Evaluation of the Direct and Indirect Assimilation of Radar Reflectivity using the WRFDA 3D-Var

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Abstract

It is known that developments have being made in the concern of radar data assimilation and many studies point out some improvements on the quantitative precipitation forecast. However, it is not clear whether the most common way of assimilating reflectivity, i.e., directly as a control variable, is the best choice. We have made experiments using the Weather Research Forecasting model three-dimensional data assimilation system (WRFDA 3D-Var) over Brazil and we have found that the improvement achieved when using the direct assimilation is short-lived. Besides that, there are some works which point out this problem and suggest that the best way of assimilating reflectivity is indirectly through the assimilation of rainwater mixing ratio obtained from reflectivity. It would avoid problems related to the linearization of the reflectivity-rainwater mixing ratio relationship (Z-qr) that is needed in the incremental formulation used in WRFDA 3D-Var. Therefore, the aim of this work was to perform experiments over a specific region in Brazil to evaluate whether the indirect assimilation of reflectivity outperform the results obtained using the direct assimilation. It was chosen six cases of precipitation and 3 experiments for each case were performed. The three experiments were: i) a control without any radar data assimilation; ii) using direct assimilation and; iii) indirect assimilation of reflectivity. Radial velocity was assimilated in both cases. The Fractional Skill Score (FSS) and the Root Mean Square Error (RMSE) were used to compare quantitatively the performance of each experiment against observations. The results have shown that the indirect assimilation can produce better QPF than the one where reflectivity is assimilated directly and the improvement tends to last longer.

CHUVA Project

This work was carried out using the Paraiba Valley data, including the X-band Dual-Polarization radar. Six convective cases were chosen to examine whether the indirect assimilation is better or not, for our cases, compared to the direct assimilation. The radar position and grid model are shown in Fig. 1.

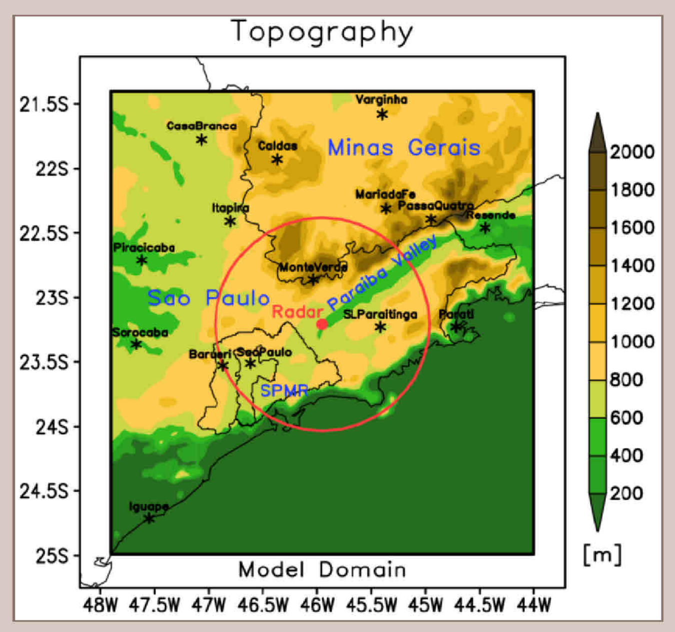

Figure 1: Topography, model domain and weather stations. The radar position and its maximum range is also shown.

WRFDA 3D-Var

The assimilation system used in this study is the WRFDA 3D-Var version 3.4. It iteratively minimizes the cost function that is defined using the incremental formulation:

$$J = J_b + J_o = \frac{1}{2} v^T v + \frac{1}{2} (d - H'Uv)^T R^{-1} (d - H'Uv) \quad (1)$$

where J_b and J_o stand for the background and observation terms, respectively. The term **v** is the control variable (CV) defined by $\mathbf{v}=\mathbf{U}^{-1}(\mathbf{x}-\mathbf{x}_b)$, where **U** is the decomposition of the background error covariance **B** via $\mathbf{B}=\mathbf{U}\mathbf{U}^T$, **x** is the full analysis variable, and $\mathbf{x}_b$ is the background variable. The innovation vector that measures the departure of the observation $\mathbf{y}_o$ from its counterpart computed from the background $\mathbf{x}_b$, is given by $\mathbf{d} = \mathbf{y}_o - \mathbf{H}(\mathbf{x}_b)$. **H'** is the linearization of the nonlinear observation operator **H**, and **R** is observation error covariance matrix.

