Propagation of radar rainfall uncertainty through urban hydraulic models

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1 Introduction

Weather radars provide valuable rainfall information to use in urban hydrology, due to the high spatial and temporal resolution of available radar rainfall (RR) records. In fact, some of the early studies on urban hydrology showed the need of having rainfall data with high spatial (1 km) and temporal resolutions (minutes) (Schilling, 1991). This highlights the need of using weather radars for such purpose and in fact previous studies have shown the potential of radar for the real-time control of drainage systems (Yuan et al., 1999; Han et al., 2000). However, various sources of error affect the accuracy of RR estimates and therefore restricting the application of RR estimates in urban drainage systems. Some of the RR errors are due to ground clutter and anomalous propagation, attenuation (at shorter wavelengths), melting snow (bright band), extrapolation of reflectivity measured aloft to the ground, variations of the drop size distribution, etc. Despite the application of quality control and correction techniques to improve RR estimates, residual errors often remain.

Therefore, the aim of this work is to quantify the uncertainty associated with RR estimates and the way this uncertainty propagates in the sewer system of an urban area. We attempt to explain how much of the uncertainty in the simulated flows can be explained by the uncertainty in the RR measurements.

There are several approaches that attempt to quantify the RR residual errors in order to develop RR ensemble fields that are able to represent the uncertainties in the RR estimates (e.g. Ciach et al, 2007; Germann et al, 2009; Dai et al, 2014). For instance, Ciach et al. (2007) developed the product-error-driven (PED) approach in which the relation between the true rainfall and the RR can be described as the product of a systematic bias and the random error. In Germann et al. (2009) model, the RR uncertainties can be modelled by using stochastic perturbations that have similar spatial and temporal correlations of the RR residual errors. Dai et al, (2014) developed a method to model the RR uncertainties based on the t-copula function and autoregressive models.

In this work, we used Germann, et al. (2009) model (GM) to produce the RR ensembles, which are used to assess the propagation of RR uncertainty in urban drainage flow modelling. This paper is organized as follows. Section 2 presents the data sets and methodology used in this work. Section 3 presents the RR ensemble results and Section 4 summarizes the main conclusions of this work.

2 Data sets and methodology

In this work we used the RR composite product from the UK Met Office (UKMO) at 1km/5min of spatial and temporal resolutions respectively. The RR composite product has been quality-controlled by the UKMO using different correction techniques described in Harrison et al. (2000; 2009). For instance, some of the corrections include identification and removal of non-meteorological echoes (e.g. ground clutter and echoes due to anomalous propagation), correction for beam blockage, attenuation correction, mean field bias adjustment, etc. Rainfall data from 18 C-band radars are included in the RR composite product that covers the whole of the UK, but only 3 radars exist within the study region (see Figure 1).

There is also a tipping bucket raingauge network operated by the Environment Agency and accumulated at 5min intervals for the purpose of this work. Daily rainfall accumulations from gauge data were compared to rainfall accumulations from nearby gauges to identify potential malfunctioning gauges or periods with suspected corrupted data. In this analysis raingauges are used as ground truth even though they represent point measurements whereas RR estimates represent areal (or volume) measurements. Therefore, some of the differences observed when comparing radar with gauge measurements are due to the sampling errors. However these differences are relatively small compared to other sources of error in RR. In fact, the variance reduction factor VRF (point-to-area variance with respect to the variance of the gauge measurements) is less than 10% for a gauge randomly located in a 1km^2 radar pixel and assuming hourly accumulations. The VRF increases for larger pixel areas.

The model of the sewer system of the urban area was built and calibrated by Yorkshire Water (YSW) in Infoworks CS for research purposes. The model includes gullies and manholes as well as the main pipes of the drainage system. The sewer system carries both rainfall and domestic waste water (i.e. combined system). The urban area has approximately 11km^2 and comprises several flow and depth monitors and 4 additional raingauges. The description of the urban model is given in Liguori et al. (2012) and Schellart et al. (2012, 2014). The urban sewer model was calibrated by YSW and no additional calibration was performed in this analysis.

