Earth System Research Laboratory
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Ensemble Data Assimilation of Satellite Radiances

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***EDA systems do very well with sparse data*.**

Q: How do they do in a modern NWP setting with O(10^6) obs?

Ensemble bias correction for radiances.

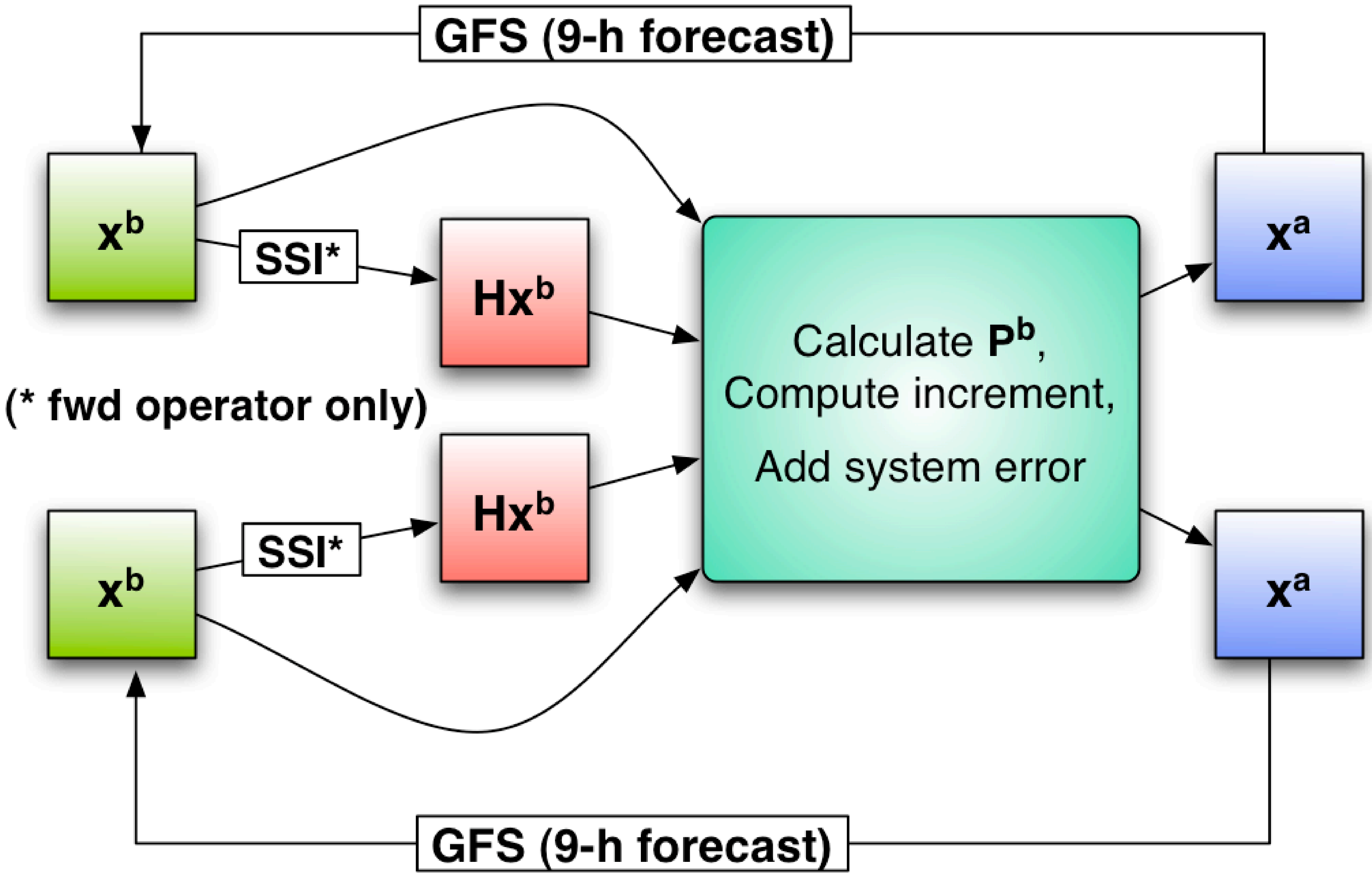
Why Ensemble Data Assimilation?

• **Automatic initialization** of ensemble forecasts.

