

Nowcasting

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1. Introduction

The somewhat inelegant term, *nowcasting*, was devised in the mid-1970s (Browning, 1980). It encapsulates a broad spectrum of observation intensive techniques developed for predicting the weather up to a few hours ahead. These techniques are reliant on the rapid processing of high resolution data sets collected by weather radars and satellites. As such, the evolution of nowcasting as a branch of operational meteorology has been closely bound up with post-second world war advances in remote sensing, telecommunications and digital computing. A comprehensive treatment of the subject matter is beyond the scope of this Chapter. In a book about Doppler radar the authors make no apology for focusing on radar based nowcasts of precipitation.

We begin with a brief justification for the use of nowcasts in operational meteorology. This is followed by an overview of nowcasting techniques. A description of some of the key, historical developments in nowcasting is followed by sections on deterministic extrapolation-based nowcasting techniques, errors in precipitation nowcasts and their treatment within nowcasting system frameworks. The remaining sections consider advances in high resolution Numerical Weather Prediction (NWP) model-based nowcasting and review some of the issues and developments surrounding the application of quantitative precipitation nowcasts (QPN) to hydrological forecasting and warning. The Chapter closes with a brief consideration of future prospects for nowcasting.

2. An overview of nowcasting techniques

Operational weather forecasts are produced by primitive equation models known collectively, as Numerical Weather Prediction models. The predictive skill of these models is limited by a number of factors including the accuracy and coverage of routinely available weather observations, the extent to which their model formulations and grid lengths allow the relevant physical and dynamical processes to be modelled accurately, and the non-linear response of the atmospheric system to small perturbations in its state.

Whilst current, operational NWP models are now beginning to resolve important processes such as convection (Lean et al., 2008), their predictive skill generally remains very limited at the convective scales. Furthermore, current computational constraints restrict their operational forecast update cycles to hours, whereas convective phenomena typically exhibit life times of tens of minutes. Thus, NWP-based forecasts of local weather (Browning, 1980) have tended to be rather poor and their use for local forecasting has, until very recently, often been limited to general guidance at the regional scale.

From the 1960s onwards, the availability in near real time of increasingly sophisticated, spatially contiguous, radar and satellite observations, particularly of precipitation or proxies for it, offered the prospect of very short range, local forecasting by extrapolation – the concept of exploiting persistence, either in an Eulerian or Lagrangian reference frame (Germann & Zawadzki, 2002), to make weather predictions with sufficient rapidity to circumvent the perishability of the data. Browning (1980) clarified the relative merits of extrapolation nowcasts and NWP forecasts (see Figure 1), suggesting that the former were of superior accuracy up to 6 hours ahead.

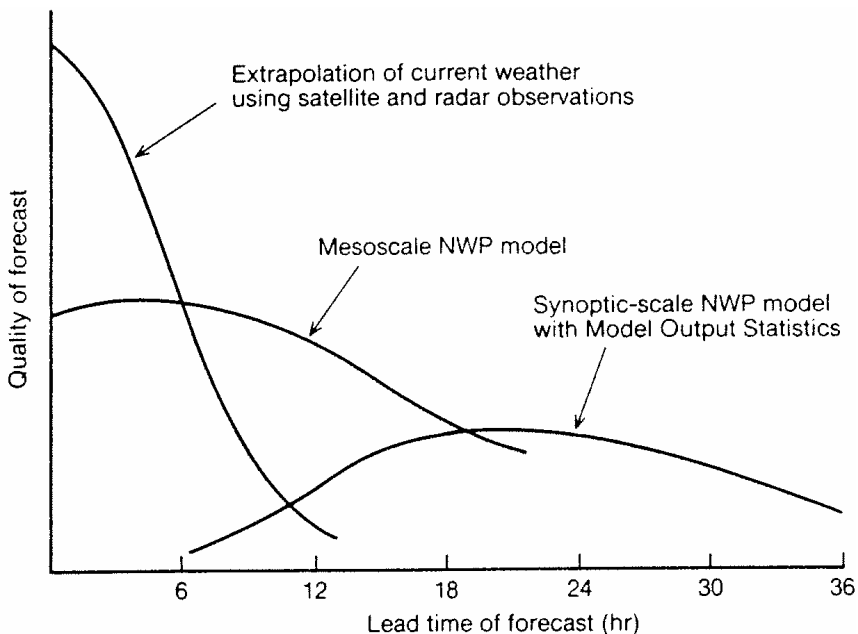


Fig. 1. A schematic diagram after Browning (1980) conceptualizing the relationship between forecasting methodology, skill and forecast range.

The predictability of extrapolation-based precipitation nowcasts and the forecast range at which these nowcasts must hand over to NWP to achieve optimal predictive skill have been explored by a number of authors (e.g. Browning, 1980; Zawadzki et al., 1994; Germann & Zawadzki, 2002; German et al., 2006; Bowler et al., 2006). Recent implementations of convective scale NWP model forecasts are now reducing the useful range of extrapolation-based nowcasts to a few hours ahead, as discussed later in this Chapter.

In the following section, we describe some of the key milestones in radar-based precipitation nowcasting and review these in the context of parallel advances in relevant areas of science and technology.

3. Radar-based nowcasting – A brief history

3.1 Origins of weather radar, and early research

Operational weather radar has its origins in the development of military radar during World War Two. The invention of the resonant cavity magnetron by John Randall and Harry Boot at the University of Birmingham in England in 1940 allowed the construction of high powered, centimeter-band radars, suitable for detecting precipitation. The sharing of this technology with American scientists early in the 1940s facilitated its subsequent development for meteorological applications.

Important early papers include those on rain drop size distributions (Marshall & Palmer, 1948) and shapes (Browne & Robinson, 1952; Hunter, 1954; Newell et al., 1955), the measurement of precipitation (Ryde, 1946; Byers, 1948; Bowen, 1951; Twomey, 1953; Battan, 1953; Stout & Neill, 1953), its vertical structure (Langille & Gunn, 1948) and associated estimation errors (Hitschfeld & Bordan, 1954), and those on thunderstorm identification, behaviour and dynamics (Wexler & Swingle, 1947; Byers & Braham, 1949; Wexler, 1951; Ligda, 1951; Battan, 1953).

3.2 Extrapolation techniques

The concept of extrapolating radar echoes for the short term prediction of precipitation was first proposed by Ligda (1953). The earliest demonstration of the application of objective extrapolation to radar echoes is described by Hilst and Russo (1960), whilst Noel and Fleischer (1960) were amongst the first radar meteorologists to explore the predictability of precipitation echoes using this approach. Further noteworthy papers are those published by Russo and Bowne (1962) and Kessler and Russo (1963). Kessler (1966) and Wilson (1966) explored the use of cross correlation statistics to diagnose a best estimate of echo pattern average motion. Wilson (1966) used the maximum value of the cross correlation coefficient as an indicator of pattern development.

Two important conclusions were drawn from these early studies. The first of these was the positive correlation between the predictability of precipitation features and their size: large features tend to be longer lived than small ones. The second conclusion is an adjunct to the first, namely that small scale features are generally short lived – typically a few tens of minutes. These findings are consistent with early investigations into the multi-scaling properties of the atmosphere and associated limits on atmospheric predictability (Lorenz, 1963; 1973).

The 1970s saw the further development of cross correlation-based nowcasting algorithms and their automation. Zawadzki (1973) developed an optical device for measuring the space-time statistical properties of radar inferred precipitation fields. Austin and Bellon (1974) evaluated an automated, computerized pattern matching programme for nowcasting precipitation up to 3 hours ahead. They concluded that the useful range of these nowcasts varied with the nature and extent of the precipitation. Nonetheless, this approach was shown to be consistently skilful up to one hour ahead over a wide range of events.

This latter work led to the operational implementation of an algorithm based upon global cross correlation at McGill University in the mid-1970s. Bellon and Austin (1978) reviewed the operational performance of this scheme, known as SHARP (Short-Term Automated Radar Prediction), on two years' worth of data. The experience gained allowed subsequent enhancement of their cross correlation method to enable independent tracking of different echoes (Austin & Bellon, 1982) using a nine vector motion field. Rinehart (1981) describes a similar, multi-vector, cross correlation approach to determine and extrapolate the motion of individual storms within a multi-storm system.

3.3 Cell tracking

Algorithms founded on the tracking of radar echo centroids evolved in parallel with field-based pattern matching techniques. These were developed specifically for nowcasting thunderstorms, initially in North America. Amongst the earliest of these echo centroid trackers were those described by Wilk and Gray (1970) and Zittel (1976). The extrapolation vectors were diagnosed using a linear least squares fit through successive positions of the echo centroids. Duda and Blackmer (1972) and Blackmer et al. (1973) formulated clustering techniques to resolve difficulties in cases involving the merging and splitting of echoes.

Refinements to these early techniques were subsequently developed and implemented within operational tools during the following decades. Several good examples are the Storm Cell Identification and Tracking (SCIT) algorithm (Witt & Johnson, 1993) and the Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN) system (Dixon & Wiener, 1993).

3.4 Steady state versus growth and decay

The proto-type, operational nowcasting algorithms developed during the 1970s were generally reliant on the steady state assumption. Tsonis and Austin (1981) explored echo size and intensity trending with a view to improving the prediction of long lived convective cells. They found negligible improvement in skill, even using sophisticated non-linear time trending schemes. Wilson et al. (1998) drew similar conclusions in a study involving the use of the TITAN system (Dixon and Wiener, 1993). These results are consistent with the findings of theoretical and NWP modelling experiments showing that the evolution of convective scale features in the atmosphere is non-linear and, to a degree, chaotic (Tsonis, 1989).

3.5 Fractal properties of precipitation

During the 1980s and 1990s, an improved understanding of the chaotic influence of atmospheric processes such as turbulence on the predictability of precipitation was reflected in a growing number of publications exploring the so called *scaling* or *multi-fractal* attributes of meteorological fields, including those of radar derived precipitation fields. Scaling behaviour or self-similarity implies that similar features can be observed in the atmosphere over a wide range of space and time scales, and that the relationship between certain statistical attributes of a precipitation field measured at different scales can be described by equations which incorporate a scaling factor. The formative papers in this area include those by Lovejoy and Schertzer (1985, 1986).

3.6 Exploration of statistical and statistical-dynamical models of precipitation

This same period saw the development of a number of statistical (Krajewski & Georgakakos, 1985; Cox & Isham, 1988) and statistical-dynamical predictive models of precipitation (Georgakakos & Bras, 1984a, b; Lee & Georgakakos, 1990; French & Krajewski, 1994; Bell & Moore, 2000a). The latter were formulated to assimilate radar estimates and surface observations of precipitation and make forecasts using a simplified treatment of the governing atmospheric equations, focusing on the conservation of water mass. These studies were motivated by the operational forecasting requirements of the hydrological community and the limitations of “steady-state” nowcasting techniques and the first generation of operational, mesoscale NWP models.

3.7 Impact of forecast uncertainties

A growing recognition of the need to account for and communicate meteorological forecast uncertainty (Murphy & Carter, 1980; Krzysztofowicz, 1983), particularly in relation to precipitation, led to the development of a range techniques for probabilistic precipitation nowcasting. Andersson and Ivarsson (1991) evaluated an advection-based nowcasting scheme in which the probability of precipitation at a given location is estimated from the areal distribution of precipitation in a neighbourhood surrounding it (see also Schmid et al., 2000) This approach accounts for the impact of extrapolation errors on the location of advected precipitation. Other authors have adopted similar approaches. For example, Germann and Zawadzki (2004) used a local Lagrangian method to produce probabilistic extrapolation nowcasts.

