THE RUC 3DVAR: OPERATIONAL PERFORMANCE AND RECENT IMPROVEMENTS

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1. INTRODUCTION

The Rapid Update Cycle (RUC) is a mesoscale operational data assimilation and numerical forecasting system. Different versions of RUC have been implemented since 1994, when the first version (RUC1) became operational at the National Centers for Environmental Prediction (NCEP). The most recent one is called RUC20 and it has 20km horizontal resolution, 50 vertical levels, and utilizes a 1-h intermittent data assimilation cycle. RUC20 is uniquely formulated in a hybrid isentropic-terrain-following vertical coordinate for both its data assimilation and forecast model components.

To support the 1-h forward intermittent data assimilation cycle, many different observations are assimilated by RUC20. These include RAOB, METAR, buoy observations, commercial aircraft (ACARS), wind profilers, geostationary (GOES) and polar orbiting (SSM/I) satellites, ground based GPS, and radars (VAD winds). For a detailed description of the RUC 20-km hourly assimilation cycle, including a discussion of design issues and a demonstration of capabilities, see Benjamin et al. (2003).

The RUC hourly update cycle utilizes a unified analysis framework (Benjamin et al. 2003), encompassing data ingest and quality control routines, and interchangeable three-dimensional variational (3DVAR) and optimum interpolation (OI) based analysis solvers. Following several years of research and development, the operational version of the RUC (run at NCEP) switched from the OI analysis to the 3DVAR analysis on 27 May 2003. Several earlier versions of RUC 3DVAR were successfully implemented at the Forecast Systems Laboratory (FSL) in real-time test mode.

In this paper, a brief overview of the RUC 3DVAR is given (sec. 2), then its operational performance is discussed (sec. 3) and new

developments are presented (sec. 4). Future directions for the RUC 3DVAR are described in sec .5.

2. OVERVIEW OF RUC 3DVAR

In this section only the main features of RUC 3DVAR are presented. For further details, see Devenyi and Benjamin (2003) and Benjamin et al. (2003).

The RUC 3DVAR is formulated in incremental space (Courtier et al. 1994) and performed on a 56-level version of the native RUC coordinate system. The control variables are streamfunction and velocity potential (both scaled by grid distance), unbalanced height, virtual potential temperature, and logarithm of water vapor mixing ratio. The analysis variables are wind components (u and v), height, virtual potential temperature, and water vapor mixing ratio. Observations are pre-processed and transformed as it is described in Devenyi and Benjamin (2003).

The variational analysis is performed in three successive steps similar to the earlier optimum interpolation based analysis. These steps include 1) a multivariate height/wind analysis, 2) a virtual potential temperature analysis, and 3) a univariate moisture analysis. Because of inherent non-linearities, outer/inner iterations are utilized in the moisture analysis part.

For most observation types, the observation operators are linear interpolation operators. The observation standard deviation errors (including representativeness and measurement errors) are specified by diagonal matrices. The matrix values are deduced from corresponding values in the OI method.

Linear balance is provided by a regression scheme originally proposed by Parrish and Derber (1992). The balanced part of the height and streamfunction is regressed using the NMC method (see further details below). The balancing relationship is applied in the height observation

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operator. At present, no correlation between streamfunction and velocity potential is applied.

The (univariate) background error correlations are approximated by convex linear combinations of discrete Gaussian filters with different filter scales and weights, following the technique developed at NCEP (Purser et al. 2003a,b). Using this filtering method, approximate representations of SOAR (second order autoregressive) correlation functions are obtained for different variables at different levels. In the present version of RUC 3DVAR, two Gaussians are employed in the approximations. Filter weight coefficients are determined semi-empirically.

Minimization is accomplished by a simple conjugate gradient method wherein the full background error covariance matrix is used for preconditioning (Derber and Rosati 1989)

3. OPERATIONAL PERFORMANCE

Since its introduction into operations, the RUC 3DVAR has performed reliably. The code is very robust, and no convergence problems have ever been detected. It uses less computation time than former optimum interpolation code. It runs on a single processor only on the IBM SP at NCEP or on different versions of FSL's Linux cluster.

As anticipated, the RUC 3DVAR produces smoother analysis fields than did the OI. A noise parameter, the mean absolute pressure tendency,

$$N_1 = \overline{\left| \frac{\Delta p_{sfc}}{\Delta t} \right|}^{x,y} \quad,$$

has a typical initial (t=0) tendency value around 9 hPa/h for the OI analysis and about 5 hPa/h for the 3DVAR analysis. Prior to initiating RUC model forecasts, these values are further reduced by use of a digital filter initialization. Even after digital filter initialization, 3DVAR fields are less noisy than their OI counterparts. For further discussion of the noise issue, see Benjamin et al. (2003).

