Implementation and evaluation of assimilating NCEP Stage IV precipitation using WRFDA 4D-Var

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Direct four-dimensional variational data assimilation (4D-Var) approach is used to assimilate precipitation data in Weather Research and Forecasting Data Assimilation system (WRFDA). Three experiments for a 14-day period in June 2010 are performed to assess the impact of precipitation assimilation on short-range forecasts. The assimilated precipitation experiment has a positive impact on model fields, particularly temperature and humidity on the lower atmosphere for analysis, 12-h and 24-h forecast, as compared with upper air soundings. Precipitation scores also systematically improved for the threshold from 1mm to 20mm and the forecasts of precipitation quantity and pattern are more close to observation.

1. Introduction

A proper description of the hydrological cycle is vital for short-period forecasting with regional operational Numerical Weather Prediction (NWP) models [*Macpherson*, 2001]. Meanwhile, the accuracy of short-range NWP is largely affected by the model initial condition. Many studies [Zupanski and Mesinger, 1995; Zou and Kuo, 1996; Tsuyuki 1996a, 1996b, 1997; Guo et al., 2000; Xiao et al., 2000] indicate that the assimilation of precipitation observations can provide accurate mesoscale initial states, and hence, it is expected to improve the skill of short-range forecasts.

The first attempt to assimilate precipitation observations using 4D-Var approach was made by Zupanski and Mesinger in 1995. They demonstrated the technical feasibility of the approach and showed an improvement of precipitation forecast in mid-latitudes by using a regional NMC eta forecast model and an incomplete adjoint model. Later, many studyies [Zou and Kuo 1996; Tsuyuki 1996a,b, 1997; Guo et al. 2000; Xiao et al. 2000] indicated that the precipitation assimilation leads to a reduction in the spin-up time, improves the moisture distributions in model initial conditions and improves the skill of short-range forecasts. Some operational weather services also assimilate precipitation operationally using 4D-Var method, including Japan Meteorological Agency (JMA) [Tsuyuki et al. 2002] and European Centre for Medium-Range Weather Forecasts (ECMWF) [Lopez 2011]. Although the results of studies mentioned above are encouraging, the precipitation assimilation in 4D-Var is still a challenging issue.

The assimilation of precipitation-related observations is potentially very different than that of more conventional observation types for a variety of fundamental and practical considerations [Errico et al. 2000]. In order to use precipitation data in 4D-Var, it is necessary to include parameterization schemes of moist processes into tangent linear model and corresponding adjoint model. However these processes are strongly nonlinear and contain discontinuous (non-differentiable) on/off switches, especially in the case of a cumulus convection parameterization. This makes the tangent linear approximation less valid for a linearized model with physics than for the same model without physics [Tsuyuki, 1997]. Thus, development of techniques of the 4DVAR data assimilation with realistic, full-physics forecast models must be related to examining and solving these problems first [Zupanski and Mesinger, 1995]. Zhang et al. [2013] reports that the tangent linear and adjoint codes of the WRF model (WRFPLUS) have been redeveloped. It includes all major model physics (e.g., the parameterizations for cumulus, microphysics, and radiation). Moreover, a simple boundary layer process, horizontal and vertical diffusions are also incorporated into the model. Taking advantage of the redeveloped WRFPLUS, it is possible and natural extension to assimilate precipitation data using 4D-Var method in WRF Data Assimilation System (WRFDA) [*Barker et al.*, 2012].

This study explores for the first time the feasibility and the impact of the 4D-Var assimilation of precipitation data in WRFDA system. Considering the compute resource saving, multi-incremental method is employed to reduce the cost. Conventional data and NCEP stage IV 6-hourly accumulated precipitation are assimilated. A 14-day period from 1 to 14 June 2010 has been selected to evaluate the impact of precipitation assimilation on short-range forecasts.

2. Observations used in assimilation experiments

2.1. NCEP stage IV precipitation data and data processing

The observations to be assimilated in this paper are NCEP stage IV precipitation data, which combine precipitation estimates from about 150 Doppler Next Generation Weather Radar (NEXRAD) with about 5500 hourly rain gauge measurements over the continental United States [*Baldwin and Mitchell*, 1996; *Lin and Mitchell*, 2005]. Hourly, 6-hourly and 24-hourly analyses can be downloaded on the NCAR CODIAC web page at: http://data.eol.ucar.edu/codiac/dss/id=21.093. NCEP Stage IV data is in GRIB1 format and it cannot be ingested into the WRFDA directly, therefore, the original data is converted into the WRFDA readable data format. Quality control is performed in data reading process to reject observations which innovation vector is greater than 5 times the assumed observation error standard deviation. Original 4km resolution data is thinned to experiment resolution.

