An Ensemble Data Assimilation System for CAM

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DAI Building Global Assimilation / Prediction System with CAM GCM

CGD Gains	DAI Gains
Prediction System Capability	Experience with Global Models
Compare CAM to Forecast Models	Experience with Standard Observations
Model Deficiency Detection	Testbed for Assimilation Systems
Enhanced Model Credibility	Demo of Ensemble Filter Capabilities

Assimilation Algorithm:

Ensemble adjustment filter (Monte Carlo approach)

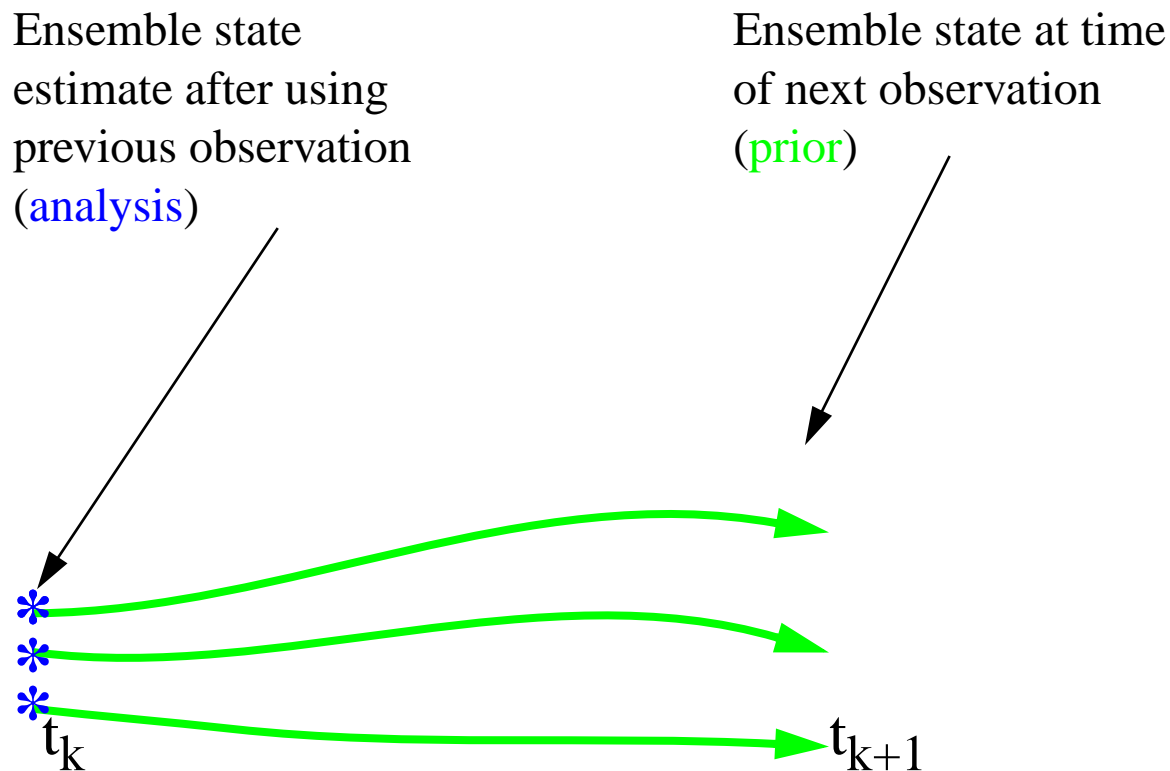Hierarchical group filter used to control sampling error
4 groups x 20 ensemble members = 80 members total

Systematic error correction for prior bias in observation space

Verified by comparing to observations in observation space

How an Ensemble Filter Works

1. Use model to advance ensemble (3 members here) to time at which next observation becomes available

Ensemble state estimate after using previous observation (analysis)

Ensemble state at time of next observation (prior)

