Improving GFS 4DEnVar Hybrid Data Assimilation System Using Time-lagged Ensembles

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Ensemble-Variational Hybrid Data Assimilation

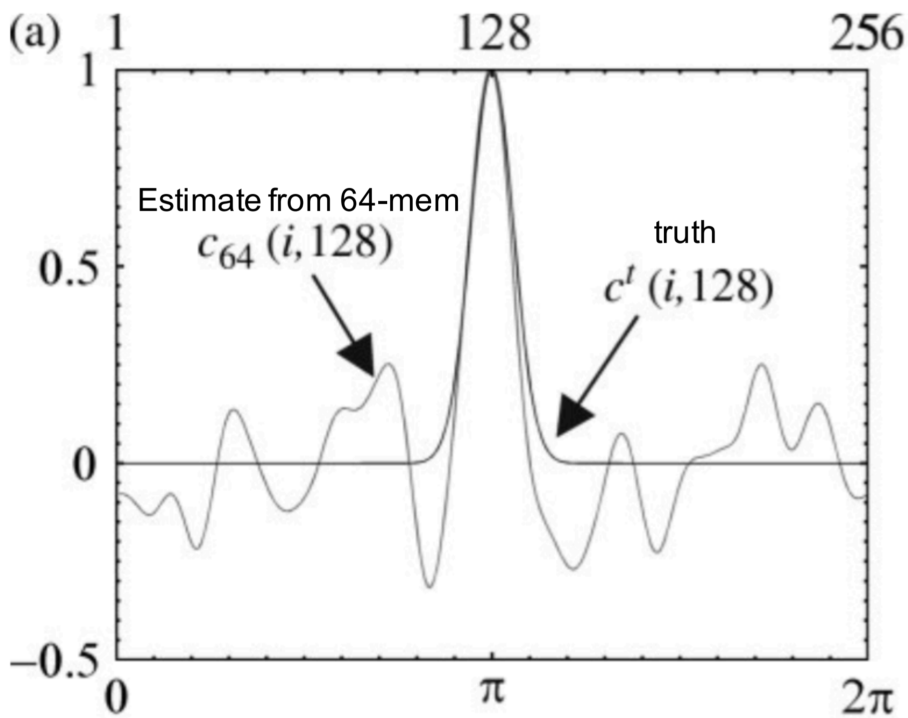
- GSI-based 3DEnVar hybrid was operationally implemented for GFS at NCEP since 2012. 4DEnVar hybrid is implemented operationally for GFS at NCEP recently. Significant improvement was found for global forecasts (e.g., Wang et al. 2013, Wang and Lei 2014; Kleist and Ide 2015; Mahajan et al. 2016) .

- Use of ensemble covariances allows simulating spatial, temporal and multivariate covariances in a flow-dependent manner.

- Although flow-dependent, ensemble covariances may still have issue due to
  - Sampling error
  - Model error

Sampling Error

- Caused by the use of limited ensemble size (~100) due to the computational cost.
- Typically characterized by the spurious correlation with the distant regions.
- Results in filter divergence that filters diverge from the true state (Hamill, 2006).



Bishop and Hodyss, 2007

Treatments for Sampling Error ---Covariance localization

- Distance-dependent localization (e.g., Houtekamer and Mitchell, 2001)
  - Remove distant spuriously correlation by the use of a distance-dependent function.

- Adaptive localization (e.g., Anderson, 2007; Bishop and Hodyss, 2007)
  - Can be a function of time, space, observation types, etc.

