Radar-raingauge data combination techniques: a revision and analysis of their suitability for urban hydrology

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ABSTRACT

The applicability of the operational radar and raingauge networks for urban hydrology is insufficient. Radar rainfall estimates provide a good description of the spatiotemporal variability of rainfall; however, their accuracy is in general insufficient. It is therefore necessary to adjust radar measurements using raingauge data, which provide accurate point rainfall information. Several gauge-based radar rainfall adjustment techniques have been developed and mainly applied at coarser spatial and temporal scales; however, their suitability for small-scale urban hydrology is seldom explored. In this paper a review of gauge-based adjustment techniques is first provided. After that, two techniques, respectively based upon the ideas of mean bias reduction and error variance minimisation, were selected and tested in an urban catchment (865 ha) in North-East London. The radar rainfall estimates of four historical events (2010-2012) were adjusted and applied to the hydraulic model of the study area. The results show that both techniques can effectively reduce mean bias; however, only the technique based upon error variance minimisation can correctly reproduce the spatial and temporal variability of rainfall, which proved to have a significant impact on the associated hydraulic outputs. This suggests that error variance minimisation methods may be more appropriate for urban hydrological/hydraulic applications.

KEYWORDS

Gauge-based adjustment, merging/combination, pluvial flooding, radar, rainfall, urban hydrology.

1 INTRODUCTION

Rainfall constitutes the main input for urban pluvial flood models and the uncertainty associated to it dominates the overall uncertainty in the modelling and forecasting of this type of flooding (Golding, 2009). The rainfall events which generate pluvial flooding are often associated with thunderstorms of high intensity and small spatial scale (~ 10 km), whose magnitude and spatial distribution are difficult to monitor and predict (Collier, 2009; Golding, 2009; Vieux and Imgarten, 2012).

The sensors that are commonly used for estimation and prediction of rainfall at catchment scales are raingauges and radars (Cole and Moore, 2008); however, the applicability (i.e. achievable accuracy and resolution) of the currently operational radar and raingauge networks for urban hydrology is insufficient. In general, raingauges provide accurate point rainfall estimates near the ground surface; nonetheless, they cannot capture the spatial variability of rainfall which has a significant impact on the physical processes and thus on modelling of urban pluvial flooding (Tabios and Salas, 1985; Syed et al., 2003). Moreover, since dense raingauge networks cannot cover large areas, it is difficult to forecast rainfall with longer lead time based on raingauge data only (Looper and Vieux, 2012). In contrast, radars can survey large areas and can capture the spatial variability of the rainfall, thus improving the short-term predictability of rainfall and flooding. However, the accuracy of radar measurements is in general insufficient, particularly in the case of extreme rainfall magnitudes (Einfalt et al., 2005; Harrison et al., 2009); this has a tremendous effect on the subsequent rainfall forecast (which uses radar estimates as starting point) and on the associated flood forecast (whose main input is the rainfall forecast) (Ligouri et al., 2011). The low accuracy of radar measurements is mainly due to the fact that, unlike raingauges, which directly collect rain droplets, radar devices obtain rainfall measurements through an indirect process, which introduces more uncertainty. This indirect process comprises the following sub-processes: (i) noise filtering, (ii) identification of clutter and occultation, (iii) removal of anomalous propagation, (iv) attenuation correction, (v) calibration or conversion of reflectivity to rain rate and (vi) raingauge-based adjustment. The last two sub-processes involve calibration or adjustment of radar estimates based on raingauge measurements; nonetheless, the scale at which this is done cannot ensure that radar estimates capture high intensities and local conditions accurately. The conversion of reflectivity to rain rate (i.e. Z – R conversion function) is the result of a calibration process based on the comparison of a large number of coincidental observations of radar and raingauges. In order to obtain statistically optimal results, the conversion function has to compromise the capacity of deriving extreme values since the frequency of their occurrence is relatively low; hence, the $Z - R$ conversion performs in particular poor at capturing intense rainfall rates (Einfalt et al., 2004, 2005), which is vital for urban applications. In addition, the conversion functions are in general static; i.e. they are not dynamically updated (they only change according to the storm type; however, for each storm type the conversion function is fixed). After the conversion or calibration process and with the purpose of further enhancing the suitability of radar estimates for hydrological and hydraulic applications, gauge-based adjustment techniques, also referred to as "re-calibration", "combination" or "merging" in the literature (Einfalt et al., 2004), are widely used to dynamically correct the bias between radar estimates and the coincidental raingauge measurements (Fulton et al., 1998; Seo et al., 1999; Harrison et al., 2009). However, these adjustment techniques are mostly applied in catchments of large area (~1000 km^2) and use hourly rainfall rates, and although they provide benefits for hydrological applications at large scales, the suitability of the resulting rainfall estimates for urban hydrological applications is still insufficient. For example, Smith et al (2007) re-investigated 35 rainfall events selected from the US NEXRAD (network of 159 high resolution Doppler weather radars operated by the US National Weather Service (Fulton et al., 1998)) during the period 2003 - 2005, and compared them with the coincidental point observations recorded by a dense network of raingauges (one raingauge per km^2 in average) over a small urban area (≈14.3 km^2). In this comparison large and event-varying bias were observed over the study catchment even though NEXRAD rainfall products had been dynamically adjusted with raingauge measurements (similar to the UK Nimrod rainfall data and adjusted based upon hourly scales).

Moreover, the feasibility of applying the existing gauge-based adjustment techniques at smaller spatial and temporal scales (i.e. for urban applications) has not yet been fully analysed.

