From Radio Detection and Ranging (RADAR) to Meso-Analysis System (MAS)

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1- Introduction, or the limits to the traditional approach

Since the introduction of weather radar more than a half century ago, the processing of radar observations of the atmosphere has undergone two stages: first, we used a qualitative and subjective interpretation of visual observations on a cathode ray tube displaying in real time returns from precipitation. With the introduction of computers in the late 70s an effort was made to match the skill of subjective visual interpretation by the radar operators using an objective Radar Data Processor (RDP). The algorithms for this are based on simple ideas derived from conceptual models of storm structure and storm circulation and occasionally making use of AI. For example, to resolve the inherent ambiguity of observing only one component of the 3D air velocity, radar wind profiling is based on the assumption of linear dependence with space of the components of the horizontal air velocity; a Rankine vortex is the geometrical model for tornado or mesocyclone detection; and so on.

In the 90s data assimilation was recognized as an opportunity to resolve the limitations and ambiguities of radar surveillance of a limited number of atmospheric variables. This path, proposed some twenty years ago, was slow in producing results with operational potential. At McGill, we have initiated the development in this direction following a methodology that appeared particularly adequate for operational implementation: assimilation of radar data with numerical model used as a weak constraint.

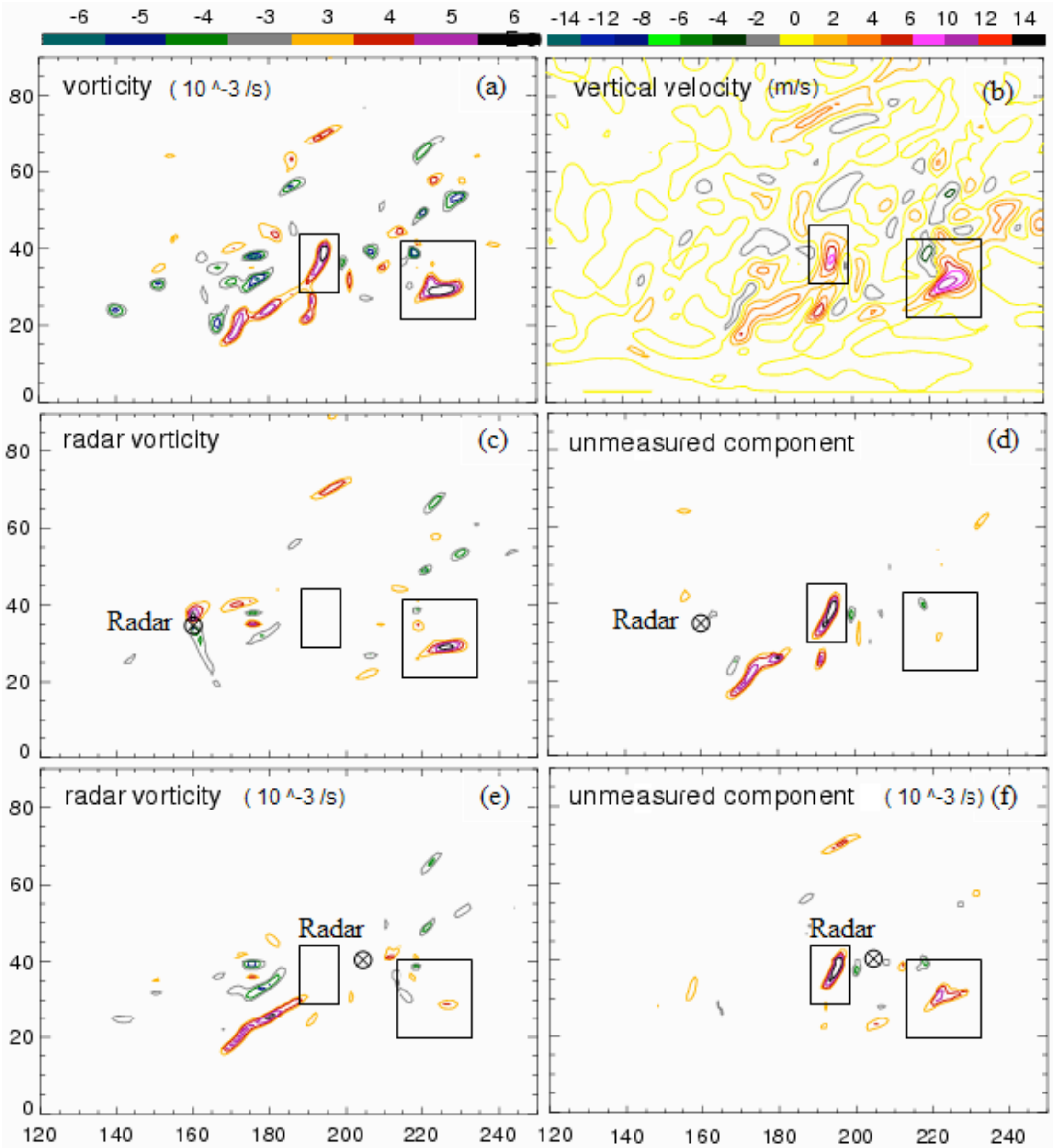

Fig. 1 - *The upper two panels show the fields of vorticity and vertical air velocity computed from numerical simulations of a tornadic storm. Model (MC2) resolution was 1km. The other panels show the vorticity of the radar radial wind component (left) and the vorticity of the tangential wind component (right) at the indicated radar positions.*

With an example, let us first emphasize the need for a radar data analysis system that goes beyond the present heuristic approach. Figure 1 shows a numerical simulation of a severe tornadic storm (a and b) using the MC2 model (Laprise et al 1997). Note the good correspondence between strong vorticity and updrafts.

The other panels show the vorticity fields as seen by radars in different locations. It is clear that radar can fail in detecting significant features and only vortexes that have a nice radial symmetry can be properly detected independently of storm position with respect to the radar. In addition, when only the radial velocity U_r is measured, the vorticity ζ and shearing deformation