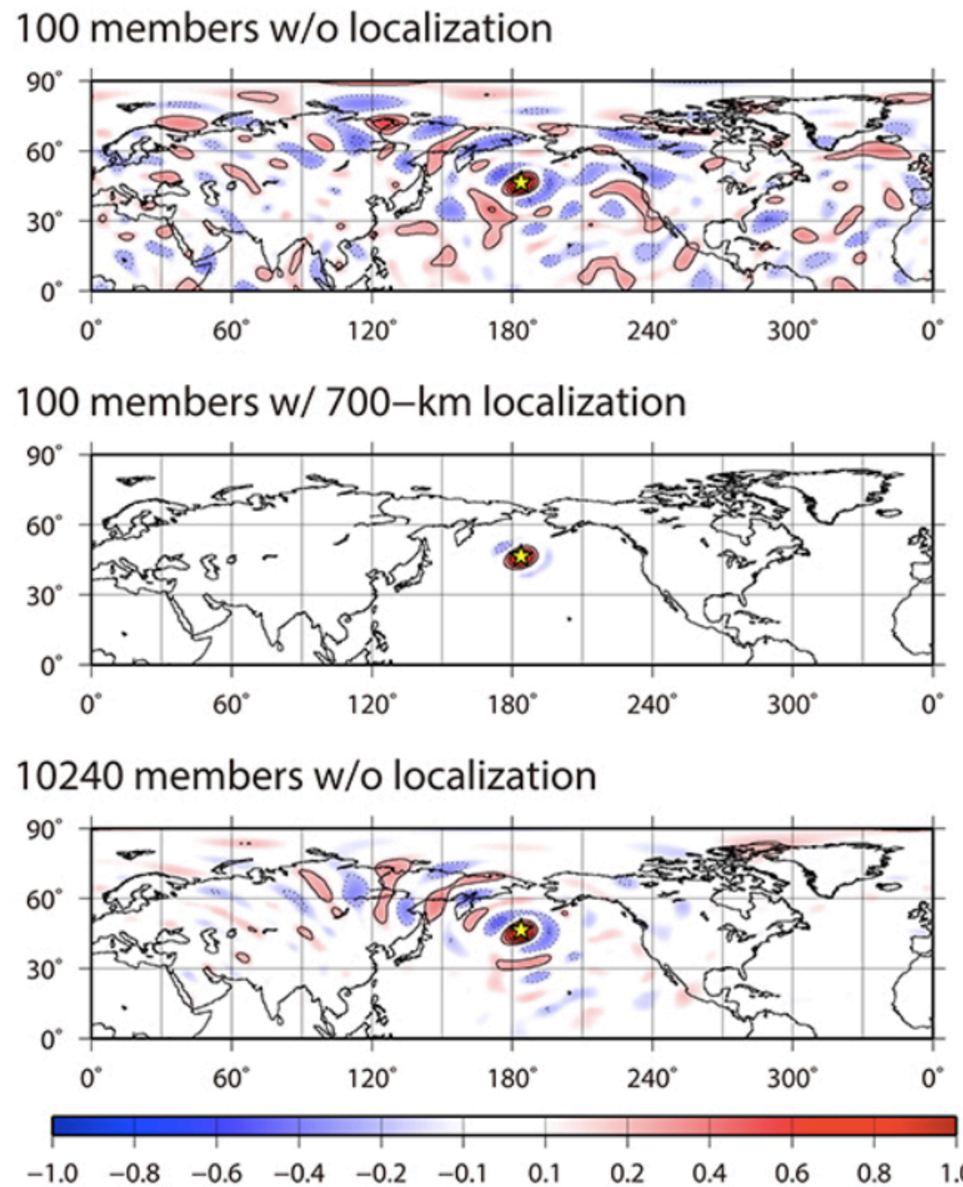
- Spectral localization (e.g., Buehner and Charron, 2007)
  - Assumes that the correlations in spectral space decreases as the absolute difference in wave number between pairs of spectral components increases.

- Variable localization (e.g., Kang et al., 2011)
  - Zeroing out the background error covariance between physically unrelated variables.

- Etc.

Treatments for Sampling Error
---Increasing ensemble size

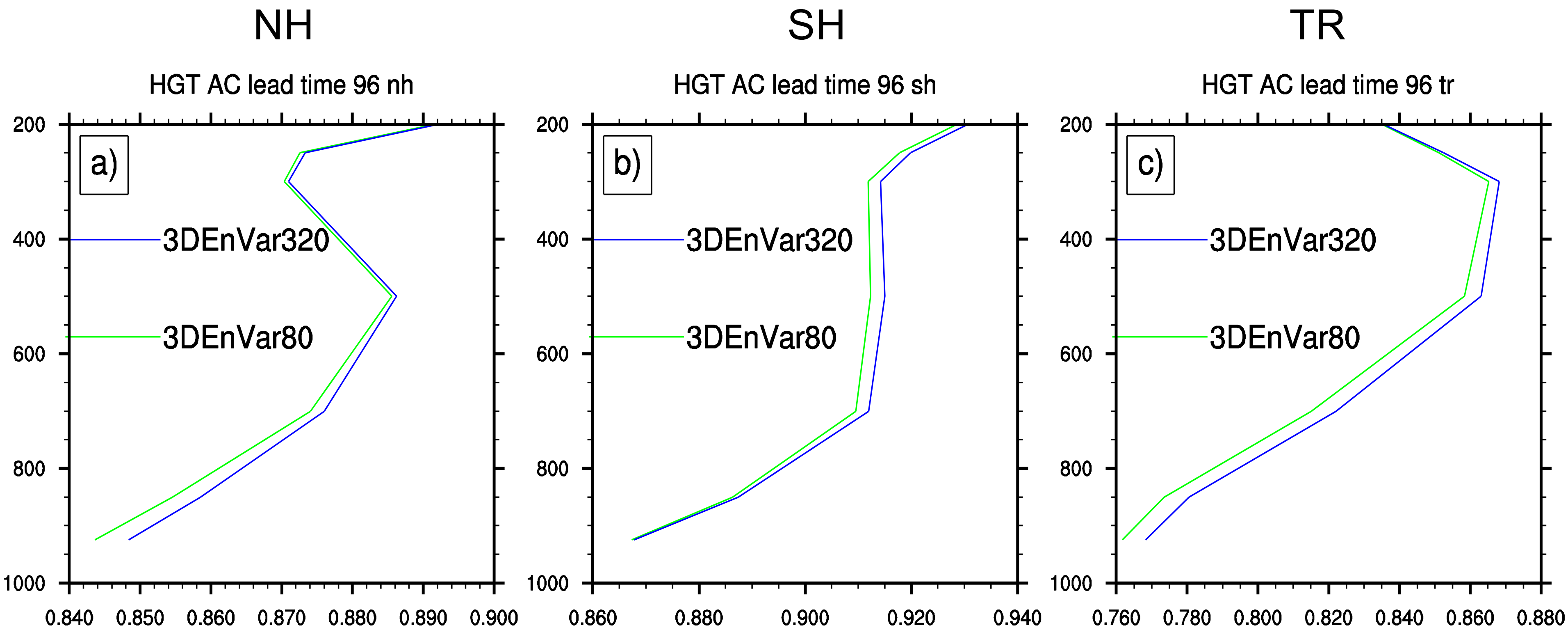
- Large-sized ensemble reveals long-range error covariance at the continental scales, while localization will remove this signal.
- Extremely expensive computations are required.



