19A.1

# ASSIMILATION OF RADAR REFLECTIVITY DATA IN THE MET OFFICE CONVECTIVE-SCALE FORECAST SYSTEM

Lee D. Hawkness-Smith and S. Ballard
Met Office, Reading, Berks., United Kingdom

## 1. INTRODUCTION

A number of operational centres are now routinely running convection permitting atmospheric models for regional Numerical Weather Prediction. The Met Office is currently running a variable resolution version of the Unified Model (UM; Davies *et al.* 2005), the UKV, with outer resolution 4km and inner resolution of 1.5km over the United Kingdom. The high horizontal resolution of the atmospheric model, and associated high resolution representation of orography, and improved physical parameterizations, allows the model to produce mesoscale and convective features with a high degree of realism. The major challenge for the nowcasting application, i.e. forecasting in the range 0 – 6 hours, is to support the improved realism with improved accuracy by the optimum application of data assimilation.

The UKV modelling system runs 8 times per day, with 3-hourly cycling 3D-VAR. Observations assimilated in 3D-VAR include 3 hourly cloud cover, hourly SYNOP reports: screen temperature, relative humidity, wind, pressure and visibility, any available radiosonde ascents, hourly AMDAR, wind profiler, GPS time delay, scatterometer winds, AMVs, and hourly SEVIRI infra-red. In addition, hourly radar-derived surface rain rates are assimilated by latent heat nudging, where model profiles of latent heat release are scaled by the difference between modelled and observed precipitation.

Latent heat nudging has been shown to have a beneficial impact on precipitation forecast skill, particularly during the first three hours where its impact exceeded that of 3DVAR (Dixon *et al.* 2009).

Precipitation forecasts derived from the operational UKV are beaten by advection based methods in the first three hours. Therefore the current operational Met Office nowcasting system of post-processed data (UKPP/STEPS, Bowler et al 2006) uses information blended from an advection based scheme and the UKV model.

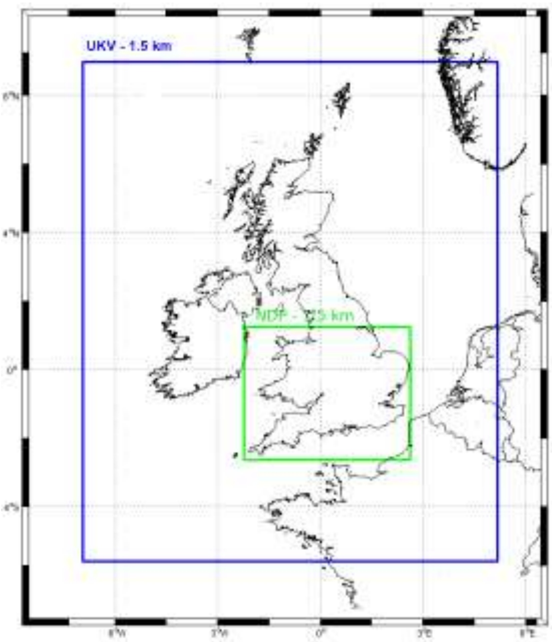


Figure 1. Model domain of Southern UK nowcasting demonstration project (NDP), nested within the UKV model.

With continued increases in the availability of computer resources and observations, including new data types and more frequent observations, the Met Office developed an NWP based nowcasting system, as part of the Nowcasting Demonstration Project (NDP) which ran as a demonstration over Summer 2012. The system provided 7 hour forecasts hourly, for a Southern UK domain, nested within the UKV, shown in figure 1. The forecast model part of the NDP system was essentially the same as the UKV model, except on a smaller domain, but with fixed 1.5 km horizontal grid spacing and the same parameterizations. However, there were a number of differences in the data assimilation system. The NDP system used hourly cycling 4D-VAR data assimilation for all observations except radar derived rainrates, which were assimilated via latent heat nudging. The use of 4D-VAR allows the optimum use of high temporal (5-15 minutes) resolution observations, although at considerably increased cost relative to 3D-VAR due to the

* *Corresponding author address:* Lee D. Hawkness-Smith, Met Office, Meteorology Building, University of Reading, Reading, Berks, RG6 6BB, United Kingdom; e-mail: lee.hawkness-smith@metoffice.gov.uk

requirement to iterate a linearized version of the forecast model.

Observations assimilated in 4D-VAR included Doppler radial winds from 5 radars, every 10 minutes; winds from 4 wind profilers every 15 minutes; MSG SEVIRI satellite radiances, channels 5, 6 and window channels (sea only) every 15 minutes; hourly 3D moisture from satellite and surface cloud observations; hourly MSG cloud- and humidity-tracked winds; hourly aircraft temperature and wind; and hourly surface temperature, relative humidity, wind and pressure.

Alongside the development of the NDP system, the Met Office is investigating the use of novel observations in convective-scale data assimilation.

Radar observations which are being actively researched include Doppler winds, refractivity, and reflectivity. The assimilation of radar Doppler winds has recently been introduced for the UKV operationally, giving a 1-hour improvement in forecast skill at low rain rates.
This paper discusses research into the assimilation of radar reflectivity at the Met Office. The UK Weather Radar Network is shown in figure *2*. Whilst latent heat nudging of radar-derived surface rain rates is beneficial for precipitation forecasts, there are advantages to using radar reflectivity data directly within the variational assimilation system. Variational assimilation does not require the assumption of latent heat nudging that latent heat release occurs in same column as precipitation. The use of all observations together in a common framework should alleviate sub-optimal interactions and allow the consistent use of complementary information. A further advantage of 4D-VAR is that it evolves the background error covariances.

