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 using as case study an urban catchment (∼8.65 km²) in North-East London. The radar rainfall estimates of four historical events (2010–2012) were adjusted using in situ raingauge estimates and the adjusted rainfall fields were applied to the hydraulic model of the study area. The results show that both techniques can effectively reduce mean bias; however, the technique based upon error variance minimisation can in general better reproduce the spatial and temporal variability of rainfall, which proved to have a significant impact on the subsequent hydraulic outputs. This suggests that error variance minimisation based methods may be more appropriate for urban-scale hydrological applications.

Key words | gauge-based adjustment, merging/combination, pluvial flooding, radar, rainfall, urban hydrology

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 & Imgarten 2012).

The sensors that are commonly used for estimation and prediction of rainfall at catchment scales are raingauges and radars (Cole & 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 well capture the spatial variability of rainfall which has a significant impact on the physical processes and thus on modelling of urban pluvial flooding (Tabios & Salas 1985; Syed et al. 2005). 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 & 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

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the associated flood forecast (whose main input is the rainfall forecast) (Liguori et al. 2011; Schellart et al. 2012). 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 upon 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 (so-called Z–R conversion) is the result of a calibration process based upon the theoretical exchange and the empirical comparison of a large number of coincidental observations of radar reflectivity and raingauges. In order to obtain statistically robust results, the conversion has to compromise the capacity of deriving extreme values since the frequency of their occurrence is relatively low; hence, the Z–R conversion performs poorly at capturing intense rainfall rates in particular (Einfalt et al. 2004, 2005), which is vital for urban applications. In addition, this conversion is in general static; i.e. they are not dynamically updated (they only change according to the storm types; however, for each storm type the conversion is invariant). After the conversion or calibration process and with the purpose of further enhancing the suitability of radar estimates for hydrological 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 (∼1,000 km²) 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 (a 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 km² in average) over a small urban area (∼14.3 km²). In this comparison, large and event-varying bias were observed over the study catchment even though NEXRAD rainfall measurements had been dynamically adjusted with raingauge measurements (similar to the UK Nimrod rainfall data and adjusted based upon hourly scales; see Golding (1998) and Harrison et al. (2009) for the Nimrod rainfall product).

Moreover, according to Ciach & Krajewski (1999) and Seo & Krajewski (2010), the radar rainfall error may significantly increase at small spatial and/or temporal scales; this may not be well tackled by the existing gauge-based radar rainfall adjustment. Therefore, a thorough assessment of the feasibility of applying the existing gauge-based adjustment techniques to urban-scale applications is essential.

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.

**REVIEW OF GAUGE-BASED ADJUSTMENT TECHNIQUES**

Gauge-based adjustment techniques aim at combining the advantages and overcoming the drawbacks of radar and raingauge rainfall estimates; that 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 the common idea of these techniques is to reduce the bias (or errors) between raingauge and radar measurements, but according to the approaches that are used to characterise the bias these can be in general classified into two types: (1) mean bias reduction techniques; and (2) error variance minimisation techniques. The former assumes that the mean raingauge data over a specific area can satisfactorily represent the areal rainfall volumes; in other words, the raingauge measurements are fully trusted and used as truth, and the adjusted radar rainfall estimates shall have the same mean as raingauge records. Unlike the first type of techniques, neither raingauge nor radar rainfall estimates are fully trusted in the second type of techniques; what is taken as
trustworthy is that their individual or joint estimation errors can be used to approximate the error between the (imaginary) true and the estimated rainfall values.

A detailed review of these two types of gauge-based adjustment techniques is provided as follows.

