New Applications of Data Assimilation: Observations and Model Improvements, Strongly Coupled Ocean-Atmosphere DA, and Surface Fluxes Estimations

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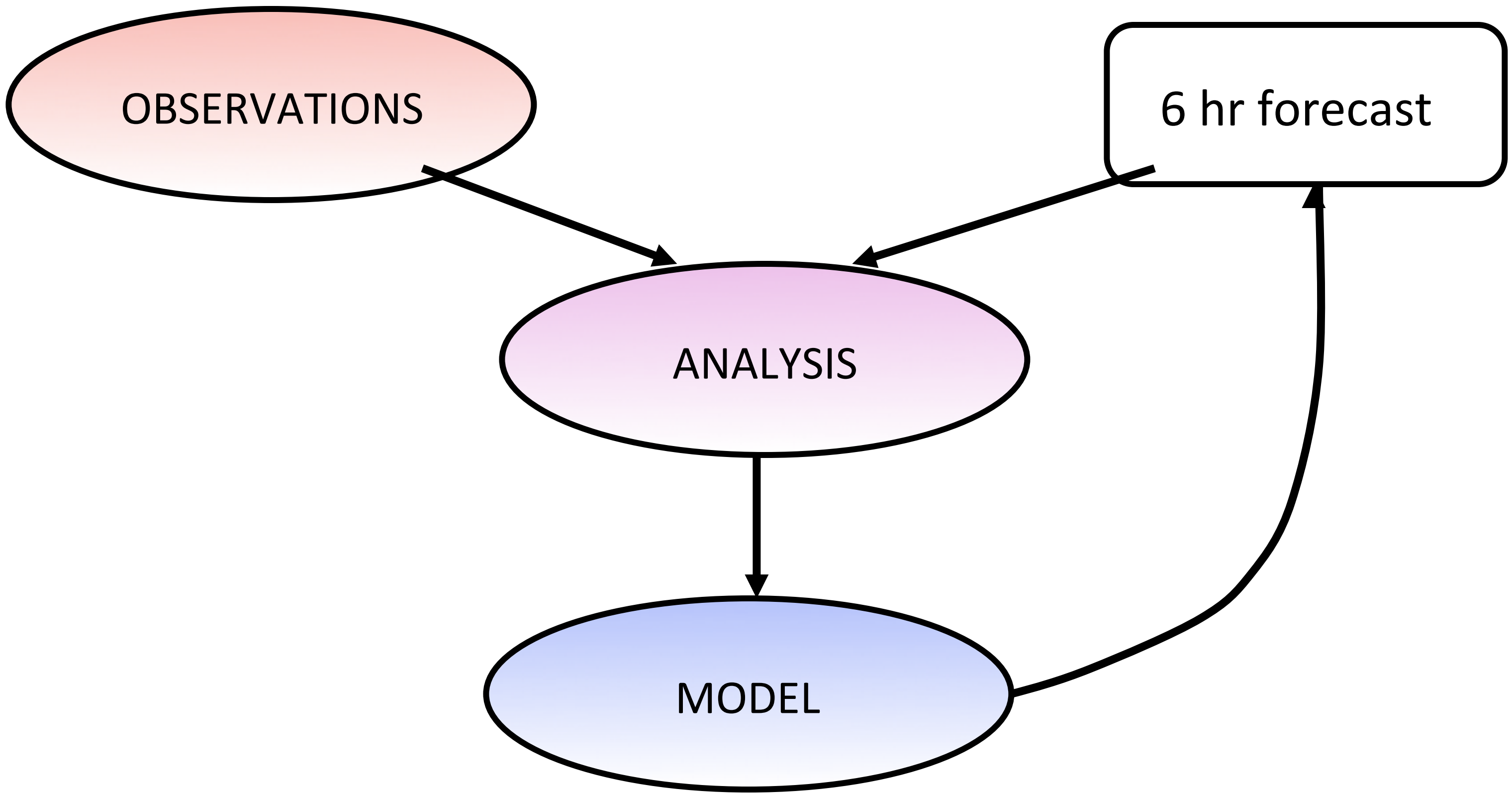
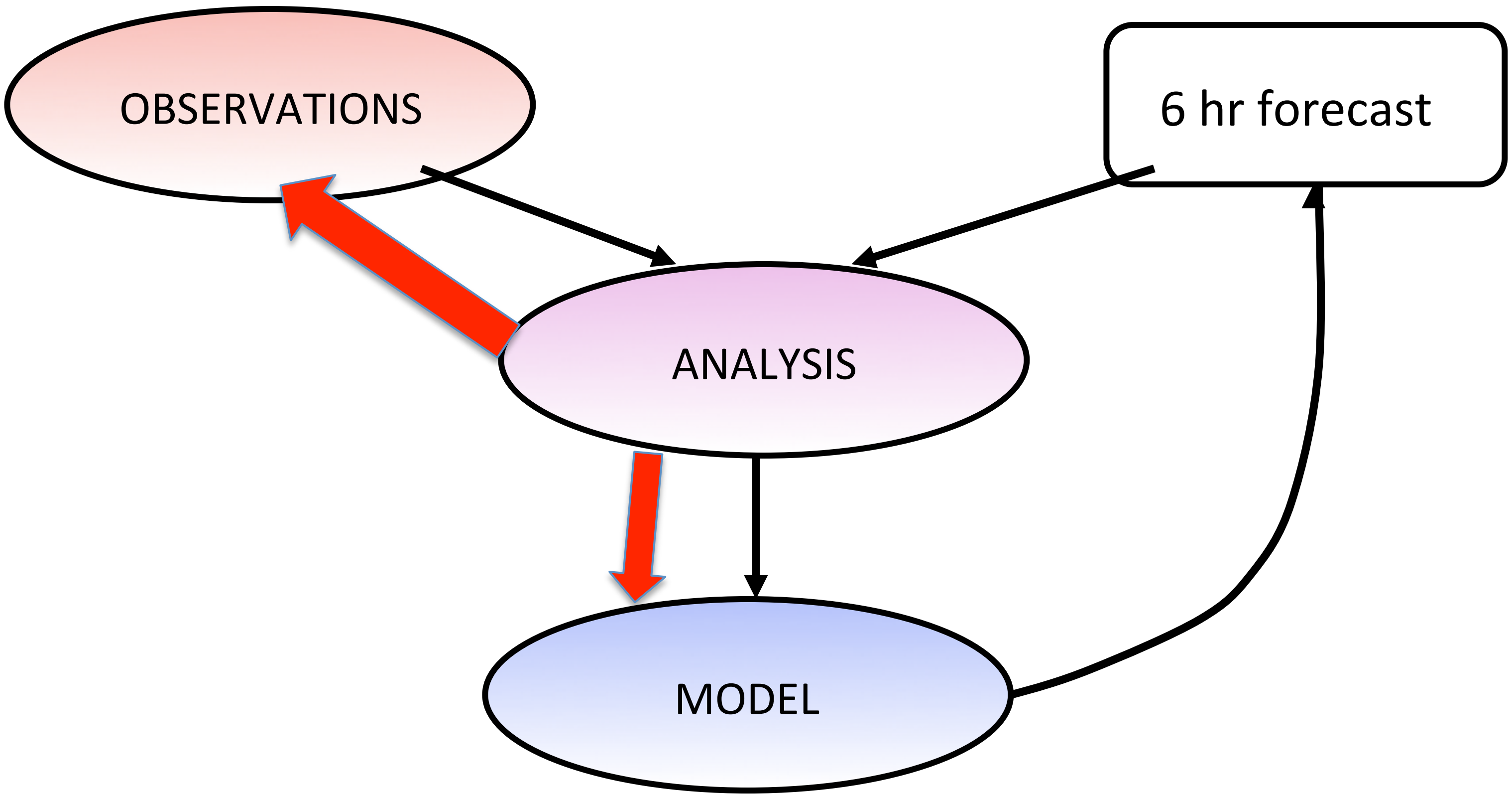
with many thanks to students, friends and colleagues
from the University of Maryland

NCEP- 17 March 2015

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

- We should also use DA to:

  2) Improve the observations

  3) Improve the model

- Also, do more truly coupled DA:

  4) Example: The ocean and the atmosphere are coupled: obviously the best DA should be coupled

- Currently the Earth System models used by IPCC for climate change do not predict population, they obtain it from UN projections.

  5) We should do DA of the coupled Earth System-Human System

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

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

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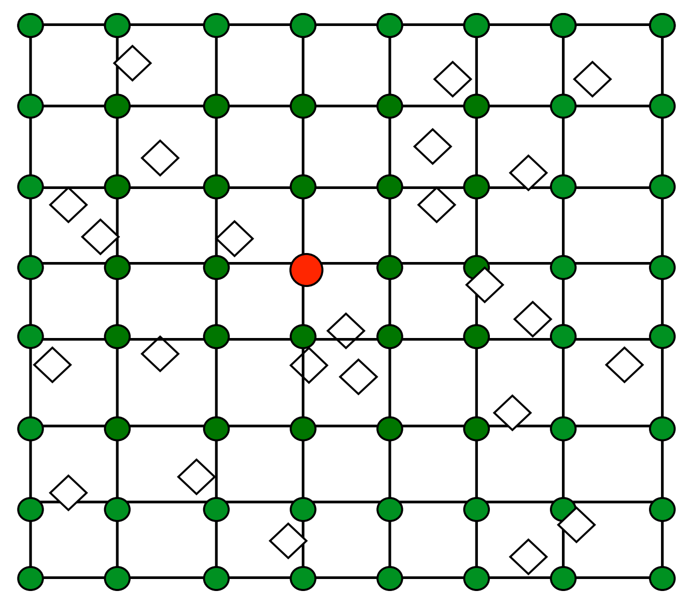
Traditional approaches to coupling

- In a typical coupling scheme for an ocean-atmosphere model, the ocean model passes SST to the atmosphere, while the atmosphere passes back heat flux components, freshwater flux, and horizontal momentum fluxes. (Neelin, Latif & Jin, 1994)
- In standard data assimilation, atmospheric observations are assimilated only by the atmospheric model, and ocean observations are assimilated only by the ocean. We call this **weak** (or standard) coupling.
- SST in the ocean model is frequently nudged from "Reynolds (OI) SSTs", not assimilated from observations.
- SSH and Salinity may not be even be used.
- The data assimilation windows for the ocean are much longer than for the atmosphere.
- We introduce the concept of strongly coupled data assimilation.

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

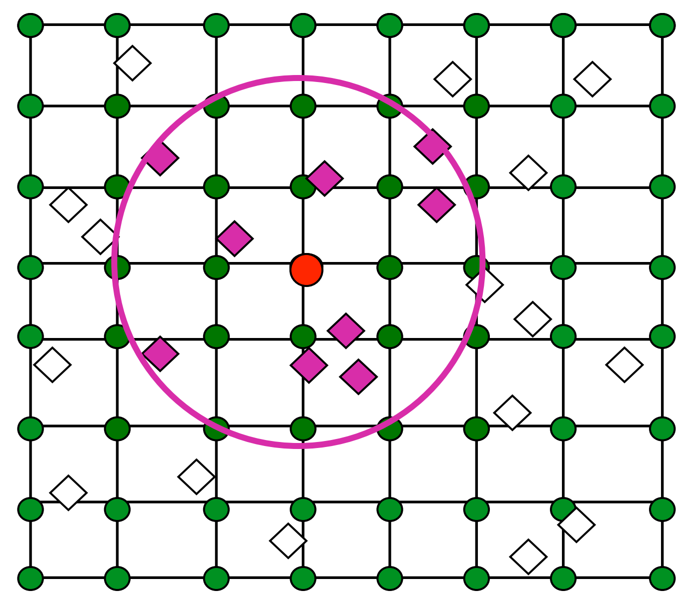


LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot

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 (LETKF)

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

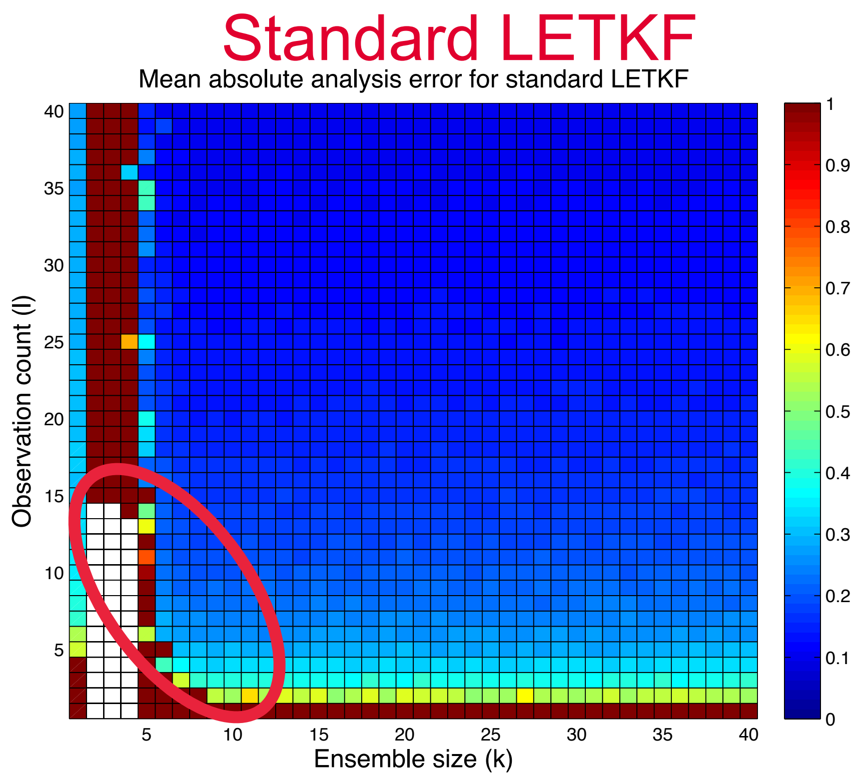
and add to $\mathbf{W}^a$ **to get the analysis ensemble in ensemble space.**

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.**

Hybrids between Var and EnKF

- So far **Covariance-Hybrids** have been used, combining an existing Var system with an ensemble that provides the flow dependence of the background error covariance.
- Penny (2014) developed a **Gain-Hybrid**, very simple to implement, that starts with the LETKF analysis and adds a Var analysis. ECMWF tested it with excellent results (Hamrud et al. 2014, TM733).
- The LETKF analysis is used as first guess by the Var, and the analysis is αVar+(1- α)LETKF + (LETKF perturbs).
- Penny tested it with the Lorenz 96 model: The analysis error is plotted as a function of the number of ensemble members (2 to 40) and the number of observations (1 to 40).
- Student Matthew Wespetal tested it with SPEEDY global atmospheric model with the LETKF coupled with 3D-Var.

Gain-Hybrid with a simple local 3D-Var (Penny, MWR2014) applied to the Lorenz 96 model



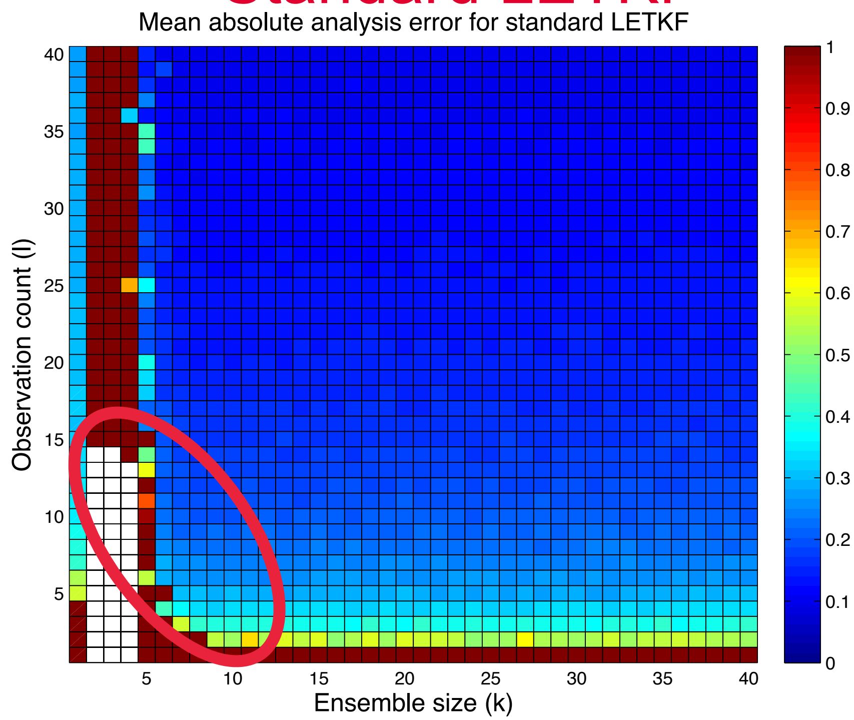
This is the corner where we are in ocean EnKF: too few obs, too few ensembles

The total model dimension is K=40

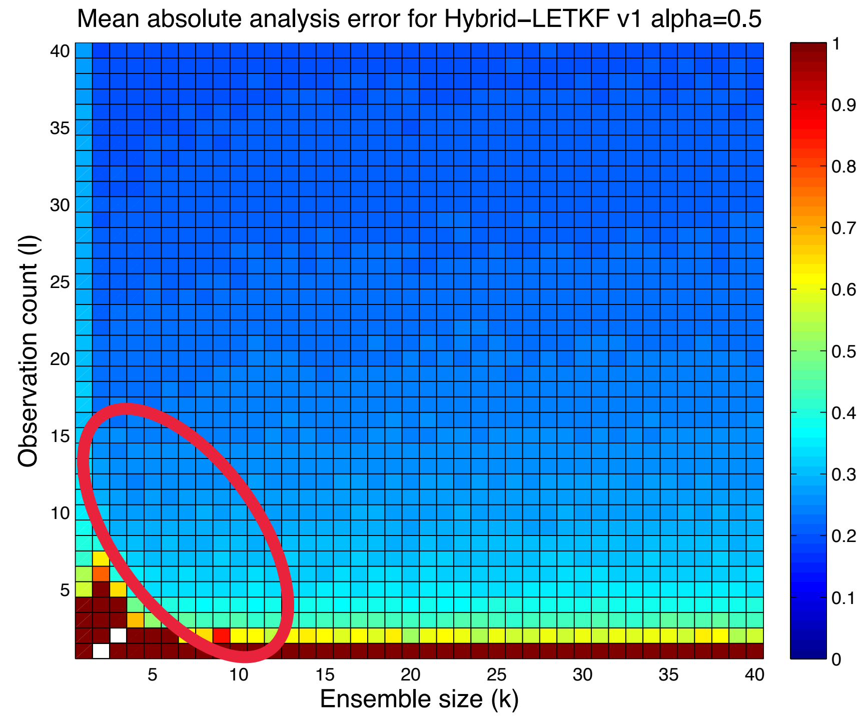
The LETKF is extremely accurate as long as k>7, number of obs>7.

