JP2.11 APPLICATION OF THE BRATSETH SCHEME FOR HIGH LATITUDE INTERMITTENT DATA ASSIMILATION USING THE PSU/NCAR MM5 MESOSCALE MODEL

Xingang Fan* and Jeffrey S. Tilley
University of Alaska Fairbanks, Fairbanks, Alaska

1. INTRODUCTION

Interest in mesoscale forecasting in high latitudes has increased. For high resolution mesoscale forecasting at high latitudes, the conventional data that enters an initializing analysis is spatially sparse compared to lower latitudes. Therefore, it is prudent to investigate 4-dimensional data assimilation (FDDA) methods, particularly utilizing remotely sensed information into forecast systems to improve both the initializing analyses and the resulting forecasts.

The standard PSU/NCAR MM5 modeling system contains a Newtonian nudging FDDA method (NNFM) (Grell et al, 1994). Nudging to both gridded analyses and/or conventional observations is examined in a companion paper (Tilley and Fan 2001). The result shows that NNFM has a positive simulation capability. However, since the nudging is done before the observation time, it is difficult, from a forecast systems point of view, to use the nudging coefficients afterwards for forecasting purposes. Therefore other FDDA approaches need to be investigated for such purposes.

The so-called ‘intermittent data assimilation' (IDA) method is one such alternate approach, in which the successive correction method is widely used as an objective analysis technique. Schemes following Cressman (1959), Barnes (1973), Bratseth (1986) and others are possible ways of obtaining the analyses used in IDA. Among those, the Bratseth scheme avoids errors associated with the fact that in the other successive correction schemes the analysis always converges to the data, which should not be the case when errors exist in both the observations and the background. The solution of the Bratseth scheme converges toward a solution obtained by Optimal Interpolation (OI). This method alleviates the shortcomings of the Cressman scheme and of other successive correction schemes and also requires much less computational costs than performing a full OI procedure.

Sashegyi et al (1993) used the Bratseth scheme for analysis of Genesis of Atlantic Lows Experiment (GALE) simulations with the U.S. Naval Research Laboratory (NRL) mesoscale model. The analysis was done with a multivariate successive correction approach. Ruggiero et al (1996) examined an assimilation approach where surface observations are used in the NRL model while the Sashegyi et al (1993) method is applied to the upper air analysis.

The MM5 model has its own data preparation procedures and initialization procedures, including Cressman and Multiquadric objective analysis (e.g., Grell et. al 1994). In this study we apply the Bratseth scheme in the objective analysis, and perform the analysis in the both univariate and multivariate contexts. We further utilize the Bratseth scheme in tandem with the IDA method in MM5 simulations of the summer Alaskan heavy rain event examined in the companion paper with the NNFM method. In an assimilation cycle, the 6-hour model forecast is reanalyzed using the Bratseth scheme by ingesting new observations at the forecast time. Then the analysis is initialized for an MM5 forecast run.

Section 2 discusses the IDA cycle used in this study with MM5 model. Section 3 briefly describes the Bratseth objective analysis scheme. Section 4 gives a summary of the case we are studying and experiment design. Section 5 gives the results of the experiments, with discussion and conclusions in Section 6.

2. INTERMITTENT ASSIMILATION CYCLE

The IDA experiments in this study consider a 48-hour period during the event. A cycle begins with a 6 hour MM5 forecast from the initial time. An analysis from the 6-hour forecast is constructed with the aid of observations and used to re-initialize the model for another 6 hour forecast period. Figure 1 shows a flowchart of the IDA cycle with the MM5 model. The cycle is repeated for a total length of 24 hours. The model is then run continuously for another 24 hours to

Corresponding author address: Xingang Fan, University of Alaska Fairbanks, Geophysical Institute, Fairbanks, AK 99709;
Email: xfan@taku.iarc.uaf.edu
* On leave of absence from Chinese Academy of Meteorological Sciences, Beijing, 100081

the end of the 48-hour period. This approach simulates a real time forecast during which observations are available only before the current time.