The control variables used in this study are velocity components u and v, temperature T, surface pressure Ps, and pseudo relative humidity RHs (humidity divided by its background), following Sun et al. (2014)[2].

Indirect Radar Data Assimilation

According to Wang et al. (2013)[3], we have:

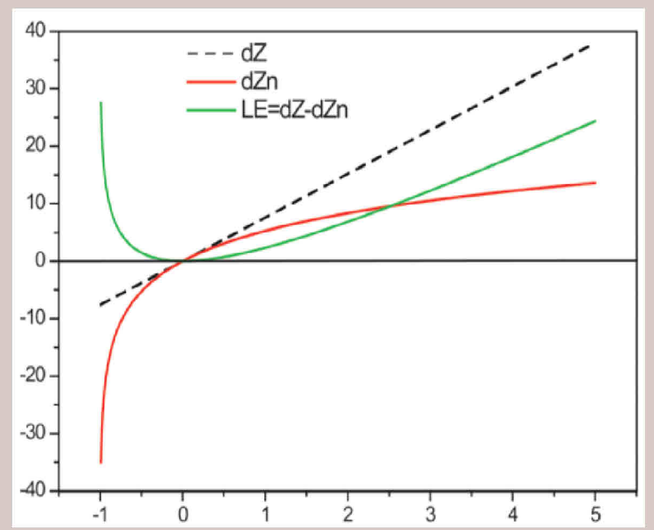

Figure 2: Linear pertubation dZ, non-linear difference dZ_n, and the LE-k relation. Source: Wang et al. (2013)[3].

$$Z = c_1 + c_2 \log_{10}(\rho q_r) \qquad LE = dZ - dZ_n = \frac{c_2 k}{\ln(10)} - c_2 \log_{10}(1-k)$$

$$dZ = \frac{c_2 dq_r}{q_r \ln(10)} \qquad k = \frac{dq_r}{q_r}$$

$$dZ_n = c_2 \log_{10}[(q_r + dq_r)/q_r]$$

Where, Z is reflectivity in dBZ, c_1 and c_2 are constants, ρ is the air density, q_r is the rainwater mixing ratio in $g.kg^{-1}$, dZ is the linear increment of Z and dZ_n is the pertubation of reflectivity caused by a pertubation on q_r (dq_r).

Background Error Covariance Matrix

The background error covariance matrix was created using the *gen_be* utility from WRF package[4], and the NMC[1] method was chosen. For that purpose, 3 months (Dec-Jan-Feb/2012) of 24-h simulations were run, starting from 00 UTC and from 12 UTC.

Model and Experiment Setup

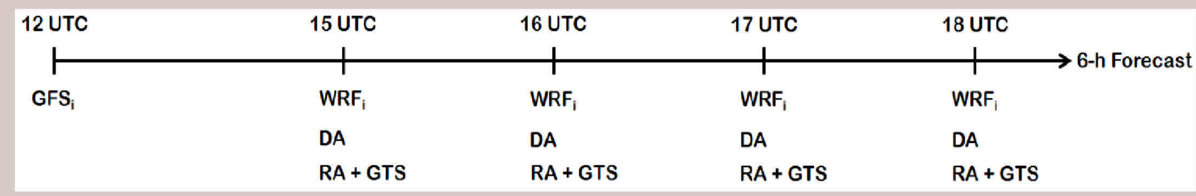

Figure 2: Illustration of the cycling strategy. GFS_i and WRF_i mean initial conditions from GFS and WRF, respectively; DA means data assimilation and RA and GTS mean data from radar and GTS, respectively.