Gain-Hybrid with a simple local 3D-Var (Penny, MWR2014) applied to the Lorenz 96 model

Standard LETKF



Add a simple 3D-Var to LETKF



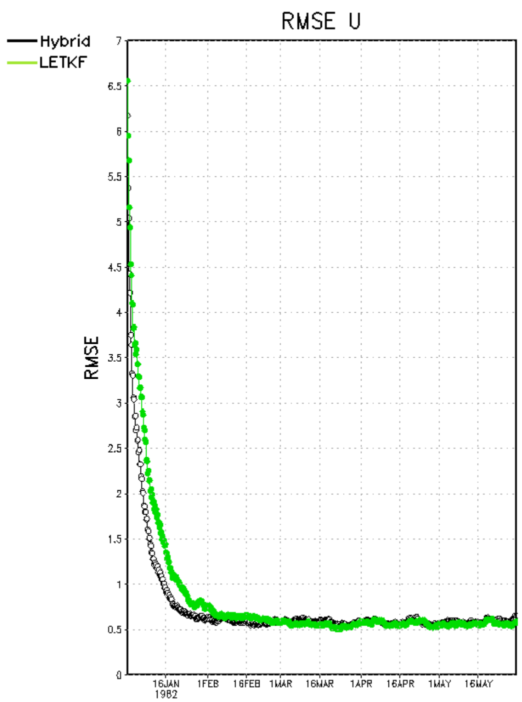
The hybrid LETKF- 3D-Var is more robust for few ensemble members and few observations, as in the ocean.

ECMWF implemented Penny's Gain-Hybrid with excellent results, even slightly better than their operational EDA

LETKF and Hybrid on the SPEEDY model

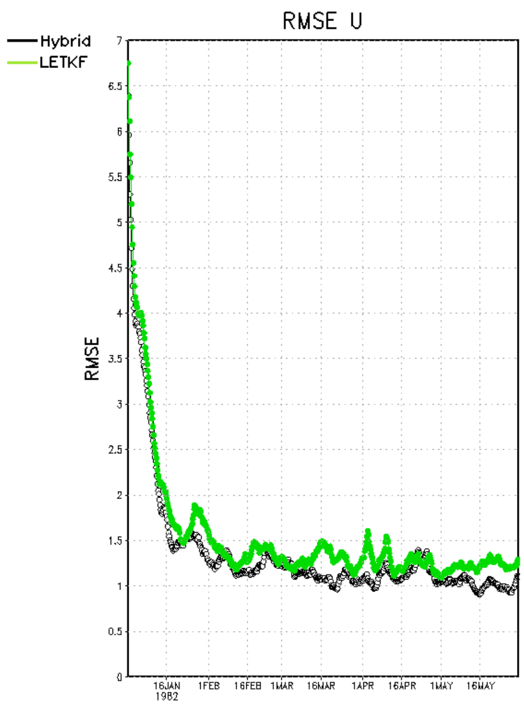
Hybrid vs LETKF (20 members) RMSE

- **satellite + rawinsondes**
- alpha = 0.5



rawinsondes only

alpha = 0.5



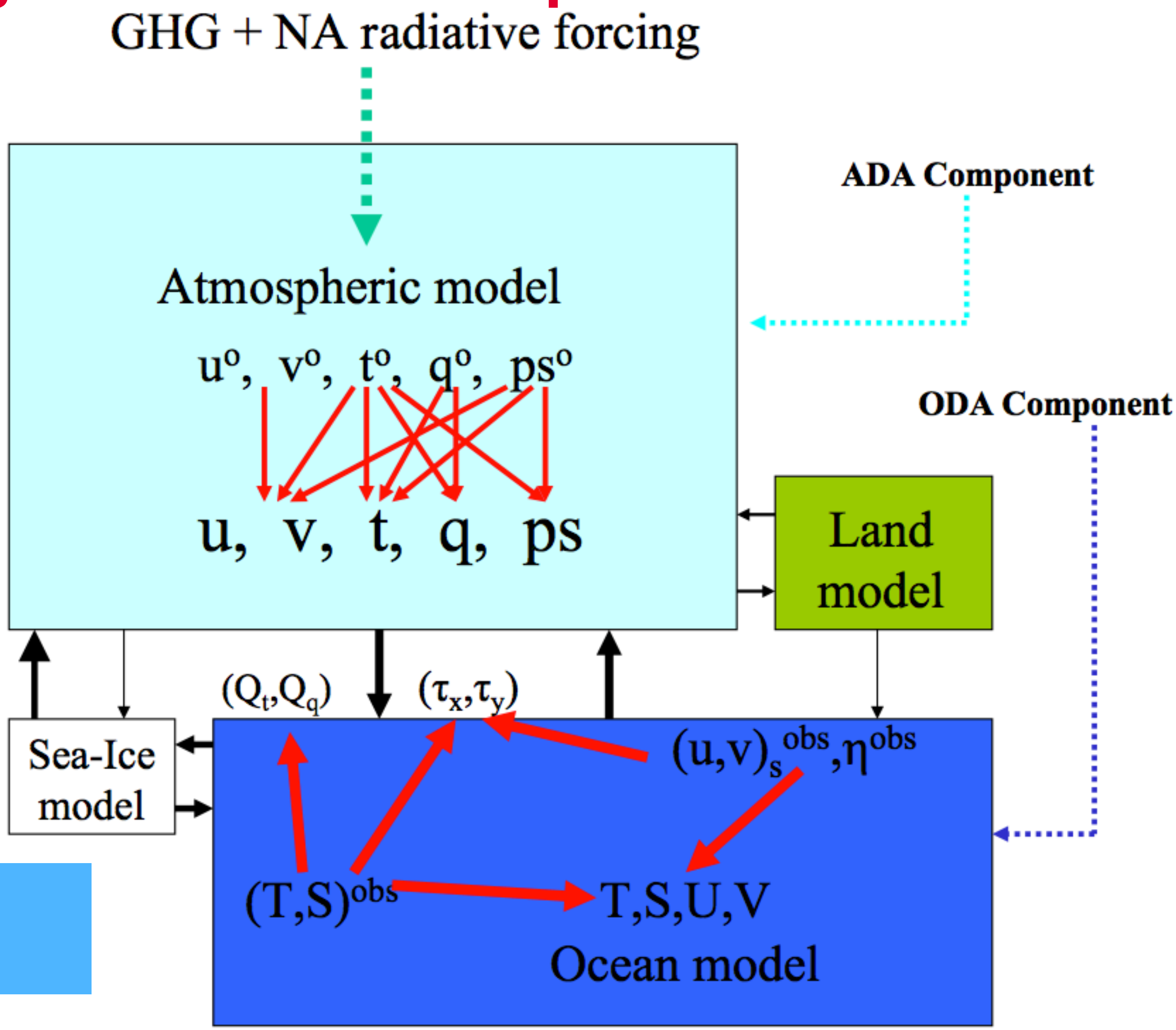
As expected, for the **data rich case**, the hybrid converges faster but becomes slightly worse than the LETKF.

For the **data poor case**, the **hybrid is better** than the pure LETKF.

(from Matthew Wespetal).

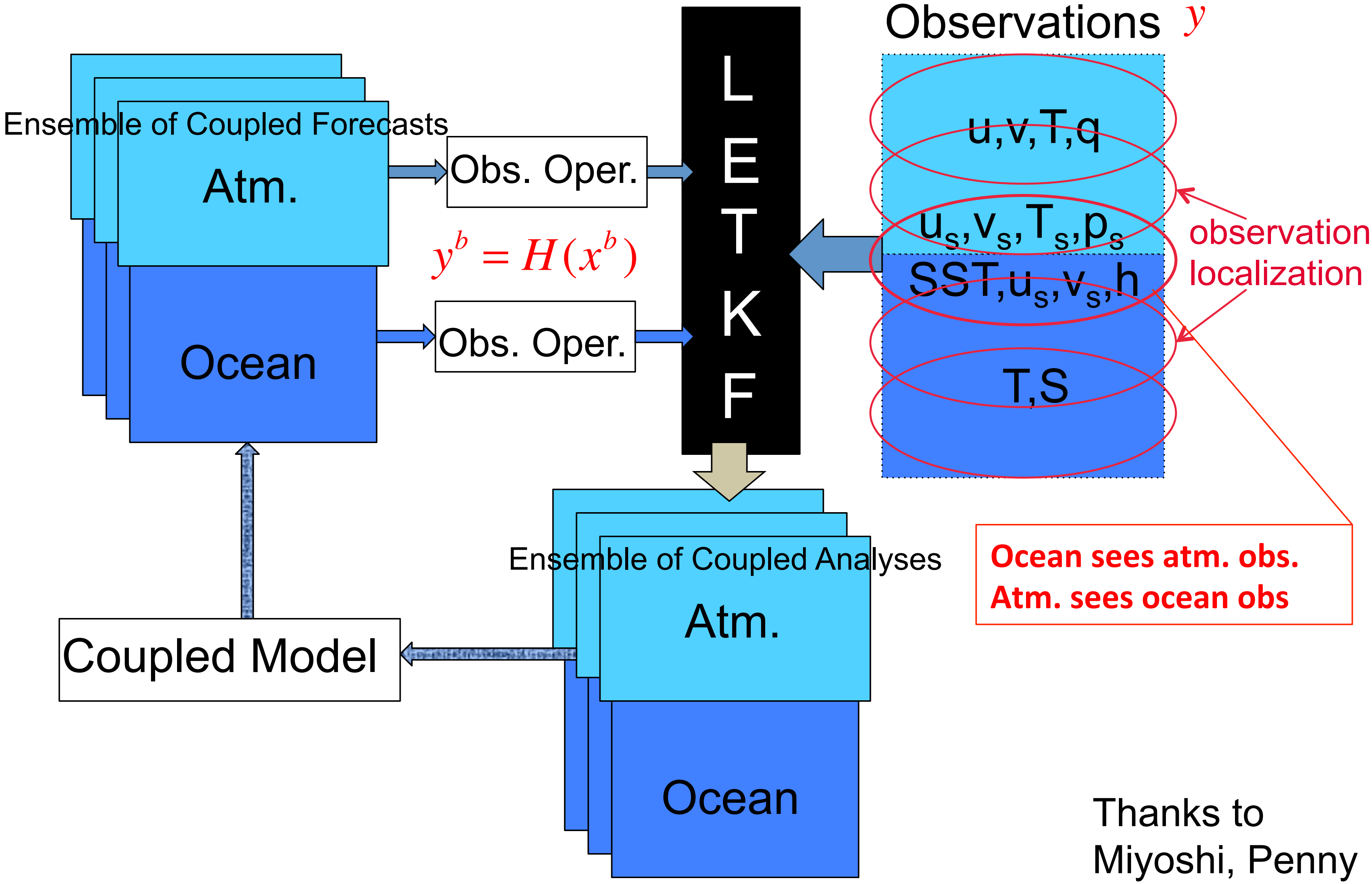
Data Assimilation: STANDARD (WEAK) COUPLING
S. Zhang et al.: GFDL Coupled Ocean-Atm EnKF

Atmosphere assimilates only atm. obs.!



Ocean assimilates only ocean obs.!

Our strongly coupled LETKF assimilation



Thanks to
Miyoshi, Penny

Impact of strong coupling of the ocean-atmosphere LETKF (Travis Sluka)

- SPEEDY-NEMO coupled model (from F. Kucharski, ICTP)
- Standard (weak) coupling as a control
- Test strong coupling: the ocean sees the atmospheric observations and the atmosphere sees the ocean observations

Experiments: 1) Only atmos. obs.

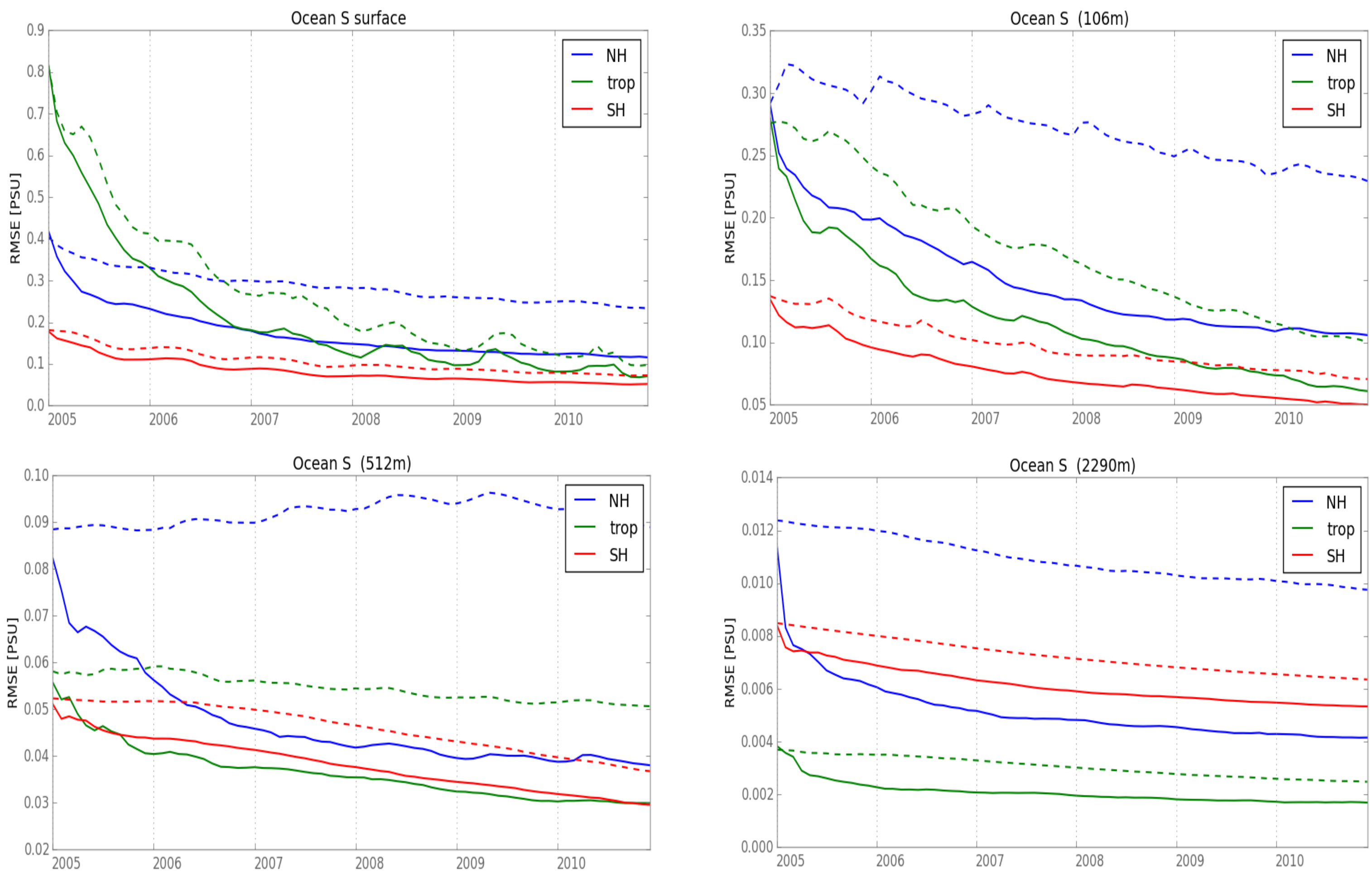
(2) Only ocean obs.)

- CONTROL: Weakly coupled data assimilation: Only the atmosphere assimilates atmos. observations.
- Strongly coupled DA: ocean also assimilates atmospheric observations (and vice versa).

