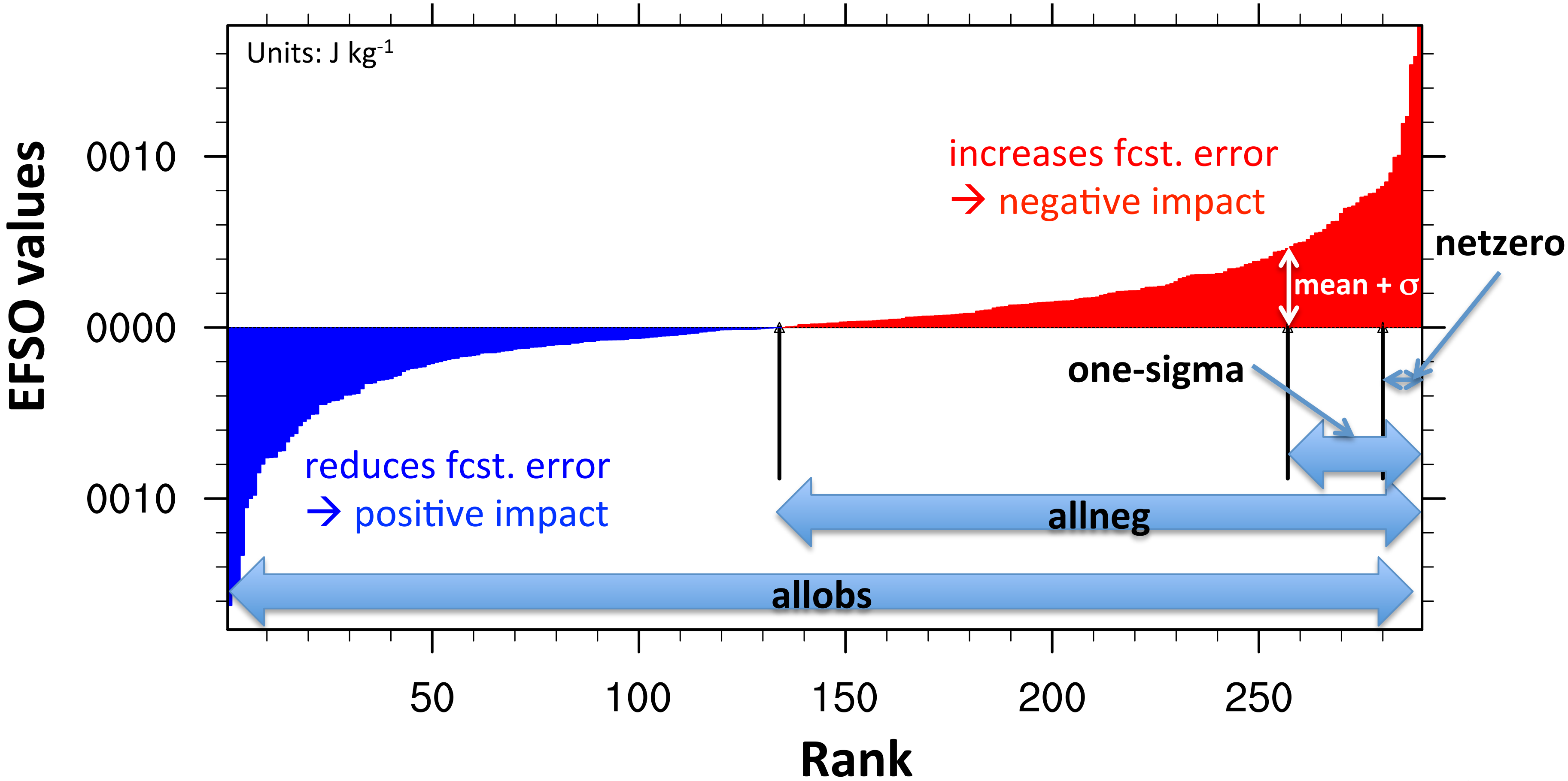
Data Denial Experiments

Selection of the Obs. to be denied

→ Try four criteria, perform data denial for each

Distribution of EFSO values from each observation

Example: MODIS wind near the North Pole



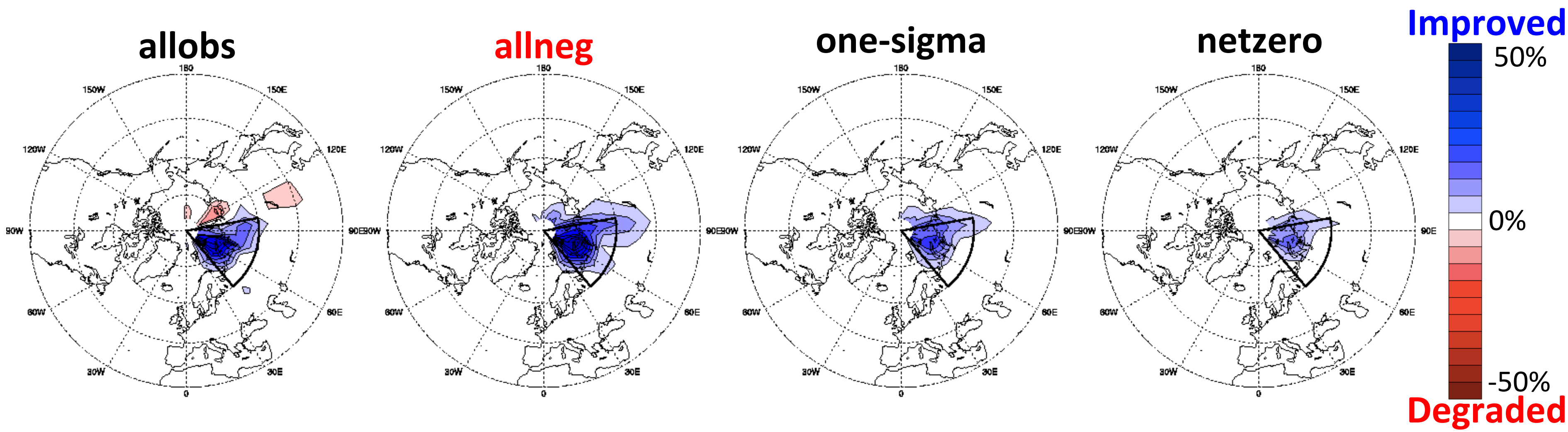
How many obs. should we reject?

Case study (1): MODIS case

2012-Feb-06-18Z, [60°N—90°N] x [40°E—100°E]

Relative **24-hr** fcst. improvement:= $(\mathbf{e}^{\mathbf{f}}_{\mathbf{beforeQC}} - \mathbf{e}^{\mathbf{f}}_{\mathbf{afterQC}}) / \mathbf{e}^{\mathbf{f}}_{\mathbf{beforeQC}} \times 100$ [%]

Data selection based on **6-hour** EFSO



- **allobs**: overall improvement, but with several areas with degradation
- **allneg**: enhanced improvement, reduced degradation
- **one-sigma** & **netzero**: less improvement, but with further reduced degradation

Data Denial Experiment

Summary of the relative 24-hr forecast improvement for 20 cases (20x4x2=160 experiments)

