Two new ways to improve reanalysis: Use future observation to improve the analyses and forecasts, and minimize reanalys "jumps" when introducing new observing systems.

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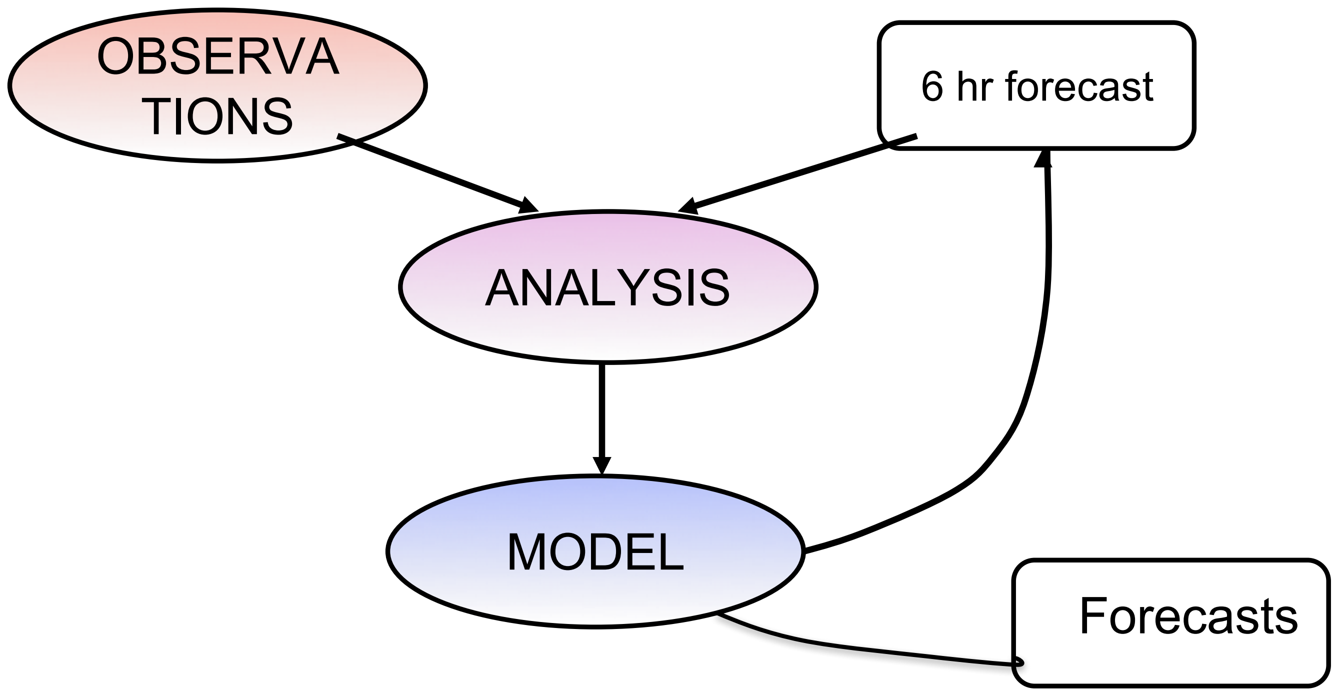
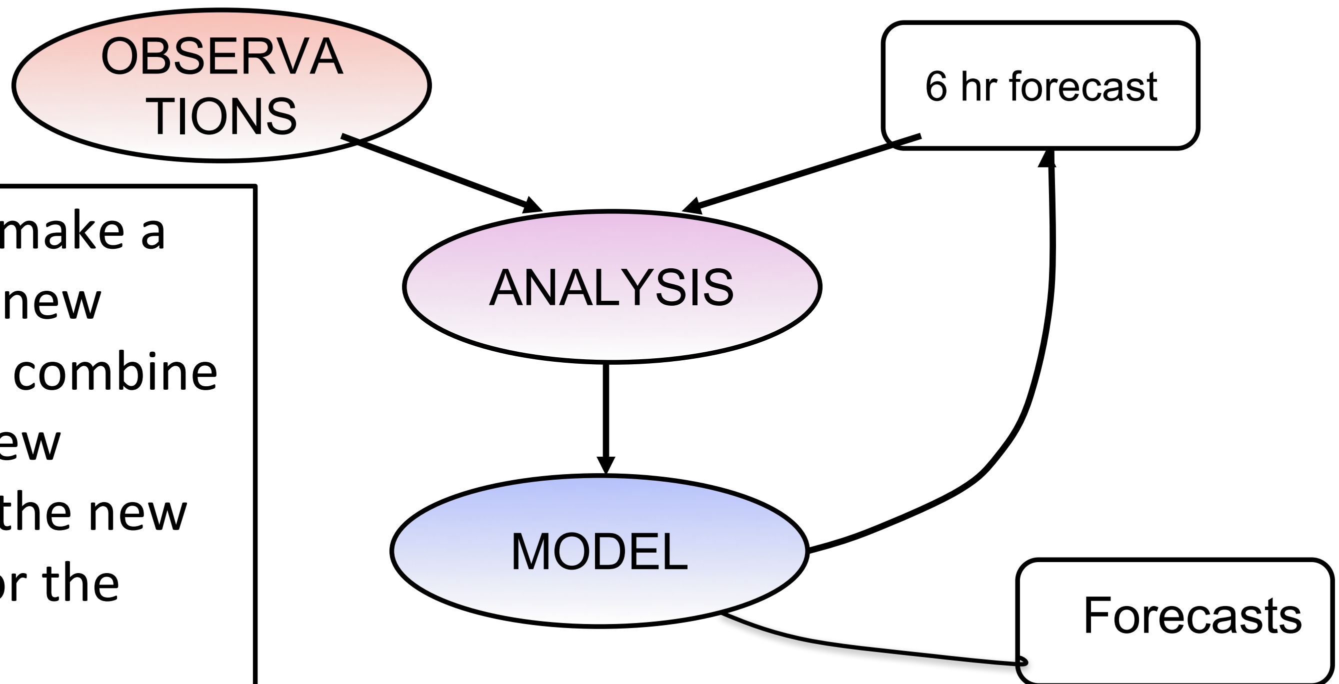
Classic Data Assimilation:
To improve Numerical Weather Prediction (NWP) we need to improve observations, analysis scheme and model



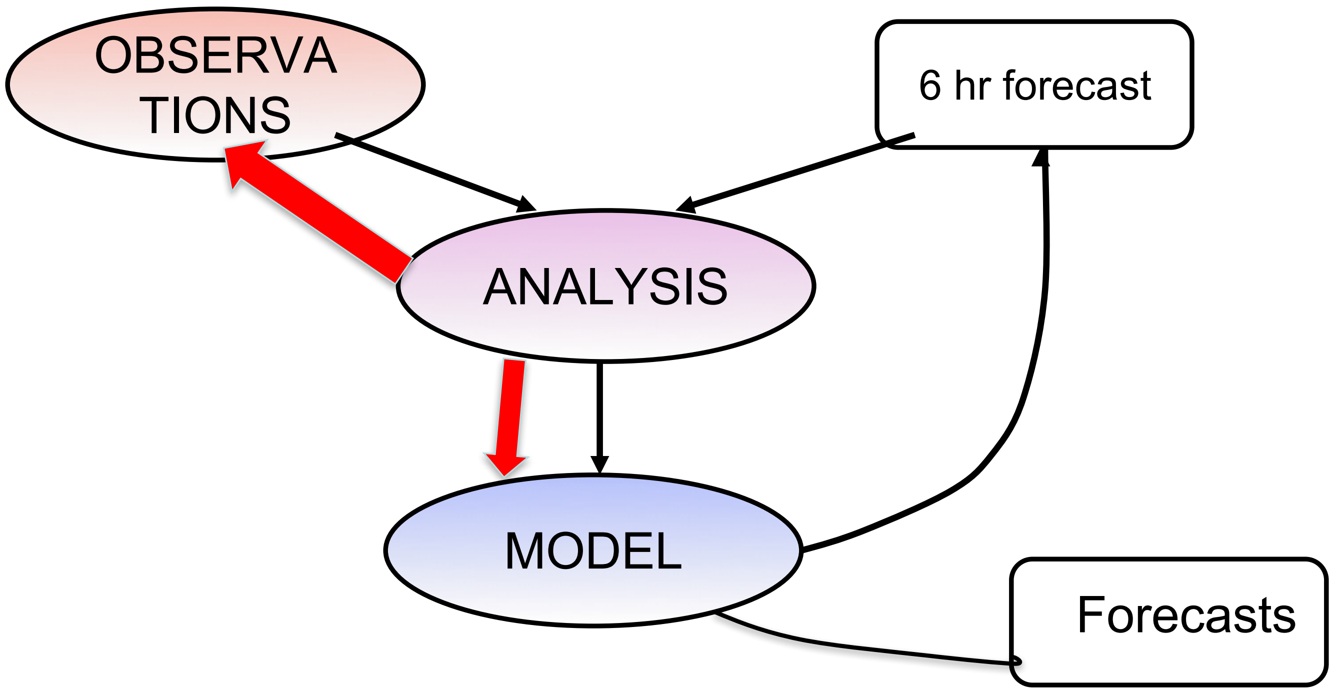
Classic Data Assimilation:
To improve Numerical Weather Prediction (NWP) we need to improve observations, analysis scheme and model

CLASSIC DA:

Every 6 hours we make a new forecast, get new observations, and combine them to get the new analysis, which is the new initial condition for the model forecast.



NEW applications of modern Data Assimilation:
We can **also** use DA to improve both observations and model



Using Analysis Increments to Estimate and Correct Systematic Model Errors

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1. Systematic Model Errors

Systematic errors limit the performance of Numerical Weather Systems and data assimilation schemes.

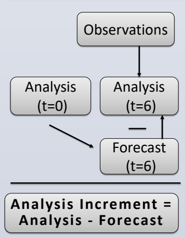
$$\mathbf{x}_m^e = b + \sum_{l=1}^{L} \beta_l(t) e_l + \sum_{n=1}^{N} \gamma_n(t) f_n + \mathbf{x}_m^{rand}$$

Bias | Periodic | State dependent | Random

2. Objectives

I. Estimate the time averaged Systematic Error, i.e. bias in Ps, Q,T, U and V
II. Estimate the periodic component of Systematic Errors by analyzing Empirical Orthogonal Functions
III. Implement an adaptive Online Correction scheme that corrects GFS in real time during the model integration

3. Estimation Of Bias Using Analysis Increments (AIs)



6-hr AIs are the corrections observations make on 6-hr forecasts while the errors are still growing linearly

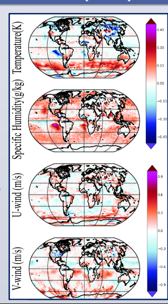


Figure 1: JJA average AIs for 2014 indicate large scales biases

4. Adaptive Online Correction Scheme

Bias correction term

- Calculate the bias correction term based on the average of past N days 6-hr Analysis Increments
- AIs calculated every 6-hrs

$$< \delta \mathbf{x}_6^{ai} > = \frac{\sum_{\tau=1}^{4*N} \delta \mathbf{x}_{\mathbf{6-hr}}^{\mathbf{ai}}(t-\tau)}{4*N}$$

Get corrected model

- Divide the correction term by 6 hours
- Add to the model tendency equation to get online corrected model

$$\dot{\mathbf{x}}(t) = M[\mathbf{x}(t)] + \frac{< \delta \mathbf{x}_6^{ai} >}{6 - hr}$$

5. Reduction In Bias After Online Correction

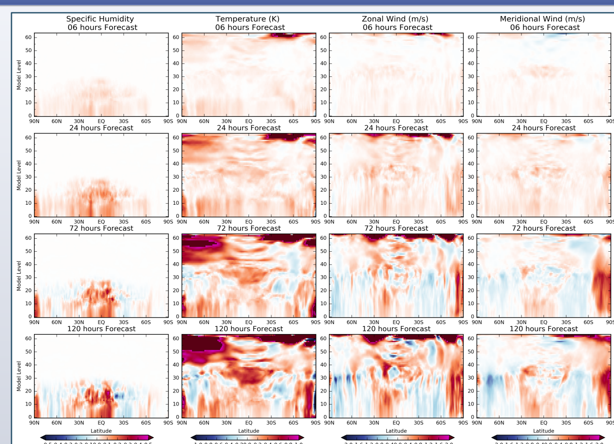


Figure 2: Improvement in bias (shown in red) after applying Adaptive Online correction using training period of past 7 days

5. Reduction in Bias ...

- ❑ Bias in all tested variables reduced until 1 day with no impact on random errors
- ❑ After 1 day, all variables generally improved in the tropics and near top levels
- ❑ Random errors increase slightly after 1 day but not significantly
- ❑ Improvement achieved is almost as strong as the correction applied at 6 hours

6. Diurnal Cycle Errors

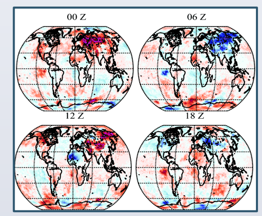


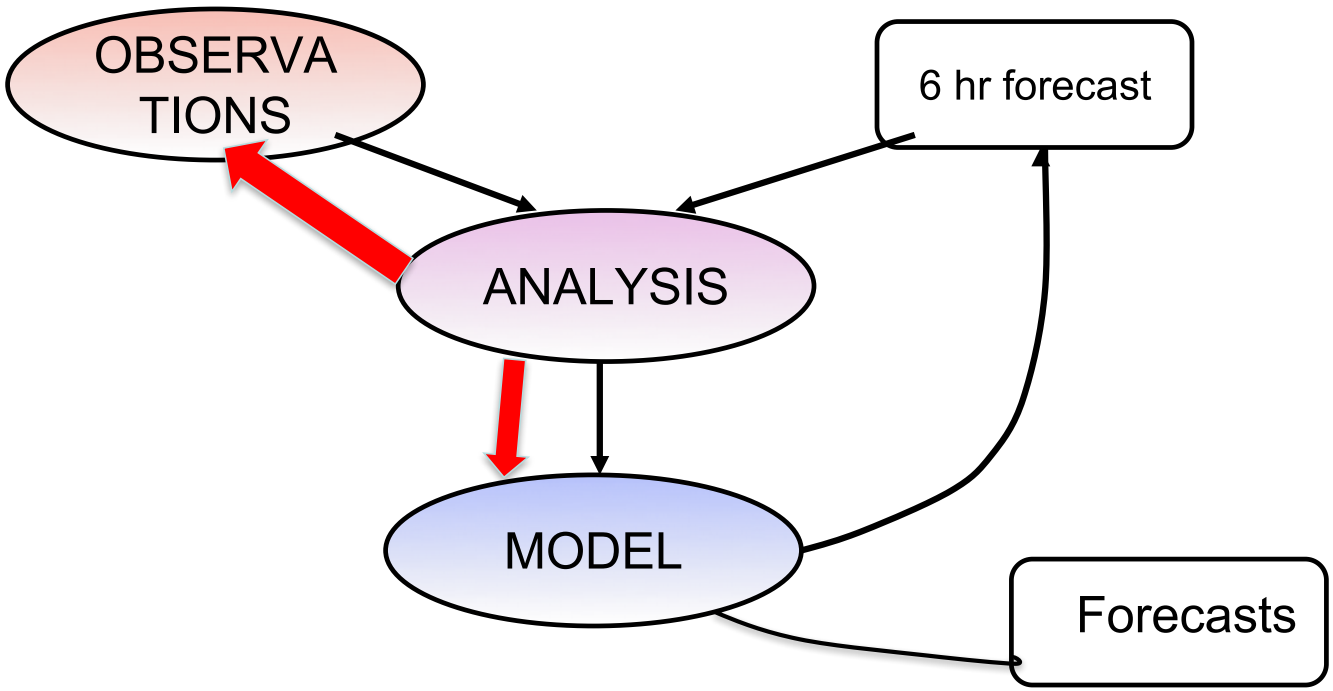
Figure 3: JJA Temperature (K) AIs at 6-hrs