Miyoshi et al, 2014

Impact of Increasing Ensemble Size in GFS Hybrid 3DEnVar System

- Hybrid 3DEnVar in GFS was further improved by directly increasing the original 80 members to 320 members (Lei and Wang, 2016). Similar is found for 4DEnVar (Lei and Whitaker talk).



Motivation

- Aside from increasing ensemble members directly, is there a cheaper way to increase the ensemble size while still improving the analysis and forecast?

- GFS has ensemble forecasts freely available. Would increasing the ensemble size by using the lagged ensemble help? How to optimally use the lagged ensemble? To what extent it would help?

System Development

--- Baseline 4DEnVar System

- GSI based 4DEnVar is a direct extension of GSI based 3DEnVar by including the time dimension (Wang et al. 2013; Wang and Lei 2014; Kleist and Ide, 2015).

- Avoid the tangent linear model and its adjoint in 4DVar.

Add time dimension in 4DEnsVar

$$J(\mathbf{x}_1', \boldsymbol{\alpha}) = \beta_1 J_1 + \beta_2 J_e + J_o$$

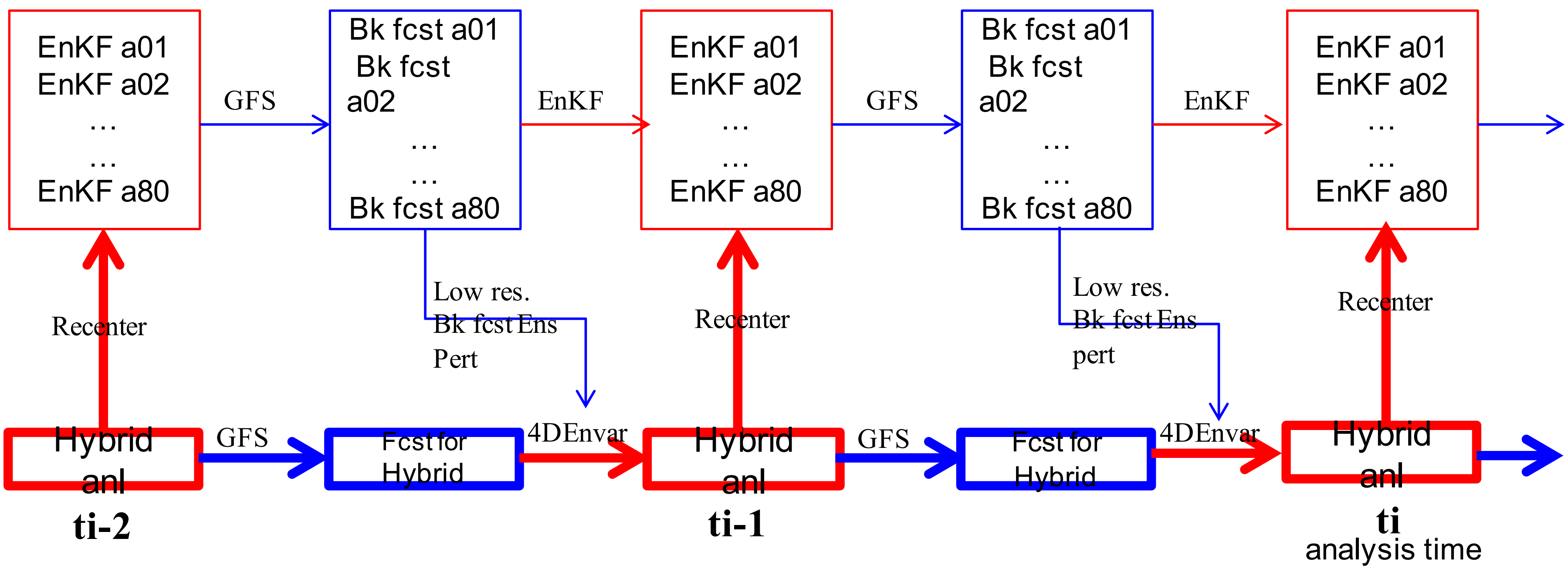
$$= \beta_1 \frac{1}{2} \mathbf{x}_1'^{T} \mathbf{B}_{static}^{-1} \mathbf{x}_1' + \beta_2 \frac{1}{2} \boldsymbol{\alpha}^T \mathbf{C}^{-1} \boldsymbol{\alpha} + \boxed{\frac{1}{2} \sum_{t=1}^{T} (y_t^{o\prime} - \mathrm{H}_t \mathbf{x}_t)^{\mathrm{T}} \mathrm{R}_t^{-1} (y_t^{o\prime} - \mathrm{H}_t \mathbf{x}_t)}$$

