JP1J.10 TOWARDS A 1D+3DVAR ASSIMILATION OF RADAR REFLECTIVITIES: ONGOING RESULTS

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1. INTRODUCTION

Radar data encounter increasing interest for Numerical Weather Prediction (NWP), and in particular for the next generation of high-resolution NWP models. Indeed, most meteorological centers plan to run operational nonhydrostatic models with resolution 1–4 km before the end of this decade. Radar data will be well placed to provide high-resolution information about wind and precipitation which the verification and initialization of such high-resolution models require. Our aim is to prepare the use of radar data in the future high-resolution nonhydrostatic NWP model (named Arome) of Météo-France. We are developing the framework for assimilating both reflectivity and Doppler velocity radar data, focusing in a first time on the assimilation of reflectivity data.

Reflectivities or reflectivity-derived quantities are already assimilated in some models. For instance, a latent heat nudging (LHN) technique is used to assimilate radar-derived precipitation rates into the UK Met. Office Mesoscale Model, at a horizontal resolution of approximately 17 km (Jones and Macpherson, 1997). The assimilation of radar-derived 2D precipitation rates with an LHN technique into the Lokal-Modell Kürzestfrist (LMK), a high-resolution (2.8 km) NWP model based on the German LM model, is currently being tested (Stephan et al., 2005).

At present, promising studies about the assimilation of radar reflectivities into high-resolution limited area models focus on variational data assimilation (see e.g., Sun and Crook, 1997, 1998; Xiao et al., 2004) and Ensemble Kalman Filter (EnKF, see e.g., Tong and Xue, 2005).

We also follow this approach for the Arome model, but with a 1D retrieval step that provides profiles of model variables such as humidity (q), temperature (T), vertical velocity (w),... prior to the 3DVAR assimilation of these profiles. Fig. 1 sketches the 1D+3DVAR assimilation scheme adopted for ground-based reflectivities. The Arome model will possess a sophisticated microphysical scheme with explicit mixing ratios of various hydrometeor types that allow to derive simulated reflectivities. However, it is believed that a model forecast is more affected by a change in humidity and other model variables rather than by a correction of microphysical fields (Ducrocq et al., 2000). This method is similar to what has been done by Marécal and Mahfouf (2000) at the European Centre for Medium-Range Weather Forecasts (ECMWF) with Tropical Rainfall Measuring Mission (TRMM) satellite-derived surface rainfall rain rates, except that the 1D inversion is based on a 1DVAR and is applied to a larger scale model with a less sophisticated physical package.

The Arome model is developed from building blocks originating from several existing models: same 3DVAR assimilation system and dynamic core as the Aladin model, same microphysical package as the Meso-NH model. Further developments are needed in order to assimilate new observation types like radar data which are presented here.

Sec. 2. presents the work done concerning the processing of data before the 1D inversion (part denoted A in Fig. 1): pre-processing, observation operator, and quality control.

In Sec. 3., first tests of a Bayesian 1D inversion through twin experiments are presented (part denoted B in Fig. 1).

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2. DATA PROCESSING

A new processing chain was set up to handle raw reflectivity data and make them available to the assimilation system: these data are first pre-processed in order to remove artefacts and weight each pixel by a quality flag. For instance, ground clutter is detected by comparing observations with a climatological map of ground echoes and comparing the standard deviation of reflectivities with a threshold (Parent du Châtelet et al., 2001). The Surfillum software (Delrieu et al., 1995) is used to identify beam blockage.

Besides, an observation operator for radar reflectivities has been implemented in the 3DVAR assimilation system. This observation operator simulates reflectivities from model hydrometeors (rainwater, snow, graupel, and primary ice) taking into account the radar beam shape

