New Applications of Advanced Data Assimilation for Reanalysis

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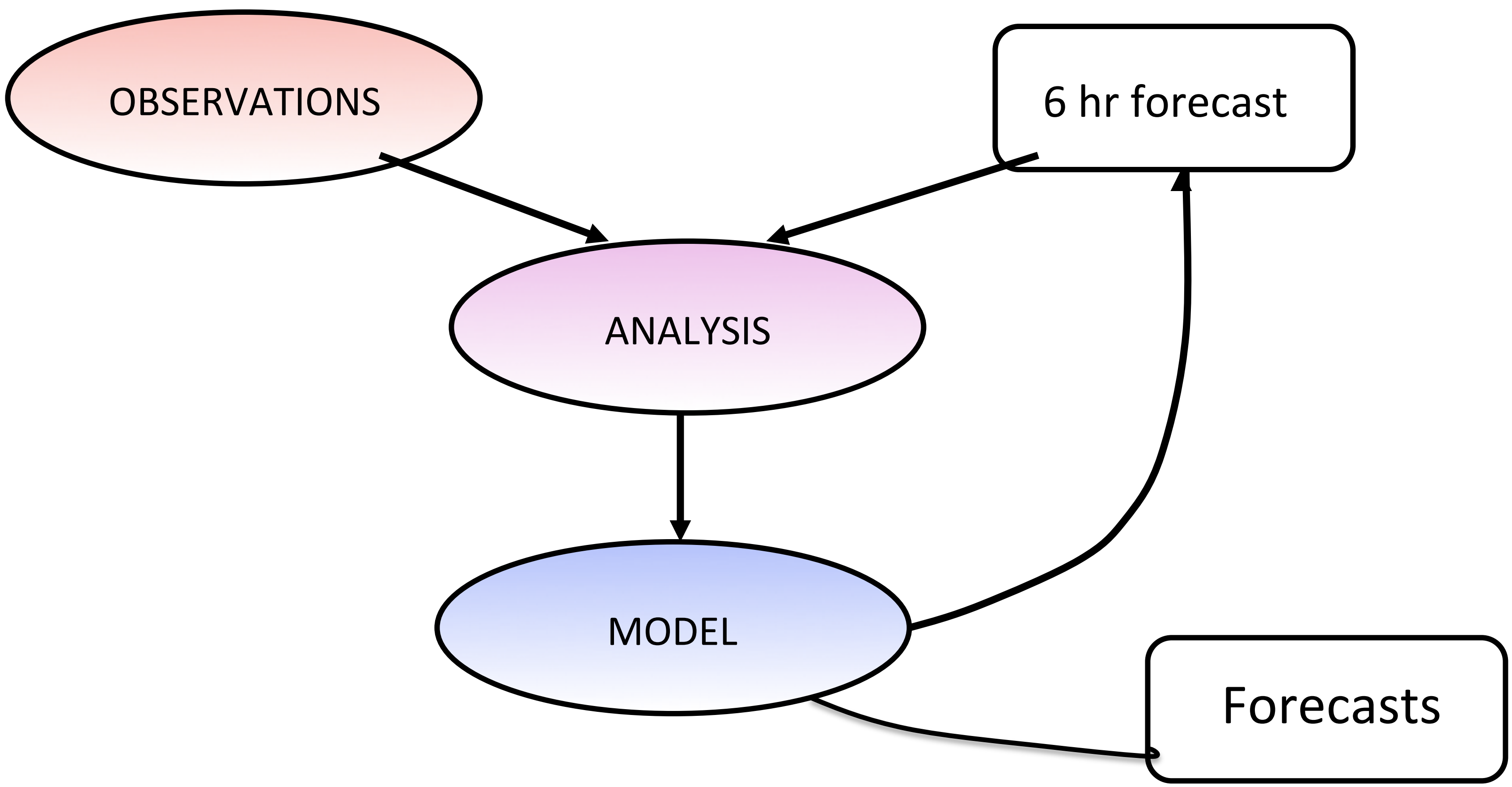
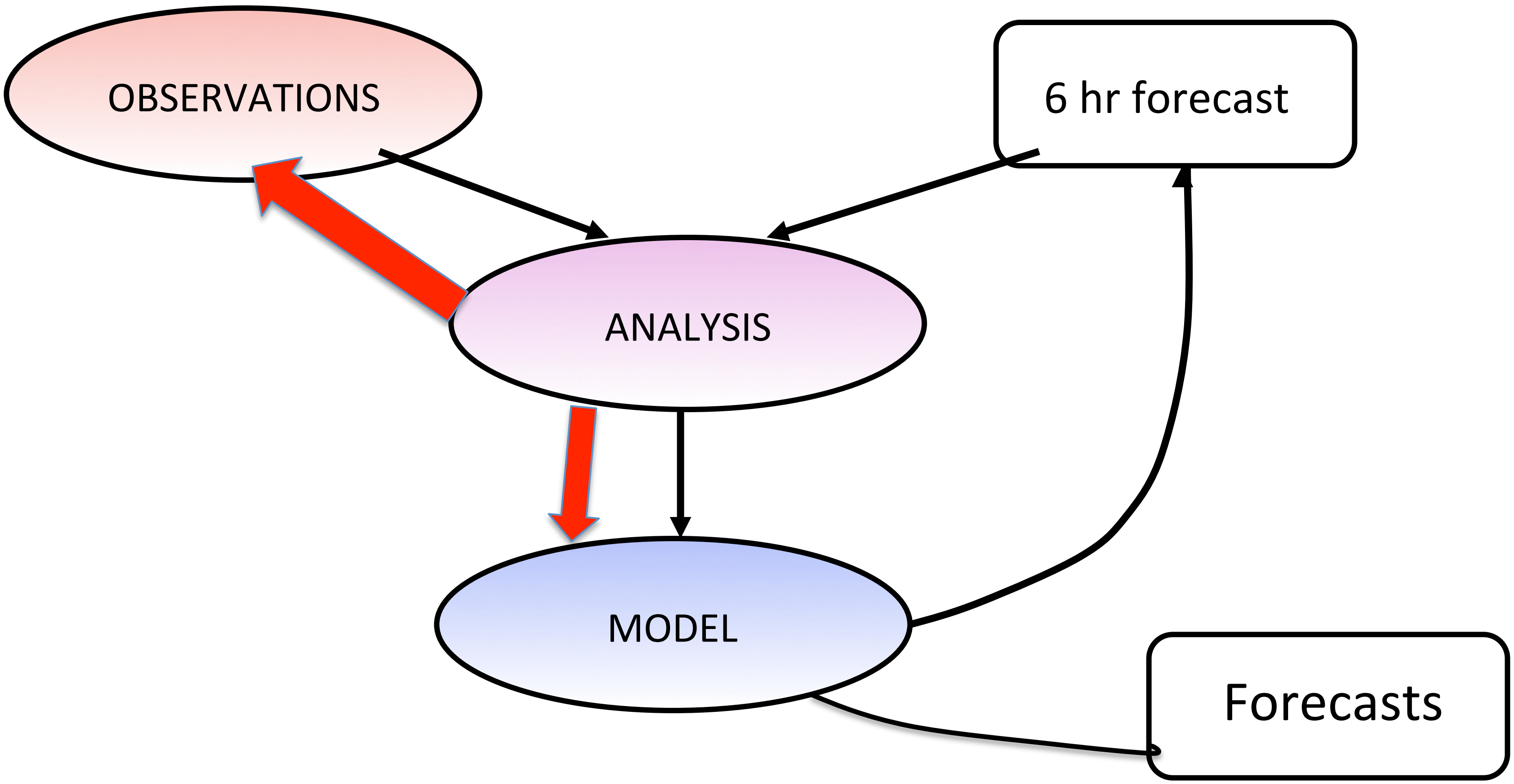
With many thanks to students, friends and colleagues
from the University of Maryland

Classic Data Assimilation: For NWP we need to improve observations, analysis scheme and model



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



The simplicity and power of EnKF should encourage the use of DA for improvements beyond its main goal

Combine optimally observations and model forecasts (mostly done! ☺)

- We should also use DA to:

Improve the observations

Improve the model

- Improve the models by parameter estimation

Example: Estimate the surface carbon fluxes as evolving parameters.

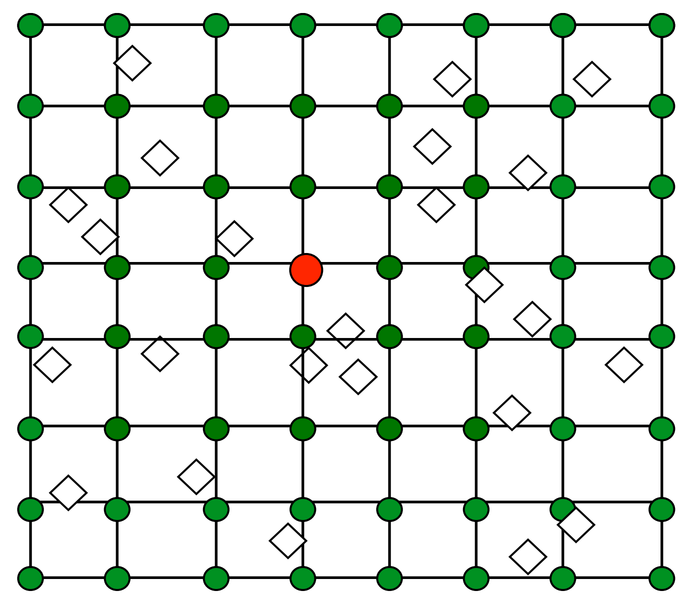
- Earth system models used by IPCC have many sub-models, but they don't include the Human System, with the feedbacks that totally dominate the Earth system.

