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Making Forecasts of Extreme Rainfall and Managing their Consequences for Flood Forecasting

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ABSTRACT: During extreme rainfall events reliance cannot be placed upon local measurements of rainfall or river flow as hydrometric networks may be destroyed. Therefore, forecasting procedures are increasingly dependent upon remote sensing systems such as radar, satellite-based instrumentation and high resolution Numerical Weather Prediction (NWP) models. In addition, it is necessary to have knowledge of antecedent catchment conditions, conditions at the beginning of an event and a suitable hydrologic modelling structure. However, all these elements introduce uncertainty throughout the forecast chain, and it is necessary to understand the propagation of uncertainty and present it as an integral part of the forecast. In this paper we discuss the preparation of rainfall analyses for use in forecast procedures aimed at warnings an hour or so (nowcasts) to days ahead. The discussion includes procedures for improving the quality of radar and satellite estimates of rainfall, and the development of data assimilation techniques for NWP models. In spite of efforts to specify accurate model initial conditions in a non-linear dynamical system the growth of initial uncertainties in space and time is flow-dependent. To determine the predictability of this flow-dependency, an ensemble of forecasts for small perturbations in model input conditions may be generated and analysed. Similarly, sources of uncertainty in hydrological forecasts may be addressed using ensemble approaches. The uncertainties in hydrological forecasts need to be incorporated in cost-loss analyses in order to decide what decisions regarding flood mitigation and/or adaptation are best taken to minimize flood losses.

INTRODUCTION

In arid climates rainfall may generate crusting of the soils, but in other regimes initially all rainfall infiltrates the soil surface. The areas adjacent to the stream channels become saturated as here the ground water table is shallow. Continuing rainfall causes the water table to rise to the ground surface, and the lower catchments slopes become saturated with rain falling here flowing overland to the river channel.

Elsewhere in areas not saturated rainfall is either stored in the soil or moves beneath the ground surface. Some of these areas may become saturated due to sub-surface water convergence in zones caused by soil heterogeneity. The groundwater is recharged near the river channel and at convergence points from underground slope cavities. This leads to an increased groundwater contribution to the river hydrograph. The existence of convergence pathways, and the increased level of the water table, determine the timing and magnitude of the runoff generated by a given rainfall amount. The river channel slope and roughness govern the hydrograph shape at locations downstream. In steep upland catchments where soils are sparse runoff may be rapid resulting in a flash flood.

Floods are also often accompanied by other hazards such as landslides, mud flows, bridge collapses, damage to buildings and businesses and psychological damage to people with, in extreme situations, deaths of individuals. The floods themselves maybe exacerbated by accumulations of debris producing local damage, particularly at bridge constrictions which on failure may suddenly release large amounts of water.

Any warning system must depend upon the accurate real-time provision of rainfall information and hydrological model structures that function during extreme conditions. In addition flooding may be intensified by changes of land use which increase the rate and volume of run-off, lack of maintenance of flood defences, canalisation that is modification and diversion of rivers and water courses and the building of structures such as embankments which may increase flood risk both up stream and down stream.

During these events one cannot rely upon local measurements of rainfall or river flow as hydrometric networks may be destroyed. Hence, forecasting procedures are increasingly dependent upon remote sensing systems such as radar, high resolution Numerical Weather Production (NWP) models, knowledge of antecedent catchment conditions, model state at the beginning of an event and hydrologic modelling which recognises the importance of dealing with uncertainty in observing systems, the modelling structures themselves and the assumptions made about the error formulations used.

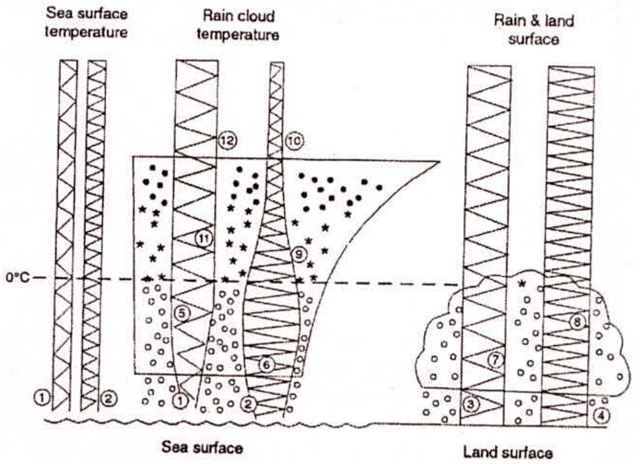

Fig. 1: The interactions of high (e.g. 85 GHz) and low (e.g. 19 GHz) frequency passive MW with precipitation clouds and the surface. The width of the vertical columns represents the intensity or temperature of the upwelling radiation. In this figure the illustrated features and their demarcations are: (a) the small emissivity of sea surface for both low (1) and high (2) frequencies; (b) the large emissivity of land surface for both low (3) and high (4) frequencies; (c) the emission from cloud and rain drops, which increases with vertically integrated liquid water for the low frequency (5), but saturates quickly for the high frequency (6); (d) the signal of the water emissivity at the low frequency is masked by the land surface emissivity (7); (e) the saturated high frequency emission from the rain (8) is not distinctly different from the land surface background (4); (f) ice precipitation particles aloft backscatter down the high frequency emission (9), causing cold brightness temperatures (10), regardless of surface emission properties; (g) the ice lets the low frequency emission upwell unimpeded (11), allowing its detection above cloud top as warm brightness temperature (12)

As pointed out by many authors, the quality of any flood prediction that is based upon hydrological simulations depends to a high degree upon the quality of the measurements and forecasts of precipitation. In what follows we begin by describing this aspect of flood forecasting. However, we recognise that hydrological simulations of peak flow are themselves very uncertain, and consequently it is essential to understand the propagation of uncertainty through the flood forecast chain. Presenting this uncertainty to users, particularly in a changing climate, may itself place limits on predictability.