Results – rawinsondes only

- Ocean **Salinity**, RMSE, CONTROL vs STRONG

CONTROL (dashed) **STRONG** (solid)



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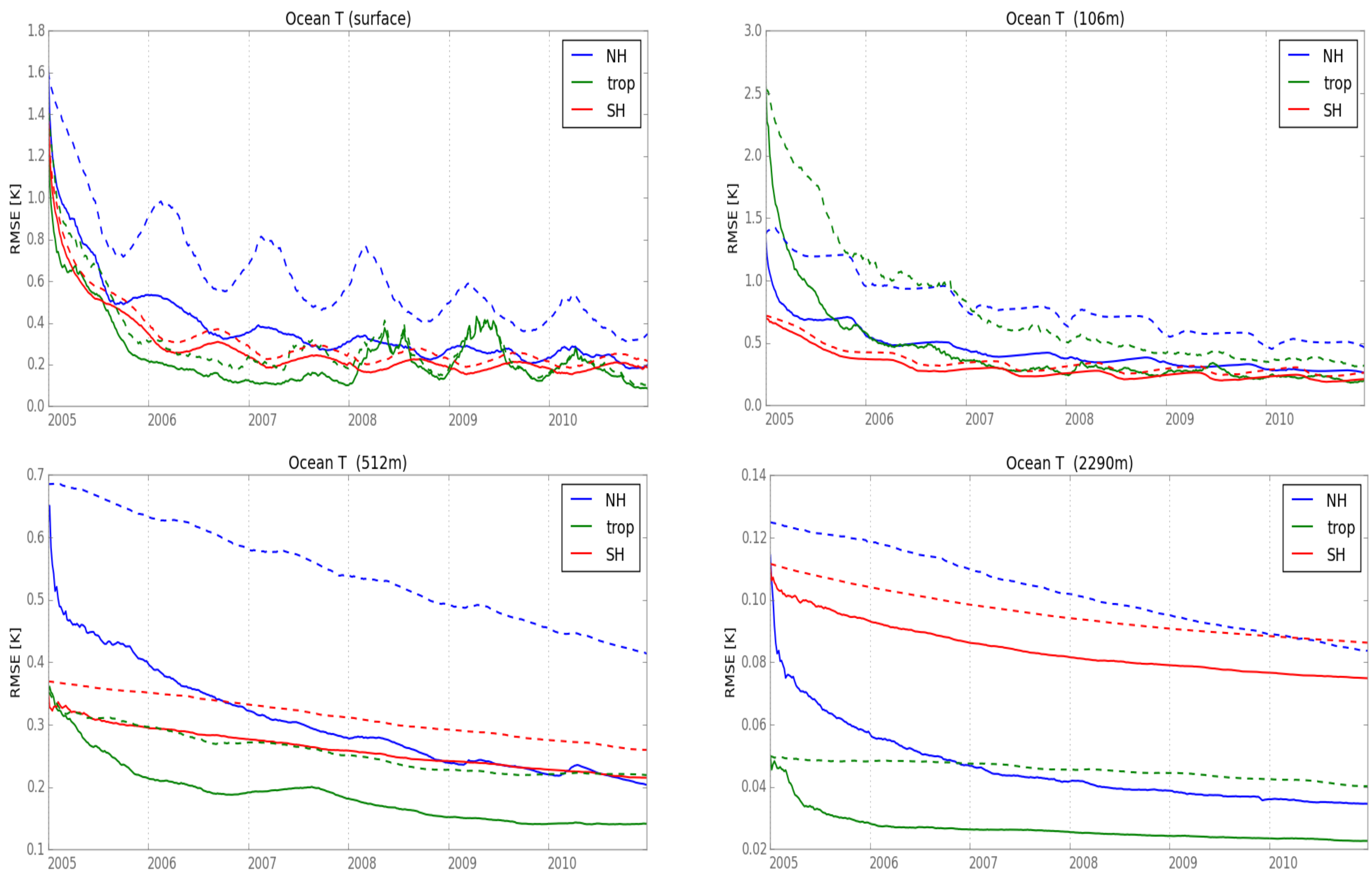
Results – rawinsondes only

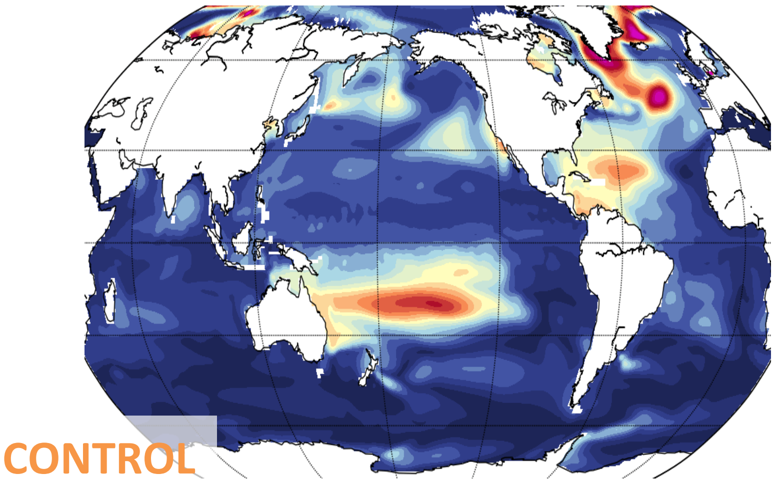
- Ocean **Temperature**, RMSE, CONTROL vs STRONG

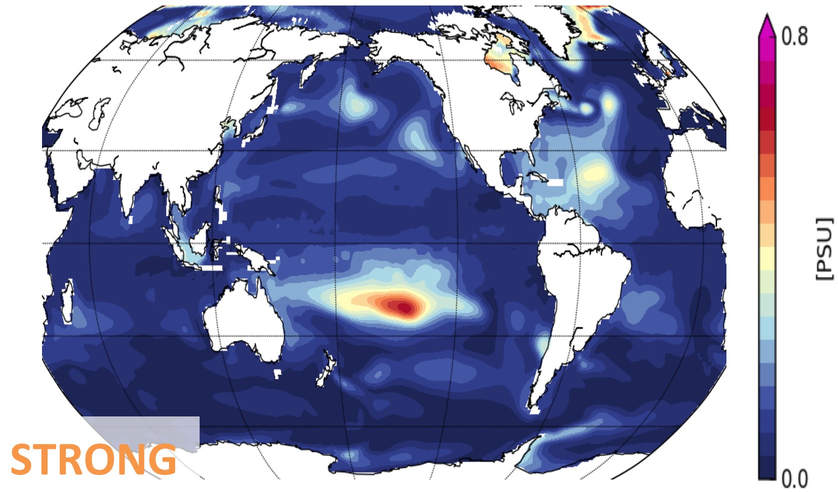
CONTROL (dashed) **STRONG** (solid)

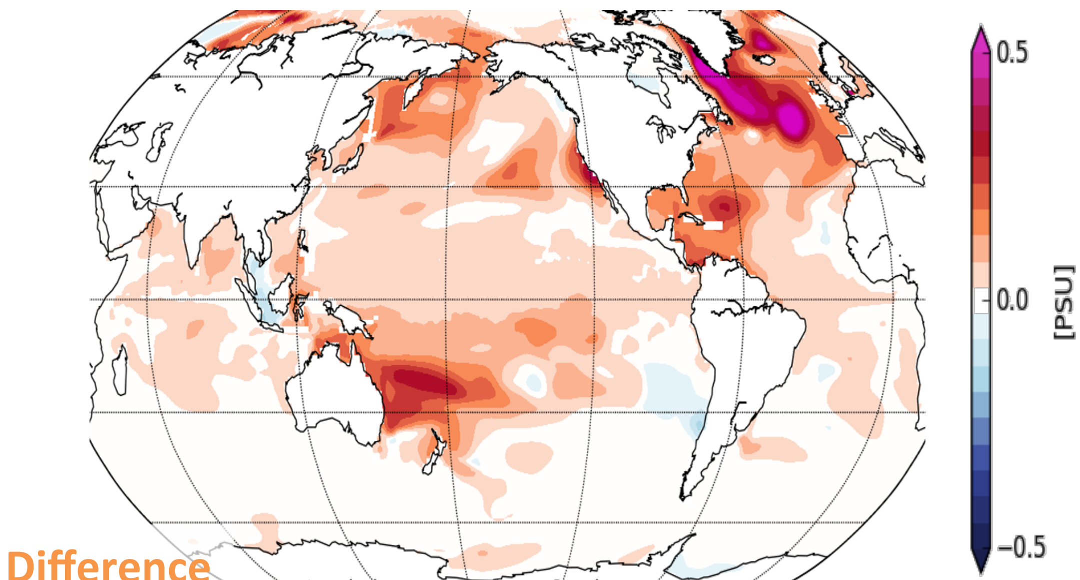


Results – rawinsondes only

- Ocean **Salinity** RMSE - upper 100m, avg of last 5 years

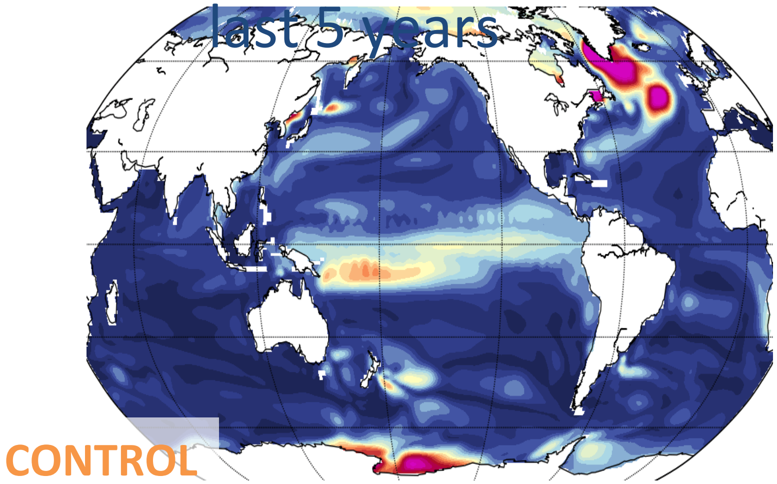


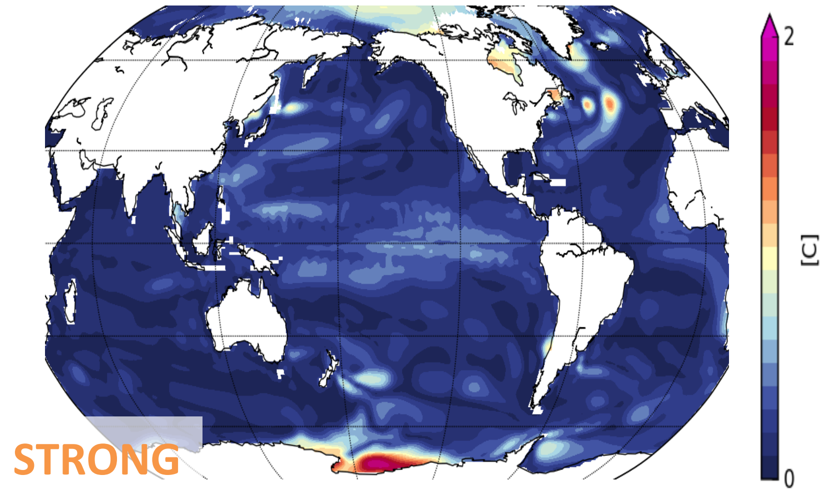


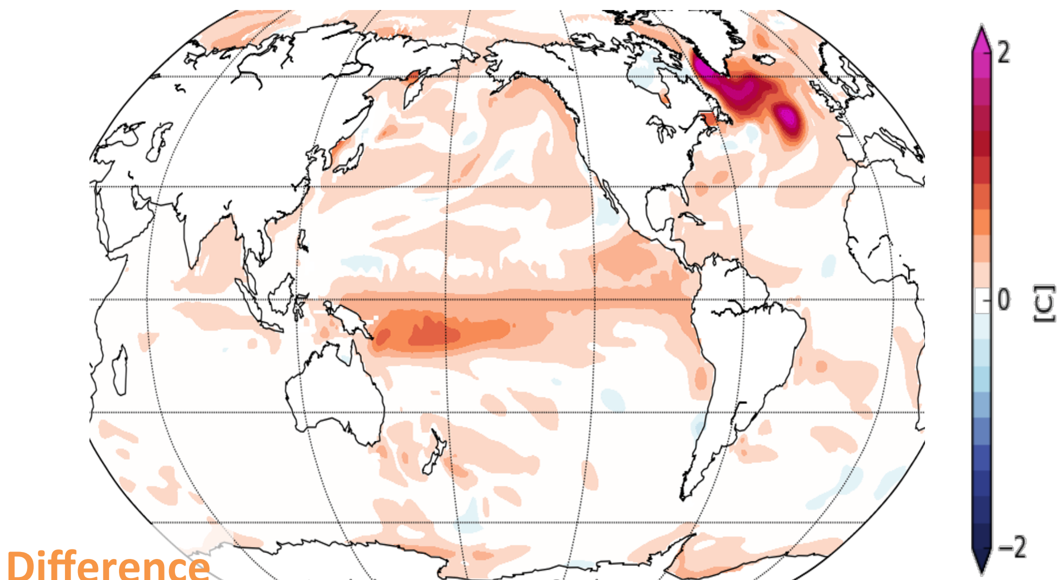


Results – rawinsondes only

- **Ocean Temperature** RMSE - upper 100m, avg of last 5 years

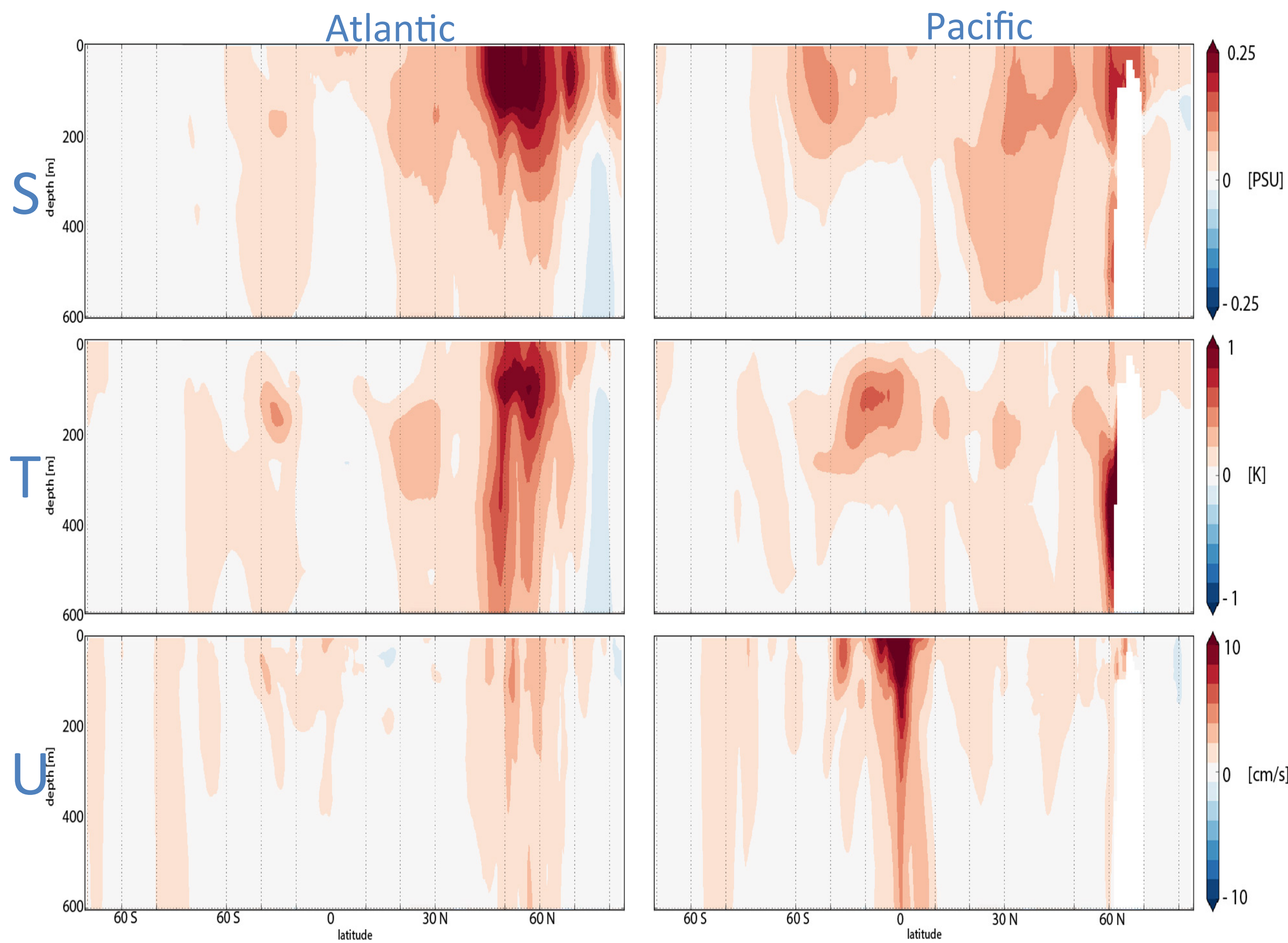






Results – rawinsondes only

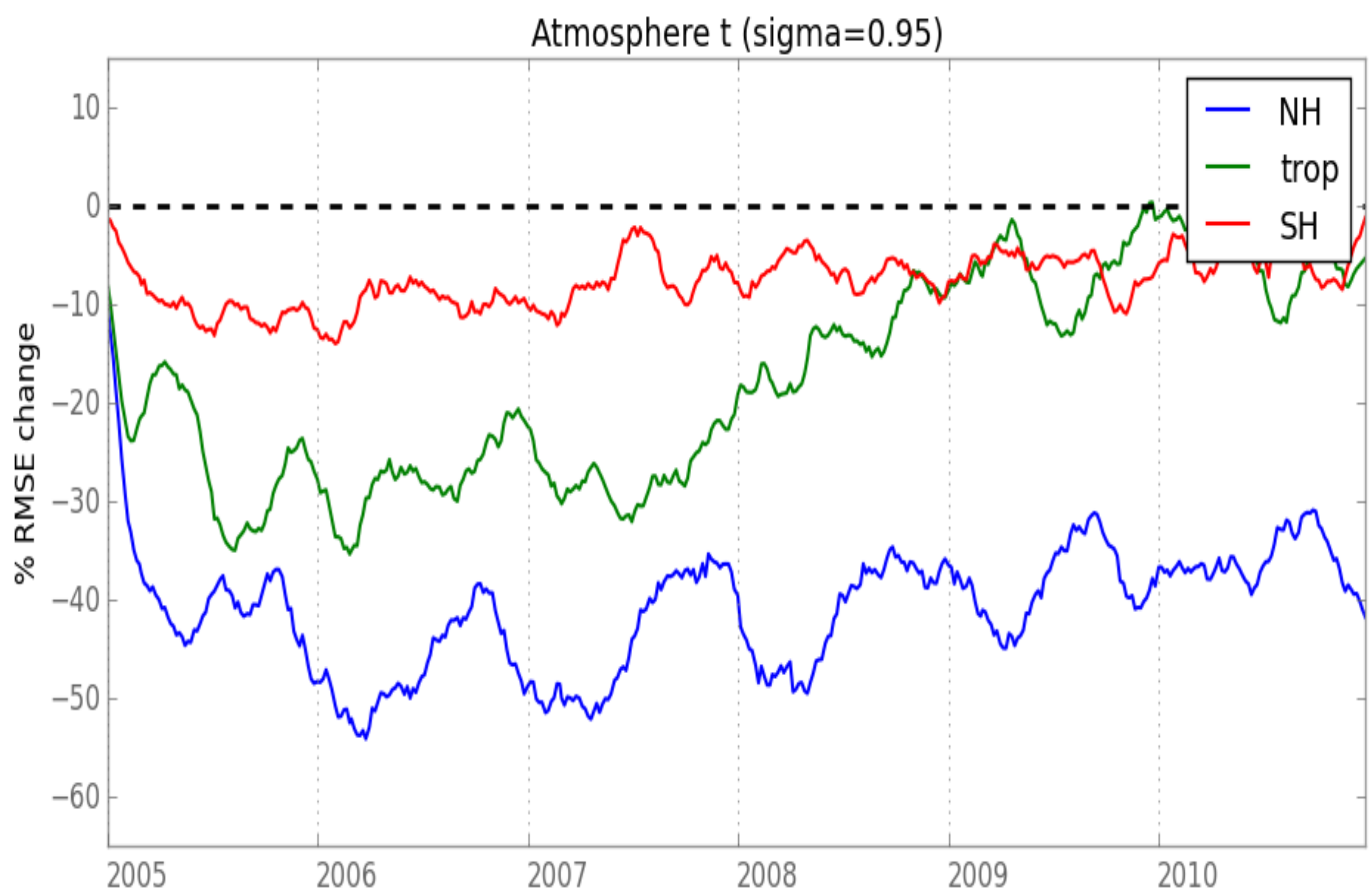
- **Ocean** zonal average (RMSE improvement of last 5 years)



