Improving the applicability of radar rainfall estimates for urban pluvial flood modelling and forecasting

Paper 19 – Session 6: Operational Monitoring & Control

Susana Ochoa-Rodriguez[1]*, Li-Pen Wang[1,2], Alex Grist[3], Richard Allitt[3], C. J. Onof[1], Č. Maksimović[1]

[1]Imperial College London, UK; [2]Katholieke Universiteit Leuven, Belgium; [3]Richard Allitt Associates Ltd., UK

***Presenter: Susana Ochoa-Rodriguez**
Imperial College London, Department of Civil and Environmental Engineering, London SW7 2AZ, UK
E-mail: s.ochoa-rodriguez@imperial.ac.uk

ABSTRACT

This work explores the possibility of improving the applicability of radar rainfall estimates (whose accuracy is generally insufficient) to the verification and operation of urban storm-water drainage models by employing a number of local gauge-based radar rainfall adjustment techniques. The adjustment techniques tested in this work include a simple mean-field bias (MFB) adjustment, as well as a more complex Bayesian radar-raingauge data merging method which aims at better preserving the spatial structure of rainfall fields. In addition, a novel technique (namely, local singularity analysis) is introduced and shown to improve the Bayesian method by better capturing and reproducing storm patterns and peaks. Two urban catchments were used as case studies in this work: the Cranbrook catchment (9 km^2) in North-East London, and the Portobello catchment (53 km^2) in the East of Edinburgh. In the former, the potential benefits of gauge-based adjusted radar rainfall estimates in an operational context were analysed, whereas in the latter the potential benefits of adjusted estimates for model verification purposes were explored. Different rainfall inputs, including raingauge, original radar and the aforementioned merged estimates were fed into the urban drainage models of the two catchments. The hydraulic outputs were compared against available flow and depth records. On the whole, the tested adjustment techniques proved to improve the applicability of radar rainfall estimates to urban hydrological applications, with the Bayesian-based methods, in particular the singularity sensitive one, providing more realistic and accurate rainfall fields which result in better reproduction of the urban drainage system's dynamics. Further testing is still necessary in order to better assess the benefits of these adjustment methods, identify their shortcomings and improve them accordingly.

KEYWORDS: radar, gauge-based adjustment, urban drainage, pluvial flooding, 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). Traditionally, urban drainage modelling applications have relied mainly upon raingauge data as input, given that these sensors provide accurate point rainfall estimates near the ground. However, they cannot capture the spatial variability of rainfall, which has a significant impact on the urban hydrological system and thus on the modelling of urban pluvial flooding (Tabios & Salas, 1985; Syed et al., 2003). With the advent of weather radars, radar rainfall estimates with higher temporal and spatial resolution have become increasingly available and have started to be used operationally for urban storm-water model calibration and real-time operation. Nonetheless, the insufficient accuracy of radar rainfall estimates, which is particularly critical in the case of extreme rainfall magnitudes (Einfalt et al., 2005; Harrison et al., 2009), has proven problematic and has hindered its widespread practical use (Schellart et al., 2012). In order to improve the accuracy of radar rainfall estimates while preserving their spatial description of rainfall fields, it is possible to dynamically adjust them based on raingauge measurements. Studies on this subject have been carried out over the last few years and gauge-based radar rainfall adjustment techniques have been widely employed by country-scale meteorological services (Cole & Moore, 2008; Goudenhoofdt & Delobbe, 2009; Harrison et al., 2009). However, these studies and applications have focused on large-scales and, in general, their applicability to urban hydrology is insufficient. Local re-adjustment is therefore required before radar rainfall data can be used as input to urban hydrological/hydraulic models (Wang et al., 2013).

This work explores the possibility of improving the applicability of radar rainfall estimates to the calibration and operation of urban storm-water drainage models by employing a number of local gauge-based radar rainfall adjustment techniques. The adjustment techniques tested in this work include a simple mean-field bias (MFB) adjustment, as well as a more complex Bayesian radar-raingauge data merging method which aims at better preserving the spatial structure of rainfall fields. In addition, a novel technique (namely, local singularity analysis) is introduced which improves the Bayesian method by better capturing and reproducing storm patterns and peaks.

Two urban catchments for which raingauge, radar, flow and depth measurements are available were used as case studies in this work: the Cranbrook catchment (9 km^2) in North-East London and the Portobello catchment (53 km^2) in the East of Edinburgh. In the former, the potential benefits of gauge-based adjusted radar rainfall estimates in an operational context were analysed (storm events outside of the verification period were used in the analysis). In contrast, in the Portobello catchment the potential benefits of adjusted estimates for model verification purposes were explored (the dataset used in the analysis corresponds to the flow survey used for the verification of the model). Different rainfall inputs, including raingauge (distributed using Thiessen polygons), block-kriged interpolated raingauge, original radar (i.e. Met Office Nimrod product (Golding, 1998)) and the aforementioned merged estimates were fed into the urban drainage models of the two catchments. The different rainfall estimates and the associated hydraulic outputs were inter-compared. In addition, the hydraulic outputs were also compared against available flow and depth records.

