Quality and Assimilation of Radar Data for NWP — a Review

P. P. Alberoni,[*] V. Ducrocq, G. Gregorič, G. Haase, I. Holleman,
M. Lindskog, B. Macpherson, M. Nuret, and A. Rossa

1 Background

Radar data have exciting potential for improving forecasts from operational Numerical Weather Prediction (NWP) models in Europe. The potential arises from a combination of developments. NWP models of the European National Meteorological Services (NMS's) are now running routinely at the 10km grid scale and in a few years will be moving to resolutions of order 2km. Such high resolution models require correspondingly high resolution wind and moisture data for initialisation, which radar networks are well placed to deliver. Secondly NWP data assimilation techniques have advanced considerably in the 1990's, with the arrival of techniques capable of extracting information from time sequences of observations only indirectly related to model prognostic variables. The next few years are likely to see further improvements in computing power, microphysical parametrisation and assimilation methods which will enable better exploitation of the information available from weather radars. Thirdly, developments in radar networking and processing around Europe are beginning to reach a maturity which makes feasible the routine operational delivery of quality controlled radar information of an accuracy sufficient for worthwhile NWP assimilation.

The COST-717 Action entitled "Use of Radar Observations in Hydrological and NWP models" (Rossa, 2000) offers a framework in which European radar and NWP scientists, along with those from the hydrological community, can work together to realise this potential. COST-717 is divided into 3 working groups, of which the first and second are described in Bruen (2000) and Frühwald (2000). The third is entitled "Using Radar Information for Assimilation into Atmospheric Models", and was described briefly by Macpherson (2000).

This review by members of Working Group 3 seeks to inform the radar and NWP communities about each other's disciplines and provide an accessible introduction to the literature for those working at the intersection of these fields. In the second half of the paper we review the development of methods for assimilating radar data into NWP models, but we begin with the quality control which must accompany those methods in any successful application.

2 Quality Control of Radar Data

2.1 Introduction

The recent articles of Meischner et al. (1997), Serafin and Wilson (2000), and Fulton et al. (1998) give a detailed overview of the abilities and limitations of the current generation of operational weather radars. Here, an up-to-date overview of processing techniques and limitations of radar data is presented. Issues which are relevant to the assimilation of reflectivity and/or wind data into NWP models have

[*]Authors are listed in alphabetical order

been stressed. The overview is divided into four sections, referring to the types of radar data relevant for assimilation purposes.

Issues addressed first concern the measurement of radar reflectivity: calibration, attenuation and problems concerning radar echoes from non-hydrometeor target objects. Then, the problem of estimating the on-ground rainfall from radar reflectivity data aloft is described, and the currently applied methods are reviewed. Thirdly, the extraction of wind information from Doppler radar and the problems due to aliasing and representativeness are outlined. Finally, the methods for the construction of wind profiles from radial wind measurements are discussed, and some verification results are highlighted.

2.2 Reflectivity data

2.2.1 Radar equipment

For the extraction of quantitative information from a weather radar, it is essential that the radar equipment is accurately calibrated and perfectly stable. During operation of the weather radar, the receiver has to be calibrated on a regular basis and samples of background noise have to be taken almost continuously (Meischner et al., 1997; Serafin and Wilson, 2000; Manz et al., 2000). In this way, the repeatability of the system parameters during normal operation can be well within 0.2 dBZ, i.e. within 3% of the equivalent rain rate.

The absolute calibration of the radar equipment is more difficult. Koistinen et al. (1999) give a detailed description of their efforts to accurately calibrate the radars in the Nordrad network. Both extensive single-radar calibrations and comparisons between adjacent pairs of radars have been performed. Existing signal differences of 6-13 dB between Ericsson and Gematronik systems have been detected and partly corrected in this way.

With high-quality hardware and thorough calibration, it should be possible to keep the absolute calibration error of the radar equipment below 2 dB (30% of equivalent rain rate) (Joss and Waldvogel, 1990; Smith, 2001).

2.2.2 Attenuation and amplification

The radar antenna is normally positioned in a radome in order to protect it from rain and wind. The radome can, however, affect the radar beam in several ways: via absorption and phase shifting by the dry radome wall, via scattering from the radome joints, via the geometrical distribution of the radome joints, and via absorption by rain or snow on the radome (Manz et al., 1998). The absorption by the dry radome is typically a few tenths of a dB for a C-band radar, while for a wet radome values of up to 5 dB (100% of equivalent rain rate) for two-way transmission have been found (Manz et al., 1998; Germann, 1999). The geometrical distribution of the radome joints can have impact on the beam profile of the radar by, for instance, an increase of the sidelobes. Generally, no correction methods are applied for the radome influences apart from correcting for the losses caused by the dry radome.

On its way through the atmosphere, the radar beam encounters atmospheric gases, cloud droplets, and rain drops which may attenuate the radar beam by absorption and scattering of the radiation. For wavelengths between 3 and 10 cm, the attenuation by the atmospheric gases is only 0.008 dB/km (Collier, 1989) and the radiation is hardly affected by the presence of cloud droplets. The attenuation of X- and C-band radiation due to scattering from rain drops can be significant, i.e., up to 0.5 dB/km for C-band (Gorgucci et al., 1998). The typical attenuation of a C-band radar is $0.0044R^{1.17}$ dB/km with the rainfall rate R in mm/h (Joss and Waldvogel, 1990). The observed reflectivity in a certain range bin can be corrected for this attenuation by accumulation of the scattering losses in the preceding range bins. Because of accumulation of measurements errors, the corrected reflectivities, especially those at long ranges, can become unreliable.

The intensity of the radar beam is not only attenuated by propagation through the atmosphere. It can also be enhanced in a particular direction, mostly above water surfaces, by “microwave ducts” or specular reflection from the surface. A microwave duct is a region where the radiation is trapped between two layers because of gradients in the refractive index. Ducts may, for instance, form above oceans and seas through evaporation of water or through large-scale subsidence (Brooks et al., 1999). When the lower part of a low-elevation radar beam is reflected from a water surface and the two sub-beams are recombined at longer ranges, interference effects can enhance the local radiation intensities with up to 3 dB (Zhenhua, 1985). Both the ducting and the specular reflection of the radar beam result in an overestimation of the reflectivity.

2.2.3 Range effects

The atmospheric volume sampled by the radar beam grows with the range distance from the radar location. The transversal dimensions of a range bin typically change from a few metres close to the radar up to about 1.5 kilometres at about 100 km from the radar.

These considerations imply that a meteorological phenomenon can be over-sampled close to the radar and under-sampled in another part of the domain. A large number of different techniques are available to reproject the radar data from the original geometry to a more useful gridded structure (nearest neighbour, maximum value, box averaging, objective weighted analysis). These techniques are, in principle, equally good, each of them with different characteristics and range of applications. Henja and Michelson (1999) discuss this topic from an operational point of view, and they present the implementation of a scheme in their paper.

2.2.4 Clutter

The radar measurements can be contaminated by echoes due to clutter from either normal propagation (“permanent”) or anomalous propagation (“anaprop”), chaff, birds, insects, or refractive-index gradients. Clutter caused by reflection of radiation from mountains or large buildings is commonly referred to as normal propagation clutter, while clutter caused by refraction of the radar beam from temperature and/or moisture gradients and subsequent reflection from the land (sea) surface is referred to as anomalous propagation (sea) clutter. There is no definite answer on how to remove clutter yet, the preferred method depends strongly on the dominant type of clutter to be removed and therefore on local conditions at the radar site, like the orography or the proximity of a sea. Clutter removal algorithms currently in use are based on, for example, clutter maps, radial Doppler velocities, signal statistics, or geostationary satellite data.

The clutter map, which is frequently employed in non-Doppler radar systems and which is updated during dry weather situations, can be used to eliminate normal propagation clutter to a large extent (Newsome, 1992; Meischner et al., 1997). Using the radial velocities as obtained from Doppler radar and filtering of signals having non-zero velocity only, both normal and anomalous propagation clutter can be suppressed to a large extent (Keeler and Passarelli, 1990; Koistinen, 1996; Seltmann, 2000). Archibald (2000) has investigated the performance of the Doppler-based clutter removal techniques in the weather radar network of the UK and has found that roughly 80% of the clutter is removed. Kessinger and VanAndel (2001) have found that the WSR-88D Doppler-based clutter detection algorithm removes about 55% of the clutter and that it falsely removes about 7% of the rain. Wessels and Beekhuis (1997) have demonstrated that the Rayleigh fluctuations of precipitation signal and the relative stability of clutter signal can be used to flag clutter-contaminated pixels in a reliable way. They have found that

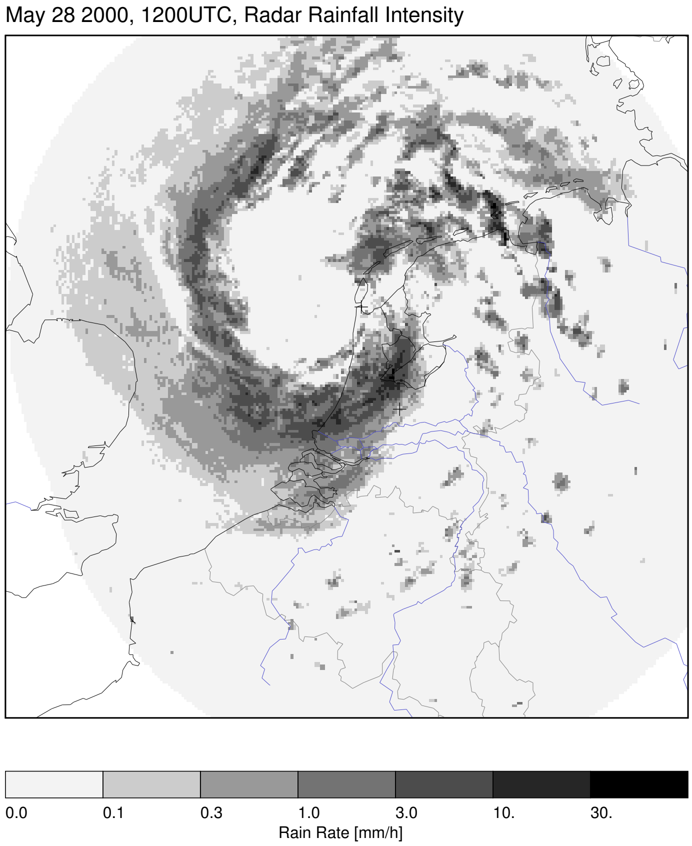

Figure 1: A rainfall intensity composite of De Bilt and Den Helder radars of the Netherlands Royal Meteorological Institute (KNMI).

clutter over land is removed almost completely (98%), while sea clutter is partly removed (40%). The Doppler-based methods also have difficulties in removing sea clutter (Archibald, 2000).