χ are indistinguishable:

$$\zeta = \frac{\partial U_\theta}{\partial r} + \frac{U_\theta}{r} - \frac{\partial U_r}{r\partial\theta} \qquad\qquad \chi = \frac{\partial U_\theta}{\partial r} + \frac{U_\theta}{r} + \frac{\partial U_r}{r\partial\theta}.$$

In the numerical simulation used to generate Fig. 1, we also explored whether there is any correlation between ζ and χ or if there is another possible closure that unambiguously would allow retrieval of vorticity. The conclusion is negative.

Thus, the heuristic severe weather algorithms are prone to false alarms and misses and, what is worst, there is no way to reasonably bound the errors in the interpretation of radar data. This is a very unsatisfactory situation even if radar has proven to be such a useful instrument for weather nowcasting.

A dense radar network can resolve these ambiguities. However, we still need a robust methodology for integrating the information from radar networks in which the uncertainties of the measurements by the various radars are taken into account within an optimal analysis.

2- The alternative

Whether we consider single radar or a radar network, the use of radar data must be based on some model of atmospheric processes. If our goal is to perform a full diagnostic and prognostic of the state of the atmosphere, the data assimilation techniques appear today the best approach. There are numerous efforts into incorporating radar data assimilation systems into regional NWP.

Another approach is to use data assimilation toward an objective interpretation of radar information. At the Marshall Radar Observatory (MRO), we have explored different aspects of this possibility for the past 15 years starting with the work of Laroche and Zawadzki (1994). This includes retrieval of information through data assimilation, description of microphysical processes based on and consistent with radar observations, the enhancement of radar observing capabilities through polarization diversity and scanning strategies, data quality improvement, characterization of error structure of radar observations. Examples of this can be seen in this conference.

From our work and the work of others, we have seen a number of encouraging results: it is possible to initialize a numerical model with radar observations and to force the presence of a convective storm with just one assimilation cycle even if the NWP background has none present. The short-term forecast that follows this initialization can be good, better than the nowcast by Lagrangian persistence. However, this is true in a research context where several trials and corrections are allowed. It is another matter to set up a system that is robust enough for a real time implementation.