The paper is organised as follows: in the next section a description is provided of the rainfall processing techniques used in this study, including the kriging (raingauge) interpolation method, as well as the gauge-based radar rainfall adjustment methods mentioned above. Afterwards, the test catchments and datasets used in the study are described, and the hydraulic models specified. Subsequently, the resulting rainfall estimates and associated hydraulic outputs are presented and discussed. Lastly, the main conclusions and implications of the study are presented and the future work in this area is discussed.

2. RAINFALL PROCESSING TECHNIQUES

As mentioned above, in this work a simple mean-field bias (MFB) adjustment technique as well as two Bayesian-based merging procedures were used with the aim of improving the applicability of radar rainfall estimates to urban hydrological applications. In addition, the original point-raingauge data was interpolated using a block-kriging method; this was done with the purpose of generating a raingauge-based rainfall field which could serve as basis for the Bayesian merging procedures and which would also allow direct comparison with other types of areal rainfall estimates. In what follows a brief description is provided of each of these techniques.

2.1. BLOCK-KRIGING (BK) INTERPOLATION

Kriging is a geostatistical technique that enables the prediction (or interpolation) of values at unknown locations by linearly combining the surrounding known values (Armstrong, 1998), and the epithet 'Block' refers to the application of this technique to predicting (interpolating) areal averages over a grid-square rather than point values. The interpolated value is thus

$$Z^*(x_0) = \sum \lambda_i \cdot Z(x_i) \qquad \text{Equation 1}$$

where $Z^*(x_0)$ represents an unknown value at a specific location x_0, $Z(x_i)$ are known values at locations x_i, and λ_i are the weighting factors. These weighting factors are determined based upon the spatial association (in terms of co-variance or semi-variogram) of the known values. This suggests that the (block-) kriged rainfall field contains not only accurate rainfall estimates, but also (part of) the spatial dependencies between these point estimates over a specific area. In addition, kriging gives the best unbiased estimates of point values or areal averages (where "best" means that the estimation error variance is minimised).

In this work Block-kriging interpolation is used to produce unbiased rainfall estimates at each radar grid location. In this way it is possible to have a raingauge-based rainfall field with the same resolution as that of the radar and merged rainfall fields. Besides allowing direct comparison with other types of areal rainfall estimates, the blocked-kriged interpolated field serves as basis for the Bayesian merging methods described below.

2.2. MEAN-FIELD BIAS (MFB) GAUGE-BASED RADAR RAINFALL ADJUSTMENT

The MFB was computed by the following equation:

$$B = \sum RG / \sum RD \qquad \text{Equation 2}$$

where RG and RD represent the raingauge and radar accumulations, respectively, over a specific time interval at a particular location. The summation is carried out using all raingauges available within the radar domain and also using a moving window that takes into account the last 1h of rainfall data to simulate real-time operation. The adjusted radar rainfall (RD') is calculated by multiplying the bias (B) obtained at a particular time step by the original rainfall field (RD), that is, $RD' = B \cdot RD$. Maximum bias correction factors were set to 3.0 in order to avoid too large adjustments.

2.3. BAYESIAN (BAY) GAUGE-BASED RADAR RAINFALL MERGING

The Bayesian merging (BAY) is a dynamic method intended for real-time applications (Todini, 2001). It has been proven to outperform many other merging techniques in numerical experiments (Mazzetti & Todini, 2004) and in urban-scale hydrological applications (Wang et al., 2013). The underlying idea is to analyse the uncertainty of rainfall estimates from different sources (in this case radar and raingauge sensors) and combine these estimates in such a way that the overall uncertainty is minimised. The first step of the method is, for each time step, to interpolate the raingauge measurements into a synthetic rainfall field using the BK interpolation method described above (steps (a) and (c) in Figure 1). This step generates comparable areal raingauge rainfall estimates to the radar estimates, based upon which a field of errors (i.e. the bias at each radar grid location) can be constructed (steps (d) and (e) in Figure 1). The covariance of this error field (representing the uncertainty of radar estimates) can be further analysed and compared with the estimation uncertainty of BK interpolation (representing the uncertainty of RG estimation). A Kalman filter (Kalman, 1960) is then applied (step (e) in Figure 1) to evaluate these two sources of uncertainty and based on this comparison, adjust the radar estimates so that the overall uncertainty is minimised (steps (e) and (f)). This method was developed for and initially applied at large temporal and spatial scales and its suitability for urban hydrological applications has just started to be explored (Wang et al., 2013).

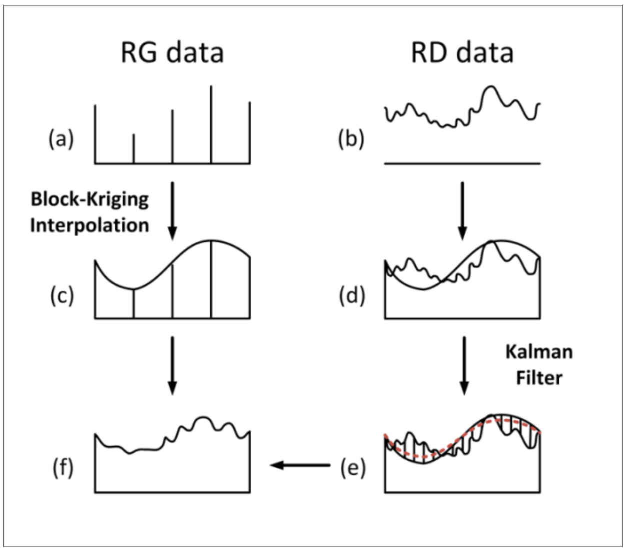

Figure 1: Schematic of Bayesian radar-raingauge data merging (Todini, 2001). This figure was adapted from Figure 3 of Ehret et al. (2008).