$$\mathbf{x}_t' = \mathbf{x}_1' + \boxed{\sum_{k=1}^{K} \left(\boldsymbol{\alpha}_k \circ (\mathbf{x}_k^e)_t \right)}$$

$\mathbf{B}$ stat 3DVAR static covariance; $\mathbf{R}$ observation error covariance; K ensemble size;
$\mathbf{C}$ correlation matrix for ensemble covariance localization; $\mathbf{x}_k^e$ kth ensemble perturbation;
$\mathbf{x}_1'$ 3DVAR increment; $\mathbf{x}'$ total (hybrid) increment; $\mathbf{y}^{o\prime}$ innovation vector;
$\mathbf{H}$ linearized observation operator; β_1 weighting coefficient for static covariance;
β_2 weighting coefficient for ensemble covariance; $\boldsymbol{\alpha}$ extended control variable. 7

System Development
--- 4DEnVar System with Lagged Ensemble

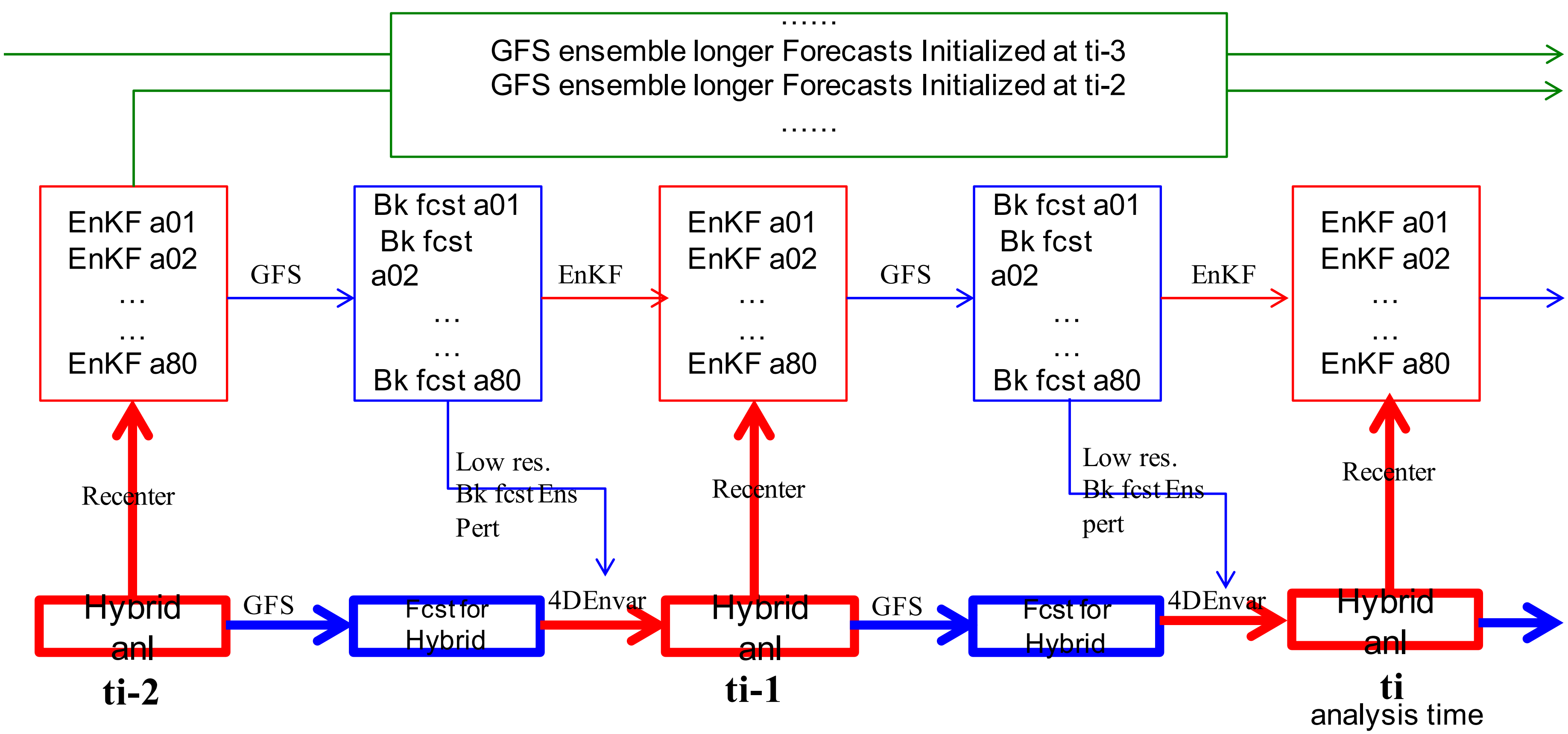
- Baseline 4DEnVar system with the use of 80-member forecasts.



