Inter-Comparison between ETR and EnKF using NCEP GFS Model

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Experimental Design

Experiments:

- (a) id → x, NCO parallel, NCEP GSI analysis, ETR perturbations, scores are based on GSI analysis.
- (b) id → r, EnKF ensemble mean as analysis, ETR perturbations, scores are based on EnKF analysis.
- (c) id → k, EnKF ensemble mean as analysis, EnKF perturbations, scores are based on EnKF analysis.
- if r is better (worse) than k, ETR perts are better (worse) than EnKF perts.
- if r is better (worse) than x, EnKF analysis is better (worse) than GSI analysis.

Ensemble Methods: (a) ETR (Ensemble Transform with Rescaling): Operational at NOAA/NCEP since May 30, 2006 (Wei *et al.* 2005, 2008). (b) EnKF (Ensemble Kalman Filter): Running an ensemble Kalman filter with each member being updated by assimilating NCEP operational observations. Forward observational operator from GSI is used. (Whitaker and Hamill 2002, Whitaker *et al.* 2008).

Test Period: 00Z Dec. 8, 2009 ---- 18Z Feb. 7, 2010.

Verification Period: 00Z Dec. 11, 2009 ---- 00Z Jan. 22, 2010.

Model and Resolution: GFS, T190L28.

Ensemble Size: 20.





Forecast days

Southern Hemisphere 500hPa Height Ensemble Mean Anomaly Correlation Average For 20091211 - 20100122



Ensemble Mean Anomaly Correlation

AC values are similar in NH and SH for shorter lead time, ETR is better for day 5-9, EnKF is better in the tropics. Results for Z1000 are very similar







NA: RMS, Spread and CRPSS

EnKF: RMSE is slightly larger, initial spread is notably larger than ETR, grows slower than ETR.

AC: similar, ETR better for lead time day 8-11. CRPSS: similar, ETR better for lead time day 8-11

Europe: ETR is better (not shown) Asia: EnKF is better (not shown)





Probabilistic Score: CRPSS

10 meter wind (v)



Skill Scores



V10m : EnKF is slightly better for short lead time, particularly in the tropics, similar for median lead time.

This is also true for u10m, t2m, u850, v850, u200,v200

Northern Hemisphere 850hPa Height Wind(U) Ensemble Mean RMSE and Ensemble SPREAD Average For 20091211 - 20100122



Forecast days

850hPa Wind (u) Northern Hemisphere 850hPa Height Wind(U) Ensemble Mean Anomaly Correlation Average For 20091211 - 20100122 0.9 0.8 0.0 Correlation Anomaly 0.3 Northern Hemisphere 0.2 Anomaly Correlation +--+ E20r 0.1 ⊶ F20k 10 11 12 13 14 15 ČΔ Forecast days

> EnKF RMSE is slightly smaller for short lead time, slightly larger in median range, EnKF initial spread is much larger than ETR, grows much slower than ETR.

AC: similar, ETR better for lead time days 8-11. CRPSS: EnKF better for short lead time.



Tropical 850hPa Height Wind(U) Ensemble Mean Anomaly Correlation Average For 20091211 - 20100122 0.9 0.8 0. **Tropics** 0.2 Anomaly Correlation +--+ E20r 0.1 ⊶ E20k 10 11 12 8 13 14 15 5 Forecast days

EnKF RMSE is smaller for all lead time, EnKF initial spread is much larger than ETR, grows much slower than ETR.

AC: similar, EnKF slightly better for larger lead time. CRPSS: EnKF better.

Ensemble Precipitation for CONUS



CRPS (Black): smaller-better Reli (Red): smaller-better

ETR is slightly better

RMSE (black): EnKF is slightly smaller for short lead time, Spread (green): EnKF initial spread is larger. ETR grows faster. CRPS (blue): similar

Ensemble Mean Precipitation for CONUS



ETS (Equitable Threat Score) and True Skill Score (TSS): ETR is clearly better for smaller threshold, as the threshold increases, the ETR advantage diminishes.

Amplification of Ensemble Perturbations

850hPa temperature

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Top panel: solid line indicates the mean amplification factor of 20 perturbations from each ensemble. dotted line: all 20 ensemble perturbations are optimally combined such that the combined perturbation has the mathematically largest growth rate.