t_k

t_{k+1}

How an Ensemble Filter Works

2. Get prior ensemble sample of observation, y=H(x), by applying forward operator H to each ensemble member

y

H

H

H
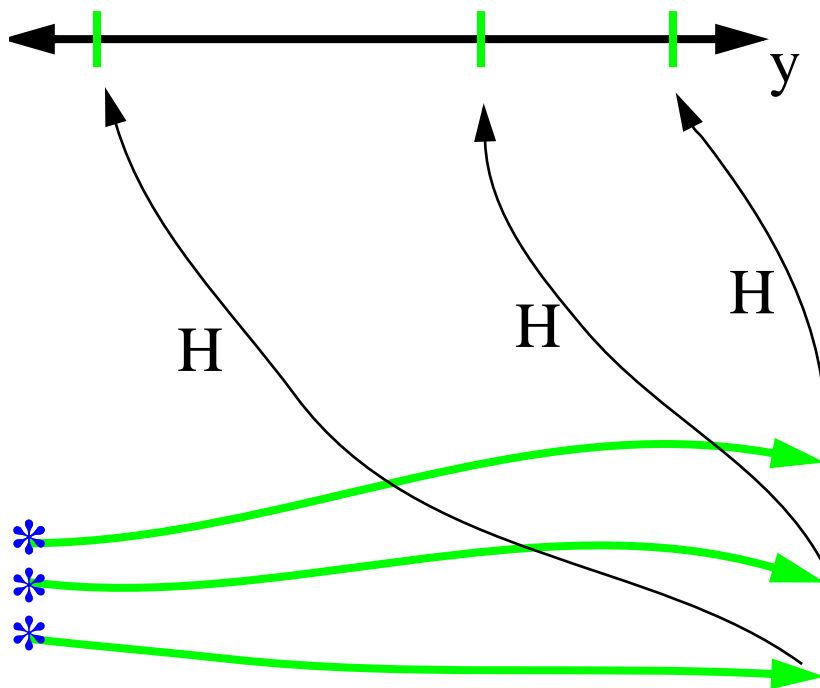
Theory: observations from instruments with uncorrelated errors can be done sequentially.
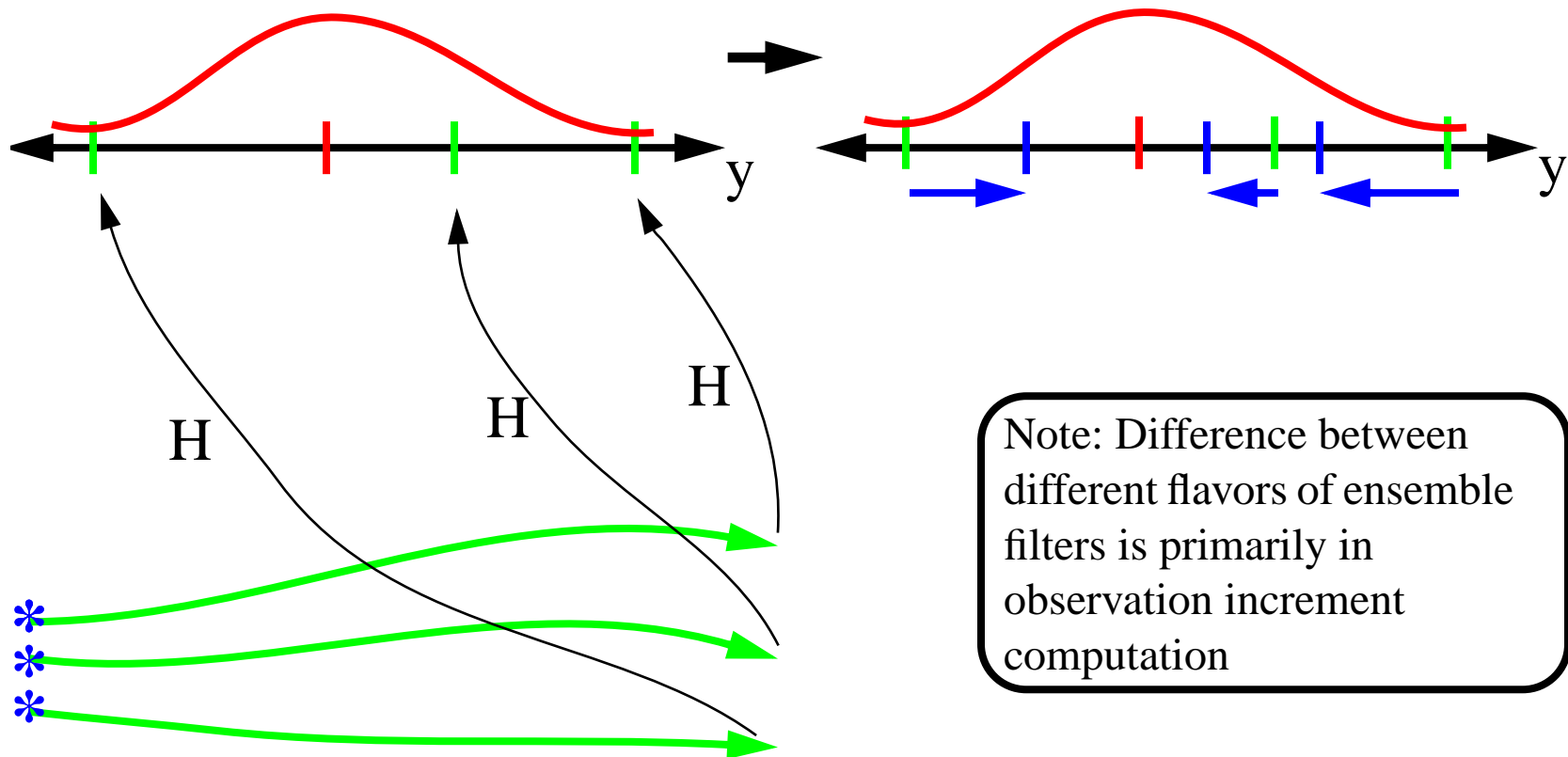
How an Ensemble Filter Works

3. Get observed value and observational error distribution from observing system

y

Verification is difference between ensemble mean and observation here.