**2. APPROACHES TO RADAR REFLECTIVITY ASSIMILATION**

Sun (2005) provides an excellent review of the approaches taken to the assimilation of radar data in convective-scale models. Convective-scale data assimilation has a number of different challenges to large-scale assimilation. The specific aim of convective-scale data assimilation is to improve quantitative precipitation forecasting (QPF), thus the accuracy of the location and intensity of precipitation is the key metric of performance for convective-scale forecasts. Balance approximations used in large-scale data assimilation generally do not apply at the convective scale, and whilst a linear approximation to dynamics at the synoptic scale may be close to a non-linear model trajectory on the order of 6 hours, convective-scale features have time scales on the order of minutes.

Modern approaches to the assimilation of radar data at the convective scale include variational and ensemble techniques, which are both able to assimilate indirect observations and produce a best-fit for the entire model domain using all available observations.

Caumont *et al.* (2009) have a developed a 1D+3D-Var system for the assimilation of radar data in the Meteo-France convective-scale Arome model. They use a Bayesian approach following Kummerow *et al.* (2001) to derive pseudo-humidity profiles which are then assimilated in 3D-Var with all other observations, and this system has improved precipitation forecasts. Similarly, Ikuta and Honda (2011) have developed a 1D+4D-Var assimilation system for the Japan Meteorological Agency (JMA) meso-scale model (MSM). The particular advantage of this approach is avoiding the difficulty of handling the non-linear relationships between radar reflectivity, rainwater mixing ratio and humidity, and the non-Gaussian probability distribution of these variables and their covariances, in a 3D or 4D-Var assimilation.

Jenny Sun has pioneered the assimilation of radar data in 4D-Var. Sun and Crook (1997, 1998) developed a 4D-Var Doppler Radar Analysis System (VDRAS), with which they demonstrated the ability to initialise a convective-scale model with a warm-rain parameterisation using only single Doppler-radar observations in a short time window. Studies using the VDRAS system have used summer cases, where the warm-rain process dominates and ice can be neglected. To avoid problems with the minimization caused by non-linearities, they made a number of changes to the microphysics scheme – keeping both the evaporation rate and the rainwater fall velocity constant for rainwater mixing ratios below a critical value, to avoid large gradients in the adjoint calculation. Unlike the Met Office 4D-Var system, VDRAS is not incremental, but instead iterates a non-linear forward model and uses the adjoint of its tangent-linear to calculate the gradient terms of the cost function.

Wang *et al.* (2011) developed the Weather Research and Forecast model (WRF) 4D-Var system to assimilate radar-reflectivity observations. The developments made include adding cloud water and rainwater as control variables, which required modelling their error covariances, developing a linear approximation of a Kessler warm-rain scheme and its adjoint, and developing an observation operator for radar reflectivity. Following Sun and Crook (1997), they calculate the rainwater mixing ratio, $q_r$, from reflectivity and assimilate $q_r$ rather than reflectivity, noting that the relationship between $q_r$ and reflectivity is highly non-linear. In their study, they used 5-minute radar data and a 30 minute time-window, having found problems with spin-up in their initial experiments with shorter time windows. Note, however, that this time window is significantly shorter than the 1-hour window used in the Met Office NDP system. To overcome the 'zero rain' problem, where precipitation in the model and the observations are not collocated, they found the use of multiple outerloops to be critical. The quality control procedure used in their study follows that of Xiao *et al.* (2005, 2007), using the NCAR "SOLO" software (Oye et al. 1995) to perform manual data quality control.

Following this work, Wang *et al.* (2013) developed an improved a scheme where the derived rain water mixing ratio is assimilated instead of reflectivity, and additionally observations of humidity saturation are assimilated where radar reflectivity exceeds a threshold above cloud base.

Sun and Wang (2013) reviews the developments and plans Advanced Research Weather Forecast and Forecasting (WRF-ARW) system for varational assimilation of radar observations at the convective-scale. They have found encouraging initial results from an incremental 4D-VAR system, but further investigations are planned, particularly in a continuous cycling context, and to take advantage of dual-polarization observations.

Kawabata *et al.* (2011) modified a convective-scale nonhydrostatic model 4DVar system (NHM-4DVAR) to directly assimilate radar reflectivity. Their system uses the full non-linear NHM model as the forward model, which includes three-ice bulk cloud physics, and an adjoint model which includes the warm rain process. The moist control variables are total water excluding rainwater ($q_v + q_c$), and the relative mixing ratio of rainwater ($q_r/q_{vs}$), where $q_{vs}$ is the background saturation mixing ratio of water vapour. These variables were chosen to give a background error probability distribution that was relatively close to Gaussian and such that the error correlations between the control variables were not large. They use a Z-$q_r$ relation as the observation operator. To avoid the ambiguity of low reflectivity signals, they treat reflectivity < 10 dBZ specially, assimilating 0 dBZ only where the background exceeds 10 dBZ, to avoid drying the background in the case where precipitation is not detected by the radar. Following impact tests to determine the observation error including the representativeness error and errors in the observation operator, they set the observation error to 10 dBZ. They used an assimilation window of 30 minutes, assimilating radar reflectivity and radial-wind data at 1-minute intervals, GPS-Precipitable Water Vapour (PWV) at 5-minute intervals, and surface and wind profiler data at 10-minute intervals. To allow the 2-km resolution NHM-4DVAR system to spin-up from the initial and boundary conditions provided by a larger domain 2-km model embedded within a 5-km NHM model, they performed 8 1-hour analysis-forecast cycles before starting the assimilation experiment. The spin-up cycles were initiated in a period of calm weather.

Through the assimilation of radar reflectivity and radial winds Kawabata *et al.* (2011) were able to produce an improved forecast over the Tokyo area. An experiment to increase the assimilation window to 1 hour, hoping to extend the influence of radar assimilation, did not reproduce the intensity of the main convective feature in their case study, and produced a worse forecast than the experiment using a 30-minute assimilation window. They also performed experiments with an incremental system, using a tangent-linear approximation to the full non-linear model in the forward integration instead of the full model. In these experiments, the assimilation converged slowly and the model runs failed to produce the strong convective feature, which they attribute to the inability of the incremental system to represent the strong non-linearity of such a convective feature.