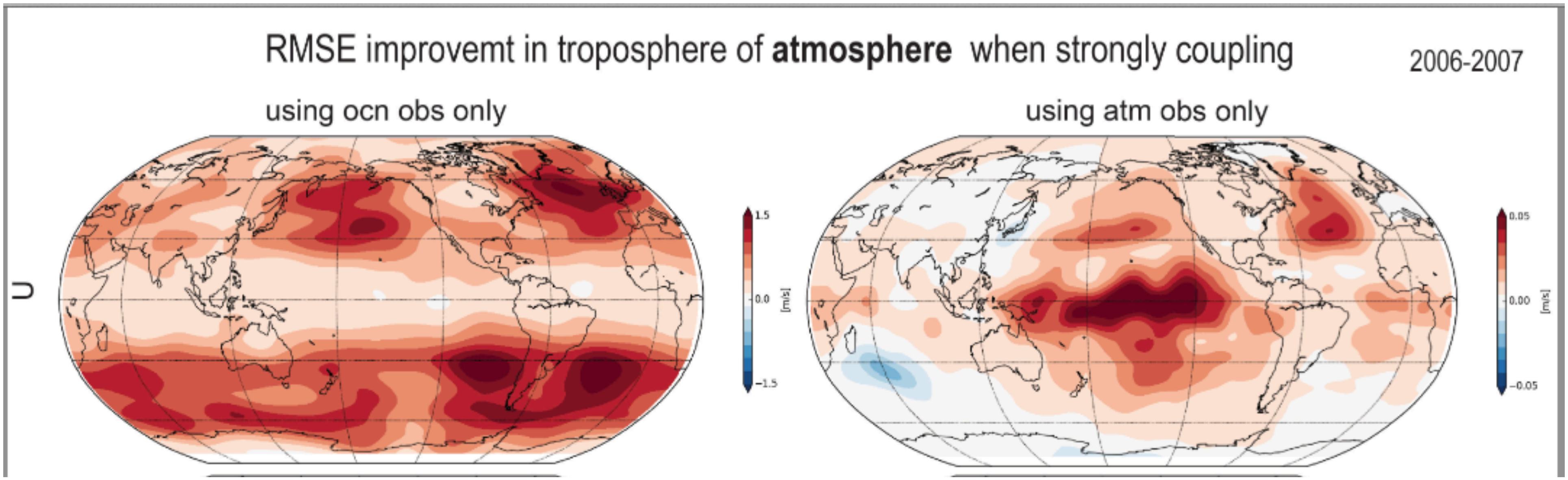
Results – rawinsondes only

- Atmosphere, % RMSE change, CONTROL vs STRONG

Atmospheric Surface Temperature



Impact on the atmosphere of strong coupling (older experiment)



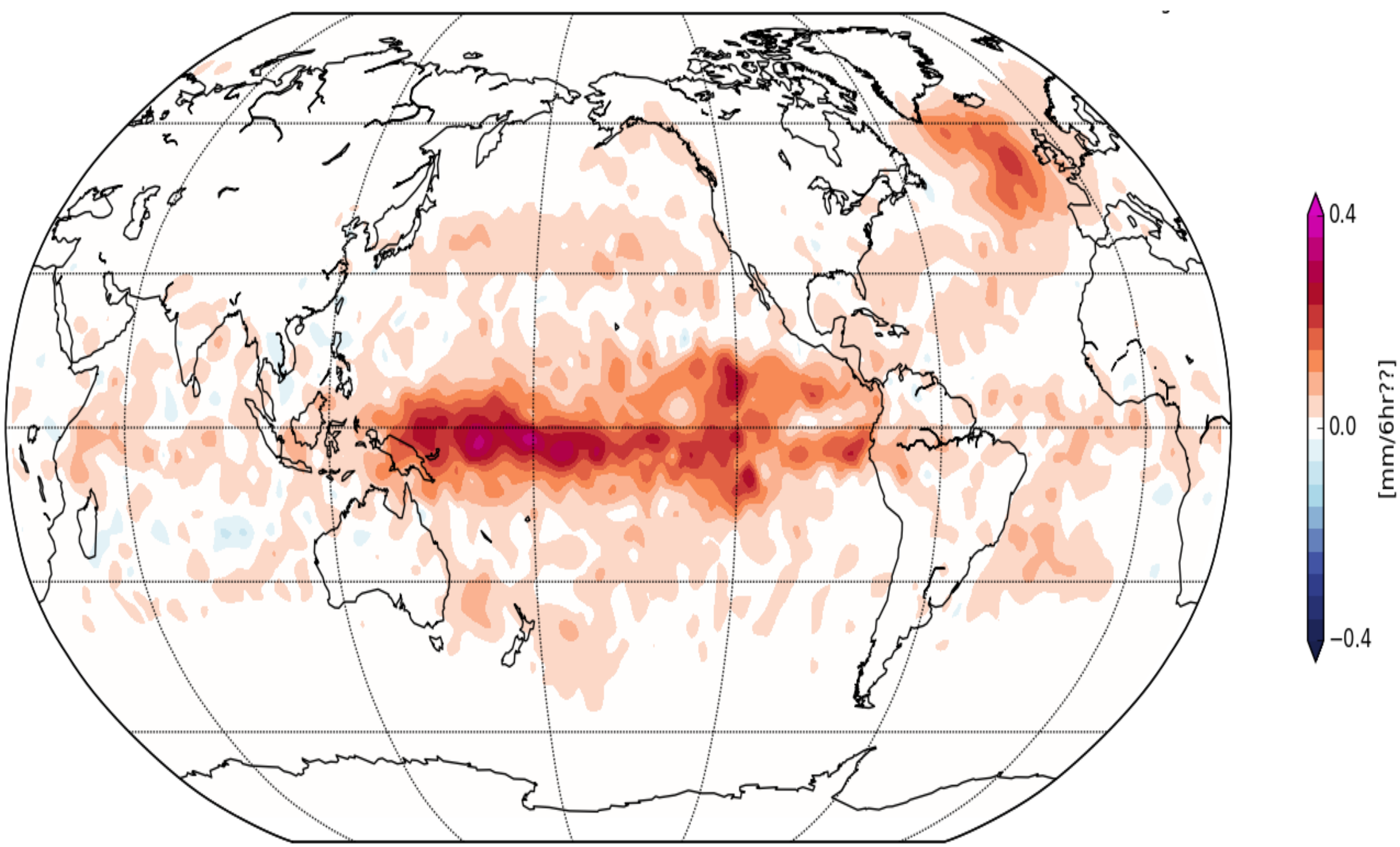
Ocean obs only

Atmos. obs only

Allowing the ocean to see the atmospheric observations **improves the ocean T and S**, more in mid-lats than in the tropics. In turn, **the ocean improvements result in better atmospheric temperature and humidity in the atmosphere.**

Results – rawinsondes only

- **Atmo Precip** RMSE - avg of last 5 years



Difference (CONTROL – STRONG)

Why do atm. obs. seen by the ocean improve mid-lats., and ocean obs. seen by the atmos. improve the tropics??

- This was a very surprising result:
  - Ocean drives atmosphere in the tropics!
  - Atmosphere drives ocean in mid-lats!
- Ocean obs. assimilated by the atmosphere (using LETKF) change the atmospheric driving in mid-latitudes. This is additional information that improves the mid-lats. atmosphere and therefore the mid-lats ocean.
- Atmospheric obs. in the tropics assimilated by the ocean change the ocean driving in the tropics. This is additional information that improves the tropical ocean, and therefore the tropical atmosphere.

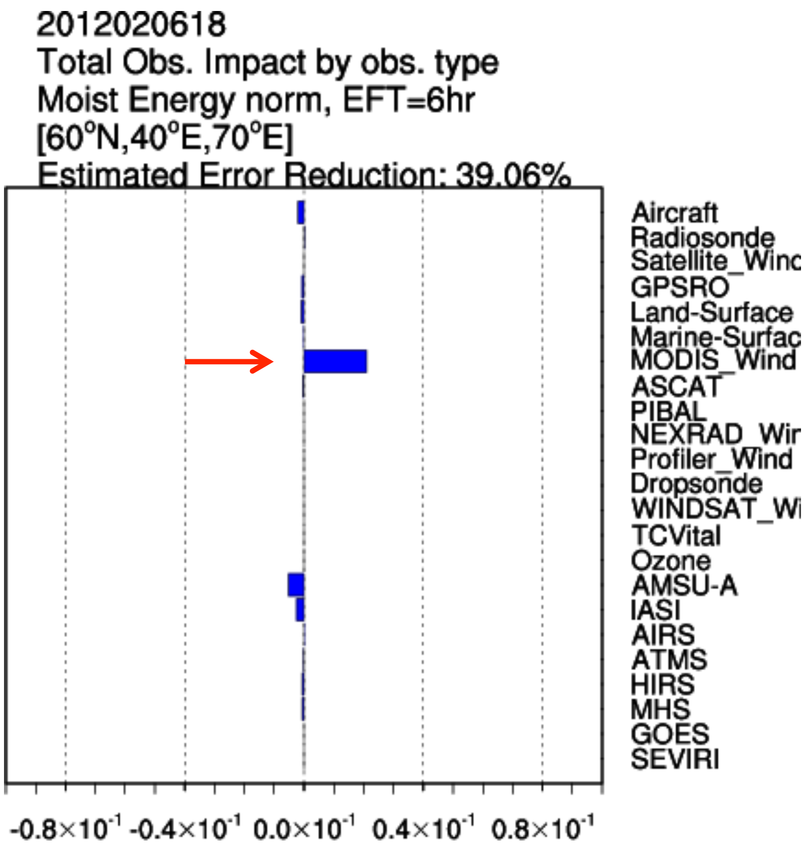
Improve the observations: Ensemble Forecast Sensitivity to Observations and Proactive QC

- Kalnay et al. (2012) derived EFSO
- Ota et al. (2013) tested 24hr 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 withdrawn and collected with useful metadata so they can be improved.
- We call this **Proactive QC**, much stronger than QC.
- Hotta also showed EFSO can be used to tune **R**
- G.-Y. Lien (2014) tested EFSO to identify useful observations of precipitation, with good results.

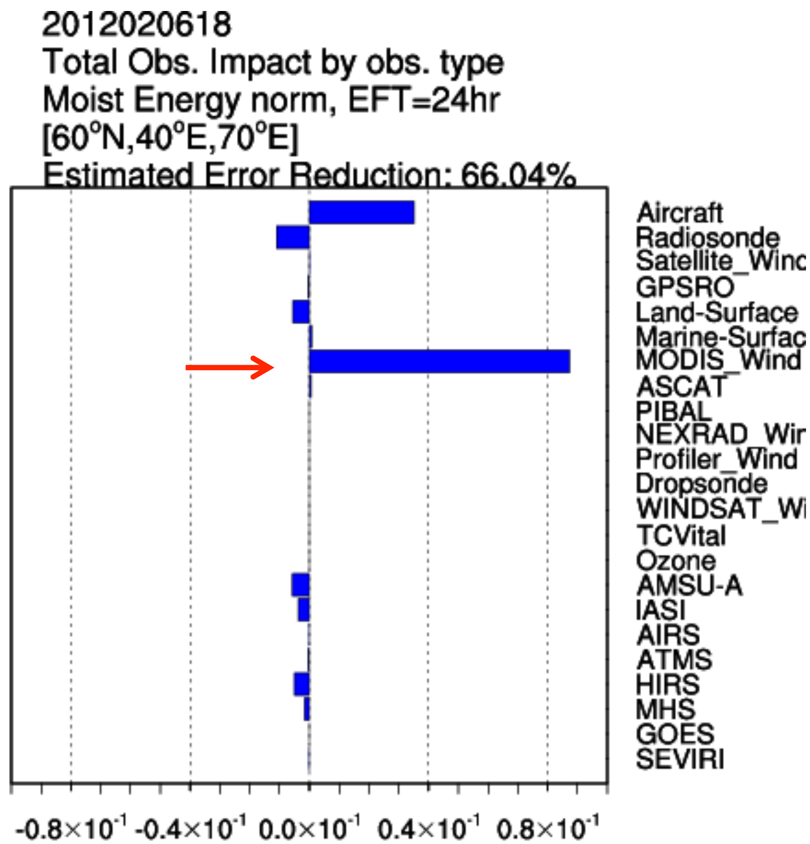
Hotta (2014)

Feb. 18 06UTC, near the North Pole (Ota et al. 2013 case). Bad obs: MODIS WIND

FT=06 hr.



FT=24 hr.

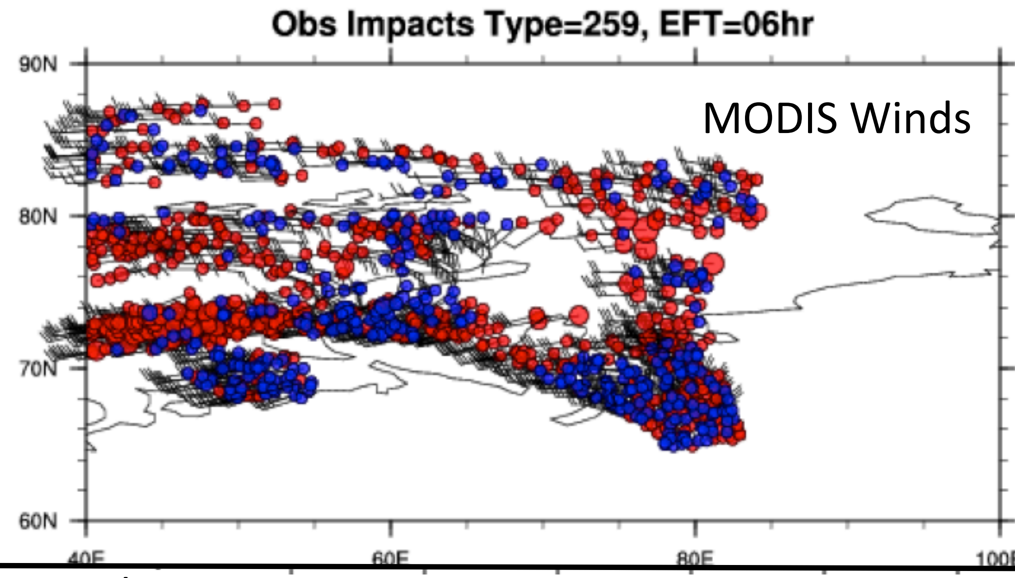


Can identify the bad observations after only 6 hours!

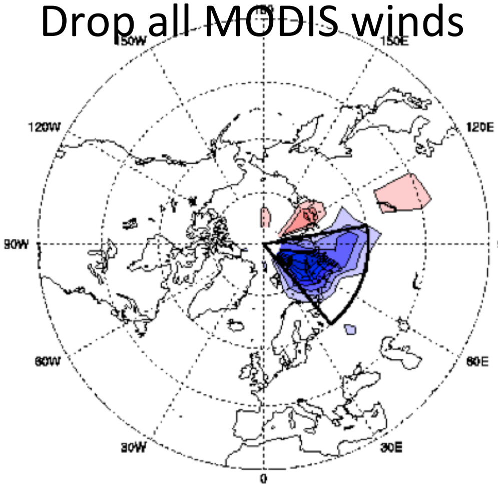
Improve observations:

Proactive QC: Find and delete the obs that make the 6hr forecast worse using EFSO

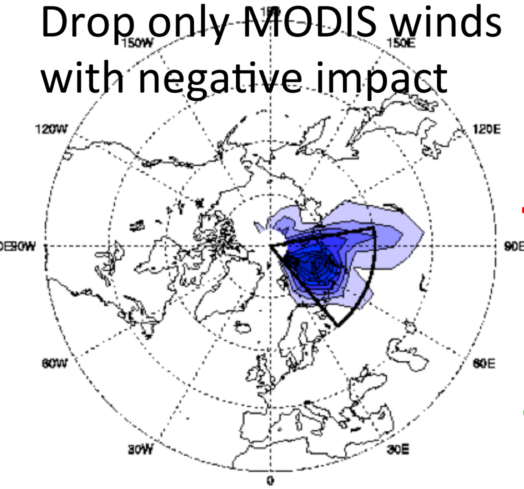
Dr. Daisuke Hotta (2014):
EFSO is able to find whether <u>each</u> observation improves (blue) or makes the 6hr forecast worse (red)



Drop all MODIS winds



Drop only MODIS winds with negative impact



Impact of 6hr PQC on 24hr fcst

PQC with metadata can be used to improve the algorithm!

It should accelerate optimal assimilation of new instruments!