On the other hand, there are signs of difficulties ahead: if model equations are not consistent with the assimilated data (as can happen with microphysics parameterization, for example), data assimilation can lead to quantitative and, what is worst, qualitative errors in the model forecast. It appears that when radar data are assimilated, their impact on the forecast is short lived. In the 0-6h nowcasting time, Lagrangian persistence still initially outperforms numerical precipitation forecast although over a limited time. The long-term benefits of radar data assimilation on NWP of precipitation are very small.

In this context we have initiated the implementation of radar data analysis based on techniques of data assimilation that we denote by Mesoscale Analysis System (MAS). Our first objective is to produce an analysis of the state of the atmosphere so that a Meso-Analysis System (MAS) from which all “radar” products can be derived replaces the traditional radar data processor. MAS also has the advantage of naturally being able to utilize information from other sensors, as well as provide a physical basis and additional background information for much of the traditional radar data corrections such as extrapolation of precipitation to the ground, dealiasing, etc. Foremost advantage is the potential for objectively defining the uncertainties of the radar products. From our point of view, it is also a necessary stepping-stone for NWP with radar data assimilation.

The diagram in Fig. 2 describes the concept of MASS as presently being implemented on the McGill S-band radar.

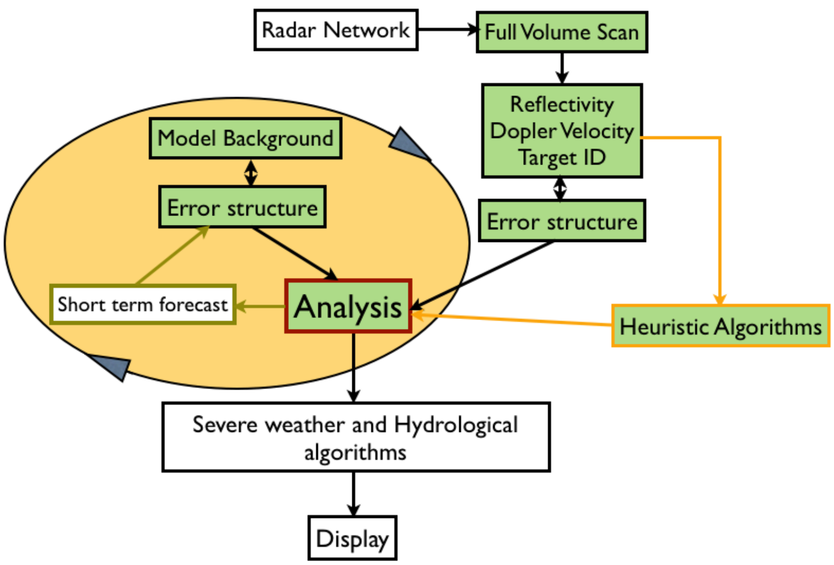

Fig. 2- *Block diagram of the Mesoscale Analysis System. The green panels show implemented elements (some at a very elementary stage), white panels show work yet to be initiated. The cycle of assimilation is in orange.*

3- Outline of MAS progress

The description of the McGill radar data assimilation system based on model as a weak constraint has been recently updated (Chung et al. 2009). Here we will be brief with details. In the variational approach, the analysis of the atmospheric state is defined by the minimization of a cost function that, in the case of model used as a weak constraint, can take the form

$$J = Background + Observations + Model$$

$$= (\mathbf{x}-\mathbf{x}^b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b) + \sum_{n=1}^{N}(H(\mathbf{x})-\mathbf{y_n})^T \mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{y_n}) + \varepsilon^{q^T}\mathbf{Q}^{-1}\varepsilon^q \qquad (1)$$

where **x** are control variables (u, v, w, p, T, etc), **y** observations, *H* observation operator, ε^q model residuals, and **B**, **R**, **Q** are the error covariance matrixes of the three terms, respectively. The minimization of (1) is done simultaneously at three times levels using three radar volume scans.

All the elements of MAS can be discussed in reference to (1).

a) Background

In the first analysis of the assimilation cycle, we use as background information the output of the Canadian operational model GEM-LAM. Given the severe positional errors of model outputs, we first perform a search of the location in the model output where radar data, reflectivity and radial velocity, are best matched, giving a greater weight on the radial velocity.