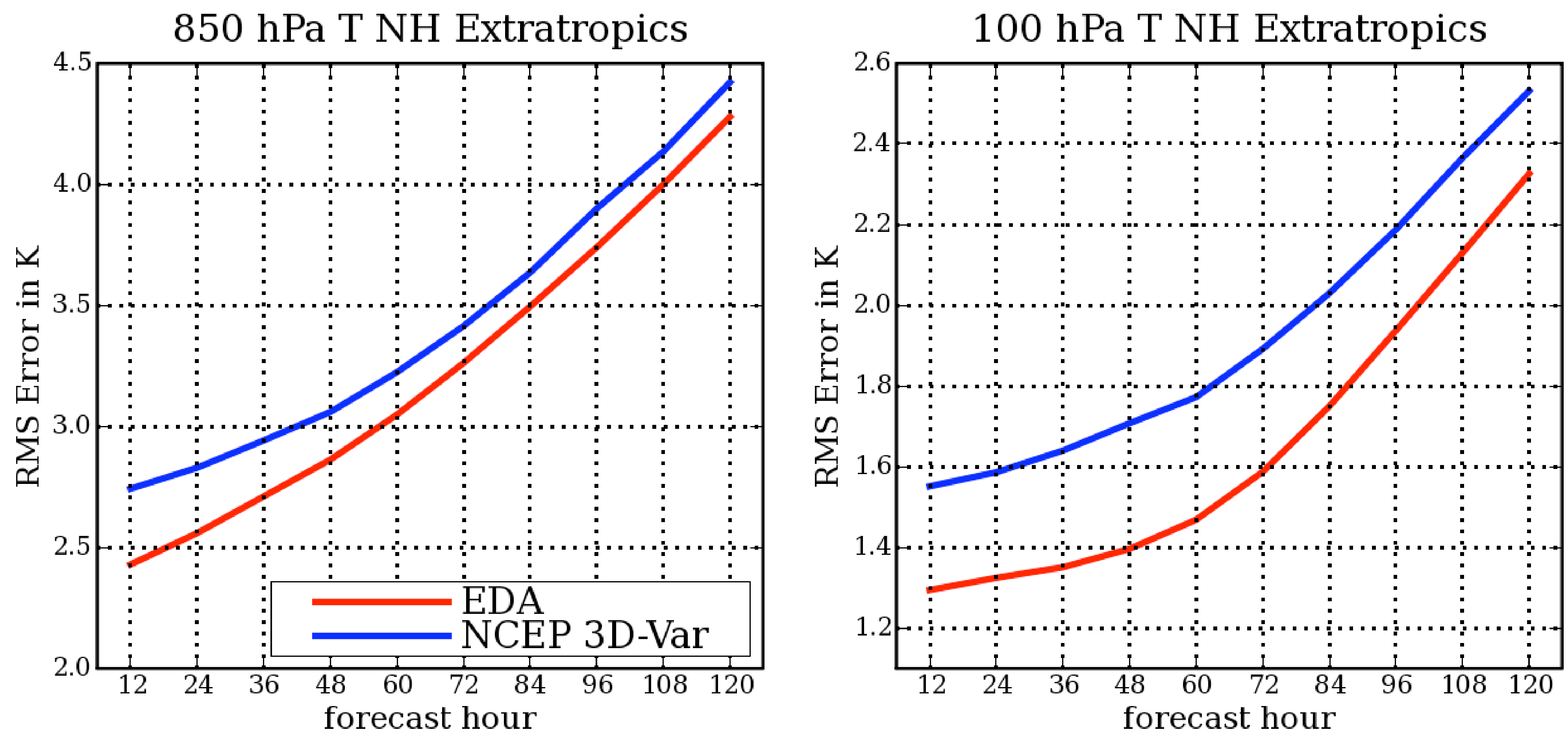
• **Flow-dependent** background (and analysis) errors.

• Relatively **simple to code** (and maintain). No adjoint of forecast model, background error covariance model needed.

Ensemble DA flow (2 members)



Forecast error (vs. AIRS T) - NOSAT



- ✓ 6-12 hr improvement in lead time at 850, more for 100 hPa.
- ✓ improvement largest in data sparse regions (SH, stratosphere).

Q: Will this carry over when radiances included?

Inclusion of Satellite Radiances

- need a radiative transfer model to compute predicted T_b given model state.

  use forward operator from operational NCEP SSI (pCRTM).

- have to specify a 'level' for radiances, so impact of observations can be localized.

  Use maximum of weighting function.

- must bias correct radiance observations prior to assimilation (scan-angle and state-dependent components).

  use NCEP code for scan-angle correction.

  include predictor coefficients for state-dependent part as analysis variables.