2.2. Conventional observation

Conventional data used in this paper includes land surface, marine surface, radiosonde, pibal and aircraft reports from the Global Telecommunications System (GTS) which originated from a wide variety of sources. Quality control is also preformed in data reading process.

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3. WRFDA 4D-Var

The prototype version of the WRF 4D-Var system is described in *Huang et al.* [2009]. It is based on the incremental variational data assimilation technique. The cost function in the incremental approach is formulated as follows,

$$\begin{aligned} J(\delta x) &= J_b(\delta x) + J_o(\delta x) + J_c(\delta x) \\ &= \frac{1}{2}\delta x^T \mathbf{B}^{-1} \delta x \\ &+ \frac{1}{2}\sum_{k=0}^{K} (\mathbf{H}_k \mathbf{M}_k \delta x - d_k)^T \mathbf{R}^{-1} (\mathbf{H}_k \mathbf{M}_k \delta x - d_k) \\ &+ J_c(\delta x) \end{aligned} \tag{1}$$

$\delta x = x_0 - x_0^b$ is the analysis increment relative to the model state (x_0) and background (x_0^b) at time k. K is the total number of time slots on which observation are available. $\mathbf{B}$ and $\mathbf{R}$ are covariance matrices for background error and observation error. $\mathbf{H}$ is the linear approximation of the observation operator H in the vicinity of x_0^b. $\mathbf{M}$ is the tangent linear model. $d_k = y_k^0 - H_k\left[M_k(x_0^b)\right]$ is the innovation vector between observed precipitation y_k^0 and model precipitation at time k . The model precipitation includes nonconvective and convective precipitation. The sum of the two part of precipitation is linear interpolated to observation location and compared with the observations to generate the innovations. H and M are the nonlinear observation operator and simplified WRF nonlinear model respectively. J_c is a balancing term. It measures the quadratic distance between the analysis and a balanced state.

4. Experiments design and verification methods

4.1. Experiments design

A 14-day period from 0000 UTC 1 to 1200 UTC 14 June 2010 has been selected for running the experiments. This period is chosen because it is characterized by many precipitation events of both convective and stratiform nature. WRF-ARW model [*Skamarock et al.*, 2008] is used as the forecast model. The integration domain of the model covers the North American continent and the surrounding oceans. The horizontal resolution is 30km and there are 40 vertical levels with the model top at 50hPa. WSM 5-class microphysics scheme [Hong et al. 2004], Kain-Fritsch cumulus convection scheme [Kain and Fristsch], and YSU boundary layer parameterization [Hong et al. 2006] are used.

A 6-h spin-up run is conducted using NCEP FNL data (horizontal spatial resolution of 1.0 x 1.0 degree) and the output from the spin-up is used as the initial condition of the COTROL experiment as well as the first guess field for the 4D-Var experiments (GTS and GTS+RAIN). The CONTROL experiment is 24-h forecast, and it serves as the benchmark for evaluating the assimilation experiments. In the second experiment (GTS), conventional observations are assimilated. The third experiment (GTS+RAIN) is the same as the second, except NCEP Stage IV 6-hourly accumulated precipitation data is also used. The assimilation window is 6 hours. 2 mm precipitation error is assigned for 6-h accumulated rainfall assimilation. The National Meteorological Center (NMC) method [Parrish and Derber, 1992] in the WRFDA package is adopted for background error calculation.

To reduce the computational cost, multi-incremental 4D-Var is used, where the innovation in outer loop is computed with a high-resolution nonlinear model (30 km) and the minimization in inner loop is done with a low-resolution linearized model (90 km). A more detailed description of multi-incremental 4D-Var can be found in Zhang et al. [2013] section 3a.

4.2. Verification methods

The Model Evaluation Tool (MET) developed by Developmental Testbed Center (DTC) [*Brown et al.*, 2009] is used to evaluate the performance of three experiments by verifying the analyses, 12-h and 24-h forecasts against corresponding observations.

Two datasets have been used to assess the analyses and forecasts. One dataset is the upper air sounding observations, which is used to evaluate model longitudinal and meridian winds, temperature, and relative humidity. Root-mean square errors (RMSEs) are used as the verification metric.

The other source of data is NCEP Stage IV precipitation data. The original precipitation accumulations are available on a 4-km resolution polar-stereographic grid. It has been regrided to 30 km lambert conformal grid before verification. We acquire 12-h and 24-h accumulated precipitation by summing of NCEP Stage IV 6-hourly accumulated precipitation. After interpolating and summing, verification are done by using a grid-to-grid comparison. The Gilbert Skill Score (GSS) [Gilbert, 1884] is used as the precipitation verification metric.

RMSEs and precipitation scores in section 5 have been calculated for the entire 14-day period of the experiments.