The potential of the ensemble Kalman Filter (EnKF) for convective-scale data assimilation has been demonstrated (Snyder and Zhang, 2004, Zhang *et al.* 2004, Caya *et al.* 2005), but convective-scale data assimilation with 3D-Var and 4D-Var systems is currently more mature, and given the investment the Met Office has made in its operational 3D and 4D-Var data-assimilation system, current Met Office research focuses on variational approaches, however, the Met Office is simultaneously developing a strategy for ensemble data assimilation at the convective-scale, and future studies will compare the assimilation of radar reflectivity data within variational and ensemble systems.

The Met Office has developed two methods for the variational assimilation of radar-reflectivity data: the indirect approach, where radar reflectivity and model background data are used in 1D-Var to produce relative humidity and temperature profiles, which could be assimilated in 3D-Var or 4D-Var, and the direct approach, where a forward model is used to assimilate reflectivity observations within 4D-Var. Research is ongoing to determine whether either variational method can beat the current method of LHN at acceptable cost.

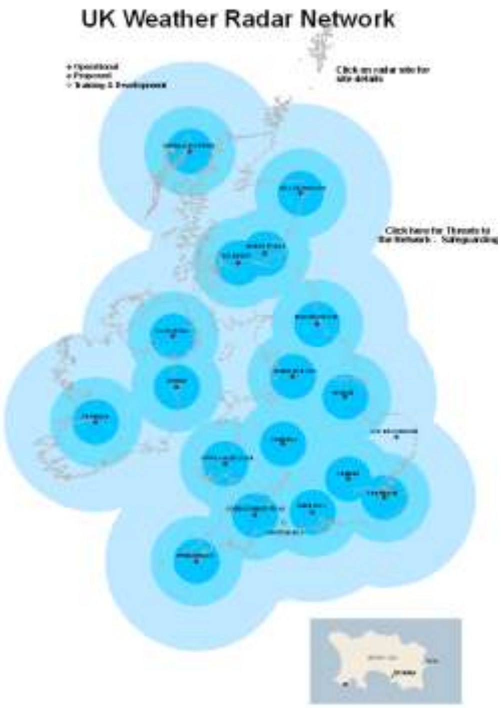


Figure 2. UK Weather Radar Network

The first step in developing a system for the assimilation of novel observations is monitoring the observations against the model background, to ensure that the observations are of sufficient quality, and the fit between the observations and the model is good enough, to fulfil the assumptions of the data assimilation method being used. For 3D-VAR and 4D-VAR, that means that the observations should be unbiased, and that the minimisation problem is only weakly non-linear. The radar data must therefore be processed to remove artefacts such as clutter and anomalous propagation, and the observations selected for assimilation must be sufficiently close to the model background to allow the assumption of approximate linearity to hold.

The Met Office has implemented a Radar Quality Management System (RDQMS) to address issues of radar data quality and reliability, which impact not only on data assimilation, but also hydrological applications (Georgiou *et al.* 2011).

Figure 3 illustrates the radar data processing chain. Data preprocessing is performed on the RADARNET server, which passes data to the Observation Processing System (OPS). Preprocessing includes options to average in range and azimuth, to recalibrate, to measure the noise level for each averaged ray and perform noise subtraction, and to set flags for clutter, partial beam blockage and speckle. The data is encoded in NetCDF and Grib2 files with all the quality control information and metadata.

The OPS performs quality checks using the model background for all observations ingested into the Met Office data assimilation system. The observations are filtered using quality control flags. A forward model is used within OPS which simulates reflectivity using the rain and ice water content from the UM. A simple correction is made for beam bending and earth curvature; attenuation and beam integration are not currently accounted for but will be included in future versions of OPS. Superobbing can be performed on either a polar or the model grid, and there is an option to Poisson thin the data. Thinning the data before assimilation is important not only to reduce the data volume and reduce the cost of VAR, but also as assimilating observations which are closer than the observation error correlation lengthscale may be detrimental to the analysis.

The 1D-VAR retrievals of humidity and temperature profiles are also performed within OPS. Quality checked and superobbed observations are provided with columns of model variables at observation locations to VAR for assimilation. VAR provides increments to the UM.

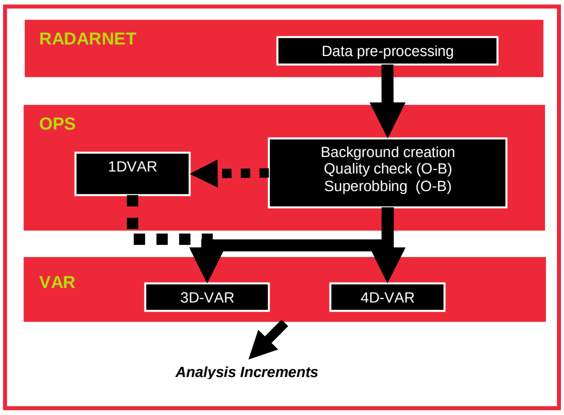

Figure 3. Radar data processing chain

Recent developments at the Met Office have focussed on the development of the 4D-VAR system to assimilate radar reflectivity observations directly, and the remainder of this paper discusses this work.

## 3. DEVELOPMENTS TO 4D-VAR

The Met Office 4D-VAR system (Rawlins *et al*. 2007) has an incremental formulation, where the UM is used to provide the background, and a simplified, linear model, the perturbation forecast (PF) model, is iterated during the minimisation procedure to provide updated values of the model guess fields through the assimilation time window. Following each run of the PF model, its adjoint, which is used to calculate gradients for the minimisation, is run backwards through time. The model variables are transformed into control variables which should be uncorrelated. The control variables used in the Met Office VAR system are velocity potential, stream function, unbalanced pressure and a humidity variable which represents total water.

