

Data Assimilation Research Testbed Tutorial



Section 18: Lost in Phase Space: The Challenge of Not Knowing the Truth

Version 1.0: June, 2005

In real applications, the **truth is unknown.**

All that we have is observations.

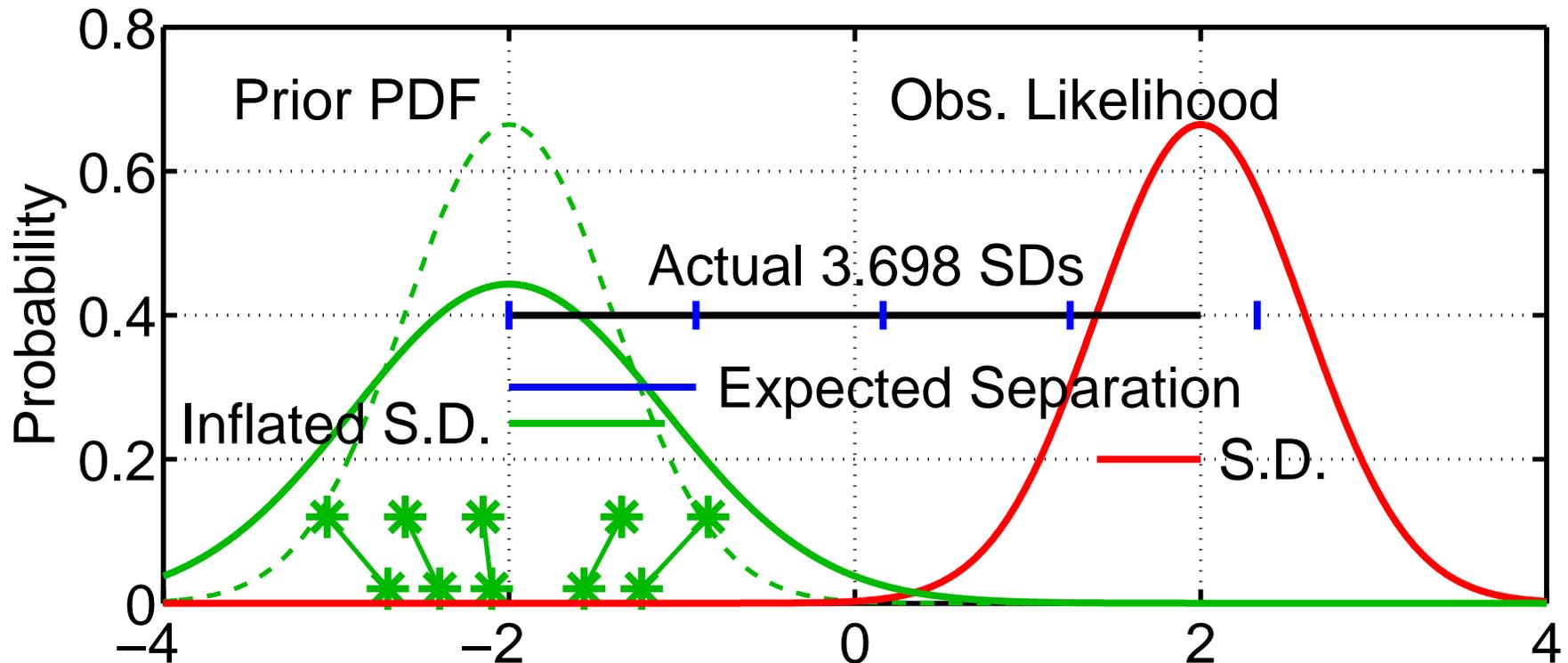
Having the truth available has been convenient, but also misleading...

Much less information is available from the observations.

They are generally functions of the state variables.

They are always contaminated with observational errors.

Recall that $\text{Expected}(\text{prior mean} - \text{observation}) = \sqrt{\sigma_{\text{prior}}^2 + \sigma_{\text{obs}}^2}$.



Error is dominated by observational noise if $\sigma_{\text{obs}} \gg \sigma_{\text{prior}}$

Suppose $\sigma_{\text{obs}}=1.0$, $\sigma_{\text{prior}} = 0.1 \Rightarrow \text{E(RMS)} = 1.005$.

Halving σ_{prior} to 0.05 $\Rightarrow \text{E(RMS)} = 1.001$; only a 0.4% reduction!

Limited Observation space diagnostics in DART:

Try them out in `lorenz_96` model.

After an assimilation, the final observation info is in `obs_seq.final`.

The program `obs_diag` post-processes this file.

The `obs_diag_nml` in `input.nml` controls this post-processing.

For low-order models, the only meaningful parameter is `rat_cri`.

This rejects ‘bad’ observations.

If $\left| \overline{y^p} - y^o \right| > rat_cri \sqrt{\sigma_{prior}^2 + \sigma_{obs}^2}$, don't use this observation.

This is **EXTREMELY DANGEROUS**, but useful.

Rejecting ‘good’ observations can lead to inflated estimate of quality.

Displaying obs space diagnostics with matlab:

Following commands are available for low-order models:

<i>fit_ens_mean_time;</i>	Mean obs. prior RMS error.
<i>fit_ens_spread_time;</i>	Mean obs. prior spread.
<i>obs_num_time;</i>	Number of observations used.
<i>fit_mean_spread_time;</i>	Mean error and spread on one plot.

Exercise with lorenz 96:

Pick a case that works relatively well and looks at obs space diags.

Pick a case that is similar, but clearly different with physical space diagnostics.

See if you can detect this difference with observation space diags.

Quick look at a real atmospheric application

Results from CAM Assimilation: January, 2003

Model:

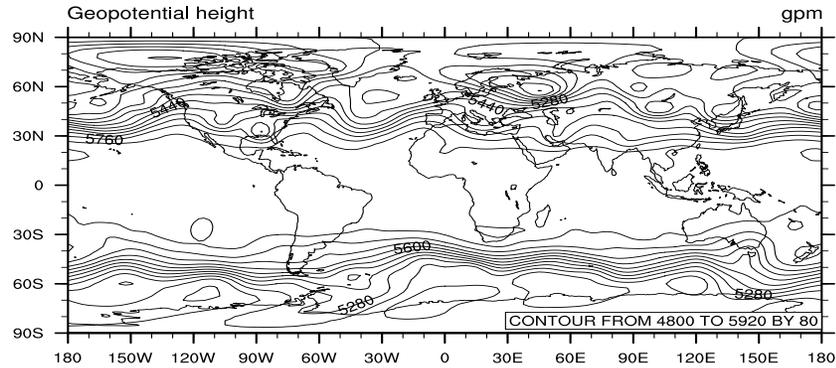
CAM 3.0 T42L26

U, V, T, Q and PS state variables impacted by observations.
Land model (CLM 2.0) not impacted by observations.
Climatological SSTs.

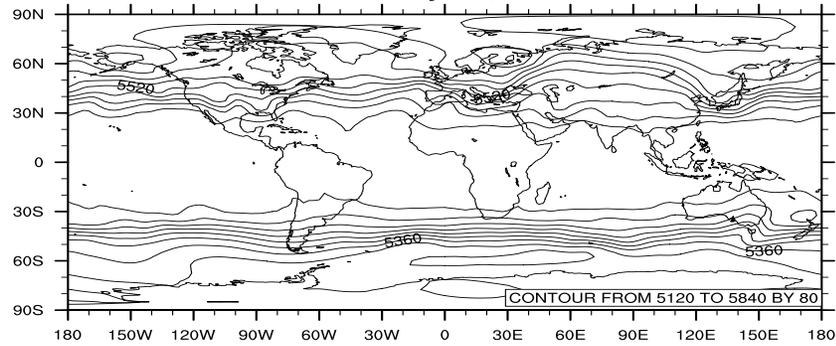
Assimilation / Prediction Experiments:

80 member ensemble divided into 4 equal groups.
Initialized from a climatological distribution (huge spread).
Initial tests for January, 2003.
Uses most observations used in reanalysis
(Radiosondes, ACARS, Satellite Winds..., no surface obs.).
Assimilated every 6 hours; +/- 1.5 hour window for obs.
Adaptive error correction algorithm with fixed variance