5. Results

5.1. Profile verification

In order to evaluate how atmospheric variables are affected by the precipitation assimilation, RMSEs are computed for U-and V-component of the vector wind, temperature and relative humidity on different pressure levels. Figure 1 and Figure 2 give the vertical profiles of U-and V-component of the vector wind RMSE for three experiments. The confidence intervals are added to help visualize the uncertainty, and the horizontal bars represent the confidence intervals at the 95 confidence level. The U-and V-component of the vector wind RMSE of GTS+RAIN is almost the same as that of GTS at analysis time (Figure 1a and Figure 2a), and the analyses have statistically significant lower RMSE then CONTROL for all levels. It indicates that 4D-Var much improved the analysis. For 12h and 24h forecast, GTS+RAIN reduced the errors slightly in the lower troposphere contrast to GTS. For temperature RMSEs, GTS+RAIN reduced the errors for analysis, 12-h and 24-h forecast in lower troposphere, but the results are not statistically significant. Figure 4 shows the vertical profiles of relative humidity RMSE. GTS+RAIN has statistically significant lower RMSE than GTS and CONTROL at analysis time and 12-h forecast at 1000hpa. *Guo et al.* [2000] also reported that humidity was much improved in precipitation assimilation experiment using MMM5 data assimilation system.

5.2. Precipitation verification

GSS is used for quantitative verification of the 12-h and 24-h accumulated precipitation at different thresholds. Figure 5 shows threshold series of GSS for 12-h (Figure 5a) and 24-h (Figure 5b) accumulated precipitation for the experiment CONTROL, GTS, GTS+RAIN. A perfect forecast for GSS is 1. For 12-h precipitation forecast, GTS produces the lowest GSS. We look into the time series of GSS for the whole period (Figure 6). In general, CONTROL gives better results than GTS at threshold 5.0mm, however, GTS and CONTROL produce similar results except the obvious difference at 0000 UTC 5, 6 and 12 for 10.0mm and 20.0mm threshold. For 12-h and 24-h accumulated precipitation, GTS+RAIN systematically improved the GSS scores. It indicates that the quantitative precipitation forecast can be much improved when we assimilate both conventional and precipitation data. In our experience and previous study [Xu et al. 2006], the precipitation forecast for GTS+RAIN experiment is sensitive to the assign of precipitation observation error and assimilated precipitation frequency. For example, the precipitation forecasts for threshold greater then 15.0mm almost have no improvement if we use a too small error such as 0.25mm.

In Figure 7, the forecasts of 12-h accumulated precipitation from 1200 UTC 10 to 0000 UTC 11 June 2010 for three experiments are compared with NCEP Stage IV. In Figure 7a, it shows the rainfall center located in eastern Nebraska, western Lowa and southeastern corner of South Dakota. CONTROL (Figure 7b) does not produce the correct location: the rainfall center shifts northward to southern Minnesota and eastern South Dakota. GTS (Figure 7c) overestimated rainfall in northeastern of South Dakota. In Figure 7d, GTS+RAIN simulates relatively proper amount and distribution of precipitation. It suggests GTS+RAIN experiment succeeded in bringing the model precipitation closer to the observations.

6. Conclusion

In this study, we use the WRFDA 4D-Var system to assimilate precipitation data. Multi-incremental 4D-Var method is implied to reduce the computational cost. A 14-day period containing many precipitation events is selected to assess the performance of precipitation assimilation in WRFDA 4D-Var. Three experiments have been conducted: CONTROL without assimilation; GTS assimilation of conventional data and GTS+RAIN assimilation of both conventional and precipitation data. The time window is 6 hours for assimilation experiments and 6-h accumulated precipitation data is used. To evaluate how atmospheric variables are affected by the precipitation assimilation, RMSEs are computed for the two components of the vector wind, temperature and relative humidity on different pressure levels. It is found that the analyses have statistically significant lower RMSE then CONTROL on all levels, as compared with upper air soundings. In 12-h forecast, the relative humidity RMSE of GTS+RAIN has been statistically significant reduced at 1000hpa. For precipitation verification, the obvious advantage is presented in GTS+RAIN experiment. The GSS is systematically improved for the threshold from 1mm to 20mm and the forecasts of precipitation quantity and pattern are more close to observation in GTS+RAIN. The results also show that the impact on precipitation forecast is very neutral if we only assimilate conventional data, although it improves the vertical profile of RMSEs for the vector wind, temperature and relative humidity. In our experience and previous study, the precipitation forecasts in GTS+RAIN experiment are sensitive to the assign of precipitation observation error and the assimilated precipitation frequency. It will be further investigated in future studies.

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Table 1. Table caption

Treatments	**Response 1**	**Response 2**
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296