Because RUC analyses are widely used for a variety of applications (nowcasts of hazardous weather, aircraft flight routing, convective storms, etc.) maintaining a fairly close analysis fit to observations is important for the RUC 3DVAR. A comparison of 3DVAR and OI fit to observations for the test period 16 Nov 2002 – 30 Jan 2003 is shown in Fig. 1. A similar fit is illustrated in Fig. 2 for the case of temperature. Results are similar for relative humidity and height (a bit closer for the height). Both figures show that the 3DVAR

(dashed line) is closer to the observations (in this case to RAOBs) than corresponding OI analysis (solid line).
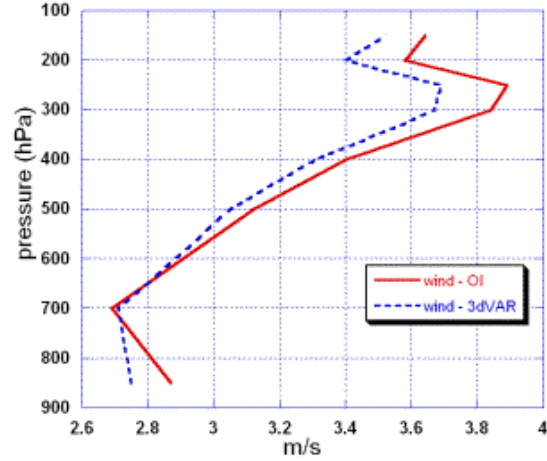

Fig. 1. Fit to observations for wind in period 16 Nov 2002 – 30 Jan 2003 as measured by the vector RMSE differences (ms^{-1}). Dashed line RUC 3DVAR, solid line OI.
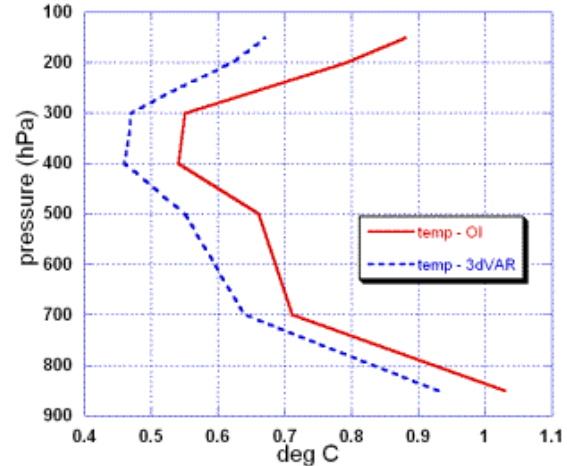

Fig. 2. Same as Fig. 1 but for temperature in units deg C.

Now considering the effect of OI and 3DVAR analyses on RUC forecast performance, Fig. 3. shows a comparison of 3-h and 12-h wind forecasts errors (verified against RAOBs) for a 2-month winter period.

Error scores are nearly identical for both systems. This comparison indicates that RUC forecasts initialized with 3DVAR analyses are equal or very close in skill to those initialized with

OI analyses, including for very short-range 3h forecasts.

RUC wind forecast error
RMS vector differences from raobs
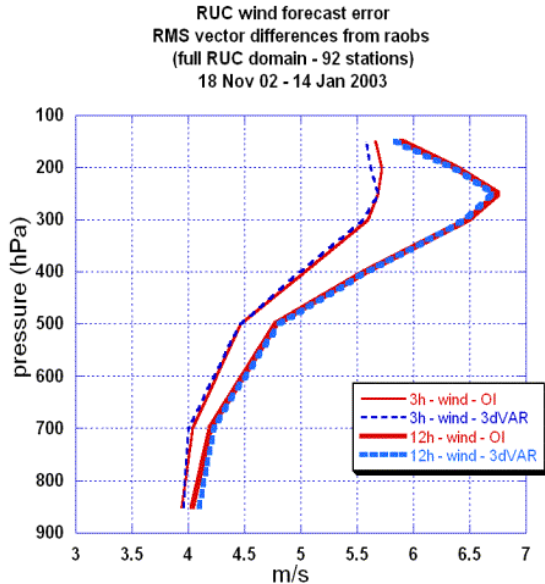**(full RUC domain - 92 stations)**
18 Nov 02 - 14 Jan 2003

Fig. 3. 3-h and 12-h RUC wind RMS forecast errors compared with RAOBS for the period 18 Nov 2002 – 14 Jan 2003. Solid lines – 3DVAR results, dotted lines – OI results.

For further verification and evaluation results see Benjamin et al. (2003) and RUC Technical Procedures Bulletin (http://ruc.fsl.noaa.gov).