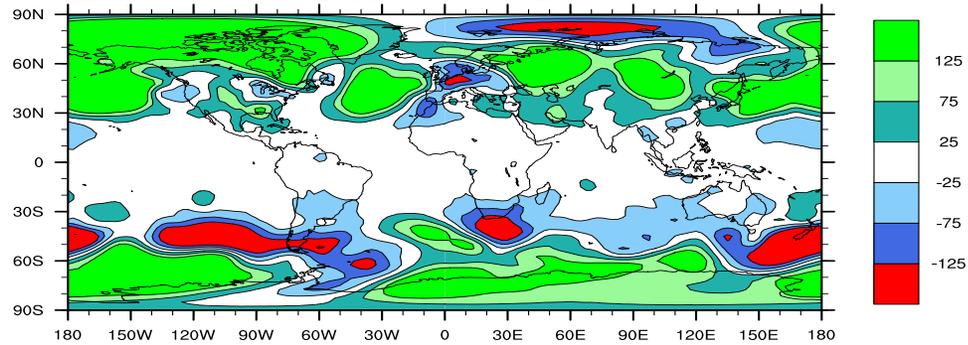
NCEP reanalyses, 500mb GPH, Jan 01 06Z



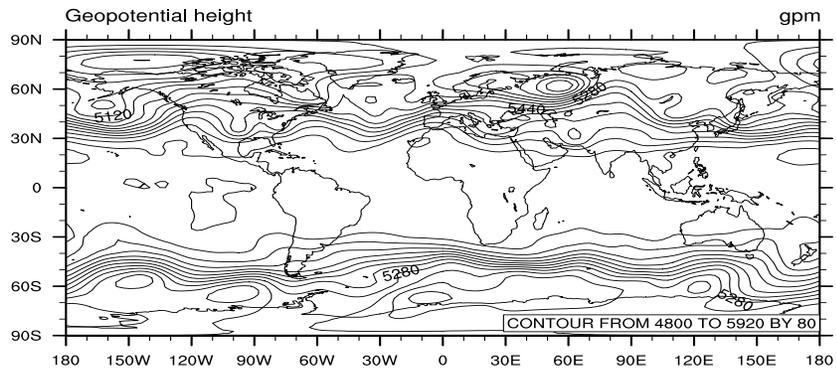
DART/CAM analyses, 500mb GPH



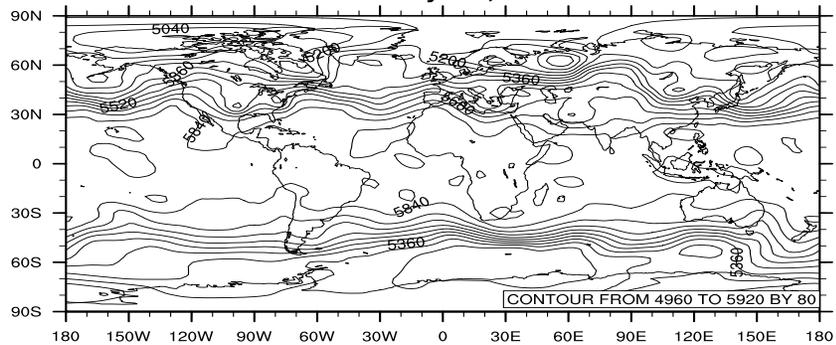
DART/CAM - NCEP



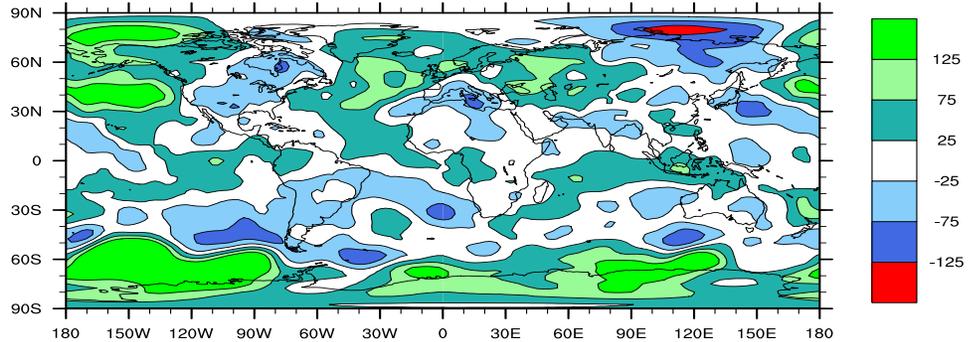
NCEP reanalyses, 500mb GPH, Jan 02 00Z



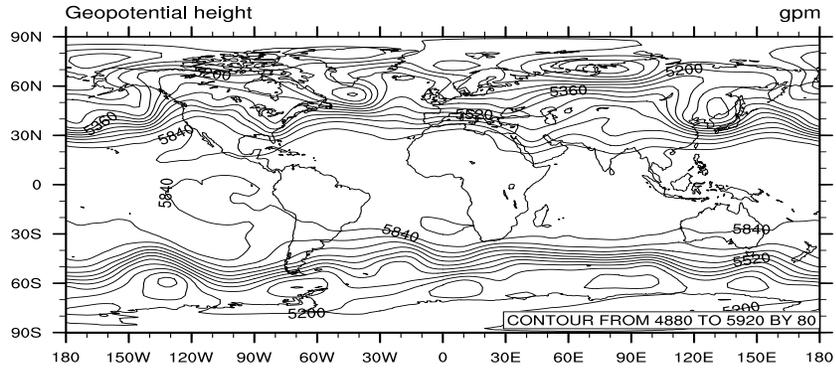
DART/CAM analyses, 500mb GPH



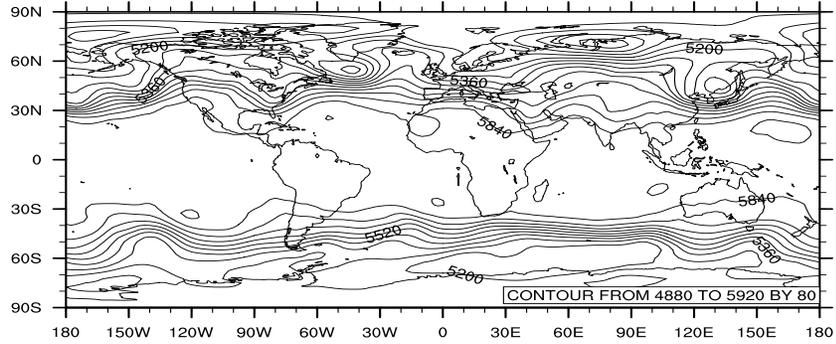