- ❑ Strong diurnal and semi-diurnal cycle errors dominate periodic component
- ❑ Scale is same as bias hence correcting these is very critical

7. Conclusions

- ❑ 6-hr Analysis Increments provide the best estimate of model bias
- ❑ GFS has robust, systematic seasonal mean and diurnal forecast errors
- ❑ Our adaptive online scheme is remarkably stable
- ❑ This scheme reduces errors globally in T& Q and in tropics in U &V even after 5 days by about 30%.
- ❑ No significant impact on random errors

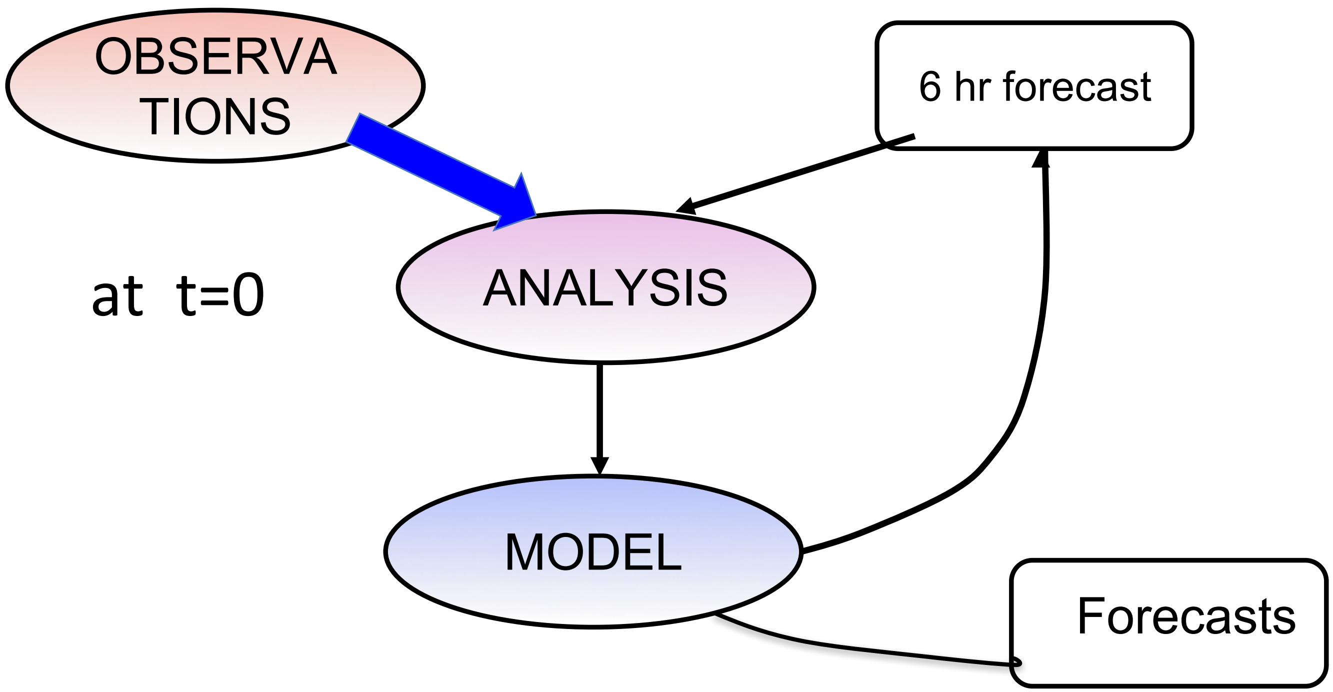
NEW applications of modern Data Assimilation:
Now will show how to use DA to improve observations



We will show how to identify and delete detrimental observations to improve the analysis and the forecasts.

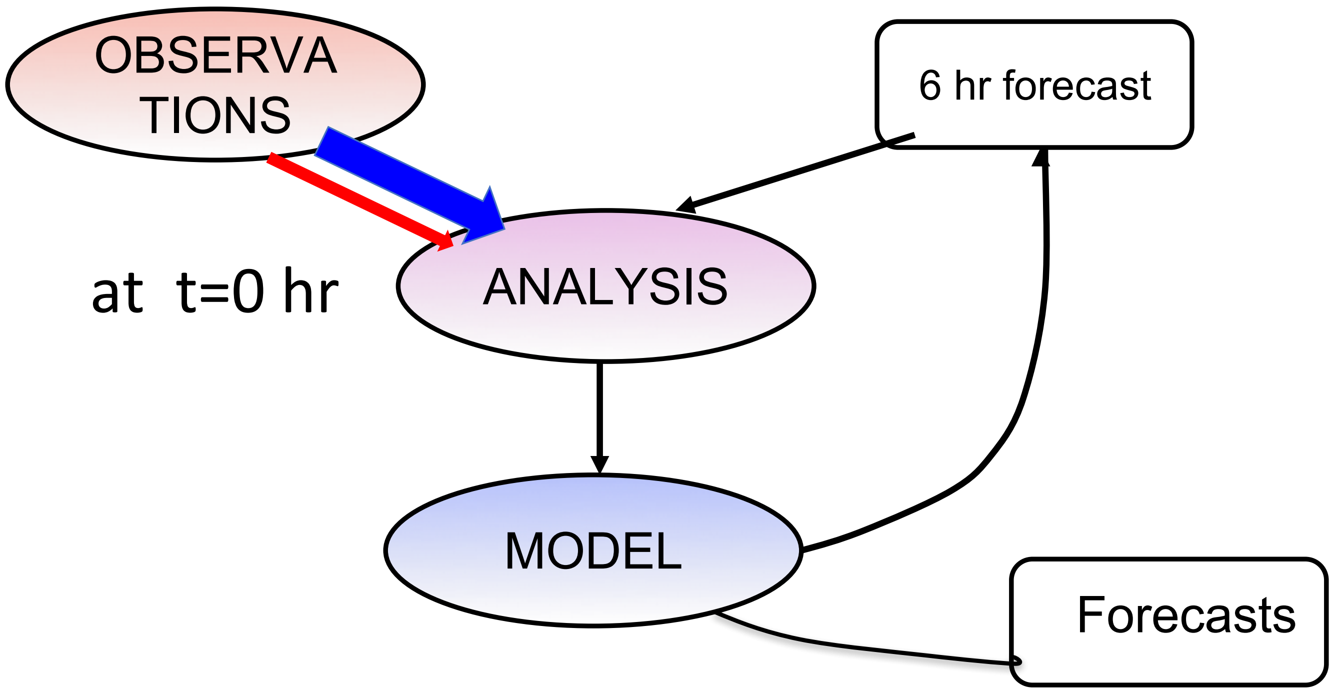
The idea is to use *future* observations to QC the *current* observations.

Many observations are beneficial: they improve the 6 hr forecast:



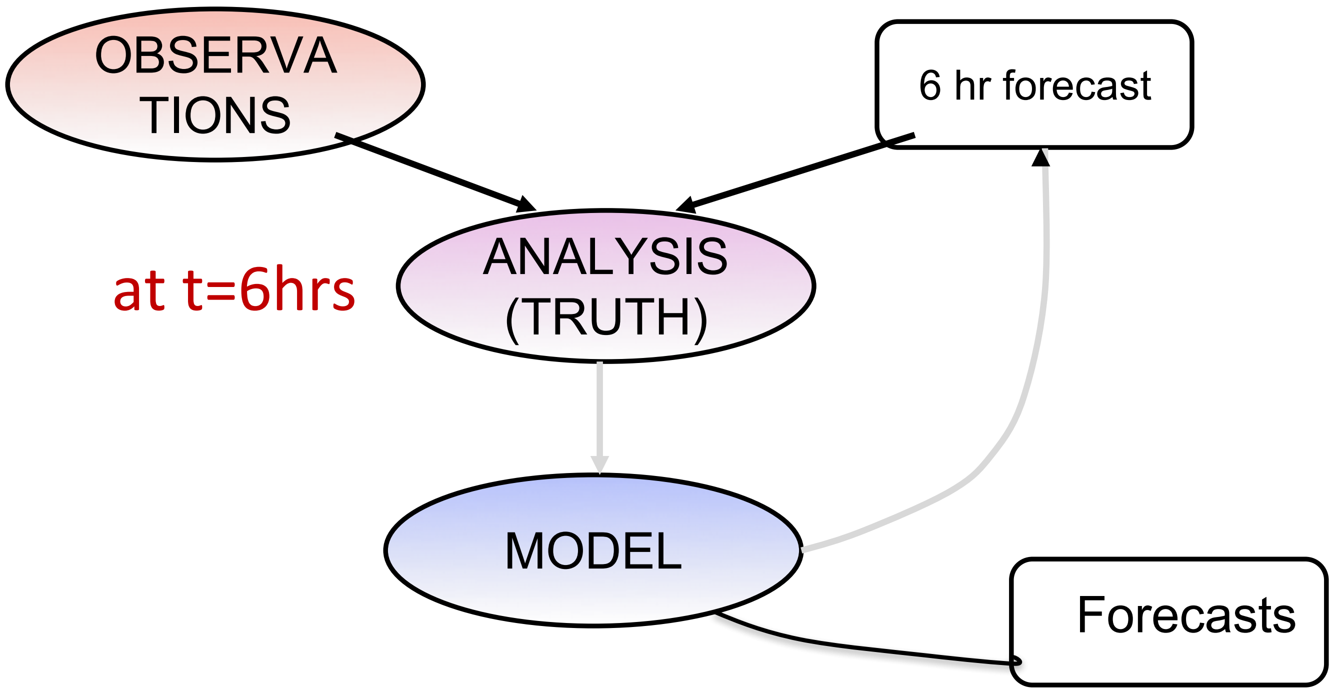
But some observations are detrimental! They make the forecast worse!

How to identify and delete detrimental observations?

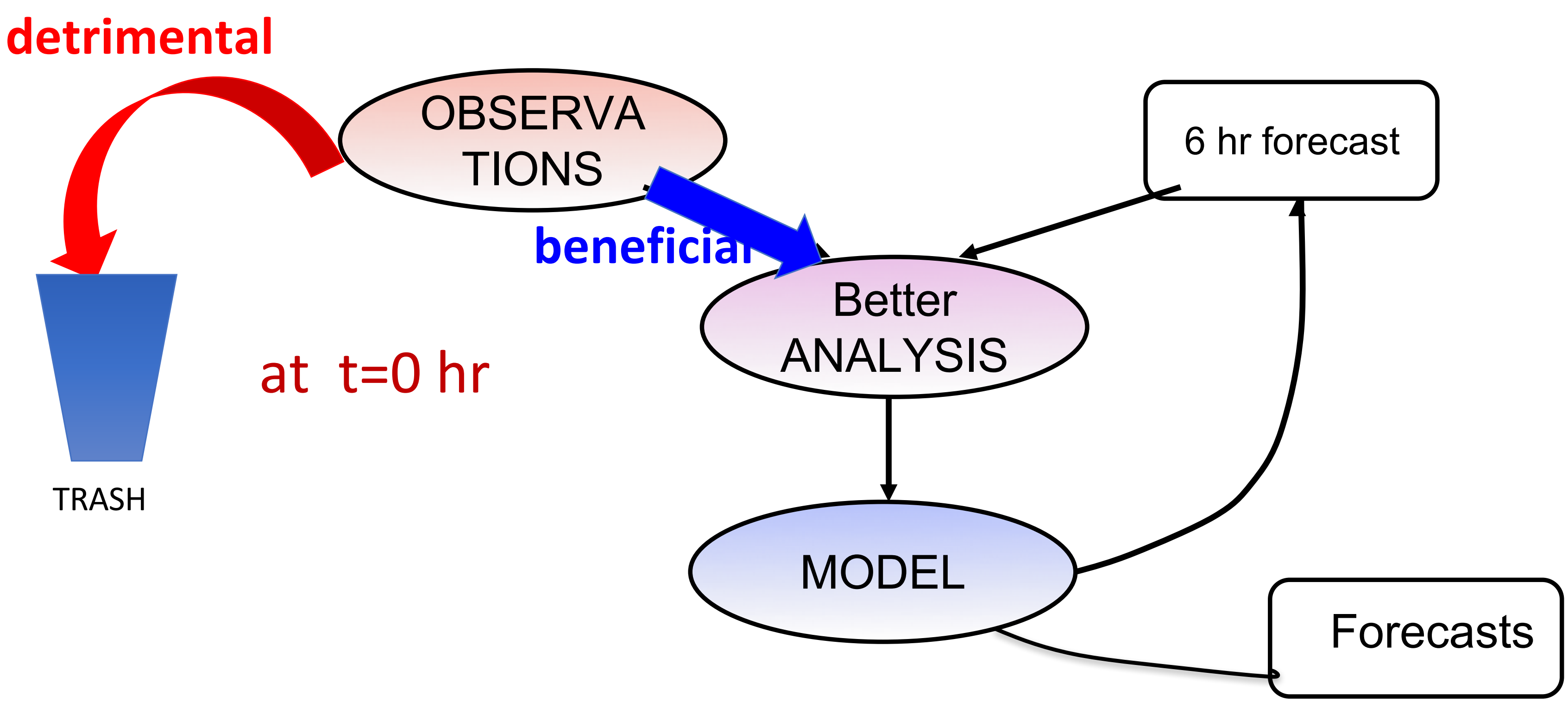


We use the observations 6 hours later, and consider the new analysis as truth for t=6hr.