A recursive filter approximates the error covariance matrix **B** of the background. The variance and spread of the filter are presently set arbitrarily for optimal result; a work is in progress to determine these parameters in a flow dependent manner by a study of the differences between GEM-LAM outputs and radar data (reflectivity and Doppler velocity).

b) Observations

A distinction is made between missing (or rejected) data and non-detectable precipitation. The latter is set to a very low reflectivity value to suppress all background precipitation outside the radar measurement.

We add additional information to the measured quantities that are treated as data (heuristic algorithms in Fig. 2): *a)* reflectivity is extrapolated from the lower elevation radar beam to ground to complete the volume of radar data (the error structure of the resulting extrapolated data has been already determined); *b)* the total radar detectable volume of the sum of the three volume scans that are assimilated is determined. Outside this volume the air vertical velocity is set to zero and allowing for a variance 0.1m/s (within the radar detectable volume vertical velocity is set as missing data). This suppresses the background convective scale activity that is not observed in the region by the radar even after the best positional adjustment is made.

A random 1m/s error is attributed to Doppler velocity at this stage. Work is in progress to determine an observation recursive filter with adaptive parameters.

c)- Model

The usual set of dynamic and thermodynamic differential equations (but in finite difference representation) defines the model (for details see Chung et al. 2009):

$$\frac{du}{dt} - fv + R(T^* + T')\frac{\partial \pi}{\partial x} = \varepsilon^q_{mx} \qquad \frac{dv}{dt} + fu + R(T^* + T')\frac{\partial \pi}{\partial y} = \varepsilon^q_{my}$$

$$\frac{dw}{dt} - g\frac{T'}{T^*} + g\frac{(M + Q_c)}{\rho} + R(T^* + T')\frac{\partial \pi}{\partial z} = \varepsilon^q_{mz}$$

$$\frac{d\pi}{dt} - \frac{wg}{RT^*} + \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} - \frac{1}{(T^* + T')}\frac{dT'}{dt} = \varepsilon^q_{co} \qquad \frac{dT'}{dt} - \alpha(T^* + T')\left[\frac{dq'}{dt} - \frac{wg}{RT^*}\right] - L = \varepsilon^q_{th}$$

All the left-had-side terms are the residuals of the equations that must be minimized in the weak constraint framework. In addition the model contains the conservation equations for cloud content, *m* and precipitation content, *M*:

$$\frac{dm}{dt} + \frac{mw}{H} - wG + S(M,m) = \varepsilon^q_m \qquad \frac{d_M M}{dt} + \frac{Mw}{H} + M\frac{\partial V_t}{\partial z} - S(M,m) = \varepsilon^q_M,$$

respectively. *G* is a thermodynamic function and $S(M,m)$ represents the transfer from cloud to precipitation. At this stage *S* is represented by a very simple Kessler type of parameterization in which a difference is made in fall velocity from temperatures below and above freezing (snow to rain).

4.- Example

Figure 3 shows the latest results of MAS in a deep stratiform system. This is a very preliminary result and it is shown solely for the purpose of illustration.