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

Can be used to tune **R**! (Hotta, 2014)

Ensemble Forecast Sensitivity to **Error Covariances**

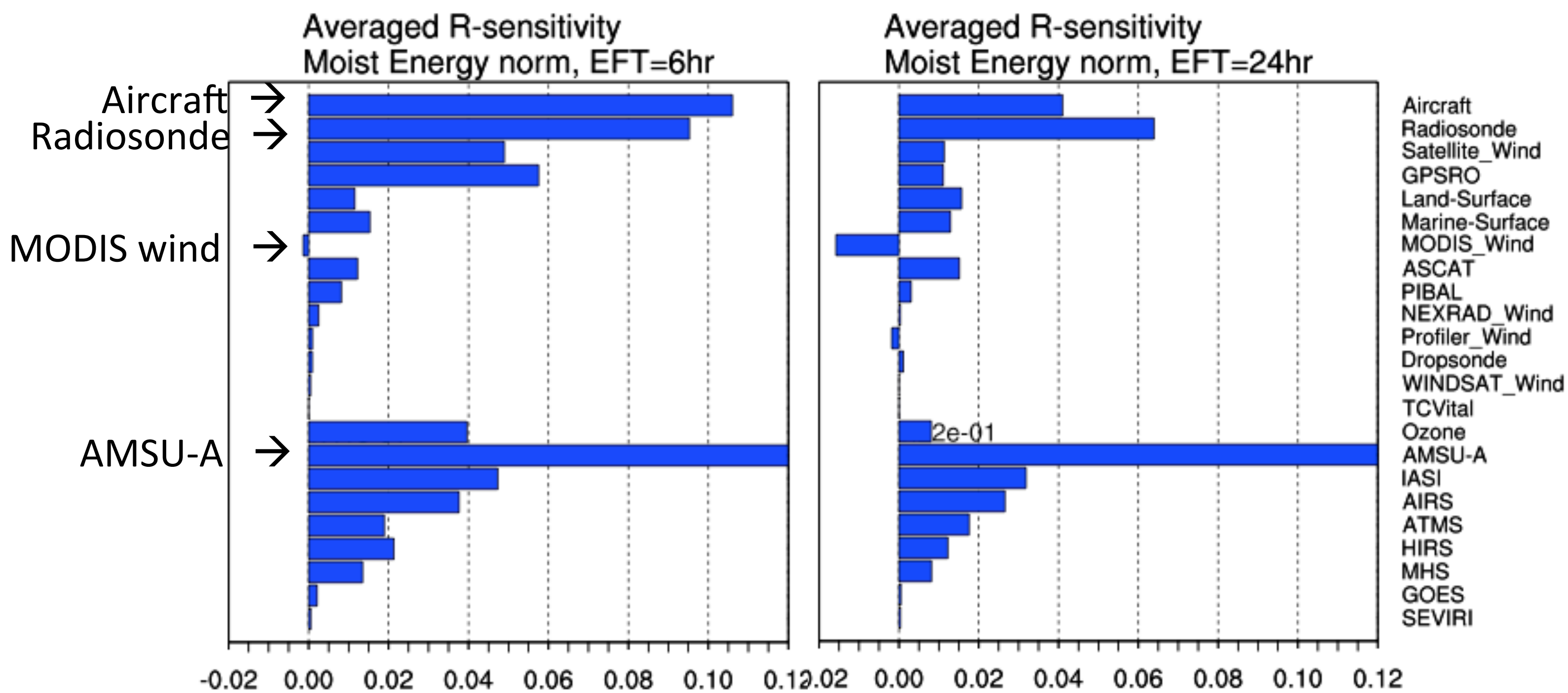
Hotta (2014)

- Daescu and Langland (2013, *QJRMS*) proposed an adjoint-based formulation of forecast sensitivity to **B** and **R** matrix.
- Daisuke Hotta formulated its ensemble equivalent for **R** using **EFSO** by Kalnay et al. (2012) :

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

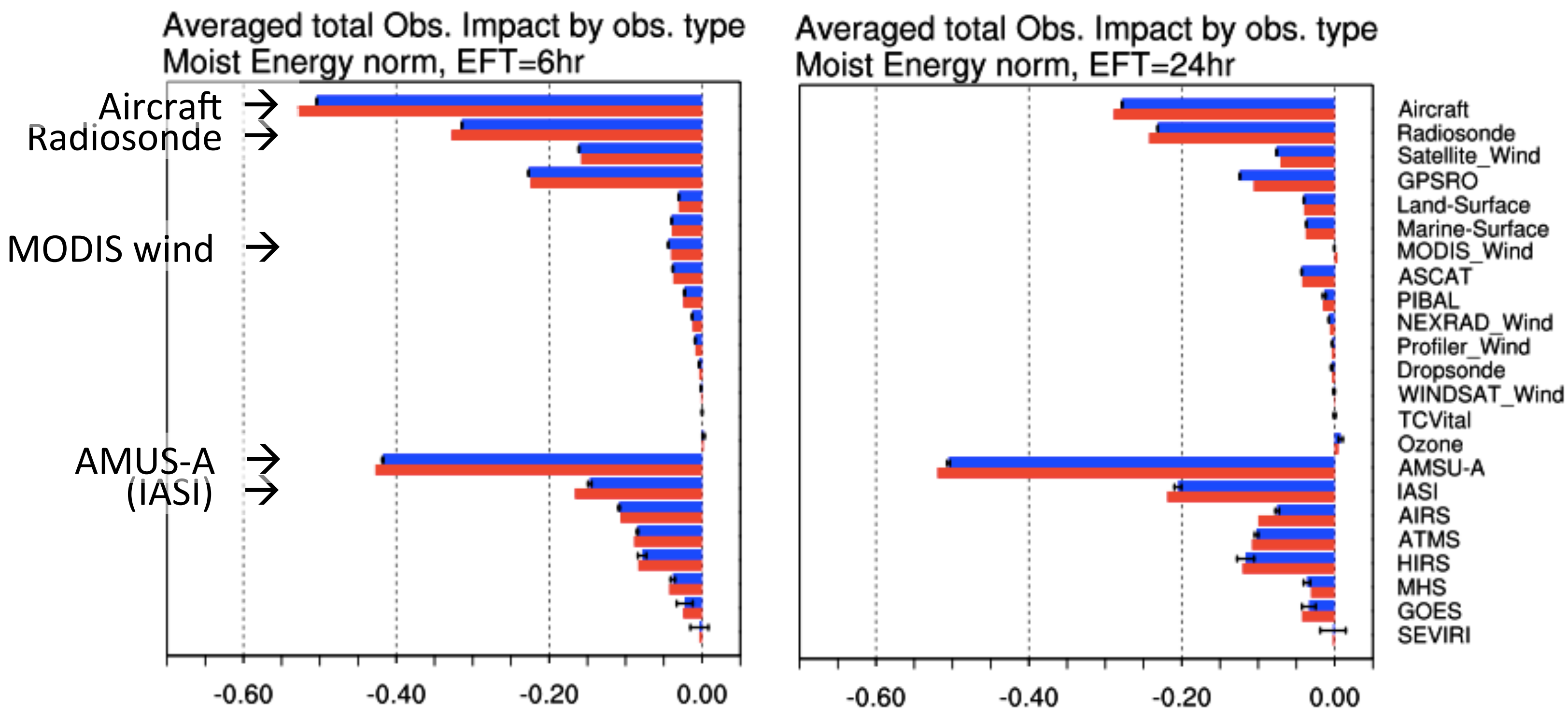
where $\mathbf{z}$ is an "intermediate analysis increment" in observation space

R-sensitivity results from GFS / GSI-LETKF hybrid



- Positive value: error increases as s_o^2 increases → should decrease s_o^2
- Aircraft, Radiosonde and AMSU-A: large positive sensitivity
- MODIS wind : negative sensitivity
- → **Tuning experiment**:
  - Aircraft, Radiosonde and AMSU-A: scale s_o^2 by 0.9
  - MODIS wind: scale s_o^2 by 1.1

Tuning Experiment: Result
EFSO before/after tuning of R



- Aircraft, Radiosonde and AMSU-A: significant improvement of EFSO-impact
- MODIS wind : insignificant difference in EFSO
- IASI: Significant improvement in EFSO although its error covariance is untouched!

Current testing of PQC on JCSDA S4 (T.-C. Chen)

- Prof. Daryl Kleist has kindly offered to lead the testing of operational PQC. JMA is implementing PQC (both Hotta and Ota will work on that).
- To implement PQC, we need to first show that:
  – Denying flawed observations works in a cycled way (tested case by case so far).
  – The EFSO approximation (constant K) can be used to replace the full analysis without the flawed observations (much faster).
  – We can use the 6hr early forecast to check the final analysis.
  – Test the tuning of **R**

Improving non-Gaussian Observations

Effective assimilation of Precipitation (Guo-Yuan Lien, Eugenia Kalnay and Takemasa Miyoshi, 2013.

Lien (2014), Lien et al. (2015a, 2015b)

- Assimilation of precipitation has generally failed to improve forecasts beyond a day.
- A new approach deals with non-Gaussianity, and assimilation of both zero and non-zero precipitation.
- Rather than changing moisture to force the model to rain as observed, the LETKF changes the **potential vorticity**.
- **The model now "remembers" the assimilation, so that medium range forecasts are improved.**

How to transform precipitation *y* to a Gaussian y_{transf}

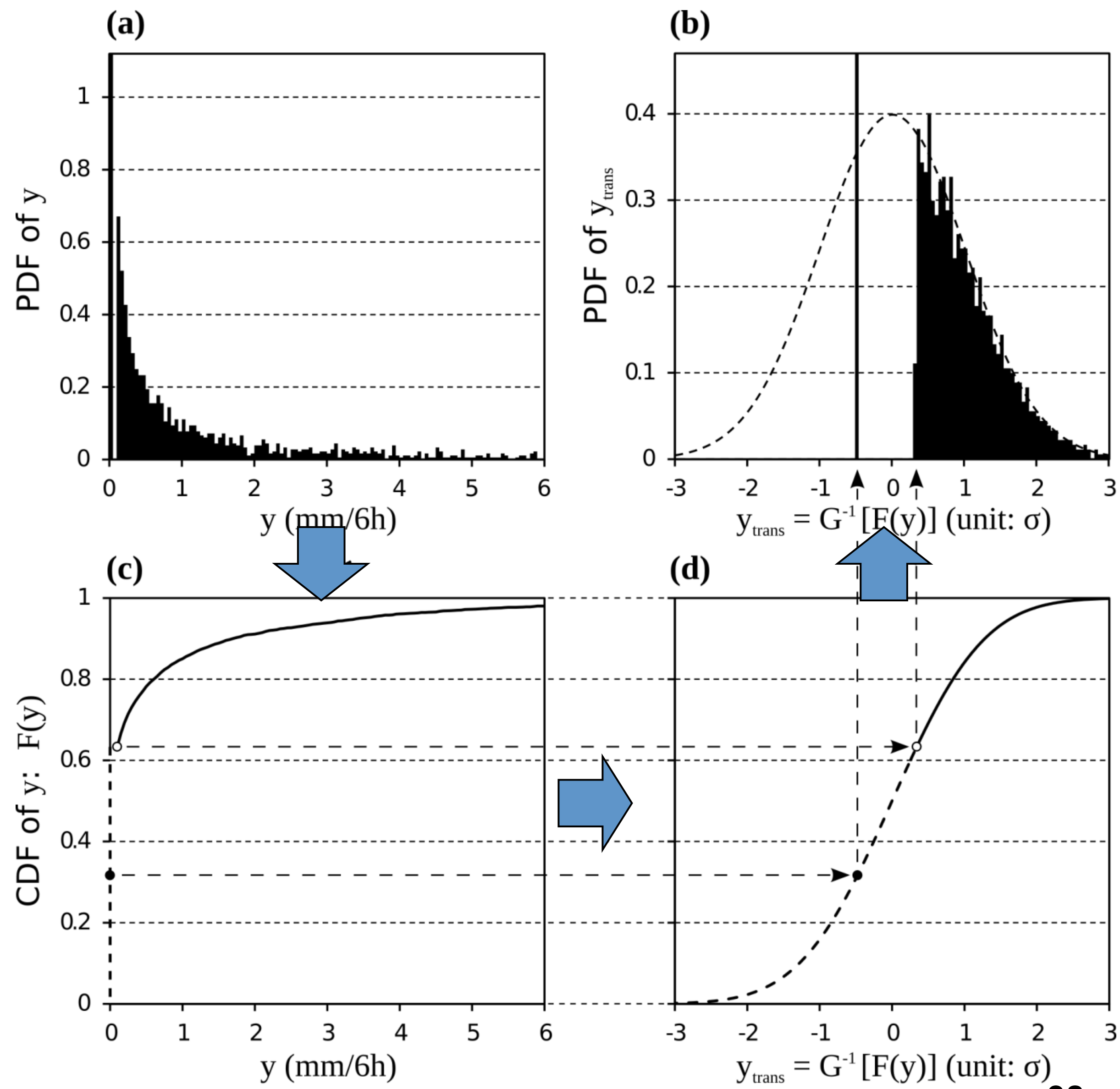
Start with pdf of *y*=rain at every grid point.

"No rain" is like a delta function that we cannot transform.

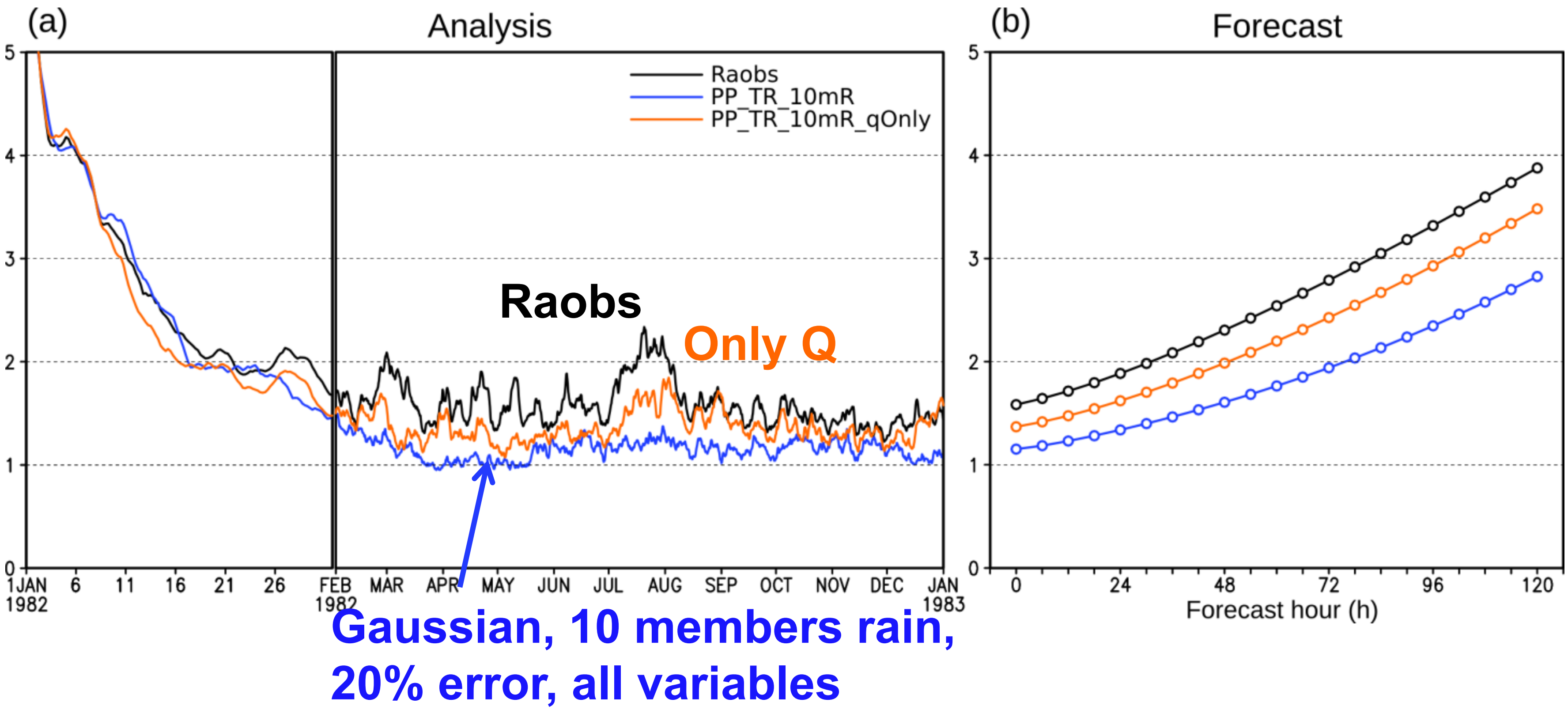
We assign all "no rain" to the median of the no rain CDF.

We found this works as well as more complicated procedures.

It allows to assimilate both rain and no rain.



$$G^{-1}(x) = \sqrt{2}\,erf^{-1}(2x-1)$$

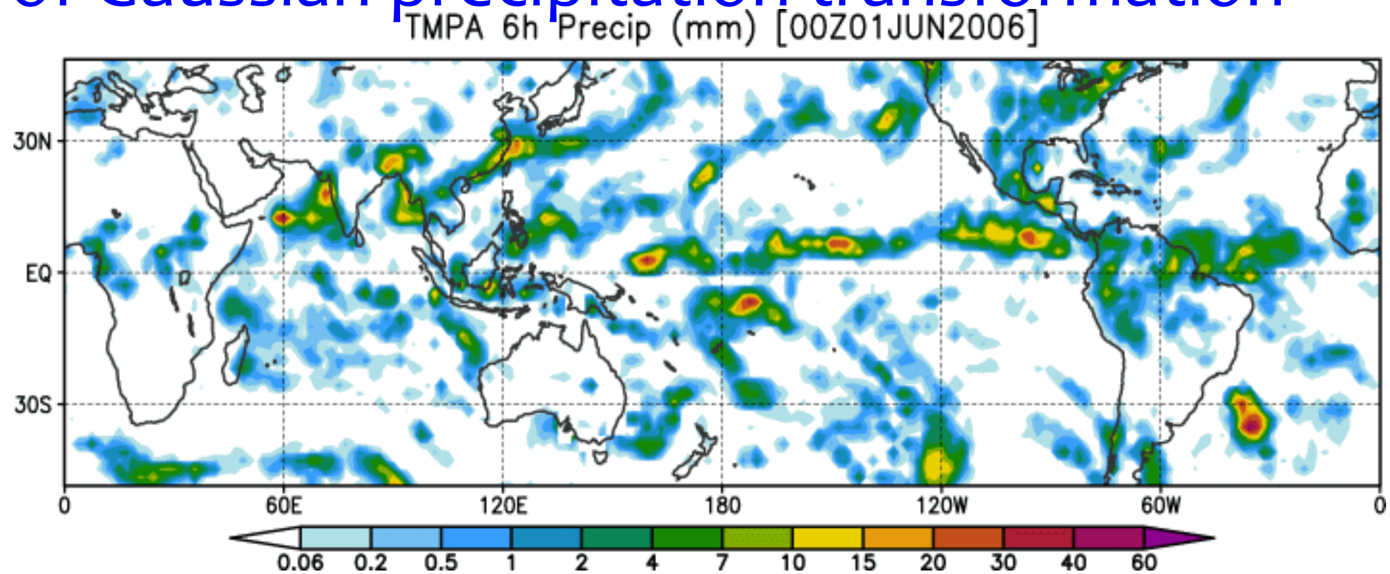


- **Main result:** **with at least 10 ensemble members raining in order to assimilate an obs, updating all variables (including vorticity), with Gaussian transform, and rather accurate observations (20% errors), the analyses and forecasts are much improved!**
- **Updating only Q is much less effective.**
- **The 5-day forecasts maintain the advantage!**