We should do DA of the <u>two-way coupled</u> Earth System-Human System, and use DA for parameter tuning

LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot



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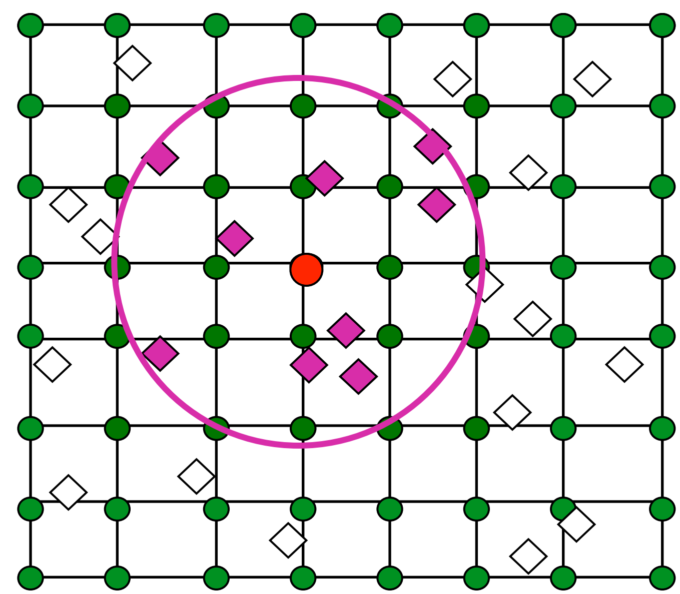


All observations (purple diamonds) within the local region are assimilated

The LETKF algorithm can be described in a single slide!

Local Ensemble Transform Kalman Filter (Hunt et al, 2007)

Globally:

Forecast step: $\mathbf{x}^b_{n,k} = M_n\left(\mathbf{x}^a_{n-1,k}\right)$

Analysis step: construct $\mathbf{X}^b = \left[\mathbf{x}^b_1 - \overline{\mathbf{x}}^b \mid \ldots \mid \mathbf{x}^b_K - \overline{\mathbf{x}}^b\right];$

$$\mathbf{y}^b_i = H(\mathbf{x}^b_i);\ \mathbf{Y}^b_n = \left[\mathbf{y}^b_1 - \overline{\mathbf{y}}^b \mid \ldots \mid \mathbf{y}^b_K - \overline{\mathbf{y}}^b\right]$$

Locally: **Choose for each grid point the observations to be used, and compute the local analysis error covariance and perturbations in ensemble space:**

$$\tilde{\mathbf{P}}^a = \left[(K-1)\mathbf{I} + \mathbf{Y}^T\mathbf{R}^{-1}\mathbf{Y}\right]^{-1};\ \mathbf{W}^a = [(K-1)\tilde{\mathbf{P}}^a]^{1/2}$$

Analysis mean in ensemble space: $\overline{\mathbf{w}}^a = \tilde{\mathbf{P}}^a\mathbf{Y}^{bT}\mathbf{R}^{-1}(\mathbf{y}^o - \overline{\mathbf{y}}^b)$

and add to $\mathbf{W}^a$ **to get the analysis ensemble in ensemble space.**

The new ensemble analyses in model space are the columns of $\mathbf{X}^a_n = \mathbf{X}^b_n\mathbf{W}^a + \overline{\mathbf{x}}^b$**. Gathering the grid point analyses forms the new global analyses. Note that the the output of the LETKF are analysis weights** $\overline{\mathbf{w}}^a$ **and perturbation analysis matrices of weights** $\mathbf{W}^a$**. These weights multiply the ensemble forecasts.**

1) Improve the observations: Ensemble Forecast Sensitivity to Observations and Proactive QC

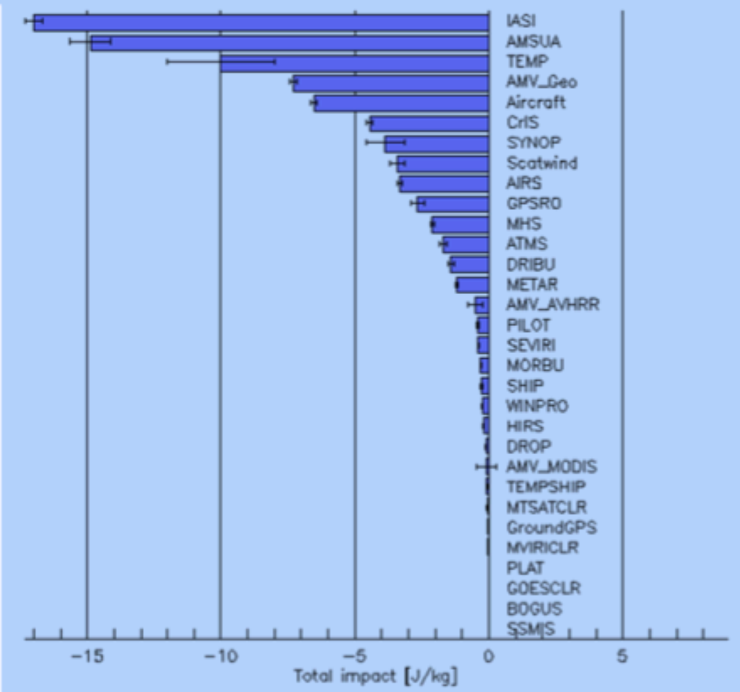
- Kalnay et al. (2012) derived EFSO.
- Ota et al. (2013) tested 24hr GFS forecasts and showed EFSO could be used to identify bad obs.
- D. Hotta (2014): EFSO can be used after only 6 hours, so that the bad obs. can be collected and withdrawn, with useful metadata, so they can be improved. The analysis is corrected with EFSO.
- We call this **Proactive QC**, much stronger than QC.
- Hotta also showed EFSO can be used to tune **R**
- Tse-Chun Chen tested impact of EFSO/PQC over 5 day forecasts: **VERY PROMISING RESULTS**

Forecast Sensitivity to Observations (Langland and Baker, 2004)

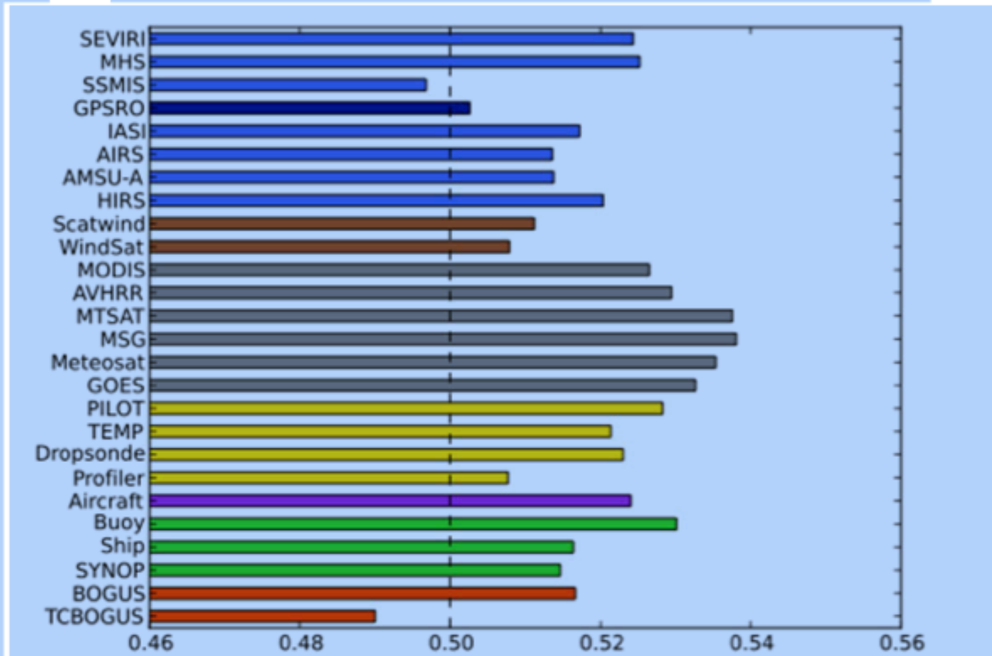
Met Office

FSOI in Global NWP

Total Observation Impact (Aug 2014)