2.4. SINGULARITY-SENSITIVE (SIN) BAYESIAN GAUGE-BASED RADAR RAINFALL MERGING

The singularity-sensitive Bayesian method has been recently developed with the purpose of improving a shortcoming of the original BAY method and of other merging methods which have similar underlying principles. The BAY method and several other merging techniques are mainly based upon 1st or 2nd order (statistical-) moment approximations and cannot properly cope with the non-normality observed in small-scale applications (e.g. urban hydrological modelling). In fact, it is often the case that the radar image captures striking local extremes (albeit the actual rainfall depths may be inaccurate), but these structures are lost or smoothened through the merging process. These striking local extremes correspond to singularity points within the rainfall field and can be identified through a local singularity analysis. With the purpose of improving this aspect, the SIN methodology has been developed which identifies the local extremes or 'singularities' of radar rainfall fields and preserves them throughout the merging process (Wang & Onof, 2013). Singularities are defined through the fact that the areal average rainfall increases as a power function when the area decreases (Schertzer & Lovejoy, 1987; Cheng et al., 1994). In its implementation, the SIN method follows a similar procedure to that of the BAY method. The only difference is that, before radar estimates are compared with the BK rainfall estimates, the singularities are firstly identified and extracted from the radar rainfall field (between steps (b) and (d)). The resulting non-singular radar field is then used in the normal merging process and the singularities are subsequently and proportionally added back to the final merged rainfall field. The issue with singularities is that these make the radar field apparently highly uncertain, thus resulting in the radar field being given less weight in the merging process (steps e and f in Figure 1). This can cause smoothing of rainfall extremes whose spatial structure was actually well captured by the radar. Therefore, by removing the singularities before the merging takes place and applying them back afterwards, it is possible to better preserve rainfall extremes within the rainfall field. It is worth mentioning that the 'degree of singularity' removed from the radar field is a tuneable parameter; an average value has been used in this study and work is underway to explore the sensitivity and impact of this parameter on the final rainfall product and associated hydraulic outputs.

3. EXPERIMENTAL SITES AND DATASETS

As mentioned above, two catchments were used for testing the suitability of the locally gauge-based adjusted radar rainfall estimates. A description of each of these catchments and the local monitoring data (including raingauge, flow and depth data) available at each of them and used in this study is next provided.

In addition to the local monitoring data, both catchments are within the coverage of C-band radars operated by the UK Met Office. Radar rainfall estimates for both catchments are available through the British Atmospheric Data Centre (BADC) with spatial and temporal resolutions of 1 km and 5 min, respectively. These estimates 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 (Golding, 1998).

3.1. CRANBROOK CATCHMENT

Catchment description: The Cranbrook catchment is located within the London Borough of Redbridge (north-east part of Greater London - Figure 2a). It is predominantly urbanised and has a drainage area of approximately 9 km^2. The main water course is about 5.75 km long, of which 5.69 km are culverted and have become part of the storm water drainage system, which is mainly separate. The storm water drainage system of this catchment discharges into the Roding River and, in turn, the Roding River discharges into the river Thames. This area has experienced several pluvial, fluvial and coincidental flooding in the past.

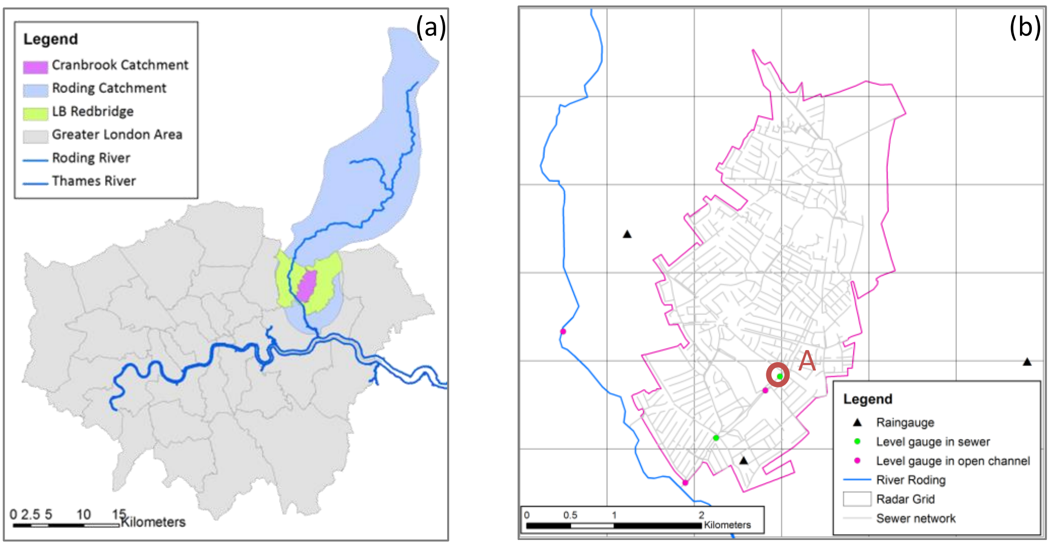

Figure 2: Cranbrook catchment (a) general location; (b) sensor location, sewer network and radar grid over the catchment.