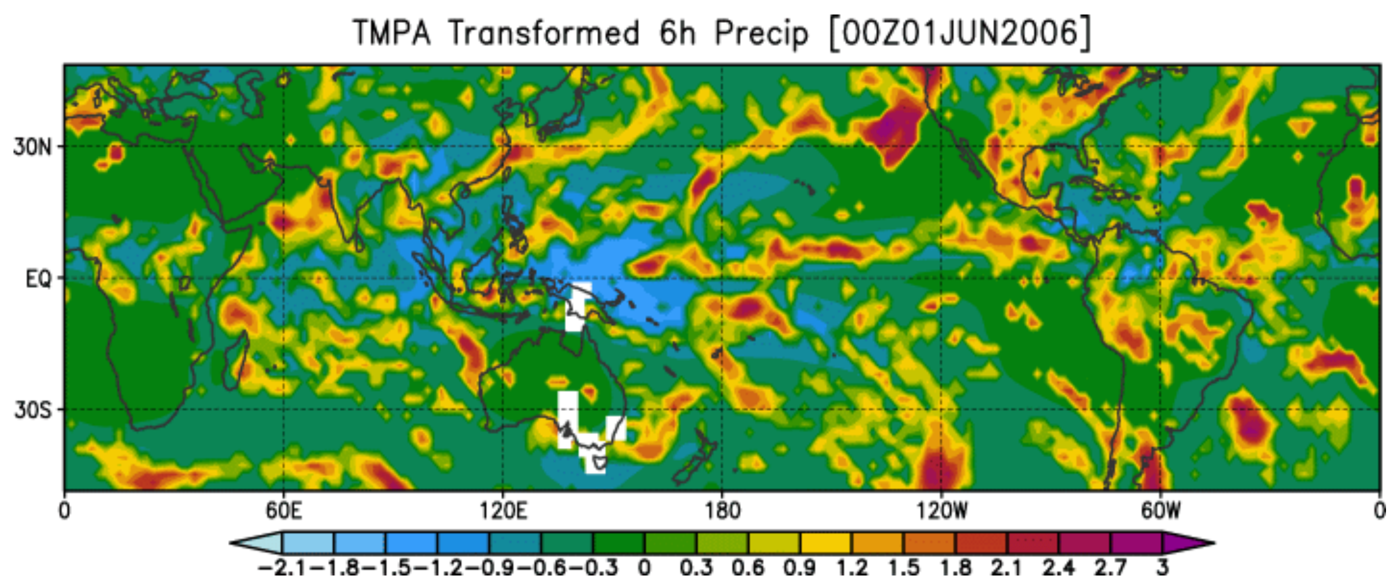
REAL OBSERVATIONS (TMPA)

Example of Gaussian precipitation transformation

Original variable



Transformed variable

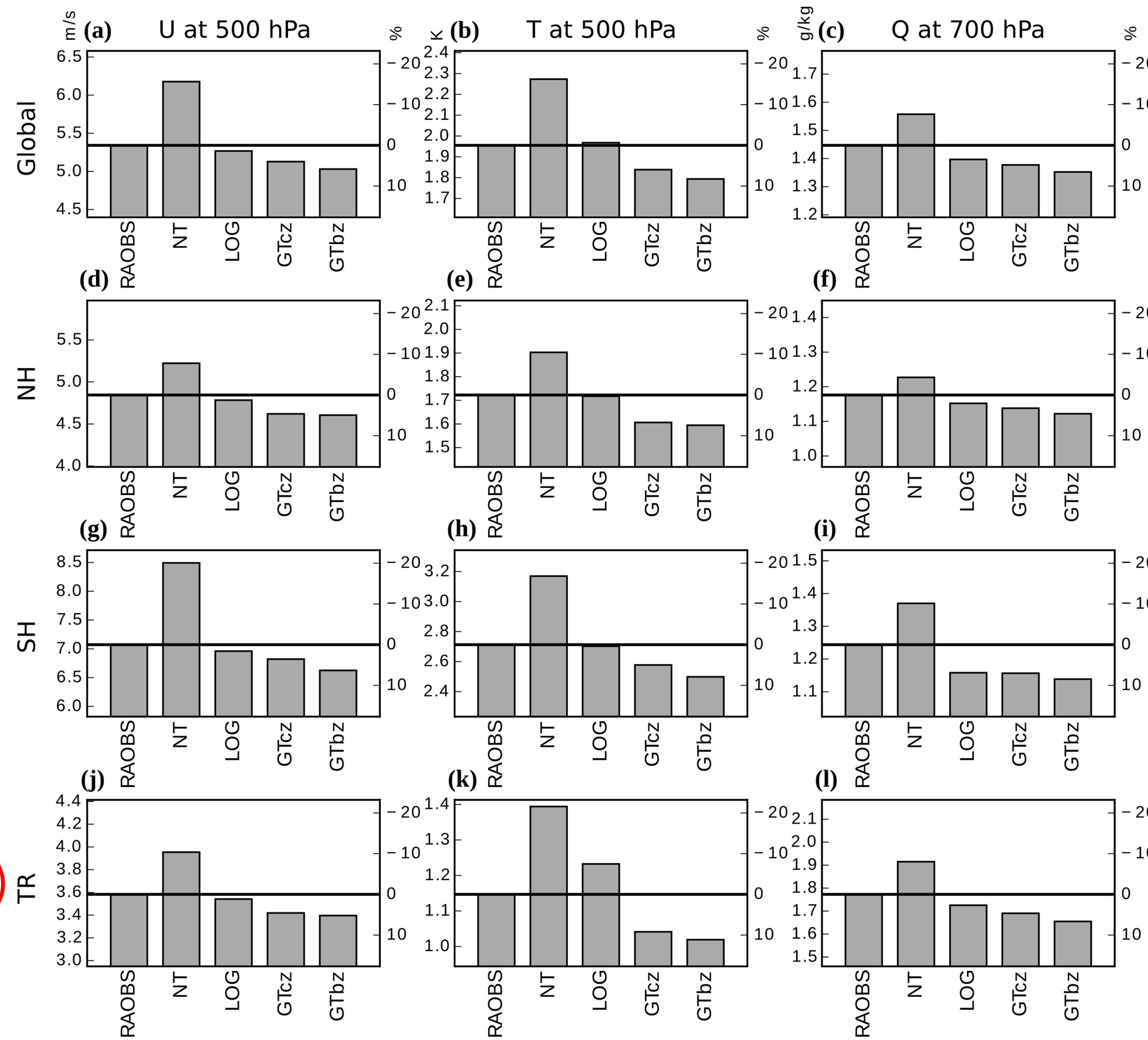


Assimilating TRMM rain with a GFS T62 model verified against ERA Interim (RMSE)

24hr forecast RMSE

Comparing RMSE of

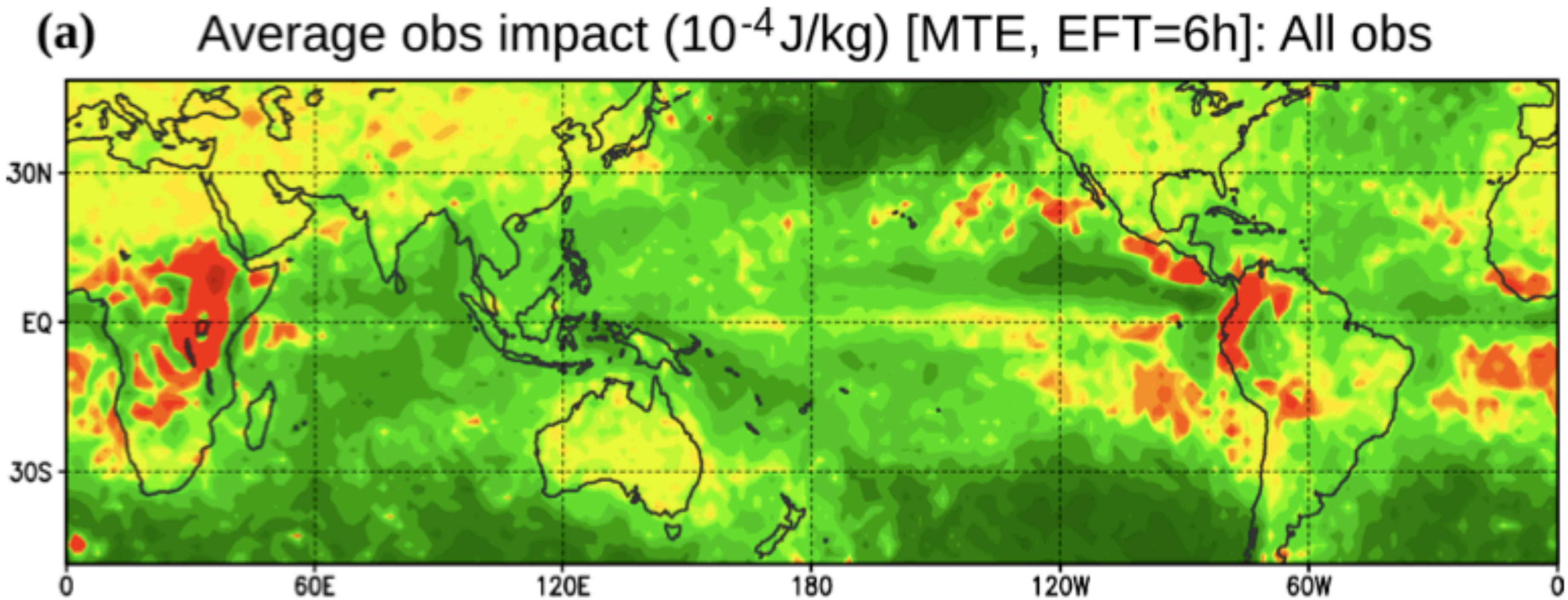
Control (RAOBS) (no assim of pp)
Assim. with No Transform
Assim. with LOG Transform
Assim. w Gaussian Transform cz
Assim. w Gaussian Transform bz



Results
No Transform is the worst
LOG Transform~RAOB (no pp assim)
GT are the best

Guo-Yuan Lien (2014): Efficient assimilation of precipitation

EFSO average impact of **rain obs.**

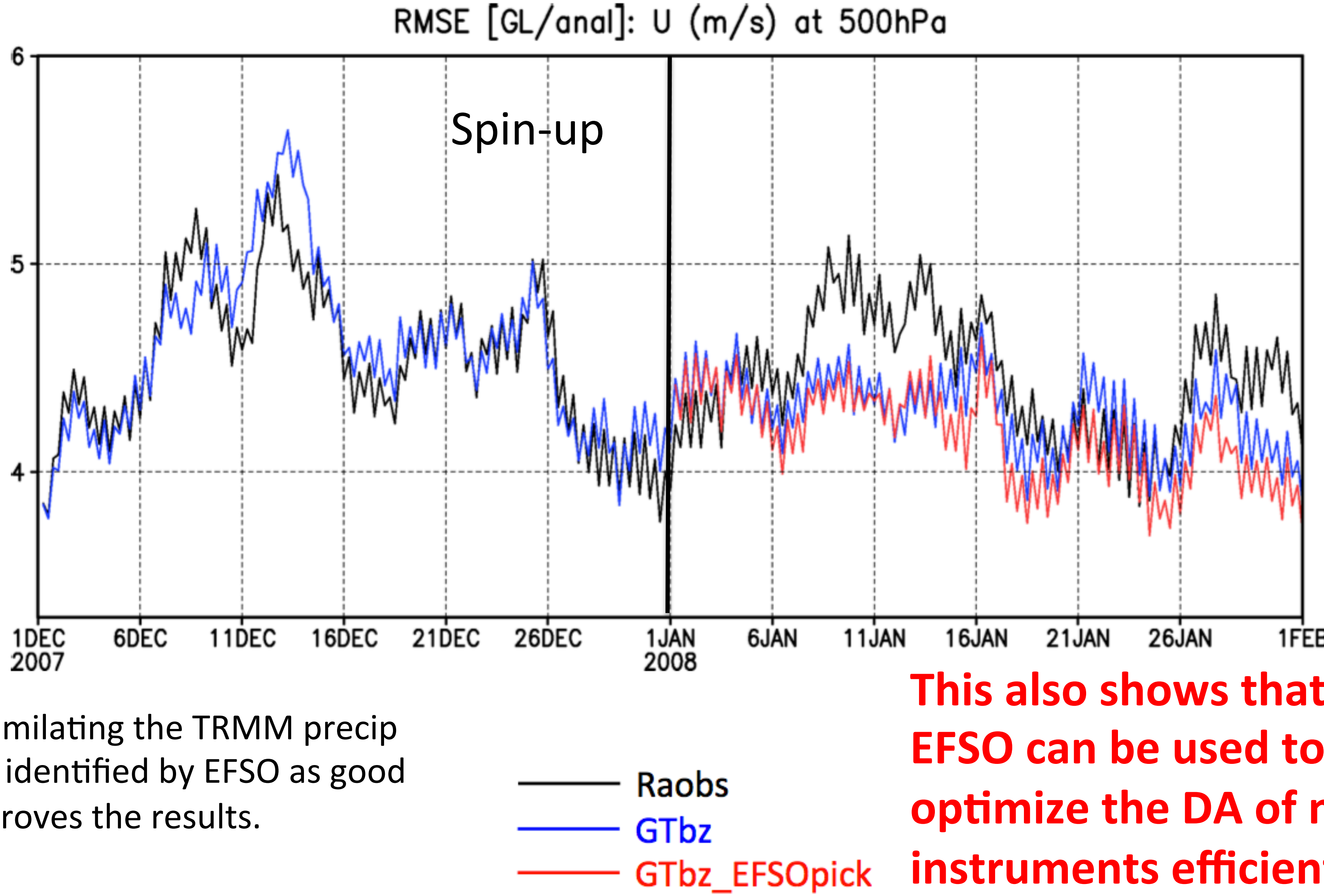


Assimilating only the precip obs identified by EFSO as good improved the results!

This also shows that EFSO can be used to optimize the DA of new instruments efficiently!

One-month time series: Analysis U (m/s) at 500 hPa

Guo-Yuan Lien (2014)



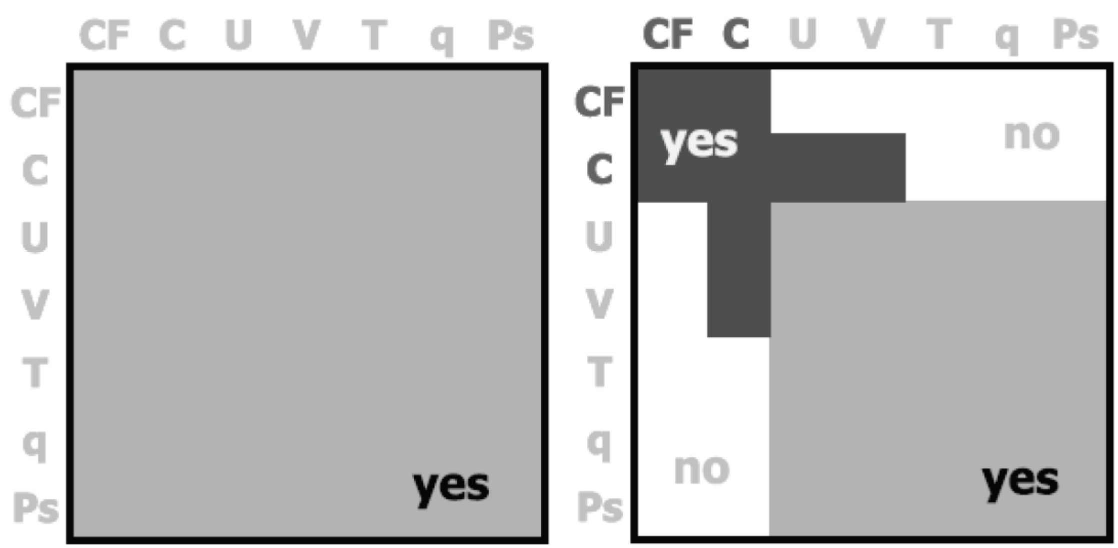
Assimilating the TRMM precip obs identified by EFSO as good improves the results.

This also shows that EFSO can be used to optimize the DA of new instruments efficiently!

Improve the models: Parameter estimation and estimation of bias using DA

- Model tuning on long time scales should be done with EnKF parameter estimation.
- Kang et al., JGR, 2011, 2012 showed that evolving surface carbon fluxes can be estimated accurately at the model grid resolution from simulated atmospheric CO2 observations (OCO-2) as evolving parameters.
- Another approach is the use of analysis increments to estimate model bias (Greybush et al., 2012, Mars) and even state-dependent model bias (e.g., El Niño bias), as in Danforth et al. 2007.

Surface carbon fluxes CF from atmospheric assimilation of meteorological variables and CO_2 obtained as evolving parameters (OSSE). Kang et al., JGR, 2011, 2012

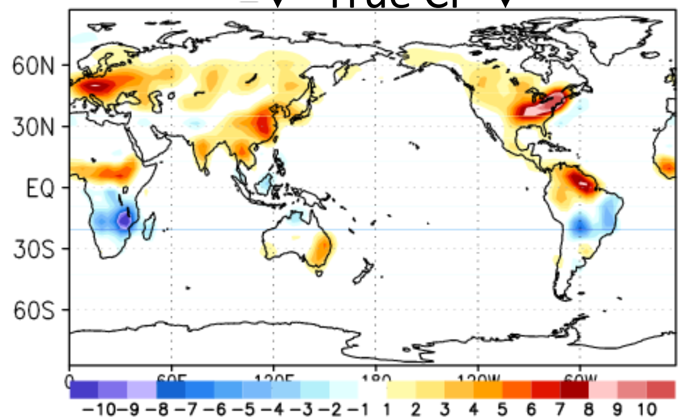


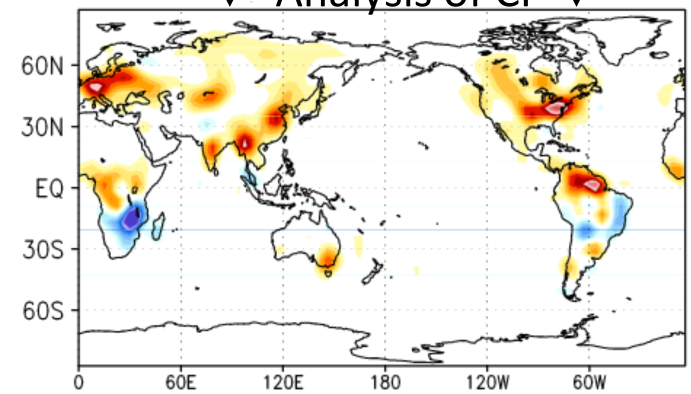
“Variable Localization”