Amplification factor (AF) for t850: ETR perturbations much grow faster than EnKFs in GL and NH

Amplification of Ensemble Perturbations

850hPa temperature



AF for t850: ETR perts grow faster than EnKF in SH. Over the tropics, individual perts of ETR grow faster, EnKF perts decay in the first 48 hours. But the optimally combined pert from EnKF has higher AF. AF for z500 (not shown): ETR perts grow faster than EnKF in all four domains.

PECA (Pert versus error correlation analysis)



Thin line: mean correlation between each pert and the forecast error; thick line: all 20 ensemble perts are optimally combined in such a way so that the combined pert has the mathematically largest correlation with the forecast error.

ETR and EnKF have similar PECA values in GL,NH and NA, ETR has slightly higher value over SH, but lower in the tropics, slightly lower in India.

Ensemble variance versus forecast error variance



Ensemble variance versus forecast error variance: shows how well the forecast error variance can be explained by ensemble variance.

T850: ETR is slightly better for smaller variance, but worse for large variance over GL, NH and Europe. ETR is better over SH, TR and NA for all ranges.

ETR is better over almost all regions for u200, v200, u850, v850, z500 and z1000 (not shown). Number of bins=150 (GL), 130 (NH), 130(SH), 120(TR), 80(NA), 80 (EU).

Tropic Cyclone Tracks **Tropic**

Tropic Cyclone: Laurence



ETR

EnKF

Tropic Cyclone Laurence started 2009121012, similar overall, ETR is slightly better.

Tropic Cyclone Tracks

Tropic Cyclone: Oli



NCEP Hurricane Forecast Project

ETR

EnKF

Tropic Cyclone Oli started 2010013100, similar overall, EnKF is slightly better.

GSI and EnKF, RMSE and Spread

500hPa height





Southern Hemisphere 500hPa Height Ensemble Mean RMSE and Ensemble SPREAD Average For 20091211 — 20100122



Z500: GSI and EnKF are similar overall, RMSE of GSI is slightly smaller for short lead time, slightly larger for longer lead time over NH and SH. Over TR, GSI is smaller.

Spread is same, both use ETR perts.

Z1000: similar results as Z500

GSI and EnKF, Ensemble Mean Anomaly Correlation

500hPa height



0.3

0.2

0.1

٥

+--+ E20x

⊶ E20r

2

3

4

TR

8 9 10 11 12 13 14 15

Enrecast days

16



Z500: EnKF is better only for large lead time in NH. GSI is slightly better in SH and clearly better in TR.

- (1). RMSE: Z500, similar for ETR and EnKF, EnKF initial spread is notably larger than ETR. This results in better probabilistic scores of EnKF for short lead time. ETR spread grows faster than EnKF. Similar results are found for other variables.
- (2). Anomaly Correlation: for Z500 AC values are similar in NH and SH, EnKF is better than in the tropics. Results for Z1000 are similar.

v10m: AC values for ETR are slightly higher in NH and SH, EnKF is slightly better than in the tropics. Results are similar for u10m, t850, u200, v200.

(3). CRPS: Z500, ETR and EnKF are similar over NH and SH, EnKF is better for short lead time and ETR is better for median lead time over the tropics. This conclusion holds for Z1000.

For V10m: EnKF is slightly better for short lead time, particularly in the tropics, similar for median lead time. This is also true for u10m, t2m, u850, v850, u200, v200

(4). ROC (not show): Z500, EnKF is better for short lead time. ETR is better for median range lead time.

It is true for Z1000.

For V10m: EnKF is better for short lead time, ETR is better for median range lead time This is also true for u10m, u850, v850, u200 v200.

For t2m: EnKF is better for short lead time, similar for median range lead time.

- (5). PECA: ETR and EnKF have similar PECA values in GL and NH, NA, ETR has slightly higher value over SH, but lower in the tropics and slightly lower in India.
- (6). Amplification factor: ETR perturbations grow much faster for almost all regions and all variables.
- (7). Ensemble variance versus forecast error variance: ETR is better for most cases and most variables.
- (8). Tropic Cyclone Tracks: either ETR or EnKF is better in a few cases.
- (9). Precipitation for CONUS: ETR is slightly better in Reliability RMSE: EnKF is slightly smaller for short lead time Spread: EnKF initial spread is larger. ETR grows faster. CRPS: similar ETS (Equitable Threat Score) and True Skill Score (TSS): ETR is clearly better for smaller threshold, as the threshold increases, the ETR advantage is diminishes.