CTR	Only conventional data have been assimilated.
DA_{dir}	Conventional and Radar data have been assimilated. Reflectivity data were assimilated directly.
DA_{ind}	Conventional and Radar data have been assimilated. Reflectivity data were assimilated Indirectly.

Table 1: Experiment setup.

The horizontal grid resolution is 2-km and the vertical resolution is about 60-m near the surface and 1-km in higher levels with a total of 45 sigma levels. The initial and boundary conditions are from the GFS 0.5ºx0.5º analysis.

Local RMSE and Fractional Skill Score

$$FSS = 1 - \frac{FBS}{FBS_p} \qquad FBS = \frac{1}{N}\sum_{k=1}^{N}[P_{M(k)} - P_{O(k)}]^2 \qquad FBS_p = \frac{1}{N}[\sum_{k=1}^{N} P_{M(k)}^2 - \sum_{k=1}^{N} P_{O(k)}^2]$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

Results

Radar DA_{dir} DA_{ind}

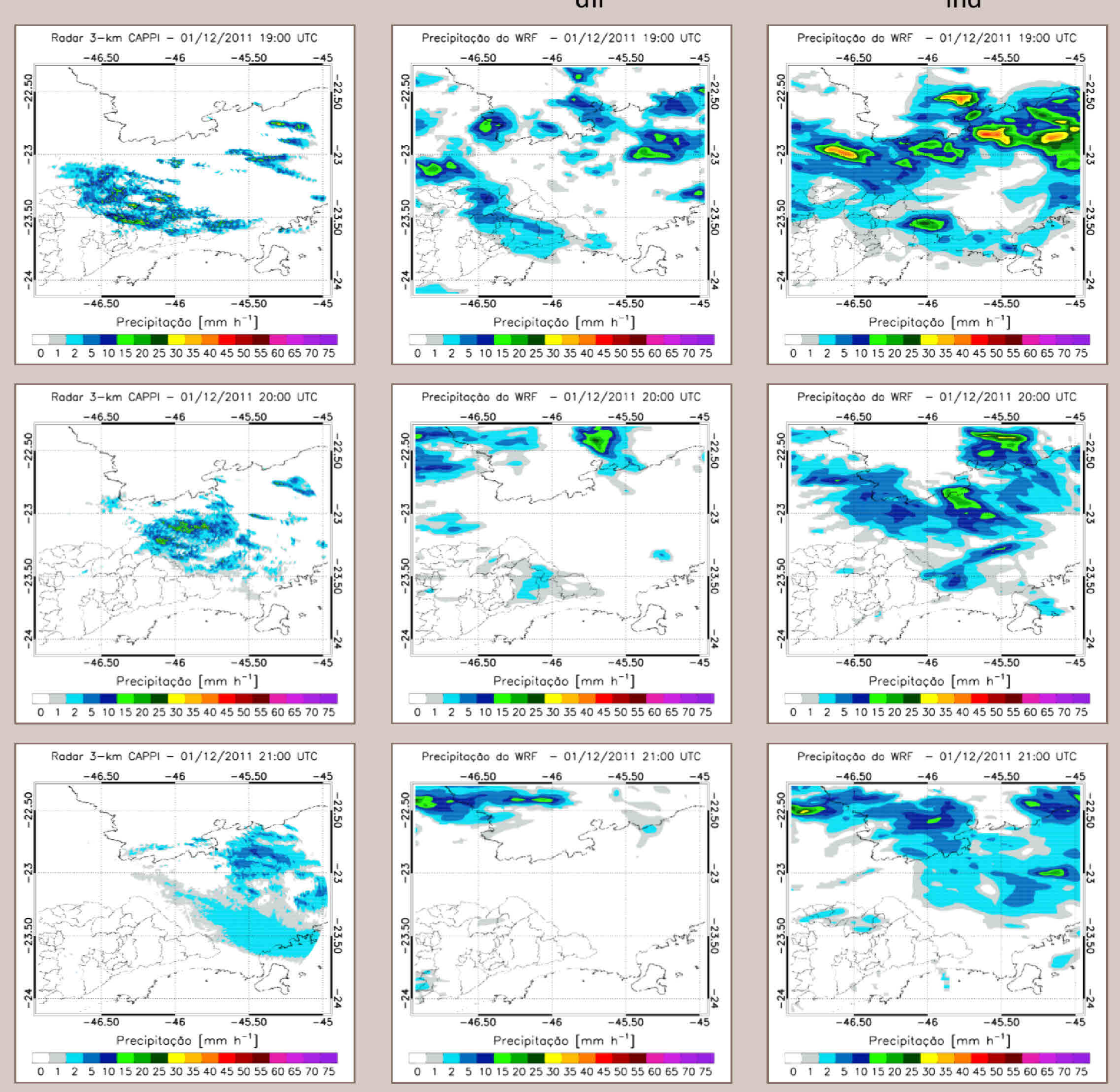

Figure 3: 1-h Accumulated precipitation from radar (left), WRF forecast assimilating radar data directly (middle) and WRF forecast assimilating radar data indirectly (right) from one of the six experiments.

Results

The reflectivity from radar and from background, the innovations and the increments of reflectivity are shown in Fig. 4.

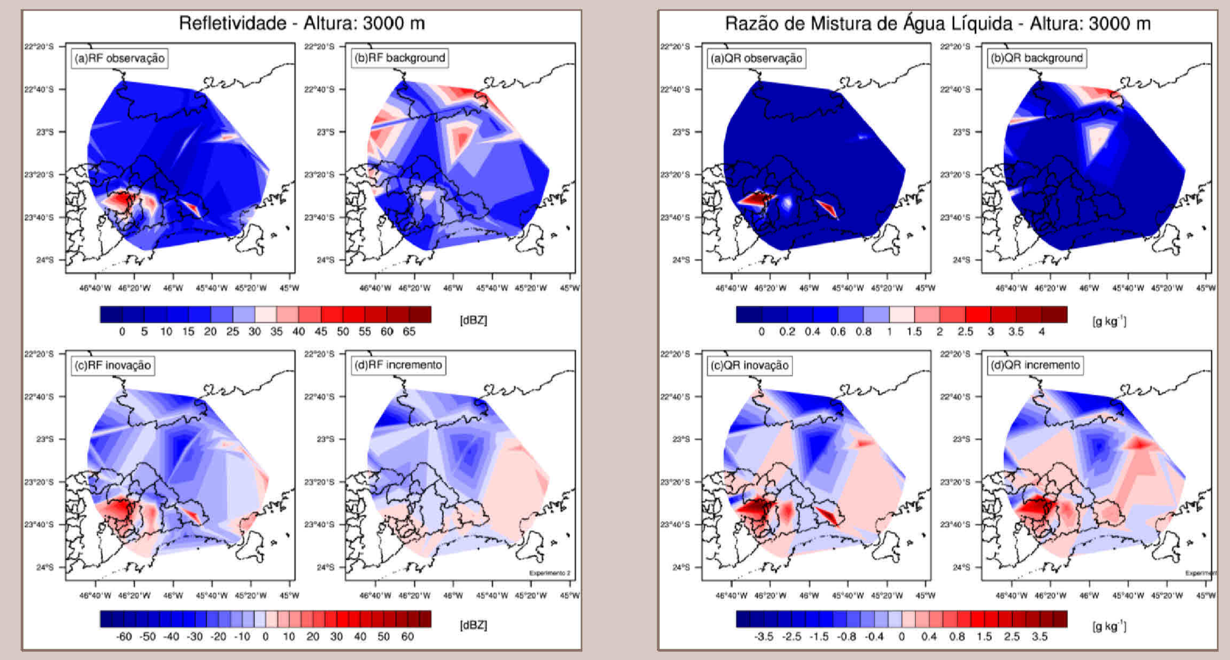

Figure 4: Reflectivity from radar(), reflectivity from background (), innovation of reflectivity (c) and increment of reflectivity (d). All figures refer to the 3-km level and are from the same case showed in Fig. 3.