REAL-TIME MEASUREMENTS OF RAINFALL

The measurement of rainfall in real-time underpins the forecasting of flash floods, from networks of rain-gauges, using weather radar or derived from satellite systems. Satellite estimates of rainfall are essential elements of flood warning systems in many countries where rain gauges or radar are sparse or non existent. The accuracy achievable using satellite systems is summarized by Rosenfeld and Collier (1998) as shown in Figure 1. This review remains largely applicable although the use of operational space-instrumentation in the future may change things. Given the time scales associated with many floods only satellite techniques using instruments mounted on geostationary platforms are appropriate for monitoring these events. However, for long rivers with large times of concentration satellite measurements from polar orbiting satellites may be very useful.

Whilst rain gauges provide the most accurate means of measuring point rainfall, they require regular maintenance, and their deployment density governs the accuracy with which catchment rainfall can be measured. Indeed, in some catchments the network density may be very low, and therefore the areal rainfall accuracy is very poor. This is likely to be the situation in convective rainfall often associated with flash floods as opposed to widespread frontal rainfall (see Figure 2).

Weather radar offers technology capable of providing extensive measurements of both rainfall and snowfall in real-time from a single location over wide areas. However, radar provides measurements of the reflectivity of the target hydrometeors which require interpretation. In addition, there are significant quality control problems which have to be dealt with such as the removal of ground clutter and the effects of melting snow (the 'bright-band') (for a summary see Collier, 1996, 2002). Work continuous to improve the quality of precipitation estimates using single frequency; single polarisation systems (see for example Bellon *et al.*, 2005; Michelson *et al.*, 2003; Mittermaier and Illingworth, 2003). Also radar data can be used to differentiate between stratiform and convective rainfall (Anagnostou, 2004).

Nevertheless, when carefully adjusted using rain gauge data areal rainfall estimates are as accurate as those from a very dense rain gauge network as shown in Figure 2. In practice, however, the use of rain gauge adjustment procedures can be detrimental in some situations and therefore they are increasingly only used for daily or longer rainfall estimates. The best achievable *operational* level of performance is illustrated in Figure 3 (Vignal *et al.*, 2000).

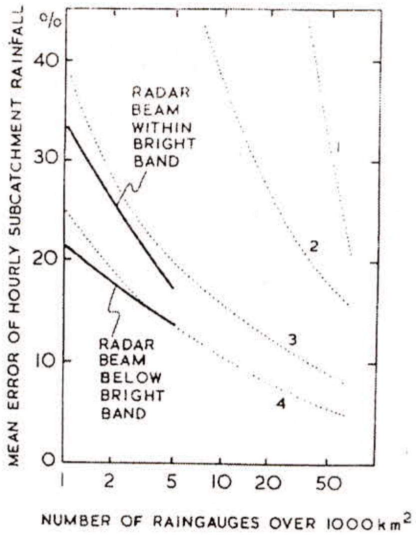

Fig. 2: Mean error of hourly rainfall totals in the Dee Weather Radar Project over catchments of area around 60 km^2. For radar the plot is of error versus number density of adjusting raingauges, and for raingauges the plot is error against the number density of the raingauges in the network where the dotted curves represent: 1: extremely isolated showers, 2: typical showers, 3: typical widespread rain, 4: extremely uniform rain from (after Collier, 1977 from Browning, 1978)

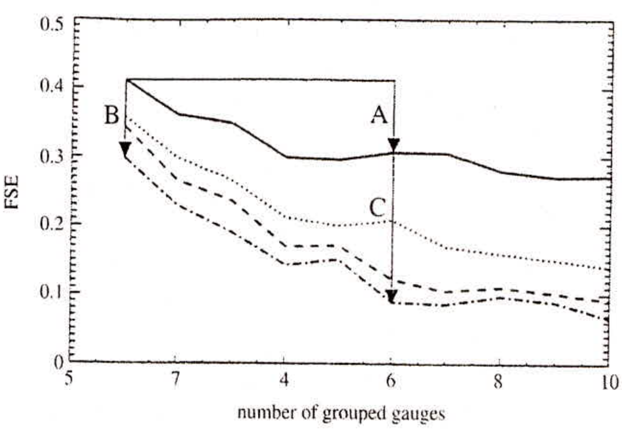

Fig. 3: Fractional Standard Error (FSE) when using measurements from groups of raingauges to adjust radar data. Curves show: A unadjusted; B mean Vertical Profile of Reflectivity (VPR) correction; C climatological VPR correction; and D VPR correction estimated from the data (from Vignal *et al.*, 2000)

Over the last twenty years or so the use of polarimetric radar techniques has promised to alleviate or even remove some of the difficulties with single frequency, single polarisation radar measurements. However, the level of improvement that can be achieved in the actual measurement accuracy over that achievable using single polarisation radar remains unclear. This is because high resolution values of polarisation parameters such as the differential reflectivity (Z_{DR}) may not be derived accurately enough in operational systems (Illingworth, 2003). Nevertheless, there is no doubt that polarimetric radar will enable significant improvements in radar data quality control such as the identification of areas subject to attenuation at C-band frequencies, the removal of ground clutter, correction for bright-bond effects and the differentiation of hail from very heavy rainfall. The US Joint Polarisation Experiment (JPOLE) (Ryzhkov *et al.* 2005) was designed to test the practicality and utility of polarmetric WSR-88 D radar. It has demonstrated potential for significant improvement in areal rainfall estimation and measurements of heavy precipitation.