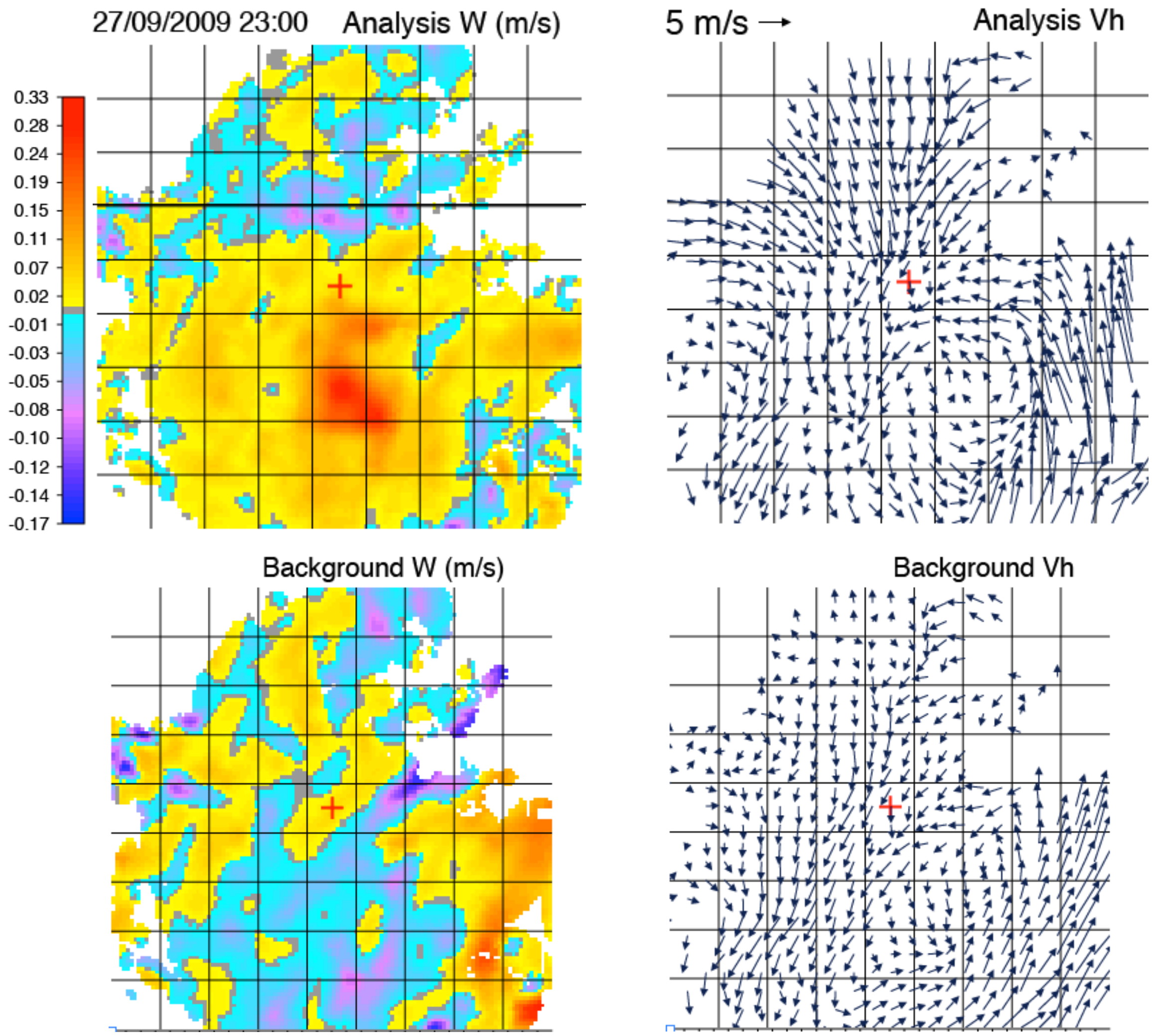

Fig. 3- *Example of MAS: the lower panels show the 3-D wind field at H=2.5km predicted by GEM-LAM on the 27 September 2009 for the region covered by the McGill S-band radar. The upper panels the field modified by the analysis.*

5- Discussion

MASS is implemented to run in real time. A cycling procedure is applied with the previous analysis, translated with the moving precipitation system, is taken as the background (it is simple to derive the error structure of this background). In the future we will use a 15 minutes forecast as background for the next analysis cycle.

From the present experience we have concluded that the issue of radar data quality must be revisited for the purpose of data assimilation. Small contaminations, such as imperfect clutter suppression may me acceptable for a semi-qualitative use of radar data but it can create artificial zones of convergence/divergence that are fatal for the analysis. Presently we adopt a strict data thinning to get rid of doubtful information.

Most of the hard work is yet to be done:

i) a more stringent signal processing and a more rigorous data quality control,

ii) complete determination of the error structures of the model forecasts and of radar data,

iii) a proper assimilation cycling with forecast as updated background,

iv) computation of radar beam trajectories from the analysis of temperature and humidity in MAS,

v) incorporation of complete microphysics and polarimetric information into the analysis,

vi) systematic evaluation of the quality of the analysis by using it for nowcasting and compare with Lagrangian persistence.,

and so on.

It cannot be overemphasized that failing to undertake any of these tasks will likely result in the failure of the approach.

References

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