Implementing assimilation of radar reflectivity within the VAR system has involved the introduction of a reflectivity operator, and a linearization of the operator and its adjoint, and enhancements to the PF model to include a rainrate model field, from which reflectivity is calculated. The reflectivity operator has the form:

$$Z\ [\mathrm{mm}^6\ \mathrm{m}^{-3}] = Z_R + Z_I \qquad (1)$$

where the rain component is given by:

$$Z_R = 181R^{7/4.67} \qquad (2)$$

where R is the model rainrate in mm hr$^{-1}$ interpolated to the observation location, and the ice component is given by:

$$Z_I = 10^{0.035(T-273.15)+3.2}\ q_I^{\,1.67} \qquad (3)$$

where $q_I$ is the model ice water content in kg kg$^{-1}$ and T is the model temperature in K interpolated to the observation location. The VAR system includes a cloud incrementing operator, by which $q_I$ is related to total water, which could be used in the assimilation procedure, alternatively the PF model could be developed to explicitly account for ice, or the ice term could be used purely for the UM background, with increments to total water calculated via the rainrate term.

When developing the PF model, a balance must be maintained between increasing physical realism, whilst avoiding unnecessary complexity which would make the system more non-linear and hence cause problems in minimisation. This is particularly challenging for cloud and precipitation microphysics which are inherently non-linear.

The current representation of the rainrate field in the PF model is as a diagnostic variable which is calculated from the condensed water increment in an autoconversion term. A set fraction of condensed water is autoconverted into precipitation during a model timestep. There is no attempt to represent evaporation, which could potentially lead to negative water contents in the linear framework. Improvements to this representation are currently being researched, and tested using linearization tests, where the PF model increments are compared to UM increments.

A limitation of this approach is that where there is no rain in the model background, there is no gradient with respect to rain in the 4D-VAR cost function, and hence no means by which to introduce rain. Where there are large differences between the model and observations, the observations will have to be rejected to avoid the introduction of strong non-linearity. Thus misplacement of convective systems in the model with respect to the observations may be particularly challenging. Where observations can be assimilated, however, the model error covariances should allow the information to spread, and assimilating radar reflectivity observations in combination with the full set of standard observations should provide complementary information, constraining the analysis.

The case studies presented in this paper use polar superobbing of the reflectivity observations followed by binning in UM gridboxes. Thus far only rain observations have been successfully assimilated, although tests for the assimilation of ice observations are being performed. The method used for identifying reflectivity observations as being due to rain is checking for the model background temperature > 3°C, to ensure that melting snow should have completed melted, avoiding ambiguities due to the bright band.

## 4. CASE STUDY - 5 APRIL 2011

A number of experiments have been performed for a case study in the southern UK, using an observational data time of 0900Z, 5 April 2011. This case was selected as it includes a number of distinct precipitation features of different scale, separated by areas of no rainfall.

The case was dominated by moist, south-westerly flow. A mature cyclonic system passed to the north of the UK, with an extended occlusion featuring secondary frontal waves passing over Wales and southern England. At 0900Z there is extensive rainfall over west and south-west Wales, over south-east England and the Thames estuary, and there is a north-west south-east oriented band of rainfall over Dartmoor in the south-west of England, shown in figure 5 (top). The model background used in the experiments described in this report was generated from a NDP model spun-up from a 1 hour forecast dump from the 0600Z operational run of the UK4 model. The background at 0900Z, shown in figure 4 (bottom) captures the overall pattern of rainfall over Wales, the south-west of England and the south-east of England, but the heavy rain in south Wales is too far south, and otherwise the rain in Wales is too tightly tied to the coast. The rain in the south-west of England is too intense and too extensive, rainfall in the south-east is insufficiently extensive, and there is spurious rainfall in central southern England. In the 4D-VAR test described in this report, the nominal analysis window was 0830Z – 0930Z, although with observations only available at 0900Z, this was effectively a 30 minute analysis window.

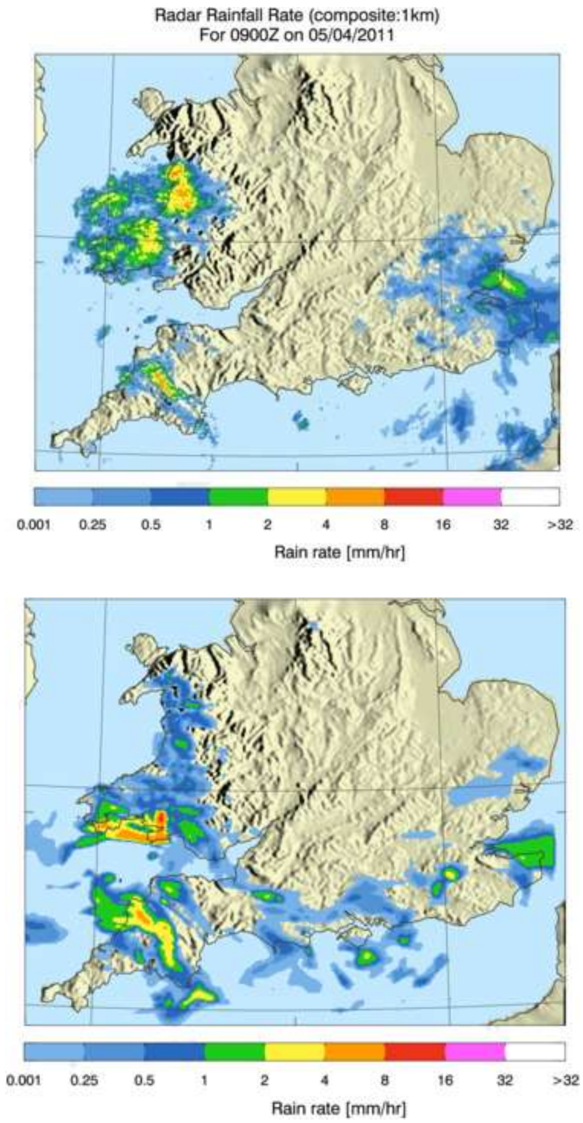


Figure 4. Radar derived surface rainrate product, NIMROD, (top) and NDP model background surface rainrate, BACKGROUND, (bottom) for 0900Z, 5 April 2011.