In this paper a review of gauge-based adjustment techniques is first provided. After that, two of these techniques were selected and applied to a study urban catchment in North-East London, with the purpose of assessing their ability to improve operational radar measurements for urban applications.

2 REVIEW OF GAUGE-BASED ADJUSTMENT TECHNIQUES

Gauged-based adjustment techniques aim at combining the advantages and overcoming the drawbacks of radar and raingauge rainfall estimates; it is, to retain the accuracy of the point rainfall information provided by raingauges and at the same time the broader description of the spatial and temporal variations of rain-fields provided by radar. As previously mentioned, the final purpose of these techniques is to enhance the suitability of rainfall estimates for hydrological and hydraulic applications, including flood modelling and forecasting.

After reviewing different gauge-based adjustment techniques, it was noticed that, in general, they can be classified into two types: (i) mean bias reduction techniques and (2) error variance minimisation techniques. A review of these two types of gauge-based adjustment techniques is next provided.

2.1 Mean bias reduction techniques

"Mean bias" is the difference between the mean radar rainfall estimates and the mean raingauge measurements at the locations of raingauges for a given time period. In the literature it is also termed "systematic error" and is thought to be the most important source of uncertainty affecting the suitability of radar rainfall estimates for hydrological and hydraulic applications (Vieux and Bedient, 2004). Consequently, many adjustment techniques focus on reducing raingauge-radar mean bias in order to improve radar rainfall estimates. The idea of the mean bias adjustment is to analyse the differences between raingauge observations and the coincidental radar measurements over a given period, and then apply this event-varying difference directly to each radar rainfall grid.

An example of this is the adjustment method implemented in the operational UK Nimrod system, where an adjustment ratio, based on comparisons between processed radar and raingauge hourly rainfall is applied to the entire domain of each radar site and is updated on an hourly basis (Harrison et al., 2009). A similar adjustment technique is used in the US NEXRAD system (Seo et al., 1999). As mentioned before, the adjustments carried out in the Nimrod and NEXRAD systems provide benefits for large scale hydrological applications; however, the resulting rainfall estimates are not accurate enough for urban applications (Vieux and Bedient, 2004; Smith et al., 2007).

Mean bias adjustment techniques have also been used at smaller scales in order to further improve radar rainfall estimates (which may have already been adjusted at larger scales, as in the case of Nimrod and NEXRAD products). For instance, in the above mentioned work by Smith et al. (2007), in which 35 rainfall events over a small urban area were re-investigated and significant bias were observed between NEXRAD products and raingauge data, the authors reduced these bias by applying a simple ratio to scale up or down the radar rainfall rates to approximate the coincidental raingauge records. This simple ratio was derived from the comparison between mean radar (NEXRAD) rainfall estimates and mean local raingauge measurements at the locations of raingauges over the duration of a rainfall event. A similar work was carried out by Vieux and Bedient (2004) over a relatively large urban catchment ($\approx$ 260 km^2). They evaluated the hydrological prediction uncertainty caused by rainfall input errors through event re-construction. Five events were selected from NEXRAD during the period 1998 – 2003. Similarly, these events were re-constructed by applying a simple ratio to reduce the mean bias between radar and the co-located raingauge observations. Results, similar to

Smith et al. (2007), show that the corresponding flow prediction could be significantly improved by using mean bias adjusted (corrected) radar rainfall estimates as inputs. These works suggest that "mean bias" is the most important uncertainty source decreasing the suitability of radar rainfall estimates for urban hydrological and hydraulic applications. In addition, they suggest that the suitability of rainfall data for these applications could be massively improved through locally and dynamically adjusting radar rainfall estimates using co-located raingauge records. However, this simple mean bias adjustment was carried out through post-event (or historical rainfall records) comparisons. It is therefore more suitable for improving the applicability of historical rainfall events to hydrological and/or hydraulic design, rather than for short-term real-time forecasting. If intended for real-time flood forecasting applications, this method would require a very dense raingauge network (or a larger area) and a longer temporal comparison basis (i.e. hourly) to obtain a more reliable ratio to scale the radar rainfall (Anagnostou and Krajewski, 1999; Seo et al., 1999). It is therefore more suitable for coarser spatial- and temporal-resolution rainfall adjustment.

A methodology for improving the local and dynamic capacity of conventional mean bias adjustment methods was proposed by Moore et al. (1989) and further modified by Wood et al. (2000). A dynamic calibration factor was introduced to carry out 15-min radar rainfall adjustment in real time. This factor is based on the comparison of raingauge and radar estimates at each time step in synergy with a positive correction value ε and a static calibration factor κ, where ε and κ are long-term derived constants. Cole and Moore (2008) further examined the applicability of this methodology over two UK catchments (Darwen and Kent, respectively 135.7 and 212.3 km^2). In this work three types of gauge-based adjustment techniques were used to correct radar estimates: (i) static adjustment, (ii) standard dynamic adjustment, and (iii) dynamic adjustment including mean bias. The first one is similar to the aforementioned simple mean-bias adjustment, but based upon a long-term radar-raingauge comparison. The second and third techniques are respectively based upon the original local adjustment methodology (Moore et al., 1989) and the modified one (Wood et al., 2000). Results suggest that the applicability of radar rainfall estimates can be significantly improved by the local adjustment methodology (i.e. the second and third techniques).