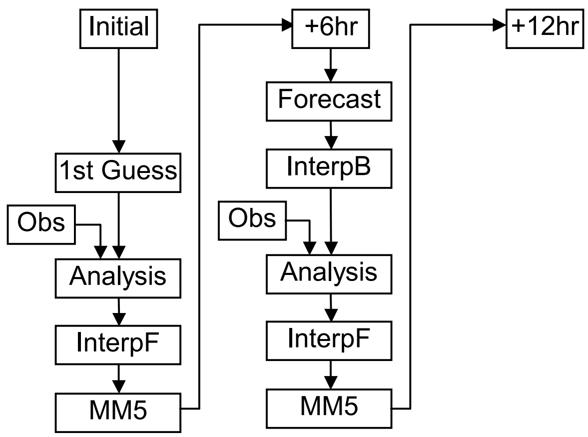

Figure 1. Illustration of IDA scheme.

3. OBJECTIVE ANALYSIS SCHEME

The Bratseth analysis scheme used in this study is similar to the one in Sashegyi et al (1993). The sea level pressure and 3-dimensional temperature, height, relative humidity and winds are analyzed first by univariate analysis. The first guess field is the MM5 forecast which is interpolated to pressure levels. Then, for efficiency of analysis, the observations are sorted into bins of dimension 10x10 analysis grid points after being subjected to quality control checks by the MM5 preprocessor program LITTLE_R. Observations that are too close to each other to be utilized individually are averaged to form 'superobs'. A univariate analysis is conducted to correct the deviations of analysis from the first guess. The Bratseth successive correction works in an iterative fashion updating both the interpolated grid correction and observation correction using the difference between the observed values and the observational estimates derived from the analysis.

For the geopotential corrections, at grid point x, the updated grid correction ϕ_x is given by:

$$\phi_x(k+1) = \phi_x(k) + \sum_{j=1}^{n} \alpha_{xj}\left[\phi_j^o - \phi_j(k)\right], \qquad (1)$$

while the observation correction is given by:

$$\phi_i(k+1) = \phi_i(k) + \sum_{j=1}^{n} \alpha_{ij}\left[\phi_j^o - \phi_j(k)\right], \qquad (2)$$

where ϕ_j^o is the value of the observation, $\phi_x(k)$ and $\phi_j(k)$ are the interpolated correction at grid point and the estimated observation correction respectively for the kth iteration. n is the total number of observations that influence a particular grid point, and α_{xj}, α_{ij} are weighting functions between (1) the grid point x and the observation location j, and (2) the observation locations i and j, respectively. The weights are defined following Sashegyi et al (1993), and contain terms to account for observational error and correlations of true values. The correlation functions follow a basic Gaussian form, though a slightly different form is used for the wind fields in order to allow for different weights for different wind components. The length scale used here is 600 km (13.3 grid points in this study). After 3 to 4 iterations, the length scale is reduced to 330 km for one more iteration to speed convergence of the scheme. The starting corrections $\phi_x(1)$ and $\phi_j(1)$ in equations (1) and (2) are zero.

After a 'first tier' univariate analysis, the second tier enhancement analysis for geopotential height and winds are conducted following the procedure of Sashegyi et al (1993).

The lateral boundary analysis result is merged with the standard LITTLE_R analysis that is used in the control run. This makes the lateral boundary consistent with both the original environment obtained from the NCEP analysis and the new Bratseth analysis.

4. EXPERIMENT DESIGN

The Alaskan heavy rain event of Aug. 11-13, 2000, described in Tilley and Fan (2001; this volume), is examined in this study. The MM5 model is configured with two nested domains with grid resolutions of 45 and 15 km, respectively. The dimensions of the two domains are 109x90 and 106x88. Both have 41 sigma levels vertically. The analysis is performed on the coarse domain and then interpolated to the fine grid domain. The control run uses the standard MM5 initialization procedure with no FDDA, and is the same as that in Tilley and Fan (2001). The model simulations are run for 48 hours. Figure 2a shows the NCEP analysis 24-hour rainfall and Figure 2b the 24-hour accumulated rainfall difference of the control run from the analysis at 12 UTC Aug. 12, 2000.

For the IDA experiments, the model is initialized from 12 UTC Aug. 11. After the initial conditions have been obtained for 06 UTC Aug. 12, the model is run continuously from that time to 12 UTC Aug 13. In order to do a comparison study of the method, assimilation cycles were done without ingesting observation data, thereby omitting the analysis step in Figure 1 (Experiment NoObs). The second experiment ingests observations but the analysis method used is the MM5 LITTLE_R preprocessor program with the Cressman scheme (Experiment Inta_R). The third experiment tests the Bratseth scheme in IDA (Experiment Inta_B). The simulation results will be given in the next section.

