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QUANTIFYING THE IMPACT OF OBSERVATIONS USING ENSEMBLES

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1. INTRODUCTION

In addition to the resources in the standard observing network, supplemental observations can be used to help generate a new analysis for a forecast model. Additional observations, collected for example by a dropsonde equipped aircraft, may improve predictions of potentially significant weather (Tuleya and Lord 1997, Szunyogh et al. 1999, Szunyogh et al. 2000). Suppose the three-day forecast for the west coast of the United States was for heavy rain. Observations might be taken upstream from the Pacific coastline to help improve that forecast. Finding the particular location for observations that minimize forecast error variance depends on estimating the error variance in the analysis field, and then propagating this error variance forward in time to predict a forecast error variance, and then see how additional observations can reduce this error variance (Bishop et al, 2001).

The error statistics for the first guess field currently used in most operational centers parameterized from a long time series of previous forecasts, and are generally spatially homogeneous and temporally invariant (Parrish and Derber, 1992). These fixed statistics cannot account for the differences between atmospheric conditions. For example, the error statistics near a cold front are likely to be very different to those in the center of a high-pressure system. To produce the analysis with the smallest error variance, the optimal error statistics are needed. Given the shortcomings of the error statistics currently used in many operational centers, better-suited error statistics are proposed. This focus of this research is to use ensembles to generate error statistics, and then apply these error statistics to data assimilation and to the selection of sites for supplemental observations.

Having the error statistics of the first guess field, and by also knowing the location and error statistics of the components in the standard
observational network can estimate the analysis error variance. The estimate of analysis error variance does not require that observations actually be taken; it only requires the error statistics that are used to make the analysis. By using ensemble members to produce the error statistics for the first guess field, this analysis error variance can be propagated into the future by using the same ensemble members valid at a later time to represent the uncertainty of the future forecast. Further, these estimates of error variance are related to the errors on a particular day, rather than an average prediction error.

Having taken observations using guidance from ensemble based error statistics, predicting the impact the observations is needed to ensure that the goal of supplemental observations, namely the improved prediction of a potential weather event, is likely to be accomplished. The impact of adaptive observations on the analysis and forecast can be estimated using the ensemble members at the observation time and the verification time. However, as with any error statistics estimation, the ensemble-based calculation will not be perfect. The ensemble based error statistics can be corrected using observed data from a later time to provide a quantitative measure of the impact of observations on forecasts.

It is this quantifying of the expected impact of the targeted observations that could have the greatest benefit in the long run. Suppose an agency wanted to take extra observations to improve a forecast. If the ET KF could be used to predict the reduction in forecast error variance, then the people charged with deciding to make the flight or not would be able to perform a cost benefit analysis of sending out the plane (or other data collection device). Not only would they know the best place to fly, they would know whether or not it would be worth it to make the flight, if the improvement would justify the cost.

2. TARGETING THEORY

The ET KF, in addition to data assimilation, can also be used to predict the impact of observations, and thus can be used as a way of selecting data-sensitive areas in which to take supplemental observations. The ET KF can estimate the reduction in error variance from the standard observational network. The formulation of the analysis error covariance matrix is given by:

$$\mathbf{P}(t_f,t_i|\mathbf{H}_q) = \mathbf{P}(t_f,t_f) - \mathbf{P}(t_f,t_i)\mathbf{H}_q^T(\mathbf{H}_q\mathbf{P}(t_i,t_i)\mathbf{H}_q^T+\mathbf{R})^{-1}\mathbf{H}_q\mathbf{P}(t_i,t_f)$$

Where $\mathbf{P}(t_f,t_i|\mathbf{H}_q)$ is the analysis error covariance matrix given observations in some observing