DART/CAM - NCEP



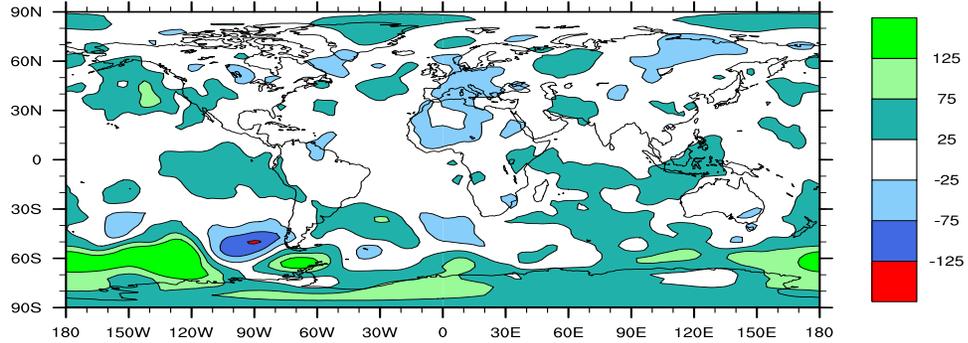
NCEP reanalyses, 500mb GPH, Jan 04 00Z



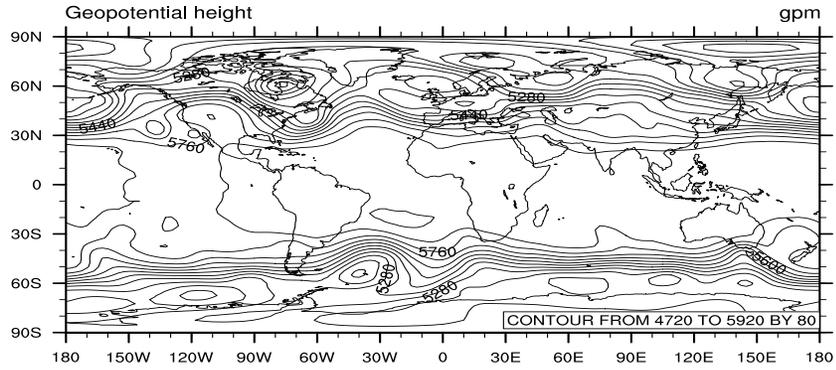
DART/CAM analyses, 500mb GPH



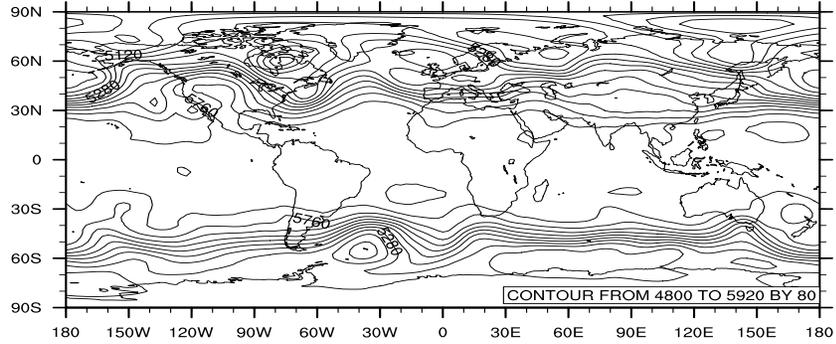
DART/CAM - NCEP



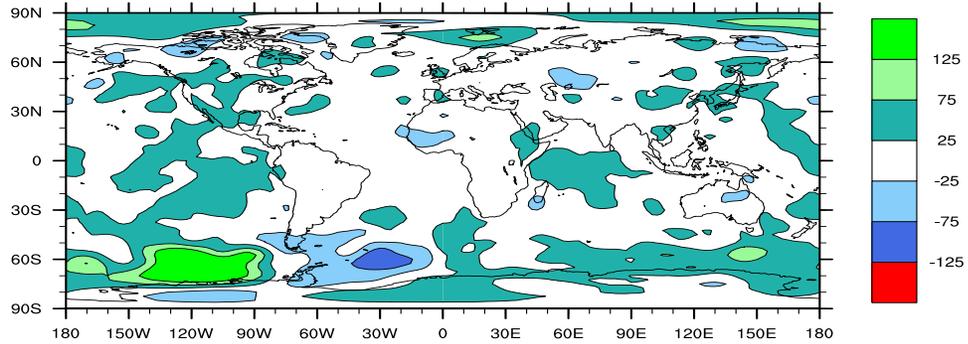
NCEP reanalyses, 500mb GPH, Jan 08 00Z



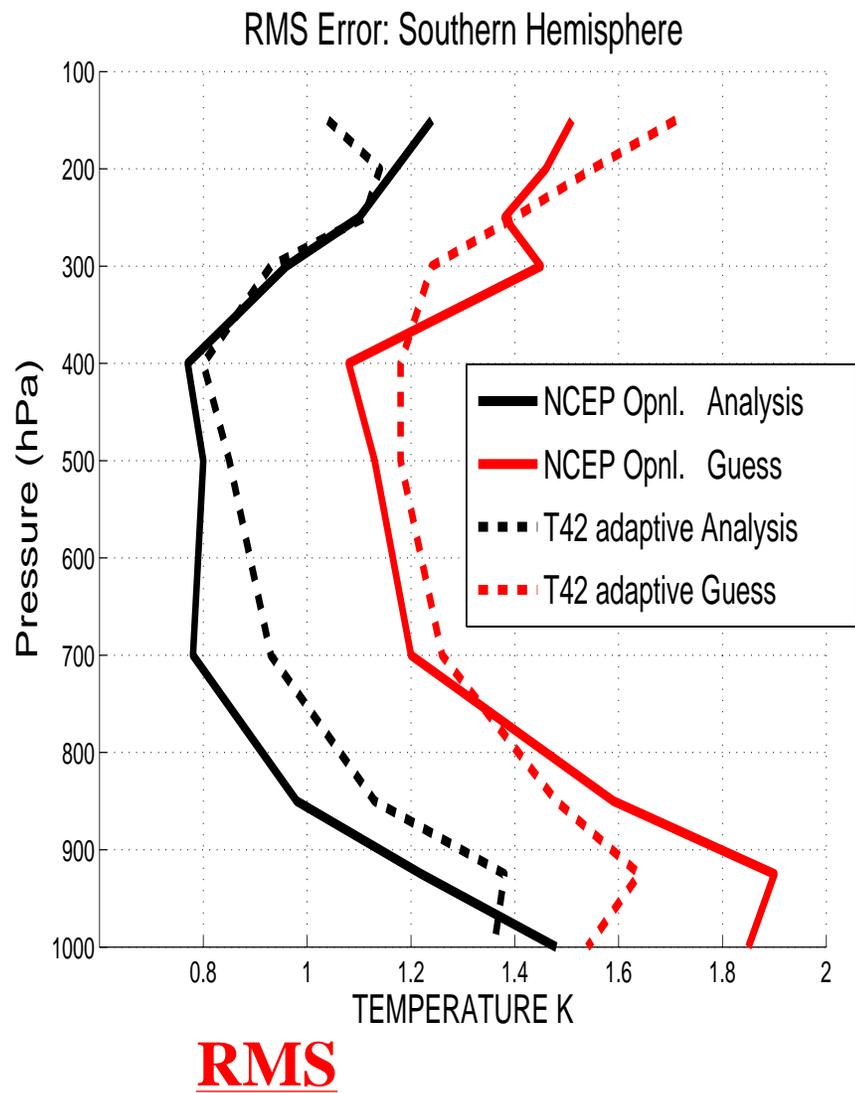
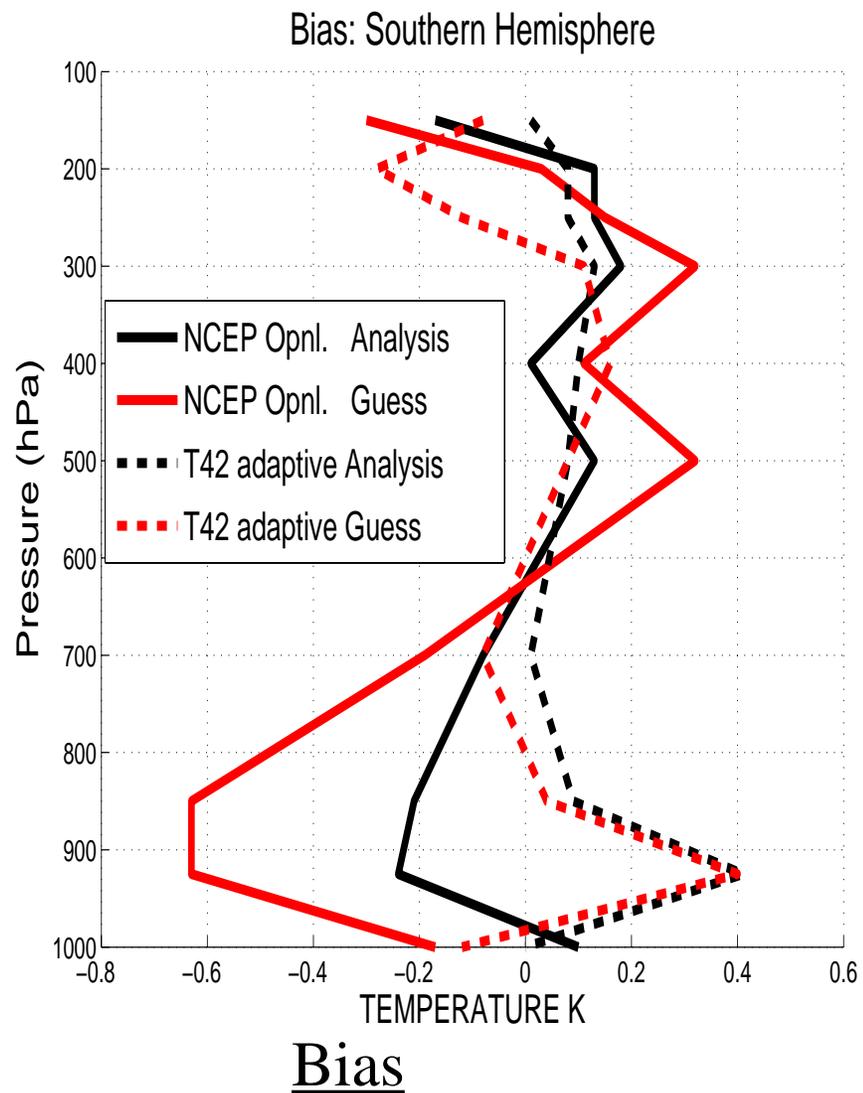
DART/CAM analyses, 500mb GPH