The previously mentioned theoretical work on multi-fractals, and empirical studies supporting a scaling model representation of precipitation fields, laid the foundations for the development of a number of stochastic precipitation nowcasting schemes exploiting scale decomposition frameworks. Seed (2003) adopted a multi-scale decomposition framework in his S-PROG (Spectral-Prognosis) scheme to nowcast the space-time evolution of high resolution radar derived precipitation fields (see Figure 2); he highlighted the potential application of S-PROG to conditional simulation and design storm modelling.

In a similar vein, the McGill Algorithm for Precipitation Nowcasting by Lagrangian Extrapolation (MAPLE; Turner et al., 2004) exploits a wavelet transform to model the predictability of precipitation as a function of scale. The aim of the scale decomposition is to filter out the unpredictable scales in an extrapolation nowcast, and in so doing, minimize the Root Mean Square nowcast error (typically measured using rain gauge observations and/or radar inferred estimates of surface precipitation rate or accumulation).

Pegram and Clothier (2001) used a power law model to filter Gaussian distributed random numbers to generate stochastic realizations of radar precipitation fields in their String of Beads Model (SBM). Noise generation techniques similar to these were combined with a stochastic model of extrapolation velocity errors in the Short Term Ensemble Prediction System (STEPS, Bowler et al., 2006) to produce operational precipitation nowcasts quantifying uncertainties in phase as well as amplitude. In STEPS, the noise serves several purposes: it enables ensembles of equally likely nowcast solutions to be generated by perturbing predicted features as they lose skill; it also downscales an NWP forecast, injecting variance at scales lacking power (variance) relative to the radar.

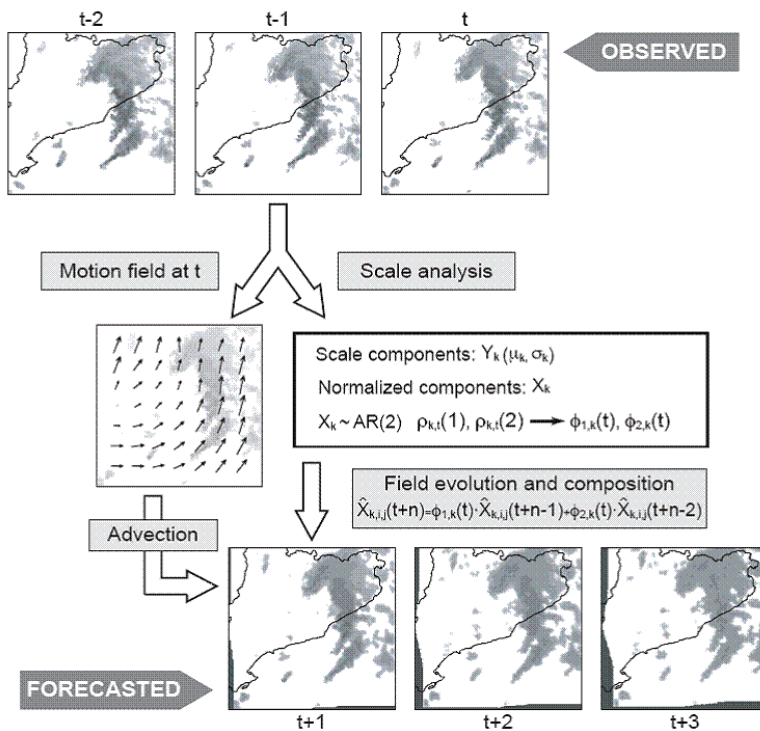


Fig. 2. The generation of an extrapolation nowcast using the Spectral-Prognosis (Seed, 2003) multi-scale decomposition (cascade) framework (after Berenguer et al., 2005). The motion of the precipitation field is derived from radar inferred analyses of precipitation rate valid at t and $t-1$ (typically a 10 or 15 minute time step). The temporal evolution of the extrapolated field is modelled on the hierarchy of scales produced by the cascade decomposition, using a hierarchy of second order auto-regressive (AR-2) models – one for each scale – and the analyses of precipitation rate valid at t , $t-1$ and $t-2$.

3.8 Improvements in extrapolation techniques

The past two decades have also seen further refinements to the extrapolation schemes exploited by precipitation nowcasting algorithms, notably in the form of COTREC (Li et al., 1995; Mecklenburg et al., 2000), Variational Echo Tracking (VET; Germann & Zawadzki, 2002) and optical flow (Bowler et al., 2004, Peura & Hohti, 2004). COTREC constrains the cross correlation diagnosed displacement vectors using the two dimensional continuity equation. This is equivalent to minimizing the divergence of velocities derived for adjacent blocks. The benefits over TREC (Rinehart and Garvey, 1978) were shown to be due to the elimination of spurious motion vectors caused by clutter, beam blockages and rapid changes in the precipitation pattern. In common with optical flow, the VET scheme diagnoses a field of motion by direct application of the optical flow constraint equation. Bowler et al. (2004) solve this equation before applying a smoothness constraint whereas Germann and Zawadzki (2002) uses a conjugate gradient method to minimize residuals from two constraints simultaneously.

3.9 NWP-based nowcasting

The 1990s saw the first attempts to run convection resolving NWP model forecasts assimilating radar data (Lin et al., 1993). These early experiments were focused on predicting convective storms.

Some success was demonstrated in cases involving convection strongly forced by the large scale environment. However, other studies showed that convective initiation in a weakly forced environment is difficult to predict because the location and timing of initiation are very sensitive to variations in low level temperature and moisture. It seems likely that the ability of convection resolving NWP models to predict convection is a function of the predominant scale of the associated forcing. In the UK, much of the convection is forced by small-scale orography, as demonstrated by the Convective Storms Initiation Project (Morcrette et al., 2007; Lean et al., 2008).

Despite these challenges, Lean et al. (2008) found that convection resolving models performed better in terms of convective initiation than a 12 km grid length model with parameterized convection, and a number of national weather services are now running operational, convection resolving NWP models. Indeed, some are trialling configurations with hourly or sub-hourly assimilation of radar data. NWP nowcast experiments in the UK show some improvements in NWP forecast skill in the nowcast time frame. Prospects for NWP nowcasting will be discussed in more detail later in this Chapter.

4. Conventional nowcasting techniques

4.1 Deterministic techniques

4.1.1 Cell tracking

Cell trackers or object-based nowcasting schemes are typically developed in areas where severe convective storms are a significant hazard, and are best suited to the generation of qualitative warnings of severe convective weather. In general, object-based algorithms are used to predict the location of a (convective) object in the future and thereby assign the properties of the object to that location. For example, a storm might be deemed to contain large hail, and therefore a warning of large hail will be issued for the locations on the forecast storm track.

The basic elements of cell tracking are:

1. devise a set of rules that will be used to identify the bounds of an object in either two or three dimensions;
2. analyse current data to identify objects and assign attributes to them (heavy rain, damaging wind, large hail etc);
3. link the objects to existing tracks and estimate the advection velocity;
4. predict the location of objects in the future.

Most cell tracking algorithms define an object, either as a set of contiguous points that exceed some threshold in radar reflectivity, typically 35, 40 or 45 dBz (e.g. Dixon & Weiner, 1993; Han et al., 2009), or as a small region of increased reflectivity (Crane, 1979), or both (e.g. Handwerker, 2002). Defining the object in three dimensions allows one to compute the volume and height of the cell. This adds value when assigning the elements of severe

weather or some sort of severity index, but does not necessarily add value to the identification and tracking of the cells. Rigo et al. (2010) used both 2D and 3D radar products and total lightning data to identify and track convective storms. A storm track is defined as a time series of cell positions. Assigning cells to tracks is the most complex aspect of these algorithms.

All cell tracking algorithms have to deal with cell initiation, mergers, splits, and terminations – the hatches, matches, and dispatches as it were – and this is often the point of differentiation between the various approaches. Errors in assigning the correct cell to a track are a major cause of error when estimating the cell velocity. The size of the object depends on the threshold that has been selected. Therefore, the predictability of the object decreases as the threshold is increased since the lifetime of a cell is related to its size. Using a high threshold to define the cell will make it more difficult to assign a cell to a track. This will increase the errors when estimating the track velocity. Using a low threshold will increase the longevity of the tracks, but will tend to limit the ability to forecast the location of the most severe cells within the storm. The concept of an “object” becomes less useful as the precipitation becomes more widespread. At some point (depending on the skill of the tracking algorithm), cell tracking algorithms fail to provide useful forecasts.

TITAN (Dixon & Weiner, 1993) and SCIT (Johnson et al., 1998) are good examples of what can be achieved in the object-tracking paradigm. Both TITAN and SCIT use the three-dimensional radar reflectivity data to identify a convective object that is defined by a reflectivity threshold. In TITAN, the current objects are linked to past objects through combinatorial optimization. This minimizes the total advection and change in cell volume between the previous and current time steps. Many other cell tracking algorithms, SCIT for example, assign the cell that is closest to the forecast location of an active track. Han et al. (2009) evaluated several extensions to TITAN including improvements in assigning cells to tracks and using TREC motion vectors to advect the cells. In assigning a cell to a track, they found that the most significant improvements were due to adding a requirement that the forecast cell from the track at the previous time step must overlap with the current cell.

4.1.2 Field-based advection

Field tracking algorithms generally divide a Cartesian grid of radar reflectivity or rain rate into a number of tiles and then find the advection of the tile that maximizes the cross correlation (or some other measure of similarity) between successive time steps in the data. The mean advection vector for each tile containing rain is then calculated by applying some form of constraint to minimize the divergence of the resulting vectors.

A number of the current field tracking-based nowcasting algorithms use COTREC (Li et al., 1995) as the basis for deriving the advection vectors. Examples include the system that has been developed at the Czech Hydrometeorological Institute (Novak, 2007), the Hong Kong Observatory system, SWIRLS (Li et al., 2000), and the system implemented at the Guangdong Meteorological Observatory system (Liang et al., 2010). Liang et al. (2010) determined that the optimum size of the tile was 30 km. Li et al. (2000) evaluated the performance of an advection scheme on a 93 x 93 grid using a 19 pixel tile: this equates to 20 km on their 256 km x 256 km domain.

Bowler et al. (2004) used the optical flow constraint (Horn & Schunck, 1981) approach that is used for computer vision applications to derive the mean advection vector for tiles with rain. Optical flow uses least squares to find the (u,v) that minimizes the two-dimensional conservation equation

$$\frac{dR}{dt} = u \frac{\partial R}{\partial x} + v \frac{\partial R}{\partial y} + \frac{\partial R}{\partial t} = 0 \quad (1)$$

over a local neighbourhood.

Bowler et al. (2004) smoothed the field using a moving average over a (15×15) pixel mask before calculating the partial derivatives using a finite difference scheme. The smoothed image was then partitioned into 48×48 km² tiles and least squares used to estimate the mean advection vector within the tile. The resulting vectors were then smoothed so as to minimize $\nabla^2 V$. Grecu and Krajewski (2000) used a similar approach over 40×40 km² tiles. Foresti and Pozdnoukhov (2011) used optical flow to track areas with rain rates that exceeded 10 mm/h. Essentially, this represents the application of optical flow to cell tracking.