(10). Computing time: not tested, EnKF is expected to cost more.

- (11). GSI and EnKF: RMSE, Z500, GSI and EnKF are similar overall, GSI is slightly smaller for short lead time, slightly larger for longer lead time over NH and SH. Over TR, GSI is smaller. Spread is same, both use ETR perts. Similar results are found for Z1000.
- (12). GSI and EnKF: Anomaly Correlation, Z500: EnKF is better than GSI only for large lead time in NH. GSI is slightly better in SH and clearly better in TR.

More results:

ETR perturbations (r) compared with EnKF perturbations (k) http://www.emc.ncep.noaa.gov/gmb/wd20mw/html/ETR_EnKF_win0910.html GSI analysis (x) compared with EnKF analysis (r): http://www.emc.ncep.noaa.gov/gmb/wd20mw/html/GSI_EnKF_win0910.html All three experiments on one figure (the same results from above two websites): http://www.emc.ncep.noaa.gov/gmb/wd20mw/html/ETR_EnKF_GSI_win0910.html ETR (r) compared with EnKF (k) for winds at 200hPa and 850hPa: http://www.emc.ncep.noaa.gov/gmb/wd20mw/html/ETR_EnKF_200uv_win0910.html Precipitation scores: http://www.emc.ncep.noaa.gov/gmb/wd20mw/enkf/ETR_EnKF_prcp/ Amplification factors: http://www.emc.ncep.noaa.gov/gmb/wd20mw/enkf/amplification/ PECA (Pert versus error correlation analysis) scores: http://www.emc.ncep.noaa.gov/gmb/wd20mw/enkf/peca/ Forecast error variance explained by ensemble variance: http://www.emc.ncep.noaa.gov/gmb/wd20mw/enkf/explained_variance/

Background Slides

Northern Hemisphere 10 Meter Wind(V) Ensemble Mean Anomaly Correlation Average For 20091211 - 20100122 **10-meter wind (v)**

Southern Hemisphere 10 Meter Wind(V) Ensemble Mean Anomaly Correlation Average For 20091211 - 20100122





Ensemble Mean Anomaly Correlation

v10m: AC values for ETR are slightly higher in NH and SH,

EnKF is slightly better than in the tropics. Results are similar for u10m, t850, u200, v200.



Probabilistic Score: ROC



Continuous Rank Probability Score



from Yuejian Zhu³⁰



from Yuejian Zhu³¹

$$\overline{CRPS} = \sum_{i=0}^{N} \left[\overline{\alpha}_{i} p_{i}^{2} + \overline{\beta}_{i} (1 - p_{i})^{2}\right]$$



from Yuejian Zhu³²

$$\overline{CRPS} = \sum_{i=0}^{N} \left[\overline{\alpha}_{i} p_{i}^{2} + \overline{\beta}_{i} (1 - p_{i})^{2}\right]$$



from Yuejian Zhu ³³



from Yuejian Zhu ³⁴

Relative Operating Characteristics area (ROC area)



Prob. Evaluation (cost-loss analysis)

Based on hit rate (HR) and false alarm (FA) rate.

1. Relative Operating Characteristics (ROC) area - Appl. of signal

detection theory for measuring discrimination between two alternative outcome.

ROCarea = Intergrated area *2 (0-1 normality)



FALSE ALARM RATE

ROC (Relative Operating Characteristics) curve for a 10-member T62 ensemble of forecasts and for T126 and T62 control forecasts for the 500 hPa height, **NH extratropics**, March-May 1997. The closer a curve is to the upper left hand comer, the more ability the forecasting system has in delineating between cases when a certain event (in this case, the occurence of one of 10 climatologically equally likely bins) did or did not occur.