Case #		6-hour allobs	6-hour allneg	6-hour one-sigma	6-hour netzero	24-hour allobs	24-hour allneg	24-hour one-sigma	24-hour netzero
1	max.imp.	12%	11%	4%	5%	12%	20%	0%	6%
	max.deg.	-9%	-1%	-1%	-1%	-9%	-1%	-1%	0%
	avg.imp.	0.0%	0.2%	0.1%	0.1%	0.0%	0.3%	-0.0%	0.1%
2	max.imp.	14%	11%		4%		10%		2%
	max.deg.	-5%	-4%		0%		-5%		0%
	avg.imp.	-0.1%	0.3%	N/A	0.2%	N/A	0.1%	N/A	0.1%
3	max.imp.	13%	7%	2%	4%	7%	12%	0%	2%
	max.deg.	-15%	-5%	-1%	-2%	-8%	-7%	0%	-3%
	avg.imp.	0.0%	0.2%	0.0%	0.0%	-0.1%	0.1%	0.0%	-0.1%
4	max.imp.	25%	27%	15%	13%	3%	4%	1%	0%
	max.deg.	-5%	-5%	-2%	-2%	-6%	-3%	-5%	0%
	avg.imp.	0.6%	0.7%	0.3%	0.2%	-0.3%	0.1%	-0.3%	-0.0%
5	max.imp.	15%	19%	23%	22%	12%	10%	1%	1%
	max.deg.	-32%	-81%	-30%	-13%	-78%	-21%	-1%	-1%
	avg.imp.	-0.2%	-0.2%	0.2%	0.3%	-1.3%	-0.4%	-0.0%	-0.0%
6	max.imp.	9%	15%	12%	3%	24%	9%	2%	3%
	max.deg.	-9%	-6%	-3%	-1%	-38%	-10%	-2%	-2%
	avg.imp.	0.0%	0.4%	0.3%	0.1%	0.0%	0.1%	0.0%	0.0%
7	max.imp.	17%	13%	2%	0%	19%	26%	0%	4%
	max.deg.	-9%	-5%	-3%	0%	-36%	-28%	0%	-1%
	avg.imp.	-0.0%	0.4%	0.0%	0.0%	0.3%	0.6%	0.0%	0.2%
8	max.imp.	41%	41%	21%	10%	41%	26%	0%	4%
	max.deg.	-18%	-14%	-5%	-2%	-18%	-10%	0%	-1%
	avg.imp.	0.9%	1.1%	0.8%	0.4%	0.9%	1.2%	-0.0%	0.2%
9	max.imp.	7%	8%	8%	8%	3%	5%	3%	3%
	max.deg.	-21%	-16%	-3%	-4%	-2%	-1%	-1%	-1%
	avg.imp.	-0.6%	-0.4%	0.0%	0.1%	-0.1%	0.1%	0.0%	0.0%
10	max.imp.	25%	19%		6%		17%		2%
	max.deg.	-6%	-6%		0%		-12%		0%
	avg.imp.	1.1%	0.7%	N/A	0.2%	N/A	0.8%	N/A	0.2%
11	max.imp.	11%	9%	2%	3%	22%	15%	1%	2%
	max.deg.	-6%	-5%	-2%	0%	-5%	-6%	0%	0%
	avg.imp.	0.5%	0.3%	0.1%	0.1%	0.9%	0.9%	0.0%	0.2%
12	max.imp.	37%	39%	19%	19%	37%	38%	1%	12%
	max.deg.	-14%	-12%	-2%	-2%	-14%	-19%	0%	-6%
	avg.imp.	0.7%	0.7%	0.5%	0.5%	0.7%	0.4%	0.0%	0.2%
13	max.imp.	24%	30%	18%	19%	24%	26%	0%	8%
	max.deg.	-9%	-9%	-10%	-12%	-9%	-10%	0%	-6%
	avg.imp.	1.4%	0.8%	0.3%	0.4%	1.3%	1.1%	0.0%	0.1%
14	max.imp.	5%	3%	1%	1%	5%	3%	0%	0%
	max.deg.	0%	0%	0%	0%	0%	-1%	0%	0%
	avg.imp.	0.3%	0.1%	0.0%	0.1%	0.3%	0.1%	0.0%	0.0%
15	max.imp.	3%	1%	1%	1%	13%	35%	1%	7%
	max.deg.	-2%	-1%	-1%	-1%	-16%	-18%	-1%	-10%
	avg.imp.	0.1%	0.1%	-0.0%	0.0%	-0.1%	0.8%	0.0%	0.2%
16	max.imp.	27%	30%	23%	16%	30%	33%	1%	7%
	max.deg.	-15%	-21%	-4%	-2%	-20%	-43%	-1%	-1%
	avg.imp.	1.9%	1.8%	1.3%	0.7%	2.1%	1.2%	0.0%	0.3%
17	max.imp.	39%	48%	26%	20%	45%	51%	0%	15%
	max.deg.	-15%	-4%	-2%	-2%	-15%	-8%	-1%	-2%
	avg.imp.	0.8%	2.1%	1.2%	0.8%	0.7%	1.6%	-0.0%	0.5%
18	max.imp.	46%	46%	25%	21%	36%	47%	0%	20%
	max.deg.	-9%	-8%	-3%	-2%	-14%	-13%	-1%	-4%
	avg.imp.	2.4%	2.2%	1.0%	0.8%	1.6%	2.1%	-0.0%	0.6%
19	max.imp.	44%	37%	17%	14%	6%	8%	0%	2%
	max.deg.	-24%	-10%	-1%	-1%	-17%	-7%	0%	-1%
	avg.imp.	2.2%	2.2%	1.0%	1.0%	-0.2%	0.2%	0.0%	0.0%
20	max.imp.	12%	10%	5%	3%	12%		1%	9%
	max.deg.	-3%	-1%	-1%	-1%	-3%		-2%	-1%
	avg.imp.	0.2%	0.3%	0.2%	0.0%	0.2%	N/A	-0.0%	0.2%

- With **allneg**:
  - **Hemispheric-scale forecast error reduced in 18 out of 20 cases.**
  - **Local improvement over 30% in 7 cases**

Data Denial Experiment

Summary of the results for 20 cases

- Data selection based on 6-hour EFSO:
  - **allobs**: improvement mixed with degradation
  - **allneg**: enhanced improvement, reduced degradation

    Hemispheric-scale forecast error reduced in 18 out of 20 cases.

    Local improvement over 30% in 7 cases.
  - **one-sigma & netzero**: diminished improvement, but with further reduced degradation
  - For all of the 7 most successful cases, MODIS wind was identified as "flawed."

- Data selection based on 24-hour EFSO: Similar to 6-hour EFSO, but with less improvements.