FORECASTING INTENSE RAINFALL

Nowcasting

Nowcasts are very short range forecasts considered by Golding (2000) to be forecasted upto 6 hours ahead. Such forecasts of precipitation have until recent years been based upon extrapolation techniques (for a review see for example Collier, 2000 and the papers contained in Collier and Krzysztofowicz, 2000) Indeed, work continues to improve extrapolation techniques (see for example Mecklenberg *et al.* 2000; Bowler *et al.*, 2004; Li and Lai, 2004). The importance of scale separation techniques in nowcasting procedures using correlation-based algorithms, Fourier low-pass filters, multifractal methods and wavelet analysis has been recognised (see for example Seed, 2003). Zawadzki *et al.* (1994) showed that spatial filtering may increase the useful forecast lead time. An alternative approach is to use statistical models of rainfall calibrated using raingauge or radar data (for a review see Wheater, 2002). This approach has shown some success, but cannot capture extreme events. However such forecasts may now be produced by high resolution numerical weather prediction models (see later) in combination with techniques for extra-polating precipitation fields derived using radar data. An operational system using this approach, known as the Met Office Nimrod system, has been described by Golding (1998).

The Nimrod precipitation nowcasting system consists of analysis and forecasting components. For lead times upto an hour or so precipitation objects (a group of pixels each exceeding a prescribed threshold rain rate usually taken as 0.5 mm/h) are identified, and their motion estimated starting with displacements obtained from vectors selected at the previous forecast run. Neighbouring pixels are searched to define a distribution of correlation coefficients from which the minimum is identified and used to define an optimum motion vector. For longer lead times upto 3 hours ahead, rain objects of 1/32 mm/h or more are identified and correlated with corresponding objects from 1 hour earlier. The optimum linear translation vector so obtained is compared with NWP model wind fields at each level in the vertical from 100 to 5000 m, and forecast times within 12 hours of the time, to select the best wind field. For lead times beyond a few hours it was found that mesoscale NWP precipitation output from the latest 6 hourly forecast run provides the most reliable forecasts which include the development of new rain areas. The level of performance achieved using Nimrod in shown in Figure 4.

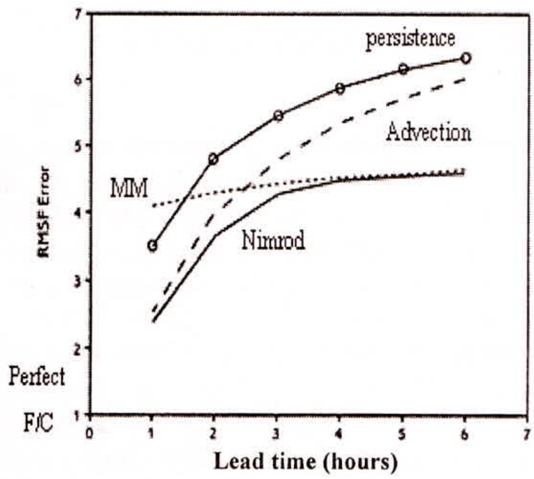

Fig. 4: Level of performance achieved by Nimrod as a function of forecast lead time (hours). Here MM is the UK mesoscale model and RMSF is the root mean square factor (from Golding, 1998)

One major limitation of the Nimrod system was found to be the way it handled convective initiation and development. In order to improve the representation of convective storms a complementary system known as GANDOLF was developed (Collier and Lilley, 1994; Pierce *et al.*, 2000). This system was based upon the use of the object oriented description of the development of convective cells as described by Hand and Conway, 1995; Hand, 1996. Attributes, including location, are associated with cloud cells. Multiple beam elevation radar data are used to initialise the state of development of each cell relative to a mature state defined from the observed population.

Unfortunately several weaknesses in the performance of GANDOLF have been recognised (Golding, 2000; Sleigh and Collier, 2002), Most notably the failure of the system to develop convection in new areas. New approaches based upon high resolution model output have sought to identify the probability of convective development (Hand, 2002) and convective development from the vorticity field (Sleigh and Collier, 2002). A new advection procedure based on optical flow ideas (Bowler *et al.*, 2004) has been shown to outperform the GANDOLF procedure based upon the identification of contiguous rain areas. This is consistent with the finding of Grecu and Krajewski (2000) who found that both spatial and temporal integrations significantly extend the predictability limits.