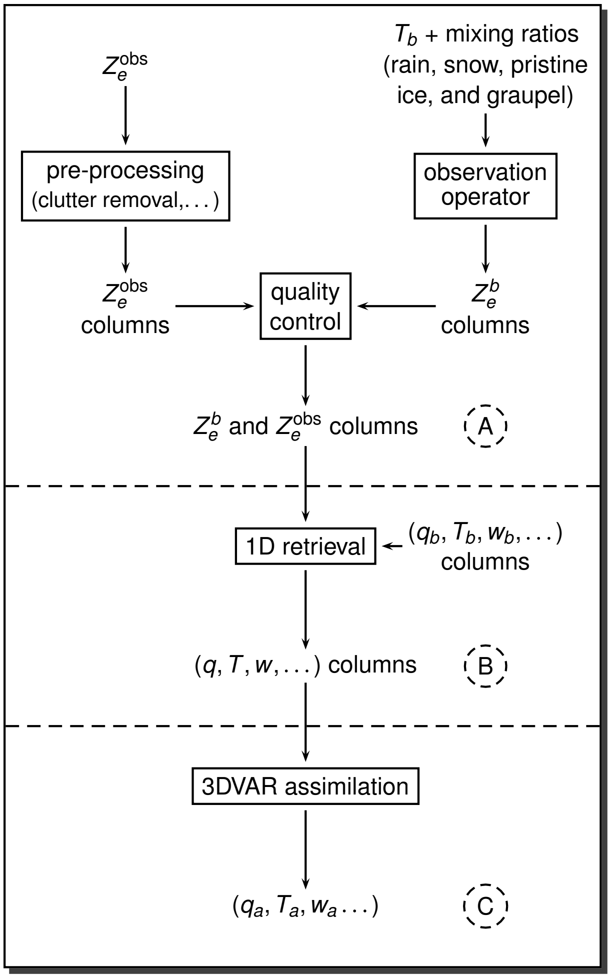

Figure 1: Strategy for the assimilation of reflectivities into the Arome model.

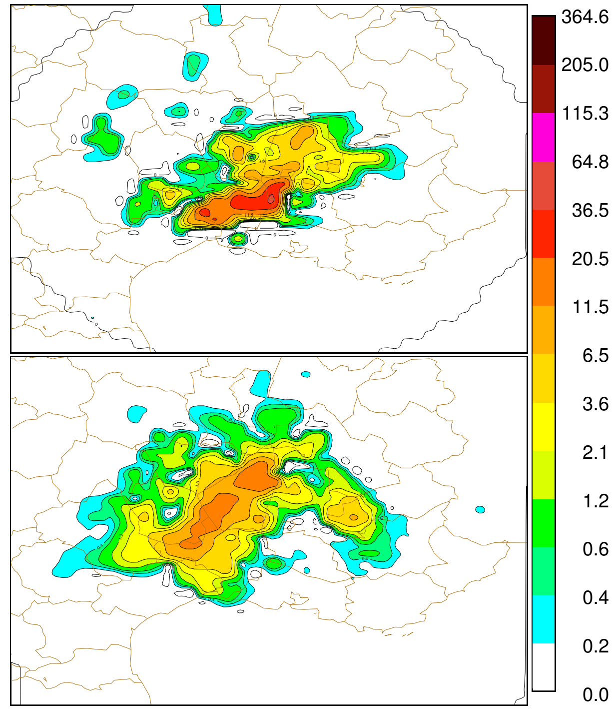

Figure 2: Observed and simulated reflectivity data. 8 September 2002 18 UTC. (a) observed data from a 1.2°-PPI scan of the Bollène radar (reflectivity converted in instantaneous precipitation rate, in $\mathrm{mm \cdot h^{-1}}$). (b) simulated 1.2°-PPI scan of the Bollène radar from a 6-hour Aladin forecast.

(Caumont et al., 2005). Model hydrometeors can be prognostic variables as in Arome/Meso-NH models or diagnosed from precipitation fluxes and empirical distributions of hydrometeors as it is done for the Aladin model.

Fig. 2 provides a comparison of the observed and simulated reflectivities for an extreme flash-flood event that occurred on 8 September 2002 in southeastern France. The observations are shown at 18 UTC for the 1.2°-PPI scan of the Bollène S-band radar from the Météo-France Aramis radar network. The simulated reflectivities come from a 6-hour range forecast from the Aladin-France operational model. The comparison of the observed and simulated reflectivities shows that the observation operator is able to produce reflectivities of the same order of intensity as the observed ones. The Aladin model failed on this case to produce the maximum of surface precipitation at the good location (not shown); this failure is also evidenced for the simulated reflectivities.

Following the pre-processing of the observed reflectivities and the simulation of the reflectivities from model variables, a quality control is performed. The quality control ensures that wrong observations are not assimilated by removing those that depart too much from the model simulations and those with a "bad quality" flag. At present, a lot of good pixels are rejected by the quality control, and work is underway to perform superobbing and allow to keep more reliable pixels.

3. 1D INVERSION

The following step of the radar data assimilation consists in deriving pseudo-observations of humidity profiles from observed radar reflectivity columns. The retrieval of pseudo-observations of temperature and vertical velocity profiles will be tested in a second time. The purpose of this section is to describe the 1D inversion method that we are currently testing on a case study of isolated convection.