Finally, overlays of radar rainfall maps with cloud maps obtained from IR images of a geostationary satellite, e.g. Meteosat, can be used to flag radar pixels with clutter (Pamment and Conway, 1997). The Meteosat-Second-Generation satellite to be launched in the near future should enhance the performance of this kind of clutter-removal algorithm considerably. Often a single method to discriminate between precipitation and clutter cannot do the whole job, and several different methods are combined using a decision tree or a statistical method to improve the performance (Lee et al., 1995; Pamment and Conway, 1997).

Not only reflections from land or sea surfaces give clutter, but also aluminum flakes (chaff) used by the military to distract enemy radars, groups of birds, swarms of insects, and refractive-index gradients. The echo reflectivities observed by the WSR-88D S-band radars from swarms of insects can in the warm season be between -5 to 20 dBZ and those from birds during heavy migration events can even be up to 30-35 dBZ (Serafin and Wilson, 2000; Gauthreaux and Belser, 1998; Riley, 1999). Wilson et al. (1994) show examples of clear-air return from C-band radars at several locations and during various meteorological situations, and they have observed reflectivity values between -5 and 30 dBZ.

2.3 Rainfall intensity

In simple schemes for assimilation of radar data and for input of radar data in hydrological models, the reflectivity values as observed at a certain range and height have to be converted to rainfall rates at ground level. This conversion introduces errors in the resulting rainfall map because of the variability of the Z-R relationship, bright band effects, vertical reflectivity profile and incomplete beam filling. Joss and Germann (2000) have given an extensive overview of the problems and solutions when applying qualitative and quantitative information from weather radar. The variability of the Z-R relationship originates from differences in the droplet-spectrum which depends on the precipitation situation and climatological circumstances. Many different Z-R relationships can be encountered in literature (Collier, 1989), but $Z = 200R^{1.6}$ is widely accepted.

Operational radar-based rainfall estimation generally uses correction for the vertical profile of reflectivity (including bright band effects) and adjustment to gauge accumulations (Joss and Lee, 1995; Harrison et al., 2000). Even after these corrections, the mean difference between radar-based rainfall estimates and gauge accumulations will typically still be a factor of two. Representativeness errors, however, make up a significant part of this difference (Harrison et al., 2000). An example of a radar rainfall intensity composite during the passage of a meso-scale depression is given in Fig. 1.

2.3.1 Vertical Profile of Reflectivity

Nowadays, gradients in the vertical reflectivity profile are believed to be the major source of observed differences between radar measurements and rain gauges (Koistinen, 1986; Joss and Lee, 1995; Anagnostou and Krajewski, 1999). Possible causes of strong vertical reflectivity gradients are interaction between droplets, updrafts and downdrafts, evaporation and accretion of drops under the cloud base, and melting precipitation (bright band). As a result, the observed reflectivity will depend on the beam-height due to strong reflectivity enhancement at the melting layer (bright band), reflectivity reduction when the radar beam samples the snow region, and nondetection at far ranges where the radar beam overshoots the cloud tops (Anagnostou and Krajewski, 1999).

The bright band with its vertical extent of less than 300 metres is only a disturbing factor at short ranges (<65 km) where the radar beam is narrow enough to resolve it. Methods for correction of the bright band enhancement use, for instance, NWP output (height of melting layer) (Harrison et al., 2000) or identification of the bright band in the vertical profile of reflectivity.

Several algorithms have been developed for conversion of radar volume data to rainfall maps that use vertical reflectivity profile correction (Joss and Lee, 1995; Fulton et al., 1998; Anagnostou and Krajewski, 1999). Generally, averaged vertical reflectivity profiles, which are obtained from high-quality and high-resolution data at short ranges, are used to extrapolate a reflectivity measured at a certain range and height to a corrected on-ground rainfall intensity. A comprehensive review on current correction methods for the vertical profile of reflectivity is given by Gibson (2001).

2.3.2 Gauge adjustment

To keep the radar rainfall estimates as accurate as possible, several operational radar systems are adjusted using rain gauge measurements on a regular basis. The precipitation processing system (PPS) of WSR-88D, which is used to produce radar-derived rainfall products, has the capability to adjust the radar rainfall estimates to hourly rain gauge accumulations (Fulton et al., 1998). In the UK, the radar data are adjusted to rain gauge accumulations on a monthly basis (Harrison et al., 2000). The Swiss radar-derived precipitation estimates are adjusted using longer-term radar-rain gauge analyses, averaged over one month to a year (Joss and Lee, 1995). Kitchen and Blackall (1992) have recognized that adjustment methods using hourly rain gauge accumulations can introduce representativeness errors due to small scale structures present in the rainfall field. In addition, differences in timing and location can occur between the precipitation observed at high-altitude by radar and that by the on-ground rain gauges. These errors can be significant, i.e., up to 150 % for the representativeness errors, and have to be separated from possible biases in the radar rainfall estimation using long-term averages or "mean-field" bias adjustments (Fulton et al., 1998). Several different techniques for adjustment of radar rainfall estimates to rain gauge accumulations are currently employed (Borga and Tonelli, 2000; Michelson and Koistinen, 2000; Gibson, 2000; Gabella and Amitai, 2000; Harrison et al., 2000).

2.4 Radial winds

A Doppler radar uses electromagnetic waves to investigate atmospheric properties: the amplitude of waves are used to estimate the reflectivity and the phase of the waves are used to estimate the radial wind. The radial velocity of scattering particles is determined from their observed phase difference between successive radar pulses.

2.4.1 Aliasing

Because a Doppler radar uses phase differences to determine the radial velocity, there is a maximum velocity that can be determined unambiguously. This maximum velocity is called the Nyquist velocity and it can be expressed as:

$$V_{Nyquist} = \frac{\mathrm{PRF} \cdot \lambda}{4} \tag{1}$$

where PRF is the Pulse Repetition Frequency of the radar pulses and λ is the wavelength of the radar (5 cm for C-band). The timelag between two successive radar pulses, and thus the PRF, also determines the maximum range that can be resolved unambiguously. This leads to the fundamental equation for the maximum (Nyquist) range and maximum velocity of a Doppler radar:

$$R_{Nyquist} \cdot V_{Nyquist} = \frac{c \cdot \lambda}{8} \tag{2}$$

where c is the speed of light. For measurements with a Doppler radar, a trade-off, therefore, has to be made between the maximum velocity and the maximum range. For a typical C-band weather radar and a maximum range of 150 km, a maximum velocity of only 12 m/s is obtained. Velocities higher than the maximum velocity will be folded back into the fundamental Nyquist interval (aliasing). The measured radial velocity, V_m, is, therefore, related to the true velocity by:

$$V_{true} = V_m + 2 \cdot n \cdot V_{Nyquist} \tag{3}$$

where n is an unknown integer called Nyquist number.

Velocity aliasing can usually be identified in radar images by detecting abrupt velocity changes of about $2 \cdot V_{Nyquist}$ between neighbouring measurements. In this case, the basic assumption is that the true wind field is sufficiently smooth and regular; this is true for the greater part of the weather situations with the exception of mesocyclones, tornado vortices or highly sheared environments. The basic de-aliasing methods are based on local statistics (Ray and Ziegler, 1977; Bargen and Brown, 1980; Leise, 1981; Mohr and Miller, 1983; Miller et al., 1986) or on local continuity (Eilts and Smith, 1990; Liang et al., 1997). Both methods need a starting point, and therefore they are not capable of de-aliasing isolated areas of radar data without additional information on the environmental wind. This information could, for instance, be provided as a profile from a nearby sounding or from a NWP model. Radar wind data can be de-aliased in a straight-forward manner by always taking the Nyquist number that results in the smallest deviation from a given wind profile (Doviak and Zrnic, 1993). More sophisticated de-aliasing techniques based on, for instance, two or more-dimensional variational methods have been developed (Merritt, 1984; Boren et al., 1986; Bergen and Albers, 1988; Desrochers, 1989; Jing and Wiener, 1993; Wüest et al., 2000).

Aliasing problems can largely be circumvented by applying different measurement techniques, like dual-PRF or staggered PRT (Pulse Repetition Time). Many operational Doppler radars in Europe have the capability of using the dual-PRF technique. During a dual-PRF measurement, radial winds are measured with alternating high and low PRFs. By combining the measured velocities at low and high PRF, the maximum unambiguous velocity can be extended by about a factor of three (Doviak and Zrnic, 1993). The dual-PRF has the disadvantage that measurements performed at slightly different times or locations are combined which can lead to representativeness errors. This problem is solved by the staggered PRT technique in which two radar pulse frequencies are transmitted simultaneously by alternating the timelag between pulses (Keeler et al., 1999; Sachidananda and Zrnić, 2000). Currently, most operational Doppler radars are not capable of running at staggered PRT, but this probably will change in the near future.

2.4.2 Quality issues

Radial wind measurements, just like reflectivity measurements, can be heavily affected by normal or anomalous propagation clutter. Clutter signal can be suppressed to a large extent from the reflectivity and radial wind data by reducing the echo power around zero radial velocity using discrete filtering techniques in the time or frequency domains. All operational Doppler radars apply this kind of filtering before the radial velocity is determined. Sachidananda and Zrnić (2000) recently introduced a new technique for clutter suppression and radial wind estimation based on staggered PRT. For a complete discussion on the problem of the bias introduced in the radar wind spectrum due to the clutter and clutter-suppression algorithms, the reader is referred to Seltmann (2000).

As noted before, non-hydrometeor targets such as insects and birds are detected by (Doppler) radar as well. While some insects can provide a help in defining the boundary layer wind (Riley, 1999; Szturc et al., 2000; Venema et al., 2000), birds and actively flying insects are mainly a problem for velocity retrieving algorithms. Erroneous wind data due to birds can be recognized by inconsistency of the wind data (Koistinen, 2000).

2.5 Wind profiles

Radial wind data are not straightforward to interpret, so some further processing is required before they can be presented to users. Also for assimilation into NWP models, some further processing of radial wind data is required either via the extraction of a representative wind profile or via averaging of raw radial wind data to the grid size of the model (formation of "super-observations").

