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CAN WE PREDICT THE REDUCTION IN FORECAST ERROR VARIANCE PRODUCED BY TARGETED OBSERVATIONS?

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1. INTRODUCTION

The Ensemble Transform Kalman Filter (ET KF) adaptive sampling technique has been used at the National Centers for Environmental Prediction (NCEP) during the quasi-operational 1999, 2000 and 2001 Winter Storm Reconnaissance (WSR) Programs (Szunyogh *et al.* 2000, Toth *et al.* 2001). The ET KF aims to identify deployments of aircraft-borne dropsondes that maximize the chance of significantly improving 1-3 day winter storm forecasts over the continental United States. It attempts to predict the reduction in forecast error variance associated with each possible deployment of adaptive (or targeted) observations, via a quantity termed the *signal variance*.

A "signal" is defined by the difference between two forecasts, initialized with and without the targeted observations. For linear error evolution, the signal variance (over all independent realizations) is equal to the reduction in forecast error variance, if observation and background error covariances are accurate and identical to those produced by the data assimilation scheme. However, since model trajectories and background error covariances assumed by the ET KF are imperfect and different to those of NCEP, the respective signals are likely to differ. We seek answers to the following questions:

(1) Does an increasing relationship exist between the ET KF signal variance and the variance of operational NCEP signal realizations?

(2) Does a similar relationship exist between the signal variance of NCEP forecasts and the reduction in NCEP forecast error variance?

If these two relationships hold, they can be combined to give ET KF estimates of the error reducing effect of targeted observations within verification regions of interest. Potential benefits include (a) making quick decisions on when and where to deploy targeted observations, (b) warning operational data quality control schemes against the rejection of observational data if the signal variance is large, and (c) estimating economic benefit due to any future deployment of observations.

The ET KF theory is explained in Bishop *et al.* (2001), and the ET KF products used during NCEP's WSR programs are described in Majumdar *et al.* (2001a). Here, we focus on the ability of the ET KF to provide quantitative estimates of the reduction of operational analysis and forecast error variance, using data from the WSR00 program. Further details of this study, such as how signals produced by the ET KF and NCEP's 3D-Var data assimilation schemes (Parrish and Derber 1992) may differ, are given in Majumdar *et al.* (2001b). In Section 2.1, we answer question (1) above by grouping together NCEP signal realizations to calculate their sample variance at the analysis time t_a (Fig.1). In Section 2.2, we do the same at the verification time t_f and then test question (2). Concluding remarks are given in Section 3.

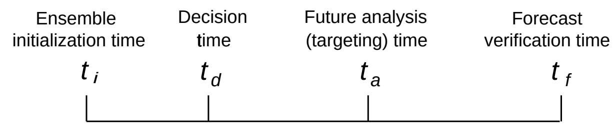

FIG. 1: Based on an ensemble initialized at t_i, a decision is made at t_d to deploy adaptive observational resources at the future analysis time t_a, to improve a forecast (initiated at t_a) valid within a verification region at t_f.

2. TESTING ET KF vs. NCEP SIGNAL VARIANCE

In this section, we test whether the ET KF can be used to predict operational signal variance at times t_a and t_f, by seeking a statistical relationship between the respective signal variances. Throughout the study, an ensemble of 25 ECMWF members (initialized +36 hours prior to time t_a) (Molteni *et al.* 1996, Buizza *et al.* 1998), 2 NCEP MRF members (+36h), and 5 NCEP MRF members (+24h) (Toth and Kalnay 1997) is used. The 32 ensemble members contain horizontal wind components at the 850mb, 500mb and 200mb levels.

2.1 *Future analysis (targeting) time* t_a

First, we test the relationship between ET KF and NCEP wind signal variance using all 242 dropsonde locations from the 12 flight days between 23 Jan – 16 Feb 2000. An example of the ET KF predicted signal variance and an NCEP signal realization for one flight day is shown in Fig.2. The squared NCEP signal and predicted ET KF signal variance at all 242 locations are plotted in Fig.3a. A small ET KF signal variance at a location ought to indicate that the NCEP signal magnitude at the same site is small. The converse is not necessarily true. A large signal variance merely suggests that the distribution of signals is broader than if it were small. We calculate sample

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variances of the NCEP signal in Fig.3a by placing signal realizations into 3 groups which contain the lowest 81, middle 81 and highest 80 values of ET KF signal variance respectively. The NCEP sample signal variance is the average of all squared NCEP signals in that group (represented by the horizontal bars in Fig.3a). These values increase monotonically with respect to the average value of the ET KF signal variance in each group.