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network 'q' and $\mathbf{P}(t_f,t_i)\mathbf{H}_q^T(\mathbf{H}_q\mathbf{P}(t_i,t_i)\mathbf{H}_q^T+\mathbf{R})^{-1}\,\mathbf{H}q\mathbf{P}(t_i,t_f)$, rewritten as $\mathbf{S}(t_f,t_i|\mathbf{H}_q)$, is the reduction in error variance resulting from observations at sites in the observational network 'q'. $\mathbf{P}(t_f,t_f)$ is the prediction error covariance matrix at the verification time, and is equal to $\mathbf{X}_f\mathbf{X}_f^T$, $\mathbf{P}(t_i,t_i)$ is the prediction error covariance matrix at the observing time, and similarly is equal to $\mathbf{X}_i\mathbf{X}_i^T$. For the prediction of the impact of observations on an analysis, none of the climatological covariances are used. This is to reduce calculation time. For any particular observing network, the manipulations of B can be calculated once and stored. However, for non-fixed observational networks, the calculations involving B are too time consuming to be practical. To find the further reduction in the prediction error when more observations are taken, the following equation is used:

$$\mathbf{S}(t_f,t_i|\mathbf{H}_r) = \mathbf{P}(t_f,t_i|\mathbf{H}_q)\mathbf{H}_r^T(\mathbf{H}_r\mathbf{P}(t_i,t_i|\mathbf{H}_q)\mathbf{H}_r^T+\mathbf{R})^{-1}\mathbf{H}_r\mathbf{P}(t_i,t_f|\mathbf{H}_q)$$

Where 'r' is the potential site of an additional observational network. The location for which the trace of $\mathbf{S}(t_f,t_i|\mathbf{H}r)$ is the largest is deemed as the optimal location for an observation, as it has the greatest reduction in error variance. Thus, it is expected that this location with produce a new forecast with the greatest reduction in forecast error. In experiments for this research, each grid point on the east side of the model domain is considered a potential observational network, and each is checked to see which has the greatest value of $\mathbf{S}(t_f,t_i|\mathbf{H}_r)$. Using the given formulation for $\mathbf{S}(t_f,t_i|\mathbf{H}_r)$, the verification region for this supplemental observation is the entire model domain. This can be changed by maximizing not $\mathbf{S}(t_f,t_i|\mathbf{H}r)$, but $\mathbf{H}_v\mathbf{S}(t_f,t_i|\mathbf{H}_r)\mathbf{H}_v^T$, where $\mathbf{H}_v$ maps out the verification region. Field experiments generally do have verification regions associated with areas of potential heavy rainfall, high winds, or other extreme weather.

Having selected the optimal ensemble generation technique and the best mix of flow-dependent and climatological covariances, a 99-day model run will be done. On each day, the ET KF will be used to predict the expected reduction in global vorticity error from the standard observing network as well as the optimal location for taking two additional observations. The observations will be made 24 hours after the time of ensemble generation, verifying 48 hours from ensemble generation. Two increments to the analysis will then be made, one using the standard observational network and the other using the standard network plus two targeted observations. The signals these increments make at both the analysis time and at the forecast time will then be compared with the ET KF predicted reduction in error variance, with the belief that a linear correlation between them exists. Having formed a statistical correlation, the ET KF predicted signal will be adjusted, and then compared to the actual reduction in error to see if the ET KF can be used to quantitatively predict the impact of observations on forecasts.

With predictions of the reduction in forecast error made from the ET KF, the observation locations chosen are sampled, and the data assimilated using 3D-var, the ET KF, or the hybrid ensemble Kalman filter / 3D-var scheme. At both the observation time and verification time, the differences between the model vorticity fields generated with supplemental observations and without the additional observations are made. The difference fields are then compared to the predicted impacts of the observations. From this comparison will come an adjustment to the ET KF predicted signal. This adjusted ET KF prediction of the reduction in error variance is compared to the improvement in vorticity forecasts resulting from the supplemental observations. From that comparison, it will be deduced whether the ET KF can predict, quantitatively, the reduction in forecast error resulting from the assimilation of targeted observations.

3. EXPERIMENTAL PROCEDURE

For each analysis cycle, the following was done: First, using the ETKF, the expected signal from a 16, 36, or 72 member observational network was calculated. After this, signal variance as a function of observation site was computed. From this, the gridpoint on the eastern side of the model domain which had the greatest signal variance, and hence, the greatest reduction in expected error, was chosen as the first supplemental observation site. The further reduction of error variance resulting from this observation was combined with the reduction from the standard network to yield a new analysis error variance. As before, the signal variance was calculated as a function of observing site, and the site with the greatest signal variance was chosen as the second site for a supplemental observation.