H

H

H
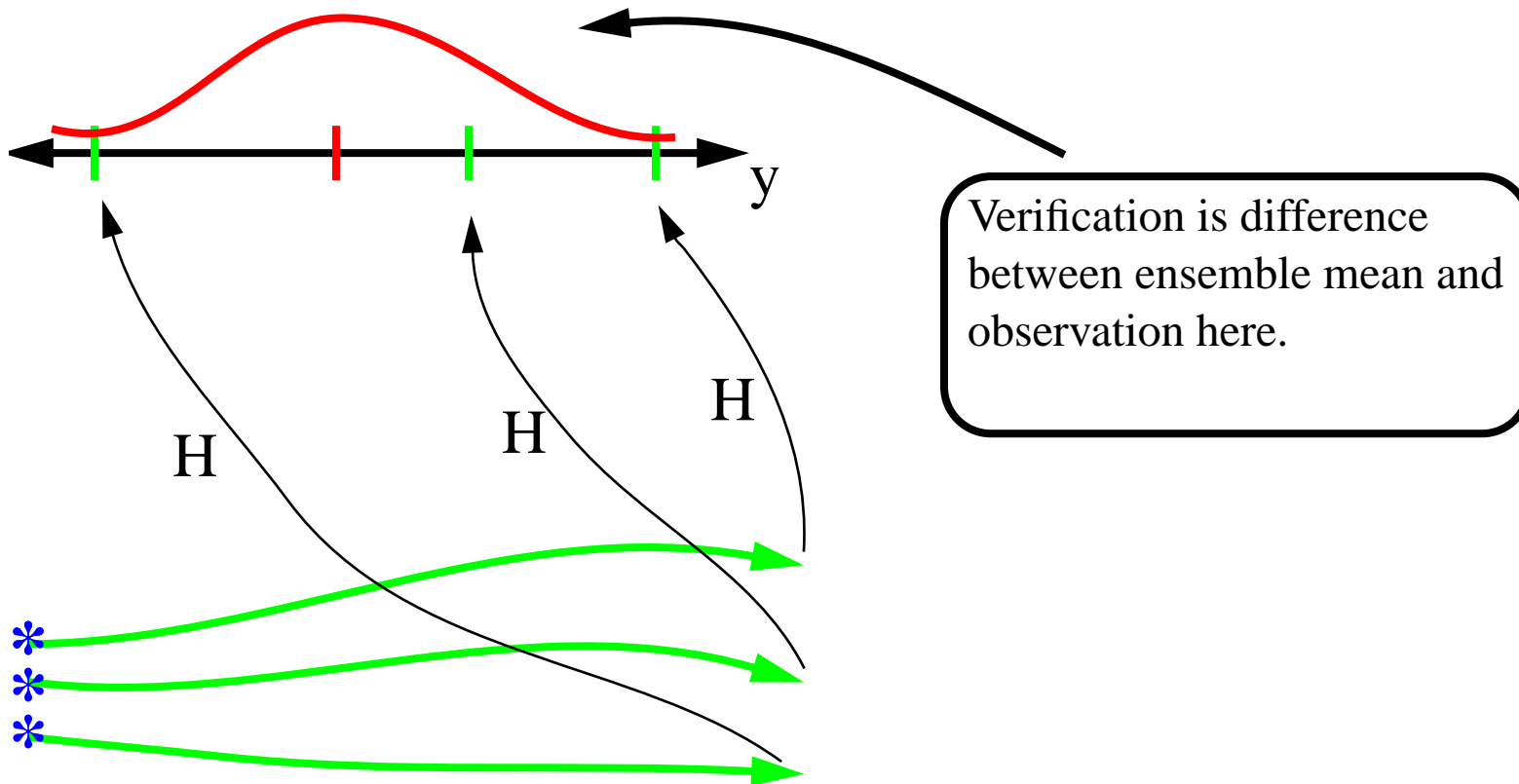
How an Ensemble Filter Works

4. Find increment for each prior observation ensemble
(this is a scalar problem for uncorrelated observation errors)

Note: Difference between different flavors of ensemble filters is primarily in observation increment computation

How an Ensemble Filter Works

5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments

H

H

H

H

Theory: impact of observation increments on each state variable can be handled sequentially!
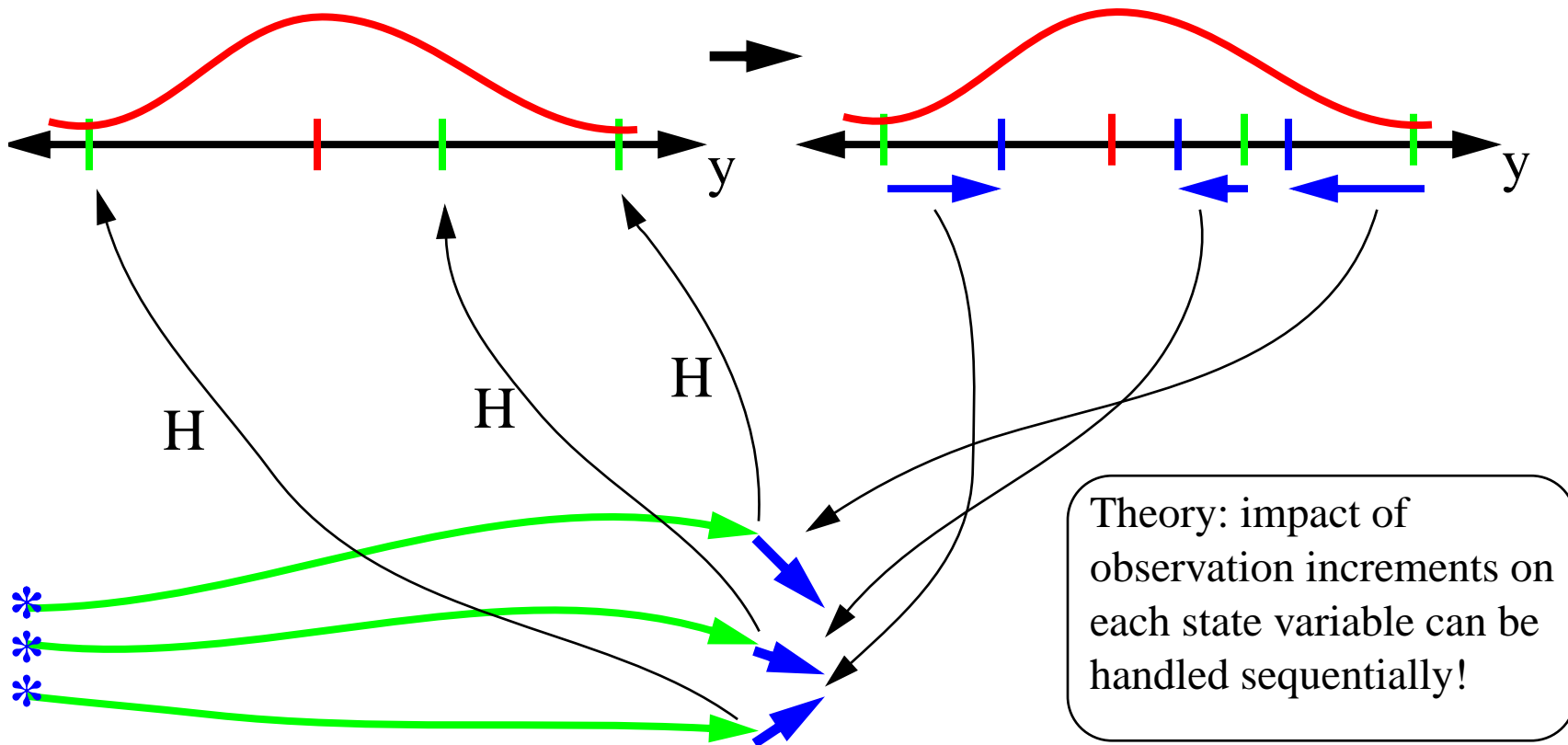
How an Ensemble Filter Works