To test statistically whether the ET KF and NCEP signal variances are related, we assume that all signals are independent and normally distributed, so the sample signal variance comes from a chi-square distribution with 80 degrees of freedom (79 in the third group). The 99% confidence interval for the NCEP signal variance of each sample is then plotted in Fig.3b versus the average ET KF signal variance in each group. The best fit lines for the linear, increasing relationship between the ET KF and NCEP signal variances, and for the upper and lower confidence limits, are also shown. The gradient of the best fit line is roughly 8. A linear statistical rescaling using this factor can enable the ET KF to give approximate predictions of the NCEP signal variance at the analysis time t_a.

A second test of the robustness of the relationship between the ET KF and NCEP signal variances is performed by eliminating data from each of the 12 flight days, and producing best fit lines similar to those shown in Fig.3b. In this manner, the variability of the ET KF – NCEP signal variance relationship with respect to the withdrawal of independent sub-samples from each flight day is tested. The 12 best fit lines in Fig.3c all lie within the regression lines for the 99% confidence interval of NCEP signal variance, except at low values. The similarity of these 12 lines implies that the relationship between the ET KF and NCEP signal variances is generally stable if data at observation locations are added or removed.

Although the two tests described above confirmed some qualitative similarities, the ET KF signal variance overestimated the NCEP signal magnitude by an order of magnitude. Possible reasons for this overestimation are given in Majumdar *et al.* (2001b). In particular, the ET KF currently overestimates components of the analysis error covariance matrix; work is under way to rectify this.

2.2 *Forecast verification time* t_f

We now test the ability of the ET KF to predict NCEP signal variance within a pre-selected verification region at the future verification time t_f. This ability may be compromised by several factors, discussed in Majumdar *et al.* (2001b). The ET KF forecast signal variance and squared NCEP forecast signal at every grid point (2.5 degree resolution) within each verification region is plotted for 30 potentially important weather events during the WSR00 period (Fig.4a). In a similar manner to Fig.3b, the points are placed into 5 groups, depending on their ET KF signal variance value (Fig.4b). To a good approximation, the NCEP sample signal variance (average of squared signals) increases linearly with average ET KF signal variance in each group. The 99% confidence limits show that

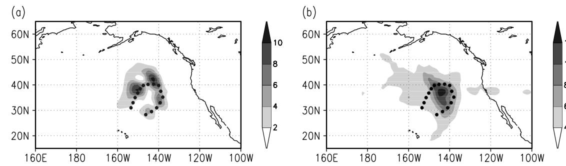

FIG. 2: (a) Squared NCEP signal of horizontal wind components at analysis time 00UTC, 11 February 2000. Dots represent locations at which dropsondes were released. (b) ET KF predicted wind component signal variance valid at 00UTC, 11 February 2000, using a 24/36h old ensemble of ECMWF and NCEP forecasts.

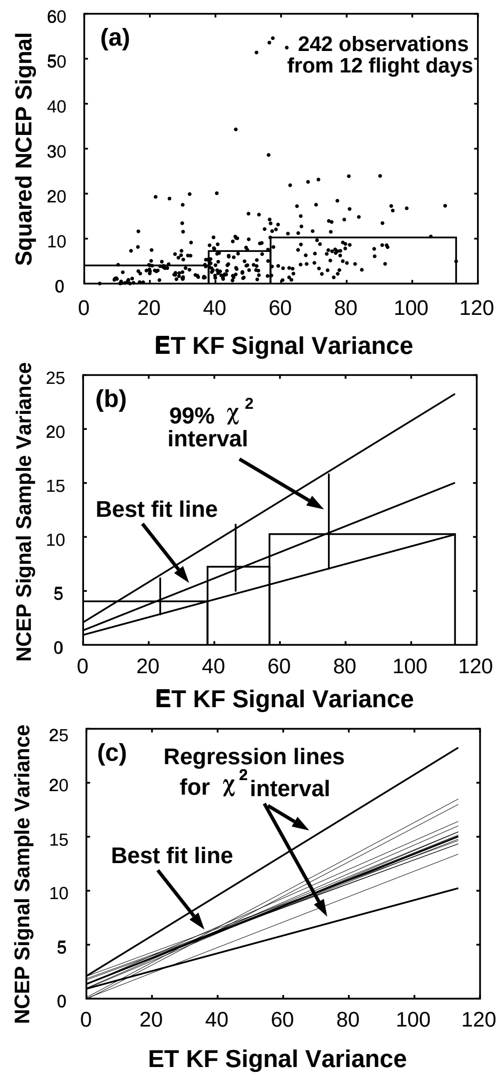

FIG. 3: (a) Squared NCEP signal and ET KF signal variance for each observation site at time t_a. Bars represent the NCEP sample signal variance. (b) Best fit line and regression lines through the 99% chi-square confidence limits of the NCEP signal sample variance. (c) Grey: Best fit lines with data from each of the 12 flight days suppressed. Black: Regression lines of Fig.3b.