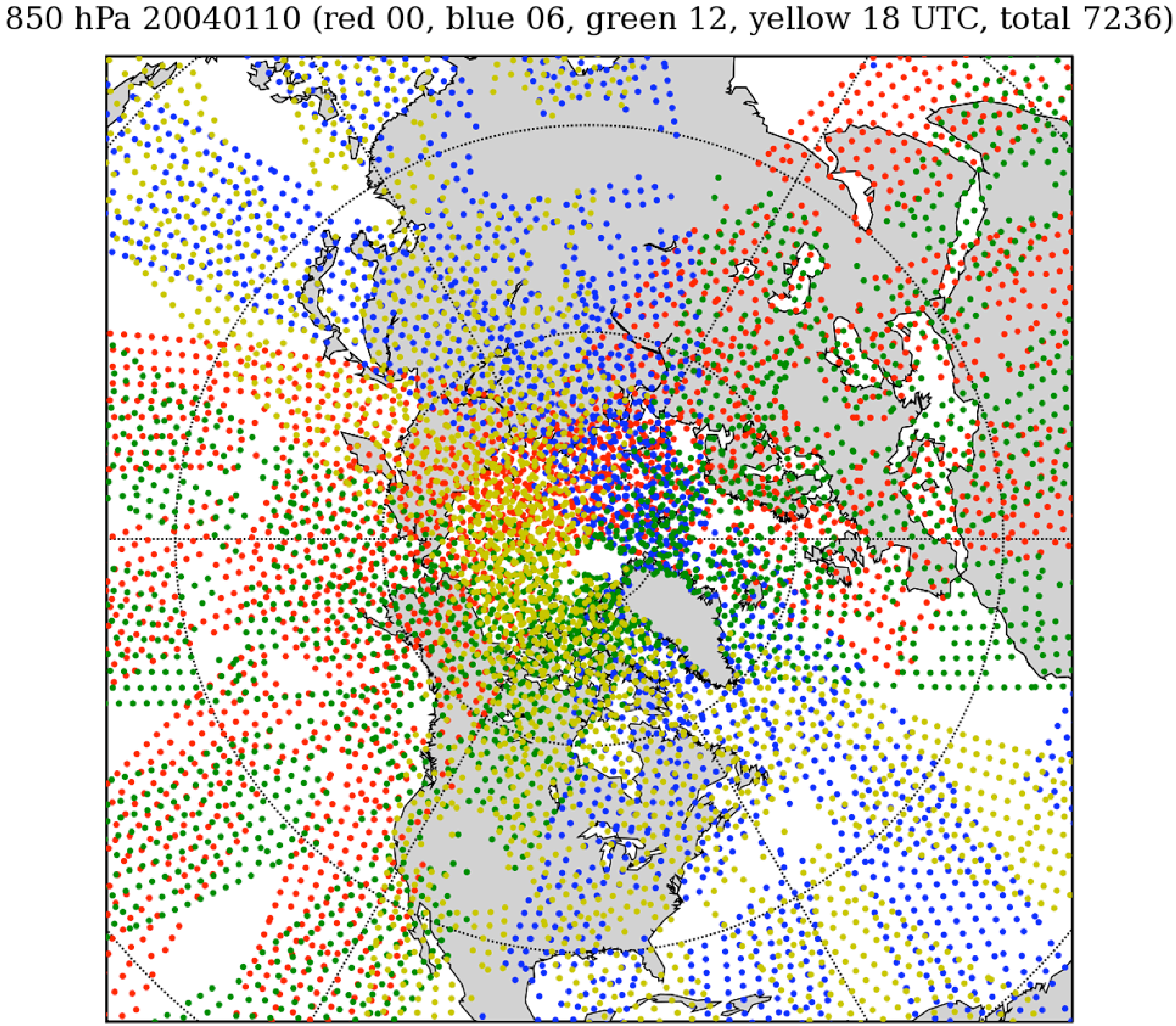
Experimental Design

- **Obs**: All ‘conventional’ obs and satellite radiances assimilated operationally at NCEP in Jan-Feb 2004.

- **Benchmark**: Operational NCEP GDAS, run at reduced resolution (T62L28).

- **Validation**: Forecasts verified against AIRS level-2 retrievals (v. 4.0.9).