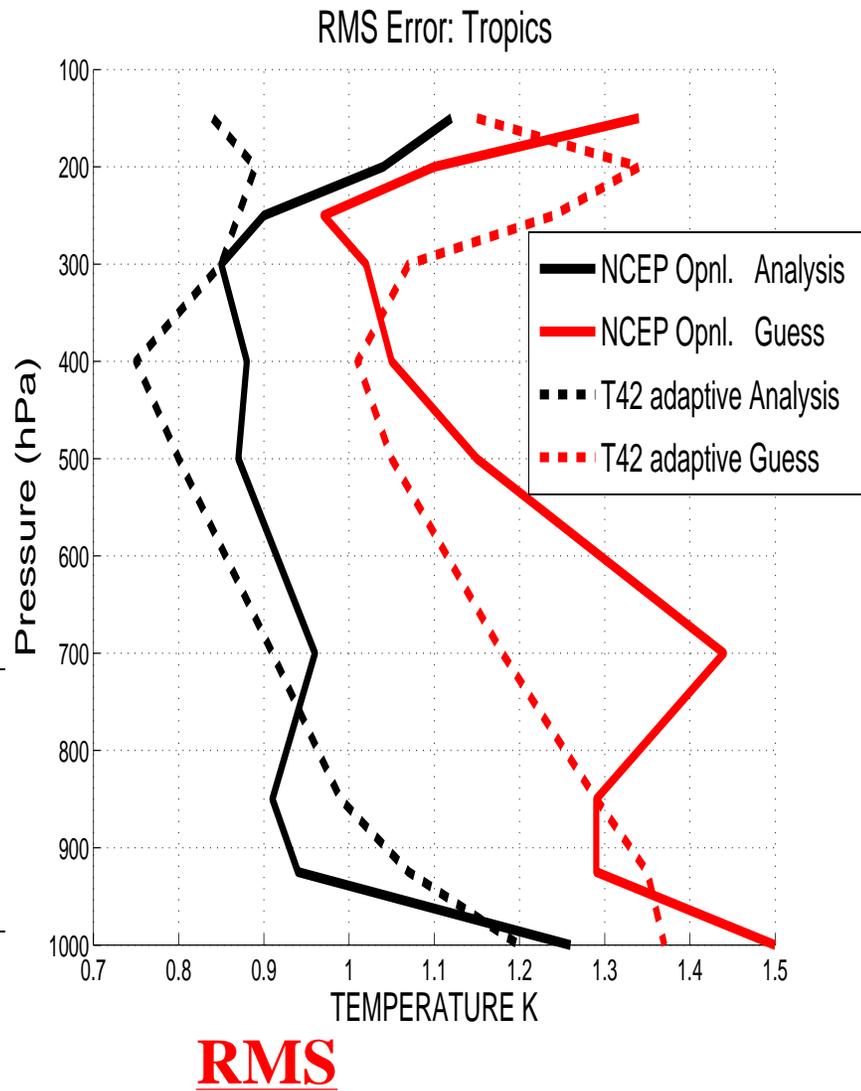
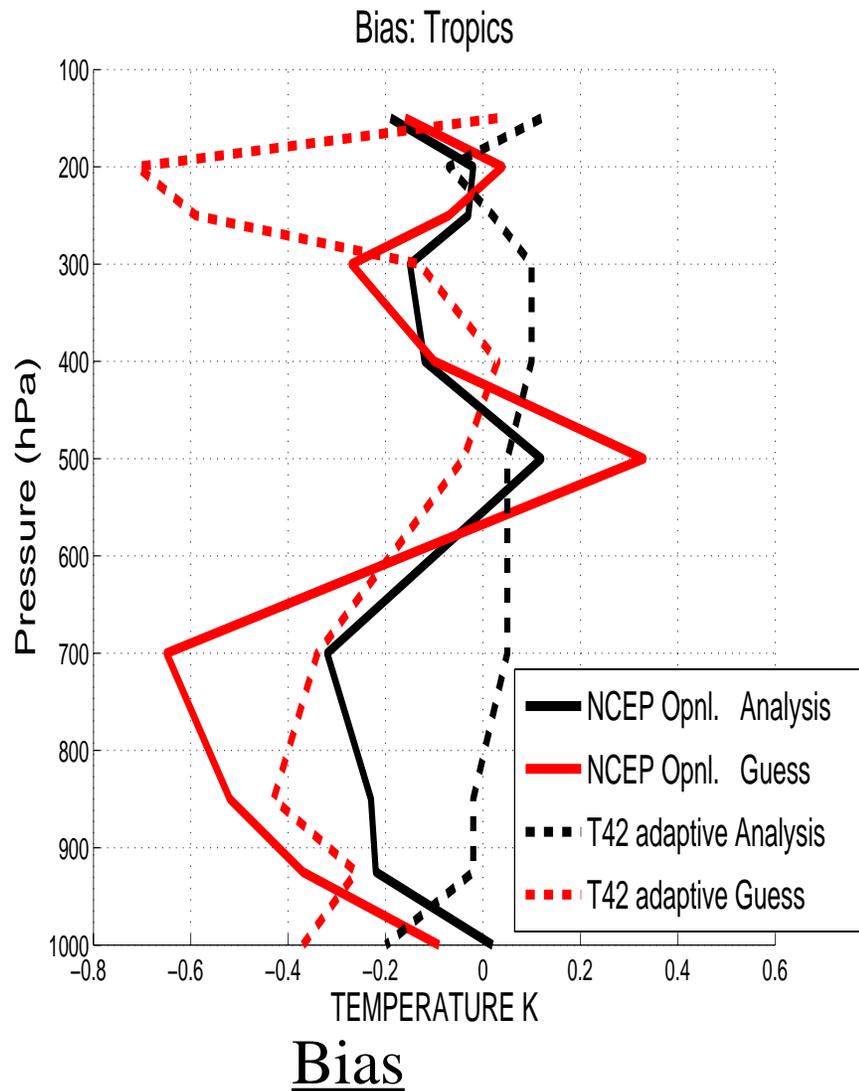
DART/CAM - NCEP