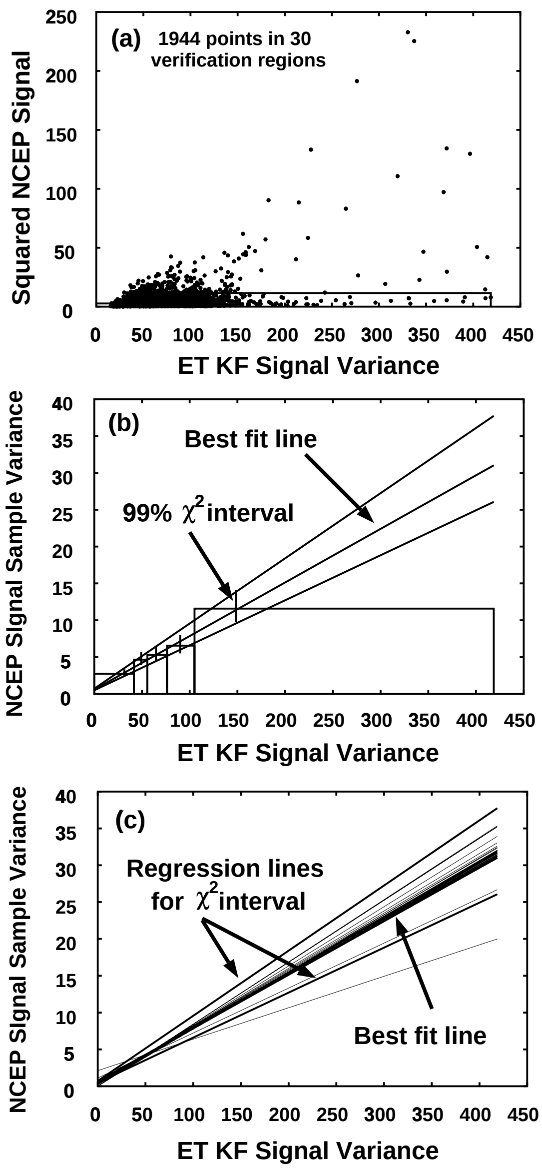

FIG. 4: (a) Squared NCEP forecast signal and ET KF forecast signal variance, for all 1944 grid points within 30 WSR00 verification regions. The points are divided into 4 categories of 389 and one of 388, arranged in order of increasing ET KF signal variance. The height of each of the 5 bars gives the NCEP sample signal variance of that category. (b) Error bars represent the 99% confidence interval of the NCEP signal variance for each of the 5 categories, plotted versus the mean ET KF signal variance for that category. The three lines represent the best fit regression line between ET KF and NCEP signal variances, and corresponding lines for the 99% confidence limits. (c) Grey lines: Best fit lines calculated in a similar manner to Fig.4b, but with data from each of the 30 verification regions denied. Black lines: Regression lines of Fig.4b (in which no data were denied).

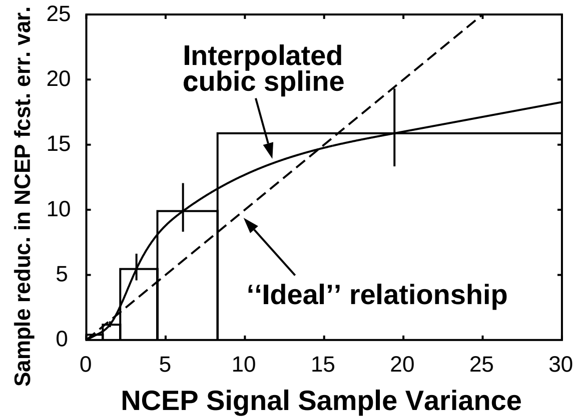

FIG. 5: The height of each block corresponds to the reduction in NCEP forecast error variance in each sample. A cubic spline is drawn through the respective sample variances. The "ideal" relationship, where the reduction in forecast error variance is identical to the signal variance, is also shown for comparison.

the probability of a non-monotonic relationship between the ET KF and NCEP signal variances is minimal. The ET KF signal variance needs to be reduced by a factor of roughly 14 to give a scale comparable to the NCEP forecast signal variance. Since this scaling factor is higher than the factor of 8 at the analysis time t_a, the growth rate of the NCEP signal is (on average) smaller than that predicted by the ET KF. To analyze the uncertainty in our estimate of the scaling factor due to sub-sampling, we remove a data set corresponding to one of the 30 verification regions, and re-calculate the best fit line in the same manner as in Fig.4b. This is done for all verification data sets. The 30 best fit lines in Fig.4c demonstrate that the variability is usually small, and hence the the linear relationship between ET KF and NCEP signal variance at the verification time is generally robust.