System Development

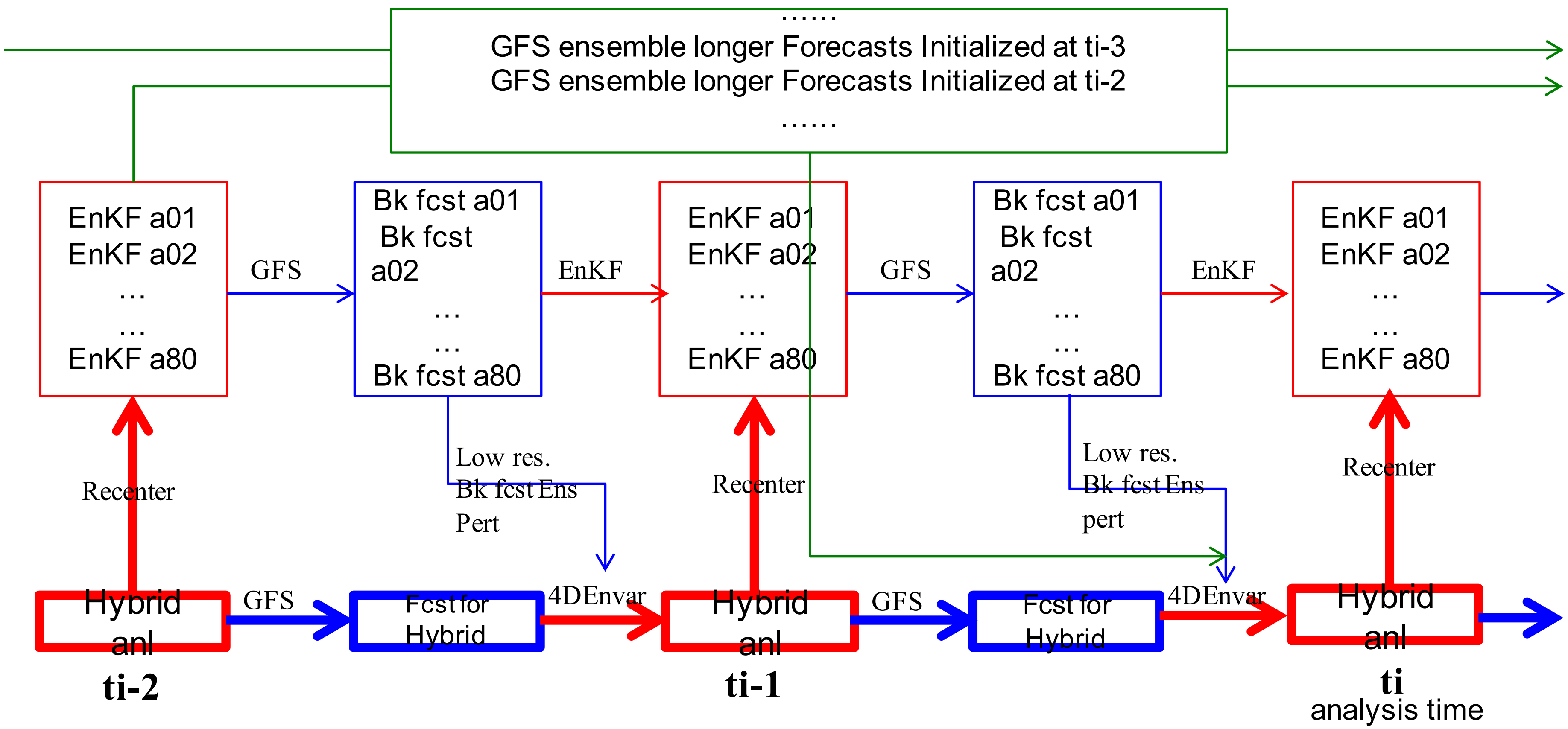
--- 4DEnVar System with Lagged Ensemble

- Generate the lagged ensemble forecasts



System Development
--- 4DEnVar System with Lagged Ensemble

- Combine the lagged ensemble forecasts with the regular 80-member forecasts for the 4DEnVar update.