4. RECENT IMPROVEMENTS

Two important factors in RUC 3DVAR performance are the background error covariances and the regression balance matrix. Because these parameters are based on forecast errors, updating of their values is an ongoing need.

4.1. Computing background error statistics

The first set of background error statistics for RUC 3DVAR was computed from a dataset collected in summer 2001. A 'mixed' approach was introduced where the background standard errors came from an application of the NMC method to RUC forecasts, but the scale information (spatial covariance) was introduced from that used with former OI analysis.

The NMC method was applied using difference fields of 6-h and 12-h RUC forecasts verifying at the same time. Utilizing an algorithm that computes streamfunction, velocity potential, and unbalanced height, standard errors of these fields are computed and scaled according to the 1-h assimilation cycle of RUC. The computed fields are also submitted to further smoothing, and only vertical and y(north-south)-dependence is taken into account.

The computation algorithm is based on the method of Sangster (1960) to compute streamfunction, velocity potential, and height deviation (unbalanced height) values from u,v wind arrays and height fields. An extended boundary zone is introduced to lessen the effect of boundary conditions.

One of the main difficulties related to this approach is the appropriate scaling of standard errors derived from forecasts that are six hours apart. Because of the limitation in Sangster (1960) method (it is a minimum divergence method – see Lynch (1988 and 1989) for further discussion), the computed standard errors between the fields may only approximately represent the real atmospheric conditions. Another question is related to the scaling of 6-h forecast differences to the 1-h cycling time of RUC. Ingleby (2001) reported similar scaling problems in the Met. Office global 3DVAR scheme, but his problem did not involve the resolution of lateral boundary problem which is characteristic for limited area models. Ingleby also reported problems with the correlation scales. This problem was addressed in RUC 3DVAR by retaining the scales used in the earlier OI system. These scales were originally obtained by comparison of forecasts with observations (Benjamin 1989 and Carriere 1991). Extensive numerical experiments were conducted with the RUC 3DVAR in a retrospective framework to determine the optimal scaling coefficients for each variable and vertical level. Scaling parameters were systematically changed according to analysis and forecast verification results.

A more extensive dataset has been collected for the purpose of recomputing the background error term. New statistics for the summer season have been computed for a 60-day period extending from 20 June 2003 through 18 August 2003. The new statistics will be tested in a retrospective framework in the near future.

4.2. Computing balancing term

One of the control variables in the RUC 3DVAR is unbalanced height, which is defined as the difference between the two terms in the balance equation:

$$-\nabla (f \nabla \psi) + \nabla^2 g Z = 0$$

The linear relationship generated by the linear balance equation is converted into a statistical relationship by regression analysis:

$$\psi = LZ + \varepsilon$$

where the regression coefficients are computed by the NMC method, using the same dataset discussed above.

In some sense the balancing relationship showed less sensitivity to the NMC method but because the regression matrix is employed in the height observation operator, its effect is influenced by the total height observation error and indirectly by the background error in unbalanced height and stream function.

5. FUTURE WORK

The 3DVAR-based RUC performs appropriately in operations, but there are several open problems, most of which are related to full variational solutions of moisture/cloud fields. One of them is the assimilation of precipitable water data from satellites and ground based GPS. An experimental version of the RUC 3DVAR with precipitable water data assimilation is being tested, but it is not ready for operational use. Currently, satellite radiances are not assimilated in the RUC 3DVAR, but development is under way to include the OPTRAN radiative forward and adjoint operators. A bias reduction method is under investigation to provide appropriate satellite radiance information.

Development of radar data assimilation procedures is also underway, with a long term goal of utilizing reflectivity and radial velocity information to modify water vapor, hydrometeor, and velocity divergence fields. Initial work has focused on updating hydrometeor and water vapor fields, using a national composite maximum reflectivity product in conjunction with satellite data and surface cloud observations (Benjamin et al. 2004). In the present formulation, the radar-based updates occur within the outer loop of the moisture minimization, allowing for an iterative solution in concert with the in situ moisture observations. Real-time parallel tests at FSL indicate a modest improvement in short-term (3-6 h) precipitation forecasts from this technique.

Additional radar assimilation work has focused on reformulating the multivariate 3DVAR solver to accommodate plane polar radial velocity components as opposed to the traditional horizontal Cartesian components. Real-data benchmark tests for conventional observations have confirmed identical results for the two formulations. Subsequently, the radial velocity formulation has been used for data impact experiments using simulated Doppler lidar observation from a polar orbiting satellite (Weygandt et al. 2004). Ongoing work is focused on utilizing the radial velocity formulation of the 3DVAR solver for assimilation of WSR-88D Doppler velocity data.

6. ACKNOWLEDGMENTS

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