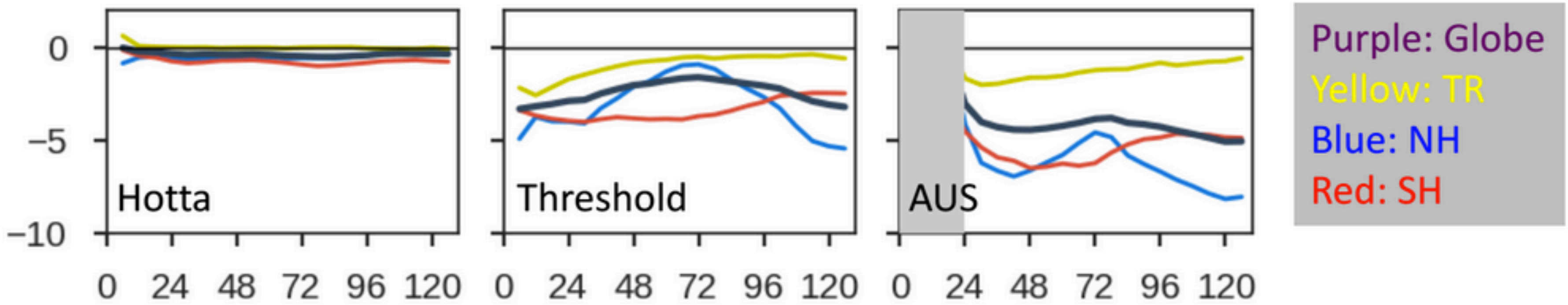
Fraction Obs that Improve Forecast



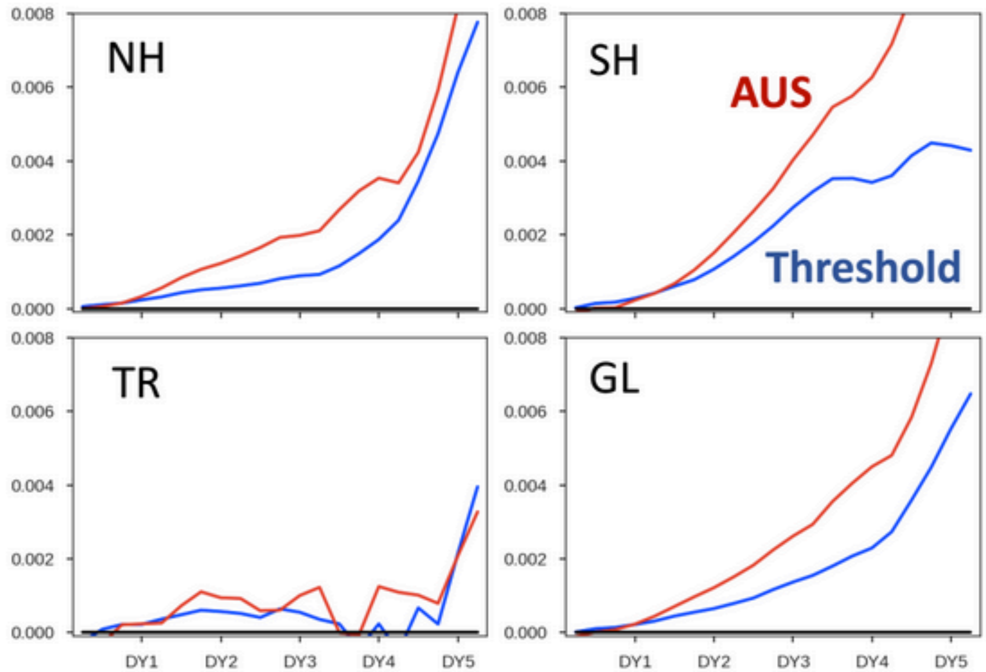
- Infra-Red (IASI) and microwave (AMSUA) radiances now biggest impact.
- Note only ~50% of observations reduce forecast error(!).
- Estimate: need 6 months time series to assess impact for single observing site.
- EFSO methodology now being considered when no adjoint available

Offline Experiment: 18 cases

MTE relative improvement (%)



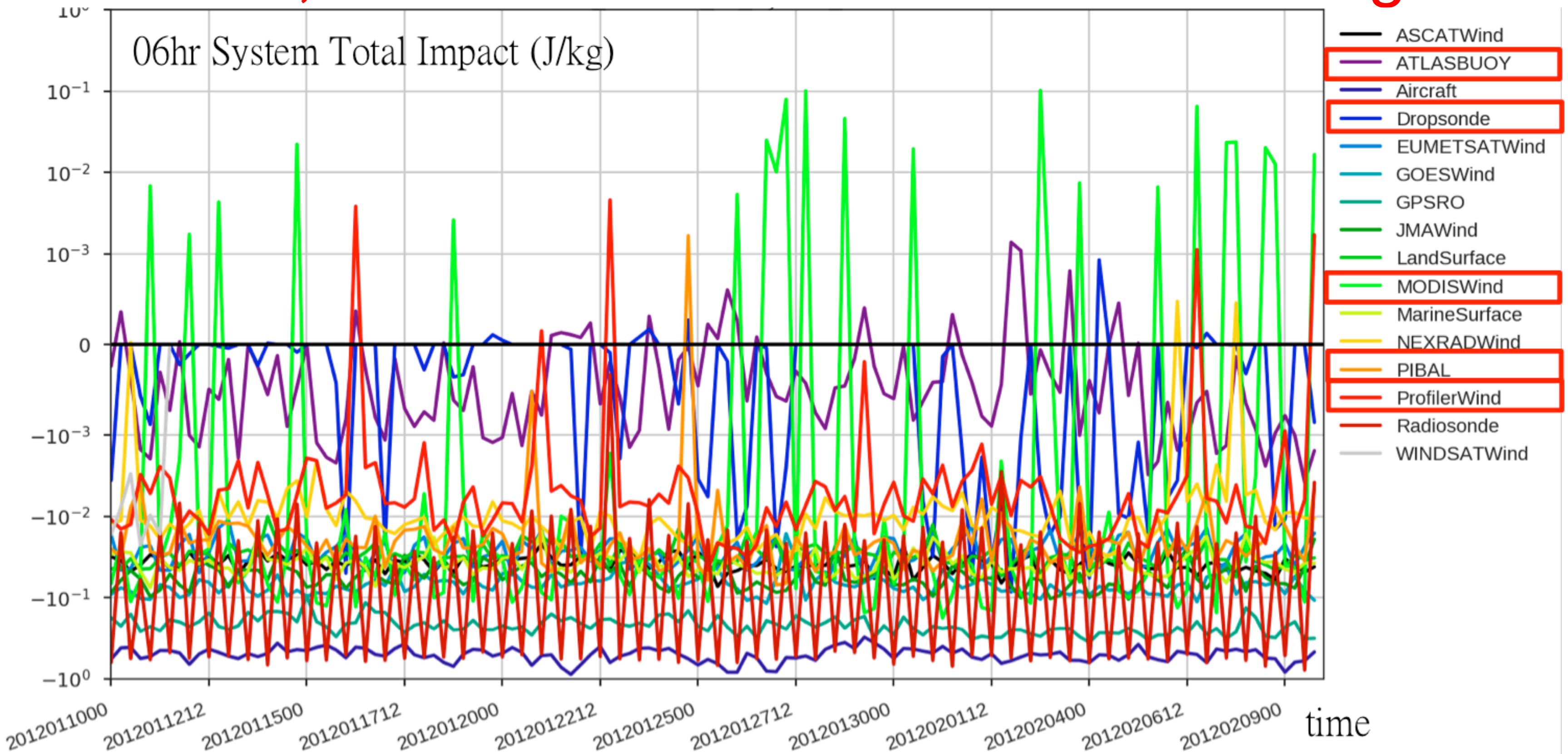
Z500 ACC Improvement: Threshold (blue) v.s. AUS (red):



- PQC corrects analysis and the subsequent forecast.
- All three methods improves model forecasts on average.
- The **AUS** and **Threshold** method have forecast improvements larger than **Hotta** method.

Alarm bells could be produced in operations!

- EFSO allows QC monitoring (Kalnay et al 2012)
- MODIS and Profiler Winds frequently detrimental
- It would accelerate implementing new instruments
- Jordan A, Krishna and T-C Chen collaborating!