More recently, a geostatistical merging method which also focuses on reducing mean bias was developed by Ehret et al. (2008) and applied to real-time small-scale flood forecasting in the Goldersbach catchment, Germany ($\approx$ 75 km^2). At each time step, the point raingauge records are interpolated into a rainfall field and further merged with the coincidental radar image. The Block Kriging interpolation technique was employed to ensure that the synthetic rainfall field is unbiased. A deviation ratio field can be then obtained by comparing the interpolated rainfall and radar rainfall at each radar grid. This deviation field is then adjusted to ensure that its mean is equal to 1 and it is further applied to the interpolated rainfall field (in this way it is ensured that the raingauge totals are retained). A merged rainfall field is therefore obtained at each time step and further used as input for flood forecasting. The quality of radar rainfall was significantly improved by this merging process and, consequently, the accuracy of the rainfall and flood forecasts was also largely improved.

Although the mean bias adjustment methods mentioned above have proven to significantly improve rainfall estimates and the associated flow estimates and forecasts, they have some common drawbacks. First, the spatial structure (e.g. spatial variability) of radar rainfall fields could be altered by simply multiplying a ratio to the rainfall estimate at each radar grid. The ability to characterise the spatial variations in rainfall is however one of the most reliable features of radar sensors and should therefore be retained. Second, the mean-bias adjustment methods have difficulty in correcting the temporal and spatial profiles of radar rainfall. For example, if the original radar rainfall estimates fail to capture the time of the rainfall peaks, this error will not be corrected by the mean-bias adjustment methods since these focus on the correction of quantitative differences (see Figure 4 of Ehret et al. (2008)).

2.2 Error variance minimisation techniques

Another type of gauge-based adjustment techniques focuses on minimising the error variances. The error herein represents the difference between true (or raingauge) and radar rainfall estimates. The concept of minimising the error variances is similar to maximum likelihood approaches; therefore, in addition to mean bias, the spatial and temporal patterns of rainfall are also taken into account in the adjustment process (Krajewski, 1987; Todini, 2001; Mazzetti, 2004; Gerstner and Heinemann, 2008). In general, these techniques assume that there is a true (or best estimated) rainfall field at each time step, made up of grids whose rainfall volume is the (linear) combination of the coincidental radar and raingauge estimates. The total rainfall of this true rainfall field is equal to the raingauge total; this means that the raingauge records are unbiased. However, it is seldom possible to have at least one raingauge per radar grid; therefore, some further assumptions are necessary. For example, Gerstner and Heinemann (2008) defined that the rainfall volume at a specific grid of the true rainfall field as follows:

$$P_a(x_i, y_i) = P_r(x_i, y_i) + \sum_{k=1}^{K} w_{ik}\left[P_g(x_k, y_k) - P_r(x_i, y_i)\right] \tag{1}$$

where $P_a(x_i, y_i)$ and $P_r(x_i, y_i)$ are, respectively, the true and radar rainfall at the grid point (x_i, y_i); $P_g(x_k, y_k)$ is the raingauge measurement at the raingauge position (x_k, y_k); w_{ik} is the to-be-determined weight and K is the number of raingauges. Through minimising the error variances, w_{ik}'s can be estimated and their values are in general inversely proportional to the distance between raingauge and radar grids. Results show that this weighting technique can effectively reflect the local point information to radar rainfall. However, the study was carried out on a daily basis and its applicability to sub-daily and sub-hourly radar rainfall adjustment is therefore unknown.

Different from Gerstner and Heinemann (2008), Krajewski (1987) and Todini (2001) employed the (Block-) Kriging interpolation technique to generate point raingauge information at each radar grid before merging it with radar estimates. In Krajewski (1987)'s Cokriging combination technique, the best rainfall estimate $V^*(x_0, y_0)$ at a specific location was defined as follows:

$$V^*(x_0, y_0) = \sum^{N_G} \lambda_{G_i} G_i(x_i, y_i) + \sum^{N_R} \lambda_{R_i} R_i(x_i, y_i) \tag{2}$$

where N_G and N_R are the numbers of raingauges and radar grids around location (x_0, y_0) and $G_i(x_i, y_i)$ and $R_i(x_i, y_i)$ are the associated measurements at location (x_i, y_i). In the process of deriving λ_{Gi} and λ_{Gi}, the information of the covariances between true and raingauge rainfall Cov_{VG} and between true and radar rainfall Cov_{VR} are required; however, it is impossible to obtain them. They are therefore approximated by the forms $Cov_{VG} = \beta_G Cov_{GG}$ and $Cov_{VR} = \beta_R Cov_{RR}$, where Cov_{GG} and Cov_{RR} are the covariances respectively between raingauges and radar grids and β_G and β_R are two to-be-determined constants ranging from 0 to 1. This approximation however largely decreases the applicability of the Cokriging technique because the values of β_G and β_R are usually determined subjectively or through a large number of simulations.

Todini (2001), different from Krajewski (1987), employed the Kalman filter algorithm to merge the interpolated raingauge and radar rainfall field to obtain the "true" rainfall field at each time step. This method (called Bayesian combination), instead of using Cov_{VG} and Cov_{VR}, uses the covariance of errors $Cov_{\varepsilon t}$ to help deriving the true rainfall field. The error ε_t is estimated by comparing the co-located Block-Kriged and radar rainfall estimates; a $Cov_{\varepsilon t}$ matrix can be therefore constructed in real time to update the original radar estimates to produce the "true" rainfall field. This Bayesian combination method has been applied to a 1051 km^2 river catchment near Bologna (Italy), where

1 km^2 C-band radar images and point rainfall information recorded by a network of 26 raingauges are available. Results show that the bias and variance between radar and observed rainfall estimates were significantly reduced. This application however was undertaken in an hourly basis and its potential to be used in sub-hourly rainfall adjustment needs to be further examined.