3.1 *The inversion method*

A Bayesian approach is used to retrieve vertical profiles of model parameters from observed reflectivities. Broadly

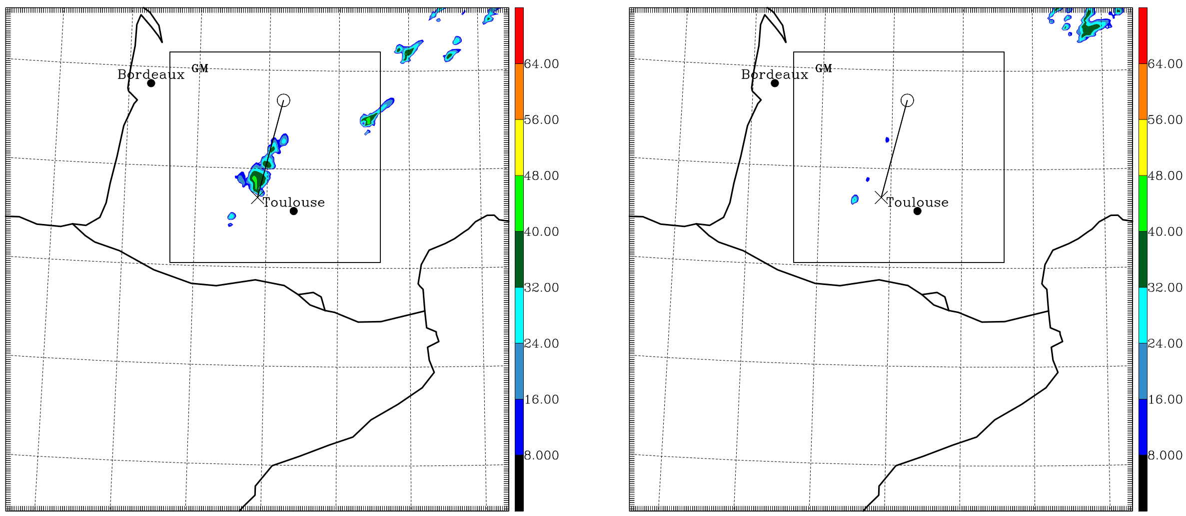

Figure 3: Reflectivities (in dBZ) at 4-km height (a: reference; b: first guess). The circles represent the location of the fictious radar (44.7°N, 1.2°E, 230 m MSL).

speaking, each $(q, T, w, \ldots)$ vertical profile $\boldsymbol{x}_{\rm po}$ is computed as a linear combination of $(q, T, w, \ldots)$ vertical profiles from the model with coefficients that are function of their departure from the observed reflectivity profile. In a similar manner to what has been derived by Olson et al. (1996), each vertical profile of model parameters at an observed location is given by

$$\boldsymbol{x}_{\rm po} = \boldsymbol{E}(\boldsymbol{x}) = \int \boldsymbol{x}\, \mathrm{P}(\boldsymbol{x})\, \mathrm{d}\boldsymbol{x} \simeq \sum_i \boldsymbol{x_i} \frac{\exp\left(-\frac{1}{2} J(\boldsymbol{x_i})\right)}{\sum_j \exp\left(-\frac{1}{2} J(\boldsymbol{x_j})\right)}, \tag{1}$$

where $\boldsymbol{x}$, $\boldsymbol{x_i}$, and $\boldsymbol{x_j}$ are model vertical profiles of model parameters at observation locations, and the cost function J is defined by

$$J(\boldsymbol{x}) \doteq (\boldsymbol{y_Z} - \boldsymbol{H_Z}(\boldsymbol{x}))^{\mathsf{T}} \mathbf{R}_{\mathbf{Z}}^{-1} (\boldsymbol{y_Z} - \boldsymbol{H_Z}(\boldsymbol{x}))\,. \tag{2}$$

In Eq. (2), $\boldsymbol{y_Z}$ is the observed vertical profile of reflectivity, $\boldsymbol{H_Z}$ is the observation operator for radar reflectivities, and $\mathbf{R_Z}$ is the observation+radar observation operator error covariance matrix. In Eq. (1), the i and j indices refer to vertical profiles that are located in the neighborhood of the vertical column that one wants to retrieve. In practice, each vertical column was retrieved as a linear combination of all available model profiles within a 60×60 km^2 square window centered to the column to be retrieved. The expected value $\boldsymbol{E}(\boldsymbol{x})$ is approximated by the last term of Eq. (1) under the assumptions that

- simulated and observed errors are Gaussian, uncorrelated, and their mean is zero,
- computed profiles have the same probability to occur as in nature.