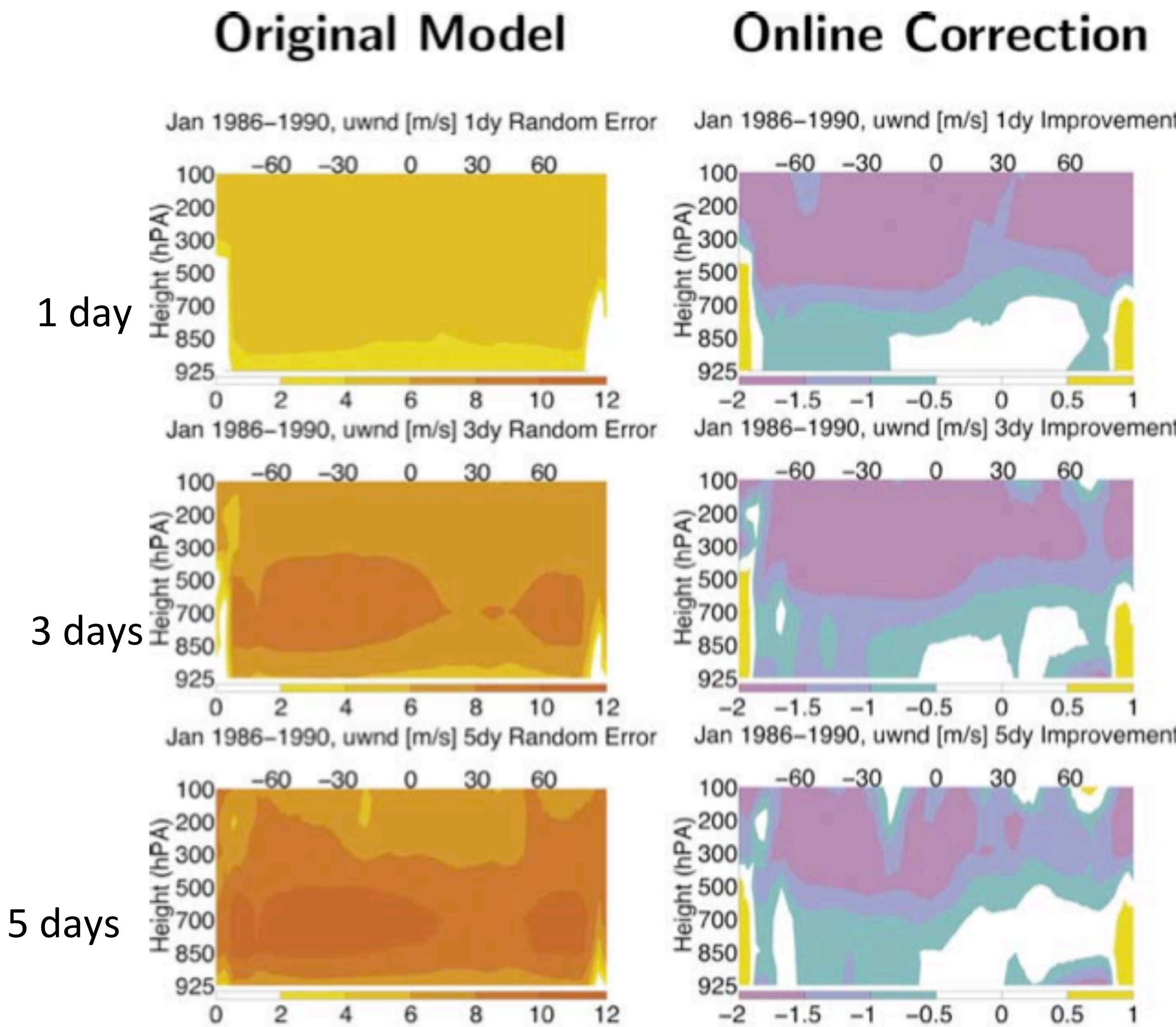


Danforth and Kalnay (2007, 2008a, 2008b)

- Danforth, Kalnay and Miyoshi (DKM-2007) estimated the 6hr errors of the SPEEDY model.
- Estimated the average SPEEDY model error (bias) by averaging:

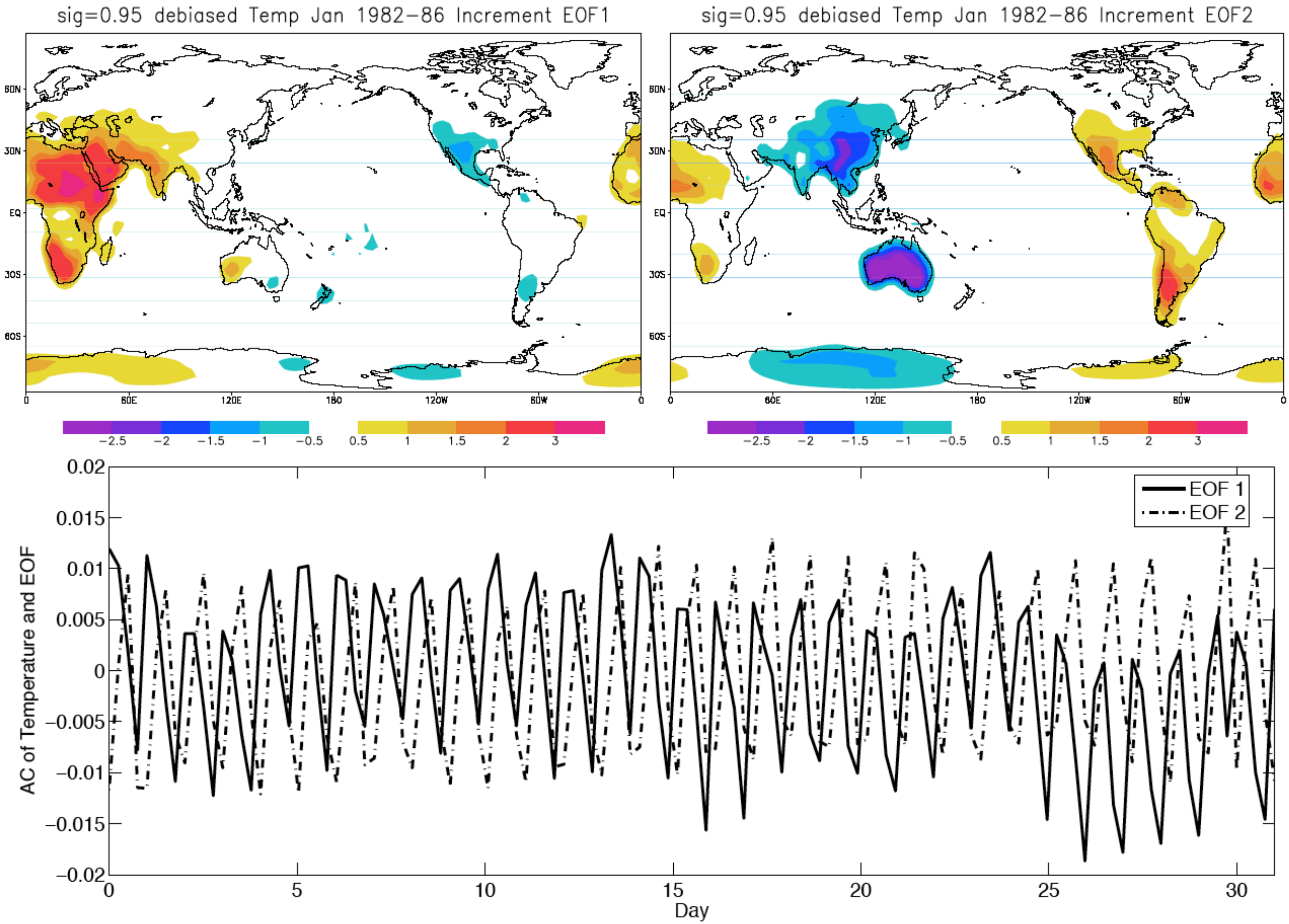
  Reanalysis R1 – 6 hour forecast $\approx \overline{\mathrm{AI}}$
- They corrected the SPEEDY model with $\overline{\mathrm{AI}} / 6hr$
- This significantly improved both the forecasts **systematic errors** and the **random errors**!

Both bias and random errors were significantly smaller when correcting the model with the model bias!



Random errors were reduced by the online model correction!

The 2 leading EOFs of the error anomalies gave the diurnal cycle errors



Can we estimate and correct model bias and random forecast errors in the NCEP/GFS?

Kriti Bhargava, E Kalnay, J Carton

- The systematic errors in the GFS (and all NWP models) are not negligible.
- They are statistically corrected *a posteriori* (offline).
- We aim to correct the GFS (online) adding the average AI/6hr to each forecast variable, like Danforth and Kalnay (2008).
- This should not only improve the forecasts but also facilitate testing model improvements.
- If the observations are biased, correcting them should reduce the Analysis Increments