### 4.1 PRELIMINARY TESTS

In preliminary investigations, following the coding of the reflectivity operator in OPS and VAR, and the introduction of rainrate increments on all model levels to the PF model, and successful adjoint tests, a very conservative 4D-VAR setup was used to produce a radar reflectivity assimilation test job which would converge, and be used as the basis for further tests seeking to improve the use of observation data in the analysis and the quality of the subsequent forecast runs.

The conservative setup which first allowed convergence in VAR for radar reflectivity assimilation featured:

- Rejection of all observations where the model temperature <3 C,
- Rejection of all observations where |O-B| > 5 dBZ,
- Rejection of all observations where the simulated reflectivity is less than the radar noise level,
- Thinning of observations to 1 observation from an individual scan per 16 UM gridspaces,
- Observation error set to 15 dBZ for all assimilated observations.

It is noted that an observation error would not normally be set less than the rejection criteria. The initial value of 15 dBZ for the observation error was chosen on the basis of monitoring statistics which indicated that this was the mean O-B value for all radars over a period of three months. It should be noted that this is a very large difference, equivalent to approximately a factor of 10 difference in rainfall rate. This highlights one of the particular challenge of data assimilation for radar reflectivity, which is the large variability exhibited by precipitation features, and hence the difficulty in producing physically reasonable linear models of precipitation processes and the observation operator.

The rejection of observations where the simulated reflectivity is less than the radar noise level excludes observations where the model rainrate is zero, and hence the gradient between reflectivity and rainrate is undefined, and also observations where the model rainrate is very small, in which case the gradient between reflectivity in dBZ units and rainrate becomes very large.

Whilst the earliest tests allowed convergence, the analysis increments were very small, and the forecast runs were almost indistinguishable from the background run. A number of further experiments were performed varying a number of parameters to allow a closer fit to the observations whilst still allowing VAR to converge. In all tests performed to date, all observations with model temperature <3 °C were rejected, but different combinations of rejection threshold for rain observations, thinning step, and observation error were tested. It was found that reducing the thinning step to 1 UM gridspacing, increasing the rejection threshold to 10 dBZ and decreasing the observation error to 0.5 dBZ gave a much greater impact of the observations on the analysis, whilst still allowing convergence. A test where the rejection threshold was set to 15 dBZ failed to converge.

### 4.2 LIMITING INNOVATIONS

Figure 5 (top) shows the observations assimilated in a test, REJECT**,** with the following observation processing settings:

- Rejection of all observations where **|**O-B**|** > 10 dBZ,
- Thinning of observations to 1 observation from an individual scan per 1 UM gridspace,
- Observation error set to 0.5 dBZ for all assimilated observations.

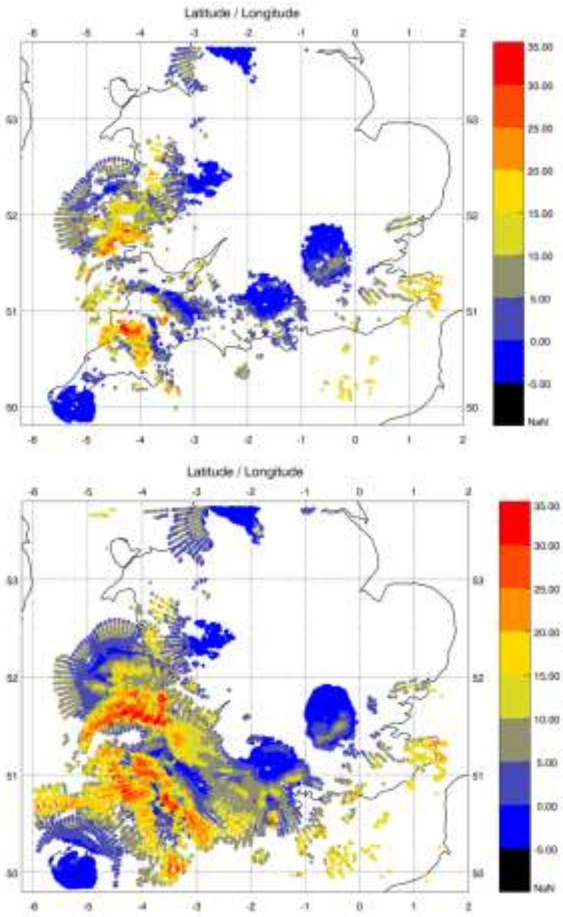


Figure 5. Reflectivity observations assimilated in test REJECT (top), where observations are rejected where |O-B| > 10 dBZ, and in test LIMIT (bottom), where innovations are limited to 10 dBZ, rather than being rejected. These plots show observations from all the available scans from all the radars in the domain in a plan view.

Figure 6 shows a comparison between the radar derived surface rainrate product (top), the surface rainrate in the background forecast, BACKGROUND (second), the surface rainrate in the REJECT test (third), and the surface rainrate in a third test, LIMIT (bottom). It appears that in areas of the domain where observations are assimilated, the analysis of surface rainrate at 0900Z in test REJECT is improved with respect to the BACKGROUND run, but a very large number of observations have been rejected, particularly in areas where the background and observations differ the most. Considering that a large difference between the model background state and the observations does not necessarily imply a large error in the observations, but could be due to a poor background, it seems that a large amount of information content in the observations is needlessly lost by rejecting observations where O-B is large. In the latent heat nudging scheme, model latent heating profiles are rescaled by the ratio between the model surface rainrate and the radar derived surface rainrate, with a limit placed on the rescaling factor to avoid excessive gridscale forcing of the model. A similar approach could be taken within VAR, where rather than rejecting large innovations, we could limit the innovation to a value which allows VAR convergence, but retains the information provided by the observations that the simulated radar reflectivity should be incremented.