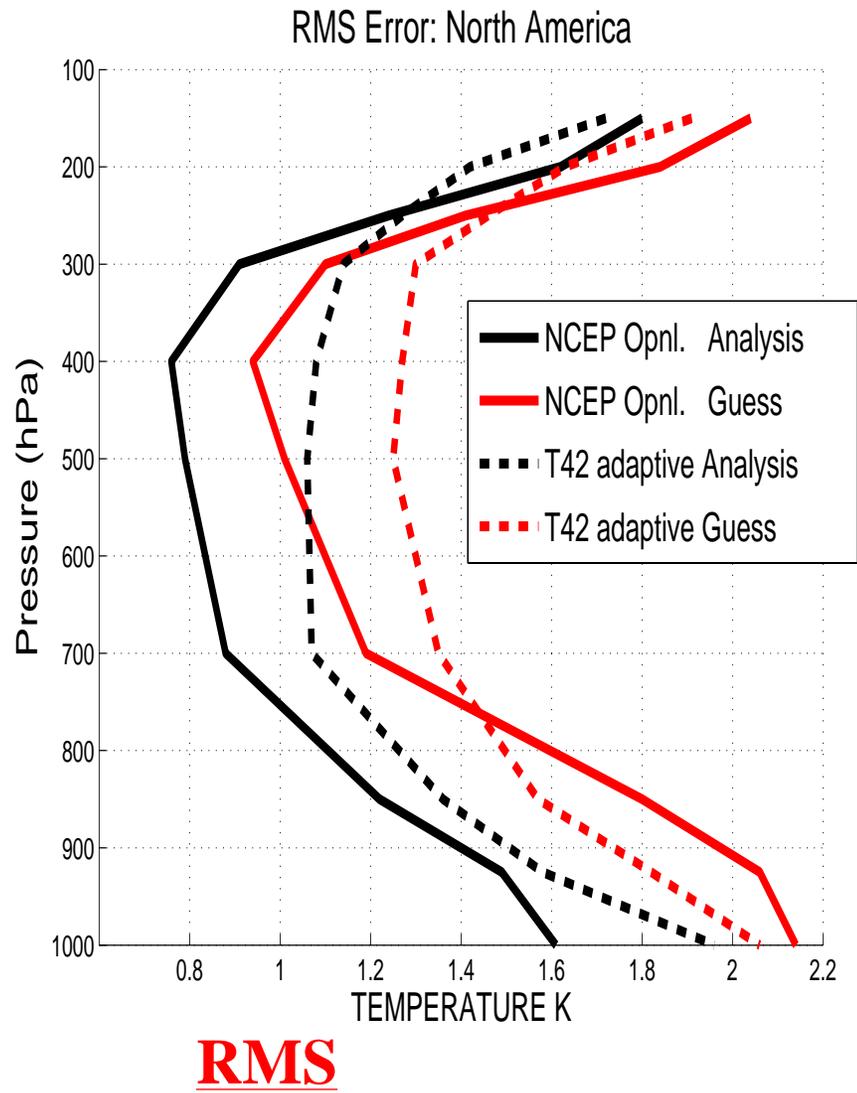
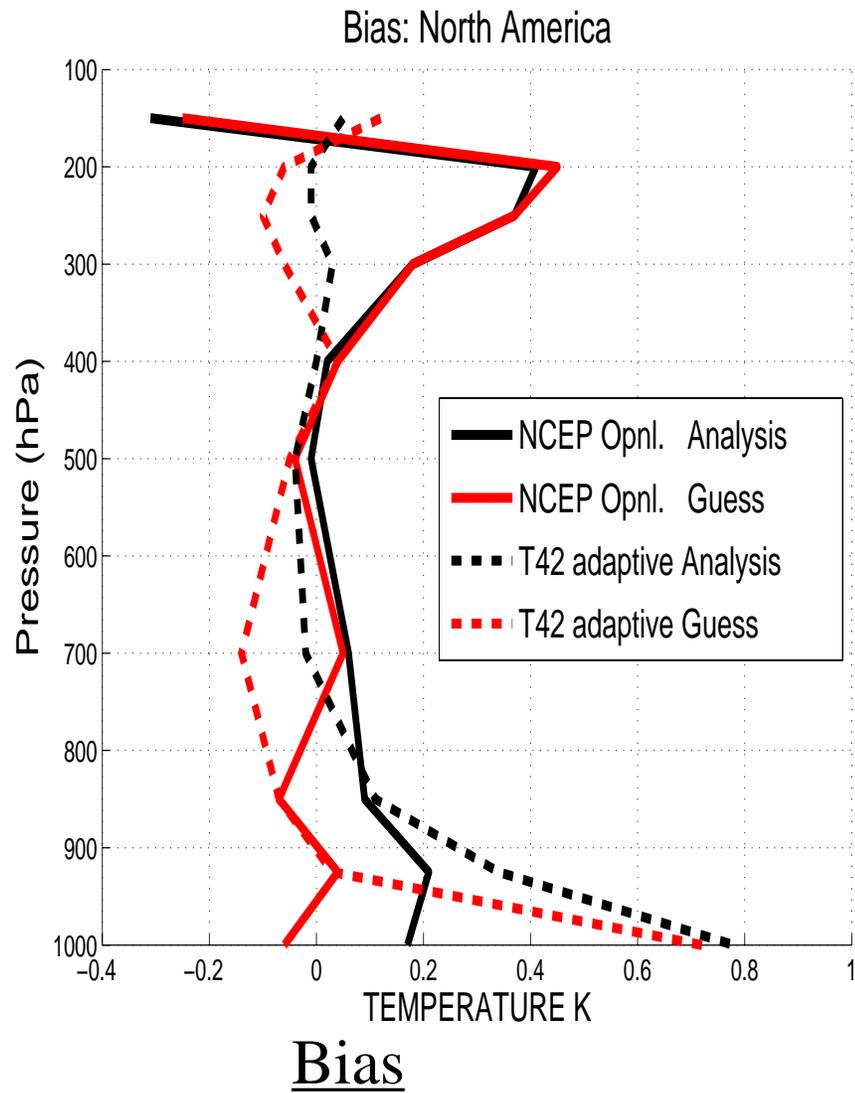
Southern Hemisphere Temperature: Bias and RMSE



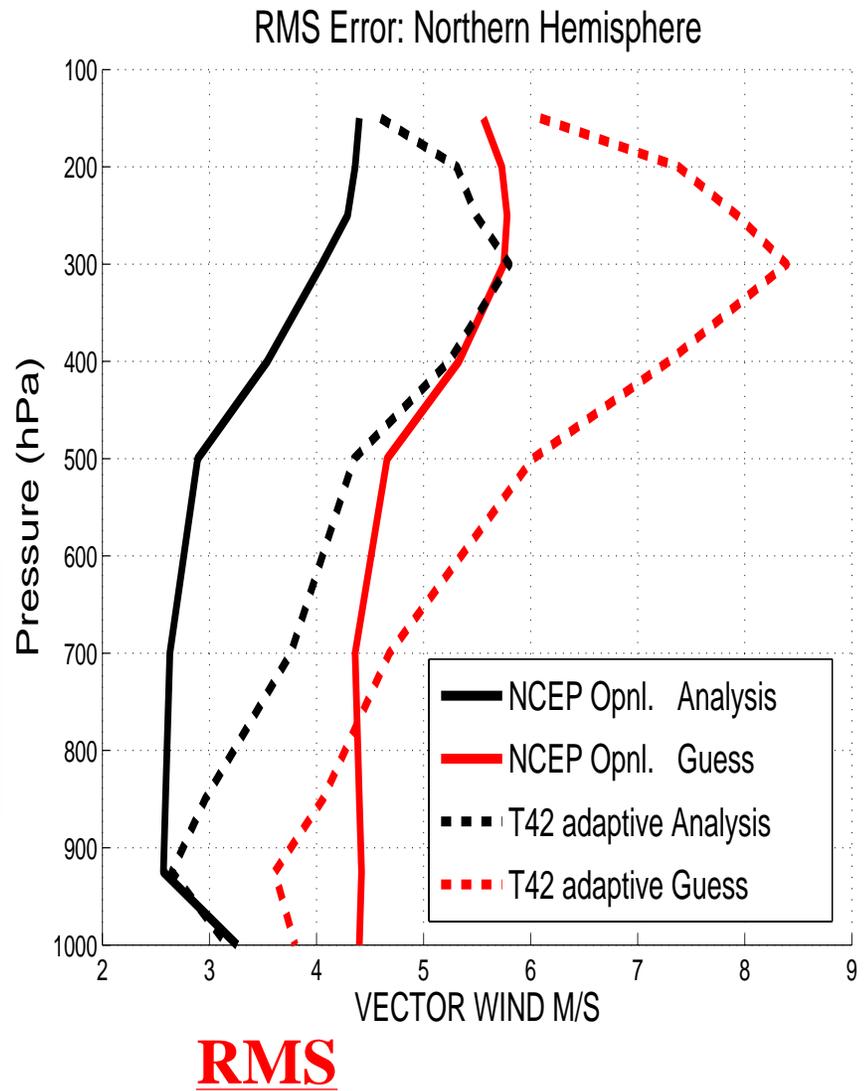
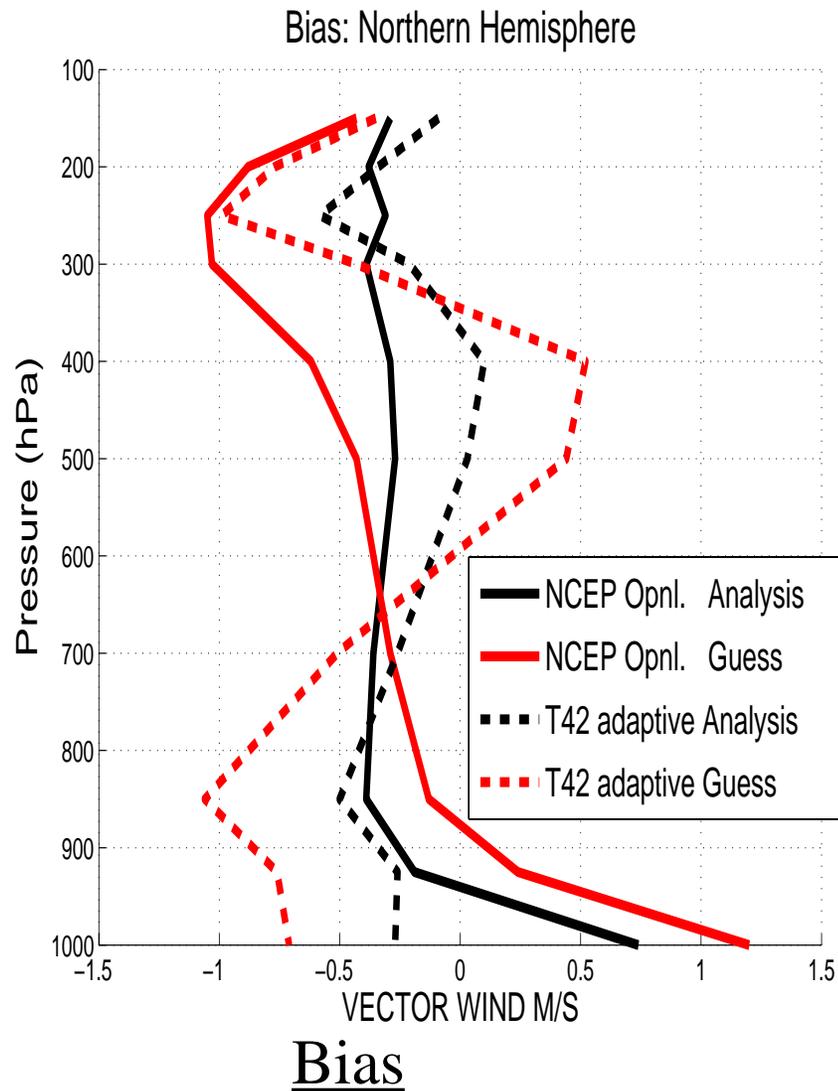
Tropics Temperature: Bias and RMSE