This method has the advantage over 1DVAR that it does not require the development of the adjoint of the physical parameterization. The main drawback is that resulting vertical profiles will be limited to what the model is able to produce at the time of assimilation. For instance, if developed convective cells are observed, while no convection is triggered in the model, the method will not be able to find neighboring columns with significant reflectivities. So as to prevent this effect, the value of relative humidity is raised to 100% where reflectivities are observed (i.e. > 0 dBZ), but none is simulated. This correction is not applied below the model condensation level.

3.2 *Twin experiments*

We run two experiments that differ in their initial conditions. The first one is the reference and provides the observations that will be assimilated to correct the second one. A « good » assimilation scheme is thus supposed to make the experiment using assimilation converge towards the reference experiment. This method allows to get rid of measurement errors and provides a quantitative way of assessing the assimilation efficiency.

The two experiments have been performed using the nonhydrostatic Meso-NH model, which shares the same microphysical parameterization as Arome, in a two-way grid-nesting configuration (Stein et al., 2000), with 10-km and 2.5-km resolution domains. The reference simulation starts from a mesoscale surface data analysis (Ducrocq et al., 2000) at 12 UTC 9 October 2004. The first guess simulation starts from the large-scale Arpege analysis at the same time. Fig. 3 displays reflectivity fields at a height of 4 km MSL at 1615 UTC. In the first guess, convection is not developed at 1615 UTC, while it is already fully de-

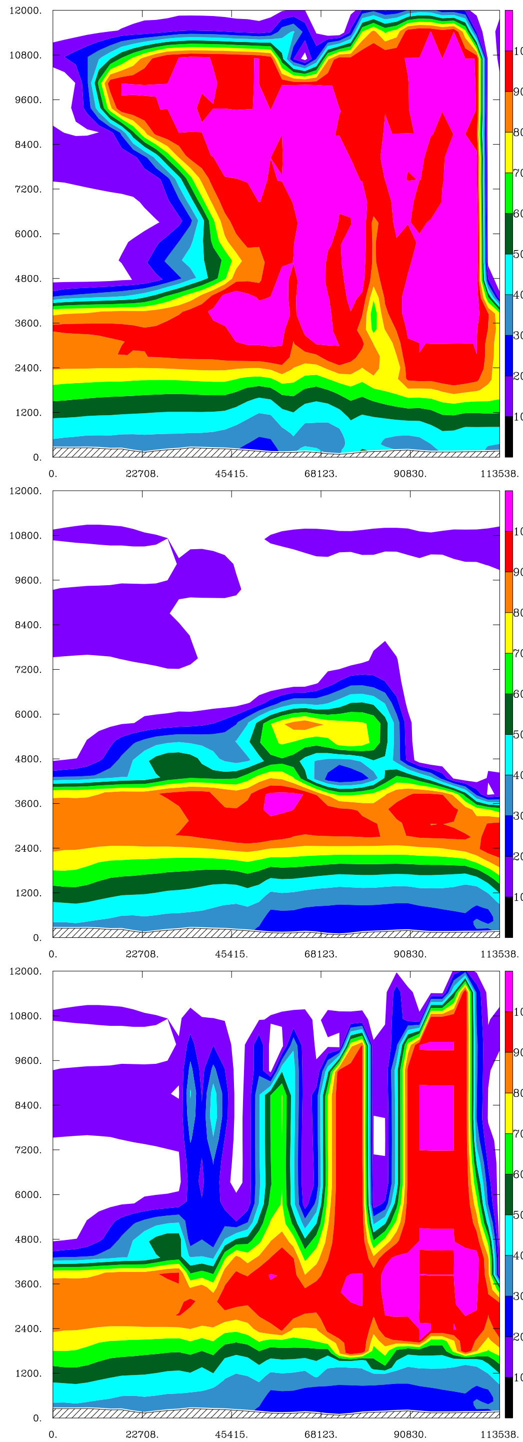

Figure 4: Vertical cross section of relative humidity (in %) along the axis shown on Fig. 3. (a) reference; (b) first guess; (c) 1D-retrieved relative humidity applied to the first guess.