More recently Van Horne *et al.* (2006) have demonstrated that filter-based nowcasting systems used at the scale of a hydrologic basin can predict rainfall amounts and their spatial distribution. Likewise, the space-time probability density functions of surface rain rate and rain accumulation have been modelled (Seed, 2003). The blending of extrapolation, noise and NWP model forecast cascades allows a forecast ensemble to increasingly reflect the influence of large scale, atmospheric dynamics on the evolving precipitation field. This is the basis of the Short-Term Ensemble Prediction System (STEPS) (Pierce *et al.*, 2004)

A different nowcasting approach using a simple mass balancing of water within air columns and the advection of the variables using information from consecutive time steps has been described by Thielen *et al.* (2000). Similar work has been described by Georgakakos (2000). The input variables are surface rainfall and vertically integrated liquid water content (VIL). The authors claim some success based upon simulation experiments in forecasting the formulation of new cells, cell splitting and decay. However, one must have doubts about the operational viability of such a procedure given the complex interaction and occurrence of both stratiform and convective rainfall together.

The recent introduction of high resolution NWP models having grid lengths of a few kilometres is likely to offer better prospects of improving rainfall forecasts, particularly if radar data are assimilated. We discuss these approaches next. However Smith and Austin (2000) argue that the forecasts from future nowcasting systems need to be probabilistic in nature. They note that, in principle, the detailed knowledge that we have about the high-order statistics of rain patterns including fractal structure should allow improved extrapolation schemes. German and Zawadzki (2004) have proposed a method of deriving probability forecasts using radar data. Cornford (2004) has shown how to achieve probability forecasts through the use of a Bayesian state space modelling framework treating radar observations as noisy realisations of the underlying true precipitation process.

HIGH-RESOLUTION NUMERICAL MODELS

Until recently operational Numerical Weather Prediction (NWP) models were used to make forecasts of rainfall employing grid lengths of an around 12 km or larger. Consequently convective cloud scale processes had to be represented by parameterisation schemes comprising representations of microphysical processes associated with the formation of cloud and rain. Such schemes have been effective on scales of two to two and a half times the model grid lengths or greater (25 km or larger). However, there is little hope of forecasting reliably the initiation and subsequent development of individual clouds and very localised heavy rain often associated with flash floods. Fritsch and Carbone (2004) stress the need to invest substantial and sustained resources to address this challenge.

Increased computer power previously available only to researchers for individual case studies (see for example Zangl, 2004) is now enabling the operational introduction of high resolution (a few kilometres grid length) NWP models (Lean and Clarke, 2003). During 2005 the UK Met Office introduced a model using a 4 km grid length. At these spatial scales operational numerical calculations are approaching those made using Large Eddy Simulation (LES) models of individual clouds (see for example Cheng and Xu, 2006).