3 METHODOLOGY

In this work, one of each type of gauge-based adjustment techniques were selected and tested at the urban scale, with the purpose of assessing and comparing their ability to improve operational radar measurements for urban applications. The selected adjustment methods are next described.

3.1 Mean bias reduction method selected for testing at the urban scale

As mentioned above, the bias between raingauge and radar rainfall estimates is widely regarded as the dominative factor in the uncertainty of the corresponding hydrological and hydraulic modelling. A mean bias adjustment method was therefore implemented in this work to evaluate the impact of bias reduction on the corresponding hydraulic outputs of an urban catchment.

The implemented technique is a post-event one, where the mean sample bias is defined as the ratio of the mean raingauge accumulations to the co-located mean radar rainfall accumulations on an event total basis, i.e.,

$$B_i = \frac{\left(\sum_{j=1}^{m} RG_{ij}\right) / m}{\left(\sum_{j=1}^{m} R_i\left(x_j, y_j\right)\right) / m} \qquad (3)$$

where B_i is the sample bias for the i-th event, m is the number of raingauges, RG_{ij} is the rainfall accumulation (in mm) for the i-th event at the j-th raingauge, (x_j, y_j) is the geographical location of the j-th raingauge and $R_i(x_j, y_j)$ denotes the radar rainfall accumulation (in mm) for the i-th event at location (x_j, y_j).

In order to correct the mean bias, the event sample bias B_i is applied to each radar rainfall grid over the study area for each selected rainfall event (the adjusted values will be referred to as “Corrected radar estimates”).

3.2 Error variance minimisation method selected for testing at the urban scale

In this work, the Bayesian combination method proposed by Todini (2001) was selected for testing in an urban catchment. The reasons for selecting this method are the following:

1. It has strong theoretical background and relatively little approximations
2. The software is available and well maintained
3. It does not require numerous simulations and historical rainfall events to determine parameters

This is a dynamic method intended for real time applications. The first step of the method is to, for each time step, interpolate the real-time raingauge measurements into a synthetic rainfall field using the Block Kriging (BK) interpolation method. After that, the interpolated rainfall field is merged with the coincidental radar image using the Kalman filter algorithm (Todini, 2001; Mazzetti, 2004).

The idea of the BK interpolation method is to synthesise a rainfall field whose semi-variogram curve is very similar to the semi-variogram curve empirically estimated from the associated point rainfall information, where the semi-variogram curve is a function used to characterise the degree of spatial dependence of a spatial random field (e.g. a rainfall field). In other words, the Block Kriged rainfall field contains not only accurate point rainfall estimates but also the spatial dependences between these point estimates over a specific area. This information can reflect the spatial structure of rainfall right above the ground; this can be very useful to correct the spatial structure observed by radar, which is at a given elevation above the ground and could be horizontally shifted by wind advection. This idea of using spatial dependences estimated from raingauge observations to improve the generation of rainfall processes has been widely used in the hydrological field (Wheater et al., 2005; Yang et al., 2005).

The Kalman filter algorithm used for carrying out the actual merging comprises two steps: predict and update (Kalman, 1960). In the "predict" step, the "a priori" estimates and status at the current time step are firstly predicted based upon the estimates and status at the previous time step. These "a priori" estimates and status are then "updated" using real-time observations and the "a posteriori" estimates and status can be obtained by minimising the variance between the "a priori" estimates and the observations (termed "error variance"). In the method proposed by Todini (2001), the radar image represents the "a priori" estimates and the interpolated rainfall field constitutes the observations to update the predicted estimates for obtaining the output field ("a posteriori" estimate) at each time step.

4 EXPERIMENTAL SITE AND DATASET

4.1 Cranbrook Catchment

The above mentioned gauge-based adjustment techniques were tested in the Cranbrook catchment. This catchment is located within the London Borough of Redbridge (North-East part of Greater London - see Figure 1). It is predominantly urbanised and has a drainage area of approximately 865 hectares; the main water course is about 5.75 km long, of which 5.69 km are piped or culverted. This area has experienced several pluvial, fluvial and coincidental flooding in the past.

4.2 Radar (Nimrod) Data

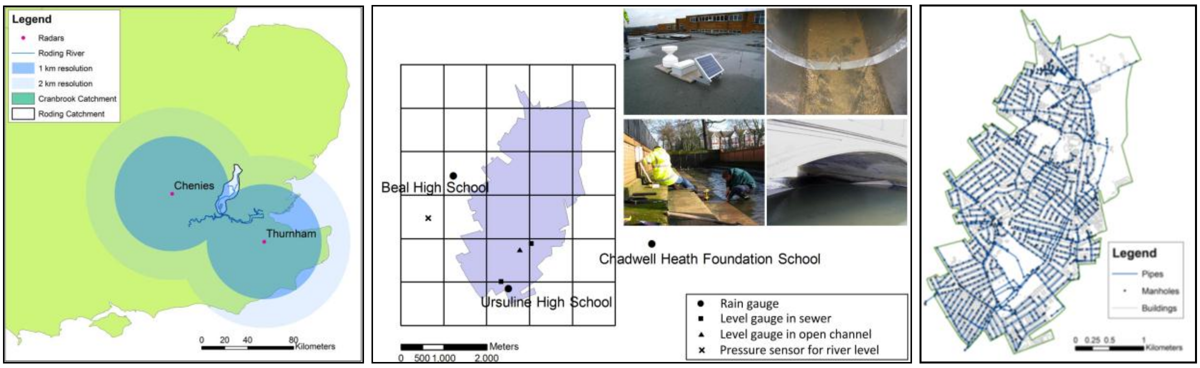
The Cranbrook catchment is in the coverage of two radars, Chenies and Thurnham (Figure 1(a)). The radar data are provided by the UK Met Office through the British Atmospheric Data Centre (BADC) with spatial and temporal resolutions of 1 km and 5 min, respectively. The radar (Nimrod) data have been quality-controlled by the UK Met Office following the correction techniques proposed by Harrison *et al.* (2009) to account for all the errors inherent to radar rainfall measurements.