**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 & 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 average difference 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 upon 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 & 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 Vieux & Bedient (2004) over a 260 km² urban catchment. 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. These events were re-constructed by applying a simple ratio to reduce the mean bias between radar and the co-located raingauge observations. This simple ratio was derived from the comparison between mean radar rainfall estimates and mean local raingauge measurements at the locations of raingauges over the duration of a rainfall event. Results show that the corresponding flow prediction could be significantly improved by using mean bias adjusted (corrected) radar rainfall estimates as inputs. Similar work was carried out by Smith et al. (2007) but over a relatively small catchment (~14.3 km²), in which 35 rainfall events were re-investigated and significant biases were observed between NEXRAD products and raingauge data. Similarly, the authors reduced bias by applying a simple ratio to scale up or down the radar rainfall rates to approximate the coincidental raingauge records. These investigations suggest that ‘mean bias’ is the most important source of uncertainty reducing 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 & 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, $c$, was introduced to carry out 15-min radar rainfall adjustment in real time (Wood et al. 2000):

$$c = \frac{RG + \epsilon}{\kappa R + \epsilon}$$

where $RG$ and $R$ are the raingauge records and the coincidental radar rainfall estimates (in mm) for a 15 min time interval. This factor is based on the comparison of raingauge and radar estimates at each time step in synergy with a positive correction value $\epsilon$ and a static calibration factor $\kappa$ (fitted from long-term study of radar–raingauge bias); both parameters are empirically derived and retained constant across raingauges within a specific area. For each time step, once the dynamic calibration factor is calculated, the ‘re-calibrated’ radar estimates at the grid squares where raingauge records are unavailable can be obtained from the
expression $R^* = c (k R + e) - \varepsilon$. Cole & Moore (2008) further examined the applicability of this methodology over two UK catchments (Darwen and Kent, respectively 135.7 and 212.3 km²). 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 focusses 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 (~75 km²). 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 (BK) 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 been 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 in Ehret et al. (2008)).

**Error variance minimisation techniques**

Another type of gauge-based adjustment technique focusses on minimising the error variances. The error herein represents the bias between true and estimated rainfall values. However, the true rainfall values are unknown, so this error is generally approximated by raingauge or radar rainfall errors, or their combination. This depends upon the assumption made by different techniques. For example, Todini (2001) used the bias between radar and raingauge data to approximate this error. 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 & 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 & Heinemann (2008) defined the rainfall volume at a specific grid of the true rainfall field as follows:

$$P_a(x_i, y_i) = P_r(x_i, y_i) + \sum_{k=1}^{K} w_{ik} [ P_g(x_k, y_k) - P_r(x_i, y_i) ]$$  \hspace{1cm} (2)

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.

Unlike Gerstner & 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:

\[
V^*(x_0, y_0) = \sum_{i=1}^{N_G} \lambda_{G_i} G_i(x_i, y_i) + \sum_{i=1}^{N_R} \lambda_{R_i} R_i(x_i, y_i)
\]

(3)

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 \( \lambda_{G_i} \) and \( \lambda_{R_i} \), the information of the covariances between true and raingauge rainfall \( \text{Cov}_{VG} \) and between true and radar rainfall \( \text{Cov}_{VR} \) are required; however, it is impossible to obtain them. They are therefore approximated by the forms \( \text{Cov}_{VG} = \beta_G \text{Cov}_{GG} \) and \( \text{Cov}_{VR} = \beta_R \text{Cov}_{RR} \), where \( \text{Cov}_{GG} \) and \( \text{Cov}_{RR} \) are the covariances respectively between raingauges and between radar grids and \( \beta_G \) and \( \beta_R \) are two to-be-determined constants ranging from 0 to 1. This approximation however decreases the applicability of the Cokriging technique because the values of \( \beta_G \) and \( \beta_R \) are usually determined subjectively or through a large number of simulations.

Todini (2001), differently from Krajewski (1987), employed a modified Kalman filter algorithm to merge the interpolated raingauge and radar rainfall fields to obtain the ‘true’ rainfall field at each time step. This method (called Bayesian combination), instead of using \( \text{Cov}_{VG} \) and \( \text{Cov}_{VR} \), uses the covariance of errors \( \text{Cov}_{\varepsilon} \) to help derive the true rainfall field. The error \( \varepsilon_i \) is estimated by comparing the co-located Block-Krilled and radar rainfall estimates; a \( \text{Cov}_{\varepsilon} \) 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 1,051 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 on an hourly basis and its potential to be used in sub-hourly rainfall adjustment needs to be further examined.

**METHODOLOGY**

In this work, one of each type of gauge-based adjustment techniques was 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 described next.