Germann and Zawadzki (2002) used the Variational Echo Tracking (VET) method of Laroche and Zawadzki (1995) to derive the advection velocities. This technique partitions the field into small tiles and then uses the conjugate gradient method to minimize a cost function in one global minimization. The cost function includes a smoothness term. The difference between this approach and optical flow is that optical flow applies the smoothness constraint after the velocity field has been calculated for each tile, thereby avoiding an expensive global minimization (Bowler et al. 2004). Ruzanski et al. (2011) describe another approach using a linear least squares technique in the frequency domain.

Cell tracking algorithms assign a velocity to each object and this is advected with a constant velocity during the forecast period. Such an approach is not optimal for field tracking algorithms because it does not allow for changes in direction and speed of motion during the forecast period. Germann and Zawadzki (2002) undertook a detailed analysis of several advection algorithms and found that a modified semi-Lagrangian backward interpolation scheme was optimal. Bowler et al. (2004, 2006) used the simpler semi-Lagrangian scheme that is applied for each time step in the forecast time series. Semi-Lagrangian advection requires a velocity at each pixel in the field and the optical flow technique does not provide advection vectors for tiles that have no rainfall. Therefore the velocity at each pixel must either be interpolated from the tiles with rain, or provided by a hierarchical approach that progressively reduces the size of the tiles that are used in the analysis (e.g. Germann and Zawadzki, 2002).

Kernel-based methods have been employed for advection by Ruzanski et al. (2011) and Fox and Wikle (2005) using

$$\mathbf{y}_{t+1} = \mathbf{H}\mathbf{y}_t \quad (2)$$

where

$$\mathbf{y}_t = [y(s_1, t), y(s_2, t), \dots, y(s_n, t)]^T \quad (3)$$

is the vector of the n pixels in the image and $\mathbf{H} = \{h_{ij}\}$ is the $n \times n$ matrix of the advection operator.

Ruzanski et al. (2011) report that their approach is computationally efficient, although the time taken to derive the motion vectors was comparable to that required for optical flow. Furthermore, the advection algorithm was an order of magnitude slower than a simple implementation of a semi-Lagrangian backward interpolation scheme. Both Ruzanski et al. (2011) and Fox and Wikle (2005) demonstrated their methods using small images. The size of the advection operator is likely to become a constraint when using this technique to advect a large (say 10^6 pixels) image.

4.1.3 Analogues

Panziera et al. (2011) provide a good introduction on the assumptions and use of analogues in nowcasting. Advection-based tracking techniques rely on the assumption that precipitation fields evolve relatively slowly in Lagrangian coordinates and, therefore, their future state can be predicted largely by extrapolation. The assumption of Lagrangian persistence becomes a major limitation on the accuracy of nowcasts in situations where a field evolves rapidly, for example in situations where new storms are initiated or existing storms grow or decay. Data mining and analogue techniques seek to predict initiation, growth and decay by matching the current weather pattern with similar, past events and then use these past events as the basis for generating a forecast.

The first step in the use of analogues is to, either identify a set of regimes in the historical data, or identify a set of predictors that can be used as measures of similarity. Thereafter, the analogue that is closest to the current situation is selected and used as a basis for the forecast. This implies that the technique must be trained for each location, and that a significant historical record is available. Panziera et al. (2011) used predictors of mesoscale airflow and air-mass stability to select 120 analogues, and then employed two measures from the radar derived rainfall fields to select a set of 12 analogues to use as a forecast ensemble. Foresti and Pozdnoukhov (2011) derived maps of where orographic enhancement was likely to occur for a set of weather types. These could then be used to correct biases in advection forecasts.

4.2 Errors in precipitation nowcasts

4.2.1 Error sources and attribution

Sources of forecast errors include errors in the initial quantitative precipitation estimates (QPE), those arising from incorrect diagnosis of the field of motion, and changes in the motion and evolution of precipitation fields during the forecast period.

Approximately half of the total forecast error in the first hour of a forecast is due to errors in the radar derived rainfall analyses (Bellon & Austin, 1984; Fabry & Seed, 2009). This is because radar rainfall estimation errors, arising from variations in the relationship employed to convert the observed radar reflectivity to rainfall, have significant correlations over about an hour in time (Lee et al., 2007) and tens of kilometres in space (Velasco-Forero et al., 2009; Yeung et al., 2011).

Dance et al. (2010) used a year of TITAN tracks to investigate how cell tracking errors varied as a function of lead time, storm intensity, speed and duration. They found that the RMS errors in track speed and direction over the year were about 10 km/h and 30° respectively. Dance et al. (2010) found that tracking errors (both speed and direction) were large when the track speeds were less than 15 km/h; also, errors in track direction decreased with increasing speed.

Mecklenburg et al. (2000) investigated the tracking errors for TREC and COTREC and found that the mean absolute displacement and direction error for a 30-min forecast of convection was about 10 km and 20° respectively. Ebert et al. (2004) showed that TITAN cell tracking algorithms had a median error of about 10 km/h for intense cells. The median tracking error for the baseline field tracking algorithm – a correlation technique finding a single advection vector for the entire field of convective storms – was found to be 20 km/h using the same data.

Hourly accumulations of rainfall typically have correlation lengths of the order of 10 km (e.g. Anagnostou et al., 1999; Gebremichael & Krajewski, 2004). The tracking error after an hour is at least the same order of magnitude as the correlation length of the accumulations. Therefore, one would expect that enhancements to the current tracking algorithms should lead to improvements in the skill of nowcasts at lead times when tracking errors become a significant fraction of the correlation length of the rainfall field: this is likely to be around $T + 30$ minutes.

Berenguer et al. (2005) found that the temporal evolution of the advection field was not a significant source of error for nowcasts with lead times less than 60 minutes. Bowler et al. (2006) discovered that forecast errors due to the temporal evolution of the advection field were negligible in the first three hours of a nowcast and accounted for 10% of the total error after six hours.

It is interesting to note that the probability distribution of cell tracking errors is highly skewed (see, for example, Figure 20 of Ebert et al., 2004) and that the maximum 60 minute location error can be as high as 70 km. The fat tail in the distribution of tracking errors is a significant issue for operational nowcasting systems. Manual editing of the tracks (e.g. Bally, 2004) adds value to the automatic forecasts by eliminating the tracks that are regarded by the forecasters as being, either unimportant from a severe weather perspective, or incorrect.

Errors due to the initiation and decay of storms during the forecast period become increasingly dominant as the lead time extends beyond 60 minutes (Wilson et al., 2010). Zawadzki et al. (1994) evaluated the limits of predictability of rainfall fields as a function of space and time and found that the time for a Lagrangian persistence forecast to reach a correlation of 0.5 ranged from 40 to 112 minutes. They also found that these predictability times depended on the scales present in the rainfall field.

4.2.2 Space-time structure of errors and their treatment

Roca-Sancho et al. (2009) examined the spatial and temporal structure of forecast errors for MAPLE. They demonstrated that the temporal correlation of forecasts errors was very low after 60 minutes and that the spatial structure of the forecast errors progressively resembled that of rainfall with increasing lead time. The latter effect was due to increasing

errors in the location of rainfall. Fabry and Seed (2009) showed that forecasts of high rain rates were generally over-predictions and that the performance of advection forecasts in the recent past is not a good predictor of future performance. The best predictors were found to be raining fraction and the rate of change in mean areal precipitation over the forecast domain.

Germann and Zawadzki (2002) demonstrated that filtering the rainfall analysis field with a 64 km, low-pass filter increased Lagrangian life times by between 40 and 60 minutes, depending on the extent to which small scale features are embedded in larger-scale rain areas. Germann et al. (2006) state that the upper bound for an advection-based nowcasting system that does not include growth and dissipation of rainfall is about six hours. The typical lifetime of a storm is closely related to the scale of the storm, and is often represented as a power law of the scale (e.g. Marsan et al., 1996; Schertzer et al., 1997; Seed et al., 1999). Therefore, some nowcasting systems improve the accuracy (in the RMS error sense) of their predictions by progressively smoothing out the small scale features present in the analysis field (e.g. Seed, 2003; Turner et al., 2004). This removes features from the nowcast that are essentially unpredictable.

An alternative way of handling the perishability of the fine scale components in advected precipitation fields is to model them stochastically. This approach will be discussed in section 4.3.

4.2.3 Performance of nowcasting algorithms

The Critical Success Index is often used to report the accuracy of nowcasting algorithms presented in the literature. Ruzanski et al. (2011) found a CSI of approximately 0.5 after 10 minutes at a spatial resolution of 0.5 km. Liang et al. (2010) calculated a CSI of approximately 0.35 after 60 minutes for echoes in the 15-45 dBZ range at 2 km resolution. Berenguer et al. (2011) report a CSI for 60 minute forecasts of reflectivity (dBZ) at 1 km resolution of approximately 0.5 for widespread rainfall, and in the range of 0.1 to 0.3 for isolated convection. Poli et al. (2008) discovered that the CSI was generally low at the start and end of a storm, reaching a peak of around 0.4 for 1 km resolution T+60 minute forecasts of reflectivity greater than 30 dBZ.

Nine nowcasting systems were implemented for the Sydney 2000 Forecast Demonstration Project (Ebert et al., 2004) and eight nowcasting systems participated in the Beijing 2008 Olympics' Forecast Demonstration Project (Wang et al., 2009; Wilson et al., 2010). Wang et al. (2009) demonstrated that the overall performance of the nowcasting systems had improved during the years from 2000 to 2008. They showed that the maximum CSI for forecasts of hourly precipitation accumulation greater than 1 mm/h increased from 0.2 in 2000 to 0.45 in 2008, although the maximum CSI for rain greater than 10 mm/h was still only 0.15.

Lee et al. (2009) found that the CSI decreased with increasing rain rate and forecast lead time: the CSI for 60 minute rainfall forecasts decreased from 0.60 for 0.1 mm/h to 0.2 for 10 mm/h rain rates. Ebert et al. (2004) reported that the CSI for rain greater than 20 mm/h is essentially zero. This implies that the use of nowcasting techniques to predict the precise location of extreme rain for flash flood warning may not be viable.

In summary then, the accuracy of a nowcast depends on the accuracy of the initial radar derived rainfall field, the degree of spatial organization of the rain, the rain rate, and forecast lead time. Also, it is likely to be higher in the middle of the storm (in both space and time) than at the edges.

4.3 Probabilistic techniques

4.3.1 Justification

Given the magnitude of the errors in a 30 minute precipitation nowcast, it is reasonable to adopt a probabilistic approach to nowcasting and attempt to convey to the users the uncertainty that is associated with a particular weather situation. As explained earlier, within the extrapolation nowcast framework, errors can be categorized into those attributable to the radar observations and processing, inaccuracies in the field of motion used to advect the observations, and errors arising from assumptions made about the Lagrangian evolution of the advected precipitation field.

4.3.2 Methods of handling uncertainties

A number of techniques have been developed for modelling nowcast errors with a view to producing probabilistic precipitation nowcast products. One of the simplest entails time-lagging a consecutive series of deterministic nowcasts using techniques similar to those demonstrated in a NWP post-processing context (Mittermaier, 2007). Each member of the time-lagged ensemble is assigned a weight which is a function of lead time. SWIRLS generates probabilistic nowcasts using this approach (Wang et al., 2009).