Wind profiles can be obtained from single-site radar data under the assumption of a linear wind model. In this model the wind in the vicinity of the radar (at the origin) is expressed as:

$$U(x,y,z) = u_0 + x\frac{\partial u}{\partial x} + y\frac{\partial u}{\partial y} + (z - z_0)\frac{\partial u}{\partial z} \tag{4}$$

and likewise for $V(x,y,z)$ and $W(x,y,z)$. Using this linear wind field, the radial wind can be calculated as a function of range, azimuth, and elevation. For a uniform wind field this results in:

$$V_{radial} = u_0 \cos\theta \sin\phi + v_0 \cos\theta \cos\phi + w_0 \sin\theta \tag{5}$$

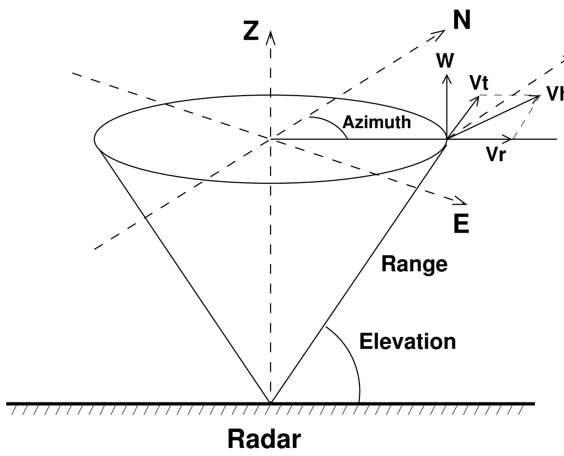

Figure 2: Radar geometry for measuring wind profiles.

When Doppler radar data is displayed at constant range and elevation (θ), the radial wind as a function of azimuth (ϕ) will have the form of a sine. The wind speed and direction can be determined from the amplitude and the phase of the sine, respectively. This technique is called Velocity-Azimuth Display (VAD), and it was introduced by Lhermitte and Atlas (1961) and Browning and Wexler (1968).

Nowadays, (Doppler) radars are recording volume scans, i.e., reflectivity and radial wind data as a function of range, azimuth, and elevation. The radar geometry used to measure these volume scans is shown schematically in Figure 2. The range, azimuth, and elevation are indicated in the figure. From the volume scans, different VADs can be extracted as a function of height, and a wind profile at the radar site can thus be obtained. Extraction of the vertical air velocity (w_0) using the VAD technique is troubled by divergence of the local wind field. Improved versions of the VAD technique, for additional extraction of divergence and vertical velocity, are the Extended-VAD technique (Srivastava et al., 1986; Matejka and Srivastava, 1991) and the Concurred-Extended-VAD technique (Matejka, 1993).

Instead of processing, for each height, a single VAD or a series of VADs (EVAD, CEVAD), one can also process all available volume data in a certain height layer at once. This so-called Volume Velocity Processing technique (VVP) has been introduced by Waldteufel and Corbin (1979). Using equation 4 of the linear wind model, the radial wind can be calculated for all points within a layer centered at height z_0. Via a multi-dimensional and multi-parameter linear fit, the parameters of the linear wind field can be extracted. The VVP technique is typically applied to thin layers of data at successive heights to obtain a wind profile. An example of a time series of VVP wind profiles from a C-band Doppler radar is shown in Fig. 3. The observed veering of the wind is due to the passage of a depression. An interesting comparison of divergence and vertical velocity obtained by EVAD, CEVAD and VVP techniques has been presented by Ciffelli et al. (1996). The results of these techniques were quite similar, although the VVP profiles often extended to greater heights. Unfortunately, no comparison of wind speed and direction was made.

Andersson (1998) has published a verification of VAD winds against radiosonde winds and winds from the HIRLAM NWP model. In this study the availability and the accuracy of the VAD winds of the Swedish radars have been investigated. The availability of the VAD winds is about 80% at 925 hPa, and it drops to about 15% at 400 hPa. The vector difference between the VAD winds and the radiosonde winds has an average magnitude of about 3 m/s. Comparison with HIRLAM winds at 850 and 700 hPa gave similar results. Operational assimilation of VAD winds at NCEP (National Centers for Environmental Prediction in the USA) started in 1997 and ended in 1999 because problems with the data became evident. Recently, a quality control for VAD winds has been developed at NCEP which

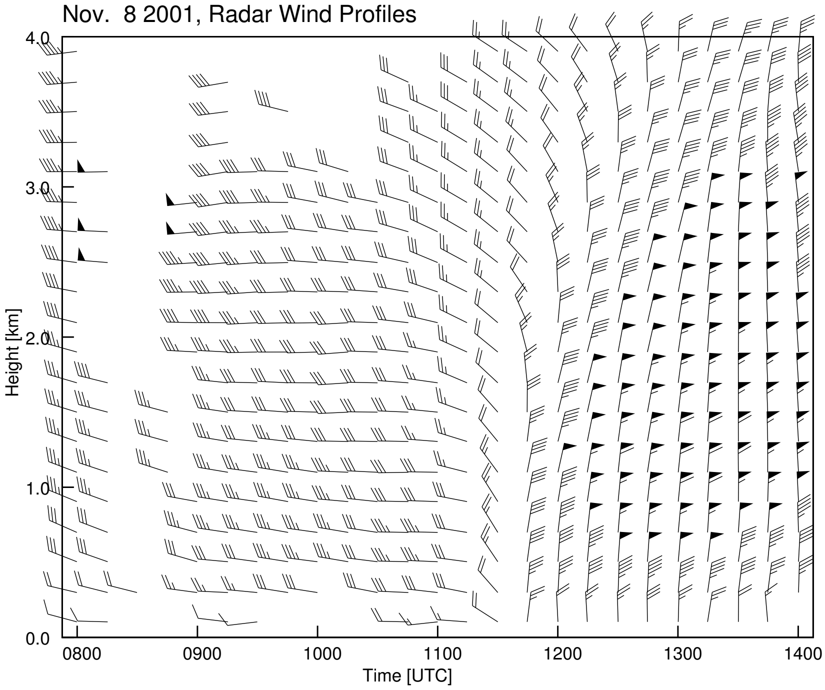

Figure 3: A time series of wind profiles from the De Bilt radar of the Netherlands Royal Meteorological Institute (KNMI). Wind speed and direction are indicated by wind vanes. Each full barb represents a wind speed of 5 m/s and each triangle a wind speed of 25 m/s.

removes winds with very small magnitude, clear outliers, and “winds” from migrating birds (Collins, 2001). The VAD data were re-admitted operationally in March 2000.

2.6 Super-observations

Raw radial wind data have a resolution that is too high to be used in LAM assimilation scheme. A super-observation is a generalized observation created through smoothing in space, based on high resolution data. Ideally, the smoothing is performed such that original characteristics of the raw data are preserved as much as possible. Albers (1995) describes the box averaging methodology used for the Local Analysis and Prediction System (LAPS). Radial wind data are averaged for each LAPS grid-box. Several levels of quality control checks are performed on the data before they are used. Lindskog et al. (2002) describe a method for generation of radial wind super-observations through horizontal averaging in polar space of the raw polar volume data. These radial wind super-observations have been used for the development of a Doppler data assimilation system for HIRLAM (Lindskog et al., 2002).

2.7 Summary

Accurate measurements of on-ground rainfall using radar are troubled by measurement errors in the reflectivity values, by clutter, and by uncertainties introduced by the translation of reflectivity values to on-ground rainfall rates. Normal propagation and anomalous propagation clutter, gradients in the vertical reflectivity profile, and nondetection of precipitation at far ranges are generally believed to be the major sources of errors in the estimation of the on-ground rainfall from radar data.

Radial winds can be aliased due to the limited maximum range and velocity measured by a Doppler radar. There are several algorithms available to de-alias measured radial winds. The aliasing problems can, however, be overcome by using different measurement techniques, like dual PRF or staggered PRT. Radial wind data can be processed to obtain wind profiles at the radar site using a VAD-like or VVP algorithm. Representativeness of the winds obtained from Doppler radars, for both the radial winds and the wind profiles, is the major problem when using this data.

3 Data Assimilation

3.1 Basic Concepts

Before reviewing assimilation of radar data, it will be useful to outline some basic concepts and techniques in this field which is unfamiliar to many, even within the numerical modelling community.

A very helpful descriptive tutorial on atmospheric data assimilation for the non-specialist is given by Schlatter (2000), whose presentation has influenced this section. He defines data assimilation as the process of estimating meteorological conditions on a regular grid from two main sources of information: (1) observations from disparate sources, whenever and wherever taken, and (2) a numerical model, which incorporates through mathematical equations what is known about the atmosphere. The goal is to construct the best set of initial conditions, known as the analysis, from which to integrate the NWP model forward in time.

A fundamental concept is that of the *data assimilation cycle*. This means that if, for example, a 6 hour data assimilation cycle is used, then a 6 hour numerical model forecast is merged with observations during the assimilation procedure to produce an initial state for a new model integration. The 6 hour forecast launched from this new model state is itself merged 6 hours later with a new set of observations to produce a new initial state, and so on.

The available observations may be of various quantities related to the atmosphere, such as pressure, temperature, wind, humidity, cloudiness, satellite radiance and radar reflectivity. These need not be the same quantities carried as prognostic variables by the NWP model. All that is required for an observation to be suitable for assimilation, is that it must be possible to estimate the observed quantity from variables carried by the model, via the so-called *forward model*, or *observation operator*. The success of this assimilation will, however, be influenced by the sophistication with which the model represents the physical processes giving rise to the measured quantity. For example, a model may have a simple diagnostic relationship to derive surface rainfall rate from prognostic variables, which could be used to assimilate observations of that quantity. But it may lack the detailed microphysics needed for a credible estimate of the reflectivity measured by a radar aloft, thus making direct assimilation of reflectivity impractical.

The observations are typically irregularly distributed in space and time and the number of observations is in general small compared to the number of variables in the initial state of the forecast model. Observations alone are inadequate to initialise the model. This is why we need to introduce *a priori* information, in the form of a short-range NWP model forecast. To combine the two kinds of information optimally, we need statistical knowledge about the errors of this short forecast, and statistical knowledge about the observation errors. We may also exploit additional *a priori* information regarding, so-called 'balance relationships' between (errors in) different forecast model variables. The best known example is probably the geostrophic relationship between wind and pressure gradient.

Given an observation at one location, assimilation schemes use statistical knowledge of the short range forecast error structures and correlations between errors in different model variables to decide how to spread the information from that observation spatially (and temporally) and how to influence different model variables. These forecast error correlations and balances are known reasonably well and can be modelled empirically. The spatial patterns of forecast error correlations are usually referred to as *structure functions*. The assimilation is said to be univariate in the case where cross-correlations between different variables are zero, i.e. each variable is analyzed independently of the other variables. Multivariate assimilation is more general, and in most cases more physically justified. When the increments to different model variables are not in good multivariate balance, this can lead to an analysis which does not represent the atmosphere's slowly varying motions realistically. Instead, the model may respond by generating spurious high frequency waves, which may also lead to some loss of observational information just added. Avoiding this by the construction of a well balanced analysis is the *initialisation problem*. For a thorough grounding in these (and many other) aspects of data assimilation, the reader is referred to Daley (1991).