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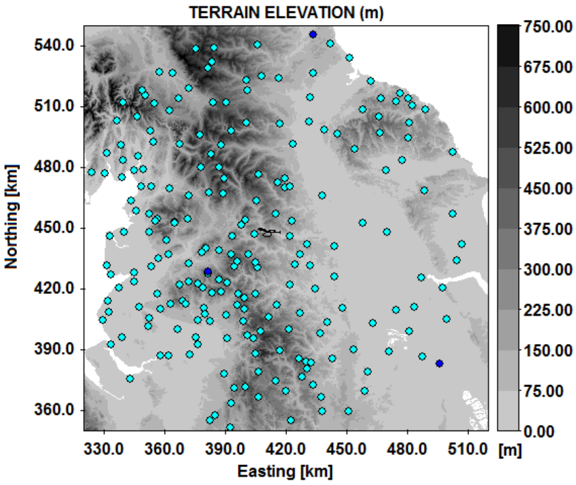

Figure 1: Map of the study area with raingauges and radars shown with the light blue and dark blue circles respectively. The urban catchment is shown at the center of the figure.

The study area is shown in Figure 1 with the locations of the radars, raingauges and the urban catchment. The data sets comprises the years of 2007 and 2008. The whole year of 2007 was used for the calibration of the RR ensembles and the year 2008 was used for validation. In fact, 20 events (approx. 50% were stratiform events and 50% were convective events) from 2008 were specifically selected for the validation of the RR ensembles.

In GM, the RR residual errors are computed at the raingauge locations using rainfall time series of radar and gauge data. The covariance (**C**) of the residual errors is then calculated and decomposed into lower and upper triangular matrices ($\mathbf{C}=\mathbf{L}\mathbf{L}^T$). The lower triangular matrix is then multiplied with a random vector with zero mean and unit variance to generate the perturbations. A second order autoregressive model is then used to impose a temporal correlation to the perturbations. The perturbations are then interpolated to produce a two-dimensional perturbation field. The perturbation fields can be added (in the log domain) to the deterministic RR field to produce the RR ensembles.

3 Results

Figure 2 shows the spatial and temporal correlations of the measured RR residual errors for the whole year of 2007. An exponential function was fitted to the spatial correlation as shown in the same figure. Figure 3 shows the spatial and temporal correlations of the modelled errors (i.e. perturbations) generated using GM. The measured spatial correlation is also shown in the same figure in order to corroborate that the spatial correlation of the perturbations agrees with the spatial correlation of the measured residual errors. For the temporal correlation, a second order auto regressive model was used and therefore the model is only able to reproduce the temporal correlations at 1h and 2h. Beyond 2h, the temporal correlation of perturbations decreases more rapidly compared to the temporal correlation of the residual errors. Note that in these simulations, 25 ensembles were generated in order to reproduce the measured residual errors. A large number of ensembles might be able to better reproduce the mean residual errors, but also represent a difficulty when running the Infoworks CS model of the urban drainage system in real-time. Therefore, 25 ensembles were used as a compromise to reproduce the RR residual errors and to be able to run the model of the urban drainage system fairly quickly.

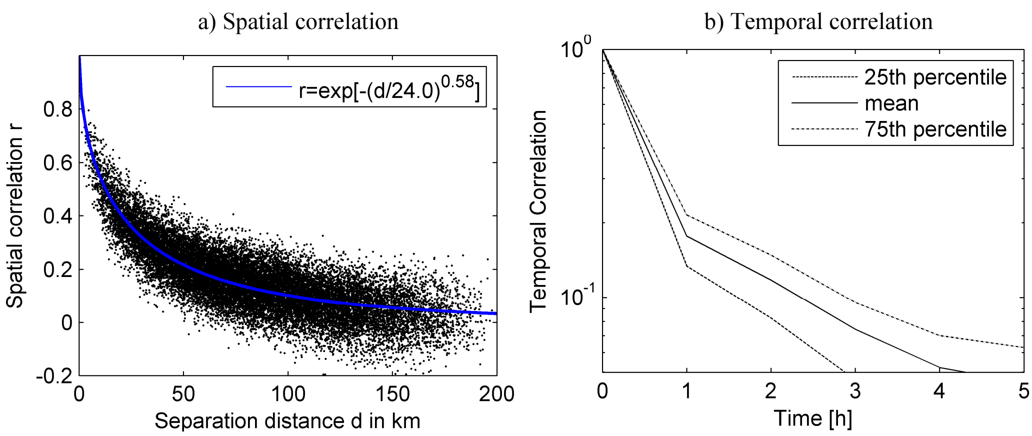

Figure 2: Spatial and temporal correlations of the RR residual errors.