5. RESULTS

Though we have run the model for 48 hours, here we only show the results of the 24-hour forecasts, focusing on the impacts of data assimilation on the precipitation forecast since quantitative precipitation forecasts are a serious forecast problem in Alaska as well as in the continental United States.

5.1 Impact of Data Assimilation

Figures 3a and 3b illustrate the results of experiments NoObs and Inta_R, respectively. In

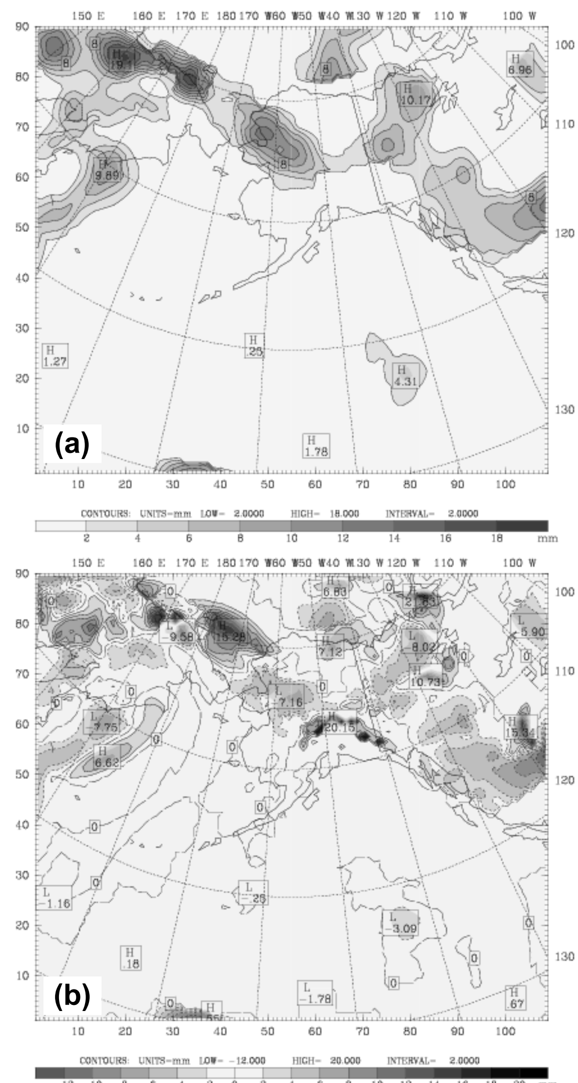

Figure 2. (a) The NCEP analysis 24-hour rainfall and (b) the difference of the forecasted 24-hour accumulated rainfall, Control Run-Analysis, at 12 UTC August 12, 2000.

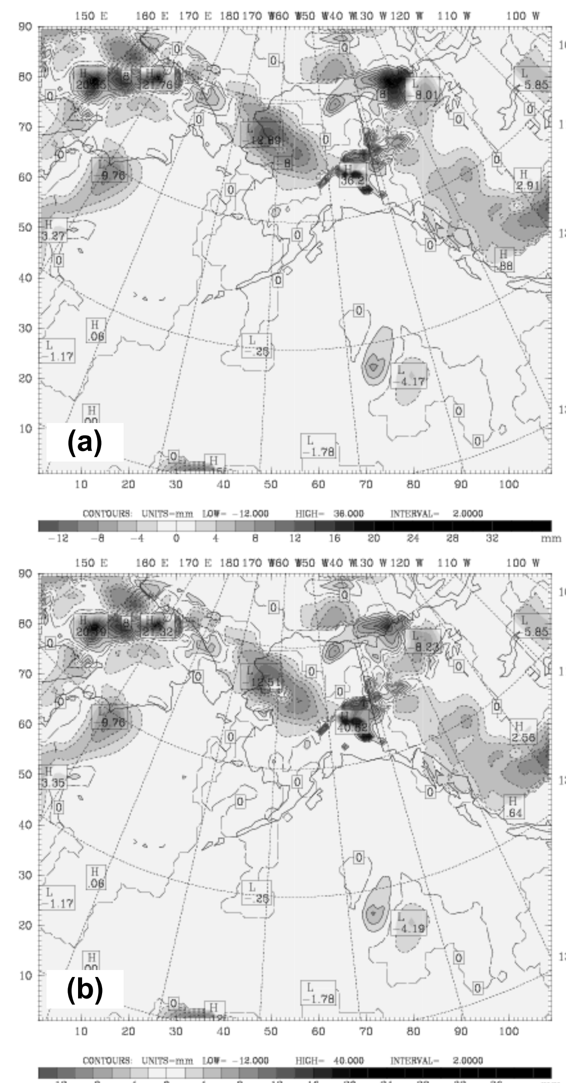

Figure 3. Differences in 24-hour accumulated rainfall between: (a) experiments NoObs; (b) experiment Inta_R, and the NCEP analysis, at 12 UTC August 12, 2000.