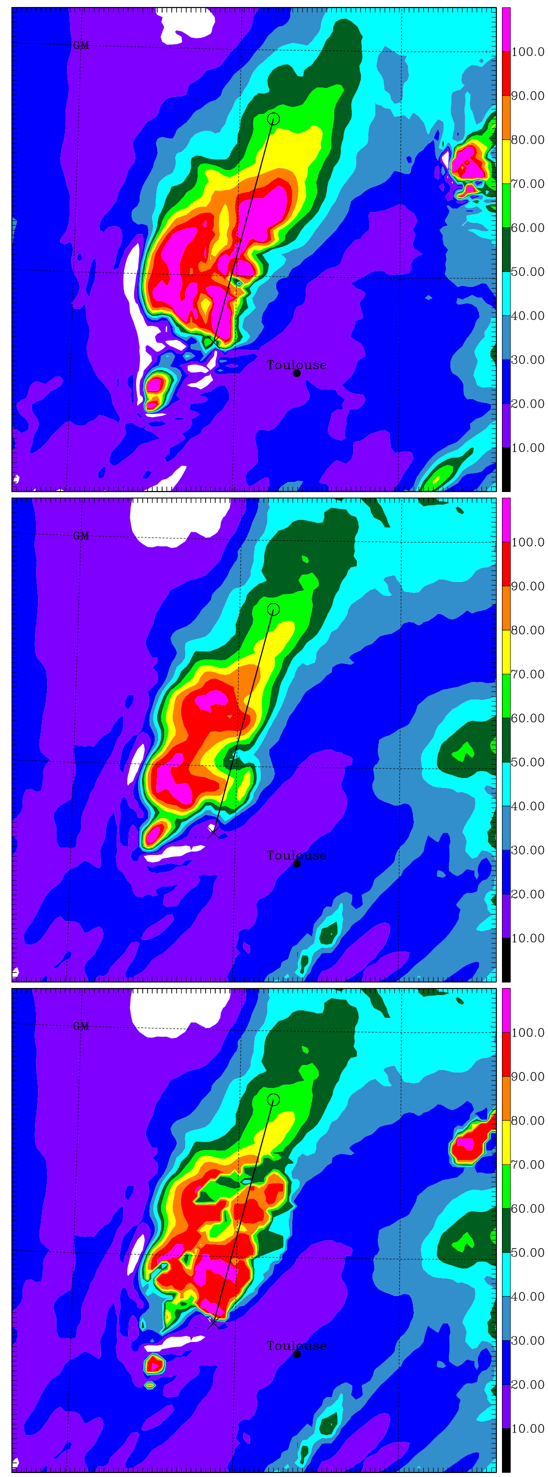

Figure 5: Relative humidity (in %) at 4-km height. (a) Reference; (b) first guess; (c) 1D-retrieved relative humidity applied to the first guess. The domain corresponds to the squares shown on Fig. 3.

veloped in the reference simulation. On Figs. 3a, one can see that the reference experiment simulates three deep convective cells which are moving northeastwards, whereas the first guess simulation only simulates weak and shallow cells.

3.3 *Results*

The Bayesian inversion described above is applied on the first guess experiment at 1615 UTC, using observations generated from the corresponding reference fields. For that, we consider a radar arbitrary located north to Toulouse (circles on Fig. 3) scanning the troposphere at 13 elevations.

Fig. 4 compares relative humidity derived from the 1D inversion with the first guess and reference experiments. Only 1D retrieval of humidity profiles is considered here. The 1D inversion moistens the atmosphere up to the tropopause where reflectivity is observed in the reference experiment. Conversely, in regions where the first guess simulates reflectivities whereas no significant reflectivities are observed, the Bayesian scheme averages vertical profiles without reflectivities and thus removes wrong saturated points: the three little reflectivity spots on Fig. 3b are not observed; on Fig. 5, one can see that the corresponding (small) area is desaturated by the 1D-inversion scheme.

Note that, in areas where both model and observation reflectivities are not significant, the 1D inversion does not modify the moisture field.

These first tests have shown that the 1D inversion method is able to dry up saturated areas where no reflectivity is observed and to moisten areas where reflectivities are observed.

4. CONCLUSIONS & OUTLOOK

An original 1D+3DVAR radar reflectivity assimilation is being developed at Météo-France for its next operational high-resolution Arome model. So far an adequate observation operator for radar reflectivities has been implemented in the 3DVAR assimilation system that is shared by Aladin and Arome. This observation operator gives reflectivities that are consistent with observations. A new pre-processing chain has been set up to attribute quality flags to each reflectivity observations. Work is in progress to tune the quality control step so that more reliable pixels are not rejected.

Concerning the 1D part of the assimilation algorithm, this study showed that a Bayes-based scheme is able to correct for model humidity profiles in a consistent manner, so that 3DVAR assimilation of these profiles can be envisaged in a near future.

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