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from Yuejian Zhu

Category Forecast: Precipitation Evaluation

1. Frequency Bias (FBI)

$$FBI = \frac{(h+f)}{(h+m)}$$

2. ETS (equitable threat score)

$$ETS = \frac{h - R}{h + f + m - R}$$

	OBS (Yes)	OBS (No)
FCST	Hit	False alarm
(Yes)	(h)	(f)
FCST	Miss	Correct Reject
(No)	(m)	(c)

where
$$R = \frac{(h+f)\cdot(f+m)}{(h+f+m+c)}$$

is randomly forecasting rate

3. TSS (true skill statistic or Hanssen-Kuipers discriminant)

$$TSS = \frac{h \cdot c - f \cdot m}{(h+m) \cdot (f+c)} = \frac{h}{h+m} - \frac{f}{f+c}$$

from Yuejian Zhu³⁷

PECA (Perturbation vs. Error Correlation Analysis, Wei and Toth 2003)

- **Goal:** design an additional ensemble verification tool to measure performance of ensemble systems that
- (a) are less sensitive to errors in analysis (and model).
- (b) evaluates the degree of independency of ensemble members.
- (c) measures how much forecast error can be explained by individual or optimally combined perturbations
- (d) reflects more on the quality of ensemble method.
- (e) higher PECA \rightarrow more skillful ensemble.

Ensemble perturbations and forecast error:

$$\mathbf{p}_{i}(t) = \mathbf{f}_{i}(t) - \bar{\mathbf{f}}(t) \qquad \mathbf{e}(t) = \bar{\mathbf{f}}(t) - \mathbf{f}_{analysis}(t)$$

 $i=1,2,...K, \quad \bar{f}$ is ensemblemean

Obtain α_i by solving the least-square problem:

 $Min \parallel \mathbf{e} - \sum_{i=1}^{K} \alpha_i \mathbf{p}_i \parallel_{L2}$

The optimally combined perturbation is defined as:

$$\mathbf{p}_{optimal} = \sum_{i=1}^{K} \alpha_i \mathbf{p}_i$$

PECA: correlation between forecast error and individual perturbations/optimally combined perturbation 38

Forecast error variance explained by ensemble variance

(Majumdar et al. 2001, 2002, Wei et al. 2006)

Goal: measures the range of forecast error variance explained by the ensemble variance for different variables and different domains.

- Step 1: choose a variable for a particular domain.
- Step 2: compute ensemble variance and squared forecast error at each grid point over this domain for a particular forecast lead time (6 hours or 12 hours).
- step 3: draw a scatter plot using ensemble variance (abscissa) and squared forecast errors for all grid points.
- step 4: divide the points into N equally populated bins in order of increasing ensemble variance.
- step 5: ensemble variance and squared forecast errors are averaged within each bin.
- step 6: draw a curve connecting the averaged value from each bin.

A better ensemble should explain larger range of forecast error variance. Thus the ensemble with steeper curve is considered better.

Goal: measures the growth rate of the individual perturbations and maximum growth rate of the optimally combined perturbation.

AF of individual perturbations:

$$AF_{i}(t) = \frac{\|\mathbf{p}_{i}(t)\|_{L2}}{\|\mathbf{p}_{i}(0)\|_{L2}}$$

i=1,2,....K, t--> forecastlead time

Max AF of the optimally perturbations:

$$AF_{\max}(t) = \max[\frac{\langle \mathbf{Z}^{f}\mathbf{e}, \ \mathbf{Z}^{f}\mathbf{e} \rangle}{\langle \mathbf{Z}^{a}\mathbf{e}, \ \mathbf{Z}^{a}\mathbf{e} \rangle}]$$

- $\mathbf{Z}^{f} = [\mathbf{p}_{1}^{f}, \mathbf{p}_{2}^{f}, \dots, \mathbf{p}_{k}^{f}]$ $\mathbf{Z}^{a} = [\mathbf{p}_{1}^{a}, \mathbf{p}_{2}^{a}, \dots, \mathbf{p}_{k}^{a}]$ $\mathbf{e}^{T} = (e_{1}, e_{2}, \dots, e_{K})$
- ← Matrix formed by forecast perturbations
- \leftarrow Matrix formed by initial perturbations
- ← Coefficients assigned to different perturbations, obtained by solving above maximization problem.