Key questions to be answered

- Are 6 hours long enough for detecting "flawed observations"?
  - **→ Yes. 6-hr EFSO is equally capable of detecting "flawed" obs. as 24-hr EFSO is.**
- What is the best criterion for rejection of observations?
  - **→ A matter of trade-off: if some degradation is tolerable, "allneg" should be favorable; else "one-sigma" or "netzero" should be used.**
- Does rejection of those observations really improve analysis and forecast?
  - **→ Yes, with >30% local improvement in 7 out of 20 cases.**

Summary for ***Proactive QC***

- **"Flawed" observations** that potentially lead to forecast skill dropouts **can be detected by EFSO** diagnostics **after only 6 hours** from the analysis.
- **Proactive QC** does improve forecast and analysis.
- Proactive QC is **innovative**:
  - The first fully flow-dependent QC
  - based on whether observations actually improve/ degrade forecast

Part 2:

EFSR (Ensemble Forecast Sensitivity to Observation Error Covariance matrix **R**) and **Tuning of R**

Motivation

- Data Assimilation combines information from background and observations with an "optimal weight."
- The "optimal weight" is determined based on the background -and observation- error covariances **B** and **R.**
- In EnKF, **B** (=$\mathbf{P}^{\mathbf{b}}$) is dynamically estimated, but **R** is still an external parameter.
  – Truth is unknown. → True **R** is also unknown.
  – NWP centers specify it empirically and subjectively.
- → We need a systematic method for tuning **R**.

EFSR Formulation

- Daescu and Langland (2013) proposed an ***adjoint-based*** formulation of forecast sensitivity to **R** matrix.
- We can formulate an ***ensemble*** version based on **EFSO** by Kalnay et al. (2012) :

$$\left[\frac{\partial e}{\partial \mathbf{R}}\right]_{ij} \approx \frac{\partial e}{\partial y_i} z_j \approx -\frac{1}{K-1}\left[\mathbf{R^{-1}Y_0^a X_{t|0}^{fT} C}\left(\mathbf{e_{t|0}} + \mathbf{e_{t|-6}}\right)\right]_i \left[\mathbf{R}^{-1}\delta y^{oa}\right]_j$$

- We know whether fcst. will be improved or degraded by the increase or decrease of **R**.

→ We can optimize **R**.

EFSR: Experiments

- Perfect-model experiment with Lorenz ’96 system
  - Run two DA cycles, one with incorrect **R**, the other with correct **R**
  - Perform EFSR to the two experiments. Examine if EFSR can detect mis-specification of **R.**

- Real NWP system experiment & Tuning of **R**
  - Diagnose forecast **R**-sensitivity for each observation type by EFSR.
  - Tune **R** based on EFSR and run the DA cycle again. Examine if the tuning improves the EFSO impacts of the tuned observation types.

Perfect-model Experiment: Experimental Setup

- **Model**: Lorenz '96 model with *N*=40 and *F*=8.0

$$\frac{\mathrm{d}x_j}{\mathrm{d}t} = x_j\left(x_{j+1} - x_{j-2}\right) - x_j + F$$

- **DA method**: 40 member LETKF, no localization
- **EFSR:** no localization
- **Observations:** available at every grid point.
- **Specification of R:**

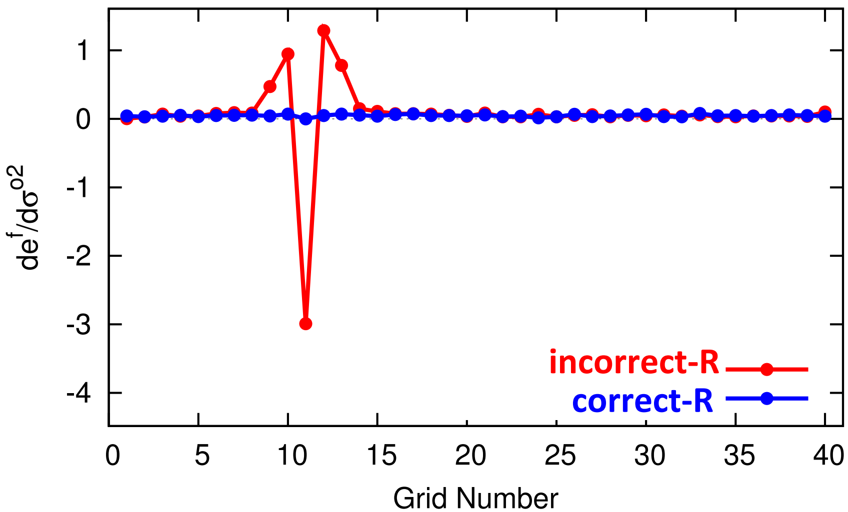
Name	True obs error variance	Prescribed error variance
SPIKE	$\sigma_j^{o,\text{true}2} = \begin{cases} 0.8^2 & j = 11 \\ 0.2^2 & j \neq 11 \end{cases}$	$\sigma_j^{o2} = 0.2^2$ everywhere
STAGGERED	$\sigma_j^{o,\text{true}2} = \begin{cases} 0.1^2 & j\text{: odd} \\ 0.3^2 & j\text{: even} \end{cases}$	$\sigma_j^{o2} = 0.2^2$ everywhere
LAND-OCEAN	$\sigma_j^{o,\text{true}2} = \begin{cases} 0.3^2 & 1 \leq j \leq 20 \text{ (“land”)} \\ 0.1^2 & 21 \leq j \leq 40 \text{ (“ocean”)} \end{cases}$	$\sigma_j^{o2} = 0.2^2$ everywhere

- Erroneous obs. variance only at the 11-th grid pt.
- DA system assumes constant **R** for all grid pts.