To test this idea, a test, LIMIT, was setup with the following observation processing settings:

- Limiting, rather than rejecting, O-B innovations to ± 10 dBZ,
- Thinning of observations to 1 observation from an individual scan per 1 UM gridspace,
- Observation error set to 0.5 dBZ for all assimilated observations.

Figure 5 (bottom) shows that a much larger number of observations were assimilated in LIMIT than in REJECT, and figure 6 (bottom) shows that this leads to an improved analysis of surface rainrate in the south-west and south Wales in particular. There is, however, an apparent bias in the impact of the observations on the analysis, with a much greater suppression of excessive rainfall than intensification of weak rainfall.

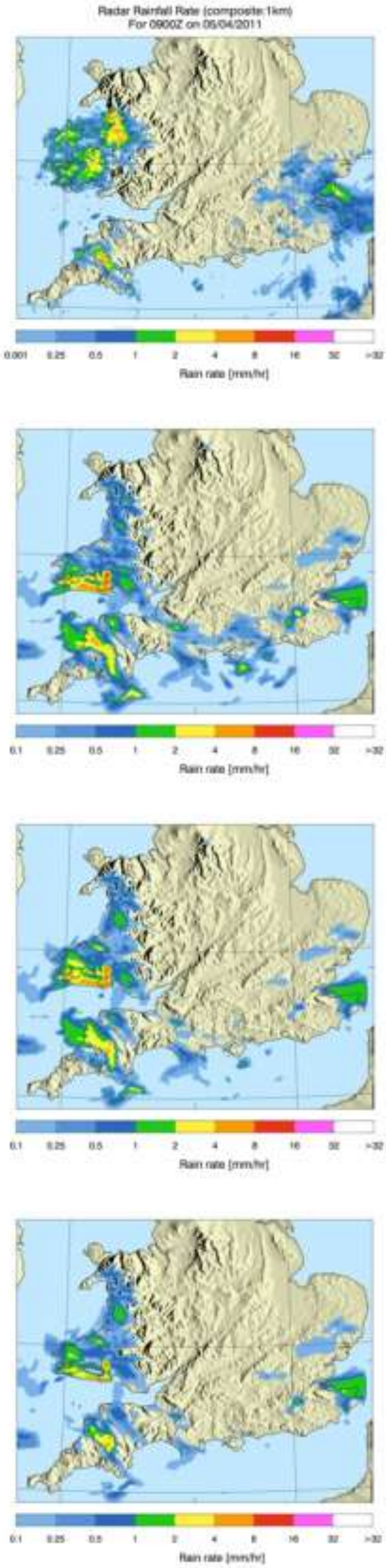


Figure 6. Surface rainrate at 0900Z in NIMROD (top), BACKGROUND run (second), REJECT test (third) and LIMIT test (bottom).

This is confirmed in figure 7, which shows the domain averaged surface precipitation rate for NIMROD, BACKGROUND, REJECT, LIMIT and a third test, SCALED-LIMIT, described later. Trials of variational assimilation of surface rainrates often had excessive rain in the early timesteps which rapidly span down as the model adjusted to thermodynamic balance. This problem is not evident is these tests of radar reflectivity assimilation, although this may be due to a negative bias in humidity increments.

The bias is in fact a direct consequence of the use of radar reflectivity in dBZ units as the assimilated variable, and the specification of observation error and rejection/limit threshold in those units. As discussed by Wang *et al.* (2011), the linearization error for the linearization of the relationship between rainwater content, or rainrate, and reflectivity, is always positive. This leads to a dry bias in rainwater increments, and hence over-suppression of excessive rainfall, and insufficient intensification of weak rainfall.

Following this bias, the approach taken by Wang *et al.* (2011) is to assimilate rainwater content. As the intention of this project is to utilise the full range of reflectivity observations including those due to ice, a more general form of reflectivity observation will be tested as the assimilated variable. Statistics of observations, simulated observations, and innovation statistics will be used to inform the design of an improved observation operator.

One further test with the current form of the observation operator, SCALED-LIMIT, was to replace the limit on innovation size with a limit on innovation scaled by *1/R*, where *R* is the model guess of the rainrate. For a relationship between radar reflectivity, *Z*, and rainrate of the form:

$$Z = aR^b \tag{4}$$

which is assumed in the radar reflectivity observation operator, the gradient between the increments in the reflectivity in logarithmic dBZ units and rainrate increments is:

$$\frac{dZ[dBZ]}{dR} = \frac{10}{\ln 10} b \frac{1}{R} \tag{5}$$

Thus, scaling the innovation limit by *1/R* effectively transforms the unit which is being limited to increments in rainrate. This should avoid excessively constraining the size of innovations at higher values of rainrate in the model guess. The observation processing settings used for the SCALED-LIMIT test were:

- Limiting of |(O-B)/R| to ± 10 dBZ/kg $m^2$ $s^{-1}$,
- Thinning of observations to 1 observation from an individual scan per 1 UM gridspace,
- Observation error set to 0.5 dBZ for all assimilated observations.

Figure 8 shows that the test SCALED-LIMIT led to greater intensification of surface rainrate in mid-Wales and the Thames Estuary, although the suppression of rainfall in central southern England is excessive, with some rainfall features which are observed in NIMROD removed in SCALED-LIMIT.

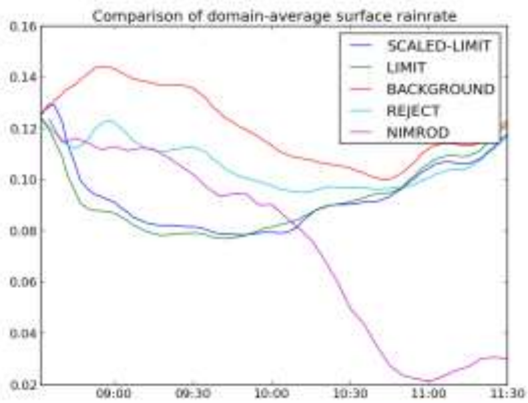


Figure 7. Domain-averaged surface rainrate in mm $hr^{-1}$ as a function of time, for NIMROD, BACKGROUND, REJECT, LIMIT and SCALED-LIMIT.