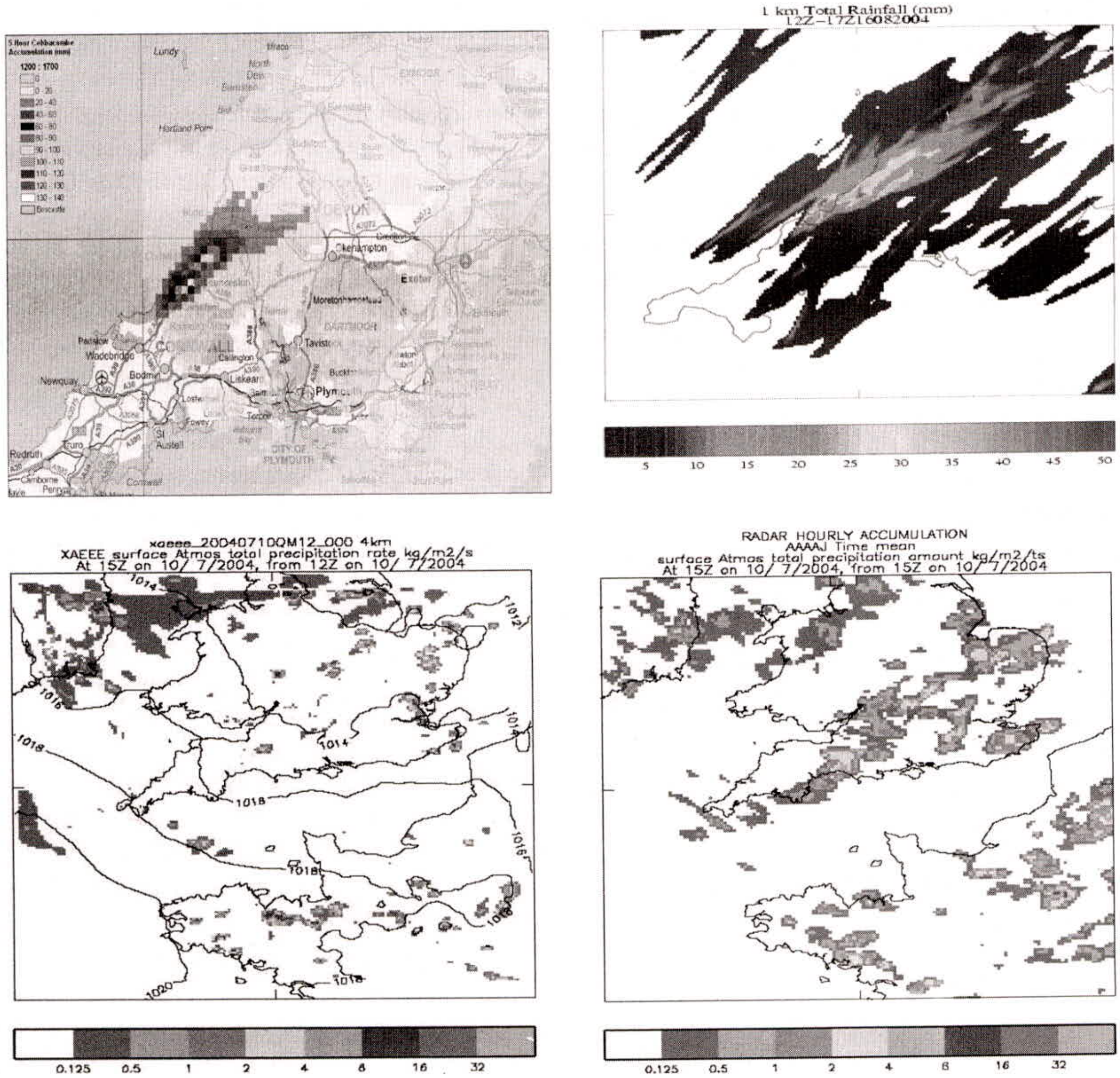

Fig. 5: Illustrating (a) Cobbacombe radar 5 hour total rainfall (mm); (b) 1 km Met Office Unified Model (um) forecast for 12-17 UTC 16 August 2004: (c) Radar hourly total rainfall at 15 UTC 10 July 2004; (d) 4 km UM 3 hour ahead forecast mode at 12 UTC 10 July 2004. [(a) and (b) courtesy P. Clark/ B.Golding, Met Office; (c) and (d) from the NERC CSIP Project]

Operational high resolution models may or may not provide rainfall forecasts which are spatially and temporally accurate, although they do offer the prospect of producing useful forecasts of convective storms on scales applicable for flood prediction (Roberts, 2005). Figure 5a shows the rainfall accumulation forecast made using the Met Office model running with a 1 km grid for the Boscastle storm compared to radar estimates of the rainfall which actually occurred, Figure 5b (Golding *et al.*, 2005). This case represents the current best achievable level of performance for the model due in part to the dynamic impact of the sea breeze with orography which induced a level of stationarity in the convective initiation. However, Figure 5d shows an unsuccessful 3 hour ahead model forecasts compared to the actual rainfall observed by radar (Figure 5c). The Met Office plan to introduce the use of a one-to-one and a half kilometre grid in about five years time giving much better performance. Nevertheless, variabilities on scales that it will still not be possible to resolve will remain, and therefore important issues in the formulation of models will need to be addressed especially in the area of data assimilation and sub-grid scale processes. This is particularly so if large rainfalls are to be predicted accurately as pointed out by Zangl (2004). These uncertainties require detailed analysis of data collected in field campaigns (see for example Morcrette *et al.*, 2006), and comprehensive data assimilation systems as discussed next.

DATA ASSIMILATION

Predictions made by Numerical Weather Prediction (NWP) models may be wrong due to the inaccuracies in the way the models are structured. In addition model outputs are sensitive to small changes in the initial conditions from which model integrations begin (Thompson, 1957; Lorenz, 1963). Errors in initial conditions tend to grow rapidly in processes that occur at smaller spatial-scales. Hence NWP is an initial boundary value problem. Specification of proper initial and boundary conditions are essential to have a well-posed problem, that is a problem which has a unique solution that depends continuously on these conditions.

Data assimilation may be described as the process through which all the available information is used to determine, as accurately as possible, the state of the atmospheric flow on a regular grid. Rihan *et al.* (2005) give an outline of data assimilation noting the broad classes namely sequential and variational. Sequential data assimilation involves an analysis produced by combining a forecast background and the observations available at a given time. The numerical procedure used is then integrated forward to the next observation time, starting from the analysis initial conditions. The variational approach includes three-dimensional (3D-Var) and four-dimensional (4D-Var) procedures in which a search is made for an optimal set of model parameters which minimise the discrepancies between the model forecast and time distributed observational data over the assimilation window. The minimization process involves a fast and accurate evaluation of the gradient of a *cost function* which may be provided by adjoint modelling (see for example, Dimet and Talagrand, 1986).

ASSIMILATION OF RADAR DATA INTO HIGH-RESOLUTION MODELS

Interest in assimilating radar-derived information has grown steadily as the resolution of operational models has improved. This is because the resolution of the raw radar data is much higher than the resolution of the models. Also if the challenge of forecasting convection is to be met then high resolution data are required for model initialisation.

Weather radars offer information that may contribute to both the initialisation of dynamic model variables such a wind and temperature from Dopper radial winds (see for example Lin *et al.*, 1993; Sun and Crook, 1997), and diabatic heating from latent heating inferred from the precipitation measurements (see for example Wang and Warner, 1998). Fabry *et al.* (1997) (see also Weckwerth *et al.*, 2005) demonstrated the retrieval of humidity via refractivity information derived from radar ground clutter echoes.

The method of assimilating precipitation information at its simplest assumes that the surface precipitation rate is proportional to the vertically integrated latent heating. Later versions of the approach use the three-dimensional information provided by radars. The technique is referred to as Latent Heat Nudging where the profiles of model latent heating are "nudged" (relaxed) towards the observations. Jones and Macpherson (1997) used this approach with radar data and found an improvement in Quantitative Precipitation Forecasts in the first six to nine hours ahead.