the result of NoObs (Figure 3a), the rainfall forecast error is greater than that of the control run (Figure 2b). This is understandable because the observation data were used in the objective analysis of the control run.

After the observation data are ingested in the experiment Inta_R through the MM5 objective analysis package LITTLE_R, the rainfall forecast error field is improved over that of NoObs. The two relatively large precipitation differences in Alaska and northwest Canada are reduced in magnitude in the Inta_R simulation. Although the main rainfall center in Alaska is still underforecast compared to the observed rainfall, the rainfall forecast in this assimilation run is still improved compared to the control run. The two large positive error centers located in the northern Bering Sea and northwest Pacific Ocean in the previous experiments (compare Figures 2 and 3) do not occur in experiment Inta_R. Nevertheless, the important point is that the IDA/LITTLE_R approach improves the rainfall forecast to some degree.

5.2 Impacts of Bratseth Analysis Scheme

Figure 4 illustrates the result of assimilation experiment Inta_B in which the Bratseth analysis scheme is used in the assimilation cycle.

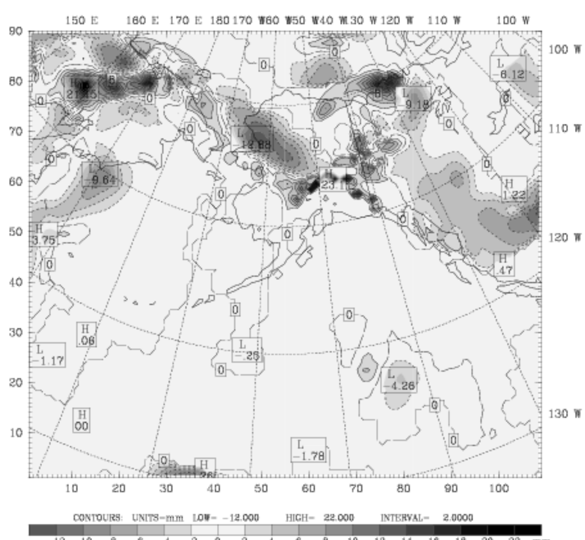

Figure 4 . Difference in 24-hour accumulated rainfall of experiment Inta_B from the NCEP analysis at 12 UTC August 12, 2000.

From Figure 4 it is clear that the IDA experiment conducted with the Bratseth scheme also produced an improved rainfall forecast over the control run. In comparison with the Inta_R result (Figure 3), Inta_B is characterized by a smaller negative error area than Inta_R within Alaska, though otherwise the results are very similar to those of experiment Inta_R. This result indicates that the use of Bratseth scheme has a positive effect on the rainfall forecast for this case.

6. SUMMARY AND DISCUSSIONS

This study focused on the IDA method using the MM5 model at high latitudes. An efficient objective analysis scheme developed by Bratseth (1986) and applied by Sashegyi et al (1993) and Ruggiero et al (1996) was incorporated into the MM5 model. Several experiments have been performed in order to investigate the effectiveness of both IDA conducted with MM5 and the Bratseth objective analysis method.

The results show that IDA in MM5 shows promise in ingesting observations and improving forecasts, while at the same time being rather simple and inexpensive. The Bratseth analysis scheme obtains better results when both observation and model forecast fields contain errors.

However, it is important to note that neither the control run nor any of the other produced sufficient rainfall in comparison with the analysis (Figure 2a). One possible reason is that the observation data is sufficiently sparse in space that there is a limit to the improvement from any of these types of methods employing conventional data.

Nonetheless, there appears to be some potential of obtaining benefit from application of an IDA system in high latitudes. Further work investigating other cases and applying the method to other regional models is indicated to see how robust this potential is. Future work related to assimilating satellite derived moisture variables will also likely bring improvements to precipitation forecasts in high latitudes.

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