6. When all ensemble members for each state variable are updated, have a new analysis. Integrate to time of next observation...
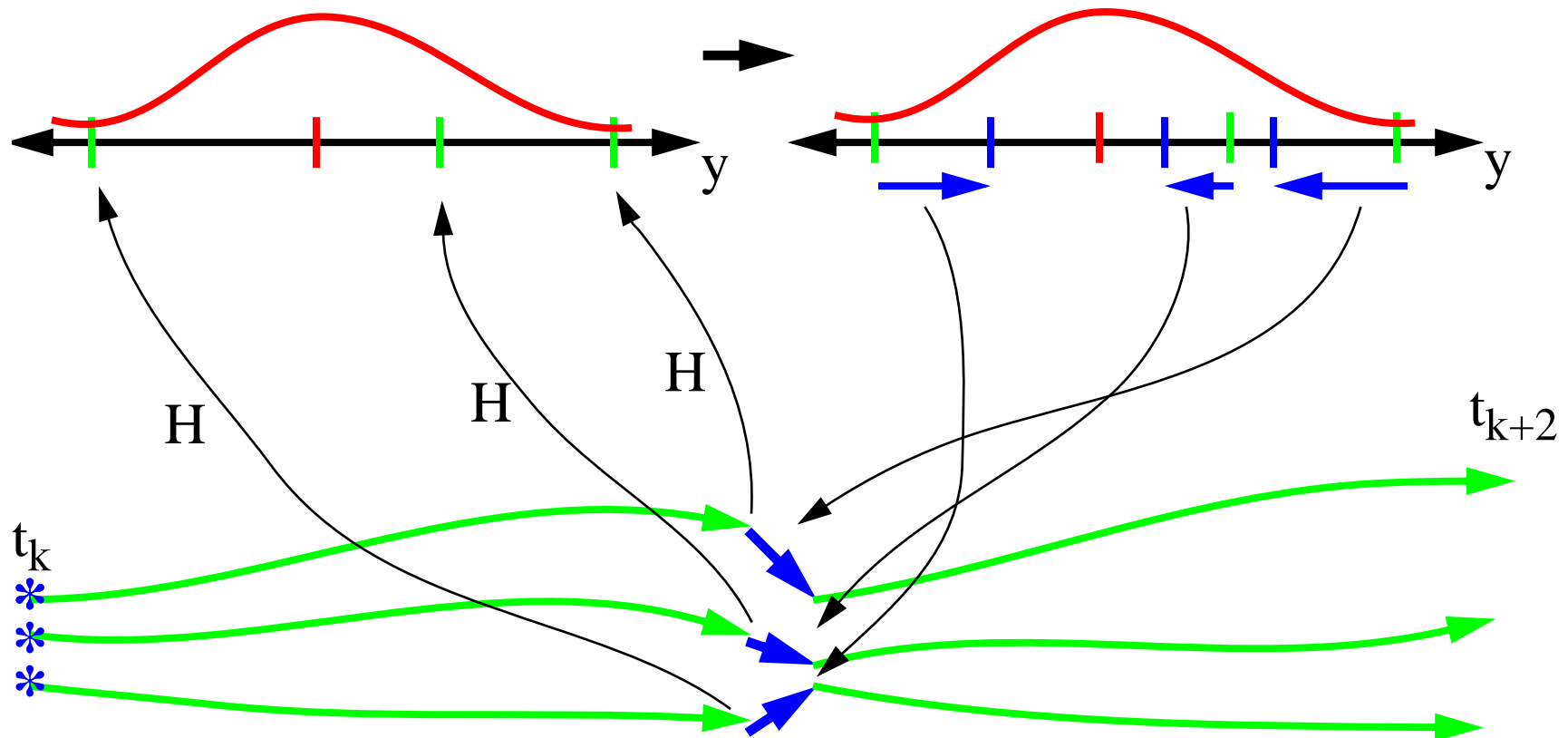
Model:

CAM 2.0 T42L26

U,V, T, Q and PS state variables impacted by observations

Restarting time stepping after each assimilation

Land model (CLM 2.0) not impacted by observations

Observed SSTs

Status of Assimilation System:

Initial version complete

Uses observations used in reanalysis
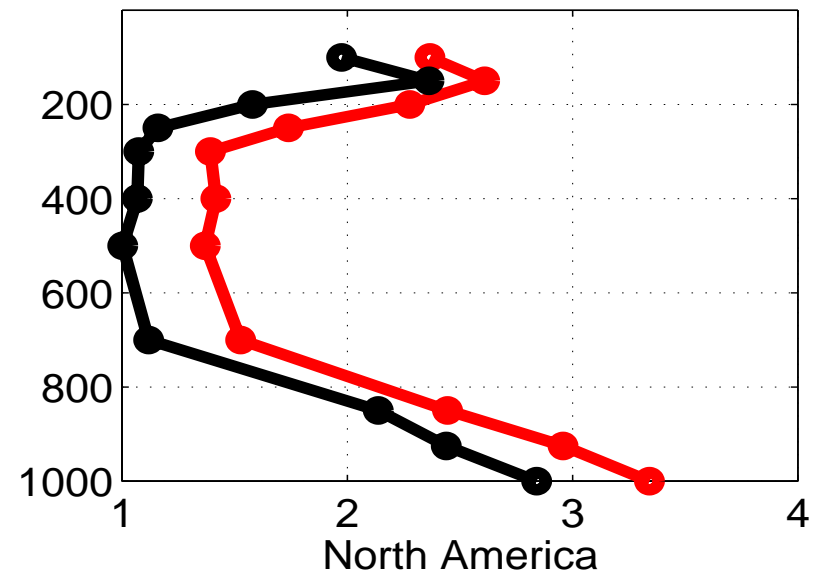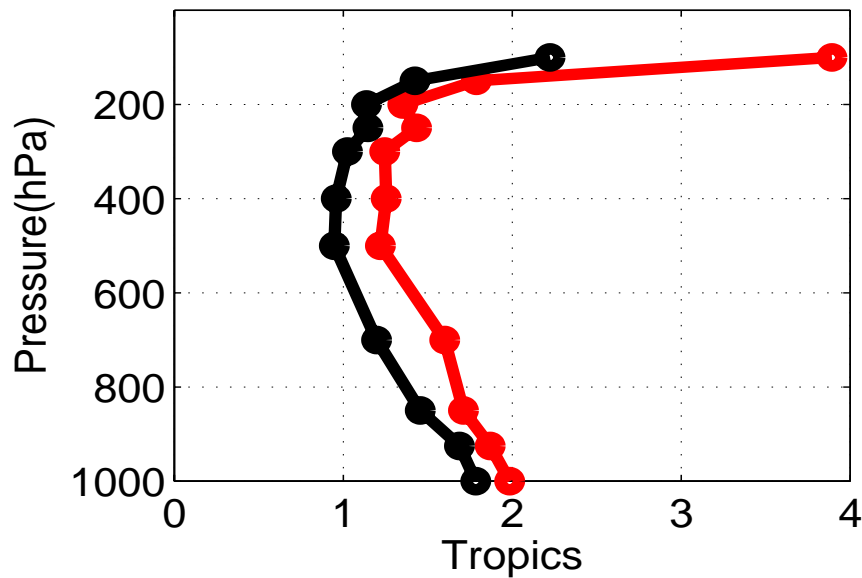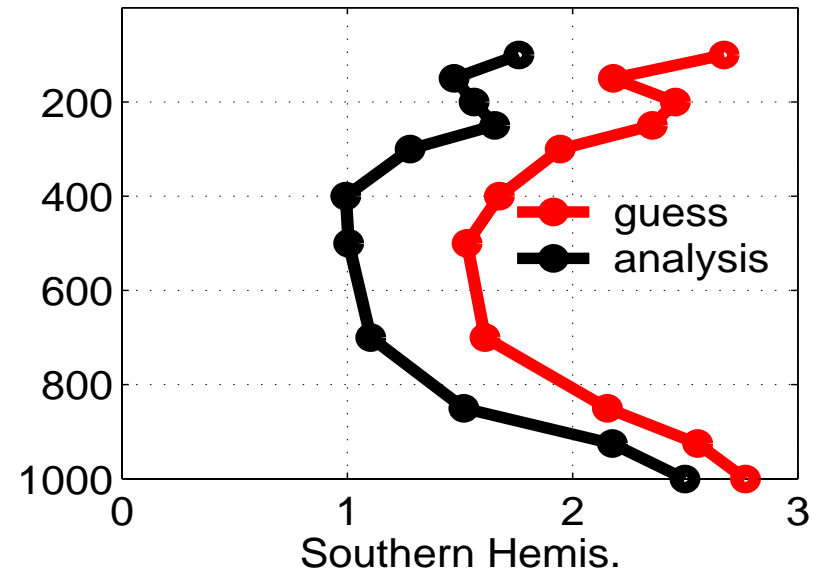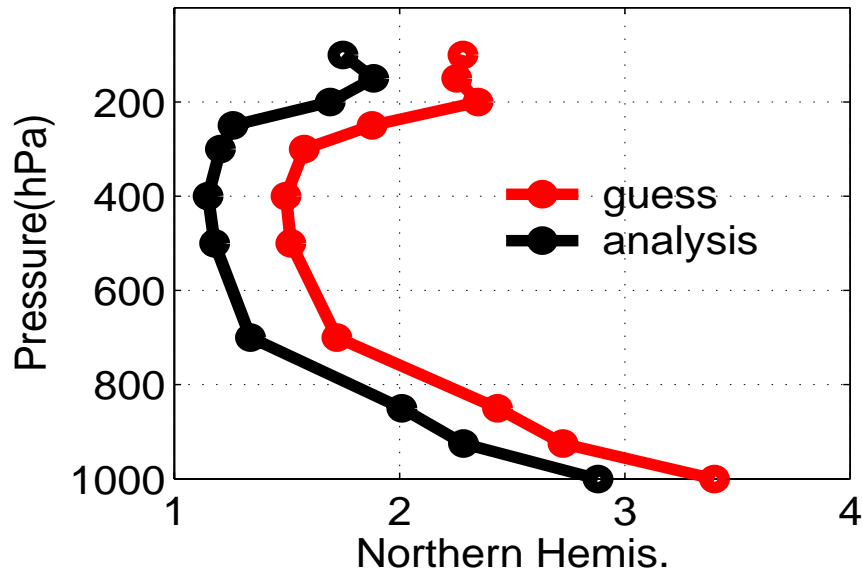
(Radiosondes, ACARS, Satellite Winds...)