Hydraulic model: The model of the sewer system of this catchment (Figure 2b) is setup in InfoWorks CS and comprises 1,763 nodes and 1,816 pipes. Rainfall is applied to the model through subcatchments and runoff is estimated using the NewUK model. This model was obtained from the water company of the area and was initially verified in 2009 using data from a medium term flow survey (using solely raingauge data as input). The model was updated and re-verified in 2010 using data from the local monitoring system described below.

Local monitoring data available for this catchment: A real time accessible monitoring system has been maintained in the Cranbrook catchment since April 2010. It includes three tipping bucket raingauges (with 1 min resolution), two 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 (with 2 min resolution) (see Figure 2b). Data collected through this monitoring system, in addition to radar rainfall data (at 1 km and 5 min resolution) obtained from the BADC were used in this study.

Storm events selected for this study: Two storm events respectively in August 2010 and May 2011 were selected to test the gauge-based adjustment methods. **These events are different from those used for the verification of the model**. The dates and main characteristics of these events are summarised in Table 1.

Table 1: Rainfall events selected for testing of adjustment methods in the Cranbrook catchment.

Event	Date	Duration (h)	RG Total (mm)	RG Peak Intensity (mm/h)	RD Total (mm)	RD Peak Intensity (mm/h)
Storm 1	23/08/2010	8	23.53	15.20	6.80	3.41
Storm 2	26/05/2011	9	15.53	36.00	4.77	7.38

RG = Raingauge; RD = Radar. NOTE: The accumulation and peak intensity values shown in this table correspond to areal mean values for the entire domain under consideration.

3.2. PORTOBELLO CATCHMENT

Catchment description: Portobello is a beach town located 5 km to the east of the city centre of Edinburgh, along the cost of the Firth of Forth, in Scotland (Figure 3a). The catchment is predominantly urban and has a drainage area of approximately 53 km^2. The storm water drainage system is mainly separate and drains from the south-west to the north-east (towards the sea).

Hydraulic model: The model of the sewer system of the Portobello catchment (Figure 3b) is setup in InfoWorks CS and was verified in 2011 based on the medium term flow survey data described below (using solely raingauge data as input). It comprises 2,916 nodes and 2,906 conduits. Rainfall is applied to the model through subcatchments and runoff is estimated using the NewUK model.

Local monitoring data available for this catchment: The only local monitoring data available for this catchment is that of the medium term flow survey used for the verification of the model. The flow survey was carried out between April and June 2011 and comprises data from 12 raingauges and 28 flow gauges (Figure 3b). Radar rainfall estimates (at 1 km and 5 min resolution) for the same period of the flow survey were obtained from the BADC.

Storm events selected for this study: During the flow survey monitoring period, three relatively large storms were recorded and were used for the verification of the model. **The same three storm events were used in this study to test the gauge-based adjustment methods**. The dates and main characteristics of these events are summarised in Table 2.

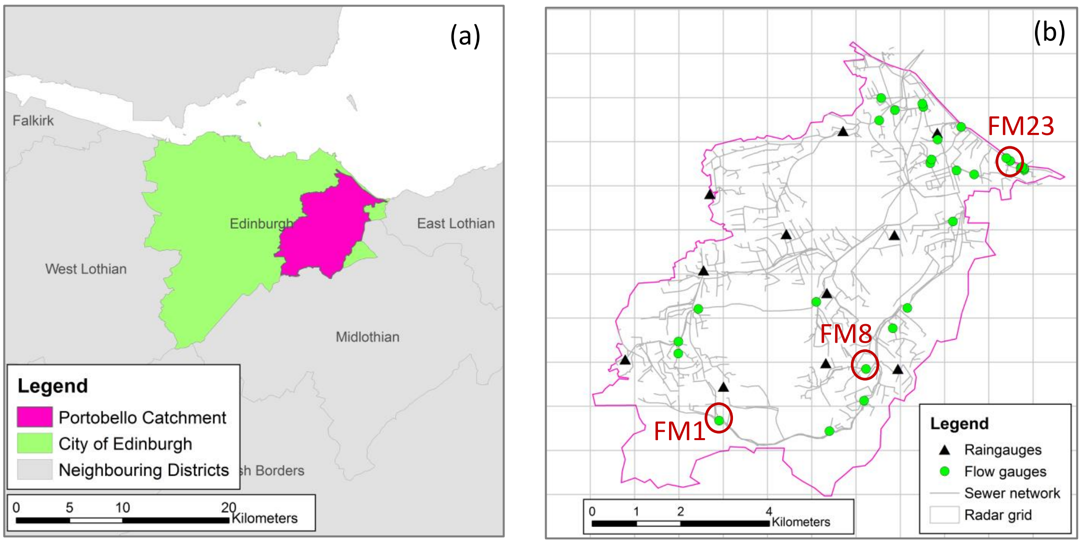

Figure 3: Portobello catchment (a) general location; (b) sensor location, sewer network and radar grid over the catchment.

Table 2: Rainfall events selected for testing of adjustment methods in the Portobello catchment.