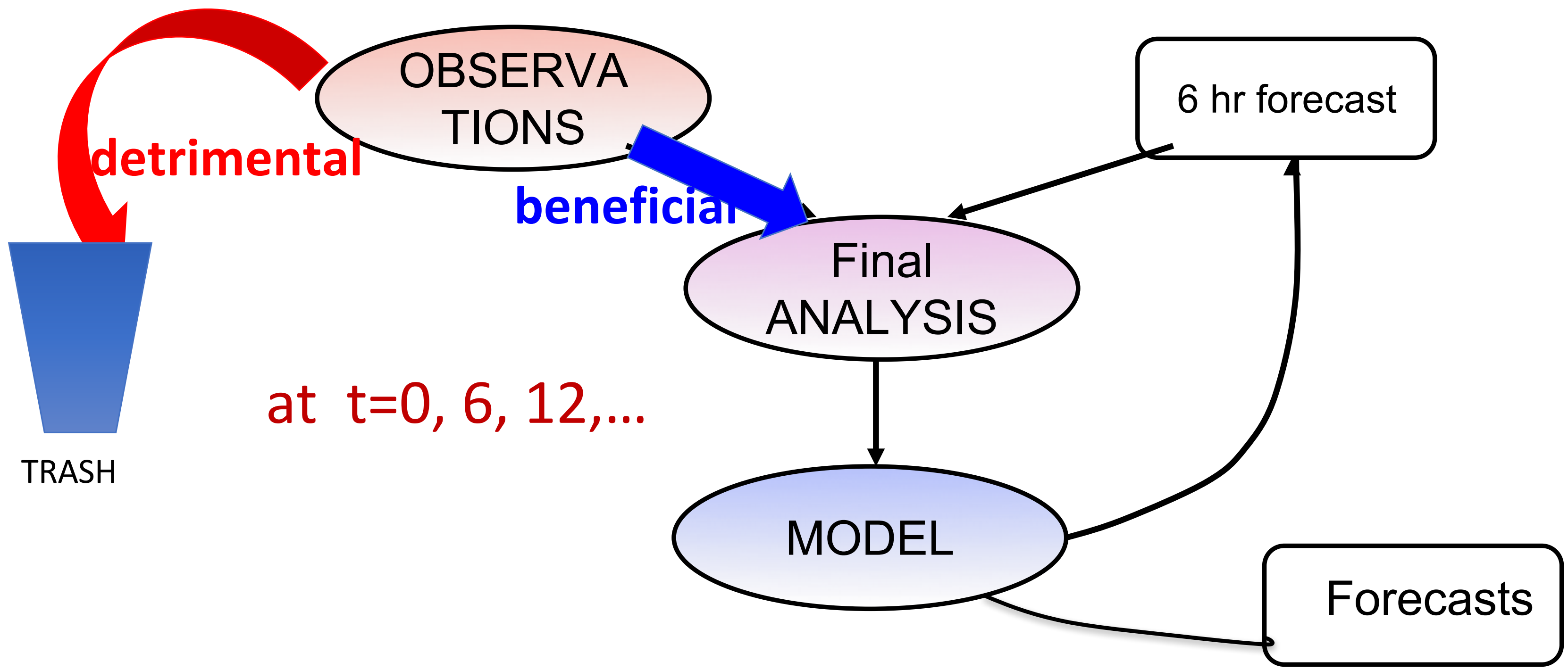
This allows to use EFSO to determine whether each observation at t=0 made the 6hr forecast better or worse



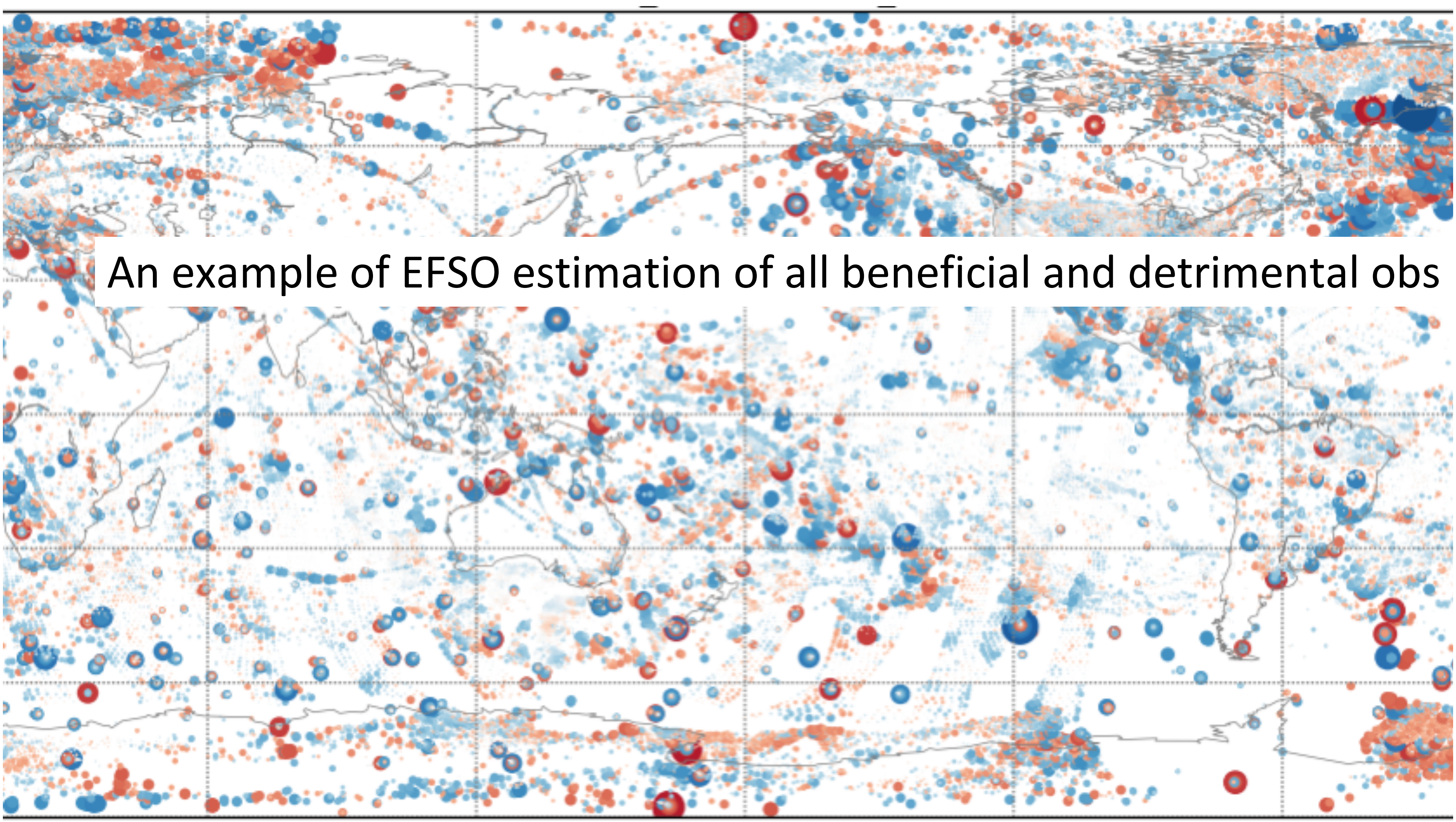
We check each t=0 observation, and (using EFSO) find whether it improved the *forecast* (beneficial) or made it worse (detrimental). We delete the most detrimental observations, and repeat the analysis at t=0 assimilating only beneficial observations.



The Final Analysis is cycled, accumulating the improvements obtained every 6 hours by deleting the most detrimental observations and assimilating all the beneficial observations (Proactive QC).



As a result, both the Analysis and the Model Forecasts improve substantially
See the example of 10-day forecasts using the GFS-LETKF system.



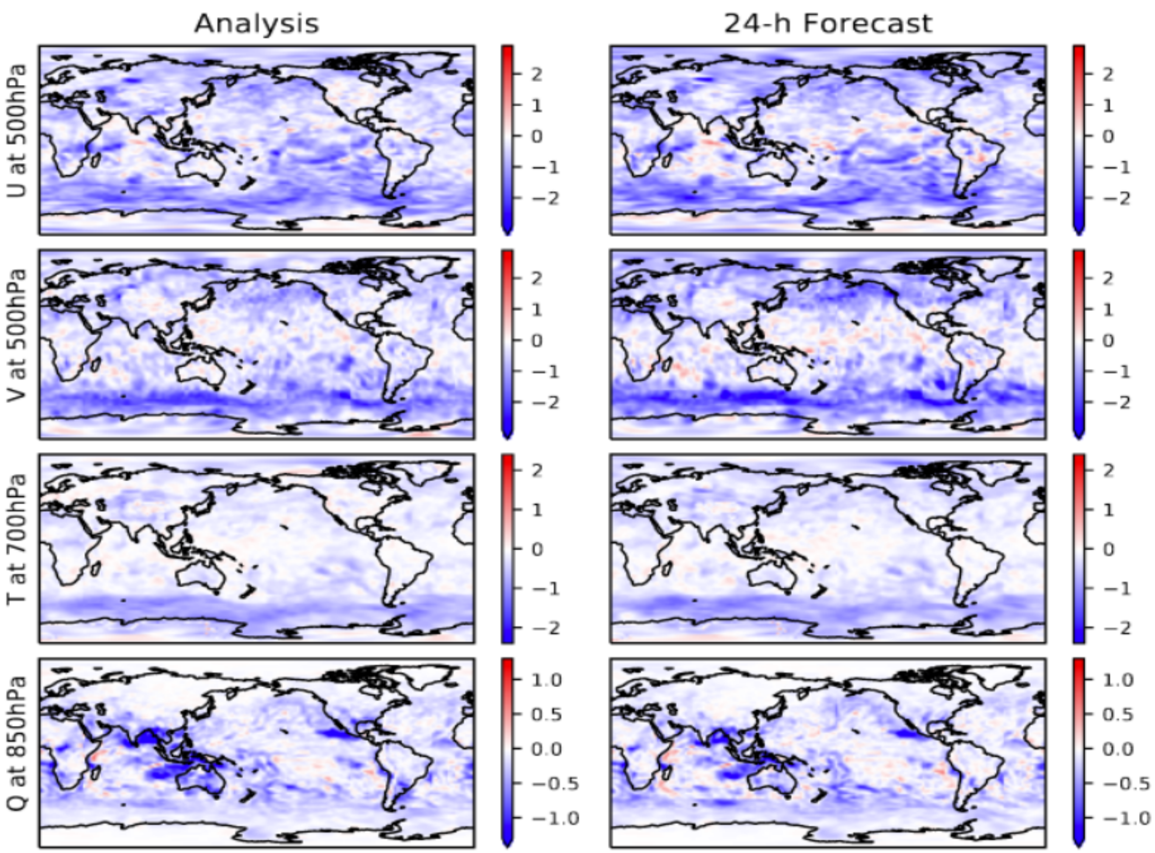
An example of EFSO estimation of all beneficial and detrimental obs

Experimental setup for GFS-LETKF (Lien, 2015, Chen, 2018)

Period (~1 month)	Jan/01/2008 00Z – Feb/06/2008 06Z (5 days for DA spinup)
Model	GFS T62 L64 (lower resolution)
DA	LETKF with 32 members ensemble size
Observations	prepBUFR data from NCEP (all obs except radiances)
Localization	Horizontal: 500 km Vertical: 0.4 scale height
Inflation	RTPP (Zhang 2004) + adaptive inflation (Miyoshi 2011)
Verifying truth	NCEP Climate Forecast System Reanalysis (CFSR)

Efficient but realistic GFS system

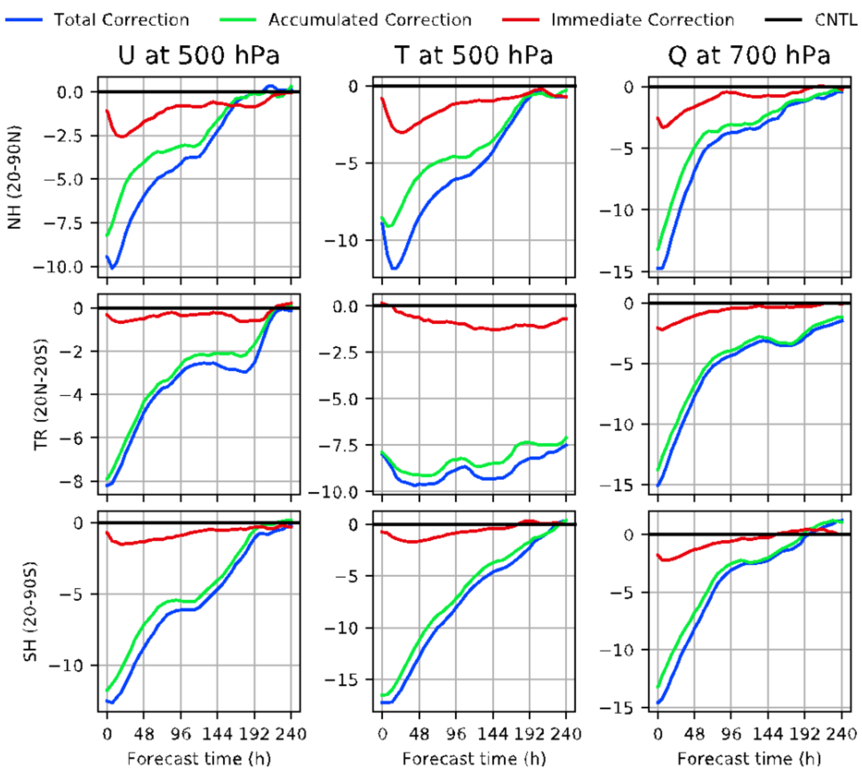
Cycling PQC accumulates the reduction of the analysis error



- **Cycling PQC reduces analysis and 24 hr forecast RMSE** (blue).
- **Essentially no red!**
- **The forecast improvements remain significative until errors saturate, at about ~10 days.**

Analysis is improved globally for every variable!

Immediate and Accumulated impact of cycling PQC



Relative Forecast Error Reduction [%]

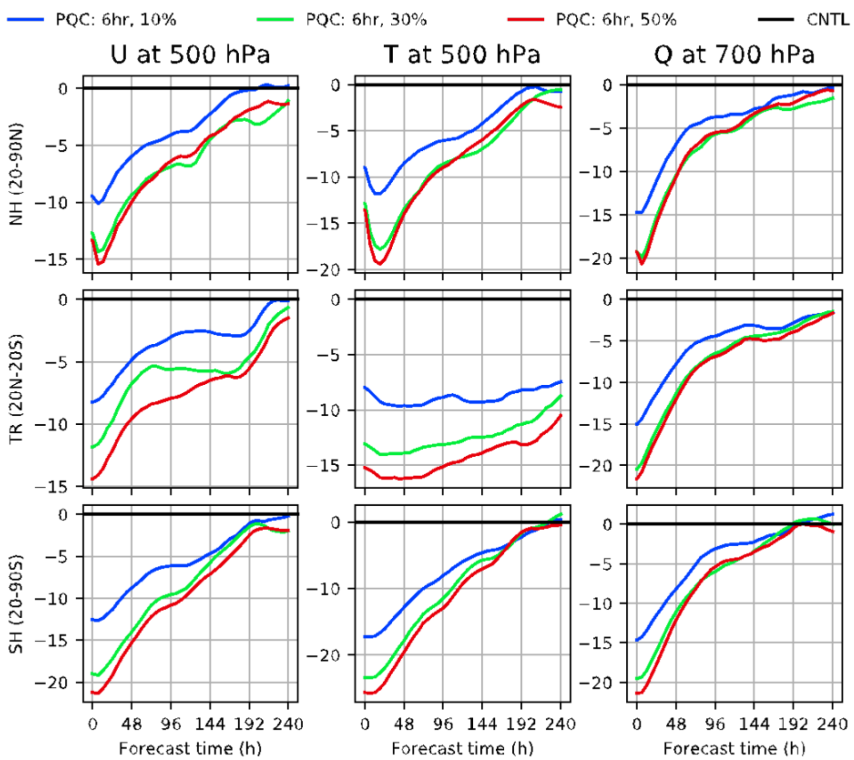
(only 10% most detrimental rejection)

- We separate **total** correction of cycling PQC into **immediate** and **accumulated** correction over 10 days.
- Most of the total correction are provided by the **cycled PQC** (**accumulated from previous corrections.**)
- This indicates that PQC is feasible for operations even if we don't have time for an immediate correction in operational tight schedule (correct only GDAS, the final analysis).