A problem general to all of these direct reflectivity assimilation tests is that observations are only assimilated where there is at least some rainfall in the background. In this case, the limitations of this constraint are most evident in the south-east of England, where NIMROD shows widespread rainfall, but the background only has isolated areas of rainfall, and as shown in figure 5, relatively few observations are assimilated in the south-east of the domain, so that the assimilations are poorly constrained by observations in this area.

At 0930Z, a spurious rainfall feature enters the domain from the western boundary, which leads to the worsening agreement between NIMROD and all of the model runs from this time on. This is because the lateral boundary conditions in this case are rather poor quality.

A new case study with better quality boundary conditions would be required to allow more meaningful investigation of the performance of the 4D-VAR assimilation methods at longer forecast ranges.

It is important to note that the NIMROD product is not ‘truth’, and is itself subject to observation and processing errors. A potential source of error in the NIMROD product in this case is the possibility of excessive orographic enhancement. As the radar scans cannot see the surface, assumptions must be made about effects such as evaporation and orographic enhancement, as the rain falls below the sight of the radar, to derive surface rainrates. Therefore rigorous verification should be performed with comparison to other observation types including clouds, not relying on the NIMROD product alone.

## 5. CURRENT AND FUTURE WORK

A number of potential improvements to the direct assimilation scheme are currently being developed. These can be classified into those increasing the realism of the reflectivity operator, and changes to the variational system.

Interpolation for radar reflectivity is currently a simple linear interpolation in space and time from model fields, as is the case for most traditional observations. Integrating over the radar beam-width in the vertical would be fairly straightforward to implement in OPS as OPS retrieves model columns corresponding to the location of each observation.

The current system does not allow for attenuation of the radar beam. Gaseous attenuation is addressed by preprocessing in RadarNet, however, attenuation by hydrometeors can have a much larger effect, and has the largest impact at high precipitation rates, which are the weather situations which will potentially have the greatest impact on the public and hence where observational data quality is most critical.

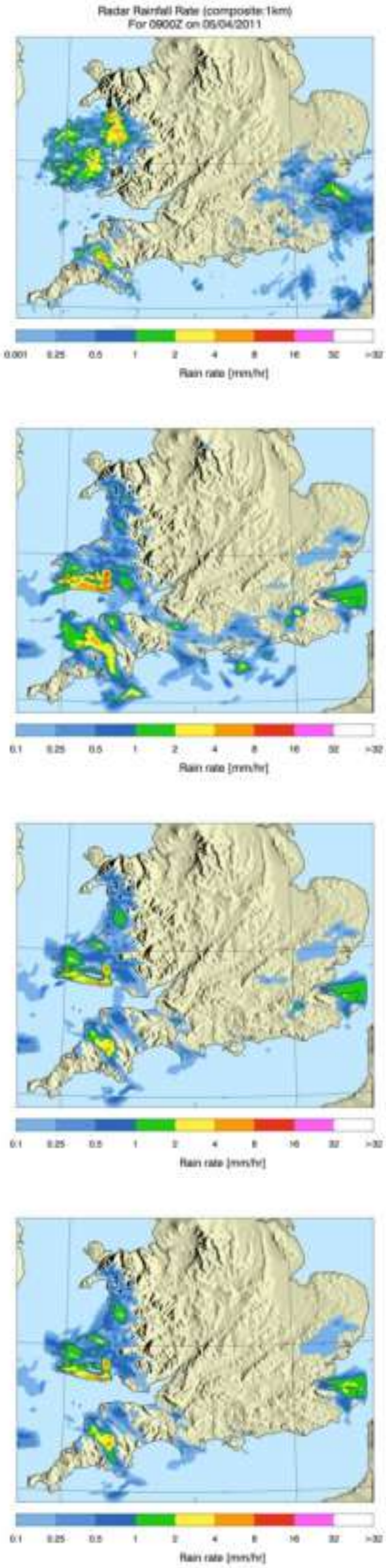


Figure 8. Surface rainrate at 0900Z in NIMROD (far left), BACKGROUND run (centre left), LIMIT test (centre right) and SCALED-LIMIT test (far right).

A consortium from the University of Reading and University of Surrey, in collaboration with the Met Office, is carrying out project funded as part of the NERC Flooding from Intense Rainfall programme. One work package includes the application of a method for constraining total path attenuation (Thompson et al., 2011), which could have a significant impact in reducing radar reflectivity errors at high precipitation rates. A method must be applied to account for hydrometeor attenuation. There are two general approaches which could be taken: one is to correct the observations for the effect of hydrometeor attenuation, as is done for gaseous attenuation. The other approach is to forward model attenuation by hydrometeors. The correction approach is taken for current RadarNet products, where the reflectivity is adjusted gate-by-gate along a radar beam. The multiplication of errors means that this method is unstable, and thus the correction has to be limited. This means, however, that in certain cases attenuation is severely underestimated. The forward modelling approach would avoid the problem of unstable error growth in the gate-by-gate method, but research will be required to develop a suitable linearization of an observation operator which includes forward modelling of attenuation.

A limitation of the current 4D-VAR reflectivity assimilation method is that only rain observations are used. Assimilating observations from ice, above the melting layer, could potentially provide much more information on the state of the mid-troposphere, allowing an improved analysis of mid-level clouds. A number of approaches to ice incrementing could be investigated: use of the cloud incrementing operator, which diagnoses the split of total water into water vapour, liquid and ice cloud; using the cloud increment in the PF model microphysics scheme, or developing hydrometeor control variables. The first two options would be straightforward to implement in the existing VAR code and these are currently being investigated.