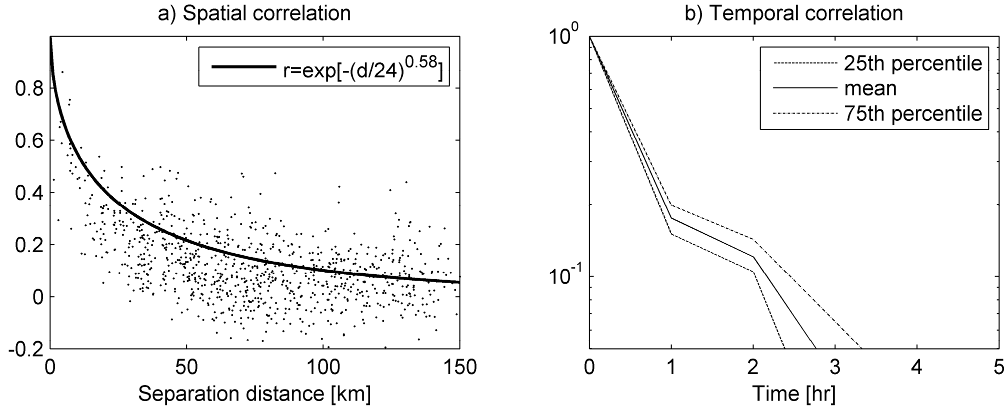

Figure 3: Spatial and temporal correlations of the modelled errors. Note that the spatial correlation equation shown in the left figure was obtained using the measured errors.