Most (~90%) benefit comes from the accumulated correction.

So, the accumulated (cycled) PQC is feasible in operations!

Rejecting more detrimental obs (up to 50%) improves the forecasts



Relative Forecast Error Reduction [%]

- More improvement when rejecting more (**10%**, **30%**, **50%**) detrimental observations.
- Rejecting all detrimental (~50%) observations gives good results.
- About 20% improvement in short-term forecast.
- The improvement remains at about 5% after 6 days.
- In the NH 30% is better than 50%.

Rejecting 50% detrimental observations improves 10 day forecasts only in the tropics, in the NH 30% is best.

We now briefly explain EFSO and show how useful it is in monitoring the quality of the observations at the analysis time t=0

Ensemble Forecast Sensitivity to Observations (EFSO)

$$\begin{aligned}\Delta e^2 &= \mathbf{e}_{t|0}^T C \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T C \mathbf{e}_{t|-6} \\ &\approx \frac{1}{K-1}\delta\mathbf{y}_0^T \mathbf{R}^{-1}\mathbf{Y}_0^a \mathbf{X}_{t|0}^{fT} C(\mathbf{e}_{t|0}+\mathbf{e}_{t|-6})\end{aligned}$$

O-B of the ens. mean

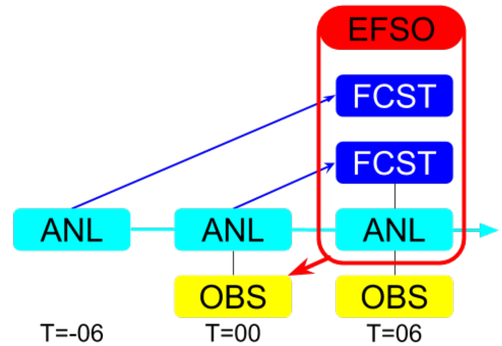
Forecast perturbation

Analysis perturbation in obs. space

Error norm

Forecast errors

Kalnay et al. 2012,
inspired by Langland and Baker (2004),
Liu and Kalnay (2008)



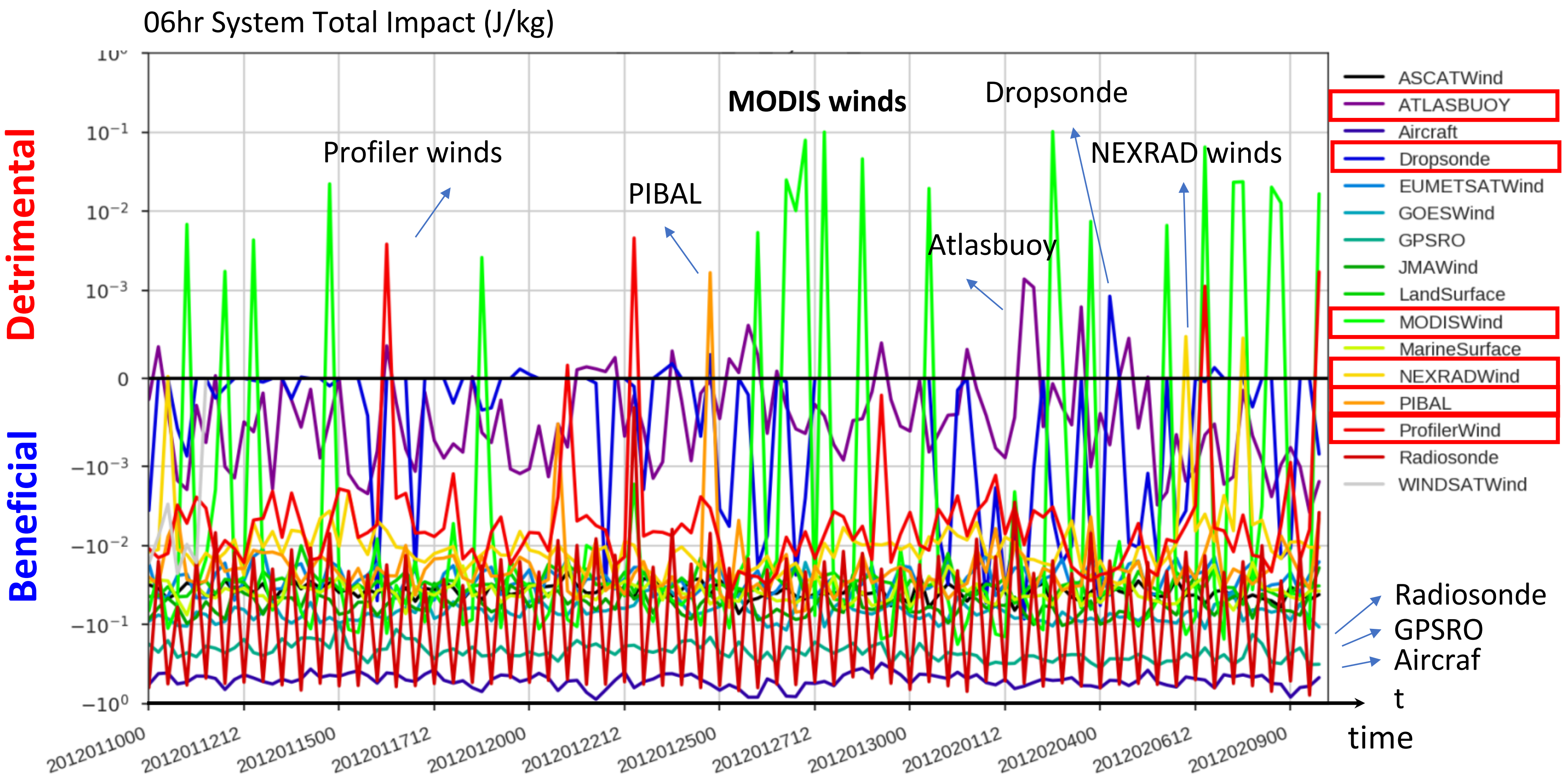
$$\boxed{\mathbf{x}_0^a = \mathbf{x}_0^b + \boldsymbol{K}\delta\mathbf{y}_0^{ob}}$$

- EFSO is a linear mapping from each observation to the 6 hour forecast error.
- Negative EFSO shows the observation reduced the forecast error (beneficial).
- Positive EFSO shows the observation increased the forecast error (detrimental)
- EFSO is efficient: the matrices above are already computed by the EnKF.
- There is no need to repeat the reanalysis without the detrimental observations.
- Simply apply the EFSO corrections (Ota et al., 2013, Chen and Kalnay, 2018).

2nd Experimental Setup: semi-operational (all observations)

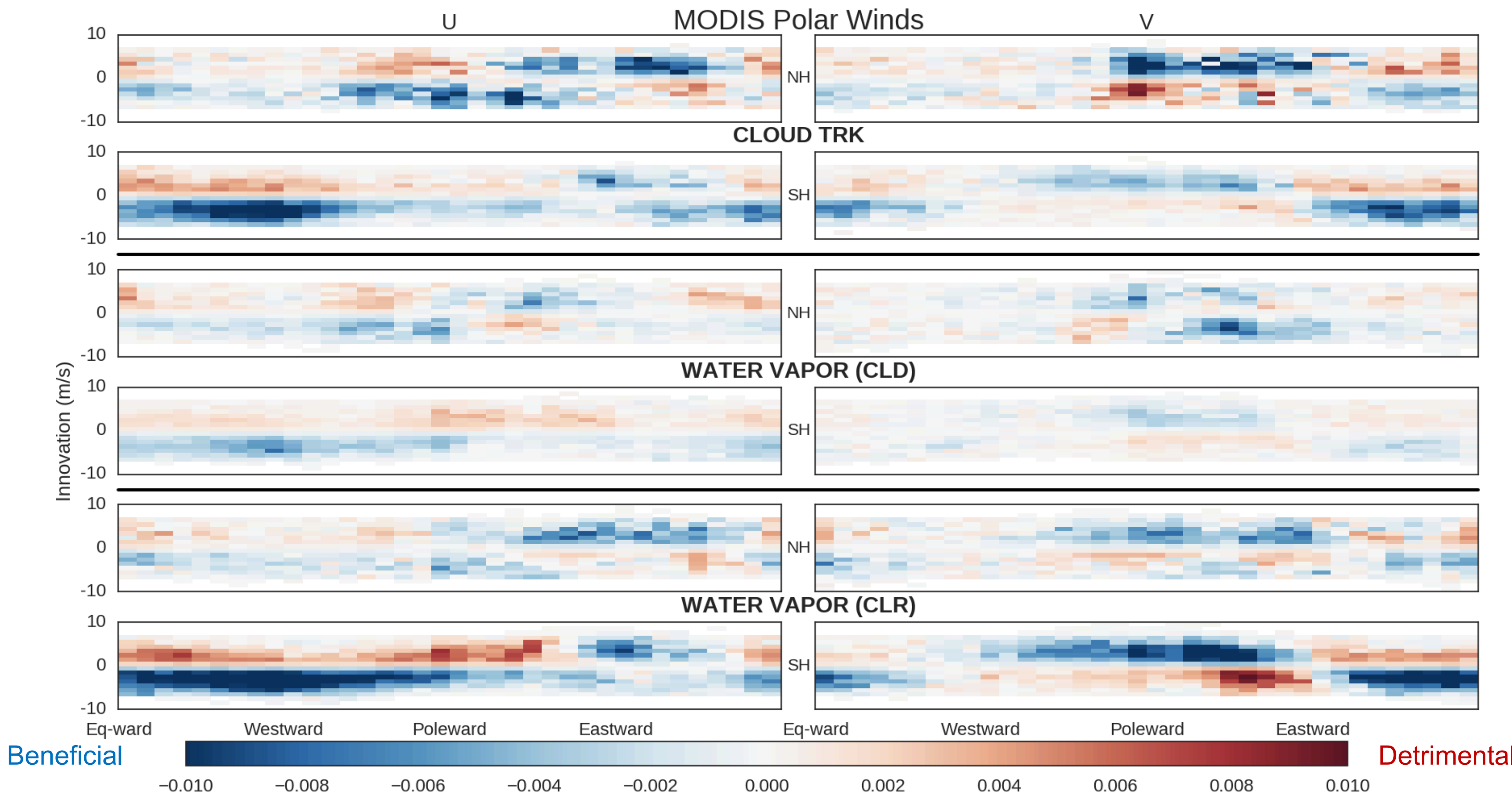
	Exp. 2012	Exp. 2017
Period (~1 month)	Jan/10/2012 00Z – Feb/09/2012 18Z (Winter, 2012)	Jun/01/2017 00Z – Jun/27/2017 00Z (Summer, 2017)
Model	GFS T254 / T126 L64	GFS T670 / T254 L64
DA	LETKF / 3D-Var Hybrid GSI **v2012**	EnSRF / 3D-Var Hybrid GSI **v2016**
Localization cut-off length	Horizontal: 2000 km Vertical: 2 scale heights	
Error norm	Moist total energy (MTE) $MTE = \frac{1}{2}\frac{1}{\lvert S\rvert}\int_S\int_0^1 \{(u'^2+v'^2)+\frac{C_p}{T_r}T'^2+\frac{R_d T_r}{P_r^2}p_s'^2+w_q\frac{L^2}{C_p T_r}q'^2\}d\sigma dS$	

Powerful QC monitoring for every system every 6hr!



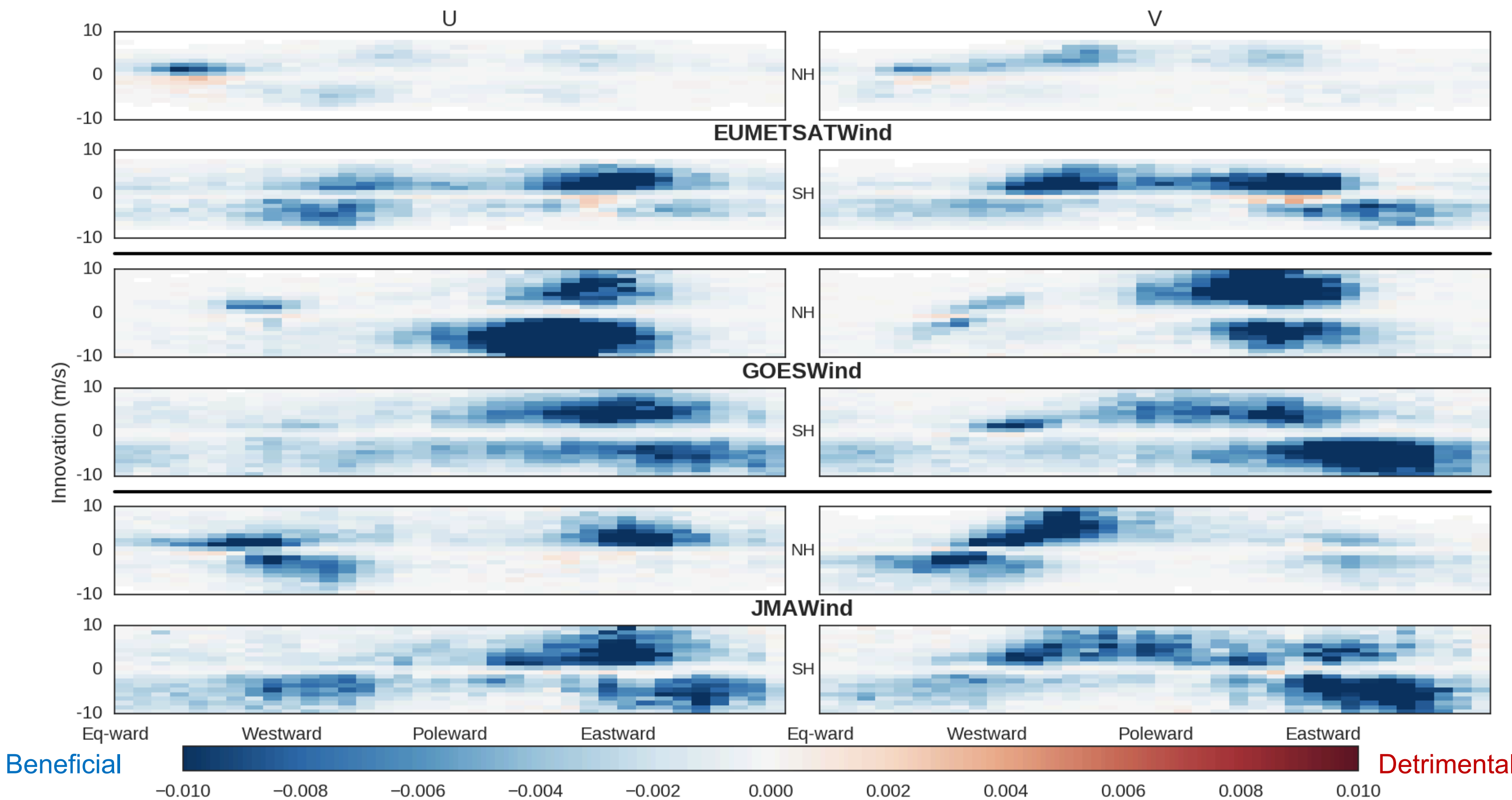
Users can see which instruments have detrimental episodes