A somewhat different approach was used by Rogers *et al.* (2000) who used the radar reflectivity to trigger a model convective cumulus parameterisation scheme to release convective activity. A development of the nudging approach to assimilating rainfall information has been described by Orlandi *et al.* (2004). Here the Kuo convective parameterisation scheme is inverted and satellite data are used. Tests with rainfall estimates derived from infrared and microwave satellite data do demonstrate some success. Major challenges remain in this area, particularly when employing 3D- and 4D-Var approaches (see for example Wu *et al.*, 2000). A comprehensive summary of progress on the assimilation of radar data into NWP Models has been given by Macpherson *et al.* (2004). They noted that currently there are no clearly preferred techniques for assimilation of radar rainfall data, although they suggested that the 4D-Var approach is likely to be the most natural, and therefore most successful, approach in the long term in spite of all its difficulties.

Doppler radial wind data have been assimilated successfully into 3D-Var systems (see for example Sun and Crook, 1997; Rihan *et al.*, 2007). Whilst these data do impact forecasts of rainfall there are difficulties in assimilating the data successfully with other wind information. This is an area of continuing research.

ENSEMBLES AND UNCERTAINTY

In spite of the effort to specify accurate model initial conditions discussed in the previous section, in a non-liner dynamical system the growth in space and time of initial uncertainties is flow-dependant. Our knowledge of the physical processes that cause this random uncertainty guides the formulation of model stochastic parameterisation schemes. (see for example Strensrud and Fritsch, 1994; Strensrud *et al.*, 2000). Examples of these schemes are the ECMWF Cellular Automation Stochastic Backscatter (CASB) scheme (Buizza *et al.*, 1999); and the Met Office Stochastic Kinetic Energy Backscatter (SKEB) scheme, which uses a cloud scale model to calibrate model error due to convection (Mason and Thomson, 1992).

However, errors in numerical models of the atmosphere are hard to remove as assumptions of the existence of deterministic parameterisations for sub-grid scale phenomenon are made (Palmer, 2001). Also excessive kinetic energy sinks, and a lack of measurable kinetic energy sources, occur in numerical descriptions of systems such as frontogenesis. Consequently it is necessary to gain an understanding of the role of error modes in weather forecasts. In a nonlinear system such as the atmosphere the growth of initial uncertainties during a given forecast period is flow-dependent. To forecast this flow-dependency predictability we may generate an *ensemble* of forecasts from small perturbations in model input conditions. Different methods of producing such perturbations have been compared by Buizza *et al.* (2005). The most commonly used techniques are:

- *Error Breeding:* A filtering method that uses the difference between forecasts from perturbed and control model runs to generate a new perturbed analysis.
- *Perturbed Observations:* A filter method which uses perturbations to the model input. This can be computationally expensive and is not used operationally.
- *Singular Vectors:* The fastest growing perturbations in the initial conditions are identified. These will grow faster than the error in the forecast.
- *Ensemble Kalmen Filter (ENKF):* An ensemble of states is sought which are consistent with the best information available. The observations are perturbed when each ensemble member is updated so quantifying the errors in the analysis (Evensen, 1994).

The Kalman filter is generally regarded as the natural frameworks for determining how the different sources of uncertainly propagate through a system. However there is no definitive method of generating ensembles. Figure 6 shows an example of the ensembles generated by the ECMWF, Ensemble Prediction System (EPS). The ensemble mean is useless on its own, and what is sought is a better way of using the full information content of the ensembles. The overall aim for meteorological forecasting is to use time varying covariance information from the ensembles to impact data assimilation procedures which we discussed previously. The second moment of the ensemble is its spread. When the spread is large a deterministic forecast will be an unreliable estimate of the truth. Palmer *et al.* (2006) discuss the relationship between the spread of the ensemble and the skill of the forecast.

The use of ensembles has led to improvements in the accuracy of general weather forecasts at medium (greater than 24 hours ahead) range lead times (Tacton and Kalnay, 1993) and at short (less than 24 hours ahead) range lead times (Du *et al.*, 1997). The STEPS system mentioned above allows the probability of precipitation to be derived from an ensemble of forecasts for several hours ahead. However, difficulties remain in pinpointing rapid development over small areas and convective initialisation leading to extreme events. Also work needs to be done on extracting useful information from the ensemble.