4.3 Local Monitoring System: raingauges and level gauges

A real time accessible monitoring system is installed in this catchment since April 2010. It includes three tipping bucket rain gauges, one pressure sensor for monitoring water levels at the Roding River (downstream boundary condition of the catchment), two sensors for water depth measurement in sewers and one sensor for water depth measurement in open channels (Figure 1(b)).

4.4 Hydrological/Hydraulic Model of the Study Area

The focus of our work is on urban pluvial flooding, which, as was mentioned before, is one of the major issues in the Cranbrook catchment. For this reason, a pluvial flood model was implemented for the study area. The model is a dual-drainage, physically-based one and was set up in InfoWorks CS 10.5. In this model the urban surface was modelled in 2D (2-dimensions), using a triangular mesh. The model of the surface was coupled with a 1D (1-dimensional) model of the sewer system (Figure 1(c)) and the interactions between the two models take place at the manholes. The implemented model was calibrated using the rainfall and water level measurements collected through the local monitoring system (Section 4.3).



(a) (b) (c)

Figure 1. Cranbrook catchment (a) location of the catchment in relation to radars and the Roding River catchment; (b) monitoring system; (c) sewer network

4.5 Rainfall events selected for testing of gauge-based adjustment methods

Four rainfall events occurring between August 2010 and January 2012 were selected to test the gauge-based adjustment methods. The dates and statistics of these events are summarised in Table 1. In this table “RG Total” is the mean raingauge accumulation, “Radar@RG Total” is the co-located mean radar rainfall accumulation, “Radar Total” is the mean radar accumulation over the whole catchment and “Peak Flow Depth” corresponds to the maximum flow depth recorded in the Valentine Sewer (located in the mid-stream section of the catchment) for each event.

Table 1. Statistics of rainfall events selected for testing of adjustment methods.

Date	Duration (h)	RG Total (mm)	Radar@RG Total (mm)	Radar Total (mm)	Peak Flow Depth (m)
23/08/2010	8	23.53	7.29	6.80	0.633
26/05/2011	9	15.53	5.10	4.88	0.672
05-06/06/2011	24	20.87	9.43	9.48	0.346
03/01/2012	13	8.93	7.72	7.55	0.547

5 RESULTS AND DISCUSSION

As can be seen from Table 1, large and event-varying bias between raingauge and radar measurements were observed in the four rainfall events that were selected for testing. In order to correct this, the two adjustment methods described in Section 3 were applied to each rainfall event. Due to space limitations, only the results associated with the event on 23/08/2010 will be presented. However, similar results were obtained for all events.

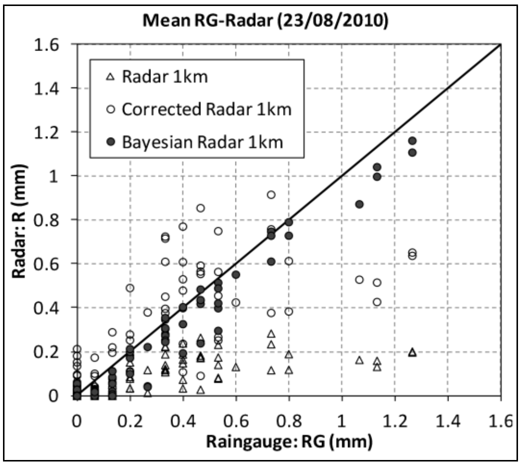
In this section, the corrected radar estimates obtained with the mean bias reduction method are referred to as “Corrected Radar 1 km” and the results of the error variance minimisation method are referred to as “Bayesian Radar 1 km”. Raingauge measurements are usually denoted “RG” and the original radar (Nimrod) estimates are referred to as “Radar 1 km”.

Figure 2 shows the results for the entire Cranbrook catchment for the 23/08/2010 event: i.e. it shows mean values of raingauge, radar and adjusted radar estimates, as well as the associated hydraulic results. Figure 3 shows the 5-min rainfall profiles and accumulations of the adjusted radar estimates, the coincidental raingauge records and the original radar rainfall estimates at the location of one of the raingauge sites (Chadwell High School) for the 23/08/2010 event. Similar results were obtained for the other 2 raingauge sites, but these are omitted due to space limitations.