Event	Date	Duration (h)	RG Total (mm)	RG Peak Intensity (mm/h)	RD Total (mm)	RD Peak Intensity (mm/h)
Storm 1	06-07/05/2011	7	9.25	11.21	9.67	7.29
Storm 2	23/05/2011	7	7.70	5.03	10.80	4.80
Storm 3	21-22/06/2011	24	32.96	8.46	25.85	5.42

RG = Raingauge; RD = Radar. NOTE: The accumulation and peak intensity values shown in this table correspond to areal mean values for the entire domain under consideration.

4. RESULTS AND DISCUSSION

Firstly, features of the rainfall estimates resulting from the different interpolation and adjustment techniques are presented and discussed. Then, the hydraulic outputs resulting from each rainfall input are presented, inter-compared and discussed. A summary of the main findings from each of these analyses is given at the end of each sub-section.

4.1. RAINFALL ESTIMATES

Summaries of the main statistics of the different rainfall estimates for the storm events under consideration in the Cranbrook and Portobello catchments are presented, respectively, in Table 3 and Table 4. In these tables comparisons are presented of the areal average and individual (i.e. point or grid square) rainfall accumulations and peak intensities for the different rainfall estimates (i.e. raingauge (RG), radar (RD), MFB adjusted, BAY merged and SIN merged).

Table 3: Summary statistics of the different rainfall estimates for the two storm events under consideration in the Cranbrook catchment

		Areal average values		**Max/min values at individual RG locations and RD grids (Max/min ratio)**	
Rainfall estimates / Storm Event		**S1**	**S2**	**S1**	**S2**
Total rainfall accumulation (mm)	**RG**	23.53	15.53	23.80/23.20 **(1.03)**	16.40/14.00 **(1.17)**
	RD	6.80	4.77	8.17/5.92 **(1.38)**	7.35/3.35 **(2.19)**
	BK	22.23	12.75	22.85/21.78 **(1.05)**	13.60/12.30 **(1.11)**
	MFB	18.06	11.11	21.70/15.59 **(1.39)**	17.62/8.10 **(2.18)**
	BAY	18.8	12.31	19.48/18.20 **(1.07)**	14.06/11.36 **(1.24)**
	SIN	19.47	14.07	22.84/16.15 **(1.41)**	17.98/11.05 **(1.63)**
Peak rainfall intensity (mm/h)	**RG**	15.20	36.00	19.20/19.20 **(1.00)**	55.20/26.40 **(2.09)**
	RD	2.43	7.38	7.69/3.31 **(2.32)**	21.00/3.72 **(5.56)**
	BK	14.57	23.89	16.03/14.02 **(1.14)**	38.55/14.94 **(2.58)**
	MFB	7.29	22.15	23.06/9.56 **(2.41)**	63.00/11.16 **(5.65)**
	BAY	13.59	25.51	15.09/12.52 **(1.21)**	34.34/20.02 **(1.72)**
	SIN	13.54	37.21	41.40/12.14 **(3.41)**	64.09/18.29 **(3.50)**

Table 4: Summary statistics of the different rainfall estimates for the three storm events under consideration in the Portobello catchment

		Areal average values			**Max/min values at individual RG locations and RD grids (Max/min ratio)**		
Rainfall estimates / Storm Event		**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Total rainfall accumulation (mm)	**RG**	9.25	7.70	32.96	11.20/8.20 **(1.37)**	11.20/5.00 **(2.24)**	40.00/24.80 **(1.61)**
	RD	9.67	10.80	25.85	15.66/7.62 **(2.06)**	19.92/6.75 **(2.95)**	44.79/17.89 **(2.50)**
	BK	9.02	7.50	30.69	10.16/8.30 **(1.22)**	9.52/5.63 **(1.69)**	36.56/25.68 **(1.42)**
	MFB	8.47	7.13	31.94	14.85/6.25 **(2.38)**	13.30/4.60 **(2.89)**	49.54/21.81 **(2.27)**
	BAY	8.80	7.51	26.94	10.93/7.96 **(1.37)**	10.82/4.97 **(2.18)**	32.62/21.25 **(1.54)**
	SIN	9.66	7.56	33.73	14.08/7.28 **(1.93)**	12.74/4.54 **(2.81)**	52.71/21.63 **(2.44)**
Peak rainfall intensity (mm/h)	**RG**	11.21	5.03	8.46	20.40/9.60 **(2.13)**	10.80/2.70 **(4.00)**	16.80/7.20 **(2.33)**
	RD	7.29	4.80	5.42	63.09/5.72 **(11.03)**	17.75/2.97 **(5.98)**	37.47/5.91 **(6.34)**
	BK	10.26	4.33	7.07	14.43/9.35 **(1.54)**	6.82/2.82 **(2.42)**	13.82/5.94 **(2.33)**
	MFB	8.33	5.20	6.35	73.02/5.28 **(13.83)**	17.12/1.96 **(8.73)**	37.32/7.31 **(5.11)**
	BAY	9.99	3.96	6.65	15.17/8.58 **(1.77)**	7.14/2.42 **(2.95)**	12.51/5.77 **(2.17)**
	SIN	12.02	5.01	7.83	58.25/5.74 **(10.15)**	15.43/2.39 **(6.46)**	58.76/8.16 **(7.20)**

As can be seen in Table 3and Table 4, the behaviour of RD estimates in relation to RG estimates changes significantly from event to event in each of the catchments. For the Cranbrook catchment (Table 3), due to serious blockage of the radar beam, the RD largely underestimates areal rainfall accumulations in both events; however, the degree of underestimation is not constant, but instead changes for different intensities and storm types. For the Portobello catchment (Table 4), the RG-RD biases (Equation 2) are relatively minor; however, similarly to the Cranbrook catchment, their magnitude is not constant. In Storm 1 of Portobello RG and RD areal average accumulation are quite similar (i.e. bias ≈ 1), but this is not the case in Storm 2 (RG areal accumulation < RD average accumulation; bias < 1) and Storm 3 (RG areal accumulation > RD average accumulation; bias > 1).