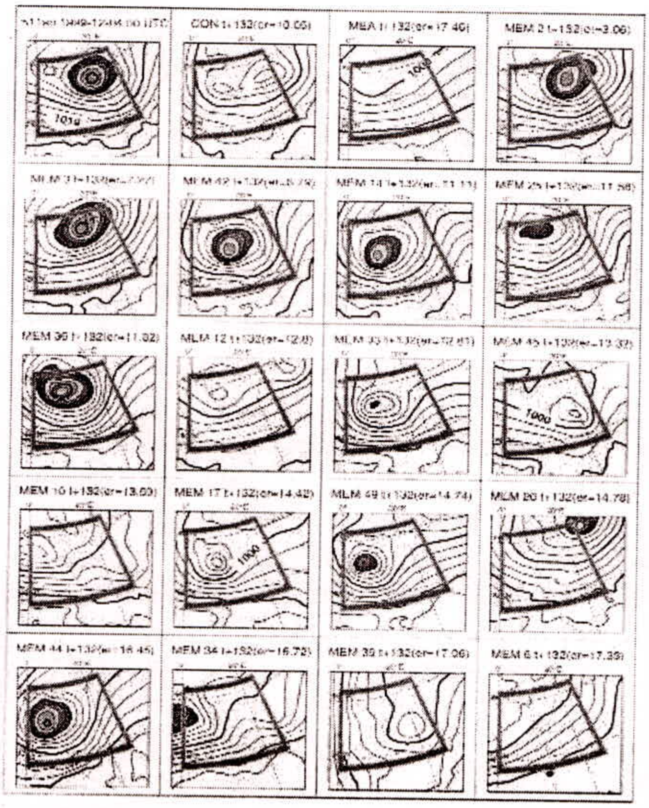

Fig. 6: Part of an ensemble generated by the ECMWF EPS (courtesy T. Palmer, ECMWF)

In practice the ensemble size from the EPS is generally too large to use each member individually as input to a high resolution NWP model. Hence, Molteni *et al.* (2001) proposed a selection procedure using a parameter space defined as the 5-day accumulated grid point precipitation over specified target area encompassing river catchments of interest. Individual ensemble members were selected such that the first and the second chosen were those which were closest and furthest away from the ensemble mean respectively. Other members were maximised.

An alternative approach is to generate the ensembles from the high resolution model outputting a representation of the statistical information contained therein. Bayesian methods of combination have been demonstrated to work well (see for example Rajagopalan *et al.*, 2002), but Stephenson *et al.* (2005) have stressed the importance of seeing the combination of ensemble members as an integral part of the forecasting process not just an optional post-processing stage. Shutts (2005) argues for the introduction of kinetic energy source terms into NWP models that counteract energy drain in near grid-scale processes. Kinetic energy is backscattered into the flow by introducing vorticity perturbbations with a magnitude proportional to the square root of the total energy dissipation rate. This allows model error to be associated with the spread of the ensemble and therefore the forecast skill can be improved. Measurements of eddy dissipation in the atmosphere are not easy to make, although Davies *et al.* (2004) have reported measurements in the urban boundary layer using Doppler lidar consistent with the values takes by Shutts (2005).

SOURCES OF HYDROLOGICAL UNCERTAINTY, DATA ASSIMILATION AND ENSEMBLES

Uncertainties in hydrological model structures and input data make it very necessary to calibrate hydrological models in order to achieve the best fit to measured hydrographs. This is particularly problematic for ungauged catchments estimated using regression or clutter techniques (Burn and Boorman, 1993) However, more recently the parameters of hydrological models are frequently estimated by minimising some form of *cost function* that involves the error (difference) between the model-generated flow and the measured flow. This approach is similar to that employed in meteorological model data assimilation variational analysis schemes (see above), although in flow forecasting data assimilation usually refers to real-time parameter updating (adaptive) procedures.

Model optimisation procedures generally assume that the observations against which the model predictions are compared are free of errors. Clearly this is not true and this, coupled with limitations in model structures, leads to a situation where several, indeed many, sets of parameters may provide acceptable forecasts. This is known as the concept of *equifinality* which is the basis of the generalised likelihood uncertainty estimation (GLUE) methodology proposed by Beven and Binley (1992). In this methodology a prior distribution of parameter values is used to generate random parameter sets using Monte Carlo simulation. A quantitative measure of performance is used to assess the acceptability of each model parameter set. The simulations for the various parameter sets may also be constrained by the model saturated area which limits the range of realistic values of the model transmissivity parameter (Blazkova *et al.*, 2002). This leads to an assessment of uncertainty in the model predictions. Such measures include the use of the sum of square errors and autocorrelation functions which maybe combined using fuzzy statistics (see for example Franks *et al.*, 1998) or Bayes equation (see for example Krzysztofowicz, 1999).

The uncertainty in model predictions may be constrained by data assimilation, the use of an adaptive procedure which uses real-time observations of flow, soil moisture or rainfall etc to correct the model predictions (see for example, Cluckie *et al.*, 1987; Houser *et al.* 1998). Young (2002) reviews the statistical framework for data assimilation with stochastic transfer function models based on the use of the Kalmen filter. (see also Young, 1984). One limitation of this approach is its assumption that the stochastic processes are Gaussian. In fact, this limitation may be removed by using Bayesian numerical methods or Monte Carlo Markov Chain algorithms (see for example Vrugt *et al.*, 2003).

Given that input data maybe derived from different sources, the obvious example being rainfall from rain gauges or radar, it maybe necessary to combine these different data. One approach to this problem is the use of a stochastic-space model which uses a Kalman filter procedure allocating weights for each data form based upon the respective uncertainty of the observations and the predictions (see Grum *et al.*, 2002). Recognising that flow predictions will nevertheless remain uncertainty, a Bayesian post processor maybe used to analyse the components of the output error associated with the particular data inputs (see for example Robbins and Collier, 2005). An example of the impact on flow predictions, made using deterministic and stochastic models, of errors in the rainfall inputs analysed using a Bayesian post processor are shown in Figure 7. Also shown is the error range in the observed hydrograph arising from the flow measurement error. Note the significant improvement produced by the use of the stochastic model.