**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 dominating 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.

\[
B_i = \frac{(\sum_{j=1}^{m} RG_{ij})/m}{(\sum_{j=1}^{m} R_i(x_j, y_j))/m}
\]

(4)

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-square over the study area for each selected rainfall event (the adjusted values will be referred to as ‘Corrected radar estimates’).

**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 a strong theoretical background and involves relatively little approximation.
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, for each time step,
to interpolate the real-time raingauge measurements into a synthetic rainfall field using the BK interpolation method. After that, the interpolated rainfall field is merged with the coincidental radar image using a modified Kalman filter algorithm (Todini 2001; Mazzetti 2004).

The idea of the BK interpolation method is to synthesise a rainfall field whose first two order spatial statistics (in terms of semi-variogram) are very similar to those empirically estimated from the associated point rainfall information, where the semi-variogram 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 (part of) 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 could be 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.

The standard Kalman filter algorithm 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), a modified Kalman filter algorithm is applied, where at each time step (i.e. 5 min in this work) the newly observed radar image is used as the a priori estimates and the interpolated rainfall field constitutes the observations to be used for updating the a priori estimates and for obtaining the output field (i.e. a posteriori estimate). In other words, the conventional ‘predict’ step is implemented by updating radar images in real time and the ‘update’ is done by minimising error variance at each time step.

**EXPERIMENTAL SITE AND DATASET**

**Cranbrook catchment**

The above mentioned gauge-based adjustment techniques were tested in the Cranbrook catchment, located within the London Borough of Redbridge (North-East of Greater London – see Figure 1). This catchment is predominantly urban 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 floodings in the past.

**Radar (Nimrod) data**

The Cranbrook catchment is within the coverage of two C-band radars (Chenies and Thurnham – Figure 1(a)), operated by the UK Met Office. The radar estimates are available through the British Atmospheric Data Centre (BADC) with spatial and temporal resolutions of 1 km and 5 min, respectively. The data available in the BADC correspond to a quality-controlled and multi-radar composite product generated with the UK Met Office Nimrod system, which includes corrections for the different errors inherent to radar rainfall measurements (Harrison et al. 2009).
Local monitoring system: raingauges and level gauges

A real-time accessible monitoring system has been installed covering this catchment since April 2010. It includes three tipping bucket raingauges, 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)).

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 concerns in the Cranbrook catchment. A dual-drainage pluvial flood model has been setup for the study area using the InfoWorks CS 10.5 software package. In this model, the urban surface was modelled in 2D (two-dimensions) using triangular meshes (generated with the Shewchuk Triangle meshing functionality of InfoWorks CS). In order for the meshing to be carried out, a bounding polygon was defined (which corresponds to the catchment boundary) and heights at the vertices of the triangles were calculated by interpolating from a Digital Terrain Model (DTM) with cell size $1 \times 1$ m$^2$ and vertical accuracy of approximately 0.15 m.

The surface model was coupled with a 1D (one-dimensional) model of the sewer system (Figure 1(c)) and the interactions between the two models take place at the manholes. The main sewer network of the Cranbrook catchment was obtained from Thames Water (the water and sewerage operations manager of the area); this model was originally built and verified in 2000 following the UK WAPUG (Wastewater Planning Users Group) standards. The model was updated by the authors in 2011 based on the information contained in the online asset database of the water company. In total, the model comprises 1,763 nodes (including manholes, gullies and inlets) and 1,816 pipes. In the model, rainfall is applied through subcatchments which are connected to nodes; each subcatchment is split into different surface types (road, roof, urban pervious, rural pasture, rural bush/scrub) and the NewUK model is used to estimate runoff at each subcatchment. The flow in the sewers and on the surface is simulated based on the full shallow-water equations (i.e. it is a fully hydrodynamic model). The updated model was re-calibrated based on three storm events recorded between April 2010 and November 2011 through our local monitoring system (‘Local monitoring system: raingauges and level gauges’ section).