The fact that the bias is event varying means that a single (or a constant) RG-RD relationship is insufficient to characterise it; this confirms the need for **localised and dynamic** adjustment of radar rainfall estimates. Beyond the bias, the most striking dissimilarity between RG and RD estimates is the large difference in the ratios between the maximum and minimum rainfall accumulations and peak intensities recorded at point or grid locations within the domain (i.e. Max/min ratio). Notice, for example, the large difference in the RG and RD Max/min peak intensity ratios in Storm 1 of Portobello catchment (this ratio is 2.13 for RG and 11.03 for RD estimates). The fact that higher Max/min ratios are observed in the RD rainfall estimates indicates that it has a significantly higher spatial variability, as compared to the RG rainfall estimates. In addition, a trend can be observed in the difference in the RG and RD Max/min peak intensity ratios to increase as larger peak intensities occur in a storm (e.g. Cranbrook's Storm 2 and Portobello's Storm 1).

As would be expected, the BK estimates exhibit areal average accumulations similar to those of the RG. However, their Max/min ratios are slightly different; this could be caused by the fact that the RG represents point estimates and the BK represents areal estimates (i.e. the area-point rainfall difference; see Anagnostou et al. (1999)).

When looking at the adjusted or merged rainfall products (i.e. MFB, BAY and SIN), it can be noticed that their areal accumulations are, in general, close to those of the RG. This means that the adjustment methods can effectively correct the bias; this is especially evident in the Cranbrook catchment, where the big cumulative biases are largely reduced. Nonetheless, from the analysis of their Max/min ratios it can be noticed that not all methods are able of preserving the highly variable spatial structure observed in the RD field. In this sense, the BAY and BK estimates exhibit a similar behaviour, with Max/min ratios (in particular for the peak intensities) much smaller than those obtained for other adjusted estimates. This indicates that during the BAY merging process, the BK raingauge interpolated estimates were largely trusted and therefore the high spatial variability observed in RD estimates was smoothed off. In contrast, the MFB and SIN adjusted estimates present higher Max/min ratios which are closer to those of the original RD estimates (this is particularly evident in the SIN estimates). This indicates that the MFB and SIN techniques are capable of reducing RG/RD bias while at the same time preserving the spatial variability of RD estimates.

The initial conclusions drawn from Tables 3 and 4 can be confirmed by looking at images of the spatial structure of the peak intensities for each type of rainfall estimate (Figure 4). It can be seen that, as compared to other estimates, the BK and BAY estimates are relatively smooth and their spatial structures are rather unrealistic; this is particularly the case for the BK estimates. Although both BAY and SIN are merged estimates and their spatial structures are somewhat the combination of those of the BK and RD estimates, the SIN estimates appear to be more spatially variable and realistic than the BAY ones and show to have preserved and even enhanced the storm cells observed in the original RD image. As for the MFB estimates, these show nearly the same structure as the RD estimates but with higher rainfall intensity at each grid square.