The next step is to test the relationship between the NCEP forecast signal variance and the reduction in NCEP forecast error variance due to the targeted observations. The NCEP forecast error at a verification location is approximated by the difference between the forecast initialized at time t_a, and the NCEP analysis made at time t_f. Using a similar technique to that shown in Fig.4, the NCEP sample signal variance in each of the 5 groups is given by the sample average of the squared NCEP signals. The reduction in NCEP forecast error variance is calculated by averaging over all realizations of the reduction in squared NCEP forecast error in each group. A monotonic increasing relationship is found between the NCEP signal variance and reduction in forecast error variance (Fig.5). If errors grew linearly and error covariances were specified accurately, one would have expected this relationship to be linear and of unit gradient. Since a linear gradient could not be established here, we fit a cubic spline to indicate the nature of the relationship.

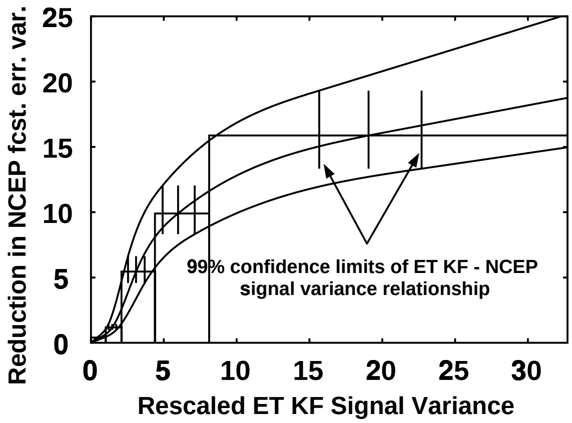

FIG. 6: 99% confidence limits and best fit spline for the reduction in NCEP forecast error variance as a function of the ET KF signal variance, rescaled by a factor of ≈14.

Combining the rescaling factor of approximately 14 for the best fit line of Fig.4b with the best spline of Fig.5, the new optimal relationship between ET KF signal variance and NCEP forecast error variance reduction is shown in Fig.6. While the error bounds in this relationship are fairly large, the potential of using the ET KF to predict the reduction in NCEP forecast error variance is demonstrated. With more confidence, these values could in turn be translated into meteorological or economic estimates of the likelihood of forecast improvements for any future deployment of targeted observations.

3. CONCLUSIONS

The ability of an Ensemble Transform Kalman Filter (ET KF) to predict (1) the NCEP signal variance and (2) the reduction in NCEP forecast error variance due to targeted dropsonde observations was tested, in a first step toward quantifying predictability. A linear, increasing relationship between the ET KF and NCEP signal variances was found to exist (a) at all observation locations selected on 12 observing days during WSR00, and (b) over 30 chosen verification regions of interest, at the verification time. However, the ET KF consistently over-predicted the operational signal variance by a factor of 8 at the analysis (targeting) time and 14 at the verification time. A statistical rescaling factor was therefore introduced to correct the ET KF's prediction of signal variance. Furthermore, a monotonically increasing, but non-linear, relationship was found to exist between the NCEP forecast signal variance and the reduction in NCEP forecast error variance. Using the rescaling factor of 14, the forecast error variance reducing effect of targeted observations was graphed as an approximate function of the ET KF signal variance.

These results were achieved despite the fact that background error covariances currently assumed by NCEP's 3D-Var data assimilation scheme and those assumed by the ET KF are very different. It is expected that error covariances produced by an ET KF would be more similar to those produced by new adjoint-based and ensemble-based schemes than the quasi-isotropic error covariances produced by 3d-Var. Hence, the above results, which also need to be evaluated for larger data samples, are likely to improve further in the future.

Regardless of the form of future data assimilation schemes, the method of statistically correcting the ET KF predictions described here provides a means by which past targeted observations can be used to improve the reliability of ET KF predictions of the error reducing efficacy of future targeted observations.

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