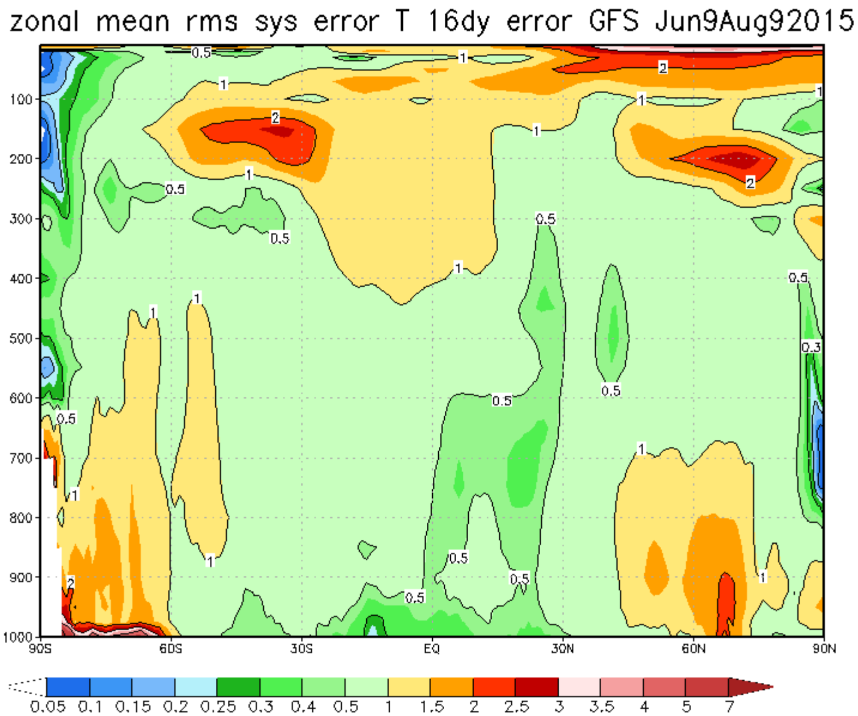
Systematic model errors – GFS

Thanks to Glenn White

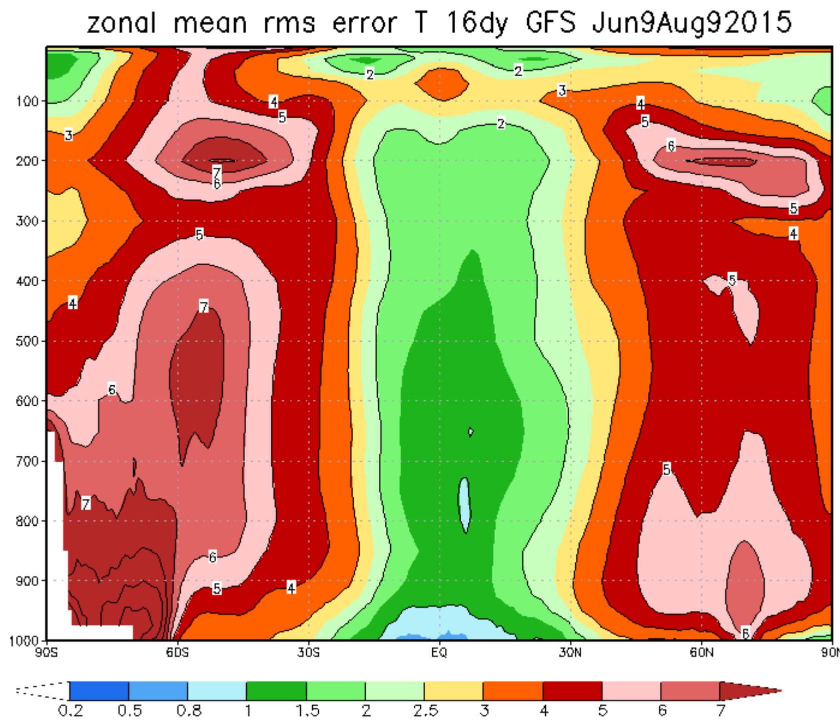
Systematic error range ~1/3 Total error range

after 2 weeks

RMS Systematic errors GFS



RMS Total errors GFS

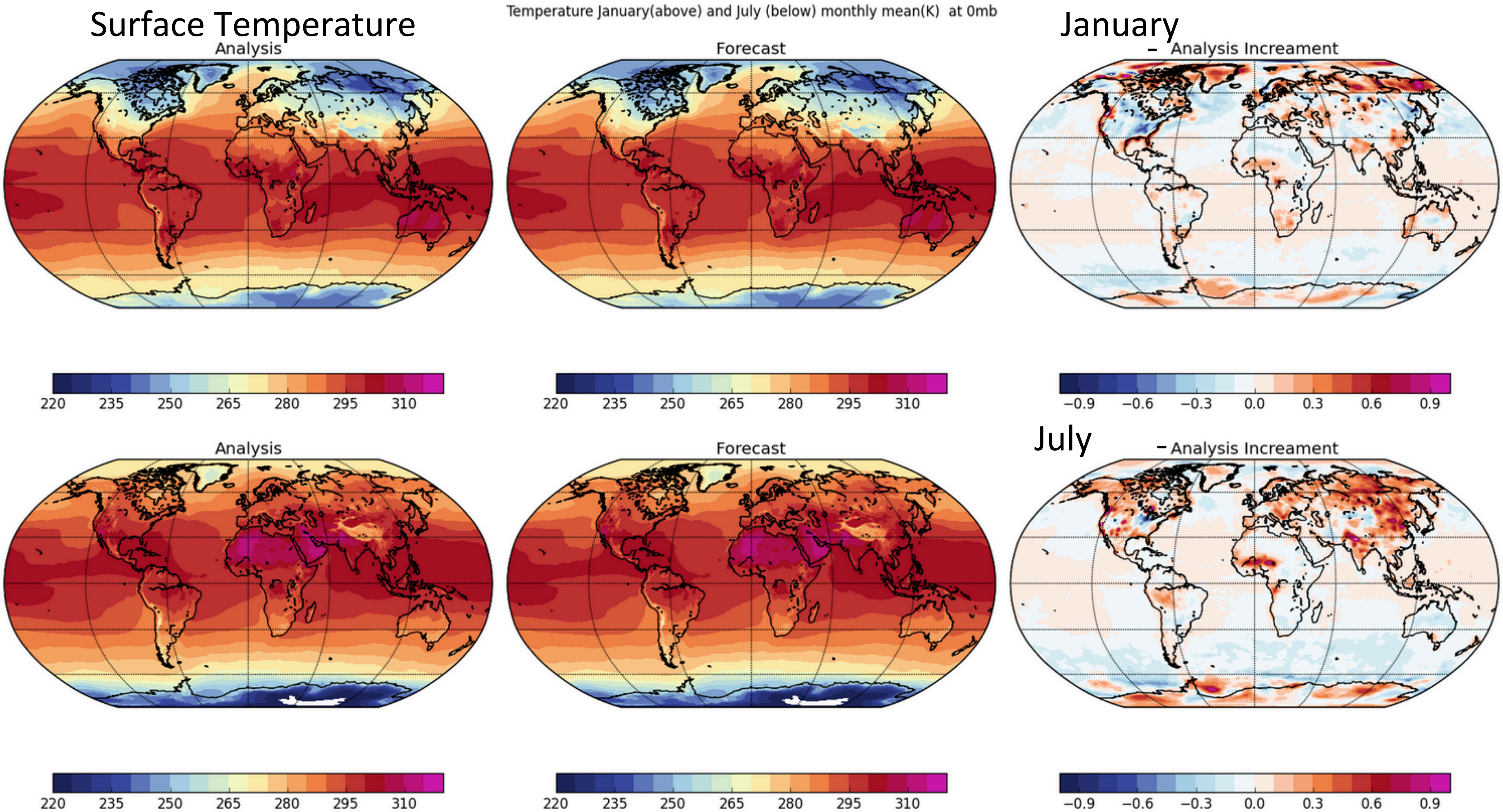


ΔT(systematic) ~ 0.5 -3K

ΔT(total) ~ 1.5 -9K

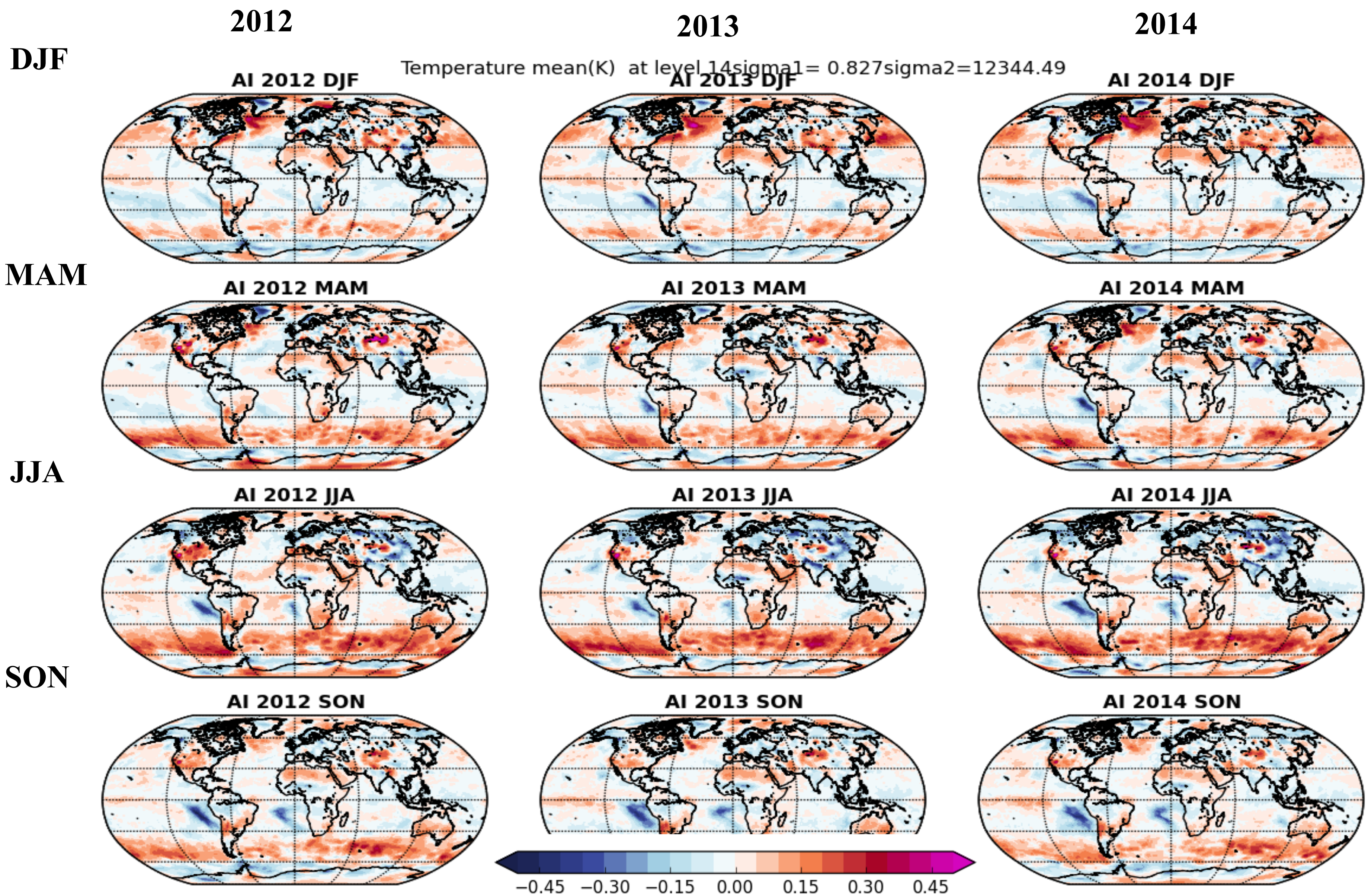
Image courtesy: Glenn White

First results: 2014 Analyses, Forecasts and Bias



The analysis and 6hr forecasts are almost identical,
but the AI are well defined.