Even with good knowledge of observation errors and forecast errors, an extra difficulty originates in the model's inability to model the physics behind the measurement perfectly, and the limited spatial resolution of the model. These manifest themselves as another source of discrepancy between observations and model estimates termed the *error of representativeness*. For example, the temperature measurement inside a cumulonimbus cloud may be very accurate, but quite unrepresentative of average conditions over a model grid-square of side, say 20km, in a model which does not resolve thunderstorms explicitly. The error of representativeness is usually treated by increasing the assumed observation error for assimilation.

3.2 Techniques

Early data assimilation techniques were based on simple spatial interpolation. For example, polynomial fitting (Panofsky, 1949) or distance weighting (Bergthorsson and Döös, 1955), were used to adjust a 12 hour forecast locally to observed values in the vicinity of each model grid point. A first step towards more advanced methods was taken with the arrival of *statistical* interpolation or *optimum* interpolation (Eliassen, 1954; Gandin, 1963). Essentially this technique applies linear minimum variance estimation of analysis errors locally at each grid point. Simplified error covariance models, assuming for example, horizontal homogeneity and isotropy, were applied for this assimilation technique. Three-dimensional multi-variate statistical interpolation schemes (Gustafsson, 1981; Lorenc, 1981) dominated operational NWP during the period 1975-1995.

During this period, another popular and conceptually simple approach was developed, generally referred to as 'nudging'. It has been used extensively in research applications, but also in some operational systems (Macpherson et al., 1996). In this method observations are 'nudged' into the model at each time-step of the integration by adding an extra term to the prognostic equations, forcing the model towards the observations. The forcing term is proportional to the difference between the observed value and the model's estimate of the observed quantity, scaled by tunable 'nudging coefficients' which may depend on the relative error of the observation and the model estimate. One advantage of nudging is that the forecast model can adjust gradually to the observed information being added. This can help the model maintain a balanced state without generation of spurious high-frequency modes, thereby addressing the initialisation problem.

With the increasing variety of observations that are non-linearly coupled to the forecast model variables, the linear spatial interpolation techniques were eventually regarded as unsatisfactory for an optimal use of the data. A new generation of assimilation schemes has been based around the variational approach. At its roots, variational assimilation is an application of mathematical techniques going back to Gauss, but it is only in the last decade or so that practical operational assimilation systems have been developed in this framework, building on some foundational work in the mid-eighties (Lewis and

Derber, 1985; Le Dimet and Talagrand, 1986; Talagrand and Courtier, 1987; Courtier and Talagrand, 1987).

Variational assimilation provides a means of deriving the optimal analysis as a combination of observations and model forecast. A key concept is that of the *cost function* (or *penalty function*) which is a sum of terms, each measuring the 'distance' between the model state and the available information. One term measures the 'distance' or 'fit' to the observations, another the fit to the previous short-model forecast or *background field*. In each term, the distance is weighted by the inverse of the error covariance matrix for that information source. Minimisation of a cost function with this structure gives the model state with minimum expected analysis error. Additional terms can be added to the cost function, for example to give constraints on gravity wave activity and alleviate the initialisation problem.

In 3-dimensional variational assimilation (often known as *3D-Var*), the minimisation takes place at a single time, using observations valid at (or close to) a single time. In 4-dimensional variational assimilation (*4D-Var*), observations distributed over a time window are analysed, and the minimisation consists in finding a model trajectory in phase space which best fits the available data. This can be very demanding computationally, relying as it does on an iterative technique and several integrations of the model before arriving at the minimum cost function. Since the analysis determined by 4D-Var is an actual space-time trajectory produced by the model, the initialisation problem is solved en route.

During the minimisation of the cost function in 3- or 4D-Var, the gradient of the cost function with respect to a change in its dependent variables must be estimated. Calculation of this gradient requires the *adjoint* of the forward model used to calculate model estimates of observed quantities. If we linearise the forward model, and represent it as a matrix, then the adjoint is obtained from the transpose of that matrix. In 4D-Var, the forward model is the full prognostic model, and many papers refer to the associated *adjoint model*, whose derivation can be a complex exercise, particularly where physical parametrisation with on-off thresholds are concerned.

4D-Var is run operationally at the European Centre for Medium Range Weather Forecasts (ECMWF), at Meteo-France and at the Japan Meteorological Agency. As we shall see later, it has also been used for a number of studies in radar data assimilation, where it holds the potential of giving a model state which best distributes the complex information present in, say, a reflectivity measurement amongst the various model variables: dynamical, thermodynamic and microphysical. 3D-Var assimilation of rainfall data is also possible, but has more limited potential than 4D-Var, since only through the time dimension can increments to thermodynamic and microphysical variables feed back into modifying the wind field which can sustain the desired precipitation structure within the model. Given its complexity and cost, however, 4D-Var is not the only current practical option for assimilation of radar data, and a variety of simpler techniques are still being applied.

4 Assimilation of radar precipitation data in NWP models

4.1 Introduction

The impetus for introducing precipitation data into NWP models came from tropical meteorology. In lower latitudes there is a relative lack of conventional data from surface and radiosonde stations (Krishnamurti et al., 1984). Perhaps more influential was the fact that in the tropics there is no dynamical balance like that described by quasi-geostrophic theory in mid latitudes which links through to the moisture field via diagnosed vertical motions (Krishnamurti et al., 1991). Tropical dynamics are also known to be heavily impacted by latent heat release from convective precipitation. Tropical models tended to suffer from large errors in the analysed moisture field and consequently (since convection is a major forcing term) in the divergent wind field. There was therefore a rather slow equilibration over a few days of evaporation and precipitation on the global scale (Heckley, 1985). Therefore a procedure that could treat rainfall data held the prospect of improving tropical forecasts substantially. Rainfall estimates derived from satellite, rather than radar, were the focus for these studies. Techniques applied usually fell into the categories of 'physical initialisation' or 'latent heat nudging', depending on the approach to dealing with the model's convective parametrisation. We review these methods separately.

In mid-latitudes there has, of course, been a need to improve precipitation forecasts, since mesoscale details are usually not represented well enough in the analysed fields. This is especially important in the first few hours of the forecast, when precipitation forecasts suffer from the spin-up problem as the model dynamical and hydrological fields come into balance. Therefore, even a short lived beneficial impact of precipitation assimilation on precipitation forecasts is very welcome for nowcasting and short range forecasting. Researchers began to use radar data in a variety of assimilation systems and in models of increasing resolution. After looking at the achievements of physical initialisation and latent heat nudging, we survey work on variational assimilation, focussing finally on efforts by all means to assimilate radar data in meso-γ scale models. These are non-hydrostatic models with horizontal resolution ranging from 6 km to 500 m. Most previous studies have worked with surface rain rate estimates, but attempts to assimilate reflectivity directly are also covered.

4.2 Physical Initialisation

Physical initialisation (PI) as formulated by (Krishnamurti et al., 1991)consists of two steps. First there is a diagnostic calculation of surface fluxes and a humidity analysis consistent with observed precipitation rates. Secondly, a nudging of the diagnosed fluxes into the model takes place during a pre-integration phase. The key concept behind the the humidity analysis is an inversion of the planetary boundary layer and convective parameterization schemes so that diagnosed precipitation rates correspond to observed ones. First, fluxes of sensible and latent heat are calculated that correspond to measured precipitation rates. Then 'reverse similarity theory' is used to obtain temperature and humidity above the constant flux layer. Finally a reverse convective parameterization scheme yields the vertical profile of humidity. PI has been found to reduced spin-up substantially and improve precipitation forecasts (Krishnamurti et al., 1984; Donner, 1988; Krishnamurti et al., 1993; Treadon, 1996).

An assimilation method based partly on PI was developed for the Japan spectral model using precipitation observations from a radar-raingauge network over Japan (Aonashi, 1993; Matsumura et al., 1997). Within this scheme, a PI method calibrates the thermodynamic and dynamic variables of the objective analysis data in such a way, that model precipitation rates agree with observations. Afterwards, a non-linear normal mode initialization (NMI) (Daley, 1991) is conducted. The combination of PI and NMI makes diabatic heating in the analysis consistent with that produced in the model forecast. Experiments showed that the method reduces both spin-up and position errors in precipitation forecasts.

Gregoric (2001) has developed a kind of physical initialisation where diagnostics from radar data are used to replace some closure assumptions in the convective parametrisation. The locations and dimensions of convective cells are identified from the radar data and stored in look-up tables accessed by the convection scheme. Convection is only triggered in the model where the radar confirms the existence of convective precipitation.

4.3 Latent Heat Nudging

Latent heat nudging (LHN) is a method of forcing an NWP model towards observed precipitation rates. It is based on the observation that since relatively little moisture is stored in clouds, the column integrated latent heating rate must be approximately proportional to the precipitation rate. The principle is to correct the model's latent heating at each timestep by an amount calculated from the difference

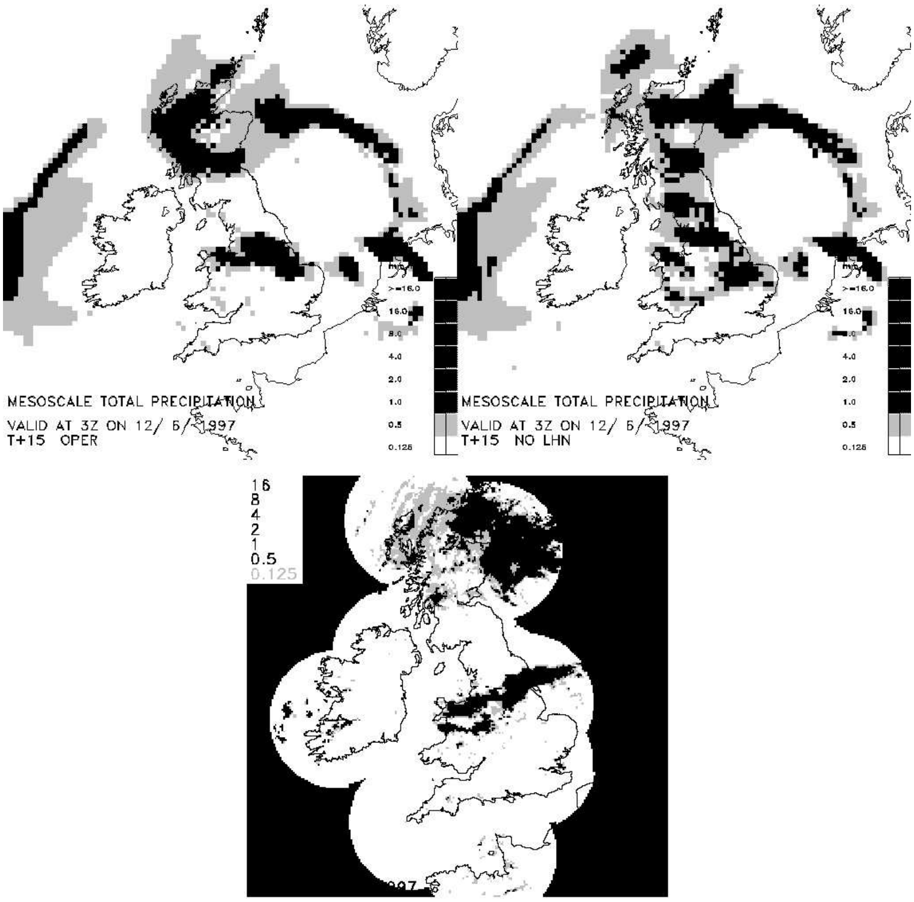

Figure 4: An unusually long lasting forecast impact of radar rain rate assimilation in the Met Office (UK) mesoscale model, taken from Macpherson (2001a). Bottom frame shows radar picture for 03 UTC, 12th June 1997, with northward moving rain band over central England. Top left frame shows operational precipitation rate forecast at t+15 hours. Top right frame is from an experiment with NO assimilation of radar data

