# Sensitivity of Analysis and Forecast RMSE to ETKF Observation Filtering in the GSI/ETKF Regional Hybrid
## (See Mizzi et al., 2011 for a discussion of the experimental design)

**Arthur P. Mizzi**
mizzi@ucar.edu
303-497-8987

**NCAR Earth System Laboratory**
**Mesoscale and Microscale Meteorology Division**
**Boulder, CO 80307**

## INTRODUCTION:

In the GSI/ETKF regional hybrid, the ETKF creates ensemble spread to represent the forecast distribution resulting from observation uncertainty with the goal of increasing the ensemble mean forecast accuracy. However, the disparity between the ensemble size (relatively small) and the number of observations entering the ETKF (relatively large) causes the ETKF to misrepresent the ensemble spread. (We refer to the number of observations entering the ETKF as the "ETKF observations.")

In the ETKF, inflation factors are commonly used to account for that disparity and correct the estimate of the ensemble spread. The efficacy of the inflation factor algorithm depends on the correlation between the innovations and the observation errors. If positively correlated, the algorithm works properly. Otherwise, it is problematic because the contribution from terms involving the ratio of relatively small innovations and large observation errors can make the inflation factor negative. That problem is sometimes addressed by excluding ETKF observations with unreasonably large error estimates.

This paper investigates the sensitivity of analysis and forecast RMSE to changes in the error characteristics of the ETKF observations. We study the effect of truncating the lower end of the error distribution by excluding relative errors that fall below a specified cutoff. We define relative error as the observation error divided by the observation.

For the experiments discussed herein: (i) the inflation factor algorithm is from Wang et al., 2007, (ii) N=20, ß=0.5, H=1,500 km, V=20 grid points, (iii) all conventional observations are used for the GSI/ETKF regional hybrid, (iv) only radiosonde observations are used for the ETKF, (v) verification is against radiosonde u, v, t, q, and surface synoptic observations, (vi) the maximum relative ETKF observation error is set to 20, and (vii) the minimum relative ETKF observation error varies with the experiment and was set to .0001 in WG07 (the control experiment).

## PRELIMINARY QUESTIONS:

1. Does reducing the number of ETKF observations affect the RMSE?

Table 1 shows RMSE for analyses (inside parentheses) and forecasts (inside parentheses) from: (i) WG07, where the number of ETKF observations ranged between O(15,000) at 00Z and O(17,000) at 12Z, and (ii) experiments where the number of ETKF observations was limited to 2,500 in R2.5, 5,000 in R5.0, 7,500 in R7.5, and 10,000 in R10. The yellow highlighting indicates the cell with the lowest forecast RMSE. For R2.5 to R10, the ETKF observations were randomly selected from those used in WG07. Table 1 shows that RMSE decreased as number of ETKF observations decreased to an optimal number. The optimal number ranged between 5,000 and 7,500 observations depending on the meteorological variable.

| UPR | R2.5 | R5.0 | R7.5 | R10 | WG07 |
|---|---|---|---|---|---|
| u (m/s) | 3.234 (2.323) | 3.232 (2.326) | 3.230 (2.325) | 3.240 (2.324) | 3.232 (2.327) |
| v (m/s) | 3.250 (2.363) | 3.249 (2.364) | 3.251 (2.365) | 3.254 (2.362) | 3.257 (2.369) |
| T (K) | 1.487 (1.210) | 1.484 (1.208) | 1.485 (1.207) | 1.485 (1.211) | 1.491 (1.211) |
| q (g/kg) | 1.297 (0.867) | 1.298 (0.872) | 1.299 (0.866) | 1.302 (0.869) | 1.305 (0.870) |

Table 1. Temporally and vertically averaged analysis and forecast RMSE for WG07 and the R ( ) experiments.

2. Does filtering the ETKF observations based on the relative observation error affect the RMSE scores?

Table 2 shows RMSE for analyses (inside parentheses) and forecasts (outside parentheses) from: (i) WG07, and (ii) experiments where the minimum relative observation error was set to 1.0 in E1p, 0.1 in Ep1, 0.01 in Ep01 and 0.001 in Ep001. Table 2 shows that the optimal minimum relative observation error cutoff is 0.01. Table 1 suggests that the improvement in Table 2 may to due to a reduction in the number of ETKF observations as the relative error cutoff increases. However, comparison of RMSE between the tables shows that Table 2 has lower magnitudes suggesting that some of the improvement may be due to filtering the ETKF observations.

| UPR | E1.p | Ep1 | Ep01 | Ep001 | WG07 |
|---|---|---|---|---|---|
| u (m/s) | 3.225 (2.323) | 3.222 (2.323) | 3.221 (2.320) | 3.232 (2.322) | 3.232 (2.327) |
| v (m/s) | 3.268 (2.375) | 3.252 (2.370) | 3.246 (2.365) | 3.253 (2.368) | 3.257 (2.369) |
| T (K) | 1.477 (1.200) | 1.478 (1.205) | 1.476 (1.202) | 1.489 (1.209) | 1.491 (1.211) |
| q (g/kg) | 1.307 (0.868) | 1.302 (0.866) | 1.300 (0.869) | 1.303 (0.867) | 1.305 (0.870) |

Table 2. Temporally and vertically averaged forecast and analysis RMSE for WG07 and the E ( ) experiments.