Verification: AIRS T retrievals (v. 4.0.9)



EDA System

- **Algorithm**: Based on LETKF (Hunt et al, 2007, Physica D, next talk). 54 ensemble members, T62L28 resolution.
- **'Air-Mass' Bias Correction**: Same predictors as NCEP, ensemble of coefficients (β_i) updated via a *global* ETKF.

$$y = h(x) + b^{scan} + b^{air}$$

$$b^{air} = b^{air}(x, \beta) = \sum_{i=1}^{5} \beta_i p_i\,(x)$$

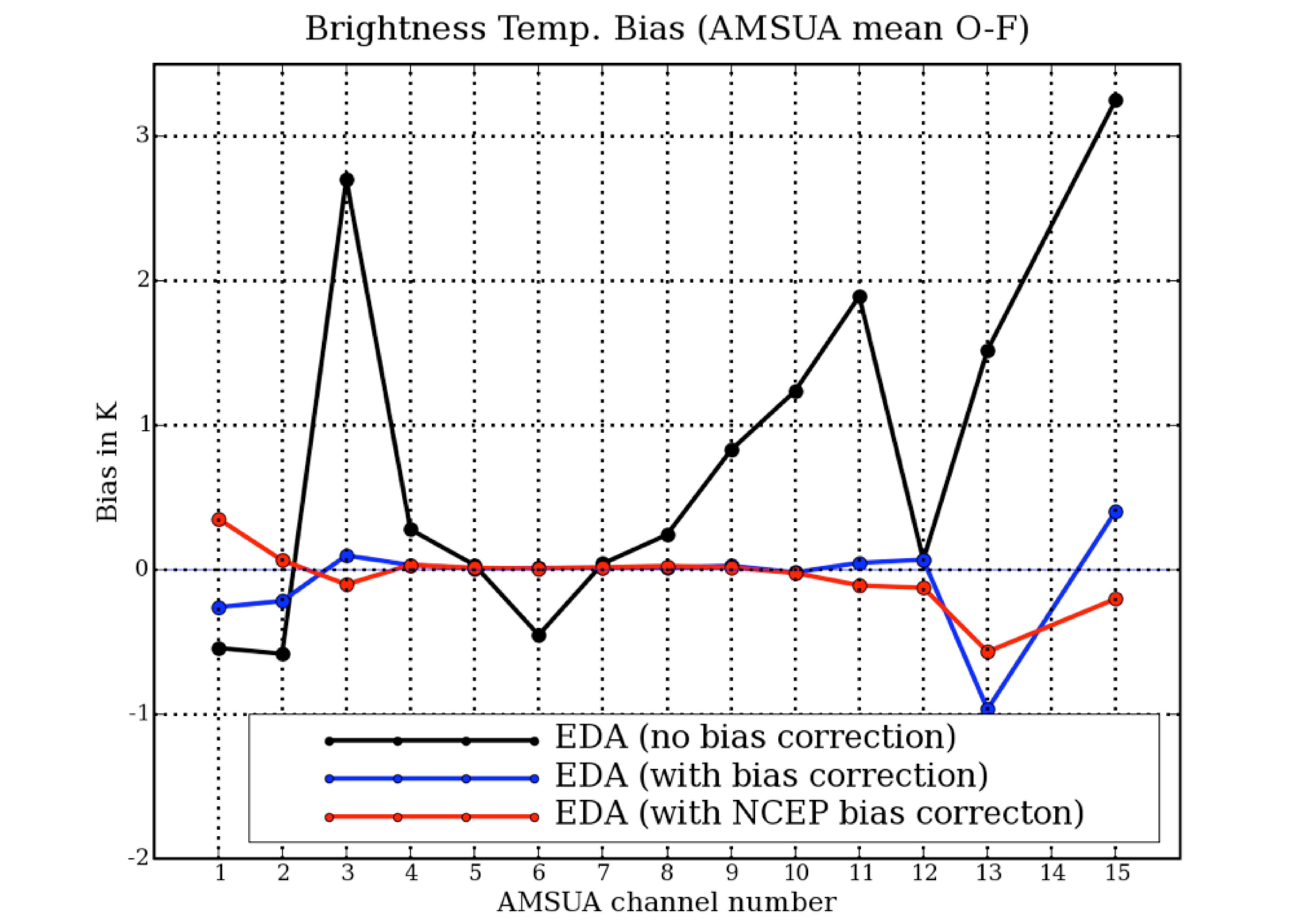
p1	constant
p2	(view angle path factor)^2
p3	cloud liquid water (AMSU only)
p4	temperature lapse rate
p5	(temperature lapse rate)^2

Bias coefficient update

- ensemble of β_i persisted from one analysis time to the next.
- β_i updated with ETKF equations (below).
- β_i ensemble renormalized to 'climatological' variance after update (determined from Jan-Feb 2004 GDAS output).