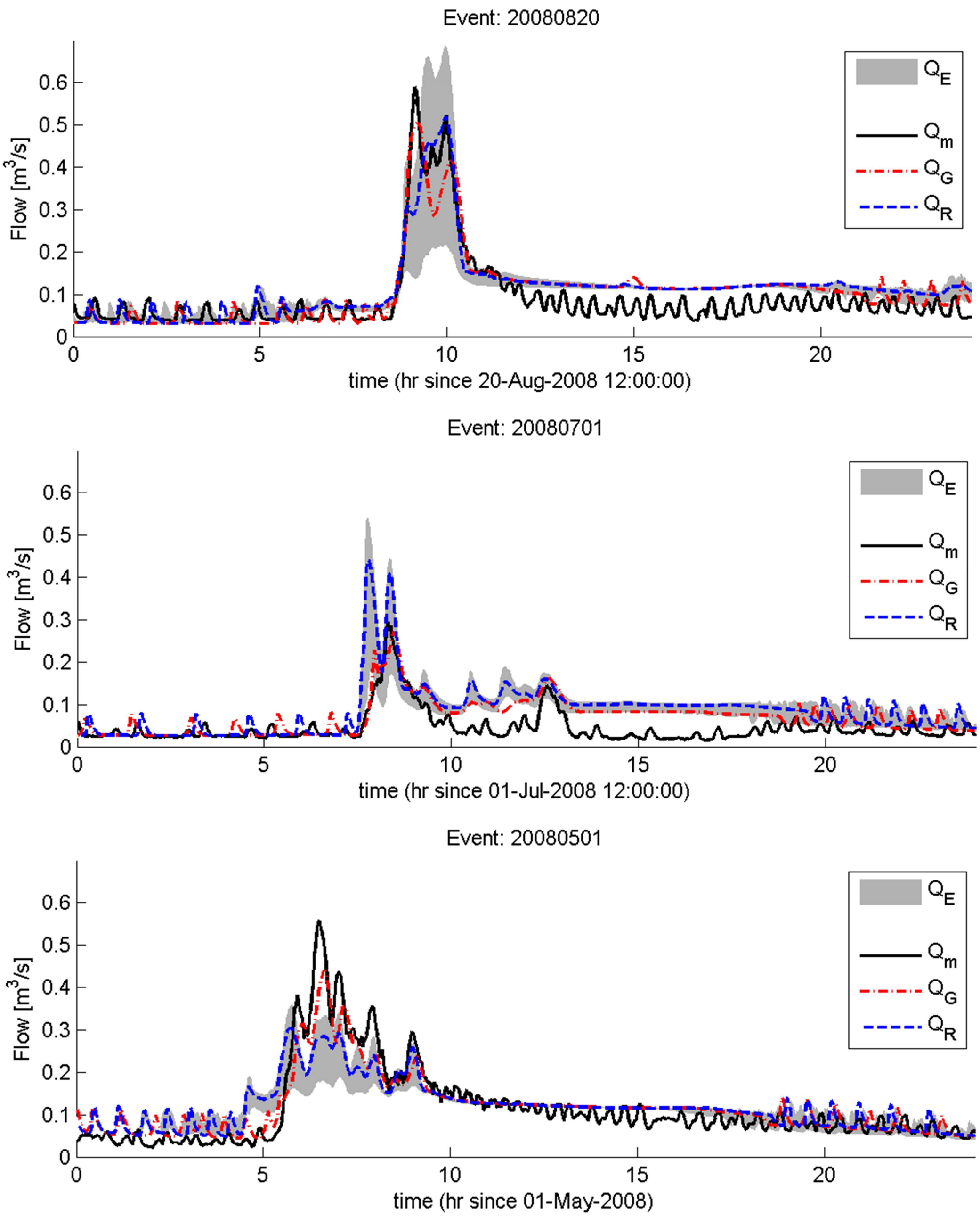

Figure 4: Flow simulations for different events. The shaded area represents the 15% and 85% percentiles of the simulated flow with the RR ensembles (Q_E); Q_m is the measured flow; Q_G is the simulated flow using raingauge measurements; Q_R is the simulated flow using RR.

The perturbations were generated at the gauge locations and were interpolated to obtain a distributed perturbation field that can be added to the original RR field. We used the bi-harmonic spline interpolation described in Sandwell (1987) (also known as V4 interpolation in Matlab) to produce a smooth perturbation fields. Figure 4 shows the results for some of the validation events. The figure shows the measured and simulated flows using radar, RR ensembles and the raingauges within the urban area. Figure 4 shows that for the first two events, the RR ensembles are able to capture some of the large flow peaks, but in the last event, neither the simulated flow using raingauges nor the simulated flow using RR ensembles were able to capture the flow peaks. We also computed the total flow volume per event and the results indicate that in 11 out of 20 events the RR ensembles are able to capture the total measured flow volume. This result indicates that in 55% of the simulated events, the uncertainties in the RR measurements are able to explain the uncertainties observed in the simulated flow volumes.

Finally, the RR ensembles provide a probabilistic estimate of the rainfall field and are implemented to drive a deterministic nowcasting model, in order to propagate the uncertainty into short-term forecasts of rainfall. The uncertainties in nowcasting methods can be broadly classified in (after Foresti & Seed, 2014): a) uncertainties in RR; b) uncertainties in the nowcasting model (e.g. TREC, COTREC, VET, tracking rain cell centroids, OFC); c) uncertainties due to the temporal variation of the diagnosed velocity field during the forecast; d) uncertainties in the temporal evolution of rainfall (i.e. growths & decays rainfall processes are not modelled). If we consider only the uncertainty in the RR, and we use the RR ensembles as input to a deterministic nowcasting model to produce short-term rainfall forecasts (0-3hr), which are fed into the urban drainage model, we obtain the results shown in Figure 5. As shown, the uncertainty in the RR measurement can explain part of the uncertainty observed in the forecasts. However, there are additional sources of uncertainty in nowcasting methods as discussed above that can explain some of the differences in the results.