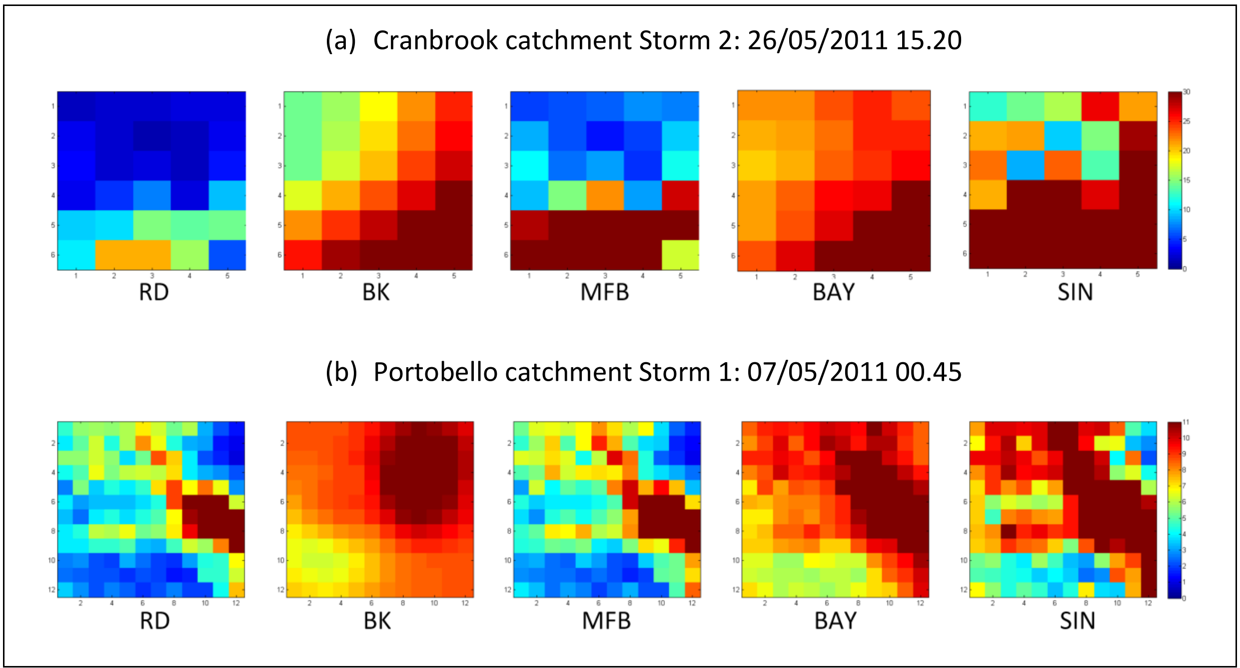

Figure 4: Images of RD, BK and adjusted rainfall estimates at peak intensity times of (a) Cranbrook's Storm 2 and (b) Portobello's Storm 1.

A further comparison of areal average RG intensities versus areal average BK, RD and adjusted estimates' intensities throughout the whole storm period is presented in Figure 5. As expected, BK estimates are in good agreement with RG estimates. With regards to RD estimates, it can be seen that for the Cranbrook storms they consistently underestimate the entire range of rainfall intensity, while for the Portobello catchment, they tend to overestimate small rainfall rates and underestimate the peak intensities. The consistent underestimation in Cranbrook is mainly caused by strong blockage interference. The situation observed in Portobello can be explained by the fact that the Z-R conversion that is used to convert radar reflectivity to rainfall rate has to statistically compromise to the range of rainfall rates that frequently occur (whereas the occurrence of very small and large intensities is relatively rare). It can be seen that both sources of error in RD estimates can be largely improved through adjustment techniques. Promising results are obtained from the BAY and, in particular, from the SIN merging methods, which are able of well reproducing low as well as high rainfall rates. As compared to the RD estimates, the MFB method does not seem to provide significant improvements in this direction and its performance is especially poor at higher intensities (which are of outmost importance in the modelling and forecasting of urban pluvial flooding).

Summary of main findings from the analysis of rainfall estimates: Based on the analysis of the different rainfall estimates, the following main conclusions can be drawn:

- The RG/RD bias (see Equation 2) can vary significantly from event to event (Table 3 and Table 4), thus the need for carrying out local and dynamic adjustment of RD rainfall estimates before these can be used for urban hydrological applications.
- All adjustment methods are able of reducing RG/RD bias, generating spatial rainfall estimates with areal total rainfall accumulations close to those recorded by RG.
- With regards to the spatial structure of rainfall fields, the MFB and SIN estimates appear to be better at preserving the spatial variability as originally captured by the RD. The BAY estimates show a smoother spatial structure, but still more realistic than simple BK interpolated fields.

- With regards to the ability of the different rainfall estimates to reproduce the rain rates as captured by RG, the performance of RD is mostly poor. There are a number of uncertainty sources which cause RD estimates to poorly reproduce rainfall intensities of different magnitudes (in comparison to the rainfall intensities captured by RG). In this respect, the MFB adjustment does not provide significant improvements over the original RD estimates. In contrast, the BAY and in particular the SIN methodologies have shown to be capable of improving the accuracy of the rainfall intensities throughout the whole range of magnitudes observed in the events under consideration.