## EFFECT OF FILTERING ON INFLATION, SPREAD, AND SPREAD VERIFICATION:

Figure 1 (left panel) shows the affect of varying the minimum relative observation error cutoff on the ETKF inflation factor. As the relative error cutoff increases, the inflation factors decrease. Figure 1 (left panel) also shows a bi-cycle oscillation in the inflation factor. Figure 1 (right panel) shows that the oscillation in the left panel is due to variations in the number of ETKF observation and that the oscillation can be controlled by keeping the number of ETKF observations constant between cycle times.

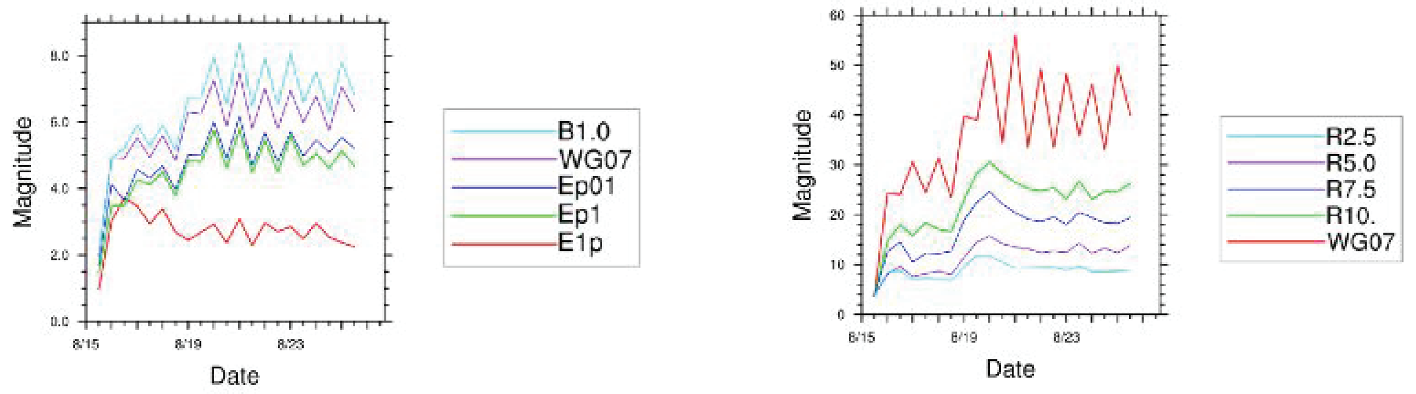


Figure 1. (Left panel) Inflation factor time series for ensemble/non-hybrid GSI (B1.0), WG07 - GSI(hybrid), and selected E( ) experiments. (Right panel) Inflation factor time series for WG07 and the R( ) experiments.