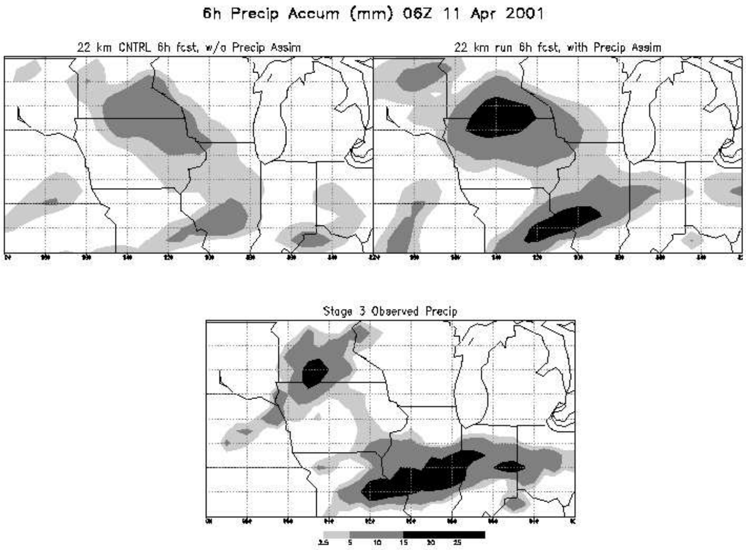

Figure 5: Impact of precipitation assimilation on the 6-hour precipitation forecast from the NCEP ETA model, for a case with data time 00 UTC, 11th April 2001. Taken from Lin et al. (2001). Upper panels show accumulated precipitation in the first 6 hours of model forecast, on the left from a run without precipitation assimilation, and on the right with precipitation assimilation included. The lower panel shows observed accumulation from a precipitation analysis based on radar data and rain gauges

between observed and model estimated precipitation. This extra heating then acts as a source term in the thermodynamic equation, which in turn brings about an adjustment in the model vertical velocity field that takes the model precipitation rate closer to that observed. LHN is simpler than PI in that it does not seek to intervene directly within the physical parametrisations to bring about the adjustment.

Since usually only the surface rainfall rate is known or available, one has to specify the vertical structure of applied heating. Two possibilities have been tried to date: idealised profiles may be constructed, or else a scaled model profile may be selected, assuming that the model has the correct structure despite an incorrect intensity. Manobianco et al. (1994) and Jones and Macpherson (1997) have chosen the second possibility. This has some advantages: it ensures consistency with the model's parameterisations and it allows evolution of the profile with time during the integration. It is assumed that the model's separation of explicit (stratiform) and implicit (convective) precipitation is correct. If one does not trust the model separation, it is possible to treat the convective part separately through closure assumptions in the parameterization scheme.

A third option to construct heating profiles could be based on the work of Cartwright and Ray (1999) who proposed an algorithm within a cloud resolving model to relate latent heating profiles to model reflectivities. The same algorithm could then be used to derive 'observed heating' from observed 3-dimensional reflectivities from radar. There are plans to test this in an LHN context at the Swiss Meteorological Institute (Rossa, 2001).

The LHN algorithm runs into difficulty in the case when the model point is dry yet precipitation is observed. In this case the algorithm must include a search for nearby points where the model is raining. Heating profiles from there can then be applied at the point where it is desired to introduce rain, but this refinement has limited success. This situation, of introducing rain absent in the model, is a great challenge for precipitation assimilation.

LHN has been found beneficial in mid-latitudes. In studies of winter cyclogenesis with satellite derived estimates of rainfall, the impact of assimilation was noted in the surface pressure field up to 30 hours beyond the end of assimilation (Chang and Holt, 1994). Some authors report dramatic impact on quality of precipitation forecasts (Wang and Warner, 1988), others working with radar data in the operational mesoscale model at the Met Office in the UK have found smaller, yet noticeable positive impact in general (Jones and Macpherson, 1997), with occasional larger benefits (Macpherson, 2001b), of which Fig. 4 is the best example. Recent results with the Met Office mesoscale model indicate that these larger benefits for short-period (6-12 hour) rainfall forecasts originate just as frequently from radar data as from other observation types such as aircraft, radiosonde and surface data.

A modified version of the LHN algorithm including elements of physical initialisation, but still based on nudging, was implemented operationally in 2001 in the ETA model (grid length 22 km) at the National Centers for Environmental Prediction (NCEP) in the USA (Lin et al., 2001). The assimilation of observed precipitation is performed with a form of nudging that is applied during the 3 hour forecasts that occur between successive analyses in the data assimilation cycle. At each time step, the observed and forecast precipitation are compared, then the model's temperature, moisture, cloud and precipitation are mutually adjusted to produce a forecast value closer to the observed value. The observed values come from hourly precipitation analyses derived from 2500 automatic reporting gauges and hourly precipitation estimates from radars. This technique produces initial precipitation rates that match observations and also ensures that the soil moisture (coupled to the model precipitation through the land-surface physics package) evolves with the observed precipitation. The soil moisture, in turn, is very important in how the boundary layer evolves in the forecast. Some noticeable improvement in the first 6 hours of the precipitation forecast (Fig. 5) is reported, along with a modest overall improvement in longer term (24 hour) precipitation forecasts.

4.4 Variational Assimilation

Some pioneering studies gave early indication of the likely value of 4D-Var for assimilation of precipitation data (Zupanski and Mesinger, 1995; Zou and Kuo, 1996). In a case study of strong convection with the NCAR/Penn State MM5 4D-Var system, Guo et al. (2000) compared the impact of various data types on the simulation. They found that hourly surface precipitation data (not from radar) were important in preserving the precipitation structure of the squall line, although wind profiler data had more beneficial impact on precipitation accuracy.

At finer scale, the adjoint of a cloud resolving model has been developed and applied to the assimilation of 3-dimensional radar data by Sun and Crook (1997, 1998). They developed a 4D-Var system that can be used to assimilate data from one or more Doppler radars. The horizontal resolution of the cloud scale model was 500 metres, and only the warm microphysical processes were parameterised. The thermodynamical and microphysical fields, as well as the 3-dimensional wind field, were determined by minimizing a cost function defined by the difference between the observed radial velocities and the reflectivities (or rainwater mixing ratio) and their model counterparts. The derivation of the adjoint of the physical processes with on/off switches follows that of Zou et al. (1993) and the microphysical scheme was modified for the evaporation of rain and the rainwater fall velocity. It was found that assimilating the rainwater mixing ratio obtained from the reflectivity data resulted in a better performance of the retrieval procedure than directly assimilating the reflectivity.

In Sun and Crook (1998), differential reflectivity data are used to produce a better estimate of the rainwater mixing ratio, and hence to improve the microphysical retrieval. Wilson et al. (1998) briefly described results of a flash flood case simulation using the variational retrieval technique of Sun and

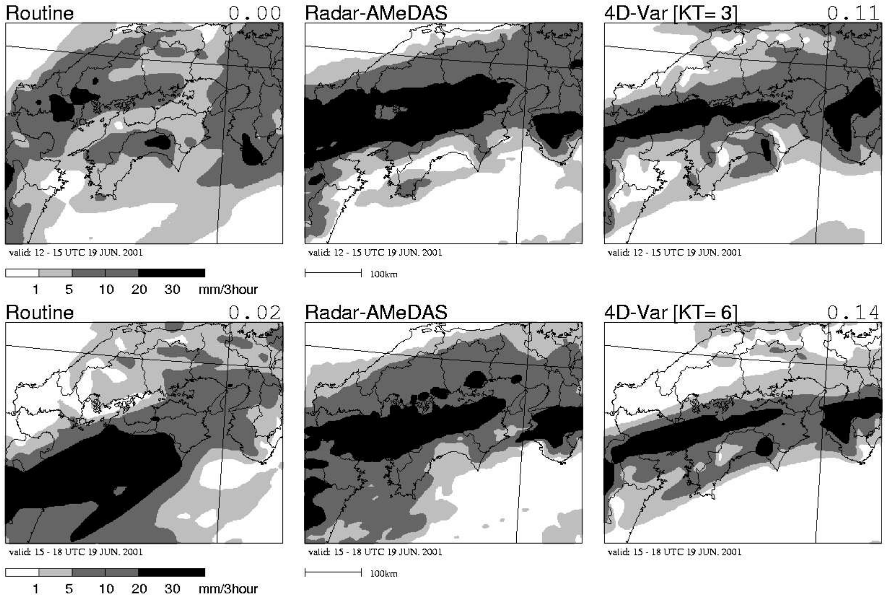

Figure 6: Forecasts and observations of 3-hour precipitation amount. Centre column shows the Radar-AMeDAS observations of the Japan Meteorological Agency, right column shows forecasts starting from a 4D-Var analysis and left column shows the forecasts from a 'routine' analysis using PI for assimilation of rainfall data. Initial time of forecasts is 12UTC 19 June 2001. Top row is for forecast period 0-3 hours, bottom row is for period 3-6 hours. Taken from Ishikawa (2002)

Crook (1997, 1998) to initialise the cloud-scale model. They found that the numerical forecasts significantly improve over persistence and extrapolation in the 60-minute time frame. Afterwards, Wu et al. (2000) have extended the application of Sun and Crook (1997) to convective storms where the ice phase plays an important role. As a complete ice microphysics parameterisation will have a complex adjoint model with poor convergence properties for the minimisation, due to many non-linearities, a simplified cold microphysical scheme was developed. This had no snow category and only one category for the non-precipitating species (cloud water and cloud ice). The differential reflectivity was used to discriminate between the rain and hail and allowed to employ phase-dependent $Z - M$ relationships. The results of this work were mixed : although the analysis system was able to retrieve all the main features of the storm, the simulations were unable to reproduce the evolution of the observed storm - the simple microphysical parameterization was unable to follow the actual cloud physics.