Design is inspired by Liu and Kalnay (2008)

Perfect-model Experiment: Result (SPIKE experiment)

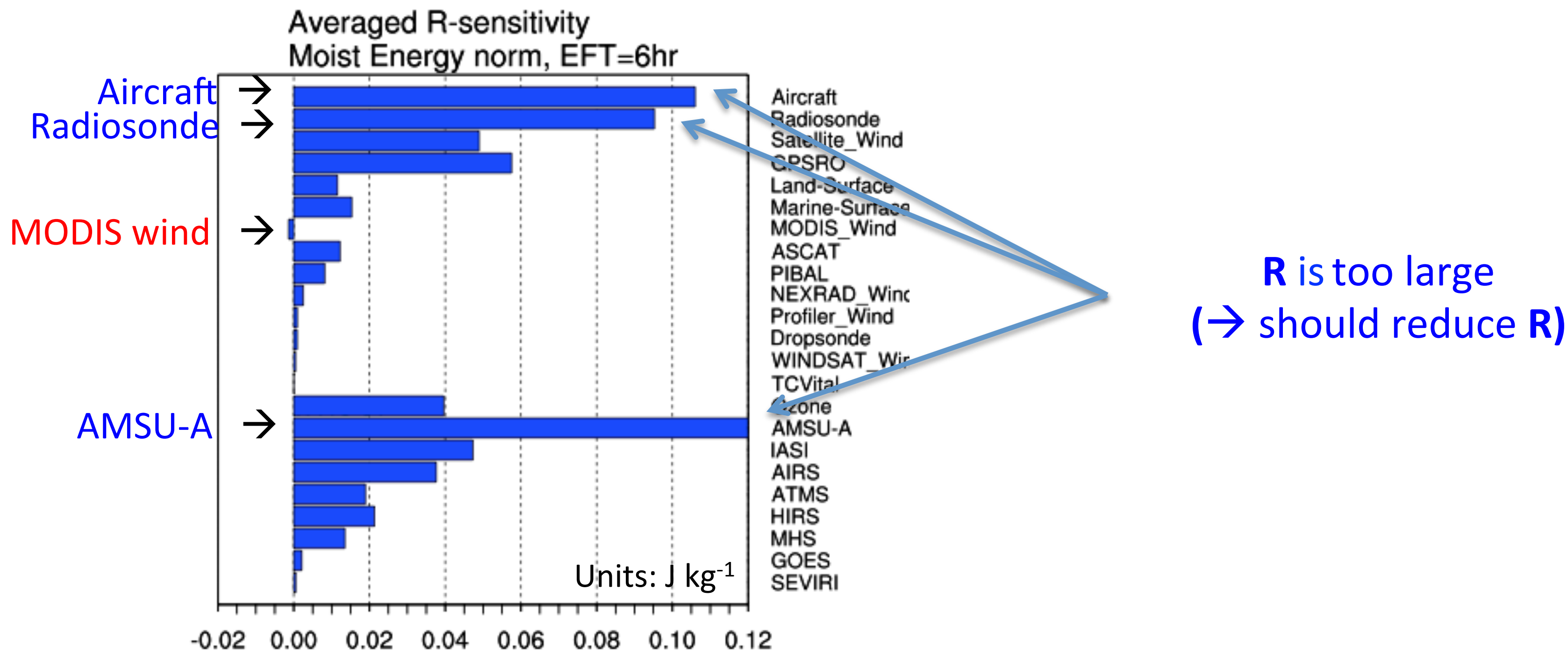
24-hr. EFSR sensitivity



Negative sensitivity: forecast error can be reduced by increasing **R**
→ **R** is too small