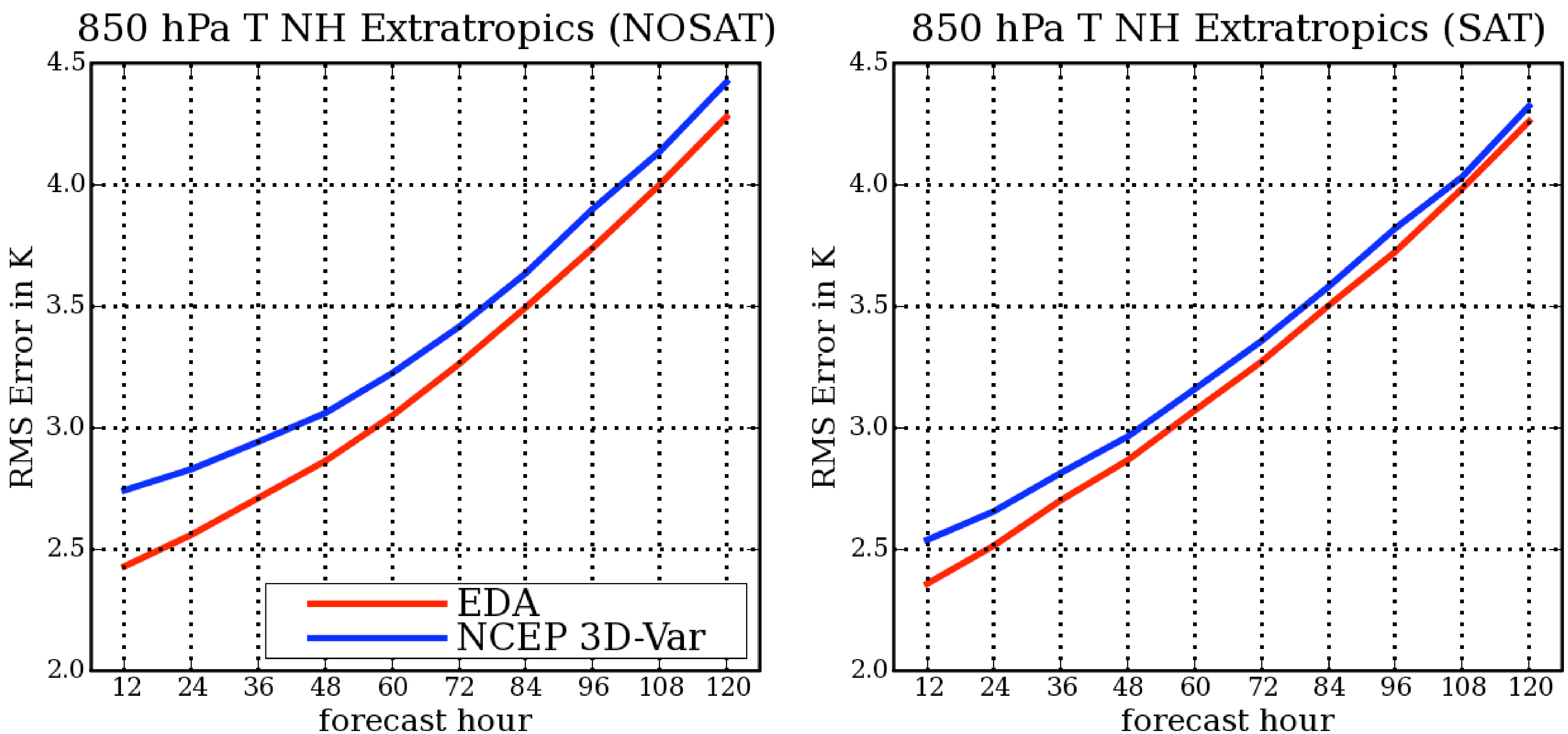
$$\bar{\beta}_i{}^a = \bar{\beta}_i{}^b + \mathbf{K}(y - h(\bar{x}^b) - b^{scan} - b^{air}(\bar{x}^b, \bar{\beta}_i{}^b))$$

$$\beta_i'^a = \beta_i'^b \mathbf{W}$$



Brightness Temp. Bias (AMSUA mean O-F)
Bias in K
3
2
1
0
-1
-2
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
AMSUA channel number
EDA (no bias correction)
EDA (with bias correction)
EDA (with NCEP bias correcton)

Forecast error (vs. AIRS T) - NOSAT and SAT



✓ EDA advantage lessened, but still significant.

Discussion

- advantage of EDA over 3D-Var greatest for sparse observing networks, diminished (but still significant) when satellite radiances are assimilated.
- ***reasons to prefer 3D-Var***:
  - ✓ cheaper (computationally).
- ***reasons to prefer EDA:***
  - ✓ no need to specify background error model.
  - ✓ unifies ensemble prediction and analysis.
  - ✓ will improve faster as model improves.
- **still to answer**: How does EDA compare at full operational resolution ? To 4D-Var?