Experiment Design

--- How to Ingest the Lagged Ensemble to 4DEnVar System

- Ensemble perturbation in each lagged group will be first calculated as the deviation from the mean of that group before being ingested to 4DEnVar update.

- Initial effort uses the simplest equal weighting
  - Give the same weight to the lagged ensemble perturbation at different leading time as the regular 80-member perturbation.

- Scaling, skill weighting, scale-dependent weighting would be needed (ongoing work).

Experiment Design

--- Lagged Experiment Design

Experiments	Ensemble members
ens80	Use 80-member 3/6/9-hour forecasts initialized at ti-1 (ti: the analysis time)
lag320	Same as ens80 but the use of equal weighting method to ingest additional 240 lagged members from: GFS 80-mem 9/12/15-hour forecast initialized at ti-2 GFS 80-mem 15/18/21-hour forecast initialized at ti-3 GFS 80-mem 21/24/27-hour forecast initialized at ti-4

Experiment Design

--- ens80 vs lag320 in Computational Cost

Ensemble Forecast

EnKF (EnSRF)

Control Forecast

Control 4DEnVar update

Experiment Design

--- ens80 vs lag320 in Computational Cost

Ensemble Forecast

EnKF (EnSRF)

Control Forecast

Control 4DEnVar update

- ens80: control 9-hour forecast
- lag320: control 9-hour forecast

Experiment Design

--- ens80 vs lag320 in Computational Cost

Ensemble Forecast

EnKF (EnSRF)

Control Forecast

Control 4DEnVar update

- ens80: control 9-hour forecast
- lag320: control 9-hour forecast

- ens80: 80-mem for 4DEnVar
- lag320: 320-mem for 4DEnVar

Experiment Design

--- ens80 vs lag320 in Computational Cost

- ens80: 80-mem 9-hour forecast
- lag320: 80-mem 27-hour forecast

Ensemble Forecast

EnKF (EnSRF)

Control Forecast

Control 4DEnVar update

- ens80: control 9-hour forecast
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- ens80: 80-mem for 4DEnVar
- lag320: 320-mem for 4DEnVar

Experiment Design

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Ensemble Forecast

EnKF (EnSRF)

- ens80 : 80-mem EnKF update
- lag320: 80-mem EnKF update

Control Forecast

- ens80: control 9-hour forecast
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Control 4DEnVar update

- ens80: 80-mem for 4DEnVar
- lag320: 320-mem for 4DEnVar

Experiment Design

--- ens80 vs lag320 in Computational Cost

- ens80: 80-mem 9-hour forecast
- lag320: 80-mem 27-hour forecast

- ens80 : 80-mem EnKF update
- lag320: 80-mem EnKF update

- Lag320,
  - almost double cost of ens80;
  - but about half of the cost by directly increasing ensemble size to 320.