The theory behind the selection of an observation site using the signal variance is described in Bishop (2001). One addition to this theory is the use of a verification region. In Bishop (2001), the optimal locations were found which reduced the global enstrophy error at the verification time. In this experiment, the sites were selected based on a verification region.

For this experiment, a 64-member ensemble was constructed each day and integrated forward 48 hours. The ensemble consisted of 64 random samples of the top 256 eigenvectors of the Parrish/Derber B-Matrix (Parrish and Derber, 1992). As shown in Etherton et al (2002), the number of ensemble members was chosen at 64, rather than 16, because having only 16 ensemble members yielded a poor estimate of the variance. For purposes of quantification, it is important that the spread of the ensemble (the trace of $\mathbf{XX}^T$, where $\mathbf{X}$ is a matrix of ensemble perturbations) is roughly the same as the magnitude of the first guess error. To accomplish this, the magnitude of the initial perturbations is rescaled using a maximal likelihood estimation as in Dee(1995).

4. RESULTS

Several experiments were done with differing numbers of observations in the standard observing network, and with different data assimilation schemes. Results in the figure shown at the right are for a 16 observation standard observing network (the sparsest of the ones used) and for a hybrid 3D-Var/ET KF data assimilation scheme.

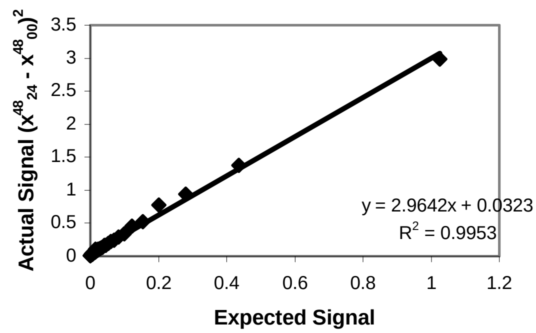
Estimated Signal Versus Actual Signal

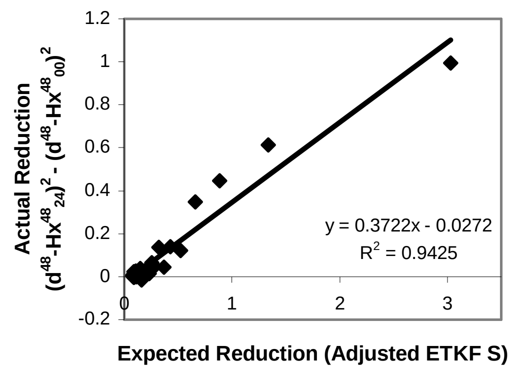
The first step in the quantification of targeted observations was to make the correlation between the expected signal and the actual signal. This was done by taking the values at each gridpoint (1024 per day) over days 2 through 98 of the 99 day run (day 1 was omitted because the re-scaling of the ensemble could not happen until day 2), for a total of 99328 realiziations. These were then binned into groups of 2048 in order of expected signal size. These binned values were then compared to their counterparts in actual signal.

The results show that the ET KF does a very good job of predicting the signal which targeted observations will have on a forecast. The points form nearly a perfect regression, with an R^2 value of greater than 0.99. Values are also always monotonicly increasing as a function of expected signal. It was seen for the other observing networks and other data assimilaton schemes that the correlation between predicted signal and actual signal was very strong, though a bit less strong when 3D-Var was used for the data assimilation scheme.

If the ensemble spread were always a direct match to the size of the error of the first guess field, it would be expected that the expected signal from the ETKF and the actual signal from the observational network would have a 1-to-1 correspondence. It is noted that the value is more like 3-to-1 than 1-to-1. The reason for this is that the ETKF predicts the reduction in error variance which from the standard network. It is then the further reduction from this reduced error variance that is compared to the actual signal. However, there is a large model error in this system, as the vorticity relaxation for the model is different than the one used for the truth/nature run. This error is NOT reduced by the standard network, but the ETKF presumes that it has been, as the model error term is not in the formulation. Thus, the actual impact of targeted observations is greater than expected.