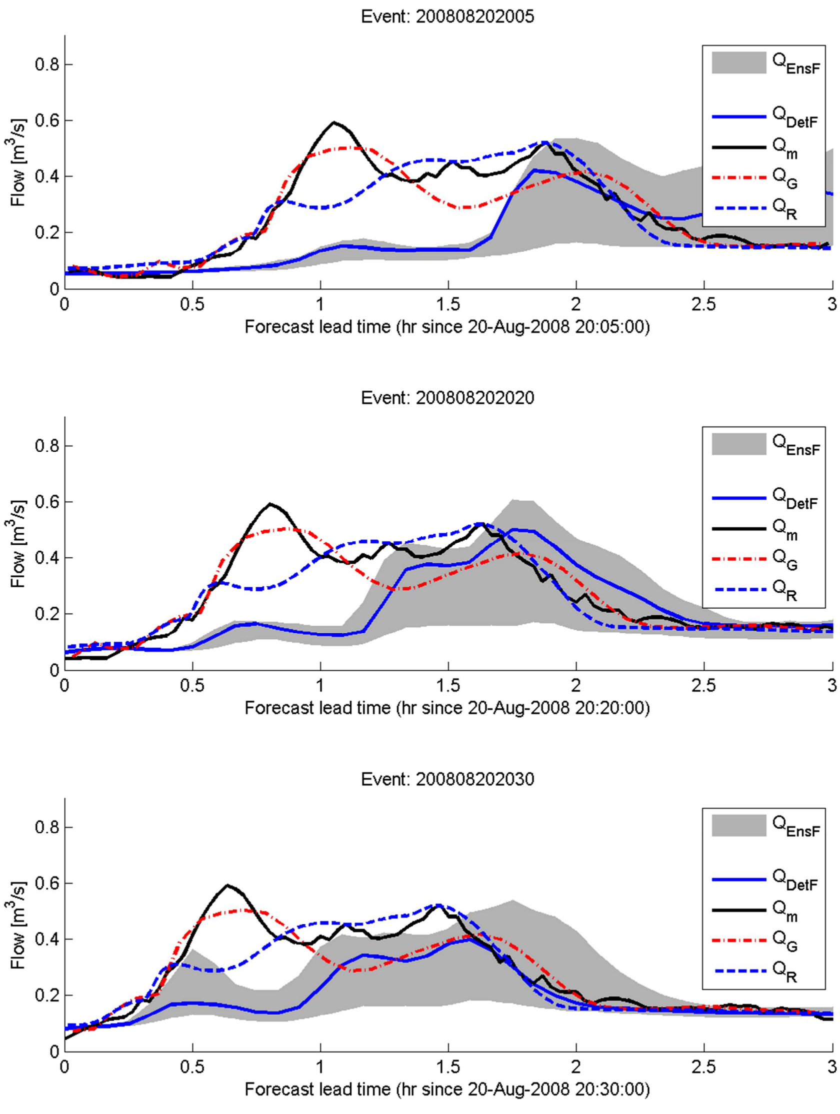

Figure 5: Ensemble flow forecast simulations with different starting times and considering the RR uncertainty only. The shaded area represents the 15% and 85% percentiles of the RR ensembles forecasted flow (Q_{EnsF}); Q_{DetF} is the forecasted flow using RR as input; Q_m is the measured flow; Q_G is the simulated flow using raingauge measurements; Q_R is the simulated flow using RR.

Conclusions

Radar Rainfall (RR) errors can be modelled by using the error covariance matrix, but this assumes that the mean error does not change over time, which is not always true. The results showed that in 55% of the flow simulated events, the uncertainties in the RR measurements are able to explain the uncertainties in the simulated flow volumes. There were cases where neither the raingauges nor the RR ensembles were able to capture the measured flow volumes and therefore additional uncertainties may come from the hydraulic model (model structure parameters). Preliminary results of the application of RR ensembles in nowcasting showed that some of the ensemble forecasts are able to capture the flow peaks, but more work is needed to further validate the probabilistic nowcasts. There is more work to do to model additional uncertainties in nowcasting models by incorporating more meteorological knowledge (e.g. to model growth & decay processes).

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