Another approach relies on the assumption that errors in the diagnosed advection velocity field predominate. Consequently, the probability of exceeding a chosen precipitation threshold at a given location can be derived from the distribution of precipitation in a neighbourhood surrounding the forecast location. The neighbourhood size increases with lead time to reflect to the growth in advection errors (Andersson & Ivarsson, 1991; Schmid et al., 2000).

Germann and Zawadzki (2004) compared four methods of generating probabilistic precipitation nowcasts based upon radar extrapolation. They concluded that the most skilful method was one based upon the local Lagrangian technique. Essentially, this produces an advection forecast using a semi-Lagrangian backward advection scheme and then uses the probability distribution of forecast rain rates in some search area centred on a pixel to calculate the probability of exceeding a threshold at that location. The size of the search area increases with lead time to reflect the increasing forecast uncertainty. This approach has since been exploited by others, for example Megenhardt et al. (2004), and more recently, Kober et al. (2011).

Other authors have focused their attentions on modelling errors using stochastic space-time models. Pegram and Clothier (2001) used a power law model to filter Gaussian distributed random numbers to generate stochastic realizations of radar precipitation fields in their String of Beads model (SBM). Noise generation techniques similar to these were combined with a stochastic model of extrapolation velocity errors in the Short Term Ensemble Prediction System (STEPS; Bowler et al., 2006) to produce operational precipitation nowcasts

quantifying uncertainties in phase as well as amplitude. In STEPS, the noise serves several purposes: it enables ensembles of equally likely nowcast solutions to be generated by perturbing predicted features as they lose skill; it also downscales an NWP forecast, injecting variance at scales lacking power (variance) relative to the radar.

4.3.3 Treatment of observation errors

Uncertainties in nowcasts of precipitation also derive from errors in the radar observations and processing. Austin (1987) categorized radar errors into physical biases, measurement biases and random sampling errors. Historically, much effort has been invested in improving deterministic estimates of precipitation accumulation at the surface by correcting physical (e.g. ground clutter and beam blockage) and measurement (e.g. Z-R conversion) biases. However, more recently, a growing number of researchers have focused their attentions on the treatment of random sampling errors and how these can be utilized within stochastic, integrated system frameworks to improve hydro-meteorological nowcasting.

Two main approaches to the modelling of random sampling errors in QPE have been described in the literature: one entails a statistical description of the difference between the radar estimates and a reference (e.g. Ciach et al., 2007; Lloort et al., 2008; Germann et al., 2009); a second involves modelling the characteristics of individual sources of error (e.g. Jordan et al., 2003; Lee & Zawadzki, 2005a, 2005b, 2006; Lee, 2006; Lee et al., 2007). The challenge with the first approach is the need for a reference field: this is usually derived from a dense network of rain gauges. The difficulty with the second approach is that the true error structure of QPEs can vary significantly depending on the meteorological conditions and is therefore largely unknowable.

Germann et al. (2009) describe a radar ensemble generator using LU decomposition (factorization) of the radar-gauge error covariance matrix to derive an ensemble of precipitation fields. Each ensemble member is the sum of the bias corrected, deterministically derived radar precipitation field and a stochastic perturbation representing the random error. The stochastic term is generated such that it preserves the correct space-time error covariances. The authors present the results of the coupling of a real-time implementation of the radar ensemble generator with a semi-distributed hydrological model.

Norman et al. (2010) implemented several radar ensemble generators and compared their performance on a selection of case study events using rain gauges. An implementation of the Germann et al. (2009) scheme was found to be marginally superior to one comprising separate models of Z-R (Lee et al., 2007) and VPR (Jordan et al., 2003) errors. Pierce et al. (2011) integrated these two ensemble generators to produce ensembles of radar-based analyses of surface precipitation rate for input to STEPS. They evaluated the impact of these ensembles on the performance of STEPS ensemble precipitation nowcasts. Verification results demonstrated that accounting for QPE errors improved the ensemble spread-skill relationship in the first hour of the nowcasts.

One alternative to the stochastic QPE and QPN schemes described above is the use of historical analogues. Panziera et al. (2011) describe an analogue-based heuristic tool for nowcasting orographically forced precipitation. The system known as Nowcasting of Orographic Rainfall by means of Analogues, exploits the strong correlation between

orographic rainfall and predictors describing mesoscale flow and air mass stability, to identify past events with predictors similar to those derived from real time observations. The authors present verification results showing that NORA performs better than Eulerian persistence for nowcasts with lead times of more than an hour.

5. NWP-based nowcasting

5.1 Introduction

In the past few years, increasing availability of high powered computers and the implementation of non-hydrostatic models have made NWP at the convective scales (1 km–4 km horizontal grid length) a reality for national weather services. Many centres are already running these models operationally with update cycles of between 3 and 6 hours to generate short-range forecasts up to about T+36 hours. Traditionally, these forecasts have been deployed in combination with nowcasting techniques to deliver optimal guidance. However, recently, centres have begun to explore the use of NWP-based systems for nowcasting.

5.2 The challenges

For nowcasting purposes, the key component of NWP is the data assimilation of high resolution observations in space and time, especially radar and geostationary satellite data. Traditional nowcasting techniques use these observations to produce forecasts of rain, cloud and associated weather with observation derived advection velocities, or NWP forecast wind fields, or a combination of both. Nowcasts are also produced from analyses of other weather elements including screen temperature, visibility, 10 m wind and wind gusts. However, these systems do not use the observations in an optimal manner and may not use all available observation types.

Data assimilation into NWP models potentially offers the ability to use all observations in a consistent and synergistic manner to provide the best estimate of the state of the atmosphere from which to produce a nowcast. At this time, nudging, variational data assimilation (3D-Var and 4D-Var) and ensemble Kalman filters (EnKF; Sun, 2005b) for high resolution data assimilation are being used in weather services or are under development in research centres around the world. Indeed, some national weather services are already running operational NWP models with data assimilation at grid lengths in the range 1 km–10 km. Most of this work relies heavily on the exploitation of Doppler radar measured radial winds and reflectivity data or derived surface rain rates.

One challenge for NWP-based nowcasting is to match the skill of traditional methods in the first two hours. Traditional nowcasts closely fit the observations because they employ extrapolation techniques and so use the observations themselves (i.e. radar derived surface rain rate) at analysis time. This is challenging for NWP because unresolved scales are excluded from the model state, data assimilation systems are designed, not to match observations, but to achieve a good and balanced forecast over a longer period of time, and the T+0 fields from the NWP system are essentially a weighted fit to both the NWP forecast and the observations.

Also, traditional nowcasts can produce forecasts within a few minutes of data time, but complex data assimilation methods and numerical integration of the governing atmospheric equations are more costly and therefore take longer. However, if these techniques produce improved forecasts at longer lead times, the benefits outweigh the timeliness issue and reduced accuracy in the first 2 hours.

Another performance issue with NWP-based nowcasts relates to the latency of the boundary conditions. This arises because domain sizes are usually small and are nested in coarser resolution forecasts or larger domain forecasts with less frequent analysis cycling and later data cut-off times. The consequences are that the boundary conditions and synoptic scale forcing cannot be refreshed as frequently or as recently on the larger domain(s) as they are on the nowcast inner domain. This limits the skill at longer forecast ranges and possibly close to the boundaries.

Nonetheless, the advantage of NWP-based nowcasting lies in the fact that model formulation, dynamical equations and physical parameterizations can predict the non-linear evolution of weather elements and, in particular, the generation and decay of precipitating weather systems.

5.3 A status report

To investigate the direct use of NWP for nowcasting, the Met Office in the UK is developing an hourly cycling 4D-Var high resolution (1.5 km) NWP system to run on a domain covering southern England (see section 5.4). This is nested within the most recent forecasts for the whole of the UK (1.5 km resolution forecasts produced every 6 hours from 3 hourly 3D-Var data assimilation cycles at 3 km resolution) to obtain boundary conditions. The latter may be up to 6 hours old. Although 4D-Var is more expensive than 3D-Var, the aim is to evaluate the benefit of assimilating high time-frequency sub-hourly data (Ballard et al., 2011): see section 5.4 for more details.

Over the past 20 years, NCAR has undertaken many studies to explore the assimilation of radar data into high resolution cloud and NWP forecast models. These have included using the Variational Doppler Radar Assimilation System (VDRAS – Sun, 2005a, 2005b; Sun & Crook, 1994, 1997, 1998, 2001; Sun & Zhang, 2008) with 4D-VAR (Sun et al., 1991, 2012). These tend to use very short time-windows and have exploited the mesoscale model, MM5 3D-Var (Xiao et al., 2005) and the Weather Research & Forecasting Model (WRF) 3D-Var and 4D-VAR, or ensemble Kalman filter (Caya et al., 2005). These were run using VDRAS as part of the forecast demonstration project during the Beijing Olympics (Sun et al., 2010).

Meteo-France has a 2.5 km, 3-hourly cycling 3D-Var scheme covering France (the Application of Research to Operations at Mesoscale – AROME-France). This has been operational since December 2008 (Seity et al., 2011; Brousseau et al., 2011). Radial Doppler winds (Montmerle & Faccani, 2009) and humidity profiles derived from radar reflectivity (Caumont et al., 2010) are assimilated. Meteo-France is also undertaking a project entitled, “AROME-Nowcasting”, to adapt their 2.5 km grid length model, AROME, to meet the requirements of nowcasting. The main difference to AROME-France is the production of an analysis every hour, but without cycling. The potential benefits of a system called AROME-airport, based at Charles de Gaulle airport near Paris, are also being explored. This model will provide an input to a Wake-Vortex forecast model. The main goal is to add new,

dedicated observations, and to run a 500 m grid length model in a configuration comparable with conventional nowcasts (Ludovic Auger, MeteoFrance, personal communication WMO/WWRP Workshop on Use of NWP for Nowcasting, Boulder 2011).

DWD has a 2.8 km forecast model with a nudging assimilation scheme (Consortium for Small-scale Modeling, COSMO) covering Germany (COSMO-DE, Stephan et al., 2008) and is developing PP KENDA (Priority Project "KENDA" - Km-scale Ensemble-based Data Assimilation) for a 1 km-3 km scale Ensemble Prediction System known as LETKF (Local Ensemble Transform Kalman Filter; Ott et al., 2004). MeteoSwiss is running a 2 km version of COSMO. Various collaborating meteorological services are running, or are planning to run versions of these systems.

The HIRLAM (HIGH Resolution Limited Area Model) European community run their 3D-Var system (Gustafsson et al., 2001) with the HIRLAM model at grid lengths down to about 3.3 km and are developing a new HARMONIE system to run at about 2.5 km. They have also run experiments comparing three hourly and hourly cycling at 11 km and are exploring the impact of GPS and Doppler radar radial wind data (Magnus Lindskog, HIRLAM personal communication WMO/WWRP Workshop on Use of NWP for Nowcasting, Boulder 2011 and HIRLAM Newsletter No. 58, November 2011).

In the USA, NCEP (National Center for Environmental Prediction) has an operational RUC (Rapid Update Cycle) system with hourly data assimilation (Benjamin et al., 2004). As of September 2011, this was due to be replaced by the Rapid Refresh. The RR uses a version of the WRF model (currently v3.2+) and the Grid-point Statistical Interpolation (GSI) analysis largely developed at NCEP/EMC (Environmental Modelling Center, NOAA), using hourly cycling and a 13 km grid length. NCEP also run a 3 km model nested in the RR, but this has no separate data assimilation (Steve Weygandt et al., Earth System Research Lab, Boulder, personal communication WMO/WWRP Workshop on Use of NWP for Nowcasting, Boulder 2011, Stensrud et al., 2009; Smith et al., 2008; Weygandt et al., 2008).