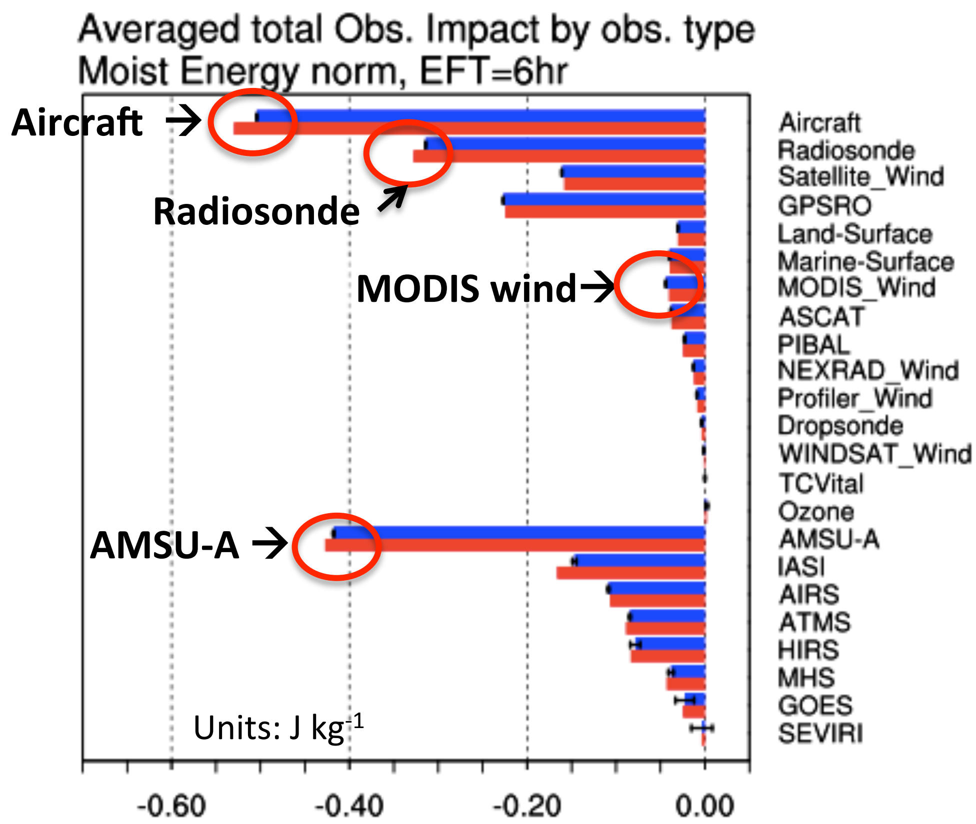
- For "**incorrect-R**," EFSR detects the mis-specification of **R** at the 11th grid point.
  → We can detect mis-specified **R**
- For "**correct-R**," EFSR diagnoses almost-zero sensitivity.
  → No "false alerts"

EFSR for GFS / GSI-LETKF hybrid



- **Aircraft, Radiosonde and AMSU-A**: large positive sensitivity
- **MODIS wind** : negative sensitivity
- → **Tuning experiment**:
  - Aircraft, Radiosonde and AMSU-A: reduce **R** by 0.9
  - MODIS wind: increase **R** by 1.1

Tuning Experiment: Result
EFSO **before**/**after** tuning of **R**



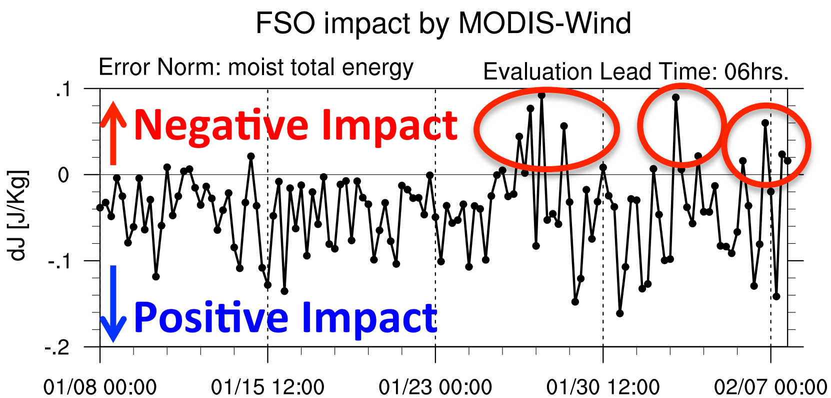
- Aircraft, Radiosonde, AMSU-A:
  - significant improvement of EFSO-impact

  (as expected)
- MODIS wind :
  - No improvement in EFSO (contrary to expectation)

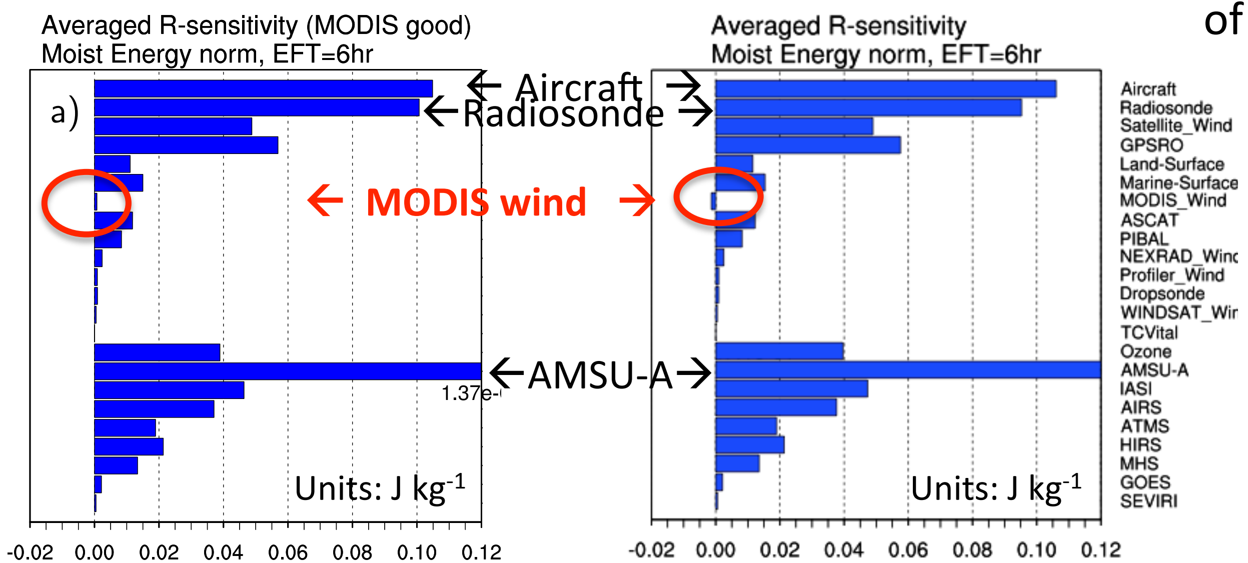
Why no improvement in MODIS?