Initial tests for first week of January, 2003
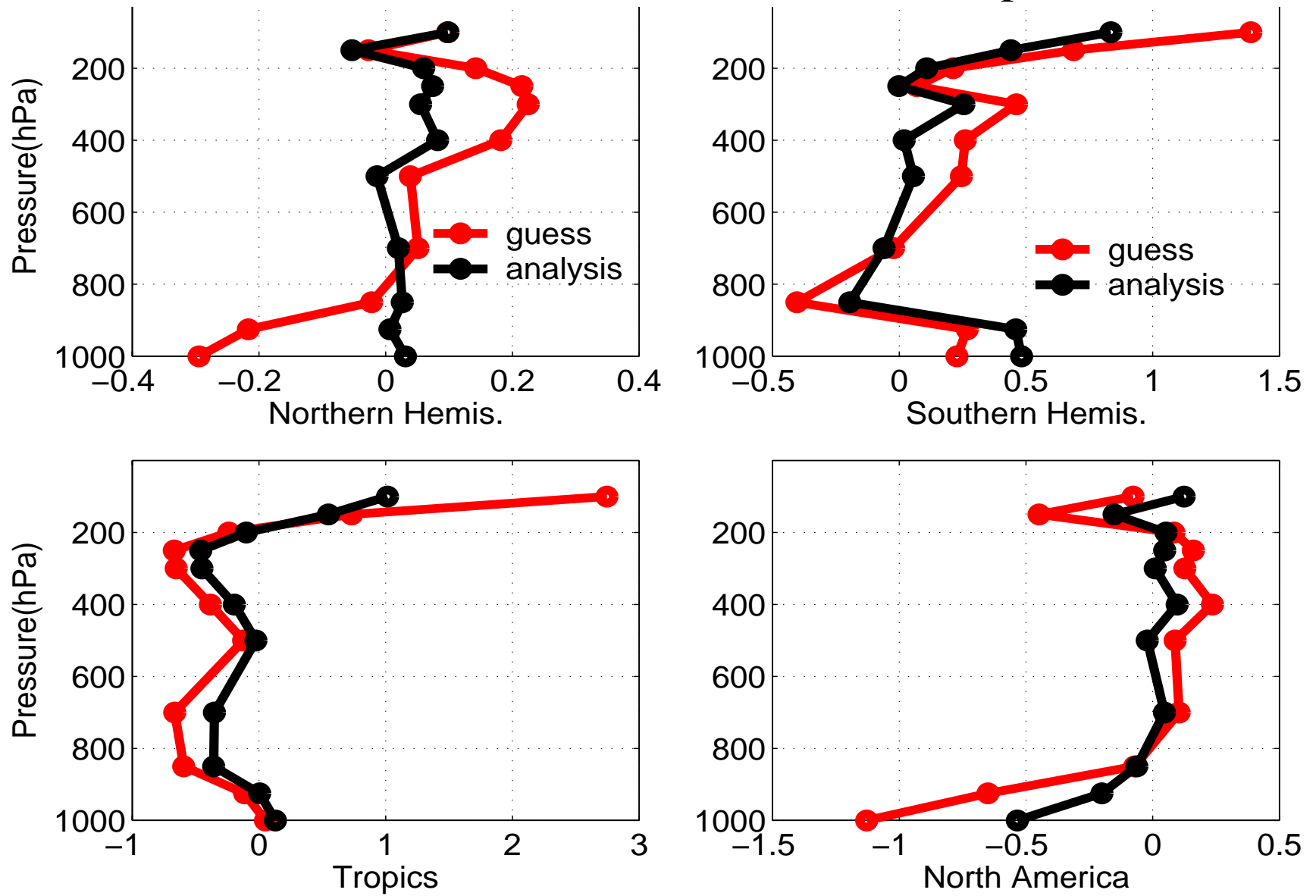
Assimilated every 6 hours