An alternative approach to examining the error in predicted flows is to generate an ensemble of output hydrographs in a similar way to that used in the GLUE methodology. This is an area of activity development in hydrology, a recent example being discussed by De Roo *et al.* (2003). Ensemble streamflow forecasts are now an integral part of the U.S. Advanced Hydrologic Prediction Service (AHPS) operated by the Department of Commerce, National Oceanic and Atmosphere Administration (NOAA) National Weather Service (NWS) (McEnery *et al.*, 2005). However, the same consideration as for the extraction of meteorological information from the ensemble will be necessary. Pierce *et al.* (2004) show ensemble flow forecasts and the observed flow for a lead time of nine hours using six hours of forecast rain produced using STEPS and a further three hours of zero rain. The ensemble members encompass the observed flow hydrograph and may be used to calculate the probability of exceedance of an alarm flow threshold at a given lead time. Mylne (2002) has shown how the added value of an ensemble forecast (when compared to a deterministic forecast) maybe exploited in conjunction with a cost-loss model to optimise decision making in terms of economic impacts.

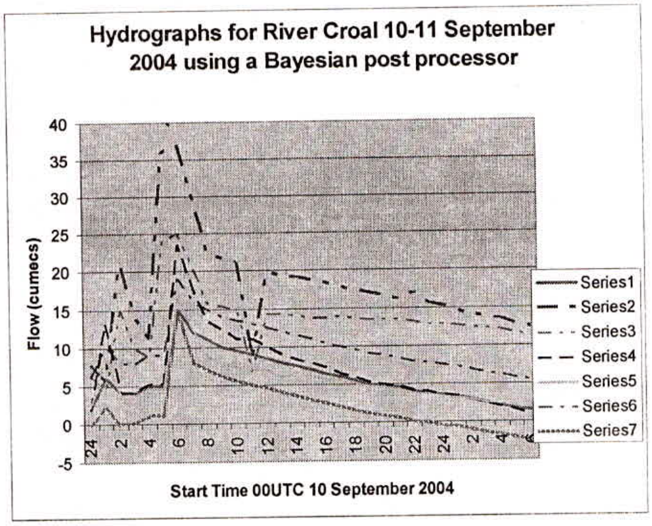

Fig. 7: The range of deterministic and stochastic 1 model hydrographs for the period 10-11 September 2004 using the errors in the flows derived from the Bayesian post processor. Also shown are the observed hydrograph and its error range based upon the mean flow measurement error. Series 1, 6, 7 observed; series 2, 3 deterministic; Series 4, 5 stochastic 1 (Collier and Robbins, 2007)

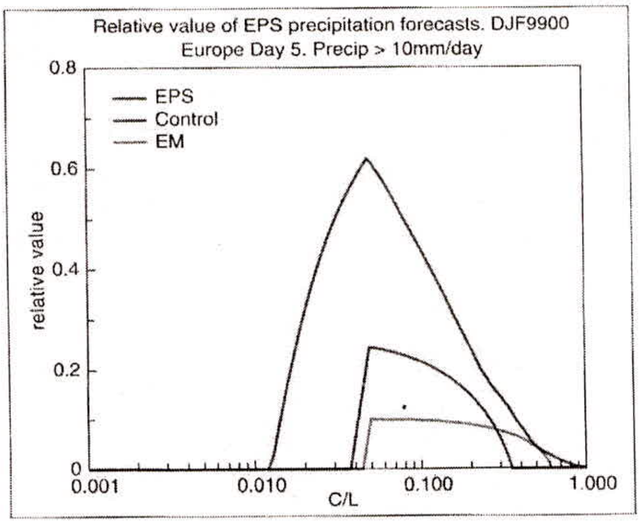

Fig. 8: The potential economic value of a probabilistic prediction based on the ECMWF EPS compared with the economic value of a deterministic prediction based on the single control forecast or on the ensemble mean forecast. The results indicate that the economic value of the probabilistic EPS prediction is highest for most cost/loss ratios (C/L) (from ECMWF, 2000)

COST-LOSS ANALYSES

A forecast of flooding can be used to predict the probability of occurrence of an event of a specific magnitude (E) and assess what amount of money (C) to spend to implement mitigation measures to protect against the resulting loss (L). The forecast can be used to predict the probability of occurrence of E and its value to the user can be assessed using a graph of the type shown in Figure 8. An important element in these analyses is the social conditions of the population at risk. Social vulnerability indices may be used to assess the socio-economic impact of flooding, see for example Tapsell *et al.* (2002).

CONCLUDING REMARKS

There are many uncertainties in forecasting heavy rainfall and the resulting flooding. It is very unlikely that all areas of uncertainty, be they in the observations used as inputs to models, or the model structures themselves, will be reduced to insignificant levels. However, there is hope that uncertainty can be constrained, measured and presented as an integral part of the forecast. This will undoubtedly involve statistical procedures, both in representing error distributions and in combining these error distributions using Gaussian, fuzzy logic or other approaches, or in introducing energy feedback to the flow equations.

The way in which we present uncertainty to users is key to providing better flood warnings. However, the initial challenge must be to predict extremes in a changing climate. The use of forecast ensembles both for rainfall predictions from high resolution numerical model, and the subsequent flow forecasts generated using adaptive approaches, offer hope of limiting the impact of errors.

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