- ens80: control 9-hour forecast
- lag320: control 9-hour forecast

- ens80: 80-mem for 4DEnVar
- lag320: 320-mem for 4DEnVar

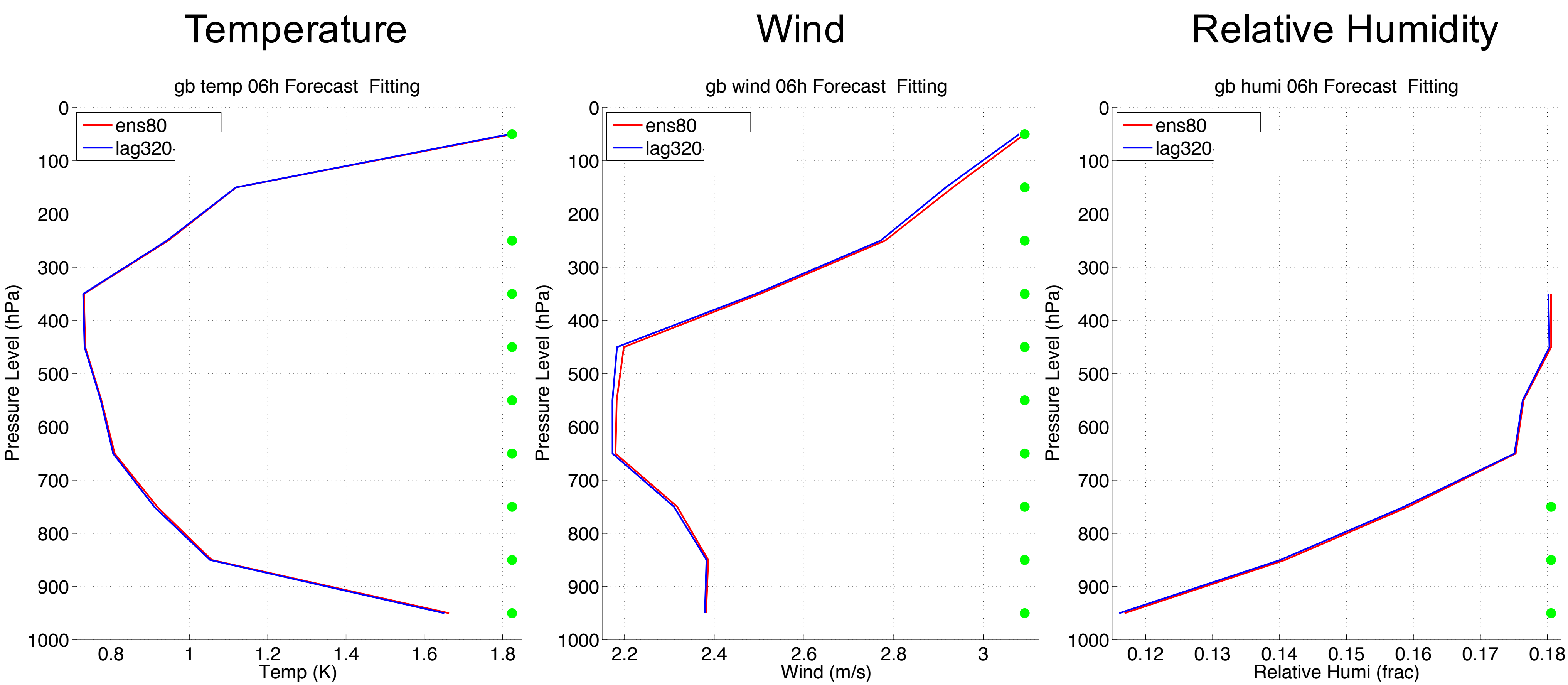
Experiment Design

--- Experiment Settings for ens80

- T670/T254 GFS model.
- 6-hourly assimilation of all operational conventional and satellite data.
- 12.5% weight on the static background error covariance and 87.5% weight on the ensemble covariance.
- Three-hourly ensemble perturbations.
- Level-dependent localization length scales.
- Multiplicative inflation with a relaxation coefficient 0.85 (Whitaker and Hamill 2012) and stochastic parameterizations (Palmer et al. 2009) for the spread issue.
- A four-dimensional incremental analysis update (4DIAU) for the imbalance issue. (Bloom et al., 1996; Lorenc et al., 2015; Lei and Whitaker, 2016)
- One-month (August 2013) cycling experiments for 6-hour global forecast verification.

Preliminary Results

--- 6-hour Forecast Fitting to In-situ Obs.



- lag320 6-h forecast shows a closer fitting than ens80, especially for the wind (green dots indicate the difference is significant at 90% confidence level).