- MODIS had “flawed” obs. along with “helpful” obs.
- The “flawed” obs. might have resulted in incorrect estimation of EFSR.

Excluding cases where MODIS wind had negative impact



- MODIS wind exhibited several negatively-impacting cases.
- **Exclude negative cases**
- **→ EFSR for MODIS becomes neutral**
- → Consistent with the result of tuning experiment



Excluding "flawed" MODIS case

Including "flawed" MODIS case

Lesson:

- Before performing EFSR, we should remove "bad" obs.

Summary for EFSR

- EFSR gives information on whether we should increase/reduce prescribed observation error covariance **R**.
- Tuning of **R** based on this diagnostics improves the EFSO.

- → EFSR can be used to *systematically* optimize **R**.

Future Directions:

Future plans

Immediate future:

- Implementation of Proactive QC into the real operational system
  - **Can the operational system**
    1. **wait for 6 hours?**
    2. **afford to do analysis again?**

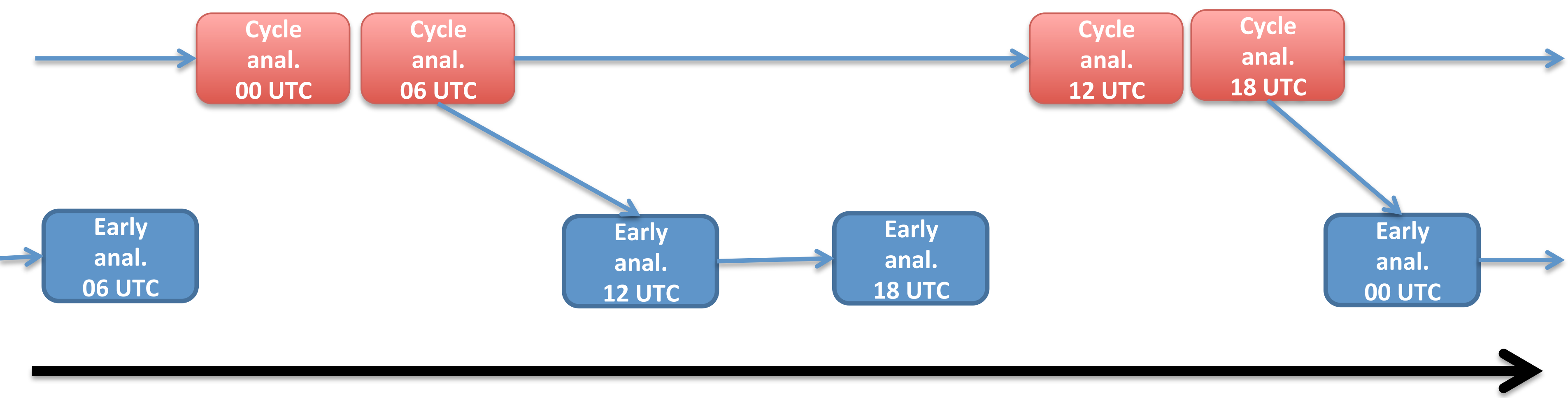
Long-term Future Directions:

- Applications of EFSO and EFSR
  - Collaboration with instrument developers
  - Acceleration of development for assimilation of new observing systems

Implementation to the real operational system
(1) Can we wait for 6 hours?