MODIS Winds bias from EFSO: O-B and Wind Direction



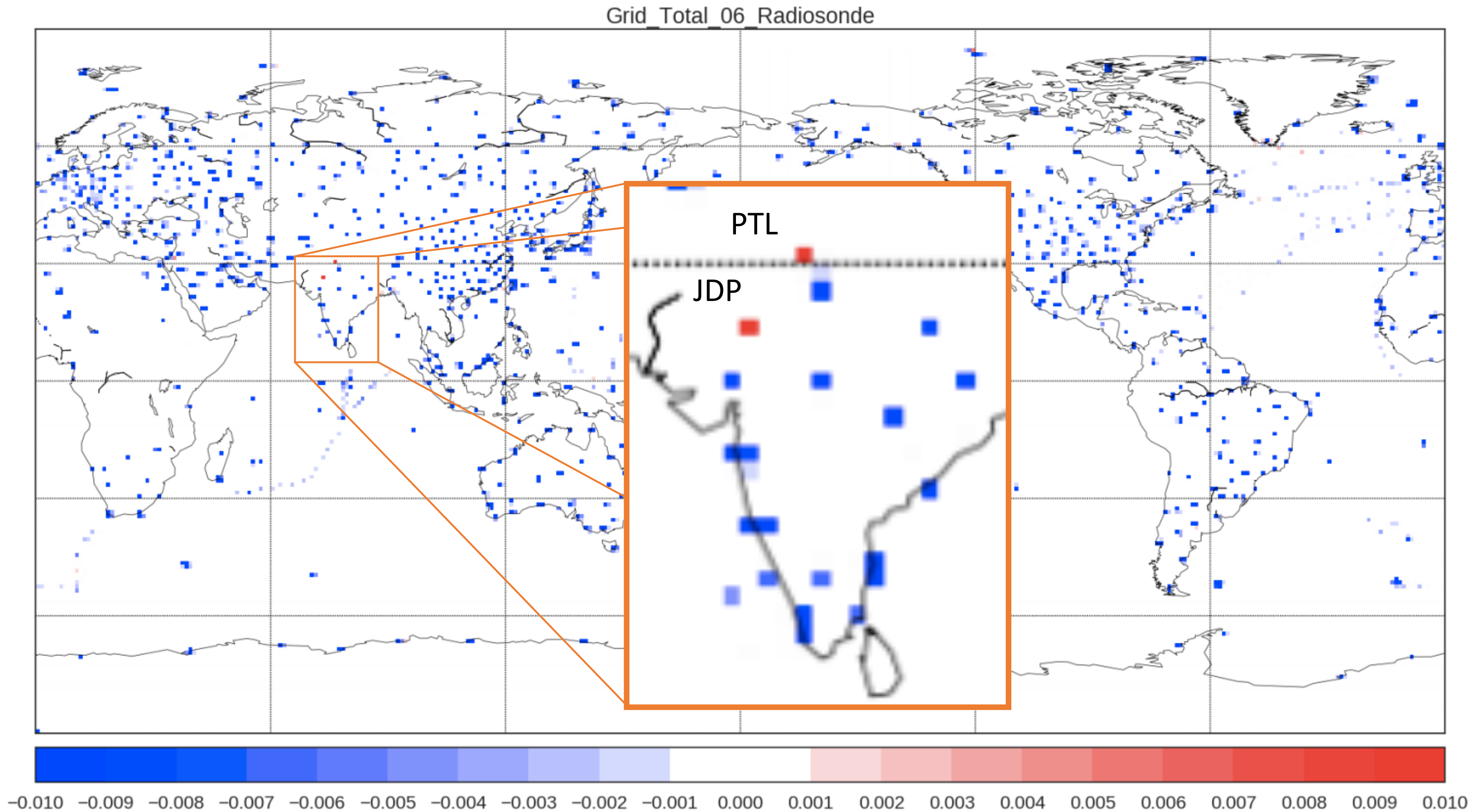
- Innovation bias of MODIS winds depends on wind direction
- Data selection can be designed from these long-term EFSO statistics

GOES Winds: O-B and Wind Direction



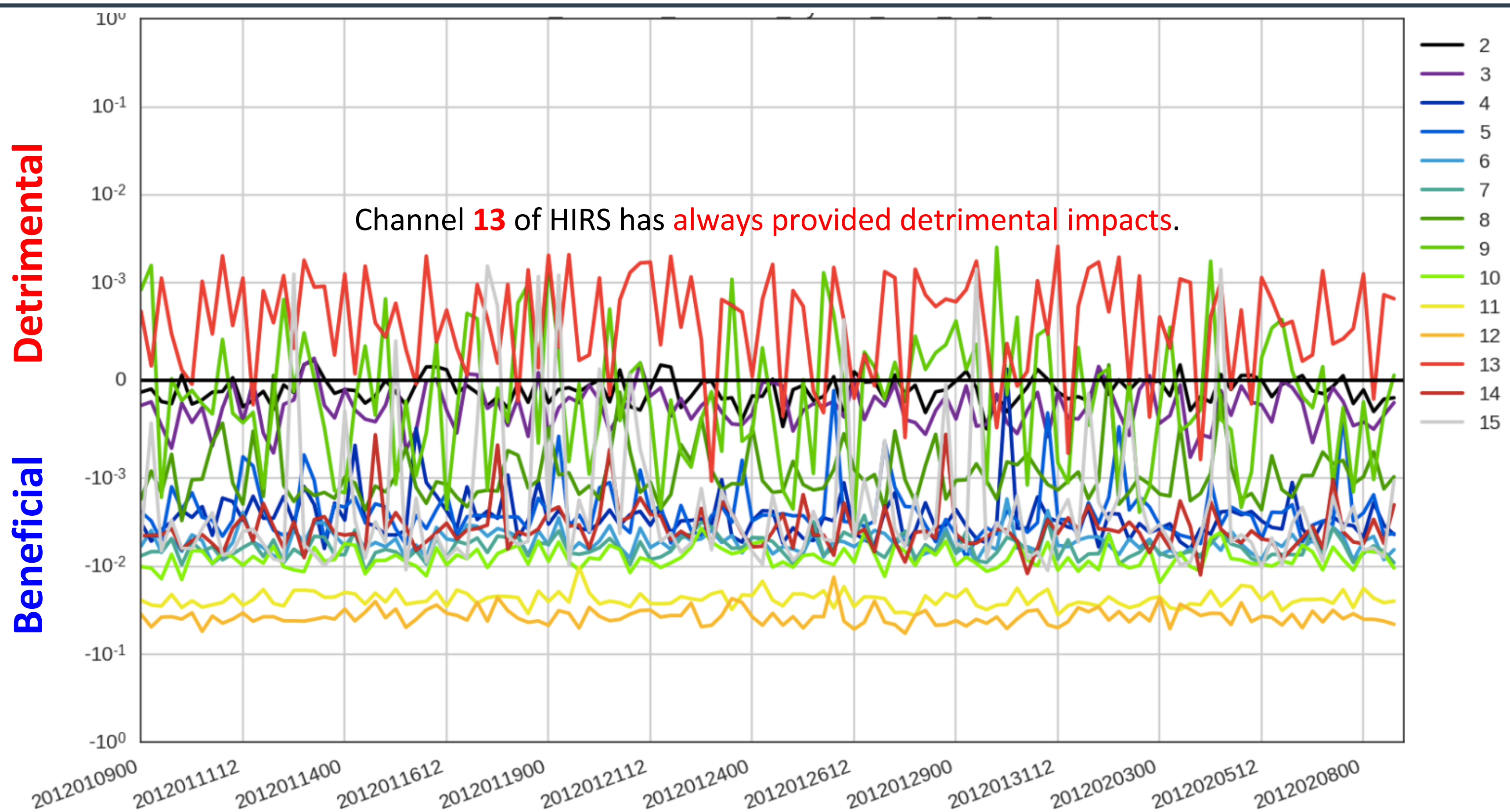
- **No such bias for any geostationary satellite winds**

Detrimental **RAOB** Stations: Monthly average



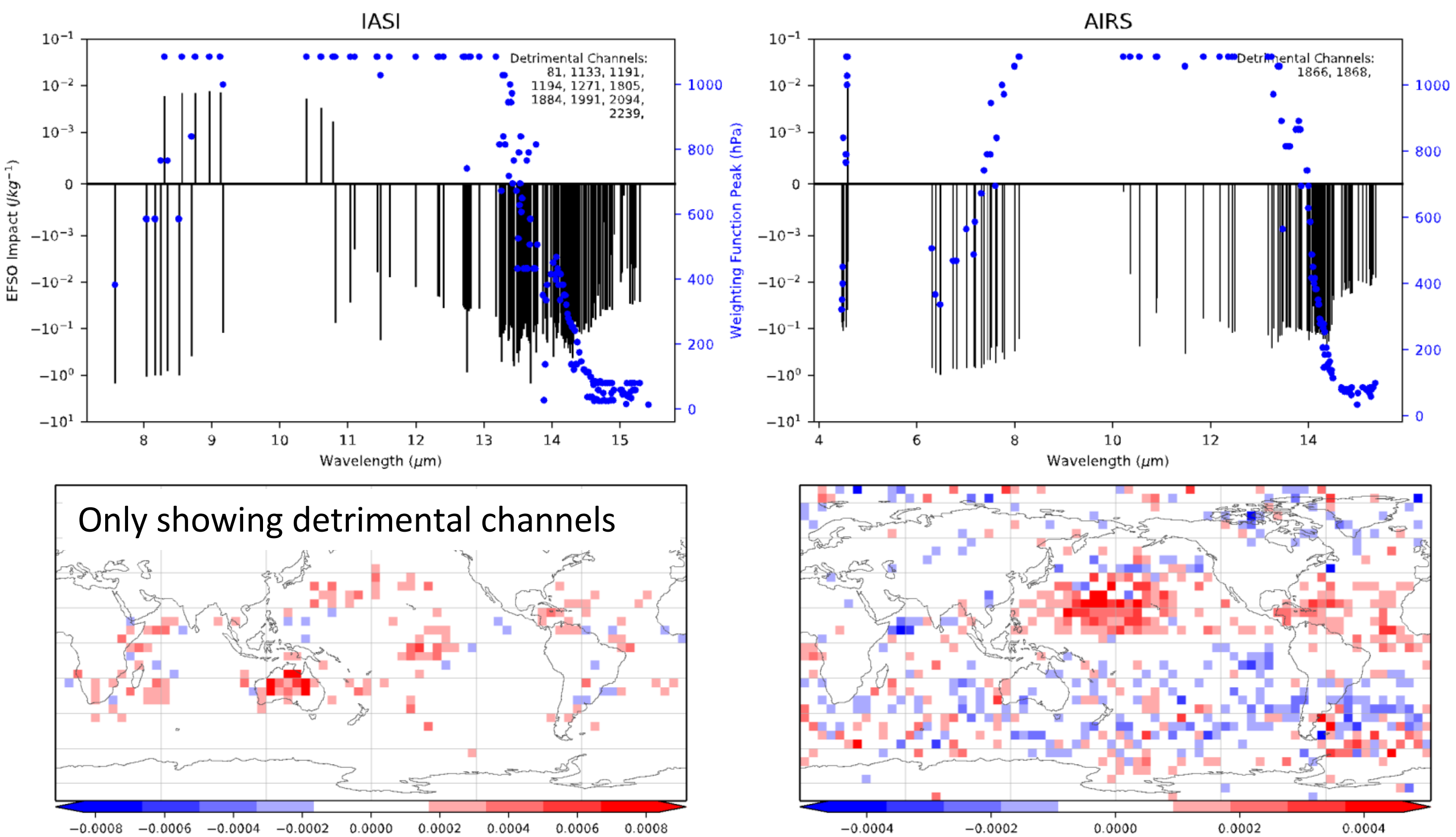
Two RAOB stations (JDP and PTL) in India were found very **detrimental** in the 1-month period.

Check Radiance Channel Selection: **HIRS**



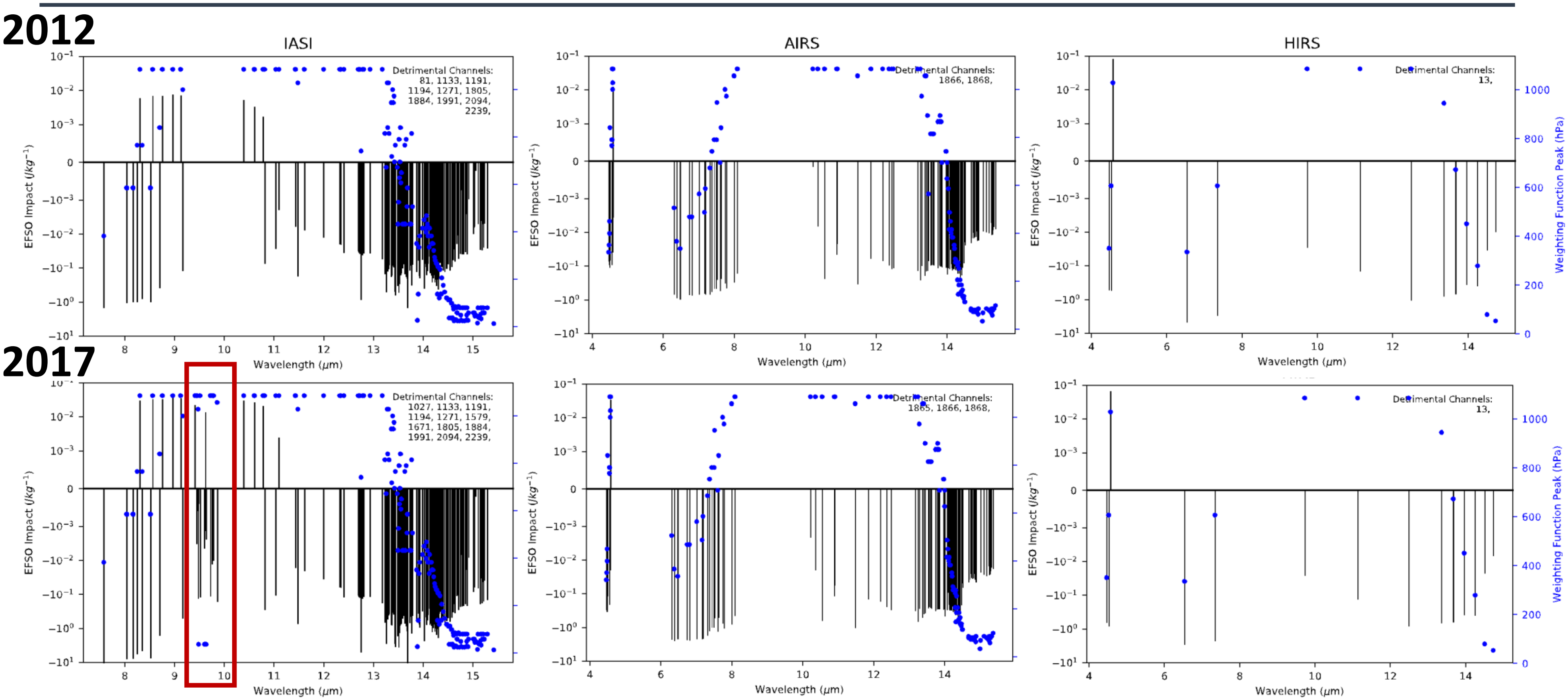
Detrimental channel 13 in HIRS is easily identified using EFSO.