No ensemble quality control yet

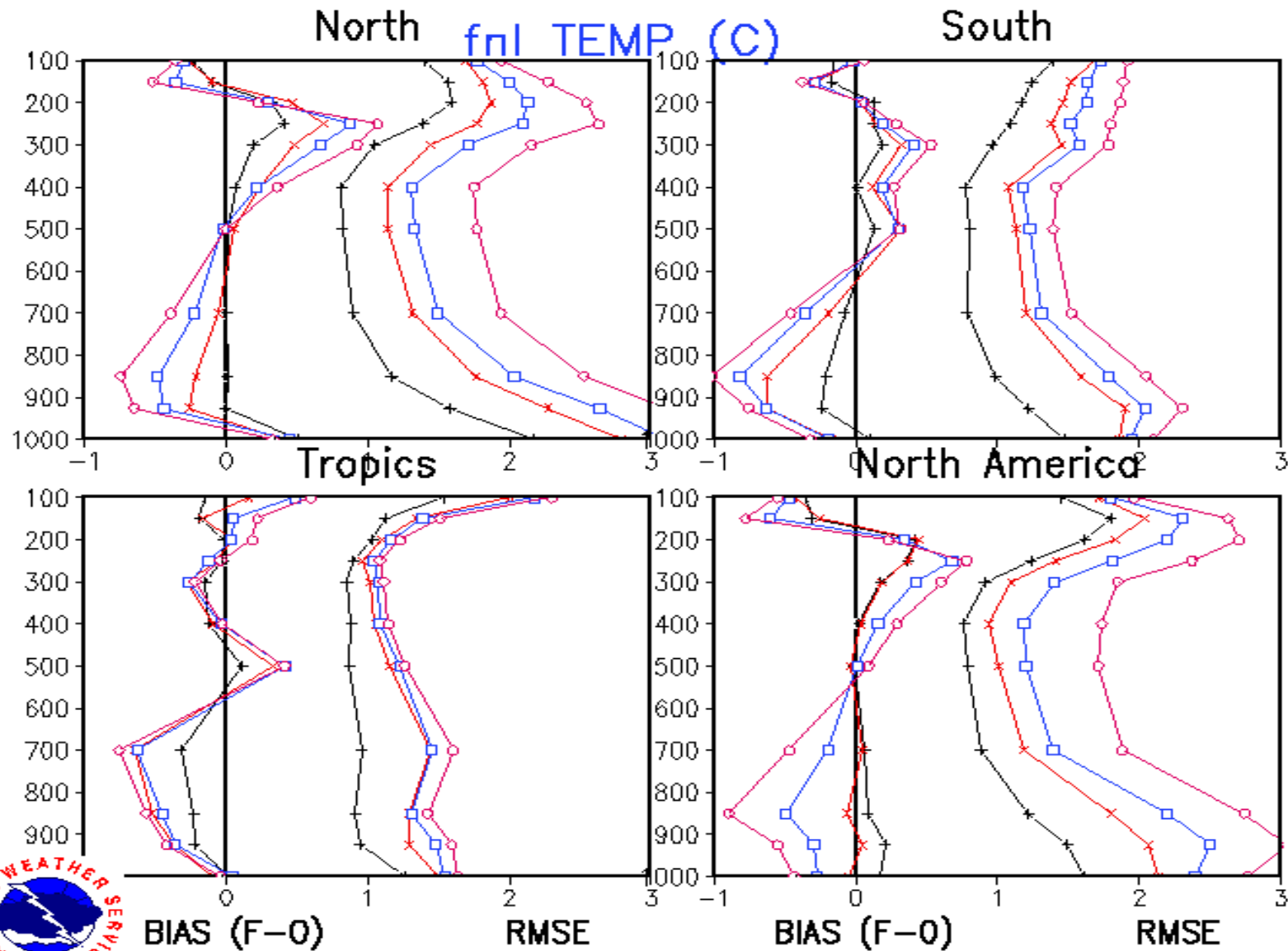Run on CGD linux cluster Anchorage

CAM RESULTS: ENSEMBLE MEAN RMS TEMP. ERROR

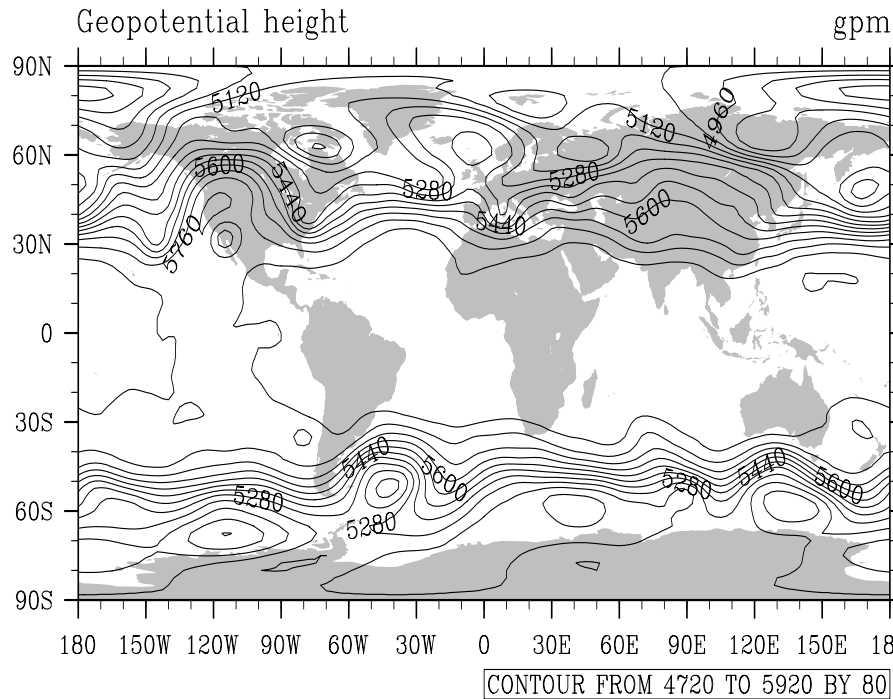# CAM RESULTS: Ensemble Mean Time Mean Temperature BIAS

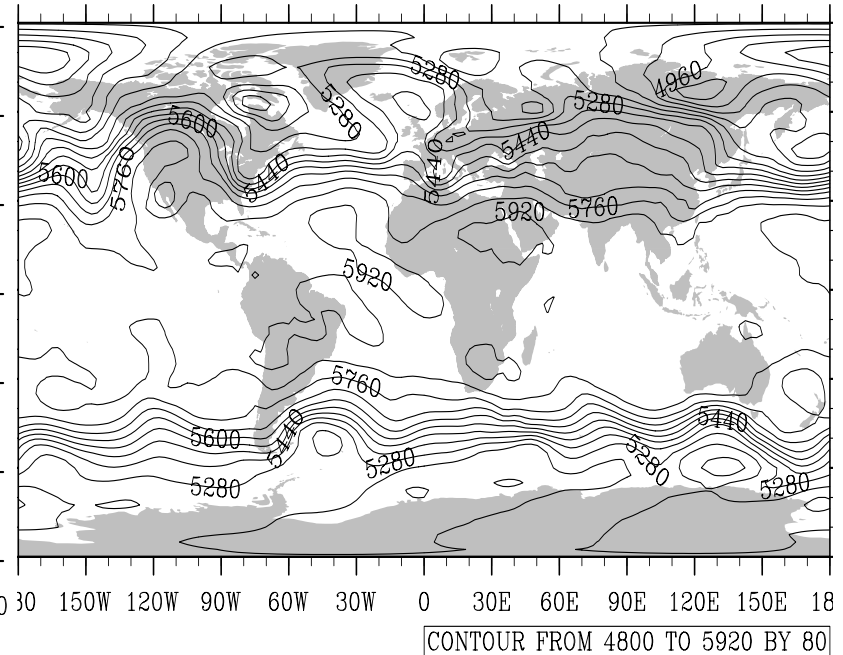# NCEP GFS BIAS (Left), RMS (right): Black Analysis, Red Guess

fnl TEMP (C)