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/Radar Total’ are the mean raingauge and radar accumulations, ‘Radar@RG Total’ is the co-located mean radar rainfall accumulation, ‘Sample bias’ is the relative difference between RG and Radar@RG totals (obtained from Equation (4)), ‘RG/Radar Max.’ are the maxima of raingauge and radar intensities for 5 min and ‘Peak Flow Depth’ corresponds to the maximum flow depth recorded in the Valentine Sewer (located in the mid-stream section of the catchment, see Figure 1(b)) for each event. It is worth mentioning that, for the 03/01/2012 event, the single-site RG maximum is actually 45.6 mm/hr; however, due to high variation in the spatial structure of this event, the averaged RG maximum appears to be smaller than the Radar rainfall rate maximum.

RESULTS AND DISCUSSION

As can be seen from the ‘Sample Bias’ in 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 the ‘Methodology’ section were applied to each rainfall event. Due to space limitations, only the results associated with the event on 23/08/2010

<table>
<thead>
<tr>
<th>Date</th>
<th>Duration (hr)</th>
<th>RG/Radar Total (mm)</th>
<th>Radar@RG Total (mm)</th>
<th>Sample Bias ($\beta_i$)</th>
<th>RG/Radar Max. (mm/hr)</th>
<th>Peak Flow Depth (m)</th>
</tr>
</thead>
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<tr>
<td>23/08/2010</td>
<td>8</td>
<td>23.53/6.80</td>
<td>7.29</td>
<td>3.23</td>
<td>11.09/3.41</td>
<td>0.633</td>
</tr>
<tr>
<td>26/05/2011</td>
<td>9</td>
<td>15.53/4.88</td>
<td>5.10</td>
<td>3.04</td>
<td>36.00/7.47</td>
<td>0.672</td>
</tr>
<tr>
<td>05–06/06/2011</td>
<td>24</td>
<td>20.87/9.48</td>
<td>9.43</td>
<td>2.21</td>
<td>5.60/2.31</td>
<td>0.346</td>
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<tr>
<td>03/01/2012</td>
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<td>7.72</td>
<td>1.16</td>
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<td>0.547</td>
</tr>
</tbody>
</table>
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 Heath Foundation School) for the 23/08/2010 event. Similar results were obtained for the other two 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 rain-gauge 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 with 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 2(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 with 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) demonstrates that the averaged deviation of rainfall estimates in space is 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 this spatial deviation 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 with the outputs resulting 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 with 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. This is mainly due to the better reproduction of rainfall profiles (both in quantity, geometry and timing) achieved with the Bayesian adjustment method. In addition, for certain intervals (e.g. 0100–0200 and 0300–0400 in Figure 2(c)), it can be observed that the Bayesian outputs are in better agreement with the water level observations than the RG outputs (even though the Bayesian adjusted rainfall estimates and RG estimates have very similar instantaneous mean rainfall rates). 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 massive impact on the associated urban hydrological/hydraulic applications.

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
In general, rainfall adjustment techniques can be classified into two types: (i) mean bias reduction techniques; and (ii) error variance minimisation techniques. Moreover, the existing techniques have mainly been applied at large scales and on hourly or daily bases; however, their suitability for smaller spatial and temporal scales (i.e. for urban applications) has not been fully analysed.
After this review, one technique of each type was selected and tested in a small urban catchment (~8.65 km²) 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 with flow level records in addition to the outputs resulting 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 provide a more appropriate framework for small scale urban hydrological/hydraulic applications. However, before further conclusions can be drawn, more work should be done to properly understand the uncertainties associated with the adjusted rainfall fields. The main challenge of this task is to identify a proper model to characterise the complex structure of urban-scale rainfall values and rainfall estimation errors. This may include selection and parameter fitting of the variogram models; for example, for small-scale rainfall distribution, the exponential variogram could be a better model than the Gaussian variogram. In addition, sensitivity study should be conducted to evaluate 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. Work is currently underway to explore the possibility of using adjusted radar rainfall estimates for calibration of urban drainage models, to quantify and analyse the different sources of uncertainty present in the adjusted rainfall estimates (as mentioned above), and to explore the potential benefits of using adjusted rainfall estimates as input to nowcasting algorithms.

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REFERENCES


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