Radiance Assimilation in WRF-Var: Implementation and Initial Results

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1. Introduction

In the past decade, the direct assimilation of satellite radiance data in numerical weather prediction (NWP) assimilation systems has proved to be an essential component for improving forecast skill, particularly for global models (e.g., Derber and Wu, 1998; McNally et al., 2000). In the past year, preliminary work has been performed to implement a direct radiance assimilation capability in the community WRF-Var assimilation system, which is expected to be able to improve the forecast for meso-scale and severe weather events. The next section will describe the implemented components relevant to radiance assimilation in the WRF-Var system, such as radiance data source, radiative transfer model (RTM), microwave surface emissivity model, quality control (QC), bias correction (BC) and observation error tuning. In the third section, one presents the preliminary results of a case study that assimilates NOAA AMSU-A radiance data to improve the hurricane Katrina forecast. Finally, one summarizes current developing status and future working plan.

2. Implementation of Radiance Assimilation in WRF-Var

a. WRF-Var Systerm

Before involving in the description of components relevant to radiance assimilation, one briefly summarizes main features of the WRF-Var assimilation system. Current WRF-Var assimilation system was designed for providing an optimal initial and boundary conditions to the WRF model by using various observation information, both from conventional data and a number of satellite platforms. It is originally based upon a 3DVAR system designed for MM5 system (Barker et al., 2004). A few improvements during the development of WRF-Var have been done relative to MM5-3DVAR. In addition to new radiance assimilation capability described in this paper, other important improvements include the change of the control variables, unified global/regional assimilation capability and preliminary 4DVAR capability. More details can be found in the WRF-Var overview of this volume by Barker et al..

b. Interface to Radiative Transfer Model

Direct assimilation of radiance data requires incorporate a fast radiative transfer model (RTM) as an observation operator into the WRF-Var system. The interface to the latest version 8 of widely used RTM RTTOV (Saunders et al, 1999) has been implemented inside WRF-Var. This includes the interface to the forward, tangent linear and adjoint models of RTTOV. RTTOV8 has ability to compute cloudy/precipitating radiance for infrared/microwave instruments. However, as a first step, current implementation only focuses on clear sky condition. It will be necessary to identify and reject radiance data contaminated by cloud and precipitation before assimilating these data.

c. Microwave Surface Emissivity Model

Accurate surface emissivity is essential to the use of window channels (e.g., channels 1~3 of AMSU-A). Infrared and microwave surface emissivity models are built in RTTOV. In addition to RTTOV inbuilt surface emissivity models, the NESDIS/NCEP microwave surface emissivity model (Weng et al., 2001) is also integrated into WRF-Var system as an optional scheme, which has more accurate emissivity computation over snow and sea-ice. This will be preferred for some particular application such as Antarctic prediction (Bromwich et al., 2005).

d. Radiance Data Source and Interface

There exists a number of radiance data sources both from geostationary (e.g., GOES, MSG, FY-2, MTSAT) and polar satellite platforms (e.g., NOAA, DMSP, Terra, Aqua), and from various instruments (e.g., AMSU-A/B, HIRS, AIRS, SSM/I). Currently, inside WRF-Var we have implemented data interface to some of NCEP BUFR radiance data such as those from NOAA series' HIRS, AMSU-A, AMSU-B and EOS-Aqua's AIRS. With the help of RTTOV (which can compute radiance for almost all available instruments) and a flexible programming design, technically adding new satellite instruments requires little additional coding effort. Different instruments can share the same code relevant to innovation computation and minimization procedure. Main additional efforts for adding new instruments are to implement separated data interface and quality control (QC) schemes.

e. Quality Control

Quality control (QC) is an important component for correctly using radiance data (also for other data). Currently, one firstly implements basic QC schemes for NOAA microwave instruments AMSU-A and AMSU-B, which were shown to have the largest impact for improvement of current global forecast skill.

During QC procedure, AMSU-A/B data contaminated by precipitation is identified and rejected by means of a so-called scatter index (SI) defined by the difference of brightness temperature (BT) of corresponding instrument's two channels (Ferraro et al., 2000):

SI(amsua)=BT(23GHz)-BT(89GHz);

SI(amsub)=BT(89GHz)-BT(150GHz).