Even Hyperspectral Instruments: **IASI**, **AIRS**



- Efficient channel-wise impact evaluation even for hyperspectral instruments.
- Detrimental impact from Australia and tropical oceans.

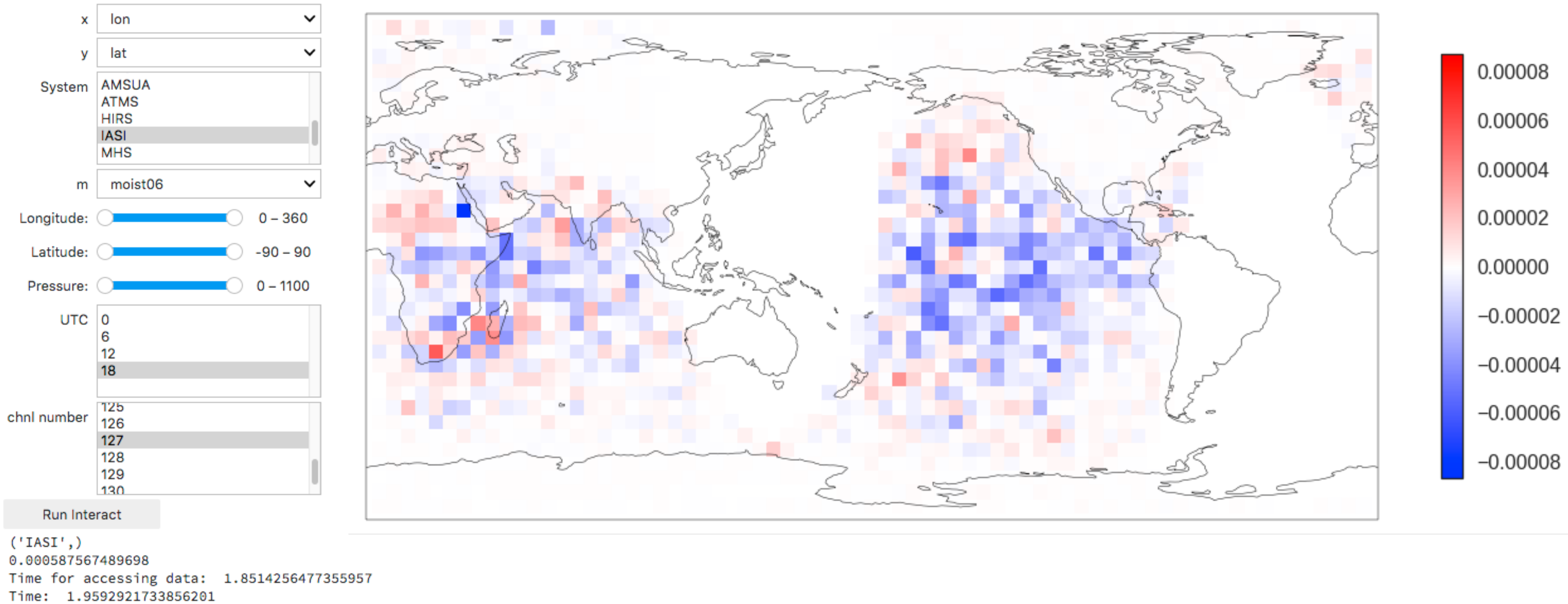
Comparing EFSO from **2012** and **2017**



- Detrimental channels are mostly the same.
- Some of the new IASI channels are beneficial and a few detrimental.

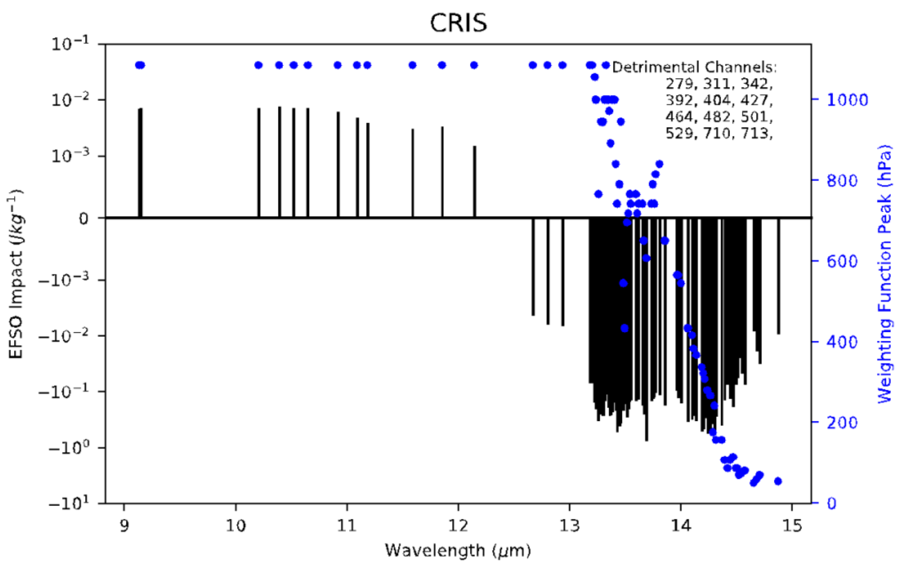
EFSO Browsing Tool created by Tse-Chun Chen

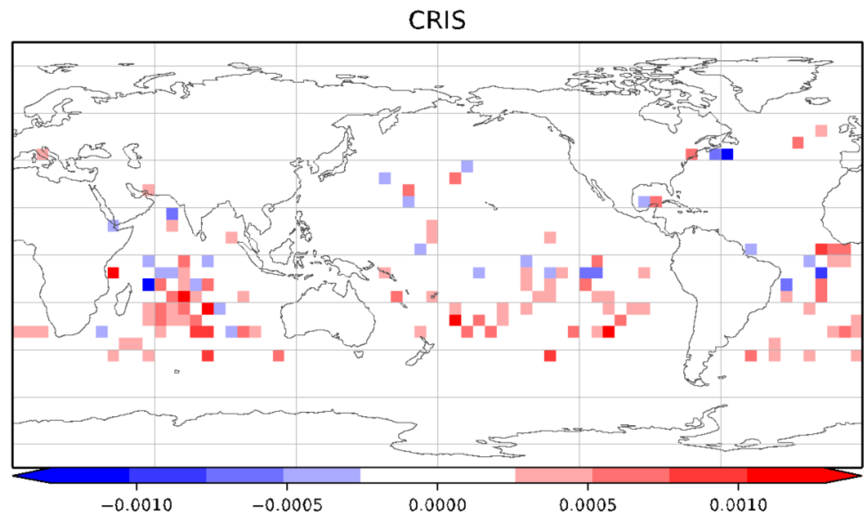
Python based



Choose location, time, instrument, and instantly get EFSO

Hyperspectral instruments: **CrIS**

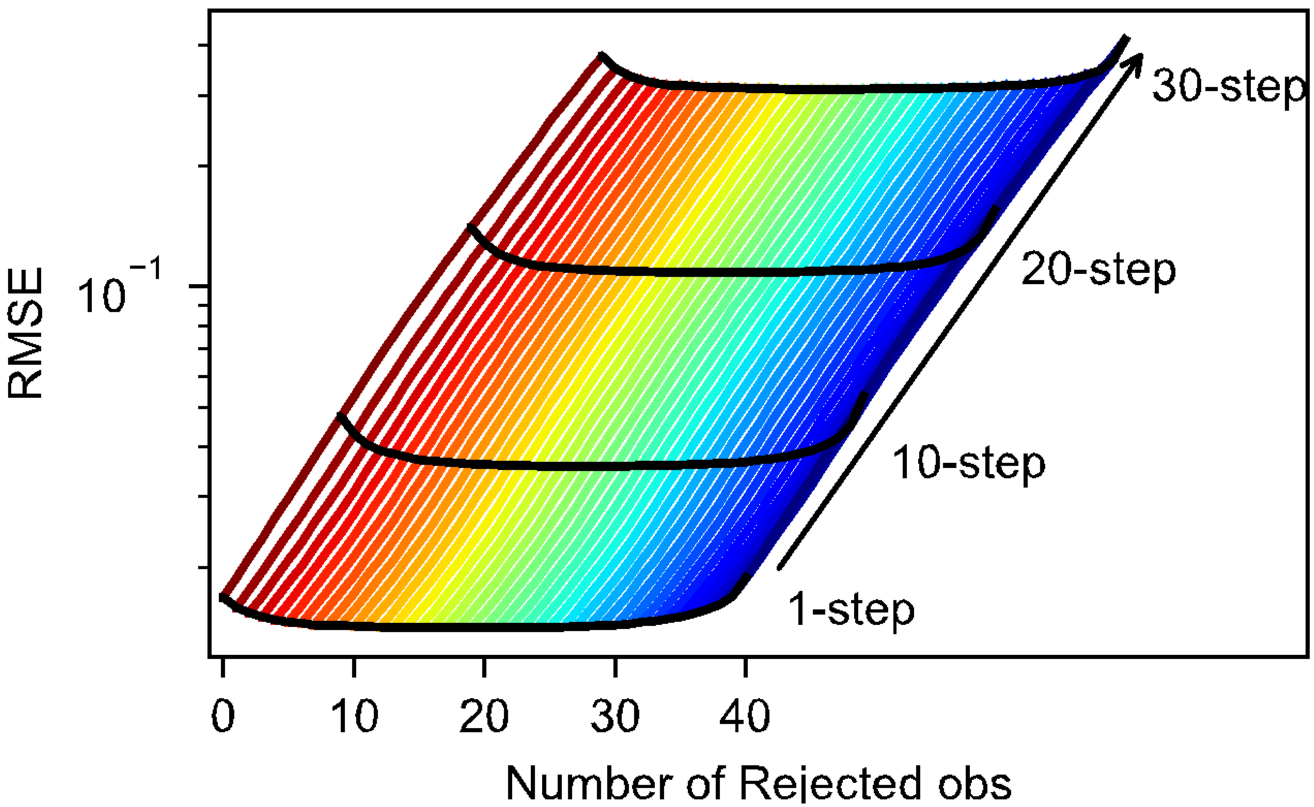




- All channels from 9-12 um (surface sensitive) are detrimental.
- The detrimental impact is from southern tropical oceans.

Non-cycling PQC with **flawless obs.** (Lorenz, 1996)

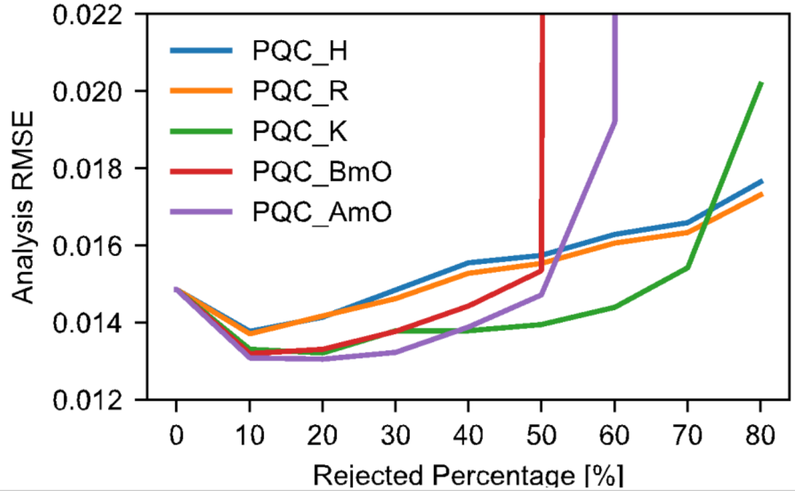
Colored: forecast error trajectory
Black: forecast error at different forecast lengths.

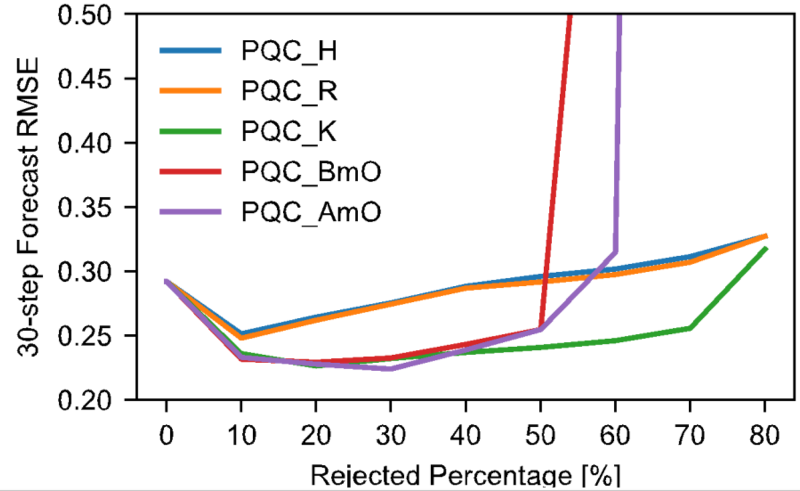


- Rejected observations from most **detrimental** to most **beneficial** EFSO impact.
- Rejecting **worst few detrimental observations** provides most of the improvement.
- The **improvement grows** as the forecast advances in time (log-scale!)

Even non-cycling PQC improves the forecast!

PQC analysis update methods: EFSO is optimal!