In Japan, JMA (Japan Meteorological Agency) runs a Mesoscale Model (MSM) for Japan and its surrounding areas using a 5 km grid length and 4D-VAR with forecasts every 3 hours to 15 or 33 hours (Honda et al., 2005; Saito et al., 2006). This is a non-hydrostatic model (JMA-NHM). Development of NWP at a higher resolution (Local Forecast Model, LFM) is also in progress to help produce sophisticated disaster-prevention and aviation information services.

A trial operation of a 9-hour LFM forecast run on a 2 km grid length was performed in 2010 and 2011, and operational implementation is scheduled to start in 2012. LFM also uses JMA-NHM as a forecast model, and its initial condition is generated from a 3D-Var rapid update cycle. The cycle uses the MSM forecast as the first guess, and runs a JMA non-hydrostatic model-based variational data assimilation system (JNoVA) - a 3DVar (a degenerate version of JNoVA-4DVar) analysis and 1-hour JMA-NHM forecast in turn - over 3 hours using a 5 km grid length.

The Korean Meteorological Agency (KMA) is currently running the WRF 3D-Var (Barker et al., 2004, Xiao et al., 2008) at 10 km but is planning to use the 1.5 km, variable resolution Met Office Unified Model (UM) system with 3D-Var in the near future. In the past they have tested a 3.3 km version of WRF 4D-Var (Huang et al., 2009).

Over recent years, CAPS (Center for Analysis and Prediction of Storms, Oklahoma, USA) has been carrying out experimental, real time forecasting including the generation of 1 km grid length forecasts on a continental U.S. domain once a day, and the production of rapidly updated NWP-model-based nowcasts producing two hour, 1 km forecasts every 10 minutes (Xue et al., 2011; Kong et al., 2011; Clark et al., 2011; Brewster et al., 2010). These forecasts assimilate US operational WSR-88D radar data and/or high-resolution experimental X-band radar data, with and without assimilation cycles.

Comparison forecasts show systematically positive impacts of assimilating radar data on short-range precipitation forecasting, lasting up to 12 hours on average. To address forecast uncertainty and to provide probabilistic forecast information, storm-scale ensemble predictions have also been carried out and the products have been evaluated at an experimental forecasting facility. Extensive research has also been undertaken using ensemble-based data assimilation methods for initializing storm-scale NWP models, with very promising results.

CAPS has investigated a Mesoscale Convective System/vortex case study exploiting nested 400m / 2 km grids and assimilating radar data at 5 min intervals using their Advanced Regional Prediction System (ARPS) 3DVAR+cloud analysis (Schenkman et al., 2011a) as well as EnKF (Snook et al., 2011). These show data impact on Collaborative Adaptive Sensing of the Atmosphere (CASA; Schenkman et al., 2011b) and probabilistic forecast skill with EnKF analyses (Snook et al., 2011; 2012).

Environment Canada has begun developing a convective-scale EnKF in order to examine the assimilation of radar data (e.g. over the Montreal region; Luc Fillion, personal communication WMO/WWRP Workshop on Use of NWP for Nowcasting, Boulder 2011). This is based on adaptation of the Global EnKF code available at Environment Canada (Houtekamer & Mitchell scheme) to a limited-area domain. The analysis step and the forecast model configuration (1 km horizontal grid length) are being validated.

5.4 Development of an NWP-based nowcasting system in the UK

5.4.1 Progress to date

The Met Office has run an operational, 4 km grid length NWP model for the UK (UK4) since December 2005. It has also run a 1.5 km UK configuration (UKV) routinely since summer 2010. Both models use three-hourly cycling 3D-Var and produce forecasts to 36 hours ahead with 70 levels. These are based on the Met Office's Unified Model (Davies et al., 2005) and variational data assimilation system (Lorenc et al., 2000; Rawlins et al., 2007), plus latent heat nudging (Macpherson et al., 1996; Jones & Macpherson, 1997; Dixon et al., 2009). They also include direct variational assimilation of analysed 3D cloud cover via associated relative humidity. The UKV has a 1.5 km grid length over the UK and a 4km stretched boundary nested in the 12 km NAE (North Atlantic and European) model. The UKV uses 3 km 3D-VAR over the whole domain. Collaborations with KMA and CAWCR (Centre for Australian Weather and Climate Research, Australian Government Bureau of Meteorology) are aiming to implement 1.5 km versions of the UM with 3D-Var or 4D-Var.

The Met Office's UK Post-Processing system (UKPP) incorporates a STEPS precipitation nowcast (Bowler et al., 2006). This combines a stochastic, radar-based extrapolation nowcast

with UK4 or UKV precipitation forecasts. An 8 member ensemble and control member (unperturbed) nowcast to T+7 h are produced every 15 minutes. Recent Root Mean Squared Factor error statistics for STEPS control member advection nowcasts and UK4 and UKV forecasts of precipitation have shown that STEPS nowcasts are superior in the first 2.5 hours (see Figure 3).

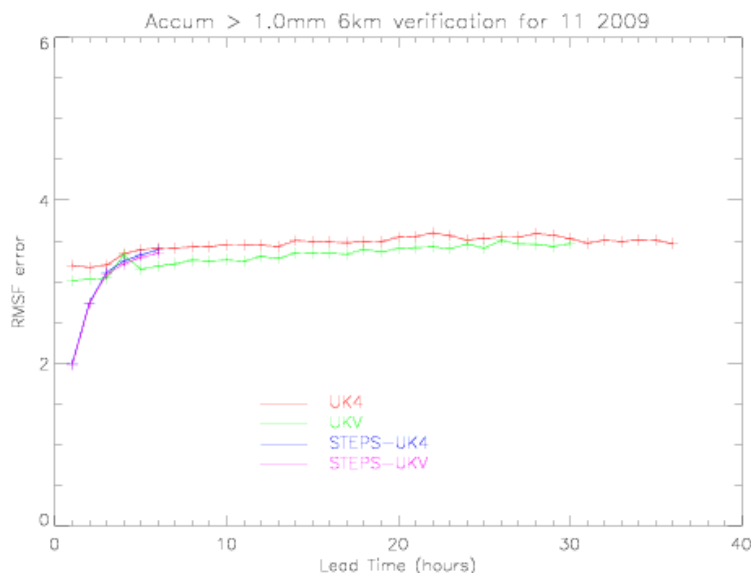


Fig. 3. Root Mean Squared Factor errors for November 2009 based on hourly accumulations greater than 1mm, smoothed to a scale of 6km, and measured using radar derived accumulations as the reference observation. The performance of 1.5 km (green) and 4 km (red) grid length, UK configurations of the Met Office's Unified Model are compared with control member STEPS nowcasts blending radar extrapolation with UM: 1.5 km (purple) and UM: 4km (blue) model forecasts. The performance of the STEPS nowcast blending extrapolation with the UM: 1.5 km forecast does not asymptote to that of UM: 1.5 km model because this was an experimental configuration run without prior calibration.

The implementation of an NWP-based nowcast system in the Met Office is focused on improving the prediction of convective storms for flood forecasting. The ultimate aim is to replace the existing extrapolation-based precipitation nowcasts and site specific forecasting techniques. Boundary conditions will be provided by the 6 hourly 1.5 km UKV system.

An hourly analysis and forecast system for southern England has been run experimentally for a limited number of cases of summer rain and convection, using conventional data and 3D-Var or 4D-Var, plus latent heat nudging of radar derived rain rates and humidity nudging based on analysed 3D cloud cover nudging (Macpherson et al., 1996; Jones & Macpherson, 1997; Dixon et al., 2009). The direct variational assimilation of cloud cover has not yet been tested in the hourly cycling system. This has used a fixed 1.5 km resolution configuration of the Unified Model and a 3 km resolution 4D-Var grid or 1.5 km and 3 km resolution 3D-Var grid.

The ultimate aim is to use 4D-VAR, if affordable and beneficial, in a real-time, routinely running NWP-based nowcast system. This will exploit high resolution (in time and space) Doppler radar measured radial winds and reflectivity or derived surface rain rates directly within the variational analysis scheme. Direct use in 4D-VAR should allow optimum extraction of information through interaction with other data sources, and the potential to modify the dynamical and physical forcing of precipitation and convective storms.

Research is also proceeding to investigate the background errors, balances and control variables required for use in convective scale data assimilation. The aim is to have a real-time system running continuously from summer 2012 for southern England.

5.4.2 A case study comparison of conventional and NWP-based nowcasts

Figure 4 compares T+1 hour, T+2 hour and T+3 hour STEPS control member nowcasts of surface precipitation rate, all valid at 2100 UTC on 3 June 2007 with a radar-based analysis of surface precipitation rate for the same time. At T+3 h, the STEPS nowcast is a combination of an extrapolation nowcast and UK4 forecast precipitation. The UK4 forecast tends to produce individual convective precipitation elements that are too large. It also fails to predict the full extent of the bands of convective precipitation to the east of the precipitation area lying through south-west England and west Wales. At T+2 hours, the STEPS scheme has re-produced the line of convection in the east but this is too narrow, possibly due to convergence in the diagnosed advection velocity field. By T+1 h, a reasonable nowcast has been produced.

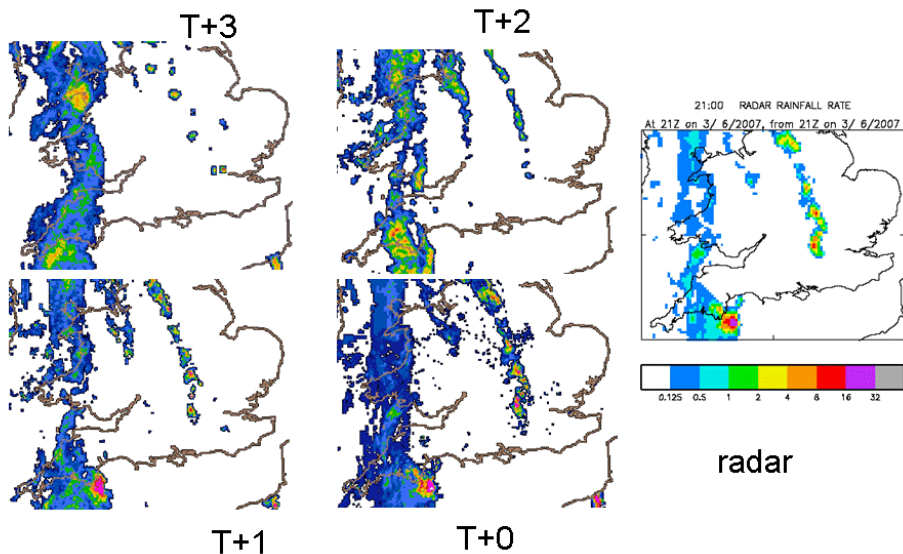


Fig. 4. STEPS T+0 h, T+1 h, T+2 h and T+3 h nowcasts of surface rain rate all valid at 2100 UTC on 3 June 2007. The key shown on the right-hand side represents precipitation rate in units of mm/h. Dry areas are shown in white. Note that dark blue areas in the STEPS nowcasts are not included in the colour key. These represent light drizzle.