Idea: Exploit the time lag between "**early analysis**" and "**cycle (final) analysis**"

(suggested by Dr. John Derber, 2013)



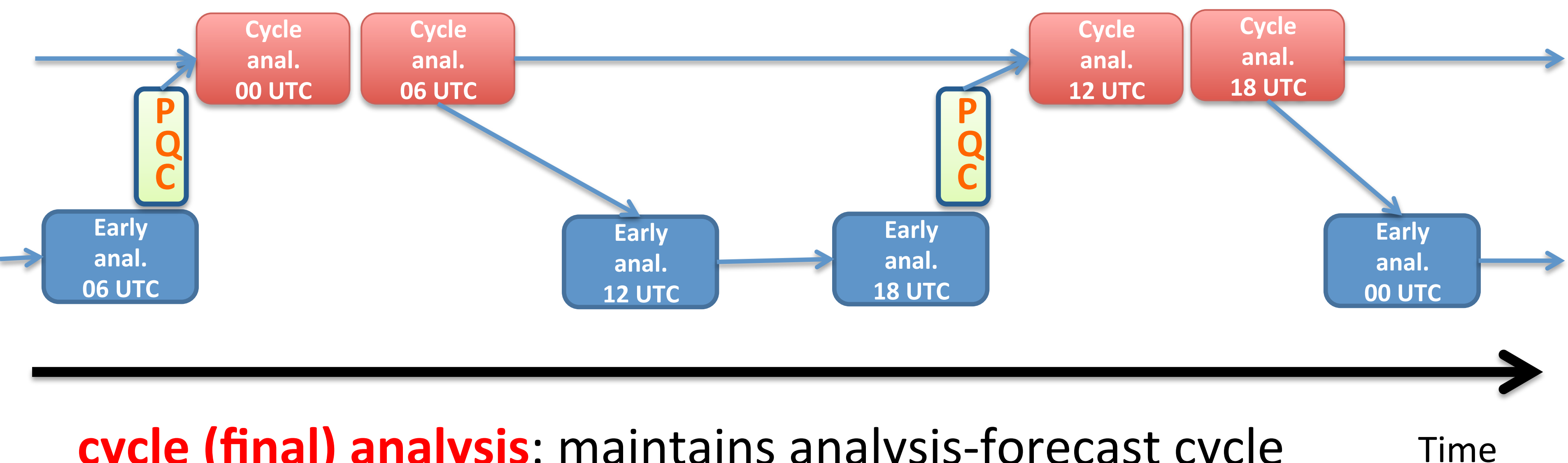
cycle (final) analysis: maintains analysis-forecast cycle

early analysis: provides initial condition for extended forecast

Implementation to the real operational system (1) we don't need to wait 6 hours!

Idea: Exploit the time lag between "**early analysis**" and "**cycle (final) analysis**"

(suggested by Dr. John Derber, 2013)



cycle (final) analysis: maintains analysis-forecast cycle

early analysis: provides initial condition for extended forecast

Implementation to the real operational system (2) can we afford to do analysis twice?

Idea: Use **approximated analysis** rather than doing analysis again:

- Using the approximation to Kalman gain:

$$\mathbf{K} \approx \frac{1}{K-1}\mathbf{X}_0^a \mathbf{X}_0^{aT} \mathbf{H}^T \mathbf{R}^{-1} \approx \frac{1}{K-1}\mathbf{X}_0^a \mathbf{Y}_0^{aT} \mathbf{R}^{-1}$$

the change in analysis by the denial of observations can be approximated by:

$$\bar{\mathbf{x}}_0^{a,\mathrm{deny}} - \bar{\mathbf{x}}_0^a \approx -\mathbf{K}\delta\bar{\mathbf{y}}_0^{ob,\mathrm{deny}} \approx -\frac{1}{K-1}\mathbf{X}_0^a \mathbf{Y}_0^{aT} \mathbf{R}^{-1}\delta\bar{\mathbf{y}}_0^{ob,\mathrm{deny}}$$

- As inexpensive as EFSO.

→ **No need to repeat analysis**

→ Can minimize the time delay

Application of EFSO:
(1) Collaboration with instrument developers

- In our experiments, in several cases, MODIS wind showed large negative impacts that caused "regional dropouts."
- → EFSO can be used to build a database of "flawed" observations along with their relevant metadata.
  – Provide such database to instrument developers so that they can fix problems with their algorithms.
  – Collaborate with instrument developers to determine which metadata would be helpful to them.

Application of EFSO:
(2) Acceleration of development for assimilation of new observing systems

- Traditional approach: compare
  - Test: with a new observing system
  - Control: without a new observing system
- Difficulty with this approach:
  - Signals from a new observing system is obscured by the many observations that are already assimilated in Control.

  → Hard to obtain statistically significant results

→ **EFSO-based data selection will enable efficient determination of an optimal way to assimilate new observing systems.**

- An optimal specification of **R** is also a difficult issue for assimilation of new observing systems.

→ **Our EFSR diagnostics should provide useful guidance**.

Conclusions

- 6-hour EFSO can successfully identify “flawed” observations.
- Rejecting them (**Proactive QC**) does improve the analysis and forecast.
- Database of “flawed” obs. can help instrument developers to improve their algorithms.

- **Proactive QC** can readily be implemented into the operational system.

- **EFSR** enables systematic tuning of **R** matrix.

- **EFSO and EFSR** together can accelerate development of the assimilation of new observing systems.

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