North | South
Tropics | North America

BIAS (F-O)   RMSE   BIAS (F-O)   RMSE

00z01jan2003 — 00z31jan2003

AMWG March 04

500mb Height Comparison to NCEP CDAS Analysis; Jan. 7, 2003

NCEP reanalyses, 500mb GPH, Jan 07 00Z

Geopotential height   gpm

DART/CAM analyses, 500mb GPH

CONTOUR FROM 4720 TO 5920 BY 80

CONTOUR FROM 4800 TO 5920 BY 80

DART/CAM - NCEP, 500mb GPH, Jan 07 00Z

-125		-75	-25	25	75	125

AMWG March 04
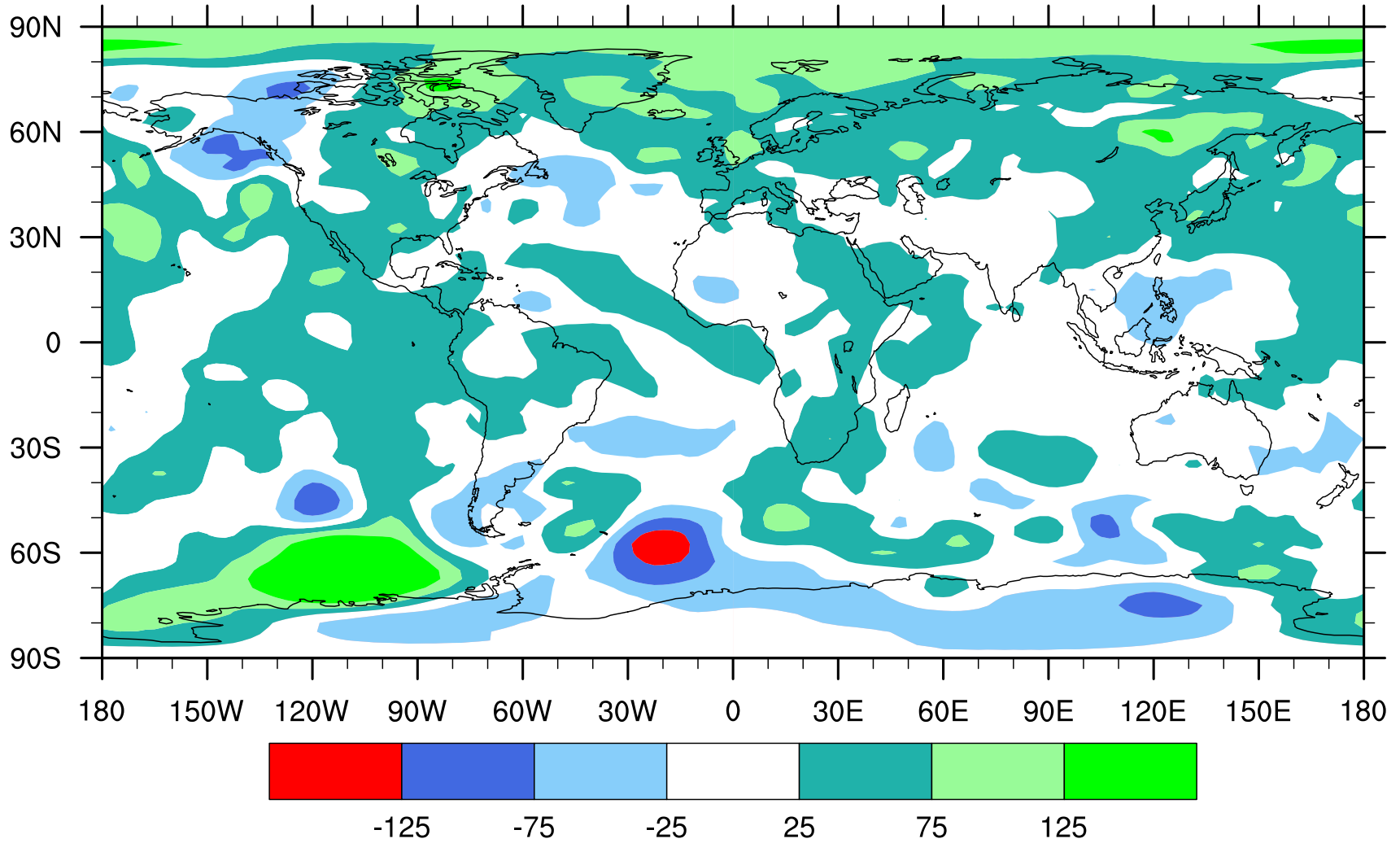
Conclusions

1. An assimilation / prediction capability now exists for CAM 2.0
2. Confront CAM with observations; see bias (tropopause height?)
3. CAM appears to have VERY low forecast bias in troposphere
4. Could look for parameterization errors?

Future plans:

1. Continue improving assimilation system
2. Ensemble quality control to eliminate bad observations
3. Longer range forecast experiments
4. Allow observations to impact CLM land state
5. Test assimilation of GPS radio occultation observations
6. Higher resolution / new versions??? (Does anyone care?)
7. WACCM??? (Can anyone afford it?)