Figure 5 shows the evolution of radar derived surface rain rate between 1200 UTC and 2100 UTC on 3 June 2007. It is apparent that a rain band in the west over Ireland at 1200 UTC reduces in intensity and moves only slightly eastward during the following 9 hours. However, bands to the east develop from about 1700 UTC onwards and intensify. The STEPS nowcast from 1800 UTC has not been able to reproduce the development of the eastern-most rain band seen in Figure 5. Nowcasts starting from later analysis times contain more precipitation but tend, incorrectly, to maintain the shape of individual features.

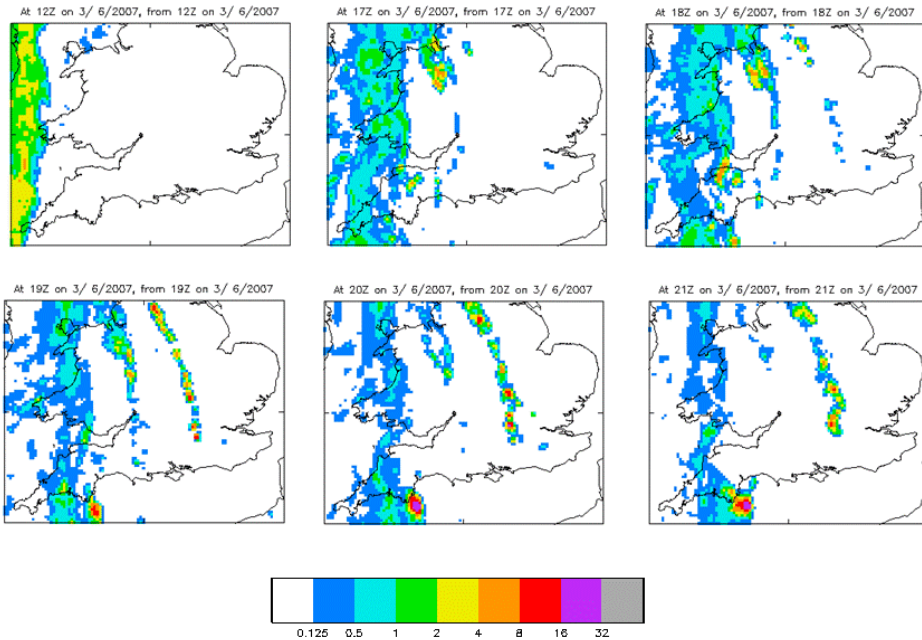


Fig. 5. Radar derived surface rain rates valid between 1200 UTC and 2100 UTC on 3 June 2007. The data for 1800 UTC, 1900 UTC, 2000 UTC and 2100 UTC were used to derive the T+3 h, T+2 h, T+1 h and T+0 h STEPS nowcasts shown in Fig. 4. The key shown below represents precipitation rate in units of mm/h. Note that dry areas are represented by the colour white.

Figure 6 compares T+1 hour, T+2 hour and T+3 hour 1.5 km NWP-based nowcasts of surface precipitation all valid at 2100 UTC on 3 June 2007 with radar derived precipitation rates for the same time. This model has used latent heat nudging of radar derived rain rates available every 15 minutes, and nudging of hourly humidity derived from 3-D cloud cover analyses in conjunction with hourly cycles of 4D-Var assimilation of conventional observations over 1 hour time windows. The NWP nowcasts improve at shorter lead times due to the benefit of data assimilation. In particular, they benefit from the latent heat nudging of surface precipitation rates derived from the sub-hourly radar data. In comparison with the STEPS nowcasts, the 1.5 km NWP nowcast has a better representation of the rain band in the east at both T+3 hours and T+2 hours. However, the representation of the rain in the south-west of England is inferior.

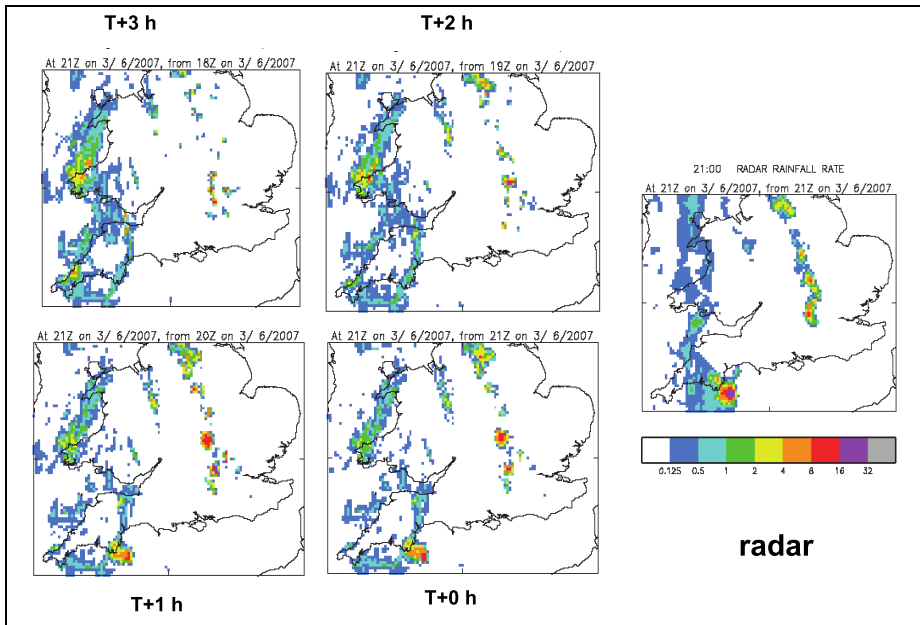


Fig. 6. A prototype Met Office NWP-based analysis (T+0 h) and T+1h, T+2h and T+3h nowcasts of surface rain rate generated using 4D-Var assimilation with latent heat nudging of the radar derived surface rain rates. All fields are valid at 2100 UTC on 3 June 2007. The area of coverage is the full domain of the prototype NWP-based nowcasting system. Note that dry areas are represented by the colour white.

Nonetheless, since this comparison is a first attempt without optimization of the data assimilation scheme and without the exploitation of more frequent conventional and Doppler radar measured radial wind observations, this is a very promising result. The forecast in the south-west can be improved by assimilation of 15 minute time frequency GPS water vapour data. At present, these are only available 90 minutes after data time so cannot be used in a nowcast system. Work is underway to make the UK GPS data available closer to data time.

Another potential source of water vapour information comes from radar refractivity by exploiting the interaction of the radar beam with ground clutter. Work is underway with Reading University to investigate the potential for obtaining this information from the UK weather radar network.

Direct assimilations of radar derived surface precipitation rates within 4D-Var is being investigated as well as direct or indirect assimilation of radar reflectivity, the latter through derived temperature and humidity increments from external 1D-Var assimilation of multiple beam elevations in vertical columns.

5.4.3 Use of Doppler radar derived winds

Potentially, weather radar provides a high resolution source of wind observations via the Doppler returns from hydro-meteors and insects. Currently, four weather radars in the south of England produce Doppler radial winds operationally every 5 minutes when there is precipitation (see Figure 7). The radars each perform scans at 5 elevations. The majority are at 1, 2, 4, 6 and 9 degrees, although one radar near London scans at 1, 2, 4, 5 and 5.5 degree elevations. Doppler winds are available to a range of about 100 km. This provides a small amount of dual or triple Doppler overlap in southern England as can be seen in Figure 7.

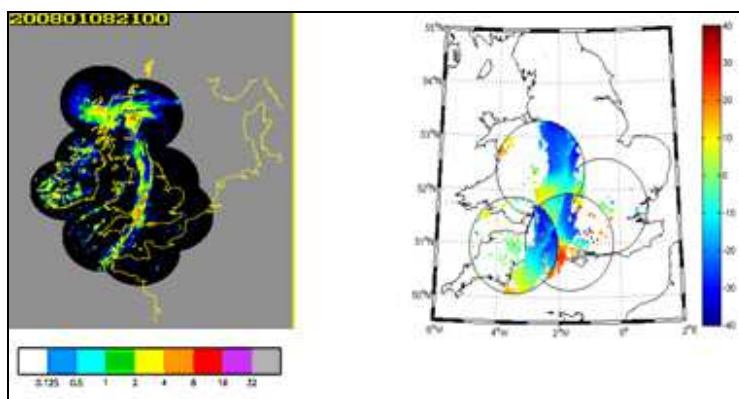


Fig. 7. A comparison of UK weather radar network coverage (left) and Doppler radar radial wind coverage (right) as of 8 January 2008. The key shown bottom-left represents precipitation rate in units of mm/hour. Note that dry areas in the left-hand graphic are represented by the colour black. The grey shading indicates areas without UK weather radar coverage.

Code has been developed to allow their processing, quality control, monitoring, super-obbing and data assimilation. Super-obbing is the process of combining observations that are of higher resolution than the forecast or analysis grid to reduce the data volume (Lorenç, 1981) and representativeness errors. Trials have been run to investigate the impact of Doppler radar radial winds on UK4 model forecasts using 3D-Var. The use of Doppler radar radial wind scans valid at analysis time was made operational in the UK configurations of the Unified Model in 2011. Three-hourly radial winds now replace hourly VAD winds from the same radars in the three-hourly 3D-Var cycles.

Much work has been done on specification of observation errors and investigating the impact of super-ob variances, errors derived from observation-background variances and errors derived from the Hollingsworth and Lonnberg technique (Hollingsworth & Lonnberg, 1986).

The impact of Doppler radar radial wind data has been assessed over southern England using a prototype nowcasting system with a 1.5 km grid length model and hourly cycling 1.5 km 3D-VAR. For the initial tests, only the radar scans closest to the analysis hour were selected from each radar for assimilation. Initial subjective and objective verification looks

promising. The location and coverage of precipitation is affected and improved in some situations. Figure 8 shows the increase in Fractional Skill Score (Roberts & Lean, 2008) of forecast hourly precipitation accumulations due to assimilation of radial winds from the four Doppler radars over southern England. These results are based on four case studies of about 10-19 cycles each, using hourly cycling 3D-Var and 11 hour forecasts. The results imply an hour's gain in skill in the earliest hours of the forecasts and a positive impact out to T+6 hours. The extent of the impact is limited by the small size of the domain and the spread of information from the boundary conditions into the domain.

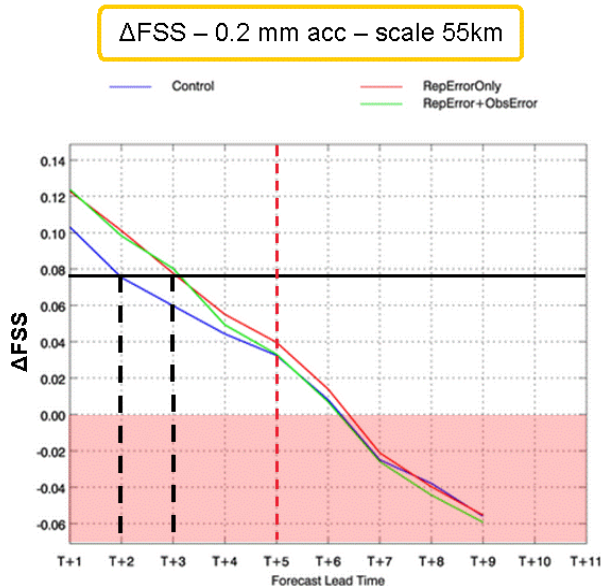


Fig. 8. Δ FSS for a 0.2 mm hourly precipitation accumulation threshold at a scale of 55km. Positive values of Δ FSS are indicative of forecast skill. The performance of the control forecast (blue) is compared with that of a forecast incorporating Doppler radial winds with a specified observation error derived from O-B statistics and referred to as representativeness error (red), and a similar forecast including Doppler radial winds with the representativeness error plus the super-observation standard deviation as the observation error (green).