As suggested by Ferraro et al., (2000), all channels are rejected if SI>3K. **Figure 1** shows the NOAA17 AMSU-B SI at 06Z on 26th August 2005. We can clearly see that the precipitation areas (most in red color) are well identified by SI. Notice that Hurricane Katrina is well observed. An additional precipitation detection is to use the cloud liquid water path (CLWP) computed from the background field (generally a 6-hour WRF forecast). We assume that precipitation happens if CLWP>0.2mm. Computation indicates that CLWP has basically consistent precipitation area pattern with that of SI (not shown).

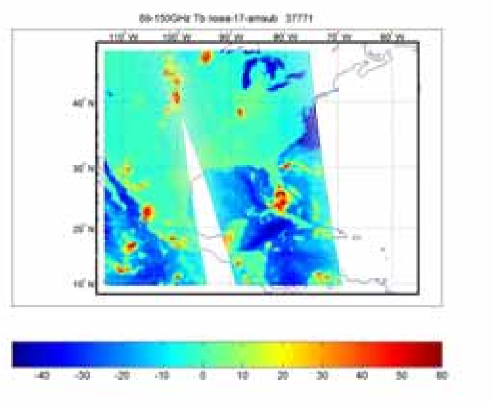

Figure 1: NOAA17 AMSU-B scatter index within a 6-hour assimilation window centered at 06Z on 26th August 2005.

Other quality controls include: only using window channels over water; rejecting channels whose weighting function peak is above model top or below surface pressure; rejecting pixels over mixture surface; rejecting channels whose innovation (observation minus background) is larger than 3 times the standard deviation of observation error. It should be mentioned that final QC decision for an operational implementation should be done according to innovation monitoring for a long period.

f. Bias Correction

Global monitoring of radiance innovation in some NWP centers often shows biased feature. **Figure 2a** gives a scatter plot of observed versus computed brightness temperatures for NOAA15 AMSU-A channel 6 within a 6-hour assimilation window centered at 00Z on 26th August 2005 and within a domain shown in Figure 1. The observed brightness temperatures have an obvious negative bias of about 1.3K relative to those computed. In general, these biases depend upon both scan angle and air mass and need to be corrected either before data enters into minimization procedure (statistics-based method, Harris and Kelly, 2001) or during minimization procedure (variational-based method, Derber and Wu, 1998). For initial implementation, a bias correction scheme based upon simple linear regression is adopted, which is also used by some authors for atmospheric temperature and humidity profile retrieval from ATOVS radiance data (Li et al., 2000). Bias correction equation can be written as

$$BT^*(X_b) = a + b \times BT(X_b) \quad (1),$$

where $BT(X_b)$ is the brightness temperature computed from the background field, $BT^*(X_b)$ the bias-corrected background brightness temperature. The bias correction coefficients a and b are obtained by a linear regression procedure (replacing LHS of equation (1) by observed brightness temperatures) for separated channels and scan angles. By-products of this statistics procedure are average, root mean square (RMS) and standard deviation of innovation, which can be used as reference of observation error assignment or a start point of observation error tuning procedure. **Figure 2b** gives the scatter plot after bias correction for the same dataset as Figure 2a. The bias is significantly reduced.

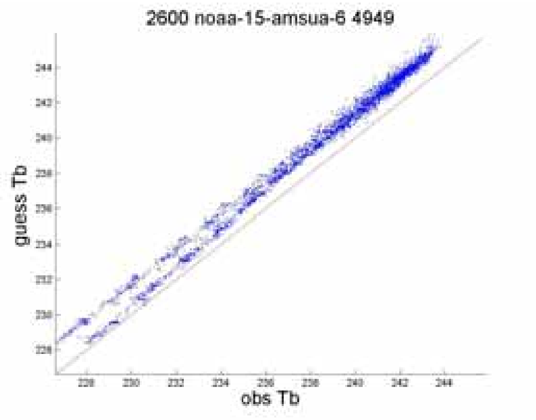

Figure 2a: Scatter plot of observed versus computed brightness temperatures for NOAA15 AMSU-A channel 6.