The impact of assimilating reflectivity observations together with other observation types should also be investigated, and a wider range of case studies examined, particularly cases from field campaigns where a wider range of results are available to validate the results of reflectivity experiments. Initial results from a number of other case studies will be presented in the oral presentation.

**REFERENCES**


Bowler, N.E., Pierce, C.E. & Seed, A.W. (2006) STEPS: A probabilistic precipitation forecasting scheme which merges an extrapolation nowcast with downscaled NWP, *Quart. J. Roy. Met. Soc.*, **132** , 2127-2155

Caumont, O., É. Wattrelot, G. Jaubert, and V. Ducrocq, 2009: Assimilation of weather radar reflectivity in the AROME model for the COPS-IOP9. Preprints, Proc. Int. Conf. on Alpine Meteorology (ICAM 2009), Rastatt, Germany.

Caya, A., J. Sun, and C. Snyder, 2005: A comparison between the 4D-Var and the ensemble Kalman filter techniques for radar data assimilation. *Monthly Weather Review*, **133**, 3081–3094

Davies, T., M. J. P. Cullen, A. J. Malcolm, A. S.M. H. Mawson, A. A. White, and N. Wood, 2005: A new dynamical core for the Met Office's global and regional modelling of the atmosphere. *Quart. J. Roy. Meteor. Soc.*, **131**, 1759–1782.

Dixon, M., Z. Li, H. Lean, N. Roberts, and S. Ballard, 2009: Impact of Data Assimilation on Forecasting Convection over the United Kingdom Using a High-Resolution Version of the Met Office Unified *Model. Mon. Wea. Rev.*, **137**, 1562–1584.

Georgiou, S., N. Gaussiat and D. Harrison, 2011: The development of diagnostics and radar monitoring capability within a newly implemented radar data quality management system (RDQMS). *35th Conference on Radar Meteorology, Pittsburgh, PA, USA. American Meteorological Society.*

Ikuta, Y. and Y. Honda, 2011: Development of 1D+4DVAR data assimilation of radar reflectivity in JNoVA. CAS/JSC WGNE *Res. Activ. Atmos. Oceanic Model*., **41**, 01.09 – 01.10.

Kawabata, T., T. Kuroda, H. Seko, K. Saito, 2011: A Cloud-Resolving 4DVAR Assimilation Experiment for a Local Heavy Rainfall Event in the Tokyo Metropolitan Area. *Monthly Weather Review*, **139**, 1911–1931.

Kummerow, C., Hong, Y., Olson, W. S., Yang, S., Adler, R. F. and co-authors. 2001: The evolution of the Goddard profiling algorithm (GPROF) for rainfall estimation from passive microwave sensors. *J. Appl. Meteor.* **40**(11), 1801–1820.

Oye, R., C. Mueller, and S. Smith, 1995: Software for radar translation, visualization, editing and interpolation. Preprints, *27th Conf. On Radar Meteorology*, 9-13 Sept. 1997, Vail, AMS, 359-363.

Rawlins F., S. Ballard, K. Bovis, A. Clayton, D. Li, G. Inverarity, A. Lorenc, and T. Payne, 2007: The Met Office global four-dimensional variational data assimilation scheme. *Quart. J. Roy. Meteor. Soc.* **133,** 347–362.

Snyder, C. and F. Zhang, 2004: Assimilation of simulated Doppler radar observations with an ensemble Kalman filter. *Monthly Weather Review*, **131**, 1663–1677

Sun, J.,2005: Convective-scale assimilation of radar data: progress and challenges. *Quarterly Journal of the Royal Meteorological Society*, **131**: 3439–3463.

Sun. J., and N. A. Crook, 1997: Dynamical and microphysical retrieval from Doppler radar observations using a cloud model and its adjoint: I. model development and simulated data experiments. *Journal of Atmospheric Sciences*, **54**, 1642–1661

Sun. J., and N. A. Crook, 1998: Dynamical and microphysical retrieval from Doppler radar observations using a cloud model and its adjoint: II. Retrieval experiments of an observed Florida convective storm. Journal of Atmospheric
Sciences, **55**, 835–852

Sun, J. and H. Wang, WRF-ARW Variational Storm-Scale Data Assimilation: Current Capabilities and Future Developments. *Advances in Meteorology*, vol. 2013, Article ID 815910, 13 pages, 2013.

Wang, H., J. Sun and Y. R. Guo**,** 2011**:** Radar Reflectivity Data Assimilation with the Four-Dimensional Variational System of the Weather Research and Forecast Model, *24th Conference on Weather and Forecasting/20th Conference on Numerical Weather Prediction*, Seattle, WA, USA, American Meteorological Society

Wang, H., J. Sun, S. Fan, and X. Y. Huang, 2013: Indirect assimilation of radar reflectivity with WRF 3D-VAR and its impact on prediction of four summertime convective events. *J. App. Met. and Clim*. **52,** 889-902**.**

Xiao, Q., Y-H. Kuo, J. Sun, W-C. Lee, E. Lim, Y-R. Guo, and D. M. Barker, 2005: Assimilation of Doppler radar observations with a regional 3DVAR system: Impact of Doppler velocities on forecasts of a heavy rainfall case. *Journal of Applied Meteorology*, **44**, 768–788.

Xiao, Q., Y-H. Kuo, J. Sun, W-C. Lee, D. M. Barker, and E. Lim, 2007: An approach of Doppler reflectivity assimilation and its assessment with the inland QPF of Typhoon Rusa (2002) at landfall. *Journal of Applied Meteorology and Climatology*, **46**, 14–22

Zhang, F., C. Snyder, and J. Sun, 2004: Impacts of initial estimate and observations on convective-scale data assimilations. *Monthly Weather Review*, **132**, 1238–1253