Work continues on the specification of observation error and to test the impact of hourly and higher time frequency data in the 4D-Var nowcasting system. The impact and areal influence of observations in a NWP analysis depends on the background error correlation and covariances (i.e. the short range forecast error) at the analysis time, in addition to the observation error itself. The background errors can have a significant impact on forecast quality and the benefit afforded by the observations. Thus, work is underway to define improved errors for the 1.5 km grid length forecasts, both in terms of correlations between variables, length scales and error variances. These need to extract longer time and synoptic scale information as well as information at shorter time and spatial scales from radar data with high spatial and time resolutions. This is very challenging work.

Work with Reading University has been undertaken to look at the potential for use of winds derived from insect returns in fine weather (Rennie et al., 2010). This will continue in collaboration with CAWCR in Australia. Radar returns only give radial winds (i.e. in the direction of the radar beam) rather than 3-D wind components, so the additional information in areas of overlapping radars (dual-Doppler) may increase the impact of wind retrievals in those locations.

5.4.4 Conclusions and further work

1.5 km grid length NWP in the Met Office is showing promise in the very short range prediction of convection over the UK. Previous sections have highlighted the potential benefits of using radar derived precipitation rates through latent heat nudging on top of 4D-Var and of using Doppler radar derived radial winds in 3D-Var.

4D-Var has the potential to exploit higher time frequency observations and to extract more information from them than 3D-Var. Therefore, research is continuing on the use of high time frequency Doppler radial winds, direct application of radar derived surface precipitation rate, and direct and indirect use of multi-elevation volume scan reflectivity in 4D-Var. Although latent heat nudging is still showing benefit in forecasts, it cannot correctly represent resolved convection where latent heat release occurs in different locations to surface precipitation, so it is hoped to obtain benefits from direct 4D-Var or indirect 1D-Var assimilation of the reflectivity data.

Unfortunately, 4D-Var is computationally expensive on the super-computer currently available to the Met Office. Therefore, research and development is being undertaken with both 3D-Var and 4D-Var systems. With a super-computer upgrade due in 2012, the aim is to start running a prototype real-time NWP-based nowcast system in 2012, hopefully with 4D-Var if the upgrade provides sufficient computer resources.

Due to the tight time constraints imposed by operational schedules, it may be necessary to move away from use of a time window centred on the analysis time to one finishing at the analysis time. High quality data sources such as GPS, which provide information on low level humidity, are currently only available 90 minutes after data time, although less accurate but more timely data may become available. There are many sources of information on different variables (e.g. GPS, radar refractivity, satellite imagery and surface observations for low level humidity). The usefulness of the different data sources will be investigated to provide an optimum system. The initial experiments reported here were undertaken nested within the UK 4 km NWP forecast system. Now, the nowcasting system is being tested embedded in the UK 1.5 km NWP forecast system.

The skill of the convective scale nowcasts is very dependent on the accuracy of the synoptic forcing conditions both within the nowcast domain itself and the boundary conditions. Both the UK models and the embedded nowcast system use the same model and essentially the same data assimilation system. Errors in convective initiation can come from errors in the synoptic flow either as a result of lack of observations to correct model errors, or incorrect or sub-optimal use of observations. Finding the best way to extract synoptic scale and convective scale information from observations in both the nowcast system itself and in the forcing at the boundaries will be key to improvements in the skill of the nowcast.

Data sources such as GPS can be problematical because they are vertically integrated measurements depending on the accuracy of the specification of the forecast background errors, and interaction with other data sources to allocate changes to humidity in the vertical can have dramatic impacts on forecast precipitation. The use of high vertical and horizontal spatial and temporal resolution Doppler radar winds and reflectivity or rain rate data, and improvements in specification of forecast background errors, can lead to changes and improvements in the impact of different data sources and the accuracy of the precipitation in the early hours of the forecast.

NWP systems can suffer from imbalances in the initial conditions leading to spin-up or spin-down of precipitation in the initial stages of the forecast. Work to improve this will help to improve skill in the early hours of the nowcasts. Improvements in the skill of the forecast model itself in terms of precipitation biases are likely to help both the forecast and the ability to assimilate observations. We tend to use radar derived rain rates to verify the NWP forecasts, for assimilate into the models and to improve the formulation of the model. However, the radar data can have quality issues, for example relating to attenuation, and improvements in quality control and data processing are needed to ensure that the radar data are of high quality.

The entire UK network of weather radars will gradually be updated to produce Doppler radial winds and also dual-polarization data and radar refractivity measurements. The use of radar data in NWP high resolution variational data assimilation has the potential to improve on current extrapolation-based nowcasts. To achieve this we need high quality radar data, fast processing (techniques and computer power), careful specification of observation and forecast background error covariances and correlations through the scientific design of the data assimilation system, and a good representation of the dynamical and microphysical processes in the NWP forecast model.

In future it is hoped to exploit ensemble techniques in both the data assimilation and production of forecasts. If there is sufficient computer power available for hourly NWP forecasts to 12 hours, this will provide the potential for 6 hours of 1 hourly lagged ensemble forecasts and a measure of the predictability of the nowcasts.

6. Application of radar-based precipitation nowcasts to hydrological forecasting and warning

6.1 Overview

Documented uses of radar data in hydro-meteorology are many and varied. They include numerous studies of the space-time structure of radar inferred precipitation fields (e.g. Harris et al., 2001), the compilation of precipitation climatologies (Panziera et al., 2011), the estimation of Probable Maximum Precipitation (Cluckie, Pessoa & Yu, 1991; Collier & Hardaker, 1996), reservoir design and safety (Cluckie & Pessoa, 1988), design storm modelling (Seed, 2003), urban drainage and waste water management (Cluckie & Tyson, 1989; Schellart et al., 2009), river flow management (Lewin, 1986) and hydroelectric power generation (Baker, 1986).

In addition to the above, operational radar-based precipitation nowcasts can be of great value in fluvial (river) flood prediction because they extend the lead time of flood warnings

by reducing reliance on crude assumptions regarding future precipitation. For pluvial (surface water) flood forecasting, predictions of future precipitation are essential because the time between the precipitation reaching the ground and any consequent flooding is very short (Golding, 2009). In this section we review some of the key developments in the use of radar for fluvial (river) flood prediction and warning.

6.2 Hydrological requirements for precipitation observations

It was the prospect of accurate, contiguous observations of precipitation over large areas that first stimulated hydrologists to explore the use of radar data for the prediction of run-off and river flow. Early assessments of the value of radar data were mixed (Anderl et al., 1976; Barge et al., 1979). This is not surprising given the reliance of these early experiments on deterministic precipitation estimates of variable accuracy, and the many factors known to impact on hydrological forecast performance.

Hydrological requirements for precipitation observations and forecasts are a function of catchment size, morphology and land use, and the hydrological model used (Hudlow et al., 1981). Many operational, hydrological forecasting models are lumped conceptual models in which the catchment response is modelled as a whole and the precipitation input is an areal average estimate. A number of authors have emphasized that the benefits of radar derived, spatially contiguous precipitation estimates can only be fully realized if used as input to distributed, conceptual or physically-based hydrological models (e.g. Moore, 1987).

6.3 Impact of the spatial and temporal distribution of precipitation

Wilson et al. (1979) found that a failure to properly represent the spatial distribution of rainfall, due to reliance on point observations from rain gauges, could produce significant errors in the total volume, peak and time to peak of an estimated hydrograph, even when the rainfall depth and its temporal evolution were accurately recorded at rain gauge sites. Errors were largest in cases of localized convective storms. Bedient and Springer (1979) demonstrated that the peak flows in a catchment could be enhanced when the precipitation moved in the direction of the stream.

More recently, Bell and Moore (2000b) explored the sensitivity of lumped and distributed catchment rainfall-run-off models to time series of rainfall observations from radar and rain gauge, gridded to a range of spatial resolutions. For a small rural catchment, they confirmed the sensitivity of distributed model run-off to the spatial variability of rainfall. A comparison of the performances of lumped and distributed models showed similar levels of predictive skill in stratiform rain, but superior distributed model predictions during convective rainfall events.

Ball (1994) examined the impact of the temporal evolution of the precipitation pattern on the time of concentration and peak discharge in a catchment. The time of concentration was shown to be sensitive to the temporal evolution of excess rainfall over the catchment, where as catchment peak discharge was not. Thus, timing errors in predicted flows can result if the time interval between precipitation observations is too long. Collier (1996) suggests that a radar scan cycle of no more than 5 minutes is required to capture the time evolution of most convective precipitation fields.

6.4 Relationship between radar data resolution, catchment characteristics and hydrological model performance

Various studies have examined the impact of the spatial and temporal resolution of remotely sensed precipitation observations on hydrological model performance (Krajewski et al., 1991; Pessoa et al., 1993; Obled et al., 1994; Ogden & Julien, 1994; Ball, 1994; Faurès et al., 1995; Shah et al., 1996; Winchell et al., 1998; Bell & Moore, 2000b; Carpenter et al., 2001).

Ogden and Julian (1994) explored the relationship between catchment size, and the correlation length and horizontal resolution of the radar derived precipitation fields input to a two-dimensional, physically-based hydrological model. They defined two, dimensionless length parameters and considered their impacts on the accuracy of predicted run-off. *Storm smearing* describes a reduction in the horizontal gradient of precipitation rate as the horizontal resolution of the radar data approaches its correlation length. *Watershed smearing* occurs when the horizontal resolution of the radar data approaches the characteristic length scale of the catchment (square root of the catchment area). Watershed smearing was shown to be the main source of error in predicting river flow over small catchments. Berenguer et al. (2005) point out that the sensitivity of hydrological models to biases in mean areal rainfall are due to the fact that river catchments act as integrators of the precipitation falling on them.

Bell and Moore (2000b) emphasized the need to calibrate hydrological models with rainfall data for a given resolution. They found that the most skilful distributed rainfall-run-off model predictions were made with lower resolution rainfall data. This finding was interpreted as evidence for the need to improve distributed hydrological model formulation.

6.5 Impact of radar intensity resolution

The impact of the intensity resolution in radar data on hydrological forecast errors was investigated by Cluckie, Tilford & Shepherd (1991). They demonstrated that 8 intensity levels were adequate for the majority of rural and urban catchments in the majority of UK precipitation events. This is because the bulk of the relevant information content is concentrated at the low frequency end of the power spectrum. Nonetheless, in convective precipitation events, a reduction in intensity resolution may have an effect similar to that of the storm smearing described by Ogden and Julian (1994).

6.6 Benefits of precipitation nowcasts to hydrological forecasting

In the absence of precipitation forecasts, the lead time of flood warnings is limited by the catchment response time, a quantity dependent on catchment size, morphology and land use. Skilful precipitation forecasts offer the prospect of some forewarning of flash floods in small, fast responding catchments, and of extending the lead time of flood warnings in other catchments (Roberts et al., 2009).