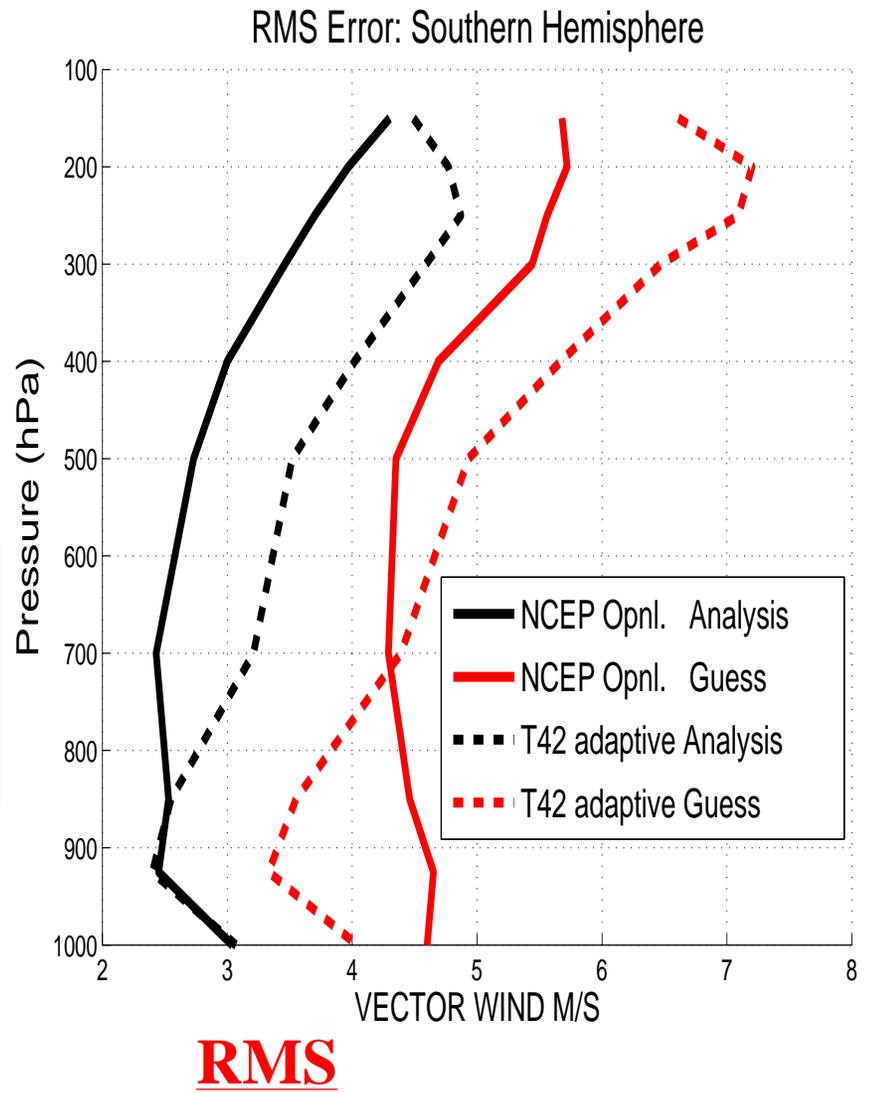
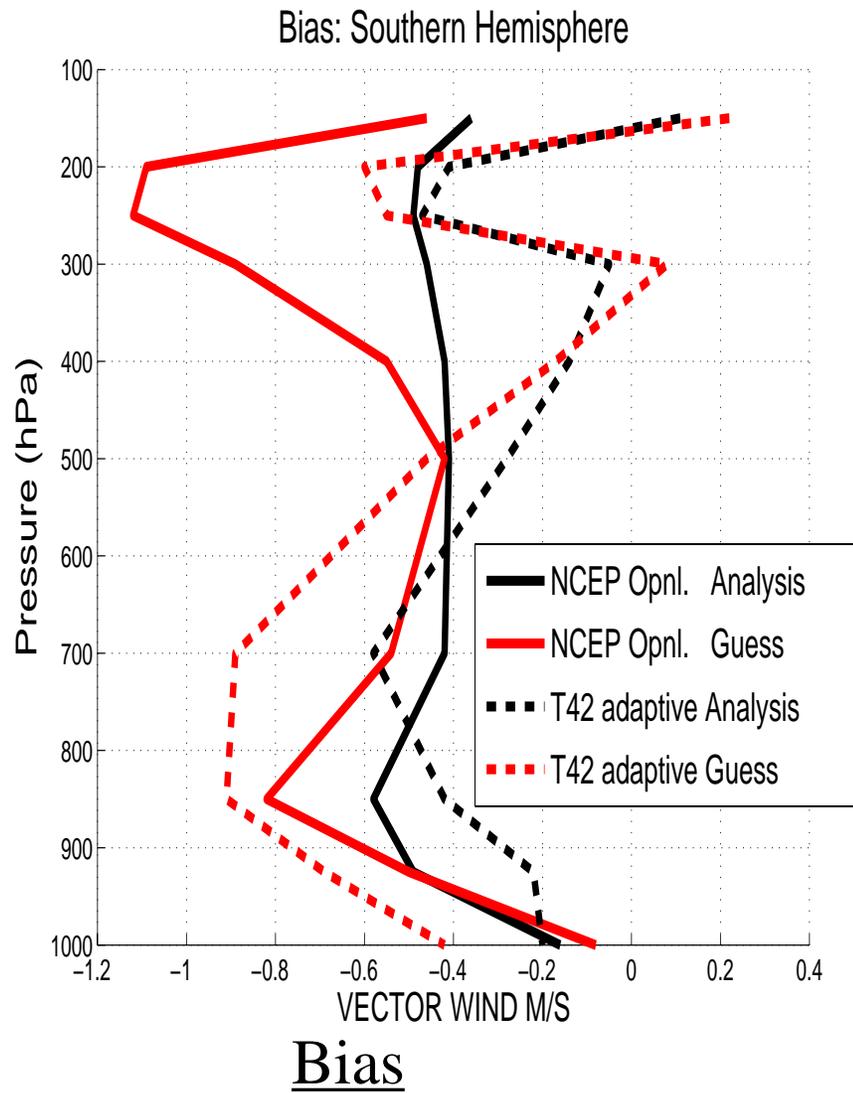
North America Temperature: Bias and RMSE