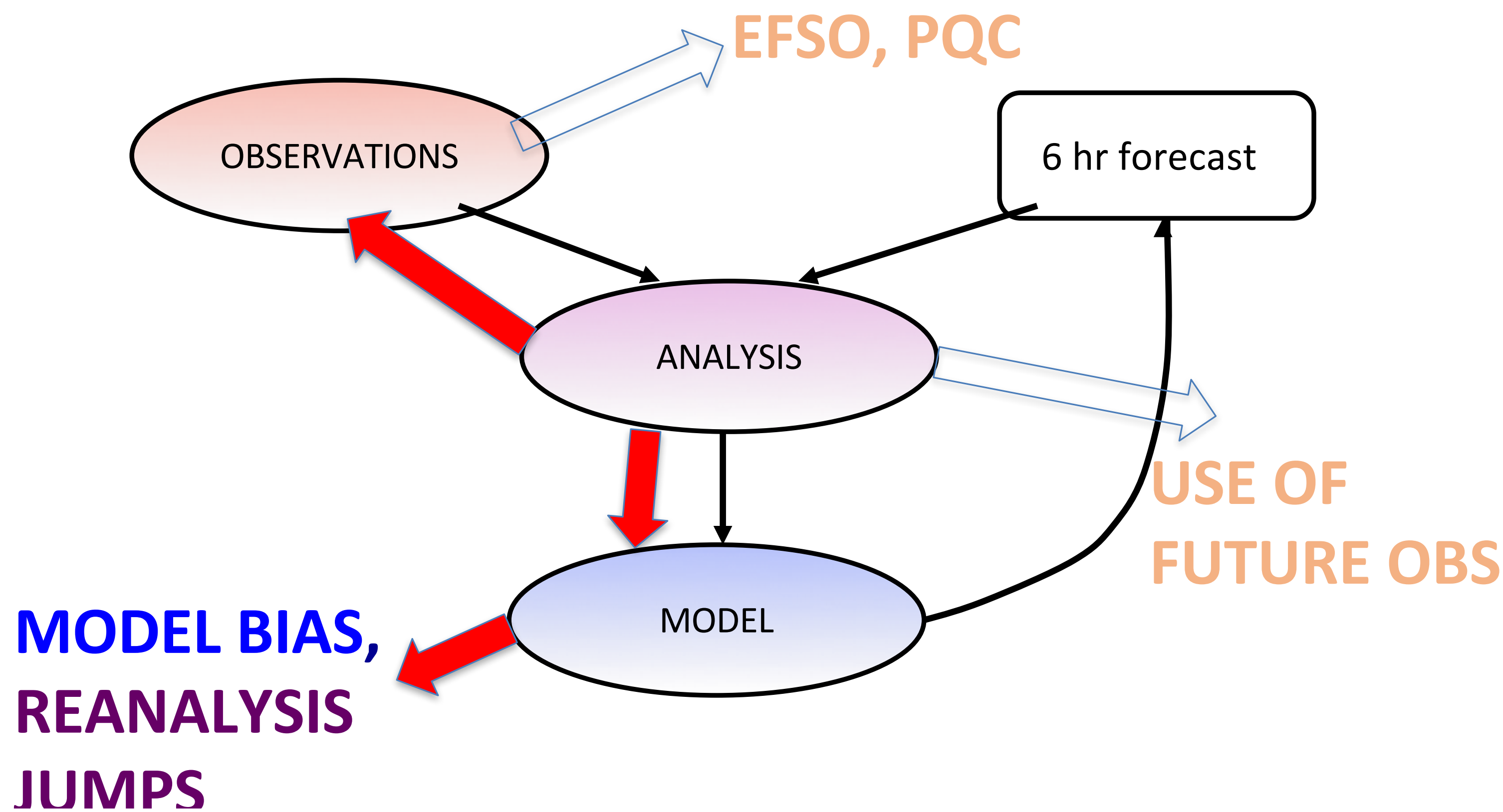
Methods	Mechanism	Change in $\boldsymbol{K}$	Change in Spread	Repeat analysis	Computational cost
PQC_H	Recompute $\boldsymbol{K}$ without observation	Large	Increased	Yes	High
PQC_R	Recompute $\boldsymbol{K}$ with up-weighted $\boldsymbol{R}$	Large	Increased	Yes	High
PQC_K	Reuse the original EFSO $\boldsymbol{K}$	None	None	No	Low
PQC_BmO	Assimilate background minus observation	Low	Reduced	(Serial update)	Medium
PQC_AmO	Assimilate analysis minus observation	Low	Reduced	(Serial update)	Medium

PQC_K is both beneficial and robust (consistent with EFSO)

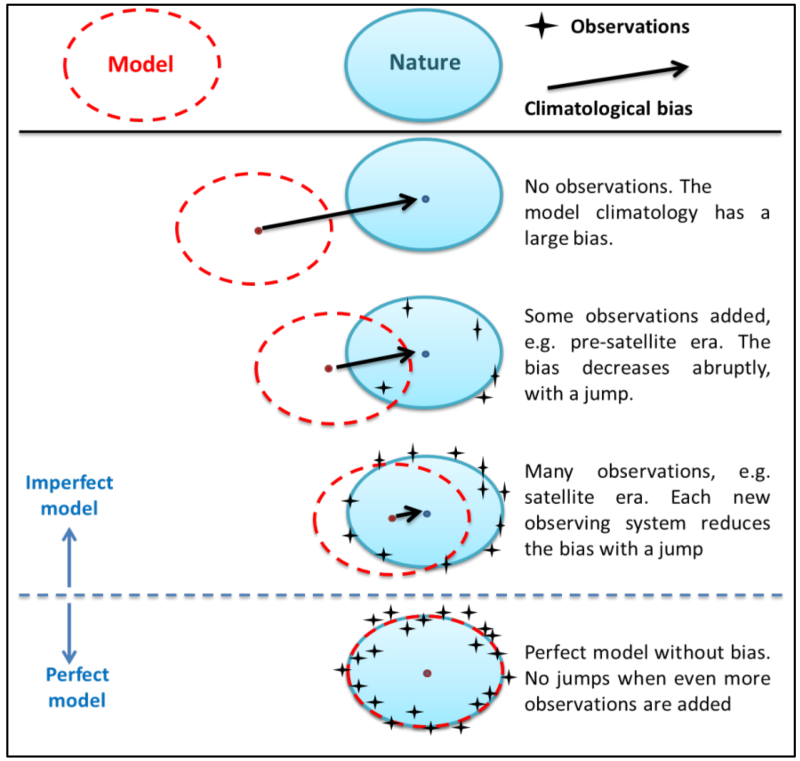
Concluding remarks for Lorenz96 system

- **PQC-K**, reusing the original Kalman gain, is most efficient in computation and most accurate in the correction!
- PQC improves even the **flawless** observing system. (Harvest additional information from the observations)
- Rejecting ~ **10%** of the most detrimental observations provides most of the improvement (it is less sensitive to additional rejections).

2) New Opportunities for Reanalysis: We can also minimize the Reanalysis Jumps that appear with new observing systems



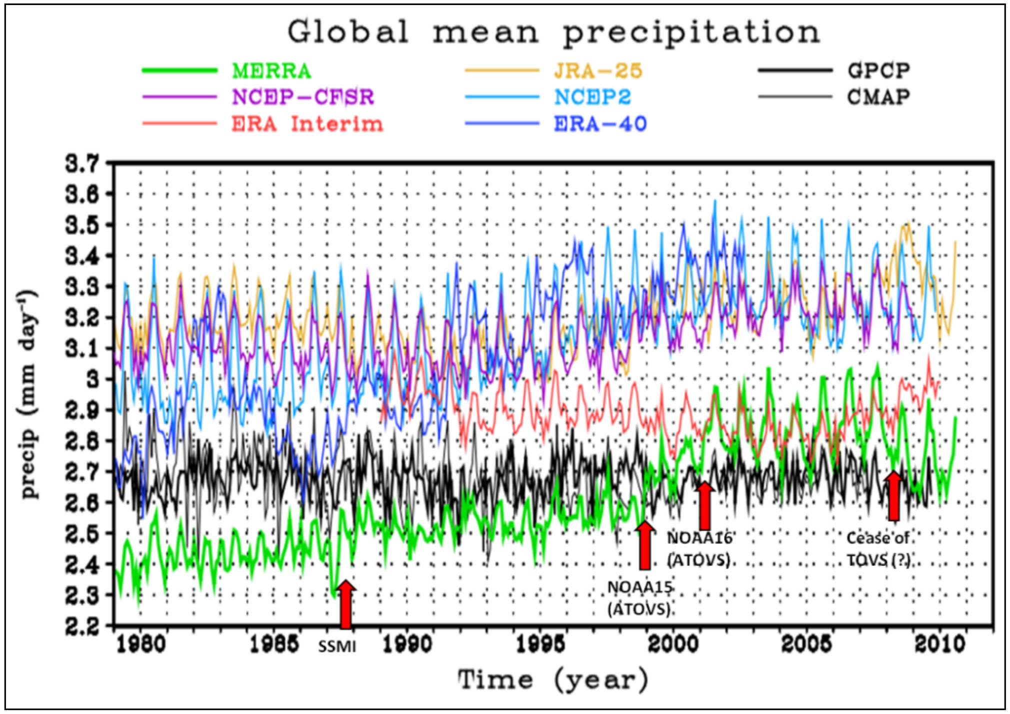
Why do we get reanalysis jumps? Model bias!



A schematic of "climate jumps" associated with observing system changes

- **The climatological bias between the forecast model and the nature decreases with a *jump* when a new observing system was assimilated.**
- **The purpose of Yan Zhou's dissertation was to find a way to minimize the "climate jumps" associated with observing system changes.**

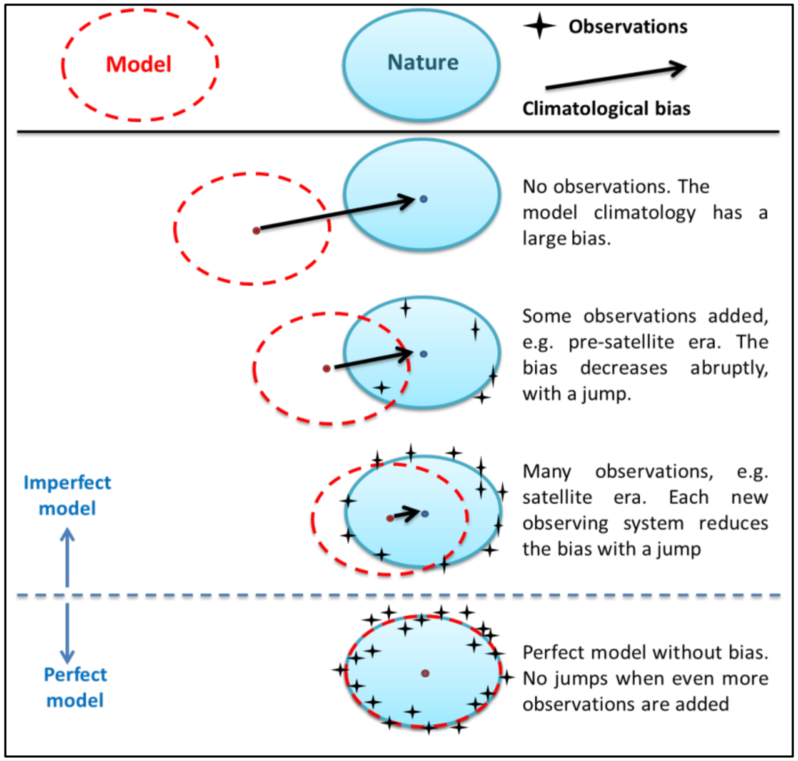
Example: MERRA and other reanalyses global mean precipitation



Global monthly mean precipitation (mm/day) time series for MERRA (green), several other reanalyses, and GPCP and CMAP (black) (Chen et al., 2012)

- **Jumps in the MERRA global mean precipitation time series appeared simultaneously with introducing or ceasing different types of satellite observations, like SSM/I and ATOVS (red arrows)**

Why do we get reanalysis jumps? Model bias!



- **The climatological bias between the forecast model and the nature decreases with a *jump* when new obs are assimilated. These jumps are the worst deficiency of reanalyses, especially long reanalyses.**
- **One solution <u>is not to include new observations</u> (Compo et al., 2009)!**
- **Another solution would be to estimate and correct the jumps.**

How can we minimize the jumps when we add new observing systems? (Yan Zhou's thesis)

Yan Zhou tested 3 plausible methods to avoid jumps

1- DKM2007 (Based on Danforth-Kalnay-Miyoshi 2007)

2- MERRA (Based on Junye Chen's idea for MERRA)

3- Climatological (suggested as a baseline by B. Hunt)

All 3 methods attempt to find the average change in analysis climatology that the new instrument introduces, and to add it to the analysis previous to the new instrument in order to correct its bias.

The best results were obtained with DKM2007. Next with MERRA. The simple climatological correction was the worst.

How can we minimize the jumps when we add new observing systems? (Yan Zhou's thesis)

- Yan Zhou tested 3 methods:

  N=with new obs; O=only old obs

  $\mathrm{AI}_{\mathrm{N}}^{\mathrm{N}}$ Analysis with New obs, First Guess with New obs

  $\mathrm{AI}_{\mathrm{N}}^{O}$ Analysis with Old obs, First Guess with New obs

  – DKM2007: $\overline{\mathrm{AI}}_{\mathrm{N}}^{\mathrm{N}} - \overline{\mathrm{AI}}_{\mathrm{N}}^{O}$ BEST

  – MERRA: $\overline{\mathrm{AI}}_{\mathrm{N}}^{\mathrm{N}} - \overline{\mathrm{AI}}_{O}^{O}$ IN BETWEEN

  – Climatology: $\overline{\mathrm{A}}_{\mathrm{N}}^{\mathrm{N}} - \overline{\mathrm{A}}_{O}^{O}$ WORST

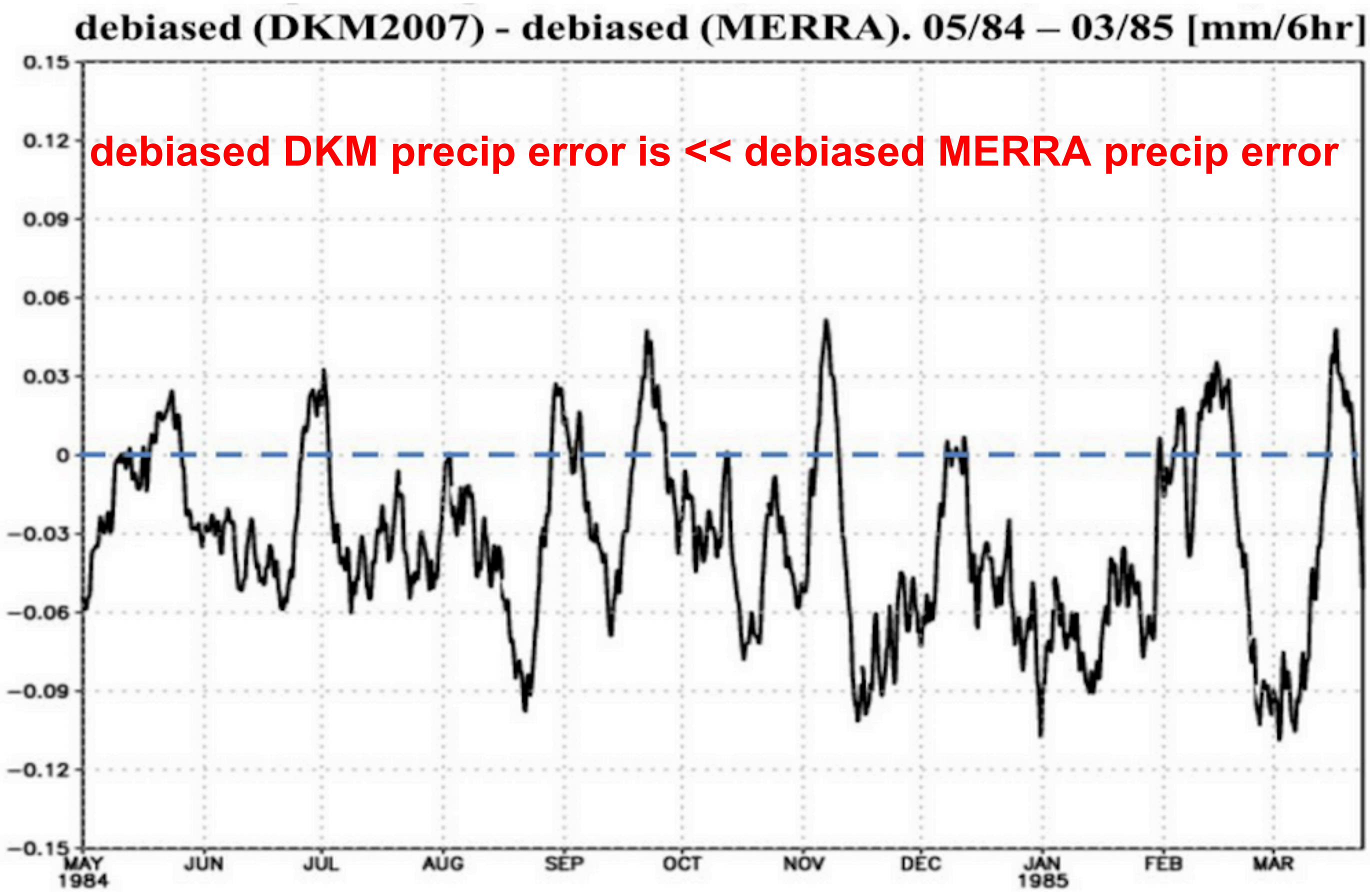


Figure 3.11 Precipitation global RMSD (with respect to RaobAirs analysis) difference, debiased (DKM2007) - debiased (MERRA).05/84-03/85 [mm/6hr]. The horizontal dashed line in the middle of the figure is the value ZERO.