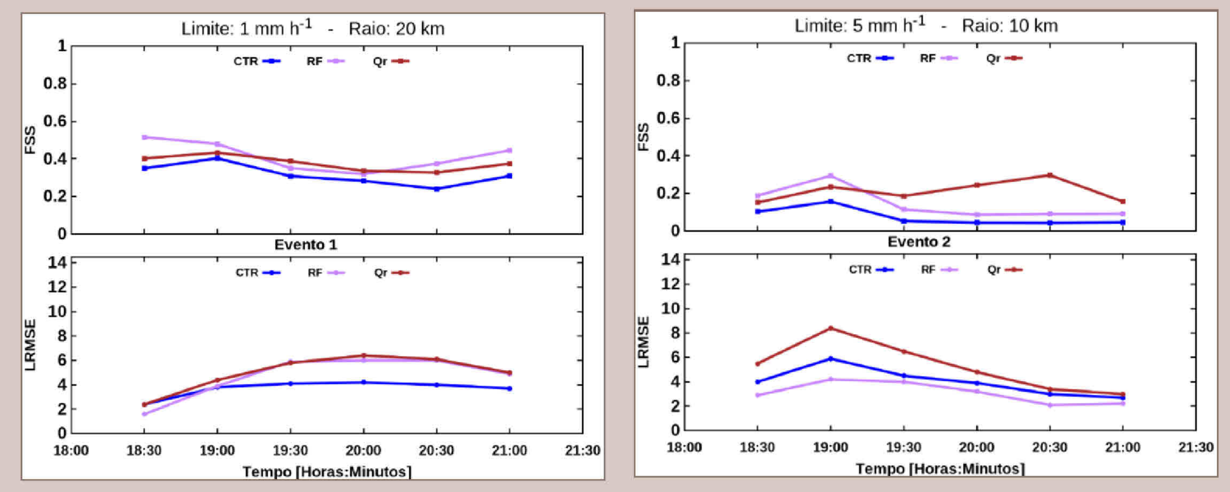

Figure 5: Averaged FSS and LRMSE over the six cases for the 3 experiments described in table 1. RF is the direct assimilation and Q_r is the indirect assimilation. In the left panel it is used a radius of influence of 20km and a threshold of 1mm to calculate FSS and the LRMSE, while in the right panel it was used a radius of 10km and a threshold of 5mm.

Conclusions

The results demonstrated that the indirect assimilation of reflectivity improves the analysis as showed in Fig. 4 and also the QPF after 2-h forecast. In our case the direct assimilation reduced too much the precipitation after 1 hour, while the indirect assimilation keeps the precipitation, which agrees better with the radar observation. The averaged FSS showed little improvement in the Da_{ind} experiment for heavier precipitation and small difference for light precipitation.

Acknowledges

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References

[1] Parrish, D. F. and J. C. Derber, The National Meteorological Centre's spectral statistical interpolation analysis system, Mon. Wea. Rev., 120, 1747-1763, 1992.

[2] Sun, J., W. Tong, H. Wang, Y. Zhang, C.-Y. Lin, and D. Xu, 2014: Comparison of the impacts of momentum control variables on limited-area high-resolution variational data assimilation and convective forecasting. Submitted to *Mon. Wea. Rev.*

[3] Wang, H., Sun, J., Fan, S., Huang, X.-Y, Indirect assimilation of radar reflectivity with WRF 3D-Var and its impact on prediction of four summertime convective events. J. Appl. Meteor. Climat., v. 52, p. 889-902, 2013.

[4] www.mmm.ucar.edu/wrf/users/wrfda/Docs/gen_be.htm.