Although numerous authors have evaluated the impact of QPE algorithms on the utility of radar for hydrological forecasting there have been relatively few investigations of the benefits of precipitation nowcasts in this area. Cluckie and Owens (1987) compared the performance of stream flow forecasts made using a linear transfer function model and radar extrapolation nowcasts from FRONTIERS (Browning, 1979) against similar flow predictions

made using average past rainfall and an assumption of no more rain. In most cases, they found that nowcast driven hydrological forecasts outperformed the alternatives, although on one occasion they showed the former to be poor.

Several decades later, a similar, case study orientated evaluation of the utility of Nimrod (Golding, 1998) extrapolation nowcasts for rainfall-run-off modelling in Scotland (Werner and Cranston, 2009) drew similar conclusions: although errors in nowcast driven predictions of river flows could be substantial, they were smaller than those of flow forecasts made assuming zero future rainfall.

Mecklenburg et al. (2001) found that COTREC-based radar extrapolation nowcasts (Lagrangian persistence) produced superior hydrological forecasts to Eulerian persistence using a lumped conceptual model. In a similar vein, Berenguer et al. (2005) compared hydrological forecasts made with the S-PROG model (Seed, 2003) with those produced using a simpler, extrapolation-based precipitation nowcast in a Mediterranean environment. S-PROG utilizes a scale decomposition framework and associated hierarchy of autoregressive models to smooth the advected precipitation field at a rate that is consistent with its loss of predictive skill on a hierarchy of scales. This approach is intended to minimize the root mean squared forecast error. Berenguer et al. (2005) concluded that radar-based precipitation nowcasts in general could extend the lead time of useful hydrological forecasts from 10 minutes to over an hour in a fast response responding Mediterranean catchment. However, the results obtained with S-PROG were not significantly better than those obtained with a simpler Lagrangian persistence technique.

Since one of the key benefits of radar is its ability to provide contiguous, instantaneous observations of precipitation over a wide area, other studies have focused their efforts on demonstrating the benefits of precipitation nowcasts when input to distributed hydrological models. In these models, the run-off response can vary within a catchment according to the temporal and spatial variability of the rainfall, surface properties and antecedent wetness (Ivanov et al., 2004; Vivoni et al., 2005). Amongst other things, this capability allows time series of run-off to be generated at ungauged sites (Moore et al., 2007).

Sharif et al. (2006) explored the potential of the National Center for Atmospheric Research's Auto-Nowcaster to improve the lead time and accuracy of hydrological forecasts made with a physically-based distributed parameter model. Rain gauge and radar observation driven simulations were used as a baseline. Results confirmed that the use of precipitation nowcasts could significantly improve flood warning in urban catchments, even in the case of short-lived events in small catchments. Similar conclusions were drawn by Vivoni et al. (2006) in relation a set of small, mixed land-use catchments in Oklahoma, in this case using NEXRAD-based extrapolation nowcasts and a distributed hydrological model.

6.7 Treatment of nowcast errors in hydrological forecasts

Vivoni et al. (2007) explored the impact of errors in deterministic precipitation nowcasts on errors in flood forecasts using a distributed hydrological model and a range of catchment sizes. Their investigations showed that increases in nowcast error with lead time produced larger errors in the resulting hydrological forecasts. They demonstrated that the effects of nowcast errors could be simultaneously enhanced or dampened in different locations depending on forecast lead time and precipitation characteristics. Differences in error

propagation between sub-catchments were effectively averaged out over larger catchment areas.

Despite continuing incremental advances in radar technology and performance during the 1970s and 1980s, a number of authors recognized that radar derived estimates of surface precipitation rate and accumulation would remain subject to hydrologically significant errors, particularly in hilly and mountainous areas. Collier and Knowles (1986) concluded that the full benefits of radar to operational hydrology would only be realized when ways could be found of accounting for these errors.

This thinking coincided with a growing awareness of the need to develop operational systems integrating meteorological and hydrological forecast models (Georgakakos and Kavvas, 1987). Early examples of such systems are the Integrated Flood Observing and Warning System (IFLOWS) implemented in the USA (Barrett and Monro, 1981), and the Regional Communication Scheme in north-west England, integrating operational weather radar data with hydrological forecasting and warning under the North-West radar project (Noonan, 1987).

More recently, a number of multi-national initiatives including HEPEX (e.g. Buizza, 2008; Pappenberger et al., 2008), MAP-D-Phase (Zappa et al., 2008; Bogner & Calas, 2008) and COST-731 (Rossa et al., 2011) have supported work to implement integrated flood forecasting systems exploiting weather radar. A number of UK-based research programmes, are relevant in this context, including HYREX (e.g. Mellor et al., 2000a,b; Bell & Moore, 2000a), the Natural Environment Research Council's Flood Risk from Extreme Events (FREE), the Engineering and Physical Sciences Research Council's Flood Risk Management Research Consortium (FRMRC) and FLOODsite.

Until Krzysztofowicz's pioneering work (Krzysztofowicz, 1983, 1993, 1998, 1999, 2001) to develop and implement an integrated hydro-meteorological systems framework, incorporating a Bayesian treatment of uncertainties in data inputs and deterministic model forecasts, errors in the precipitation inputs to operational hydrological models tended to be handled through the use of what-if scenarios (Haggett, 1986; Werner et al., 2009). The derived distribution approach (Seo et al., 2000) developed by Krzysztofowicz exploits the total probability law to derive by quasi-analytic means the conditional probability distribution of river stage given the initial and boundary conditions, including future precipitation parameterized in the form of a probabilistic QPF.

An alternative method for accounting for data input uncertainty entails the ingestion of ensemble precipitation forecasts into a hydrological model, whilst taking separate account of other sources of uncertainty contributing to the total uncertainty in the hydrological forecast variable of interest (Krzysztofowicz, 2001). Probabilities of exceeding specific river stage thresholds can then be estimated from the resulting ensemble of hydrographs (Schaake & Larson, 1998; Pierce et al., 2004). During the past decade, this ensemble approach has gained credence with the widespread implementation of operational ensemble NWP models and the development of stochastic nowcasting and post-processing techniques for the production of ensembles of high resolution precipitation nowcasts (e.g. Bowler et al., 2006).

Carpenter and Georgakakos (2006) investigated the combined effects of radar rainfall errors and catchment size on the uncertainty in predicted river flow with the aid of a distributed hydrological model. Using a parsimonious model to represent the spatial structure and variance of radar errors, they demonstrated that ensemble spread in predicted flow was log-linearly related to catchment scale.

A handful of ensemble-based probabilistic QPN schemes have been developed during the past decade or so. These were described earlier in this Chapter and include the String of Beads Model (Pegram & Clothier, 2001; Berenguer et al., 2011), the Short-Term Ensemble Prediction System (Bowler et al., 2006) and a method recently described by Kober et al. (2011). Here we draw a distinction between ensemble QPN schemes and others such as those described by Andersson and Iverson (1991) and Germann and Zawadzki (2004) which produce forecasts of the probability distribution of precipitation at a point. The latter cannot be used for ensemble-based probabilistic hydrological forecasting because they do not provide a complete description of the joint probability distribution of precipitation, which plays a key role in the hydrological response of a catchment.

In the UK, the Department of the Environment, Fisheries and Rural Affairs and the Environment Agency recently funded an R&D project to explore the benefits of high resolution precipitation forecasts to fluvial flood prediction and warning (Schellekens et al., 2010). The potential for operational use of ensemble rainfall nowcasts from STEPS (Bowler et al., 2006) was investigated in conjunction with lumped and distributed rainfall-run-off models. The evaluation included hydrological configuration issues, data volumes, run times and options for displaying probabilistic forecasts. No quantitative verification of the precipitation ensemble-driven hydrological forecasts was undertaken.

Recently, the Environment Agency has implemented a nationally configured, distributed hydrological model, known as Grid-to-Grid (Bell et al., 2007). In the near future (2012), this model will be driven by ensemble precipitation forecasts integrating STEPS ensemble nowcasts.

7. The future of nowcasting

One of the major changes in the past decade has been the increase in the ability of the general population in developed countries to receive real-time information over a range of mobile platforms. This makes it possible to deliver location specific nowcasts to millions of users. They use this information to make routine decisions regarding leisure and other outdoor activities and very occasionally decisions relating to severe weather events. Mitigating damage due to severe weather has been the motivation for developing nowcasting systems in the past, but the focus is likely to change to providing routine nowcasting services to the general public. The current generation of nowcasting systems are already capable of delivering products that are useful in this context and the focus in the short term should be on developing the ability to customize and disseminate these to a very large number of users.

Improved communications and computer capacity have also made it possible to routinely combine data from a network of weather radars into a single large domain, and to improve the algorithms that are used to provide quantitative radar rainfall estimates. Improvements in the QPE will continue as the radar hardware improves and the density of the radar networks increases. These improvements will allow for improvements in the quality of the nowcasts in the first hour.

There are still incremental gains to be made by improving the accuracy of the tracking algorithms and by combining the cell tracking and field advection paradigms into a single advection scheme. More generally, there is evidence that the cell tracking and field tracking systems are complementary, so rather than viewing them as competitors there should be value in developing a way of optimally combining the forecasts from several nowcasting systems based on an analysis of which system is likely to be providing better nowcasts in any given situation.

Predicting the initiation and decay of convective storms will continue to be a major focus for research because gains in this area will lead to significant improvements in the accuracy of nowcasts beyond 30 minutes. The problem with heuristic and analogue techniques is that they require large data sets for calibration, and the associated conceptual models that are developed tend to be location specific. This can be overcome if a way can be found to allow the algorithms to learn as they go, based on the results of routine real-time verification.

Possibly the major use of radar data in the future will be for assimilation into NWP models of the national weather services that run radar networks. Empirical advection nowcasting will continue to provide nowcasts, but for more limited lead times as the NWP models gain accuracy at shorter lead times. Not all users will be able to afford the costs of a full NWP system that is able to assimilate radar data and there will continue to be a demand for fast and cheap rainfall nowcasts for specific purposes.

Forecast errors, rather like death and taxes, will always be with us and the future lies in using ensembles or other techniques to convey the uncertainty in the current forecast to the users. Further research on quantifying forecast errors and understanding how they depend on location and meteorological situation is required before we are able to demonstrate that the spread in a nowcast ensemble fully represents the uncertainty. There is also a need to develop probabilistic nowcasting systems that do not only forecast rainfall, but are used to forecast end-user impacts, for example the traffic capacity of an air-corridor, or the water level in a river.

8. References

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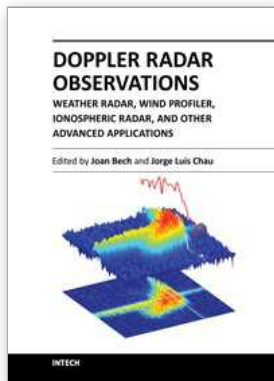
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Doppler radar systems have been instrumental to improve our understanding and monitoring capabilities of phenomena taking place in the low, middle, and upper atmosphere. Weather radars, wind profilers, and incoherent and coherent scatter radars implementing Doppler techniques are now used routinely both in research and operational applications by scientists and practitioners. This book brings together a collection of eighteen essays by international leading authors devoted to different applications of ground based Doppler radars. Topics covered include, among others, severe weather surveillance, precipitation estimation and nowcasting, wind and turbulence retrievals, ionospheric radar and volcanological applications of Doppler radar. The book is ideally suited for graduate students looking for an introduction to the field or professionals intending to refresh or update their knowledge on Doppler radar applications.

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