At the global scale, an initial approach to the complexity of variational assimilation of precipitation data has been developed by Marecal and Mahfouf (2000). These authors assimilated data from the Tropical Rainfall Measurement Mission (TRMM) into the ECMWF global model. The data were rain-rate estimates from the TMI microwave imaging radiometer which had been 'calibrated' by the TRMM precipitation radar. The distinctive feature of this study was a two step assimilation: first, an initial 1D-Var retrieval of temperature and humidity profiles from the rainfall data, then a 4D-Var assimilation of the total column water vapour (TCWV) produced by the 1D-Var. TCWV is easier to assimilate within 4D-Var than rainfall rate itself. This study found a positive impact on the humidity and wind analysis, though little forecast impact. As with LHN, it relies for success on the presence of some rain in the model background field.

Also working with TRMM TMI data, Treadon (2001) has tested a 3D-Var rainfall assimilation scheme in the NCEP global model. He noticed some improvement in the fit to pressure data with rainfall assimilation, and the impact on other fields was neutral, but the fit to other moisture data was degraded, perhaps because of some problem with the precipitation physics. Forecast impact was largely neutral, though an improvement in the track of a hurricane was noted.

At the Japan Meteorological Agency, a 4D-Var mesoscale system has been implemented operationally, including assimilation of hourly precipitation amounts from a synthesis of radar and gauge data (Ishikawa, 2002). The 4D-Var scheme has replaced a PI approach to rainfall assimilation. An example of the difference in impact on the 0-6 hours forecast period is given in Fig. 6.

The basic problem for a variational approach to precipitation assimilation is the discontinuous ("on-off") nature of the precipitation physics schemes. In the case of precipitation observations, highly non-linear parameterization schemes must be linearized for development of the adjoint version of the model required by the minimisation procedure for the cost function. Alternatively, simpler physics schemes can be coded for the linear model, which are not a direct linearisation of the full model physics (i.e. the linear model is not *tangent linear* to the full model). It is not clear what may be lost in this simplification. Bao and Kuo (1995); Xu (1996); Zou (1997) describe technical issues for the minimisation of the cost function which arise from these characteristics of the physics.

4.5 Meso–γ scale models

At the cloud-resolving (meso-γ) scale, the first assimilation procedure using radar data was developed by Lin et al. (1993), using the Colorado State University Regional Atmospheric Modeling System (RAMS). They initialised their numerical simulation with three-dimensional dynamical, thermodynamical and microphysical fields derived from multiple Doppler radar observations. The horizontal resolution of the simulation was 2 km, and only warm microphysical processes were parameterised in the numerical model. The procedure initialised the winds with the Doppler wind data, and filled the data void region in order to provide a smooth transition from the observational domain to the background state. The pressure and potential temperature perturbations were obtained from a thermodynamic retrieval method following Hane and Ray (1985). The water vapour content was set to a saturated value where the radar had detected precipitation and above the lifting condensation level. The rainwater content was derived from the reflectivities by using a $Z - M$ relationship whereas the cloud water was assumed to be zero. After feasibility of the initialisation method was established with simulated storm data, it was tested with multiple Doppler radar observations from a tornadic storm. The very short range prediction (less than 15 minute) showed good agreement with the observations, although the modelled storm seemed to evolve faster than the observed storm.

The same approach of moisture and microphysical adjustments has been developed in Xue et al. (1998), Bielli and Roux (1999), Haase (2002), Ducrocq et al. (1999 and 2000) and to some extent in Zhang (1999). All of these experiments used a cold microphysical scheme, except Haase (2002).

In their study, Xue et al. (1998) utilized reflectivity data to deduce the initial cloud water content and to moisten the initial state. A distinctive feature of this work is that the adjustments to the water vapour and cloud water fields were applied during an intermittent data assimilation period: in their experiments, the reflectivity and the radial velocity were assimilated at 15 minute intervals during the last hour of the assimilation period. They found that the assimilation of radar reflectivity had a large positive impact on the simulation of a squall line case.

Bielli and Roux (1999) used the production rate of precipitation to modulate the adjustment of the water vapour content in the observed precipitation areas: the relative humidity was assumed to be 100%, except where the production rate of precipitation was negative. In some of their experiments, the cloud water content was set empirically inside the precipitation areas and also where the production rate of precipitation was positive. The Doppler-derived 3-dimensional wind fields were also used to initialise the model. The results obtained from simulations of a tropical mesoscale convective system data set have shown that it was important to describe, even crudely, the saturated and unsaturated areas in connection with the updraft and the Rear-To-Front flow described by the Doppler winds. Initialising cloud water contents did not bring significant improvements. In his initialisation method, Haase (2002) used radar reflectivities to modify the vertical wind as well as the specific humidity and temperature profiles.

Zhang (1999) used a cloud analysis system to synthesize several data sources (radar and satellite observations) and to construct a 3-dimensional cloud analysis. This system, called ADAS (Brewster, 1996; Zhang et al., 1998), is based on the LAPS cloud analysis (Albers et al., 1996) with several modifications. The 3- dimensional radar reflectivities are used to impose clouds and to determine the hydrometeor type and mixing ratio. If the reflectivity exceeds a threshold, clouds are inserted in the radar echo region. The type of hydrometeor is determined from the wet bulb potential temperature and hail is diagnosed when the 3-dimensional radar reflectivity is above a given threshold. Then, the mixing ratio of the hydrometeors is derived from hydrometeor type-dependent $Z - M$ relationships. The outputs of the cloud analysis system are then provided to a moisture and diabatic initialisation scheme. In this, the cloud water and ice mixing ratio are simply set to the analysed values. The rainwater, snow and hail mixing ratios are usually initialised to smaller values than the analysed values, as inserting the total amount of precipitate could prohibit, by its drag, the development of updrafts. Then, the thermal field is adjusted to account for the latent heating associated with the inserted cloud water. The relative humidity field is also modified and cloudy regions are moistened. The impact of the initialisation on the meso-γ scale numerical prediction has been validated on simulated storm data.

The initialisation method of Ducrocq et al. (2000) is also based on cloud and precipitation analyses, but adapted to the French networks. The reflectivities, available only on a single PPI (Each PPI - Plan Position Indicator - is taken at a single, fixed elevation angle, and thus forms a cone of coverage in space). These were used to determine the rainy areas and to impose cloud where the reflectivities were greater than a given threshold. The vapour mixing ratio was set to saturation in cloudy regions, and a $Z - M$ relationship was used with an empirical vertical distribution to initialise the rainwater mixing ratio. In some experiments, a constant cloud water value was imposed. The initialisation scheme has been applied to simulation of a real case of a convective system. It gave a large impact on the results : use of radar and satellite observations allowed the model to trigger the convection which is not the case when simulations start from a conventional large scale analysis. These results have been confirmed on another convective case also over flat areas (Ducrocq et al., 2002). Inserting cloud water was found to have no significant impact.

So, to sum-up the assimilation of radar reflectivity in cloud resolving models, reflectivity is always used in an indirect way to modify the moisture fields. In some studies, the reflectivity data is also used for initialisation, via $Z - M$ relationships, of the contents of the non-precipitating and/or precipitating species.

4.6 Summary

The three main approaches to assimilation of precipitation data have been reviewed - physical initialisation, latent heat nudging and variational assimilation. At this stage, there is no clearly preferred technique for assimilation of radar rainfall data at all scales for all weather systems. The most natural one seems to be 4D-Var, but this still faces various technical and scientific challenges before reliable and computationally viable schemes can be produced for operational use.

5 Assimilation of radar wind data

5.1 Introduction

The growth in high resolution limited area NWP models has brought a greater interest recently in the assimilation of Doppler radar wind data. The models require observations with high spatial and temporal resolution for determining the initial conditions, for which purpose radar data are particularly appealing. Wind is also a primary prognostic variable of the models.

Radar wind data, fully or partially pre-processed (see previously) have been assimilated into a number of atmospheric models, over a wide range of spatial resolutions. A lot of different assimilation techniques have been tried, which we review in approximate order of sophistication. Most of the work described here has so far been applied in research mode, but radar winds are also assimilated operationally. It should also be noted that some of the relevant studies on Doppler wind assimilation have already been discussed under the heading of precipitation assimilation at meso–γ scale.

5.2 The successive correction method

At NOAA's Forecast Systems Laboratory (FSL) the Local Analysis and Prediction System (LAPS) has been developed (Mc Ginley, 1989). The analysis is performed on a resolution of approximately 10 km horizontally and 50 hPa vertically. The observation residuals are spread vertically using simple vertical structure functions. The analysis is then performed level by level and is based on the successive correction method (Bergthorsson and Döös, 1955), an early and more empirical forerunner of the Optimal Interpolation technique. The analysis system uses information from various data sources and radar wind data play a key role and are subject to some special treatment (Albers, 1995). Observational errors are assumed to be uncorrelated and the background error structure functions are modelled.

The LAPS analysis system has also been used at Servizio Meteorologico Regionale in Bologna, Italy. Applied to Doppler radial wind data, it was reported to refine the wind analysis (Alberoni et al., 2000).

5.3 Optimal Interpolation

Radar wind information is assimilated operationally in the form of VAD-wind profiles within the multivariate Optimal Interpolation (OI) scheme used in the Rapid Update Cycle (RUC) atmospheric prediction system (Parrish, 2000) at NCEP. The RUC atmospheric prediction system is the operational version at NCEP of the Mesoscale Analysis and Prediction System (MAPS) developed at NOAA's Forecast Systems Laboratory (FSL). The RUC system is applied on a limited area with an intermittent data assimilation cycle.

The OI scheme of the RUC system (Benjamin et al., 1991) uses a hybrid vertical coordinate system, that combines a terrain following coordinate system near the ground with a potential temperature coordinate system above. The analysis variables are the horizontal wind components, the Montgomery stream function and the condensation pressure. Due to the choice of vertical coordinate system and analysis variables, some pre-processing of observations is needed. The VAD-wind profiles are treated as standard PILOT balloon observations. The observation errors are assumed to be uncorrelated. Multivariate structure functions are used for the background error correlations.

5.4 Nudging

In passing, we note that wind data may be easily assimilated by a nudging technique. An example using simulated data comes from a study of the impact of a hypothetical network of wind profiling radars by the Swiss Meteorological Institute (SMI) (Bettems, 1999). Observing system simulation experiments (OSSE) were performed with a mesoscale hydrostatic primitive equation model and a data assimilation scheme based on nudging. A series of case studies was performed, concluding that the impact of a hypothetical wind profiler network was most noticeable for short-range wind forecasts (up to 12 hours). VAD-wind profiles from weather radars would presumably give similar impacts albeit at a reduced frequency dependent on precipitation conditions.