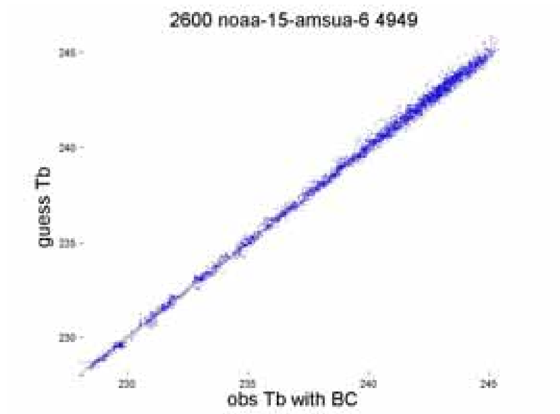

Figure 2b: Same as Figure 2a, but after bias correction.

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g. Observation Error Tuning

Observation error assignment in assimilation system determines the analysis weight of corresponding observation type and is crucial for optimal use of observations. An error tuning procedure for radiance data is developed based upon the method by Desroziers and Ivanov (2001). This tuning procedure requires two series' assimilation runs. One uses realistic observations and another uses perturbed observations.

3. Application to the Hurricane Katrina

As the first test, one applies radiance assimilation to the hurricane Katrina case. For conducting the experiments, a domain with a horizontal resolution of 12km (460*351 grid points) and 51 vertical levels (model top at 10hPa for better using some high level channels) is set up. The area covered is shown in Figure 1. With this domain configuration, **Figure 3** gives the best track (red line) of Katrina and WRF-ARW forecast tracks initialized from the NCEP AVN analysis respectively at 00Z on 25^{th} (blue line), 26^{th} (black line) and 27^{th} (green line) August 2005. The forecast track from 00Z on 27^{th} is almost perfect. But the forecast tracks from 00Z on 25^{th} and 26^{th} are much worse. Some real-time forecasts started at 00Z on 26^{th} from different NWP centers give similar bad track (not shown). One attempts to improve the Katrina forecast started at 00Z on 26^{th} by radiance assimilation. One firstly focuses on the impact of AMSU-A data.

Figure 3: The best track (red line) of Katrina and WRF-ARW forecast tracks initialized from the NCEP AVN analysis respectively at 00Z on 25^{th} (blue line), 26^{th} (black line) and 27^{th} (green line) August 2005.

Four assimilation experiments were conducted: (1) only use conventional data; (2) use conventional data plus AMSU-A data; (3) only use AMSU-A data; (4) use AMSU-A data plus a single central sea level pressure (SLP) observation located at hurricane center. AMSU-A data is within a 6-hour time window and conventional data is within a 4-hour time window* both centered at 00Z on 26^{th}. All assimilation experiments uses the same background field which is a WRF 6-hour forecast initialized from the AVN analysis at 18Z on 25^{th}. Mention that NOAA-15 AMSU-A has very good data coverage for this case and that assimilation experiments with AMSU-A data apply the bias correction scheme described in section 2f.

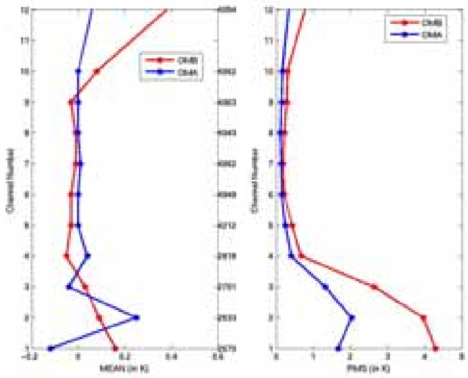

Figure 4: the domain averaged mean(left) and RMS(right) of (NOAA15 AMSU-A) observation minus background (OMB, red line) and observation minus analysis (OMA, blue line) for the experiment only using AMSU-A data, where OMB is bias corrected values.

Figure 4 gives the domain averaged mean and RMS of (NOAA15 AMSU-A) observation minus background (OMB, red line) and observation minus analysis (OMA, blue line) for the experiment only using AMSU-A data, where OMB is bias corrected values. The numbers of realistically assimilated observations after QC for different channels are also shown in Figure 4. The residual bias for most channels (e.g., channels 3~10) is small. Two window channels 1,

* In this study, using different time window for conventional data and AMSU-A data is just by historical reason, there is no particular consideration. But a shorter time window could be preferred for Hurricane application.