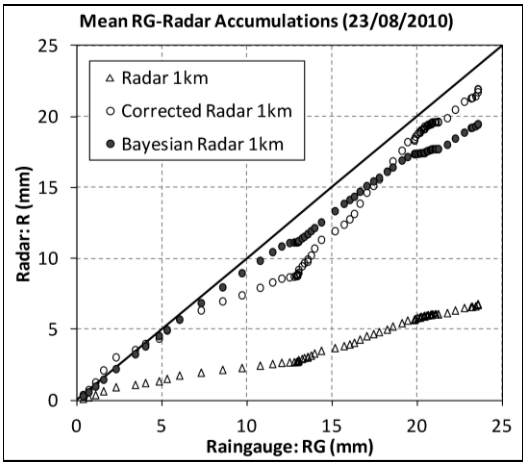
From Figures 2 and 3 it can be seen that radar rainfall rates and rainfall accumulations, both at a specific raingauge location as well as for the entire catchment, were largely improved by both adjustment methods. In terms of **total** rainfall accumulation (see Figures 2(b) and 3(b)), the "Corrected Radar 1 km" produced slightly better results than the "Bayesian Radar 1 km". For the rainfall profiles, however, the Bayesian method produced significantly better results than the mean bias one. For example, in Figures 2(c) and 3(a) some underestimation (e.g. around 00:05 - 02:05), overestimation (e.g. around 03:05 - 04:05) and faulty timing of rainfall peaks can be observed in the rainfall profiles of the "Corrected Radar 1 km", as compared to the RG profiles. In contrast, the profiles of the "Bayesian Radar 1 km" fit the RG profiles significantly better. Moreover, in Figures 2(b) and 3(b) it can be noted that the shape of the cumulative rainfall for the "Bayesian Radar 1 km" is very similar to that of the RGs, as opposed to the shape produced by the mean bias corrected estimates ("Corrected Radar 1 km"). This conclusion is further strengthened by the q-q plot of Figure 1(a): it can be seen that the "Bayesian Radar 1 km" estimates provide a better fit to the RG observations, particularly for high rain rates (it can be noted that the markers of "Bayesian Radar 1 km" estimates are more concentrated around and closer to the straight line with slope equal to 1, as compared to the "Corrected Radar 1 km" estimates). The faulty reproduction of rainfall profiles by the mean bias adjusted estimates is due to the fact that this adjustment method fully relies on correcting the accumulated difference between radar and raingauge measurements over the entire rainfall event, without taking into account the temporal variation within a storm process.

In addition to the rainfall (temporal) profiles, Figure 2(d) also demonstrates that the spatial structures of rainfall fields are largely altered by simply multiplying a given constant (i.e. the sample mean bias) to the original radar rainfall fields. In contrast, it can be seen that the spatial structure of the rainfall field is preserved when the Bayesian adjustment technique is applied. As previously mentioned, the ability to reflect the spatial variability of a rainfall field is one of the main advantages of radars and it is desirable to retain it.

After carrying out the rainfall adjustment, the different rainfall estimates were applied to the dual-drainage model of the Cranbrook catchment. The associated flow levels in one of the sewers (located in the mid-stream part of the catchment) are shown in Figure 2(c). As can be seen, the hydraulic outputs obtained with the adjusted radar measurements are quantitatively much more similar to the RG outputs and to the observed water levels, as compared to the outputs resulted from the radar rainfall estimates before adjustment. This demonstrates the predominant role of rainfall mean bias in hydrological and hydraulic modelling. However, it can also be observed that, as compared to the hydraulic outputs of the "Corrected Radar 1 km", the outputs of the "Bayesian Radar 1 km" show better agreement with the RG outputs and with the flow level measurements, particularly regarding the timing and magnitude of flow level peaks. It is mainly due to the better reproduction of rainfall profiles (both in quantity and geometry) achieved with the Bayesian adjustment method. These results suggest that, in addition to rainfall mean bias, the spatial and temporal variability of rainfall is also an important factor which has a significant impact on the associated urban hydrological/hydraulic applications.



(a)



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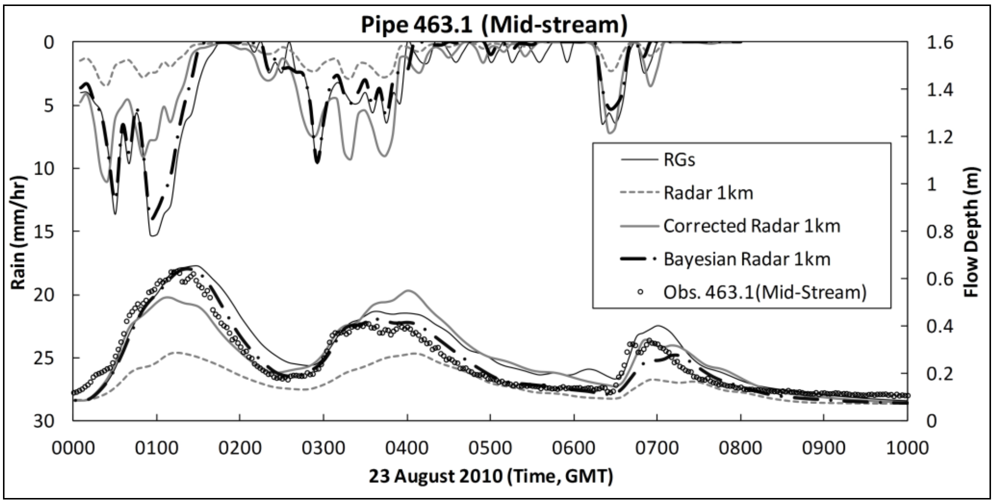
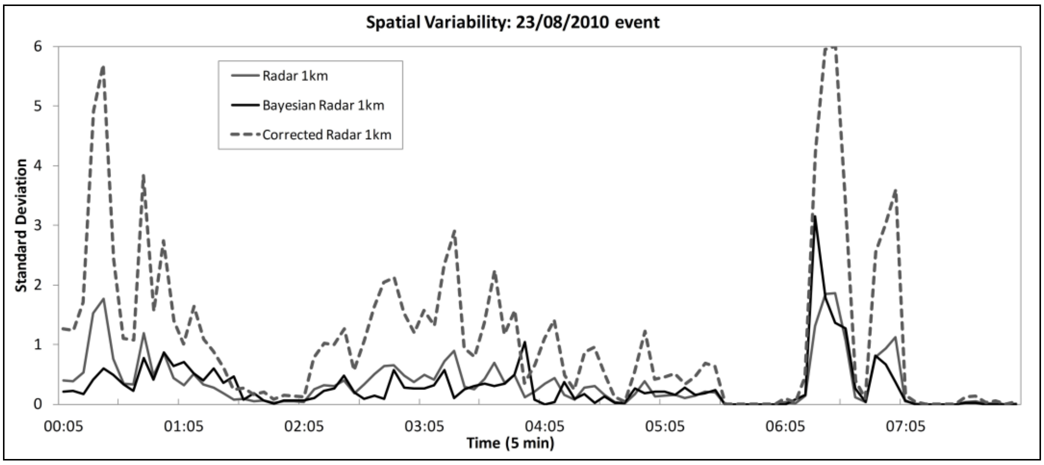