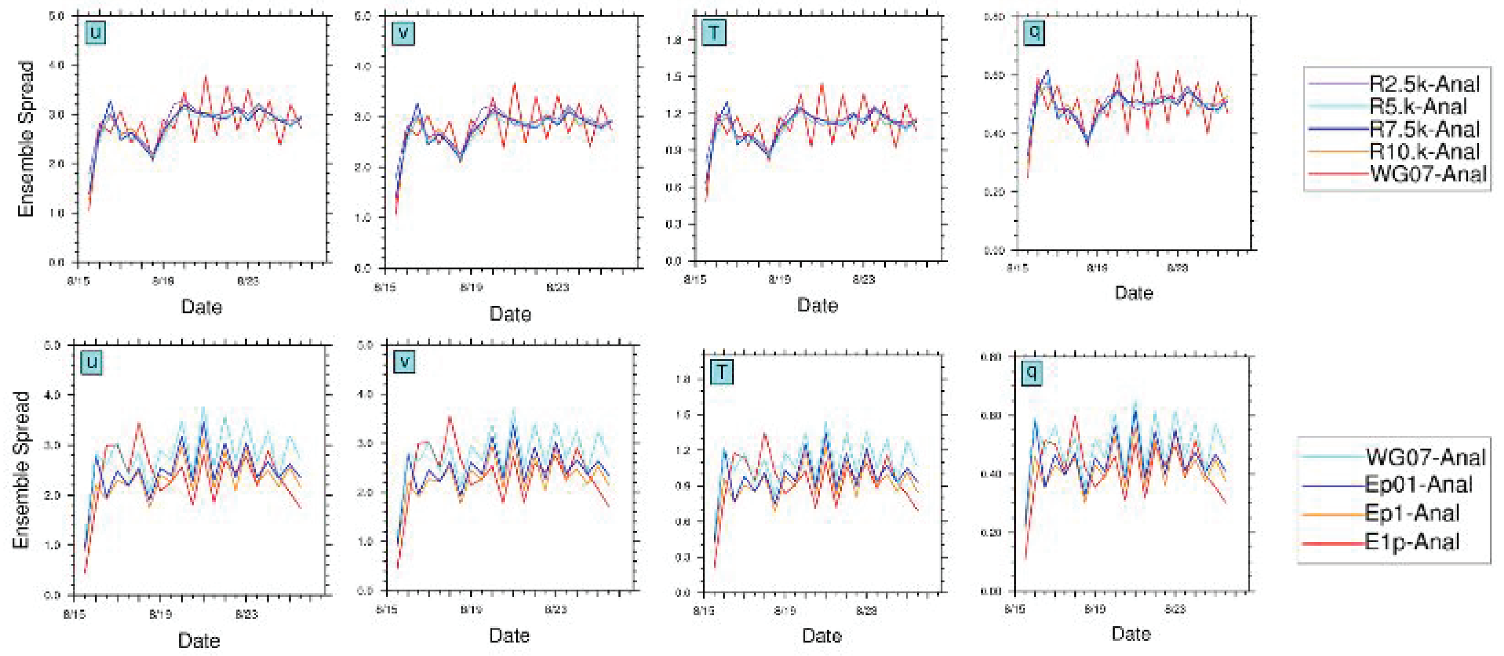


Figure 2. (Upper panels) ETKF analysis ensemble spread time series for WG07 and the R( ) experiments. (Lower panels) ETKF analysis ensemble spread time series for WG07 and the selected E( ) experiments.

Figure 2 (Upper panels) show the ETKF analysis ensemble spread time series for WG07 and the R( ) experiments. Figure 2 (Lower panels) show the spread for WG07 and selected E( ) experiments. The upper panels show that the oscillation disappeared and the inflation algorithm maintained the target ensemble spread when the number of ETKF observations was held constant. The lower panels show that as the relative error increased, the spread decreased. That result is counterintuitive. We suspect that the inflation factor was unable to maintain the target spread due to averaging and the over/under inflation issue identified by Bowler et al. 2008.

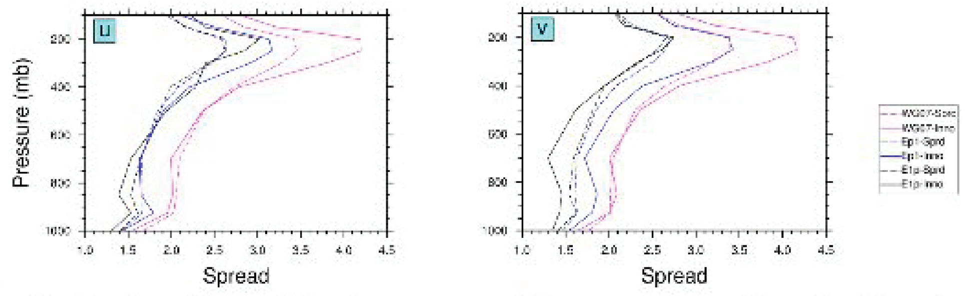


Figure 3. Vertical profiles of the background forecast error (denoted Inno) and ETKF ensemble spread (denoted Sprd) for WG07 and selected E( ) experiments.

Figure 3 shows vertical profiles of the background forecast error (defined as the root mean square of the innovations minus the observation error and denoted by "Inno") and the ETKF ensemble spread (denoted by "Sprd"). Figure 3 only contains the u and v profiles because relative error filtering excluded all T and q observations. Figure 3 shows that for all experiments the Inno and Sprd curves are nearly coincident in the middle and lower troposphere. (Ideally, the Inno and Sprd profiles for a particular experiment should be the same.) It also shows that the error/spread magnitudes are lower for the E( ) experiments than for WG07. In the upper troposphere, WG07 has the characteristic gap between the between the Inno and Sprd profiles with the spread being too small. While Ep1 and E1p show that as the minimum relative error cutoff increases, the gap between Inno and Sprd decreases. That results suggests that altering the characteristics of the observation error improves the spread verification.