2 and high level channel 12 still remain relative large residual bias. RMS is consistently reduced for all channels. Also mention that at the time of conducting these experiments, AMSU-A observation errors are not well tuned and are simply assigned by a constant factor 0.5 multiplying the standard deviation of innovation statistics of different channels.

Figure 5: forecast tracks for four assimilation experiments in addition to the best track and the forecast track from AVN analysis.

After assimilations at 00Z on 26th, a 5-day forecast is followed. **Figure 5** shows forecast tracks for these assimilation experiments in addition to the best track and the forecast track from AVN analysis. One can see that only using conventional data (green line) produces little improvement for track forecast. Using conventional data plus AMSU-A data (red dash line) further improves the track but still remains large track error. A little surprisingly, only using AMSU-A data (blue line) produces much better track forecast. The reason for this is not clear yet and needs to be analyzed with more details. Also note that using AMSU-A data plus a single central SLP observation located at hurricane center (yellow line) produces very similar track forecast to that with only AMSU-A data, but with a little better moving speed. This seems to indicate that this good track forecast is mainly controlled by assimilating AMSU-A data.

Figure 6 shows the central sea level pressure (SLP) variation with time from the best track and three forecasts. One can see that three forecasts basically exhibit similar SLP variation to the best track. The worst SLP forecast (green curve) is the one initialized from AVN analysis at 00Z on 27th although its perfect track forecast as shown in Figure 3. This may be associated with low horizontal resolution (1*1degree) of the AVN analysis. As expected, adding a single SLP observation (black curve) further improves the SLP forecast relative to that with only AMSU-A data (blue curve) due to more accurate analysis of initial position and intensity of the hurricane. Note also that the lowest SLP from the best track (red curve) attains about 900hPa, whereas the lowest SLP from three forecasts is just about 920hPa. This probably indicates that a 12km simulation is not enough to obtain more accurate Katrina intensity forecast.

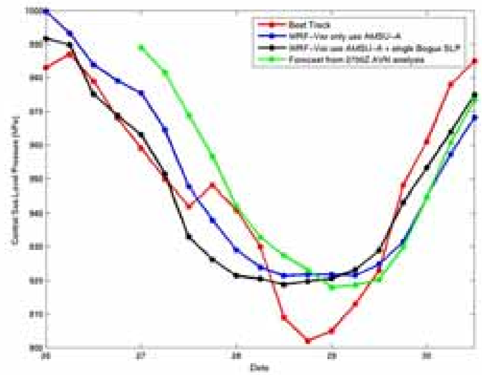

Figure 6: The central sea level pressure (SLP) variation with time from the best track and three forecasts.

4. Summary and Perspective

Preliminary radiance assimilation capability has been implemented in the WRF-Var system with some key components such as the interface to NCEP BUFR format radiance data and to radiative transfer model as well as to an external microwave surface emissivity model, quality control, bias correction and observation error tuning. Flexible programming design requires little additional coding efforts to add new instruments. An initial assimilation application of AMSU-A data to Katrina case gives encouraging results although the analysis with more details is still required.

In the near future, some observing system simulation experiments (OSEs) will be performed for a long period (for example, whole month) to test the statistical impact of radiance data, in addition to more case studies. Improved schemes for bias correction (e.g., variational BC) and observation error tuning (e.g., remove the need for perturbed assimilation run) will be also developed. Quality control schemes for other available instruments (e.g., HIRS, GOES/MSG sounders, SSM/I etc.) should be studied. A thinning and/or super-obing strategy will be useful for better use of some instruments with high horizontal resolution (e.g., AMSU-B, MODIS). Adding an new interface to other RTMs such as CRTM developed by JCSDA will be preferred for wider community usage.

From a longer term perspective, It will be more promising to assimilate radiance data by more advanced techniques developing currently, such as 4DVAR and ensemble Kalman filter (EnKF), with more consistent consideration of observation time distribution. Some high-spectral resolution infrared instruments such as AIRS and upcoming IASI as well as those to be aboard future NPOESS platforms, need to devote particular efforts for efficient use of these data. More challenging problem is to assimilating radiance data under cloudy and precipitating conditions, which should be crucial to improve quantitative cloud and precipitation forecast.

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