(c)



(d)

Figure 2. Results for the entire Cranbrook catchment for the 23/08/2010 event: (a) Quantile-quantile (q-q) comparison of mean raingauge, radar and adjusted radar rainfall estimates (mm) per 5-min time step; (b) q-q comparison of cumulative mean raingauge, radar and adjusted radar rainfall estimates (mm); (c) Mean raingauge, radar and adjusted radar rainfall profiles and associated hydraulic outputs, as represented by water depth at the Valentine Sewer – Pipe 463.1 of the hydraulic model; (d) Spatial variability as represented by the standard deviation of the original and adjusted radar rainfall fields.

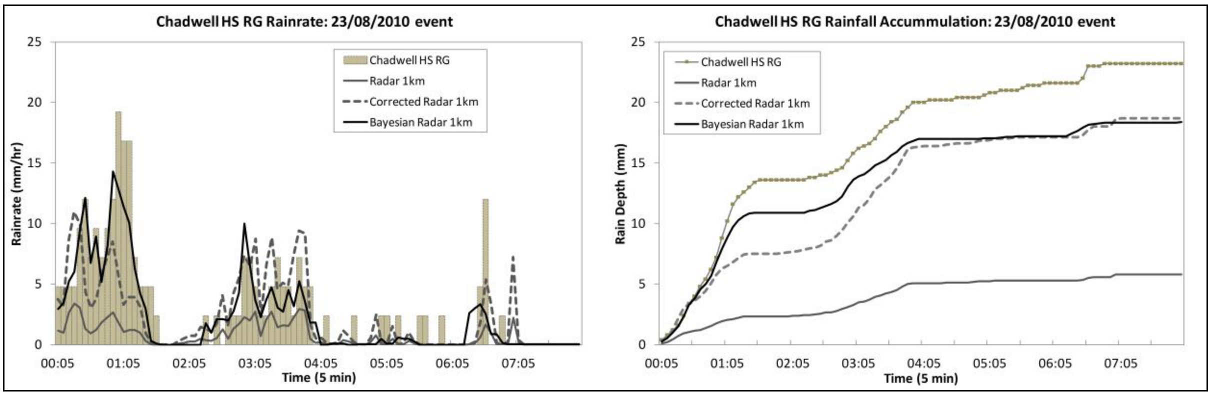


Figure 3. Comparison of 5-min rainfall profiles and accumulations for the Chadwell High School raingauge and the coincidental original and adjusted radar estimates – 23/08/2010 event.

6 CONCLUSIONS AND FUTURE WORK

In this work, a detailed review of state-of-the-art gauged-based radar rainfall adjustment techniques was firstly conducted with the purpose of analysing their theoretical foundation. In general, rainfall adjustment techniques can be classified into two types: (i) mean bias reduction techniques and (2) error variance minimisation techniques. Moreover, the existing techniques have mainly been applied at large scales and on hourly or daily basis; however, their suitability for smaller spatial and temporal scales (i.e. for urban applications) has not been fully analysed.

After this review, two techniques -one of each type- were selected and tested in a small urban catchment (865 ha) in North-East London. The radar rainfall estimates of four historical events occurring between August 2010 and January 2012 were adjusted using point rainfall measurements recorded by three in situ raingauges. The adjusted rainfall estimates were applied to the physically-based dual-drainage model of the catchment and the associated outputs were compared to flow level records in addition to the outputs resulted from raingauge measurements and the original radar data.

In these case studies, the method based upon error variance minimisation performed better, as it not only reduced mean bias, but it managed to correctly reproduce the spatial and temporal variability of rainfall, which proved to have a significant impact on the associated hydraulic outputs. These results suggest that error variance minimisation methods may be more appropriate for small scale urban hydrological/hydraulic applications. However, before further conclusions can be drawn, more work should be done to deeply understand the impact of parameters such as catchment size and geometry, raingauge network size, density and relative location. Moreover, the feasibility of using these techniques in real-time and its potential benefits for rainfall and flood forecast should be further studied.

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8 REFERENCES

Anagnostou, E. N. and Krajewski, W. F. (1999). Rea-time radar rainfall estimation. Part I: algorithm formulation. *Journal of Atmospheric and Oceanic Technology*, 16, 189-197.