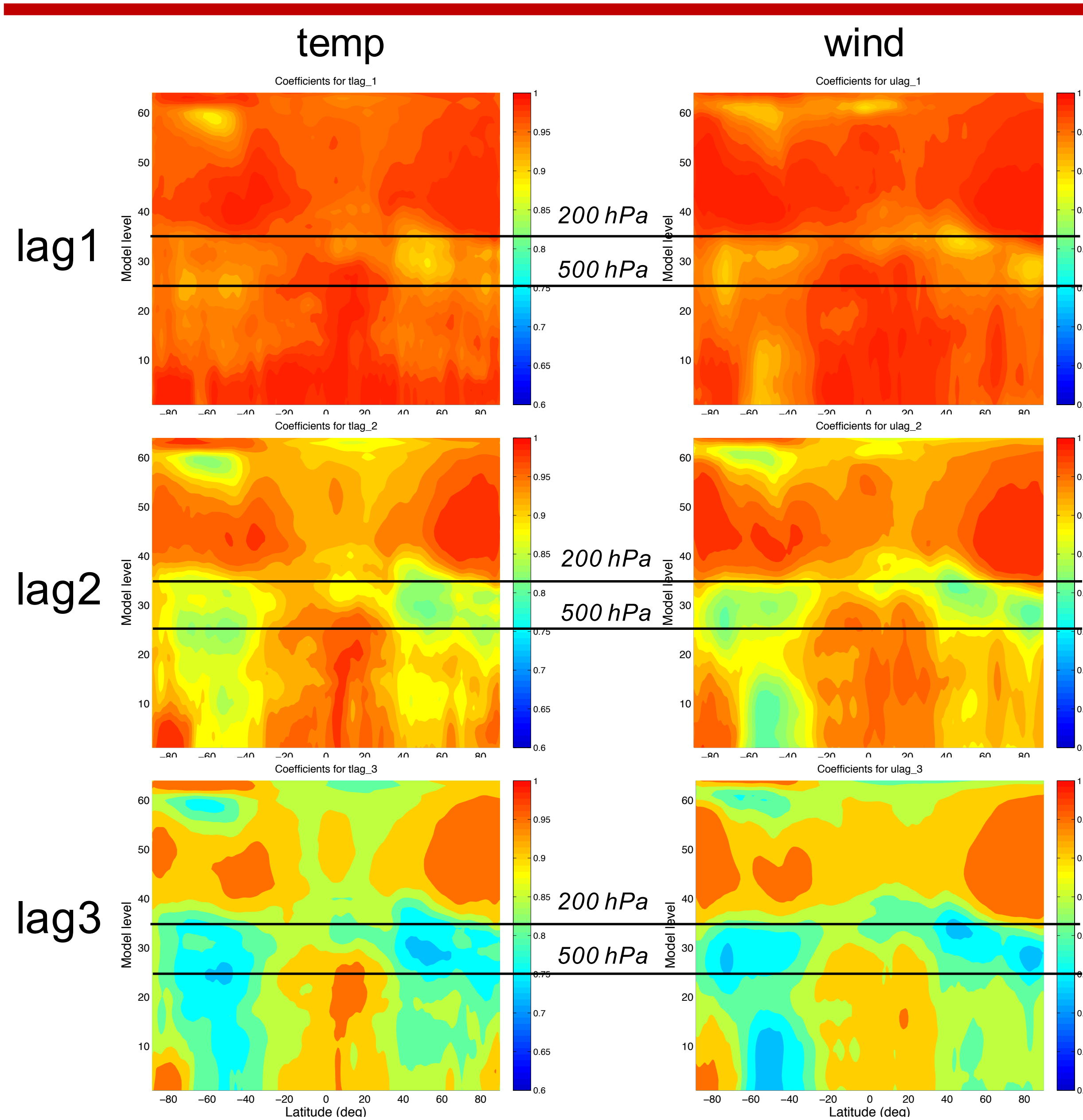
Ongoing Work
--- Skill Weighting Method

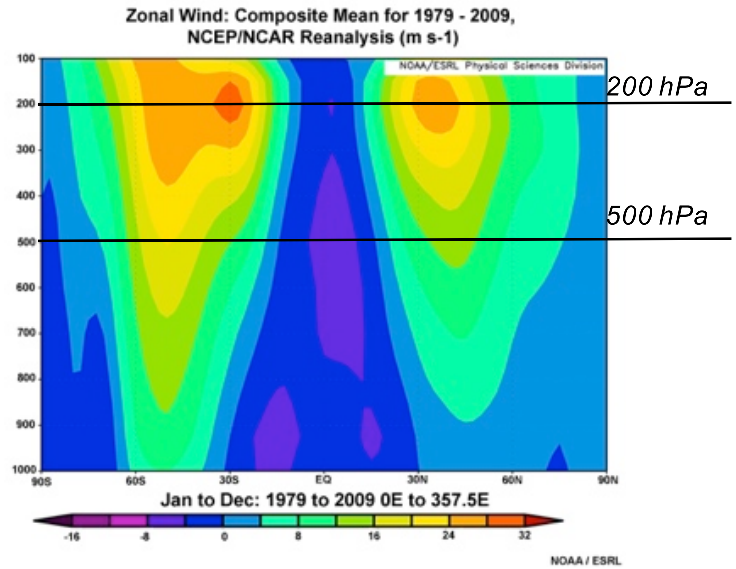
- Given that the older forecast may not represent the error as well as the newer forecast, weight the lagged ensemble forecasts based on different leading times.
  - To scale the ensemble perturbation in each lagged group.
  - 2D scaling coefficients will be calculated at different latitudes and model levels by comparing the spread from the regular non-lagged 80 members and each lagged group. For i^{th} lagged group,

$$SC(i) = \frac{Spread\_ens80}{Spread\_lag(i)}$$

Ongoing Work

--- 2D Scaling Coefficients for lag320 from One-month Average





Adapted from http://www.goes-r.gov/users/comet/tropical/textbook_2nd_edition/media/graphics/zonal_wind_xsect_1979_2009.jpg

- The smaller coefficients, the larger spread of the lagged group compared with the regular non-lagged 80-member ensemble.
- The minimum of coefficients corresponds to the maximum of zonal wind (upper-level jet regions), where is dynamically unstable and of larger uncertainty.

Summary

- 4DEnVar system with lagged ensemble was developed and experiment of increasing the ensemble size to 320 (lag320) was first attempted and compared with the baseline ens80.

- Preliminary results show that
  - Lag320 performs better than ens80 in terms of the 6-h global forecast verification.
  - The improvement for the wind forecast is larger than temperature and relative humidity forecast at 6-h lead time.

Future Work

- Evaluating longer forecasts.
- To minimize the computational cost, fully freely-available GEFS 20-member forecasts will be tested to provide the lagged ensemble.
- Run cycling experiments by directly increasing the ensemble size to 320 (ens320) to evaluate the tradeoff between the relative improvement and the cost saving in lag320 experiments compared to ens320.
- Implement scaling and skill weighting for different lags.
- Implement scale-dependent weighting on high resolution lagged ensemble (from control forecasts) and low resolution lagged ensemble.

Thanks for your attention !