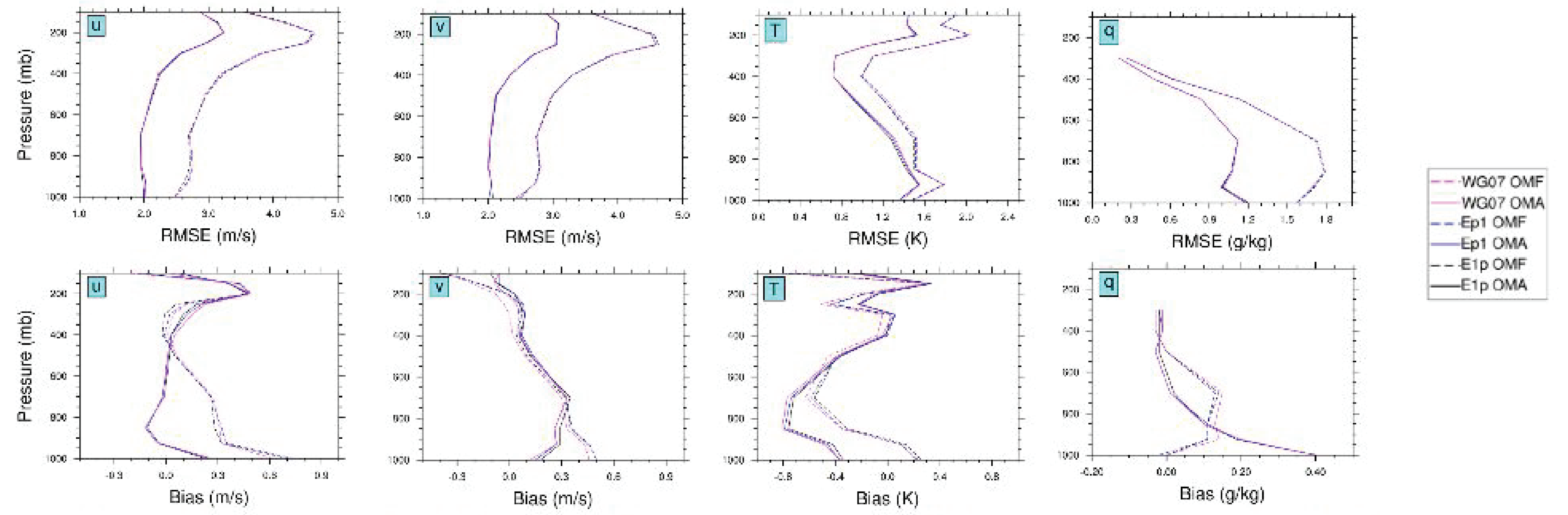


Figure 4. Vertical profiles of RMSE and bias for the analyses (OMA) and forecasts (OMF) from the E( ) experiments.

Figure 4 shows vertical profiles of the root mean square error (RMSE) and bias for the analyses and forecasts from the R( ) experiments. The upper row displays RMSE and the lower row displays bias. The RMSE panels show that varying the minimum error cutoff does not have a significant effect on the analysis or forecasts RMSE. The bias panels show more encouraging results in that there is a reduction of the forecast bias for u in the upper troposphere, for T in the middle and upper troposphere, and for q in the middle and lower troposphere. The bias panel for v shows a small increase in the forecast bias throughout the troposphere. The affect of varying the minimum error cutoff on the analysis bias is smaller but qualitatively similar to that for the forecast bias There is a small decrease in the analysis bias for u in the upper troposphere, for v in the lower and upper troposphere, and for T in the middle and lower troposphere. For q, there is little change in the analysis bias.

## SUMMARY AND DISCUSSION:

In this paper, we studied the effects of changing the ETKF observation error characteristics in the GSI/ETKF regional hybrid on the analysis and forecast RMSE. Our results showed that reducing the number of ETKF observations: (i) eliminated the bi-cycle oscillation in the ETKF ensemble spread time series, and (ii) improved the analysis and forecast RMSE. The optimal number of ETKF observation ranged between 2,500 and 7,500 and was meteorological variable dependent. We speculate that optimal number of ETKF observations is application dependent. If the resolution is changed, we suspect the optimal number will change. If separate inflation factors were used for each meteorological variable, we interpret our results as indicating that the optimal number of ETKF observations would be different for wind (u,v) , T, and q. That suggests that the ETKF and inflation factor should be applied separately to each variable.

Our results also showed that increasing the minimum relative observation error cutoff improved the analysis and forecast RMSE. We found that the optimal relative error cutoff was 0.01. For these experiments, the RMSE improved improved when the ensemble spread was decreased. That result is counterintuitive. We suspect that inflation algorithm could not maintain the target spread due to the averaging and over/under inflation issue. We recommend that the relative error cutoff experiments be rerun with the number of ETKF observations held constant.

## REFERENCES:

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