5.5 Methods employing thermodynamic retrievals

Liou (1990) developed an assimilation procedure, which is a blend of a direct insertion method (Charney et al., 1969), the Gal-Chen (1978) thermodynamic retrieval technique and a wind adjustment method. Simulated radial wind data were nudged into a dry version of the non-hydrostatic, fully elastic model of the RAMS model. The fields were then adjusted variationally to fulfill the equation of continuity and some other constraints and finally thermodynamic fields were retrieved from the wind field.

The method was demonstrated through identical twin experiments. First, a control run was conducted to generate a time series of the east-west component of the wind, which served as simulated observational data. The control run was started from a perturbed initial state for the potential temperature. During the model integration the perturbation developed to a thermal bubble which rose toward the upper boundary. A number of additional runs were performed from different initial states, without the initial perturbations in the potential temperature field. Pseudo-observations from the control run were then nudged into the integrations with different frequencies. It was shown that the potential temperature perturbation could not be completely recovered from wind data only. In addition some detailed potential temperature data were needed. The success of the assimilation was also related to the insertion frequency of the observations. Assimilation of real data from Doppler radars was among the suggestions for future work.

5.6 Variational assimilation

VAD-wind profiles can be assimilated using both Optimal Interpolation and variational methods. Variational methods, however, are also ideally suited for assimilation of Doppler radar radial winds. The observation operator projects the model wind along the radar beam direction, and only a partial preprocessing of the data is needed.

5.6.1 4D-Var

An early attempt of using 4D-Var for assimilation of radar radial winds into an atmospheric model was carried out by Wolfsberg (1987). Unfortunately the assimilation encountered severe convergence problems. Some years later further attempts for assimilation of radar wind data by using 4D-Var were reported by Kapitza (1991). Simulated radar radial wind observations were assimilated into a dry non-hydrostatic mesoscale model. The 4D-Var formulation used in Kapitza's assimilation contained no background *a priori* information.

Kapitza performed a series of identical twin experiment with the 4D-Var system. A reference model integration was started from an atmosphere at rest, but including a sub-area with a temperature excess of 1 K. The temperature excess caused a hot bubble of air rising through the initially neutrally stratified model atmosphere, as the integration proceeded. During the first 200 seconds all dependent variables were sampled at each time step and for all grid points. These data then served as observations in the experimental runs. In one experiment only the east-west wind component of the reference run was assimilated. This case represented a situation when radar radial winds were the only source of data. The assimilation only approximately managed to recover the thermal structure of the hot rising bubble. Significant improvements were achieved if temperature data from the reference run were also assimilated.

As mentioned in the discussion of 4D-Var precipitation assimilation, a 4-dimensional variational Doppler radar analysis system (VDRAS) has been developed (Sun and Crook, 1997) to assimilate radial winds and reflectivities from single or multiple Doppler radars. Before assimilation, the data are interpolated from the original polar geometry to a cartesian grid. The observation error correlations are neglected and a relatively simple model is used to model the background error covariances. The assimilation system uses univariate horizontal structure functions for the background error correlations. The VDRAS system has been applied to both simulated and real data. The application of the system to different stages of a convective storm demonstrated that the detailed structure of wind, thermodynamics and microphysics could be obtained with reasonable accuracy (Sun and Crook, 1998).

All 4D-Var schemes that so far have been used to assimilate radial wind data suffer from the lack of a multivariate formulation of the structure functions. These ensure that the radial wind observations modify also the thermodynamic fields. Instead, in the 4D-Var schemes just described the model equations and the time dimension are used to obtain the 3-dimensional wind, as well as thermodynamic fields.

5.6.2 3D-Var

Three-dimensional variational data assimilation (3D-Var) has been used operationally from 1997-1999 in the NCEP ETA forecasting system to assimilate radar wind information in the form of VAD-wind profiles (Parrish, 2000). In this scheme, like in the OI scheme of the RUC system, the VAD-wind profiles were treated as standard PILOT balloon observations. As referenced in the section on quality control of wind profiles, the data were later withdrawn pending improvements in quality control and re-admitted to the operational system in March 2000. VAD-wind profiles, as well as wind profilers and radial winds are assimilated into the 3D-Var version of the MAPS system at FSL (Devenyi, 2000). VAD-wind profiles are also assimilated into the operational models at the Met Office in the UK.

Radial winds in the form of radial wind super-observations have been assimilated into the NCEP ETA forecasting system (Parrish and Purser, 1998)as well as into the 3D-Var scheme of the HIgh Resolution Limited Area Model (HIRLAM) forecasting system (Lindskog et al., 2000). In both of these systems the radial wind raw observations are spatially averaged, to be representative of the characteristic scale of the model. The calculation of the model counterpart of the radial wind super-observation involves a relatively simple projection of the horizontal wind along the radar beam line.

An interesting comparison was made with the HIRLAM system of the relative impact from assimilating VAD-wind profiles and radial wind super-observations in the same model (Lindskog et al., 2002), from which Fig. 7 is taken. Both forms of wind information were found to give similar benefits in the model forecast. This is encouraging for the potential benefits in exchanging VAD-wind profiles within Europe for assimilation into the current generation of regional models, with resolutions of 10-20 km. It would seem likely, however, that radial wind data will be favoured in higher resolution models on the scale of a few km or less.

The 3D-Var systems described above, as well as the OI scheme of the RUC system at NCEP, include multivariate structure functions, which ensure that the observed radar wind observations affect also the thermodynamic fields. The observation errors of the radar winds are assumed to be uncorrelated.

5.7 Summary

A variety of methods for assimilation of radar wind data into atmospheric models have been tested. One of the main differences between the various approaches is the way in which the thermodynamic fields

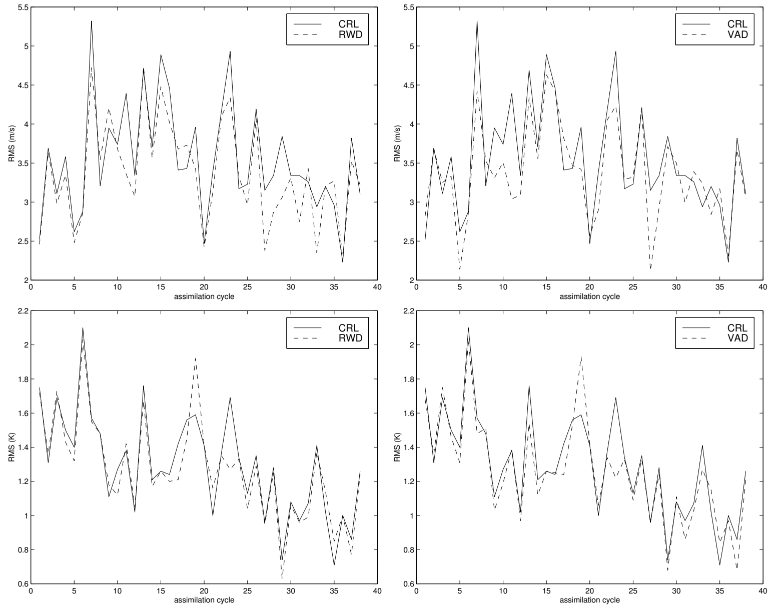

Figure 7: Day-to-day variability of the 24-hour forecast 850 hPa wind speed (upper row) and temperature (lower row) RMS scores for a run utilizing conventional observations only (CRL), for a run utilizing conventional observations and radar radial wind super-observations (RWD), and for a run utilizing conventional observations and radar VAD winds (VAD). The units are m/s and K, respectively. Taken from (Lindskog et al., 2002)

are adjusted to agree with the analyzed wind field. The OI and 3D-Var schemes presented here use multivariate structure functions, which only permit linear relations between errors in the different model variables. In the methods based on nudging and 4D-Var the governing equations of the model and the time dimension are used to ensure that the thermodynamics are consistent with the wind field. Non-linear relations as well as non-hydrostatic processes may be implicitly included in 4D-Var and nudging approaches. Still another method, used by Liou (1990) and Lin et al. (1993) is to make use of various pre-processing methods to derive the thermodynamic fields.

6 Treatment of radar data errors in assimilation

An extra challenge when merging observations with an NWP model arises when the measurements are associated with complicated error structures. A reflectivity or radial wind field measured by radar certainly comes in this category. To assimilate data with spatially correlated observation errors the assimilation scheme should, in addition to structure functions for the background errors, include structure functions for observational errors. The first challenge is to accurately describe the observational error correlations. The second is that most assimilation schemes are not designed to easily handle these observational error correlations, although it is theoretically possible to do so. These difficulties have generally been circumvented in data assimilation by applying data selection and pre-processing algorithms that are assumed to remove the observational error correlations, or else by giving reduced weight to information from data sources with correlated errors.

Lin et al. (2000) have presented some results in this area. They performed a number of identical twin experiments, using a version of the VDRAS-system of Sun and Crook (1997). They observed that the velocity field obtained with the applied smoothness constraint was insensitive to spatially correlated errors. More research is needed.

Assimilation schemes working with surface rain rate have usually included some simple treatment of the estimated errors in rainfall rate derived from the radar processing and extrapolation to ground level. In the Met Office Mesoscale Model, the initial version of Jones and Macpherson (1997) assumed that rain rate estimates were of uniformly high quality within 100km of the radar site, and of decreasing quality out to maximum range. The assumed radar errors were used to weight the combination of model forecast and observed rates to produce the analysed rain rate used as the target for nudging. Later, a more sophisticated quality measure was introduced (Macpherson, 2001a) which takes account of lower accuracy in derived surface rain rate when the beam is above the freezing level. The assimilation was, however, found to be rather insensitive to this upgraded error formulation.

In the assimilation of TRMM data into the ECMWF model, Marecal and Mahfouf (2000) did test sensitivity to the assumed rain rate error of the TRMM TMI data. When it was increased from 25% to 50% of the observed rain rate, the assimilation showed only a weak response.

In working to improve quality control of radar data for assimilation, one should bear in mind that the assimilation system itself can be an effective weapon in detecting errors. This is particularly true for the wind field on larger scales, where a variety of other good data give a good quality analysis independent of the radar data. Regular monitoring of differences between the model and radar VAD-wind profiles on a monthly timescale can detect systematic errors in radar processing which may be missed in a single analysis. These can then be reported back to the data producer for investigation. Rinne and Fortelius (2001) give an example of occasional large random errors in radar processing which led to an average difference between model and radar profiles of 2 m/s at the radar site. Of course, this kind of monitoring is harder to do on smaller scales where the model analysis is more suspect, and is unlikely to be possible for precipitation data until models improve substantially.