The quantification of targeted observations using a 16 observation standard network, values only in the "high signal" regions, a hybrid 3d-Var/ET KF data assimilation scheme, and bins of 2048 samples.





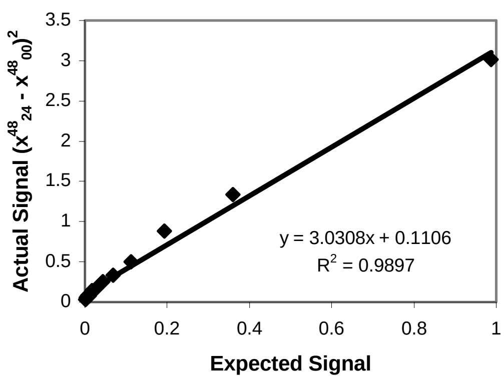
Adjusted Predicted Signal versus Actual Reduction

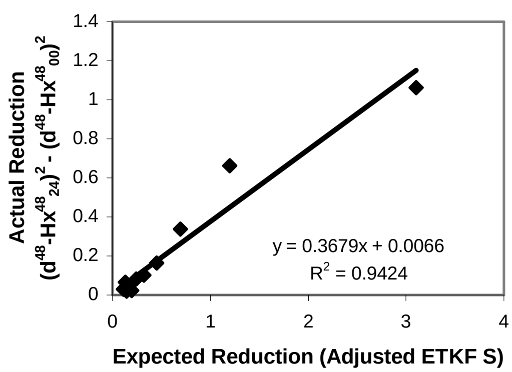
Given that there is some sort of correlation between the predicted signal and the actual signal, a next step in assessing the benefit of the targeted observations is to see how much better an analysis or a 24-hour forecast is with their inclusion.

Once again, values were binned into groups of 2048, and plotted. A linear regression was then applied. Results show that in contrast to the prediction of signal, the prediction of reduction of error is not as solid. Note that the regression line is not as good a fit to the data as was the case in the prediction of signal. Further notice that the values of actual reduction are not monotonicly increasing as a function of predicted reduction, especially when the predicted reductions are small.

A potential reason that the actual improvements are not as well correlated to the ET KF predictions of improvements has to do with the verification region, or more precisely, the lack of one. The ET KF has the tendency to produce actions at a distance from where the observations are taken. It is seen that for small values of predicted reduction, the actual reduction can increase or decrease. These small values of predicted reduction occur far from where the main feature of interest is. To try to isolate this effect, values for correlation were limited to a "high signal region".

The quantification of targeted observations using a 16 observation standard network, values only in the "high signal" regions, a hybrid 3d-Var/ET KF data assimilation scheme, and bins of 2048 samples.





Results for the comparison of actual signal to expected signal are similar to when the entire domain was used as the "verification region". The improvement is in the comparison of expected reduction to actual reduction. Values are now a bit more in line with the regression line, and have a greater look of increasing monotonically.

The points still do not lie all along the line. The points appear to lie more in a parabolic shape than a straight line, with values of actual reduction starting to asymptote for increasing values of expected reduction. It is possible that there is a quadratic relationship, but there are other possibilities.

In this experiment, there is a regime change in the dynamics in the model. Over the first 30 days, the flow is characterized by four coherent vortices and one broad ribbon of vorticity. In the last 70 days, the flow is more zonal, with two broad vorticity ribbons. These two different flow states may have an effect on the correlations between predicted signal and actual signal. It is possible that the strong localized vorticity errors in the first 30 days make a significant change in the largest set of binned values. This largest bin has both the greatest x-value and greatest y-value of the points, and thus has a high value of influence on the regression.

Results from this work are still preliminary at the time of writing, but there seems to be reason to believe that the values in this top most point are biased from errors in the early part of the model run. It has been suggested that there should be two separate regression lines, one for data from before the regime change (days 2-30) and one for after the regime change (days 31-99). This will be investigated in the weeks ahead.

5. REFERENCES

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