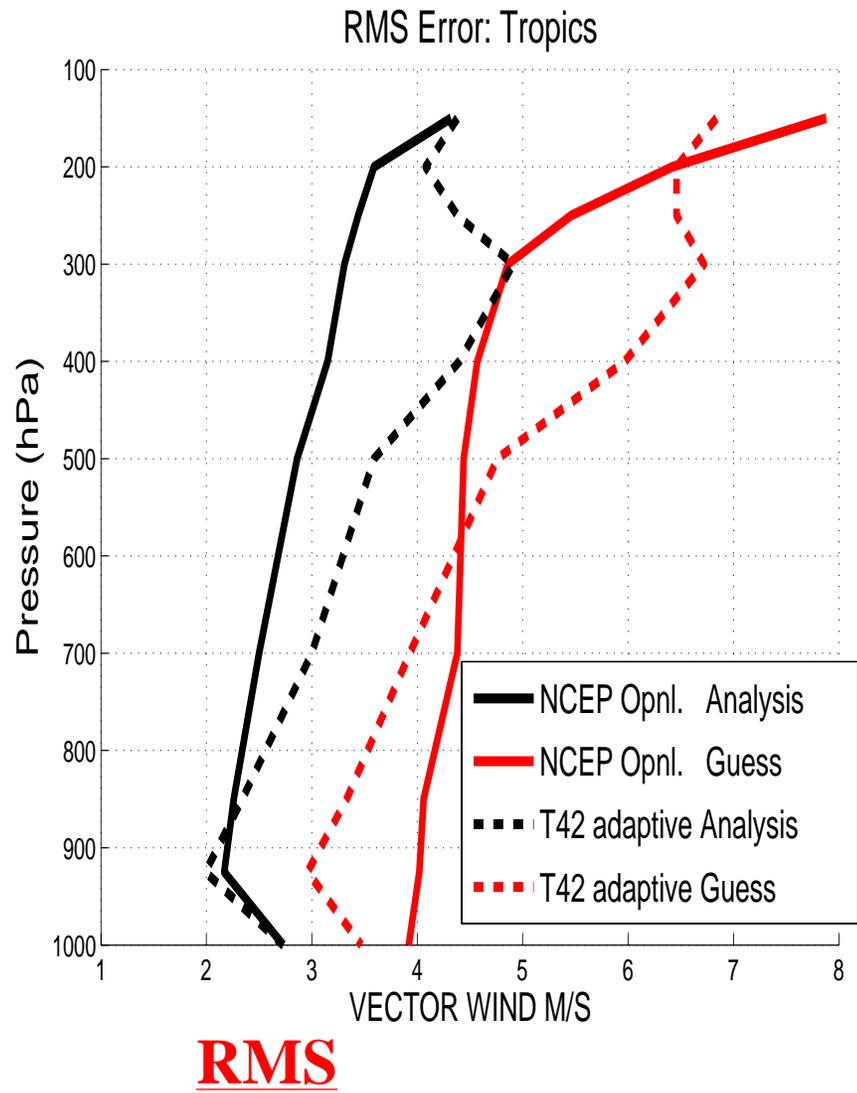
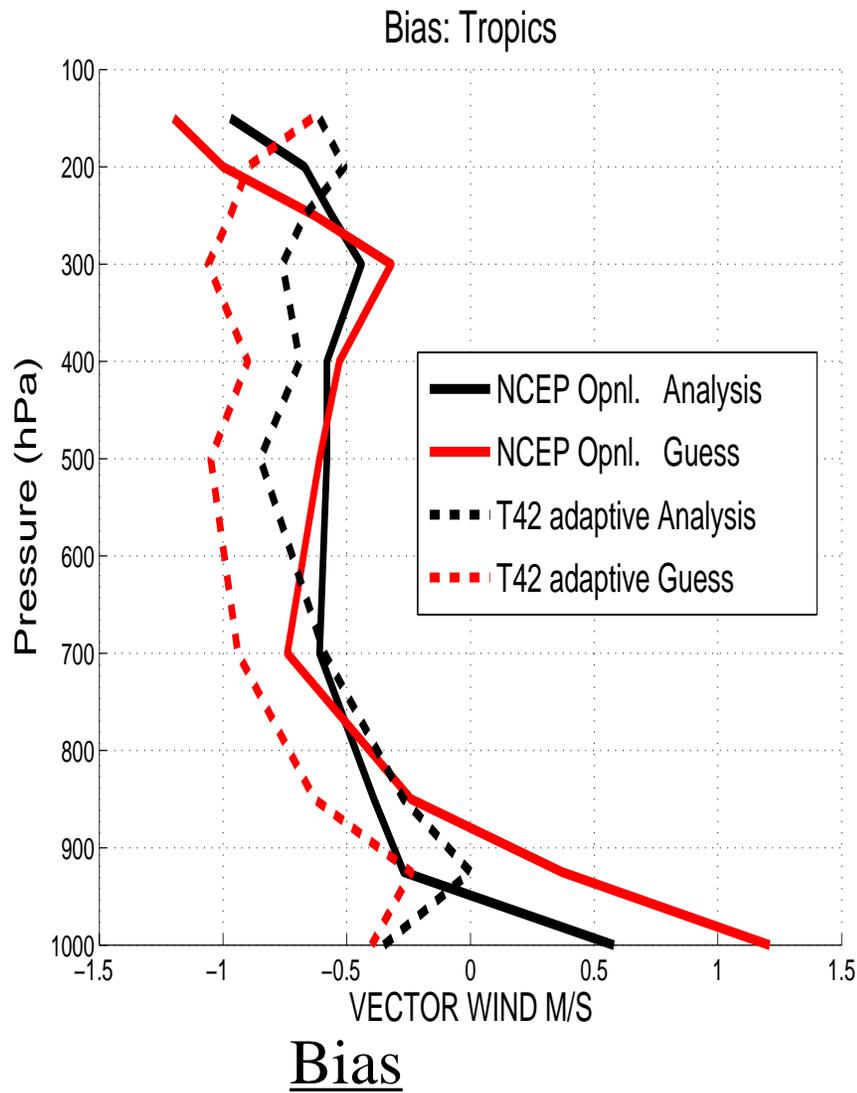
Northern Hemisphere Wind: Bias and RMSE



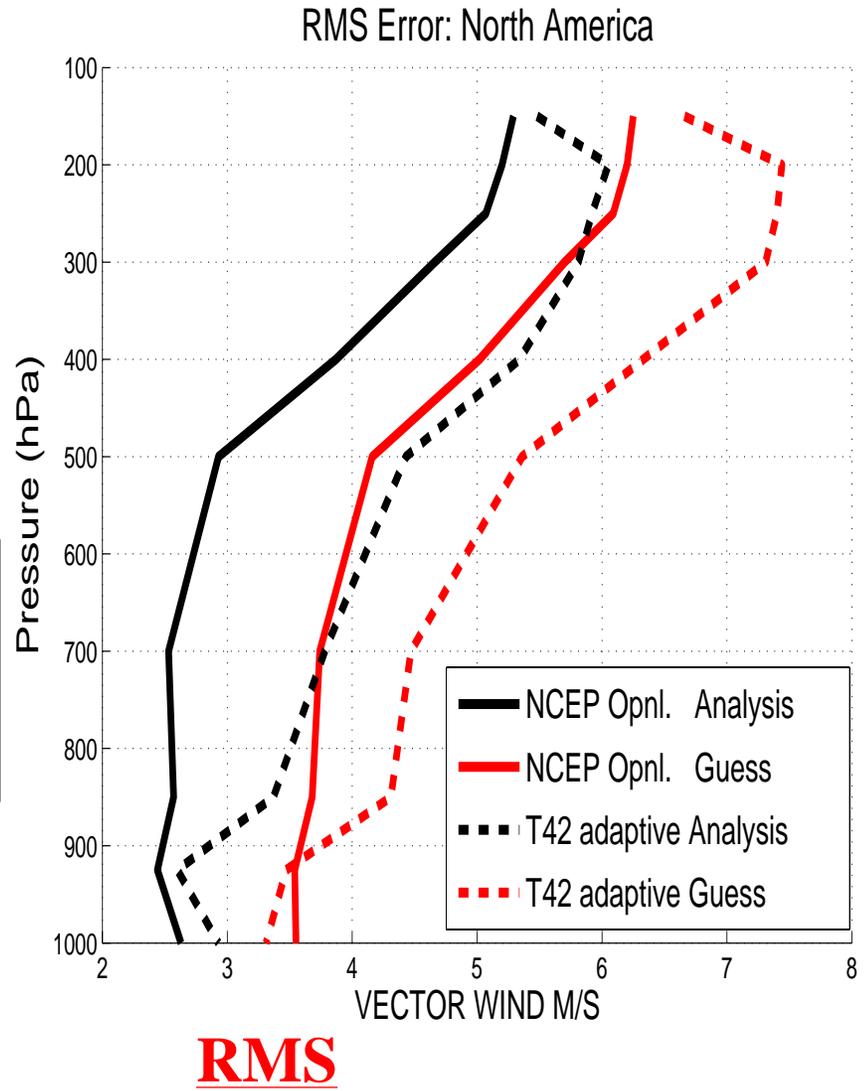
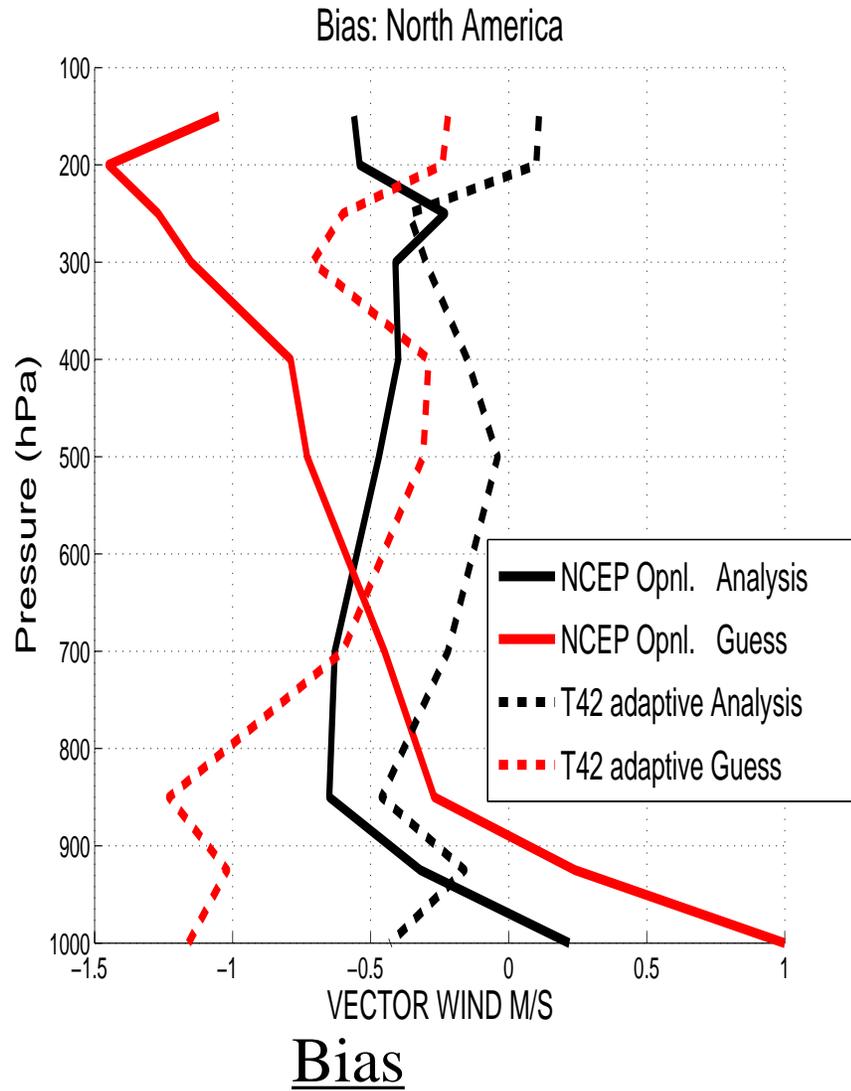
Southern Hemisphere Wind: Bias and RMSE