OSSE Results

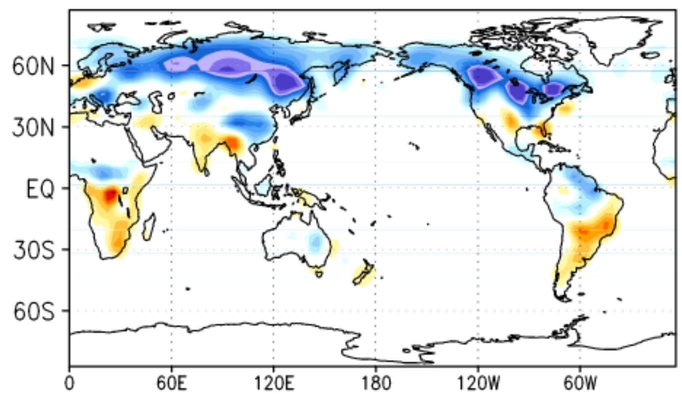
▼ True CF ▼ ▼ Analysis of CF ▼

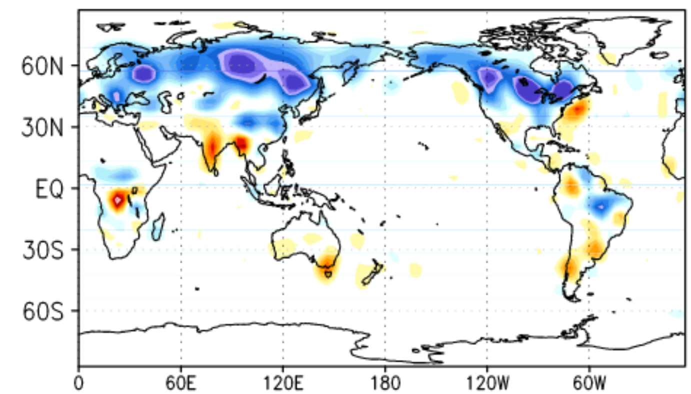
00Z01APR ▶
After three months of DA





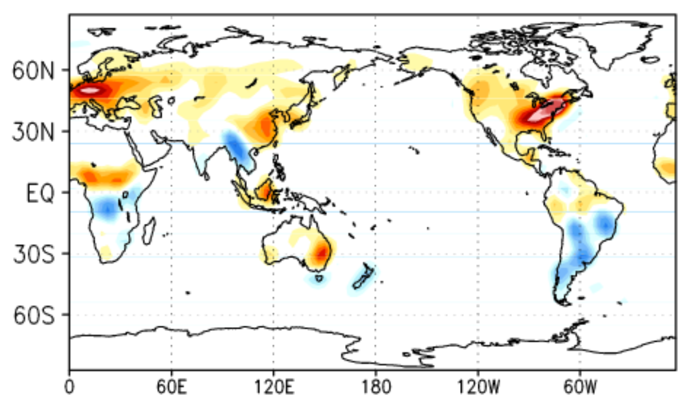
00Z01AUG ▶
After seven months of DA

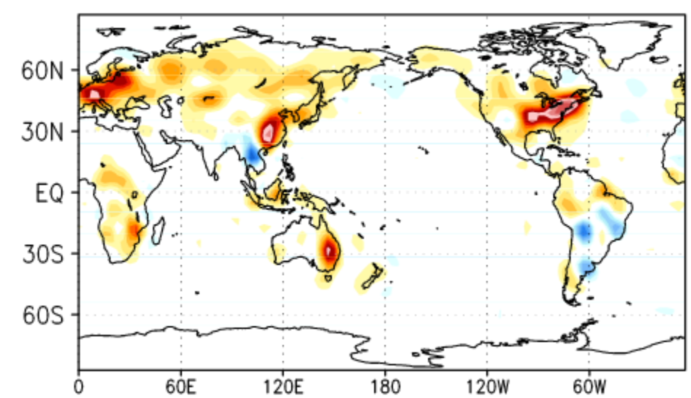




We succeeded in estimating time-evolving CF at model-grid scale

00Z01JAN ▶
After one year of DA

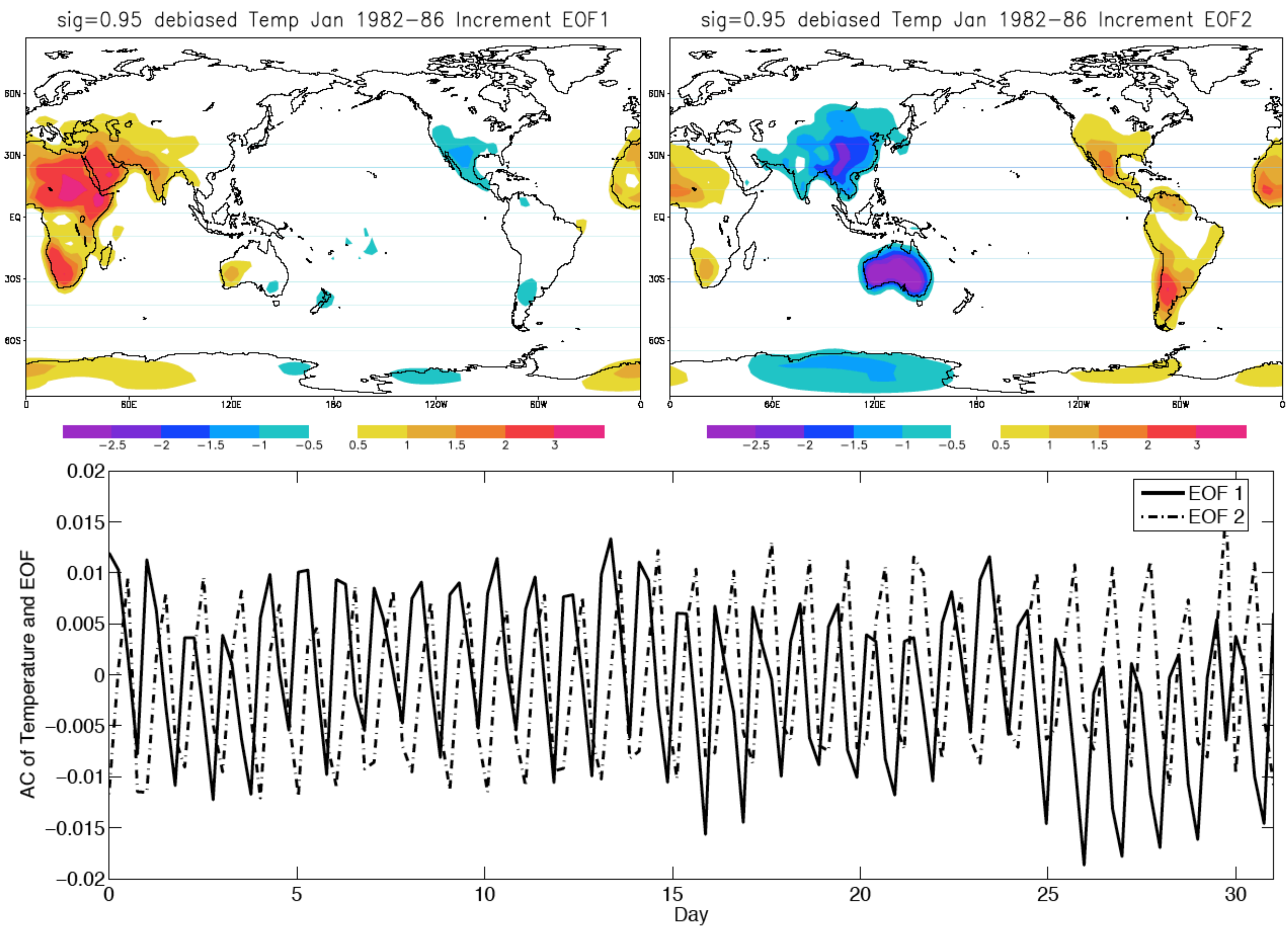




Example: How to define the diurnal model errors using EOFs from a Reanalysis (Danforth et al., 2007)

Estimated the average SPEEDY model error (bias) by averaging over several years the 6 hour forecast (started from reanalysis) minus the reanalysis.

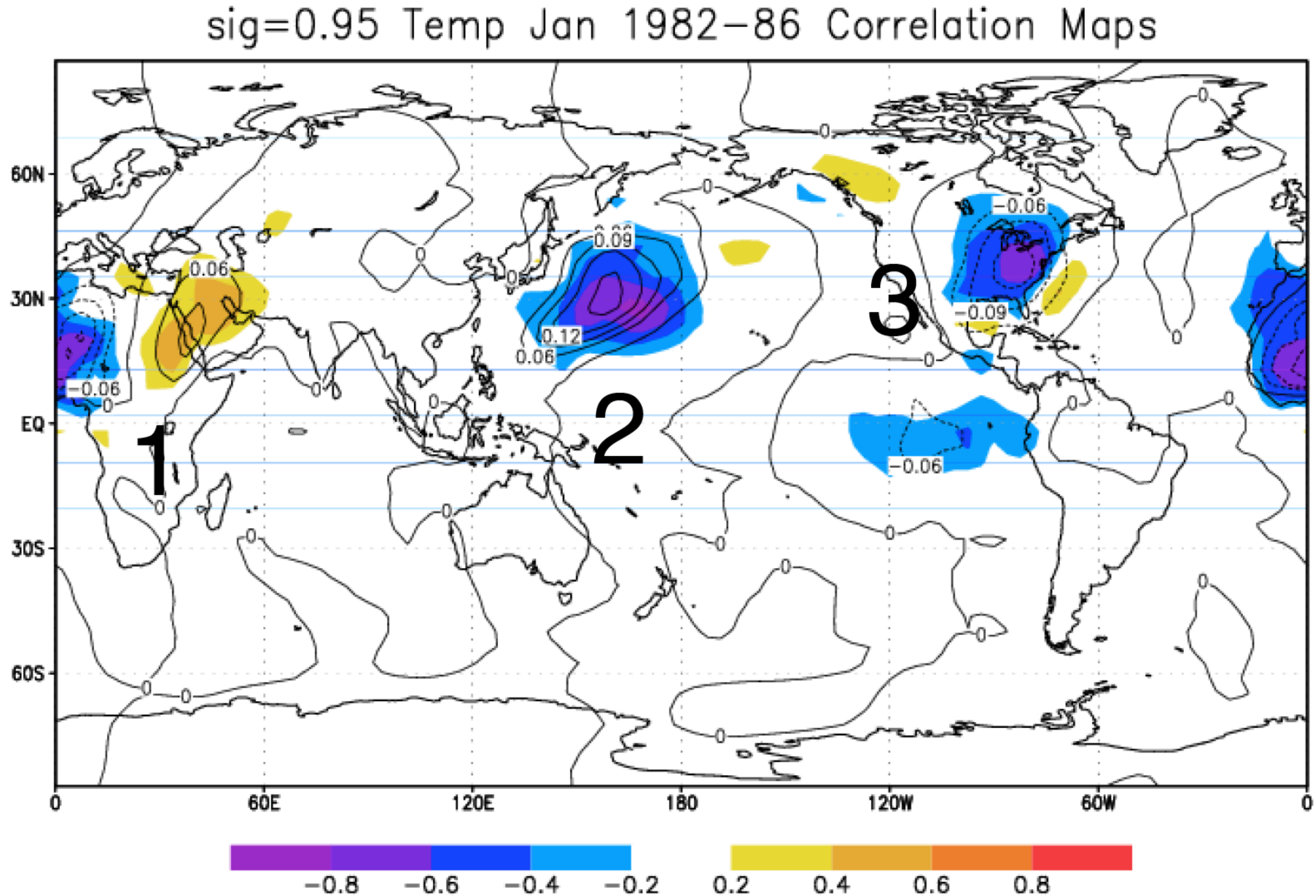
Then they computed the EOFs of the anomaly in the model error, and found two dominant EOFs representing the model error in representing the diurnal cycle:


sig=0.95 debiased Temp Jan 1982-86 Increment EOF1
sig=0.95 debiased Temp Jan 1982-86 Increment EOF2
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
-2.5
-2
-1.5
-1
-0.5
0.5
1
1.5
2
3
AC of Temperature and EOF
Day
EOF 1
EOF 2
0.02
0.015
0.01
0.005
-0.005
-0.01
-0.015
-0.02
5
10
15
20
25
30

Example: How to find the state dependent errors using coupled SVD's (from Danforth et al., 2007)

Three leading coupled SVD's of the covariance of 6 hr forecast errors and corresponding model state anomaly for T at sigma=0.95. Contours: state anomaly, colors: heterogeneous correlation with forecast errors. Note that over land, the corrections suggest the anomalous temperatures are too strong, and over ocean too weak and too far to the west.

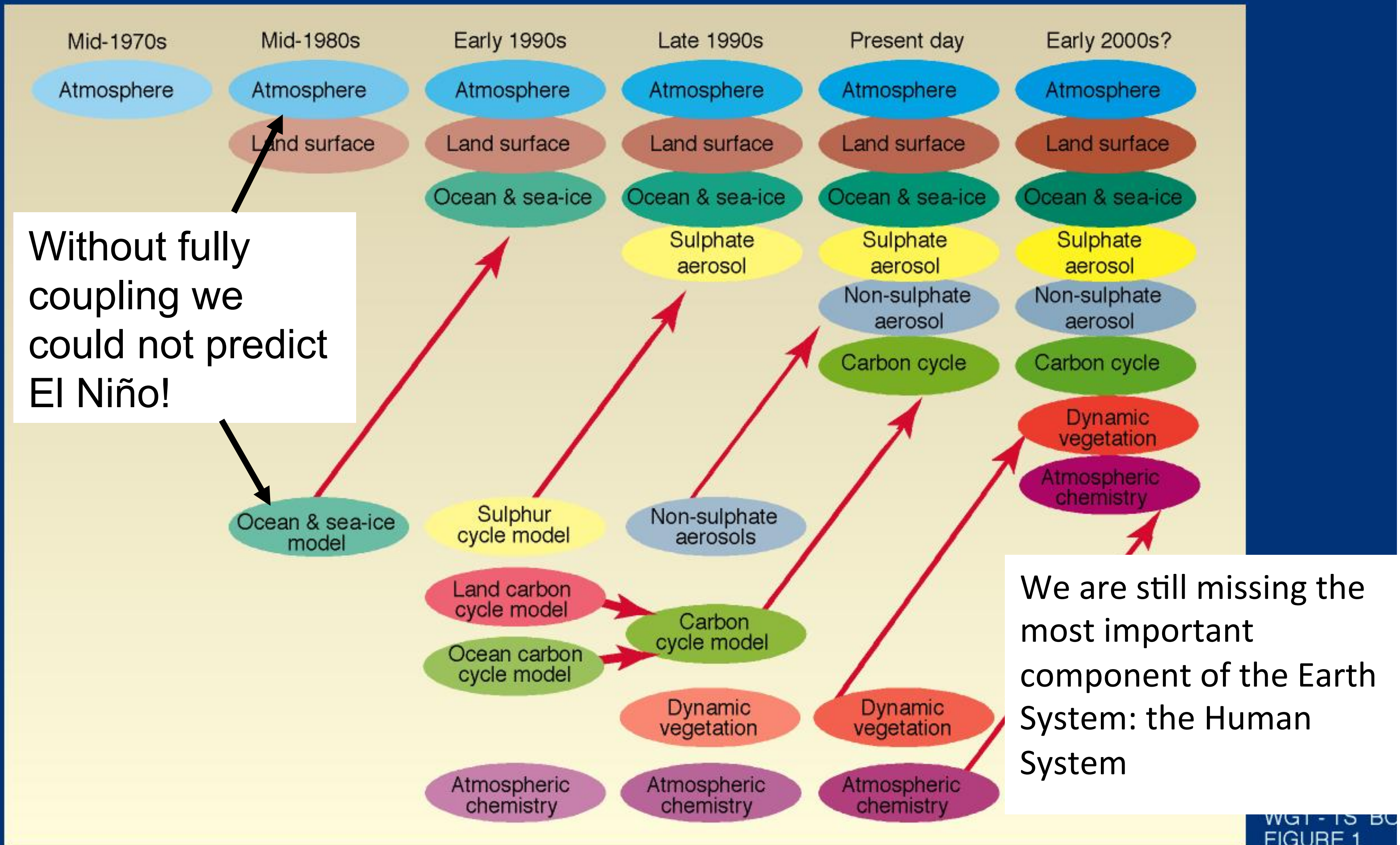
This can be extended to improving forecasts using coupled SVD's


sig=0.95 Temp Jan 1982-86 Correlation Maps
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
0
1
2
3
0.06
−0.06
0.09
0.12
0.06
−0.06
−0.09
−0.06
−0.8
−0.6
−0.4
−0.2
0.2
0.4
0.6
0.8

Earth and Human System

- The Earth System is completely dominated by the Human System.
- In order to understand their interactions we need to couple them bidirectionally, i.e., with feedbacks.
- Currently, IPCC models and even Integrated Assessment models don't include population: it is exogenously obtained from UN projections.

The development of climate models, past, present and future

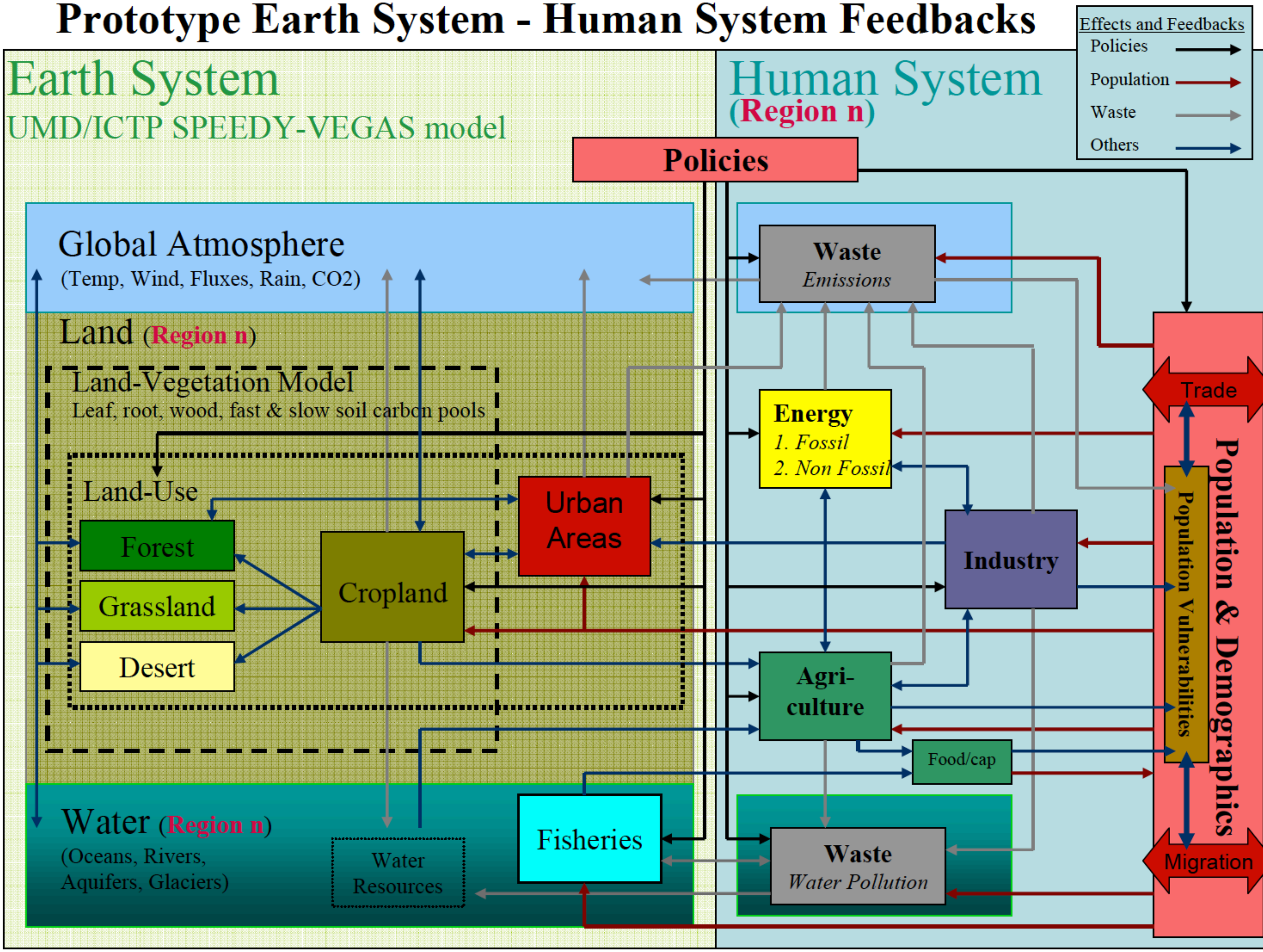


Without fully coupling we could not predict El Niño!