Summary

- In reanalysis we **know** the "future" observations, so we should use them since they improve the forecasts!
- We now know how to minimize the "jumps" due to new observing systems.
- We should compare the results with those obtained by using only SLP to avoid the "jumps" due to new observing systems.
- Can we use future data for paleoclimatology? May be…
- We expect that using more "future" observations (e.g., use observations from "the day after tomorrow" or from "next week") will increase significantly the forecast skill, but not for longer time scales.
- We need to test models that contain shorter and longer time scales, for example, both weather and El Niño time scales, like Peña and Kalnay, NPG (2014).

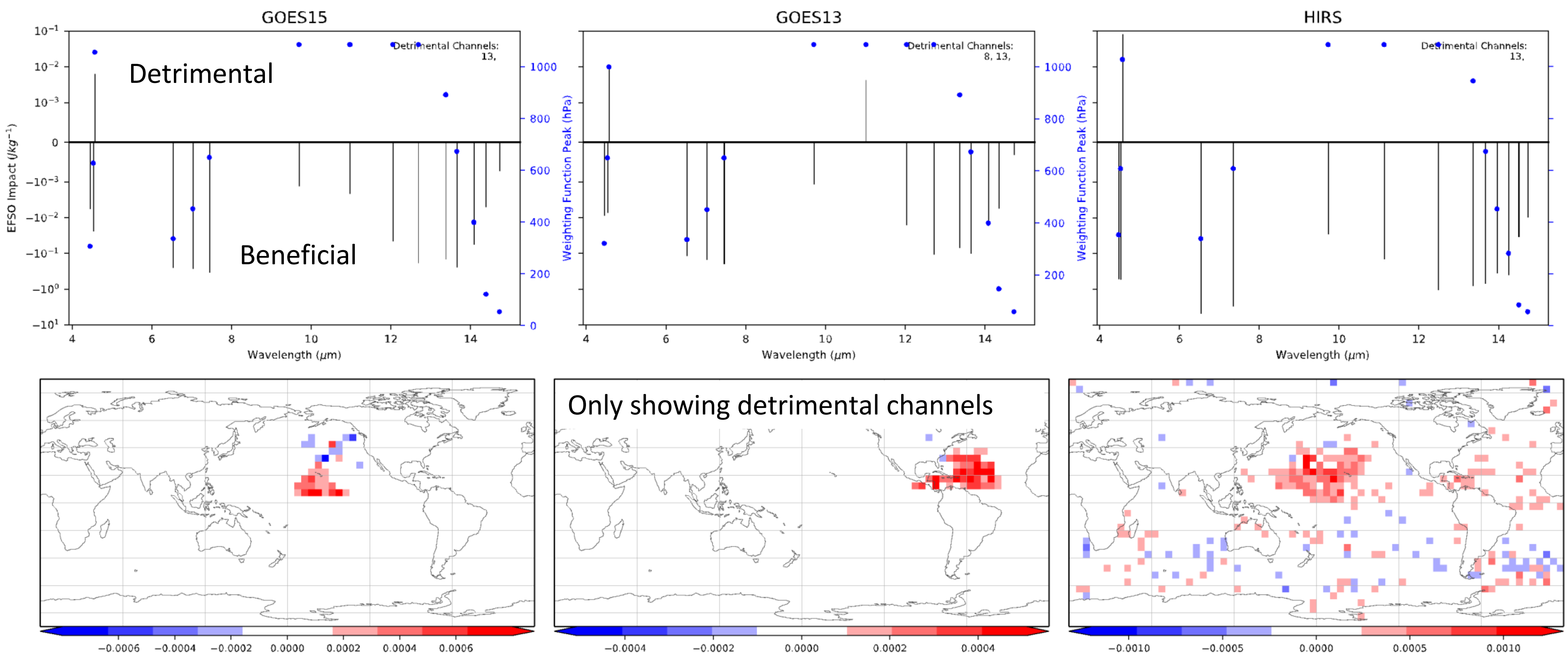
Experiments with the Lorenz (1996) model

Model	Lorenz 1996: $$\frac{dx_i}{dt} = -x_{i-2}x_{i-1} + x_{i-1}x_{i+1} - x_i + F$$ 40 variables F = 8, dt = 0.05, Integration scheme: RK4
Period	5000 cycles (plus 500 cycles of spin up)
Data Assimilation	ETKF-40 members No localization or inflation
Observations	40 variables from a nature run Obs. error: *N*(0, 0.1)

How can we minimize the jumps when we add new observing systems? (Yan Zhou's thesis)

- The best method she found (DKM2007) can be easily carried out **during** the reanalysis:
- When starting a new obs system, for 1-2 years:
  - Compute the New AI (with new obs system)
  - Compute the Old AI (without the new obs system but using the same first guess as the New AI)
  - Time average of (New AI-Old AI)= $\Delta\overline{\mathrm{AI}} = \overline{\mathrm{New\ AI}} - \overline{\mathrm{Old\ AI}}_{\mathrm{New\ FG}}$
  - **This is the correction in the model bias introduced by the new observations**.
- This should be added to the reanalysis done <u>before</u> the introduction of the new observations.
- It should minimize the reanalysis jumps.
- Cheaper than doing two reanalyses with and without new obs (the "MERRA approach).

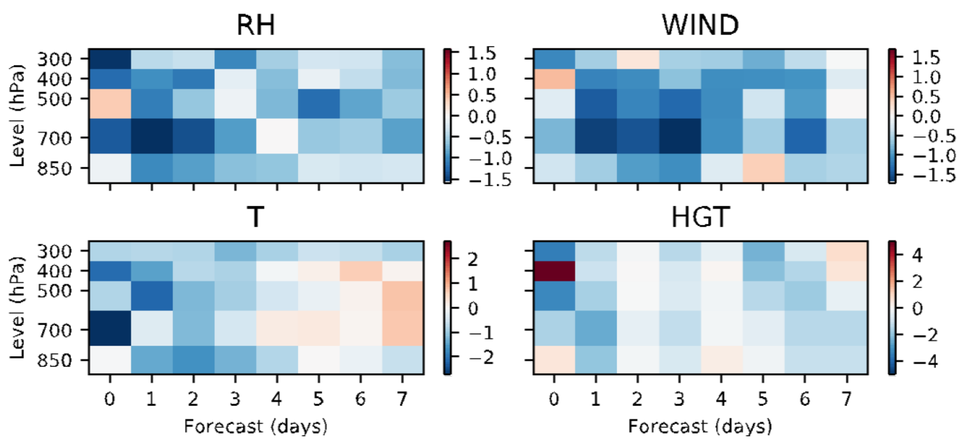
Multi-channel instruments: **GOES sounder, HIRS**



- Channel 8 (11.03 um), 13 (4.57 um): sensitive to surface and low-level temperature.
- Map shows the 2 channels are detrimental in **tropical Pacific and Atlantic**

Forecast performance of EFSO-based selection

Relative Forecast Error Reduction (Tropics, %)



Instruments:	Rejected channels:
IASI	81, 1133, 1191, 1194, 1271, 1805, 1884, 1991, 2094, 2239
AIRS	1866, 1868
GOES15 sounder	13
GOES13 sounder	8, 13
HIRS	13

- The detrimental impact is mainly from the tropical regions.
- Simply rejecting 16 channels out of hundreds improves the monthly mean tropical forecast by 1%

Rejecting the detrimental channels improves tropical forecasts

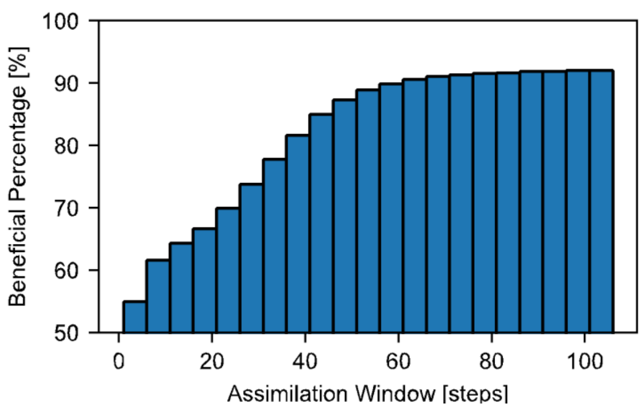
Why so few beneficial obs (~50%) in (E)FSO?

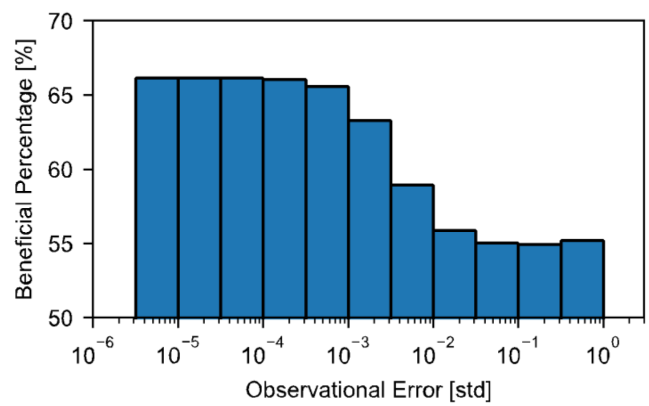
FSO studies found similar results and suggested different reasons:

- Inaccurate verifying analysis (Daescu 2009)
- Statistical nature of DA (Gelaro 2010, Ehrendorfer 2007)
- Inaccurate B and modes with different growth rates (Lorenc and Marriot 2014)

Our results suggest that:

- Background quality is as important as Observations' quality



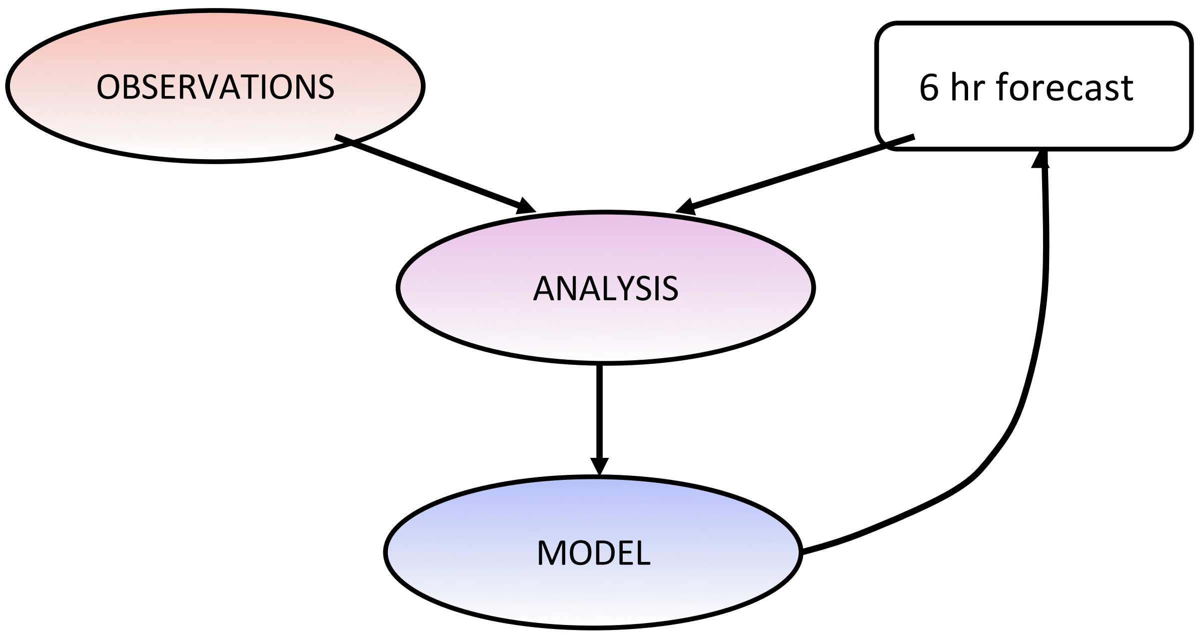


Most of the observations become very beneficial when the background is too long (inaccurate)!

Summary: Using future observations to do PQC

- Advanced DA can be used to improve both the model and the observations.
- At t=0 we use future (6 hour) observations to create a 6hr analysis that we use as the best estimate of the truth.
- We have two 6 hour forecasts from t=0 to t=6hrs, one ***with*** and one ***without*** assimilating the current (t=0) observations.
- Identify the observations at t=0 that make the 6hr forecasts worse using EFSO. (Kalnay et al., 2012).
- The results with real atmospheric observations, and a realistic but inexpensive atmospheric model **show large forecast improvements that last over 8 days**.
- EFSO is almost cost free, and since it accumulates the improvements, it does not need to use “future observations” in operational NWP.
- It only requires an EnKF data assimilation (or a hybrid).
- Reanalysis and other DA applications should use future observations!

Classic Data Assimilation: For NWP we need to improve observations, analysis scheme and model.
These improvements are done **independently**



New Data Assimilation: We can also use the DA system to improve observations and model