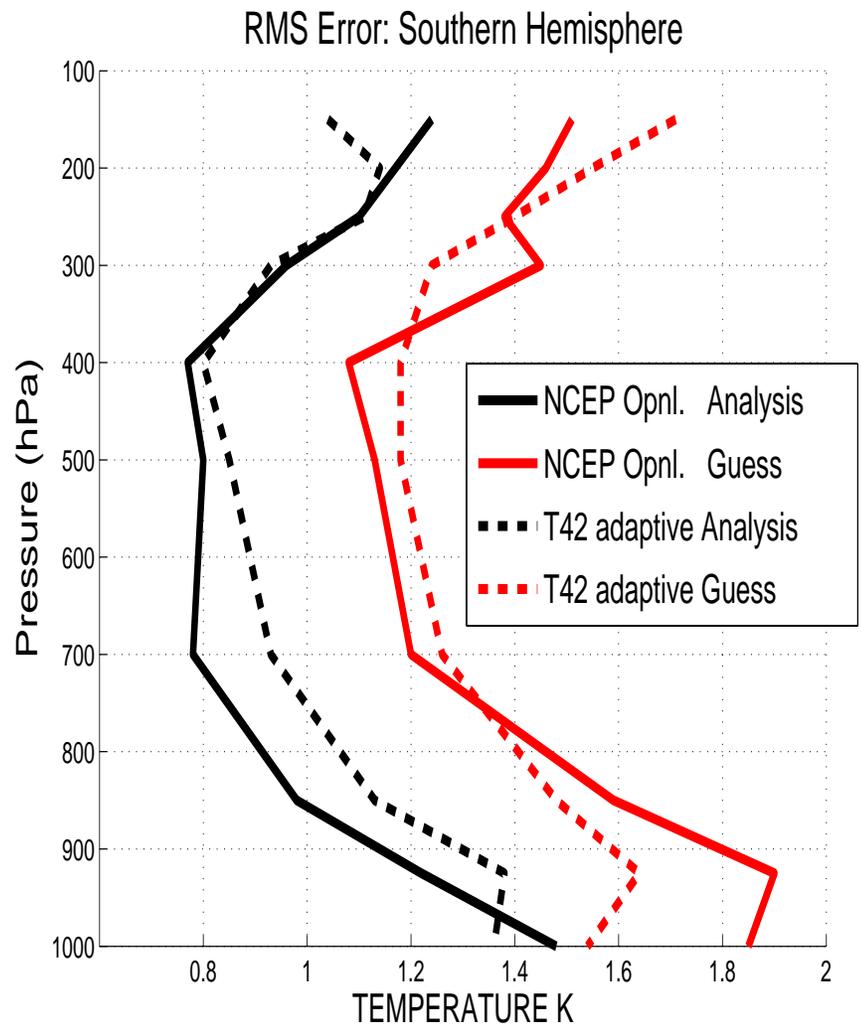
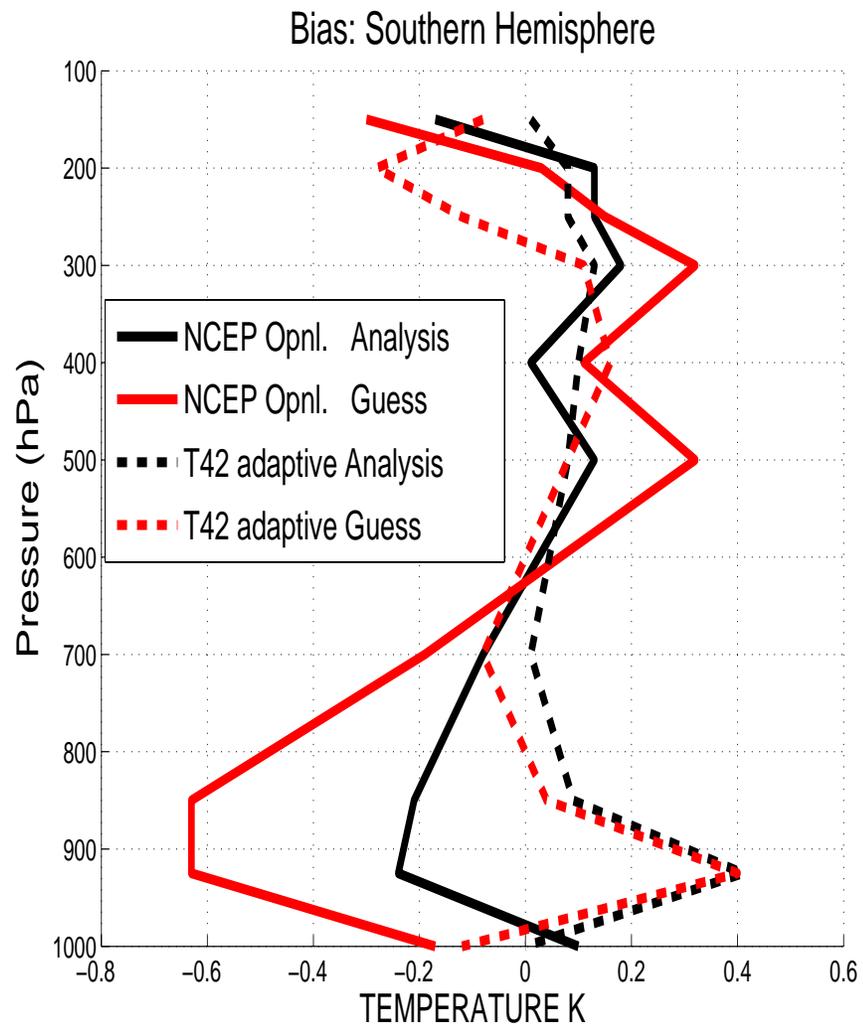


Tropical Wind: Bias and RMSE



Northern America Wind: Bias and RMSE





Sneak Preview of T85 CAM Results