We are still missing the most important component of the Earth System: the Human System

WMO UNEP

Prototype Earth System - Human System Feedbacks



Human **a**nd **N**ature **Dy**namical model (HANDY) with Rich and Poor: <u>for thought experiments</u>

Motesharrei et al., 2014, J. of Ecological Economics

Just 4 equations!

Total population: Elite + Commoners $$x = x_E + x_C$$

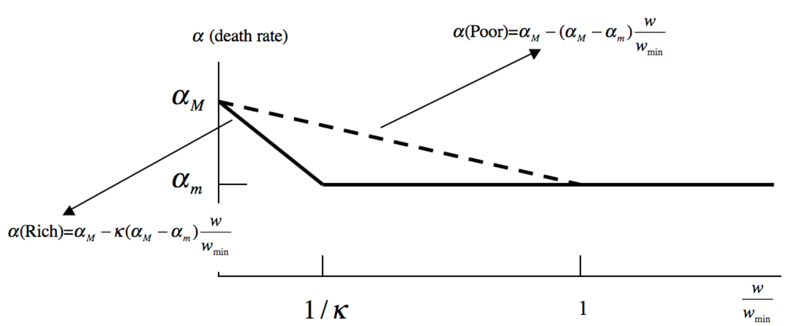
Nature equation: (only the Commoners produce)

$$\dot{y} = \text{Regeneration}\,\gamma\, y(\lambda - y) - \text{Production}\,\delta\, x_C\, y$$

The Wealth is managed by the Elites: Inequality factor $$\kappa \sim 100$$

$$\dot{W} = \text{Production-Commoner consumption-Elite consumption} = \delta x_C y - s x_C - \kappa s x_E$$

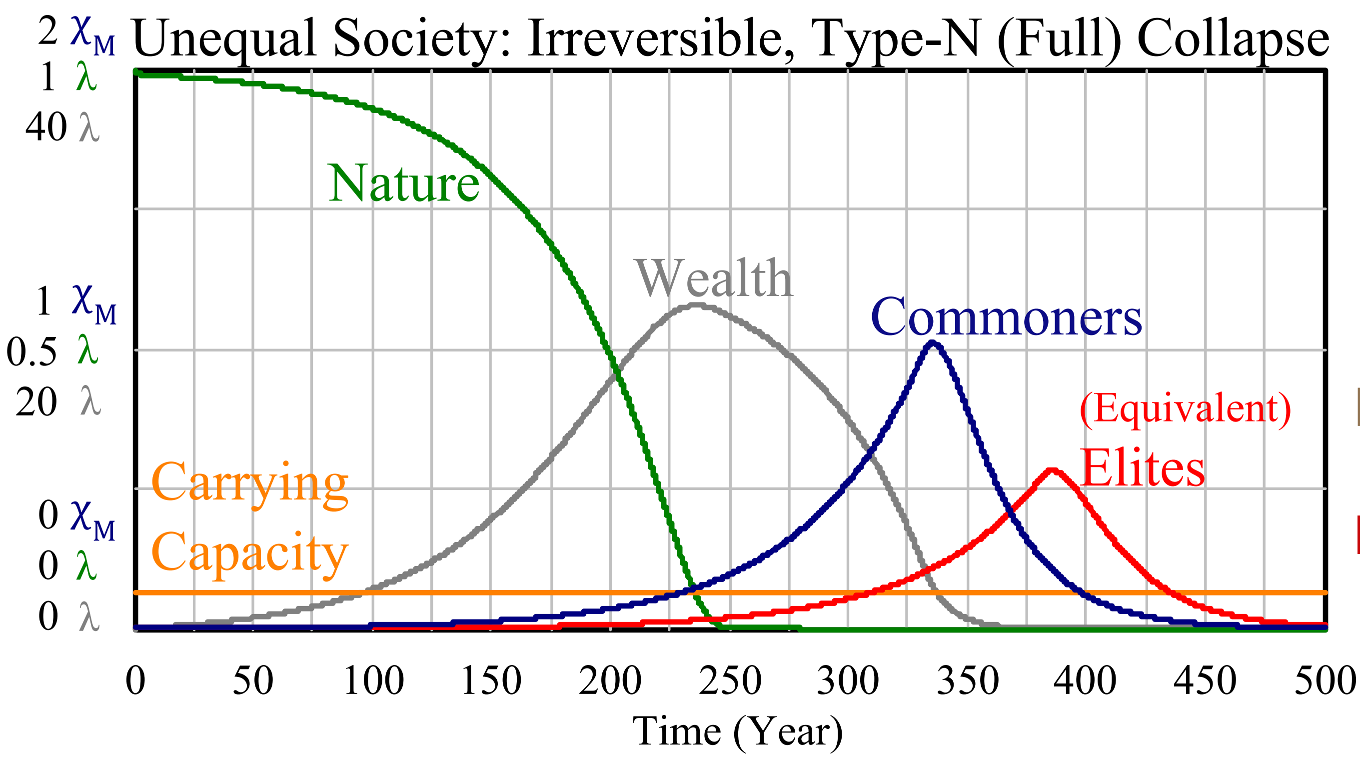
Population equations: death rate α depends on whether there is enough food:



$$\dot{x}_C = -\alpha_C x_C + \beta_C x_C$$
$$\dot{x}_E = -\alpha_E x_E + \beta_E x_E$$

The **rich Elite** accumulates wealth from the work of everyone else (here referred to as the **Commoners**). When there is a crisis (e.g., famine) the elite can spend the accumulated wealth to buy food.

Human **a**nd **N**ature **Dy**namical model (HANDY) with Rich and Poor: a thought experiment



High Inequality

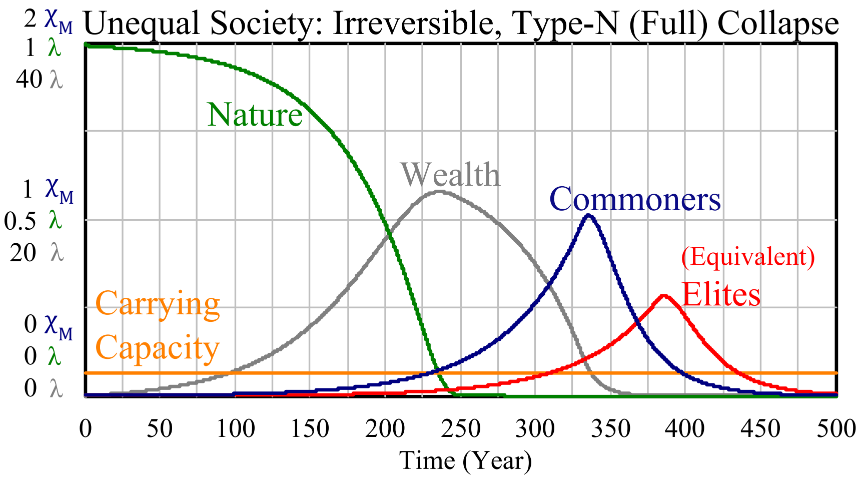
$$\kappa = 100$$

High Depletion

lead to collapse

The accumulated wealth starts decreasing at the time the total equivalent population crosses the Carrying Capacity. This "economic crisis" provides a very obvious indication that the population has grown beyond the sustainable level for the ecological system. If the overshoot is small, it oscillates towards equilibrium. If it is large, it leads to collapse.

Human **a**nd **N**ature **Dy**namical model (HANDY) with Rich and Poor: <u>a thought experiment</u>

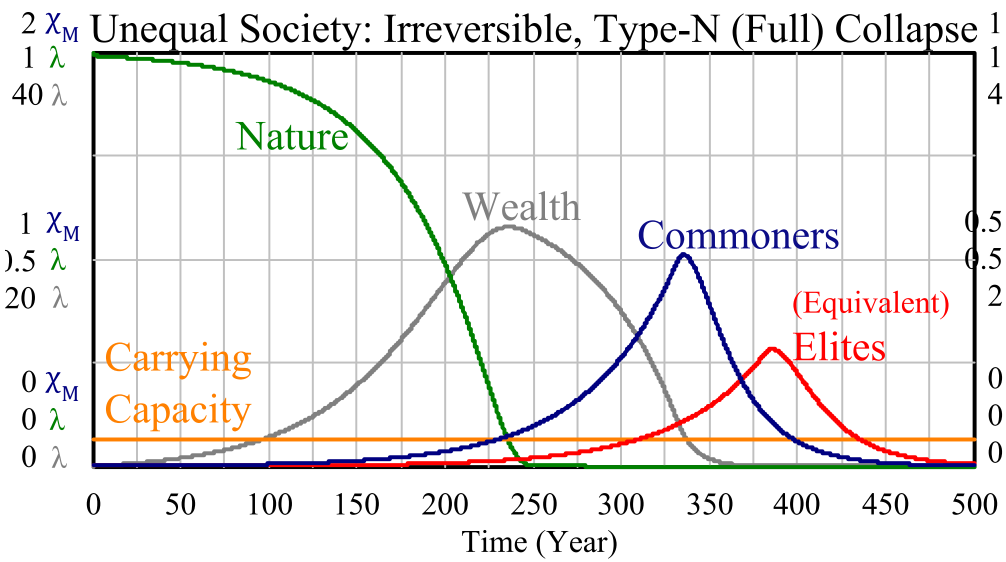


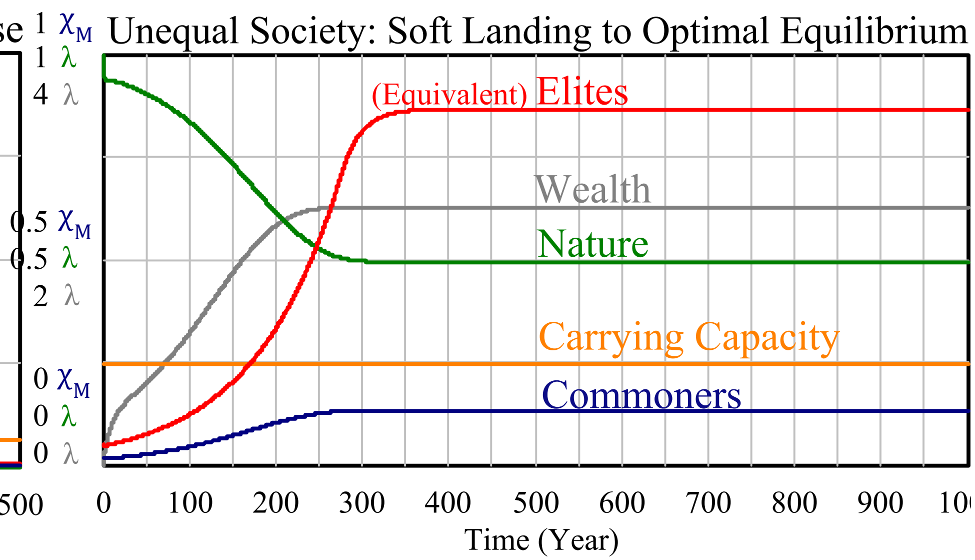
- Nature declines with population growth
- Using their wealth, the Rich can shield themselves from environmental degradation, which first affects the Poor
- Eventually it reaches the upper classes as well, when it is too late to take preventive measures

After ~250 years, having surpassed the sustainable **Carrying Capacity** of the planet, the population is drawing down the accumulated capital to survive

This thought experiment shows how a crisis can happen rapidly, even though it appears that population is rising steadily without any problems, and that the wealthy would not feel the effects of the collapse until it is too late for the poor (and then it is too late for the rich as well!).

If we reduce the *depletion per capita* to its optimal value and the *inequality* ($\kappa = 10$) it is possible to reach a steady state and survive well





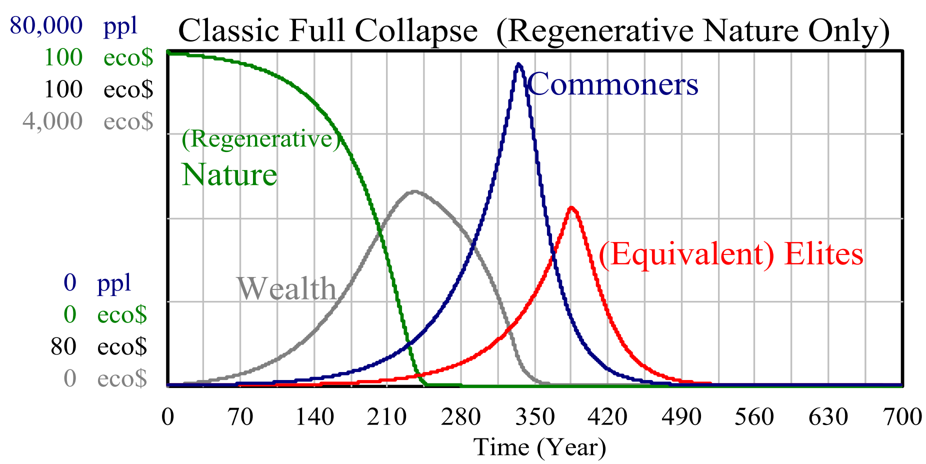
Reaching this equilibrium required **changes in policies:**

- Reduce depletion per capita
- Reduce inequality ($\kappa = 10$)
- Reduce birth rates

http://www.sciencedirect.com/science/article/pii/S0921800914000615

Journal of Ecological Economics

Consider the impact of adding fossil fuels, i.e., nonrenewable energy to Nature



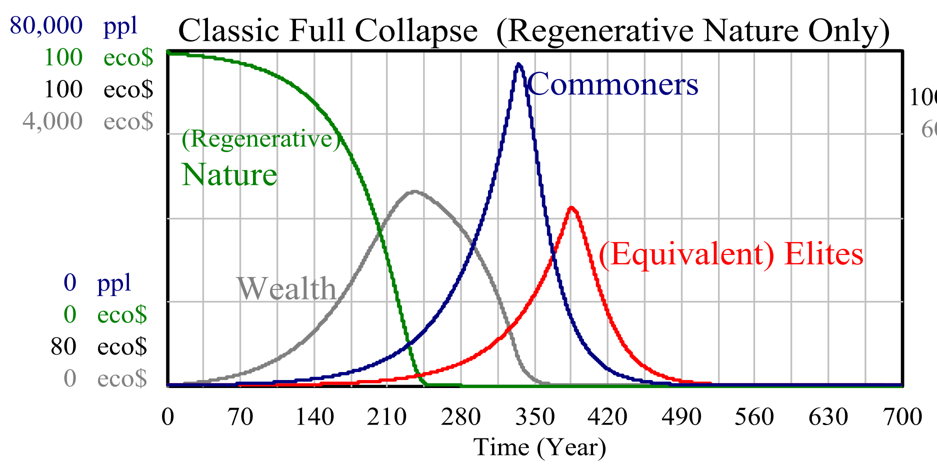
What happens when we add fossil fuels?

This is the classic HANDY1 full collapse scenario, with only regenerating Nature

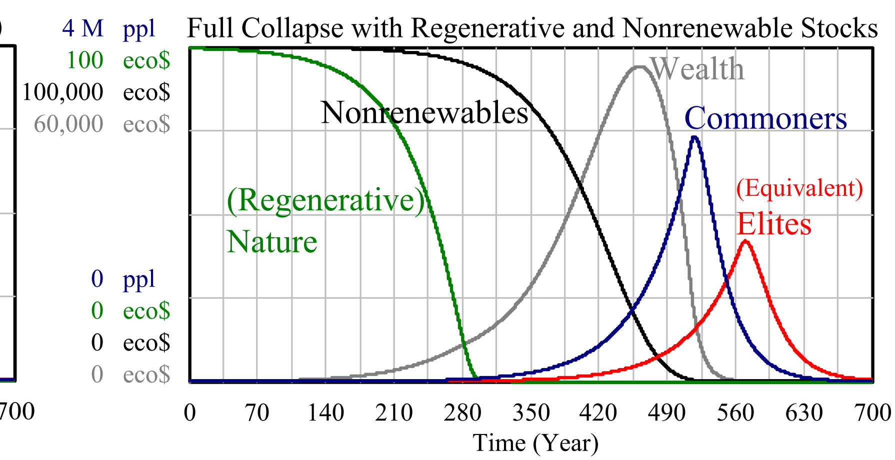
We then add to the regenerating Nature a **nonrenewable Nature**

Impact of adding fossil fuel (nonrenewable) energy to Nature

80K



4Million



This is the classic HANDY full collapse scenario, with only regenerating Nature

We added to the regenerating Nature a **nonrenewable Nature**

The collapse is postponed by ~200 years and the population increased by a factor of ~20!

SUMMARY

- Future applications of EnKF-based data assimilation
  - 1) Combine model forecast and observations to create the best initial conditions ✓
  - 2) Improve observations
  - 3) Improve models (both by parameter estimation and using the analysis increments to correct the model)
  - 4) Do more truly coupled data assimilation
  - 5) Do coupled Earth and Human modeling and DA.
- ECMWF implemented the new Hybrid (Penny, 2014) in 1 week, with great results (Hamrud et al, 2014). It needs an EnKF and a variational system.

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THANKS!