Seasonal Mean Bias: T (K) at ~850 mb for 2012, 2013, 2014

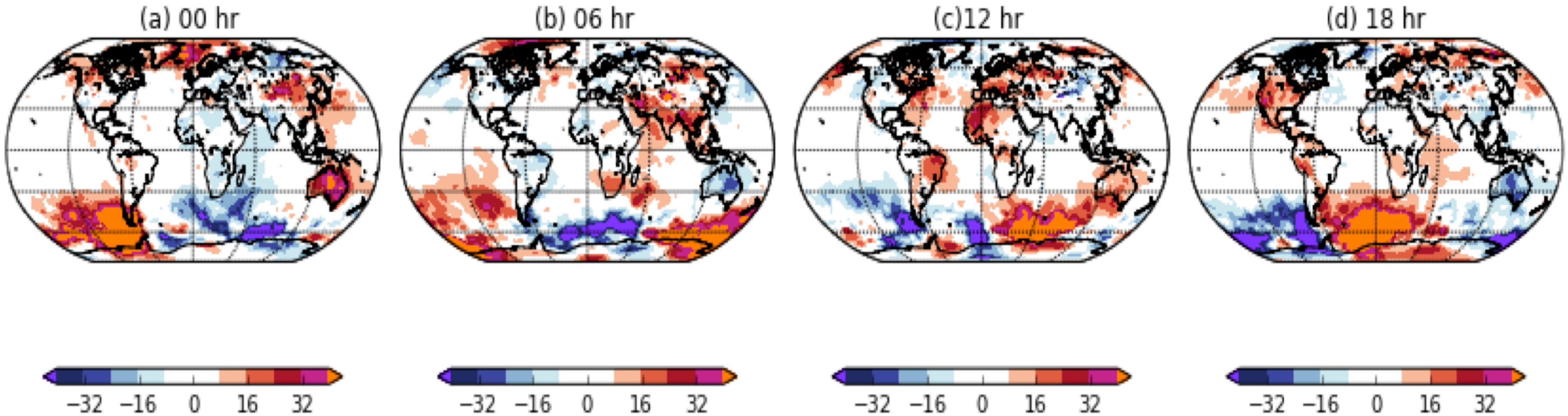


DIURNAL ERROR: First 4 vs 120 modes: P_s (mb)

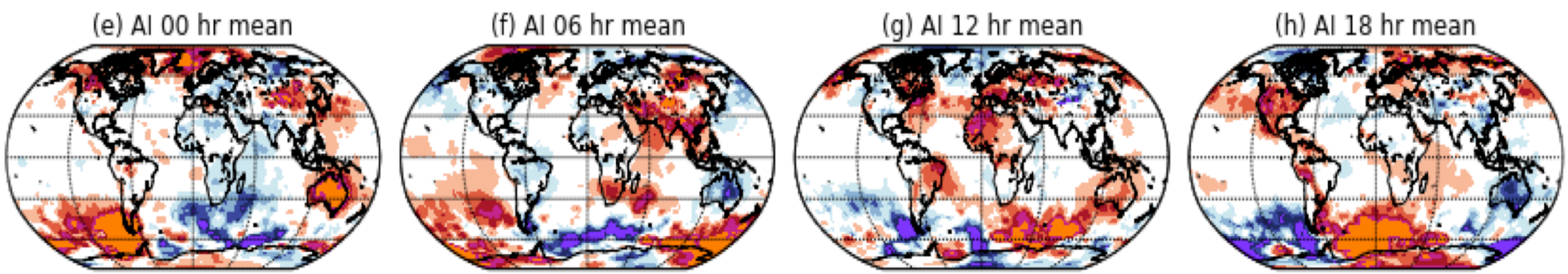
First 4 EOFs of AI capture the diurnal cycle errors almost perfectly