The errors in the forward model required for variational assimilation of radar data will also need to come under closer scrutiny in future high resolution systems. An example of a tool which could help with this is the Radar Simulation Model (RSM) developed at the University of Bonn (Meetschen et al., 2000). This allows quite a detailed simulation of the reflectivity field that would be 'seen' by placing a radar at a given location in the model atmosphere. By varying parameters of the RSM, one could build up a picture of the sensitivity of the forward model errors to, for example, details of the microphysics and aspects of the synoptic situation.

All the above studies show that the treatment of observation errors in assimilation of radar data is at a relatively immature stage. One should not conclude too soon that specification of the error characteristics (beyond removal of gross errors) is unimportant. It is acknowledged that as assimilation schemes improve, so they become more vulnerable to bad data. This suggests that the next generation of 4D-Var schemes for reflectivity and radial wind assimilation will become more demanding of effective quality control to remove gross errors in radar data, together with a realistic appraisal of the magnitude and structure of the residual errors in 'good' data.

7 Conclusion

Building on the work reviewed above, the next few years promise to be stimulating for the development of radar data assimilation and the international exchange of radar data for NWP. Progress will depend on good co-operation between radar and NWP scientists, which this review seeks to foster. Those nations and institutes which strengthen such links will be better placed to capitalise on the promise of the next generation NWP systems to deliver improved short-period weather forecasts.

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Appendix A: Glossary

Term	Explanation
3DVAR	Variational assimilation technique in which minimisation of a cost function measuring the distance between the model state and the available information yields, under certain conditions, a model state with minimum expected analysis error variance. This is done at a single time.
4DVAR	As 3DVAR but generalized for observations distributed over time. The minimisation consists in finding the model trajectory which fits best the available data.
Adjoint model	If viewed as matrix, the adjoint model is the transpose/complex conjugate of the real/complex (e.g. spectral model) tangent linear model.
Aliasing of velocity	Aliasing is the process by which frequencies too high to be analyzed with the given sampling interval appear at a frequency less than the Nyquist frequency.
Analysis field	An accurate image of the true state of the atmosphere at a given time, often produced as the optimised combination of (or simultaneous best fit to) a model background and a set of observations. It can be used as self-consistent diagnostic of the atmosphere, initial state of NWP, data retrieval used as pseudo observations, or reference against which to the quality of observations.
Analysis increment	The difference between an analysis and the background.
Anomalous propagation	When nonstandard refractive index distributions prevail, "abnormal" or "anomalous" propagation can occur and lead to spurious radar echos.
Attenuation	Any process in which the flux density (power) of a beam of energy is dissipated.
Azimuth	A direction in terms of the 360 degree compass; north at 0, east at 90, south at 180, west at 270, etc.
Background error covariances	Covariances of the error of a variable of the background field at a location with another variable at another location. The diagonal elements of this matrix contain the variances or errors of the variable in the background field.
Beam filling	The fraction of the radar sample volume filled with hydrometeors. The computation of Z from the received power assumes uniform filling, i.e. errors in Z are introduced if this assumption does not hold.
CEVAD – concurrend EVAD	see VAD
Closure assumptions in parametrisation schemes	When dealing with parametrisation of a physical process, the closure problem is concerned with establishing a closed system of equation either in terms of the average flows, or by providing an additional equation.

Term	Explanation
Clutter map	Map of echoes resulting from ground clutter (i.e. non meteorological targets). These interfere with observations of desired signals on a radar display.
Data assimilation	Analysis technique in which the observed information is accumulated into the model state in quality-weighted manner by taking advantage of consistency constraints with laws of time evolution and physical properties.
Doppler winds cartesian	Two- or three-dimensional winds retrieved by combining radial winds with physical constraints, whereby missing information can be modelled. If only one Doppler radar is involved the missing cross-beam wind component needs to be estimated from supplementary wind field information, e.g. from VAD, radio sounding, or other.
Doppler winds radial	Wind field derived from the component of motion of the target toward or away from the radar. Doppler radars only detect radial components of velocity.
EVAD – extended VAD	As VAD, but EVAD also estimates the large scale horizontal divergence and particle fall speed.
Elevation angle	The vertical pointing angle of the antenna.
Forward model	A model which computes observed variables, e.g. reflectivity and radial winds, from model variables. The NWP model itself can be considered a forward model when the time dimension is included in the analysis.
Ground clutter	The pattern of radar echoes from fixed ground targets.
Hydrostatic model	Numerical weather simulation model in which the hydrostatic assumption is made, i.e. the vertical pressure gradient force balances gravity, and vertical accelerations are neglected. This assumption becomes invalid if phenomena with strong vertical winds are involved, as f.i. in complex terrain with horizontal model resolutions below 10 km, or in deep convection when resolved by the model.
Initialisation	Procedure to remove undesired (mostly high-frequency) disturbances from an analysis.
Intermittency in data assimilation	In an intermittent assimilation method observations collected in a time window are accounted for at a distinct time, the analysis time, as opposed to continuous methods where observations are accounted for at observation time leading to analysis states that are smoother in time.
LHN – latent heat nudging	assimilation method to force an NWP model towards observed precipitation rates by correcting the modeel's latent heating released by the observed precipitation
Model phase space	Space in which one point describes one particular state of the atmosphere as represented by a numerical model. A trajectory in the model phase space describes the atmosphere's temporal evolution. The dimensionality of this space is very large and, therefore, the fundamental problem in data assimilation.

Term	Explanation
Multivariate analysis	Simultaneous analysis of several dependent variables.
NMI – normal mode initialisation	Initialisation procedure that uses the normal modes of a model to set the (high-frequency) gravity wave tendencies of the corresponding modes to zero (see also initialisation).
NWP	Numerical Weather Prediction
Non-hydrostatic model	Numerical weather simulation model in which the hydrostatic assumption is not made. Vertical accelerations are explicitly accounted for.
Nudging	Assimilation method in which the model equations are extended with a forcing term which depends on the distance between model and observed state. The larger the difference the stronger the forcing.
Nyquist frequency	The highest frequency that can be determined in data that have been discretely sampled. For data sampled at frequency f, this frequency is f/2. Doppler radar sampling frequency (rate) is equal to the pulse repetition frequency (PRF).
Nyquist velocity	Maximum unambiguous velocity that can be measured by a Doppler radar. It is determined by the PRF and the radar frequency band.
OI – optimum interpolation	Analysis technique, also called statistical interpolation, based on the least squares estimation that yields an optimum analysis in the least square sense. In practice, however, simplifications are introduced so that the analysis variance is minimised only to some extent, i.e. it becomes suboptimal.
OSSE – observing system simulation experiments	A technique used to evaluate the potential for future observing systems to improve NWP. An NWP model is used to generate a "true" reference history of the atmosphere from which then a set of artificial observations are extracted. These so simulated data are now assimilated by the NWP system to form a new history of the atmosphere that is compared with the "true" one, thus yielding the impact of the simulated set of observations.
Observation operator	Operator that derives the model equivalent of an observed variable, f.i. reflectivity as seen by a radar at a specific location.
PE – primitive equations	The primitive thermo-hydrodynamic equations describe the compressible flow in a moist atmosphere.
PI – physical initialization	An assimilation technique that carries out a Newtonian relaxation during the pre-integration phase of fluxes, rainfall rates, and cloud distributions to provide a consistent humidity analysis, a spin up of the diabatic heating and the divergent circulations.
PPI – plan position indicator	An intensity-modulated display on which echo signals are shown in plan view with range and azimuth angle displayed in polar coordinates, forming a map-like display. Each PPI is taken at a single, fixed elevation angle, and thus forms a cone of coverage in space.
PRF – pulse repetition frequency	Number of pulses transmitted per second. Typical PRFs may range from 300-1200 Hz.

Term	Explanation
PRT – pulse repetition time	Time interval from the beginning of one pulse to the beginning of the next succeeding pulse (inverse of PRF).
Parametrisation of physical processes	Atmospheric processes which are not explicitly simulated in a numerical model, are described in terms of and allowed to feedback on the model variables.
Radome	Structure built around the radar antenna to protect it from precipitation, pollutants, and wind loading. Usually made from rubberized material or fibreglass, it can cause significant attenuation of the radar beam when wet.
Range bin	The discrete point in range along a single “radial” (beam) of radar data at which the received signal is sampled. Range bins are typically spaced at 100-1000 meter intervals.
Raw data	Depending on the context, raw data can be anything from raw signal (individual pulse) data to polar scan or polar volume data. Products, in contrast, are higher-order and are based on raw data, e.g. composited rain estimates on a cartesian grid.
Side lobe	Secondary radiated energy “away from” the main beam of the radar, i.e., the main lobe. Typically contains a small percent of energy compared to the main lobe but may produce erroneous or misplaced echoes.
Spin-up effect	Lack of initialisation for the hydrological variables results in the so-called spin-up problem. It often manifests in incorrect humidity and precipitation fields in the first 6 - 12 hours of the model integration.
Structure function	Function describing the radius of influence of a particular observation, both in space and time. Structure functions can be derived from the background error covariance matrix.
Super-observations	Rescaled radar data at a spatial resolution which corresponds with that used in an NWP model, and which may include descriptive statistics which help characterize the super-observations.
Tangent linear model	Dynamical (NWP) model linearized around a particular state of the atmosphere. It is used f.i. in 4DVAR in relation with the adjoint model.
Univariate analysis	Analysis of a single independent variable.
VAD – velocity-azimuth display	VAD and EVAD (Extended VAD) are methods of guessing the large scale (up to 50km from the radar) two-dimensional winds from one-dimensional radial velocity data. They are essentially multivariate regressions which fit a simple, large scale wind model to the observed winds.
VVP – volume velocity processing	A way to guess the large-scale 2-dimensional winds, divergence and fall speeds from one-dimensional radial velocity data. Essentially a multivariate regression which fits a simple wind model to the observed radial velocities. Very similar to VAD and EVAD, except it uses different functions for the fit.
Variational assimilation	Analysis techniques that use a minimisation of a cost or penalty function to retrieve the best estimate of a particular state.

Term	Explanation
X-, C-, S-band radars	Radars emitting electromagnetic waves of different wavelengths (X $\simeq$ 3 cm, C $\simeq$ 5 cm, S $\simeq$ 10 cm).
Z-M relationship	Empirical relationship between reflectivity as seen by a radar and the equivalent water content.
Z-R relationship	Empirical relationship between reflectivity as seen by a radar and precipitation as observed by a distrometer.
analysis errors	Error of the analysis field, i.e. difference between the analysed and the “true” state, can be estimated from the observation and background errors.