Cole, S. J. and Moore, R. J. (2008). Hydrological modelling using raingauge- and radar-based estimators of areal rainfall. *Journal of Hydrology*, 358, 159-181.

Collier, C. G. (2009). On the propagation of uncertainty in weather radar estimates of rainfall through hydrological models. *Meteorological Applications*, 16(1), 35-40.

Ehret, U., Gotzinger, J., Bardossy, A. and Pegram, G. G. S. (2008). Radar based flood forecasting in small catchments, exemplified by the Goldersbach catchment, Germany. *International Journal of River Basin Management*, 6(4), 323-329.

Einfalt, T., Arnbjerg-Nielsen, K., Golz, C., Jensen, N.-E., Quirmbach, M., Vaes, G. and Vieux, B. (2004). Towards a roadmap for use of radar rainfall data in urban drainage. *Journal of Hydrology*, 299(3-4), 186-202.

Einfalt, T., Jessen, M. and Mehlig, B. (2005). Comparison of radar and raingauge measurements during heavy rainfall. *Water Science and Technology*, 51(2), 195-201.

Fulton, R. A., Breidenbach, J. P., Dong-Jun, S. and Miller, D. A. (1998). The WSR-88D rainfall algorithm. *Weather and Forecasting*, 13(2), 377-395.

Gerstner, E.-M. and Heinemann, G. (2008). Real-time areal precipitation determination from radar by means of statistical objective analysis. *Journal of Hydrology*, 352, 296-308.

Golding, B. W. (2009). Uncertainty propagation in a London flood simulation. *Journal of Flood Risk Management*, 2(1), 2-15.

Harrison, D. L., Scovell, R. W. and Kitchen, M. (2009). High-resolution precipitation estimates for hydrological uses. *Proceedings of the Institution of Civil Engineers: Water Management*, 162(2), 125-135.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Transactions of the ASME-Journal of Basic Engineering*, 82(D), 35-45.

Krajewski, W. F. (1987). Cokriging radar-rainfall and rain gage data. *Journal of Geophysical Research*, 92(D8), 9571-9580.

Liguori, S., Rico-Ramirez, M. A., Schellart, A. N. A. and Saul, A. J. (2011). Using probabilistic radar rainfall nowcasts and NWP forecasts for flow prediction in urban catchments. *Atmospheric Research*, 103, 80-95.

Looper, J. P. and Vieux, B. E. (2012) An assessment of distributed flash flood forecasting accuracy using radar and rain gauge input for a physics-based distributed hydrologic model. *Journal of Hydrology*, 412-413(0), 114-132.

Mazzetti, C. (2004). *Report on performance of the new methodology*. Deliverable 7.4, MUSIC Project (Multiple Sensor Precipitation Measurements, Integration, Calibration and Flood Forecasting), European Commission.

Moore, R. J., Watson, B. C., Jones, D. A. and Black, K. B. (1989). *London Weather Radar Local Calibration Study: Final Report*, Contract report prepared for the National Rivers Authority Thames Region, NERC/Institute of Hydrology, Wallingford, UK.

Seo, D.-J., Breidenbach, J. P. and Johnson, E. R. (1999). Real-time estimation of mean field bias in radar rainfall data. *Journal of Hydrology*, 223, 131-147.

Smith, J. A., Baeck, M. L., Meierdiercks, K. L., Miller, A. J. and Krajewski, W. F. (2007). Radar rainfall estimation for flash flood forecasting in small urban watersheds. *Advances in Water Resources*, 30(10), 2087-2097.

Syed, K. H., Goodrich, D. C., Myers, D. E. and Sorooshian, S. (2003). Spatial characteristics of thunderstorm rainfall fields and their relation to runoff. *Journal of Hydrology*, 271(1-4), 1-21.

Tabios, G. Q. and Salas, J. D. (1985). A comparative analysis of techniques for spatial interpolation of precipitation. *Journal of the American Water Resources Association*, 21(3), 365-380.

Todini, E. (2001). A Bayesian technique for conditioning radar precipitation estimates to rain-gauge measurements. *Hydrology and Earth System Sciences*, 5(2), 187-199.

Vieux, B. E. and Bedient, P. B. (2004). Assessing urban hydrologic prediction accuracy through event reconstruction. *Journal of Hydrology*, 299(3-4), 217-236.

Vieux, B. E. and Imgarten, J. M. (2011). On the scale-dependent propagation of hydrologic uncertainty using high-resolution X-band radar rainfall estimates. *Atmospheric Research*, 103(0), 96-105.

Wheater, H., Chandler, R., Onof, C., Isham, V., Bellone, E., Yang, C., Lekkas, D., Lourmas, G. and Segond, M. L. (2005). Spatial-temporal rainfall modelling for flood risk estimation. *Stochastic Environmental Research and Risk Assessment*, 19(6), 403-416.

Wood, S. J., Jones, D. A. and Moore, R. J. (2000). Static and dynamic calibration of radar data for hydrological use. *Hydrology and Earth System Sciences*, 4(4), 545-554.

Yang, C., Chandler, R. E., Isham, V. S. and Wheater, H. S. (2005). Spatial-temporal rainfall simulation using generalised linear models. *Water Resources Research*, 41, 1-13.

Zeng R. J., Lemaire R., Yuan Z. and Keller J. (2004). A novel wastewater treatment process: simultaneous nitrification, denitrification and phosphorus removal. *Water Science and Technology*, 50(10), 163-170.

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