Top: 4 modes

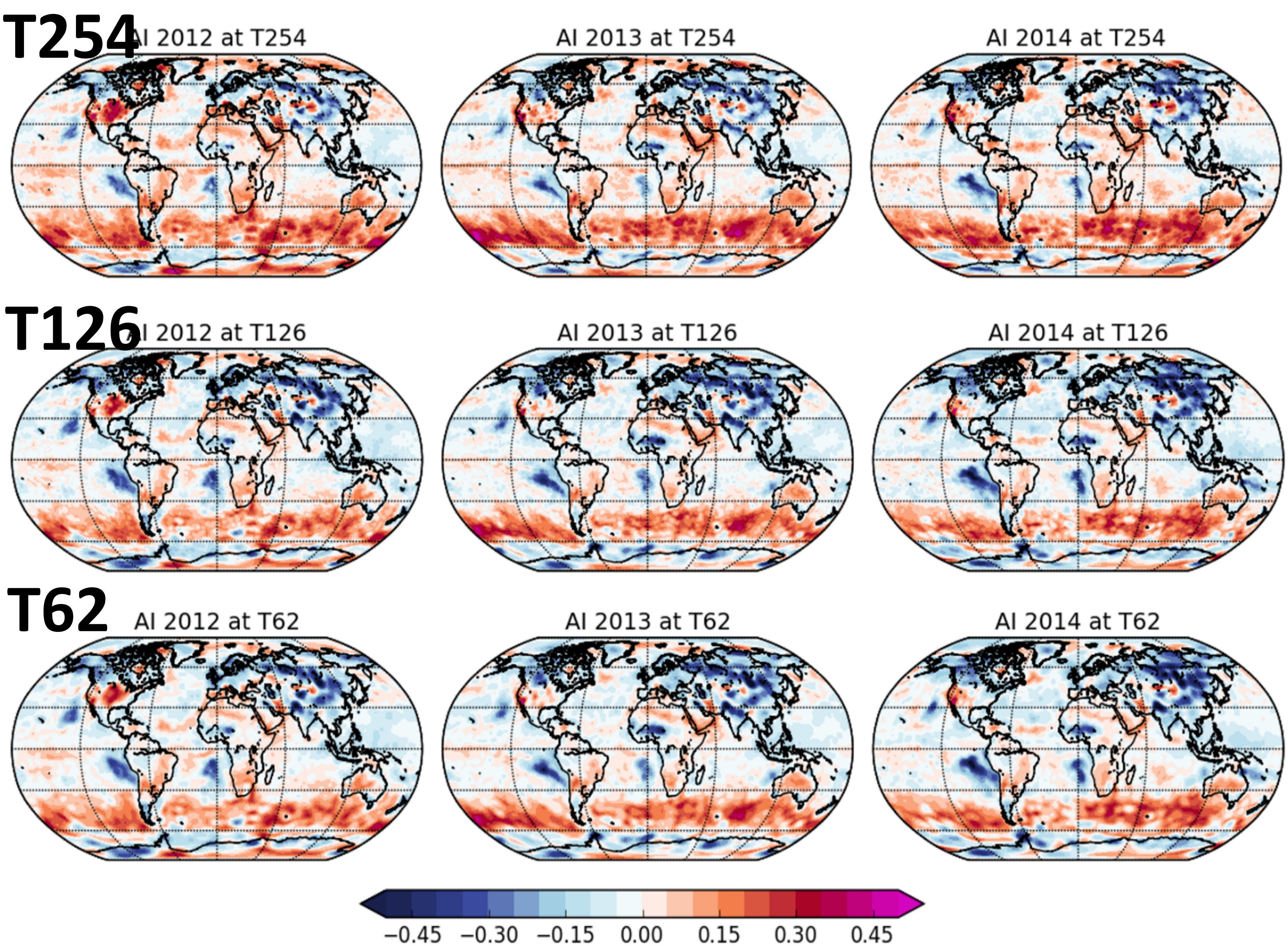
Sept'14



Bottom: 120 modes



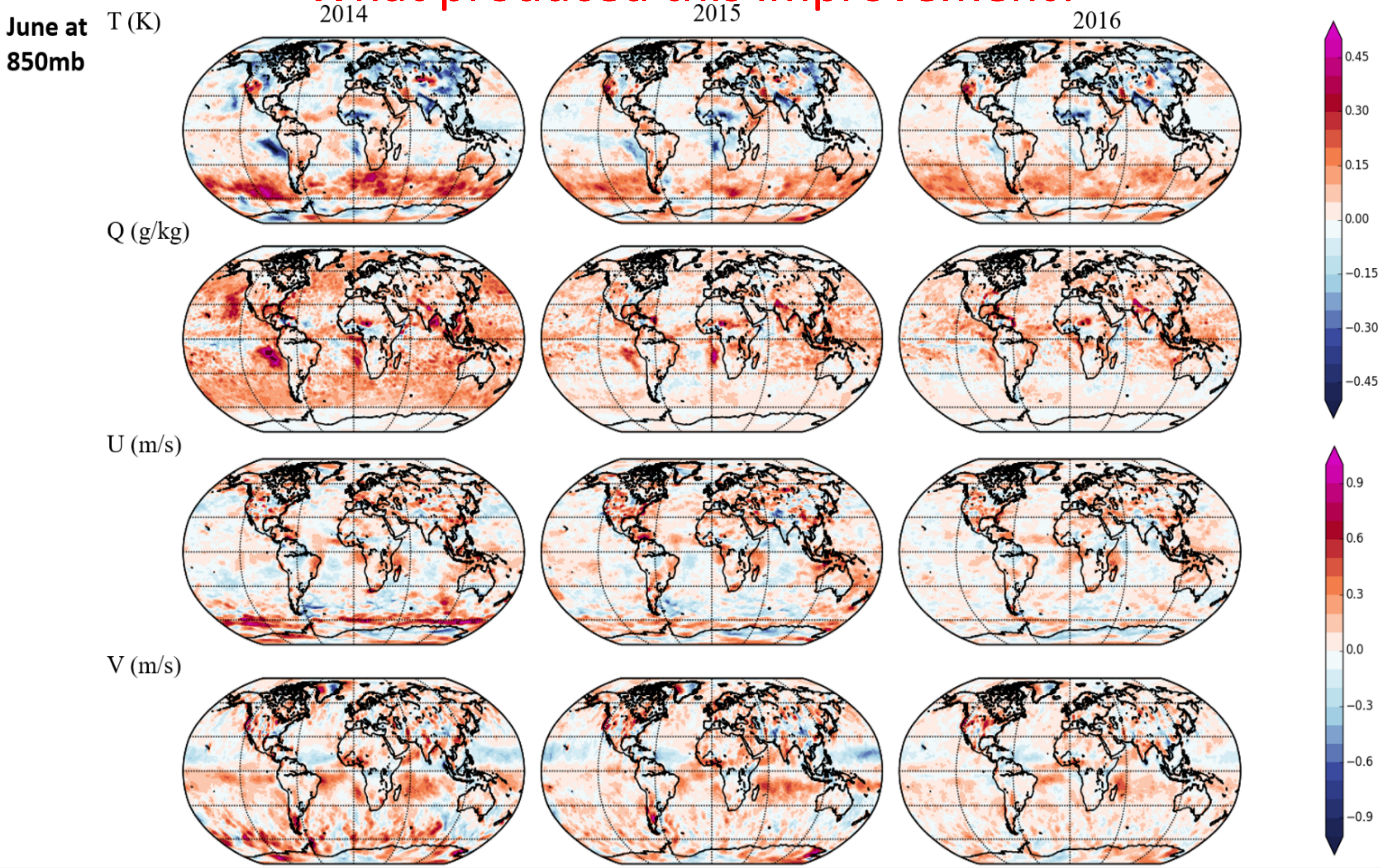
Bias is independent of resolution: it is large scale



Projecting July 2014 mean Temperature AI at T62 (top), T126 (middle) and original T254 (bottom)

Errors reduced from 2014 to 2015, 2016 over oceans

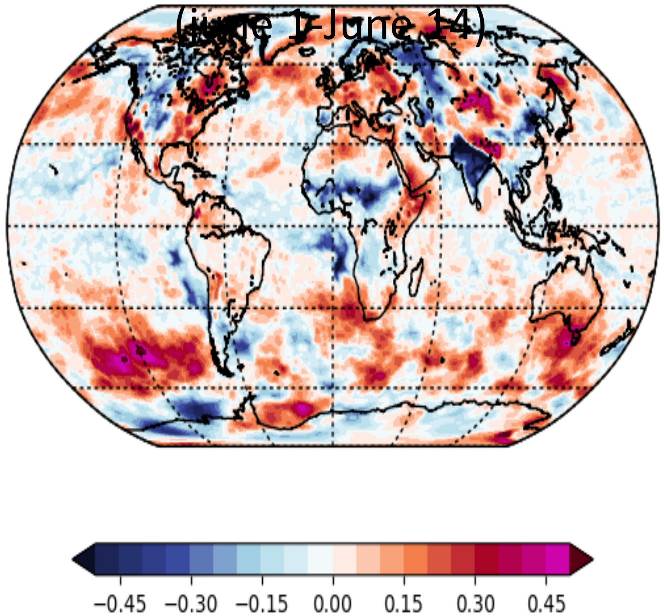
What produced this improvement?



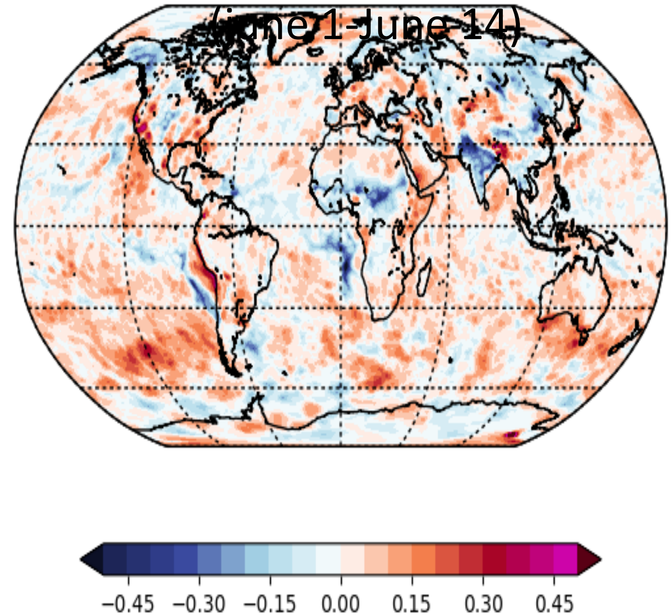
Findings (Kriti Bhargava)

- Estimate the GFS systematic mean errors ✓
- Check the robustness of the seasonal averaged AI: (2012 vs 2013 vs 2014)✓ Errors are robust
- Find errors in diurnal cycle ✓
- Check if the low dimensional approaches can be used to correct the diurnal cycle errors. ✓ Yes, need only 4/120 modes and should be able to correct the diurnal cycle!
- Check if errors can be explored at a resolution lower than operational. ✓ Yes, the errors project on low wave numbers <<T62 (large scales)
- In 2015-2016 the errors over ocean were smaller: We traced this to the replacement of weekly OI SST with daily high resolution Real Time Global RTG SST. ✓

2 week average AI for 6-hr control forecast
(June 1-June 14)



2 week average AI for 6-hr corrected forecast
(June 1-June 14)



Temperature at 850hPa:

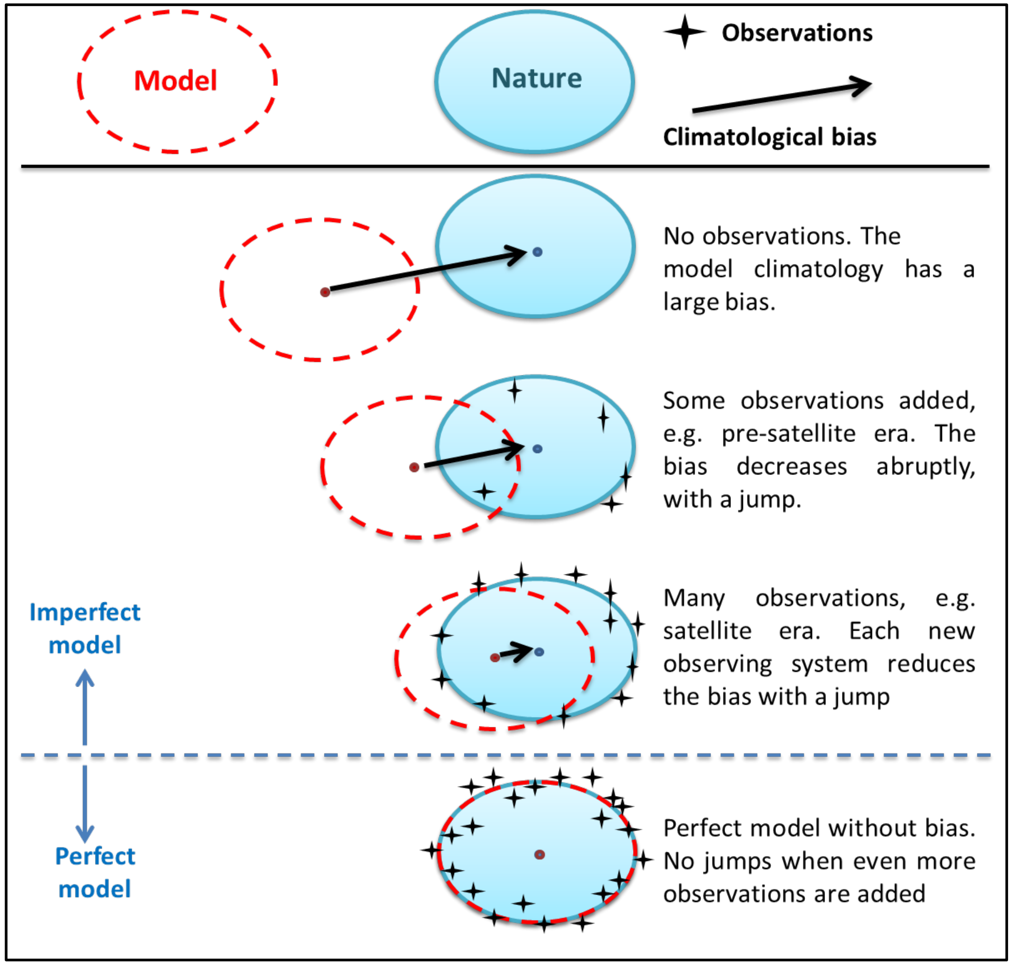
Correcting “online” with AI/6hr reduced the AI’s!

We still need to correct surface pressure

New opportunities for new reanalyses

Eugenia Kalnay
With
Yan Zhou and Junye Chen
for the correction of analysis jumps

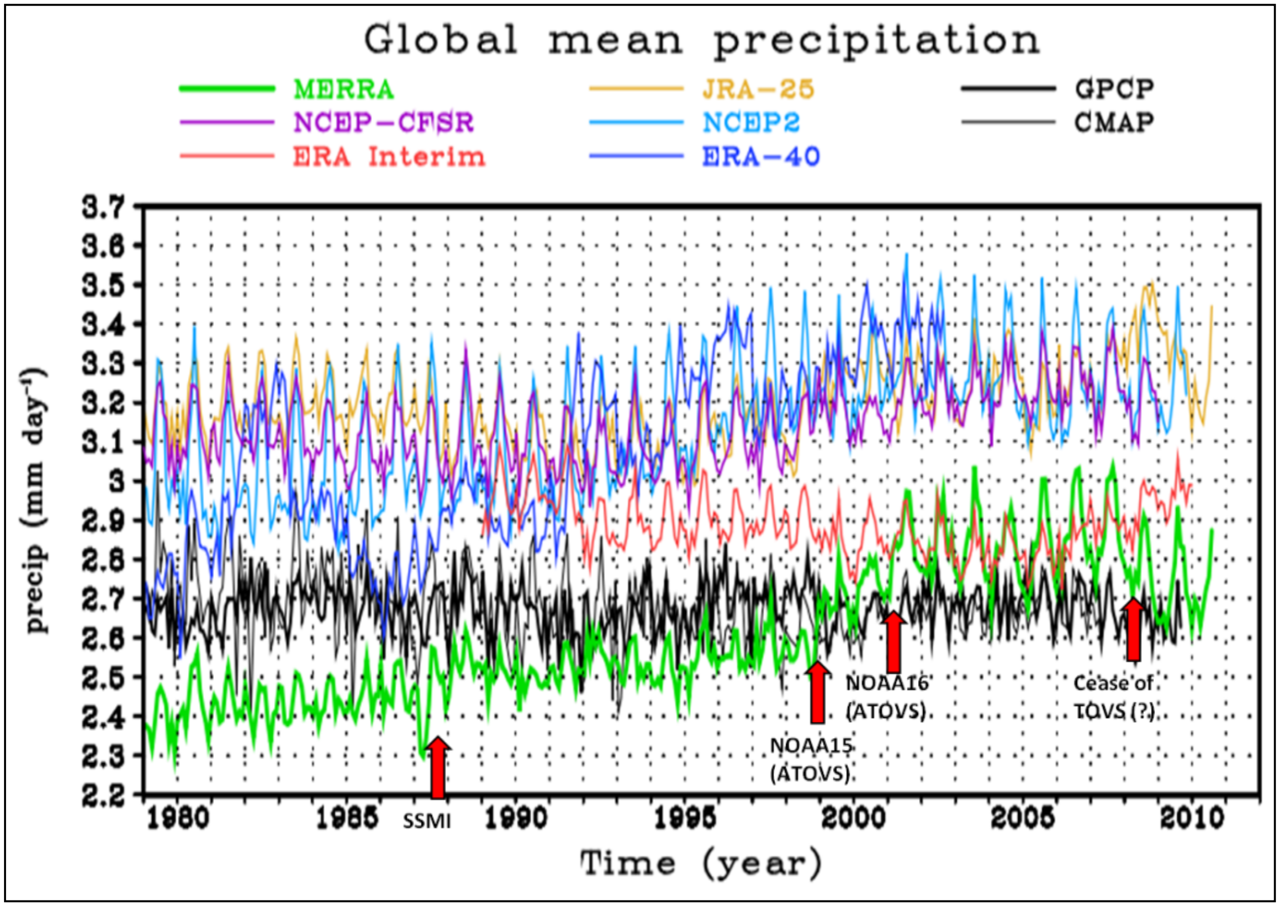
Why do we get reanalysis jumps? Model bias!



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 is to find a solution to minimize the "climate jumps" associated with observing system changes.**

Example: MERRA 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)**

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

  AI_N^N Analysis with New obs, First Guess with New obs

  AI_N^O Analysis with Old obs, First Guess with New obs

  - DKM2007: $\overline{AI}_N^N - \overline{AI}_N^O$ BEST
  - MERRA: $\overline{AI}_N^N - \overline{AI}_O^O$ IN BETWEEN
  - Climatology: $\overline{A}_N^N - \overline{A}_O^O$ WORST

Whitaker, NOAA CTB Meeting, November 9-10, 2015:

Differences between reanalyses for climate monitoring and reforecasts

- For climate monitoring, homogeneity of climate statistics is paramount.
  - If needed, sacrifice accuracy for homogeneity (by limiting observation platforms assimilated).
- For reforecasts, homogeneity of forecast errors is paramount.
  - If needed, sacrifice homogeneity of climate statistics by including all possible observing systems (in order to keep forecast error statistics as close as possible to real-time system)

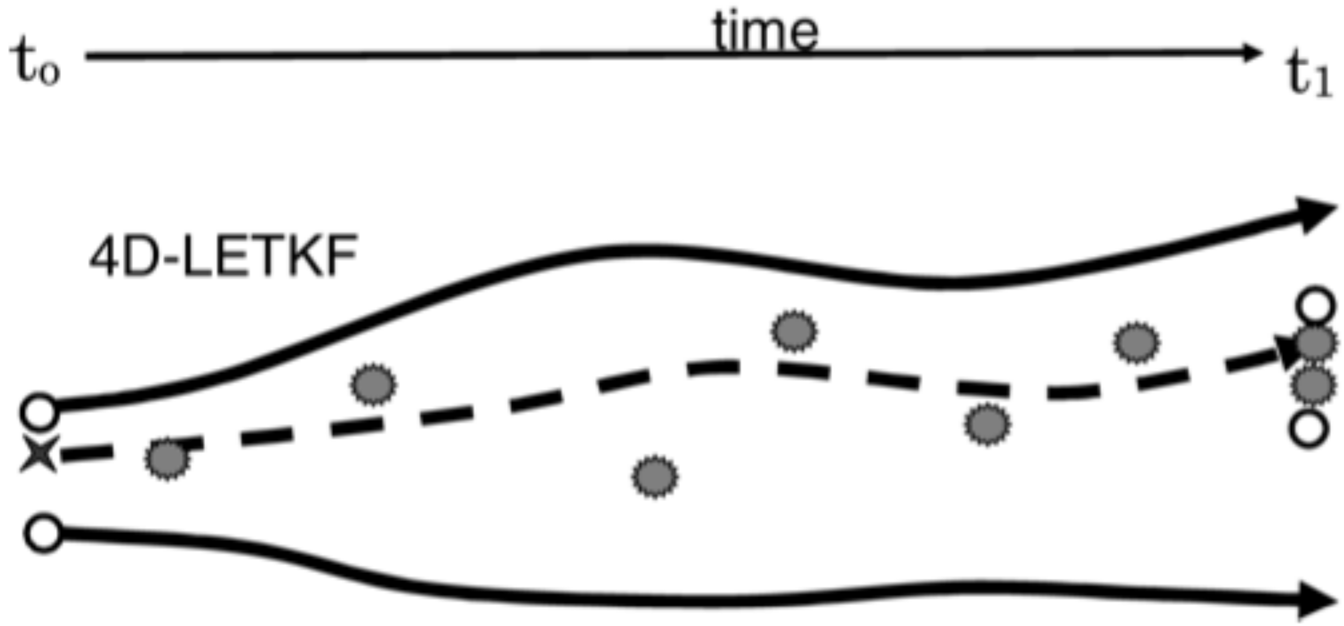
Our proposed approach addresses both problems!

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).

More accurate analysis by using future and past data

(Yun Li, Kalnay, Zeng)



No-cost smoother: The weights are valid throughout the window. The original analysis uses only past data. The cross corrects it by using the final weights. Since it uses both past and future data, it should be significantly more accurate than the original analysis (like second order differences compared to first order differences).

Summary

- We should take advantage of the opportunities that advanced DA provide!
- Estimate and correct the jumps introduced by new observing systems
- The best method is DKM2007 (Yan Zhou's thesis). The correction can be trained in 1-2 yrs. Low cost.
- Proactive QC: capture and delete flawed observations that survived the regular QC.
- Use no-cost smoother to improve the analysis at the beginning of the time window using future observations.
- Do **strongly coupled** data assimilation and apply similar ideas.