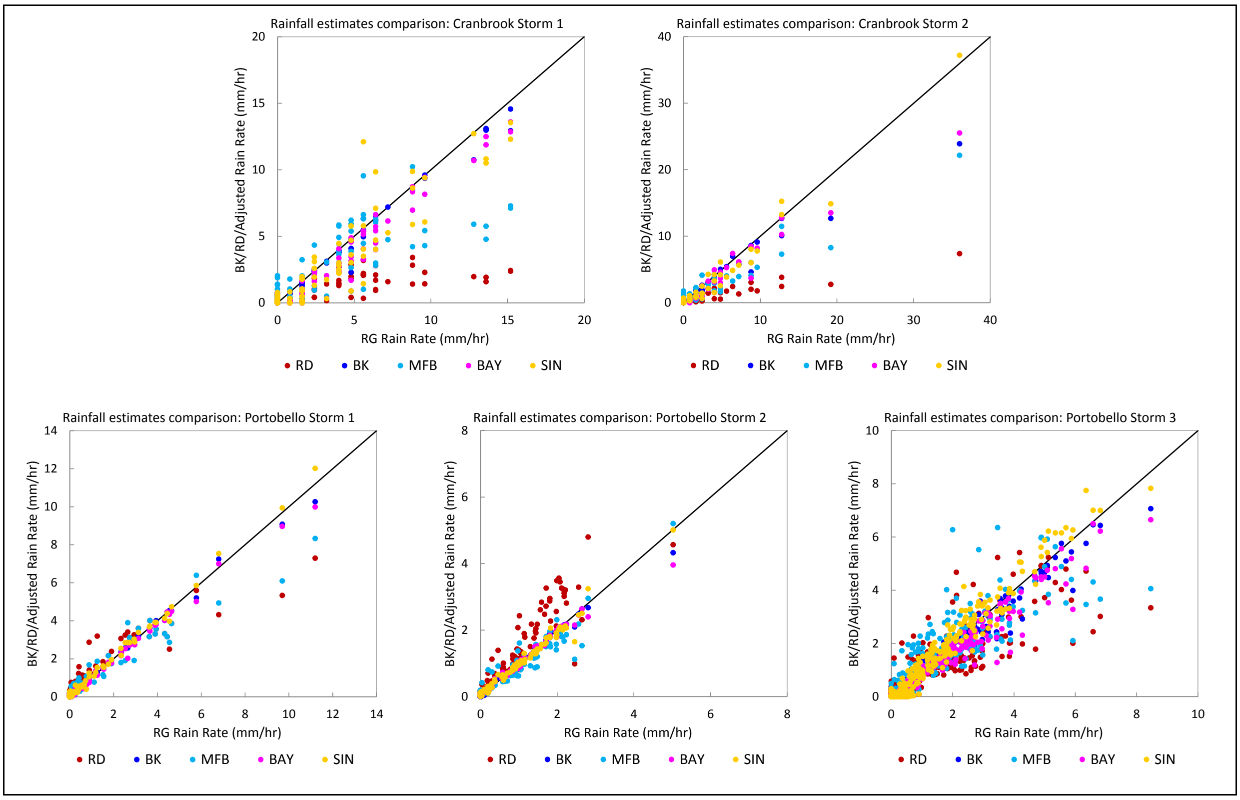

Figure 5: Scatterplots of areal average RG rain rates vs. rain rates of the different spatial rainfall estimates (i.e. RD (red markers), BK (blue), MFB (light blue), BAY (pink) and SIN (yellow)). Two selected storms over the Cranbrook catchment area: Storm 1 (top left) and Storm 2 (top right). Three selected storms over the Portobello catchment area: Storm 1 (bottom left), Storm 2 (bottom middle) and Storm3 (bottom right).

4.2. HYDRAULIC OUTPUTS

In what follows a description is first given of the measures used to evaluate the performance of the hydraulic outputs originating from the different rainfall inputs. Afterwards, the results obtained for the two case studies are presented and discussed. Since the hydraulic outputs in the two experimental catchments correspond to different contexts (i.e. operational context in Cranbrook and verification context in Portobello), these are analysed separately. However, at the end of the section general findings from the two case studies are summarised.

Measures used to evaluate the performance of the hydraulic simulations resulting from the different rainfall inputs: In addition to the direct visual inspection of simulated vs. observed flow and depth hydrographs, a number of measures were employed in this study to assess the performance of the simulation results. These measures are:

- **Relative error (RE) between simulated and observed peak flows and depths:** the RE gives an estimate of how well, in terms of magnitude, the simulation results can reproduce the true peak flows and depths, as recorded by the gauges. *RE* is estimated as follows:

$$RE = \left(S_{Peak} - O_{peak}\right)/O_{Peak} \qquad \text{Equation 3}$$

where O_{Peak} and S_{peak} represent, respectively, the maximum observed and simulated flows or depths. Negative *RE* values indicate that the model underestimates the observed peak flow/depth, while positive values indicate overestimation of the peaks. Moreover, the closer *RE* is to zero, the better.

- **Correlation coefficient (R):** *R* is a measure of the strength and direction of the linear relationship between two variables. It is estimated as follows at each gauging station:

$$R = \frac{\sum_{t=1}^{T}(O_t - \bar{O})(S_t - \bar{S})}{\sqrt{\sum_{t=1}^{T}(O_t - \bar{O})^2}\sqrt{\sum_{t=1}^{T}(S_t - \bar{S})^2}} \qquad \text{Equation 4}$$

where O_t and S_t are observed and simulated flows/depths at time step t, and $\bar{O}$ and $\bar{S}$ correspond to the mean observed and simulated values at the given gauging station. The range of *R* lies between -1 and +1 inclusive, where -1 is total negative correlation, 0 is no correlation and +1 is total positive correlation. In practical terms in the context of this study, *R* provides a measurement of the **similarity of the simulated and observed hydrograph patterns** (positive values should therefore be expected, with values closer to +1 indicating more similarity in the patterns). It is worth noticing that a model which systematically over- or under predicts can still result in good *R* scores, as long as the patterns of the simulations and observations are similar.

- **Nash-Sutcliffe efficiency coefficient (NSE)**: The *NSE* coefficient (Nash & Sutcliffe, 1970) is a widely used measure to quantify the overall predictive ability of a hydrological model. At each gauging station, *NSE* is estimated as one minus the sum of the absolute squared differences between the predicted and observed values **normalised by the variance of the observed values** during the period under investigation:

$$NSE = 1 - \frac{\sum_{t=1}^{T}(O_t - S_t)^2}{\sum_{t=1}^{T}(O_t - \bar{O})^2} \qquad \text{Equation 5}$$

NSE can range from $-\infty$ to 1, with 1 being a perfect fit. The normalisation by the variance of the observations leads to higher *NSE* values at highly dynamic points of the system (where the variability in the observations is high). Therefore, *NSE* values at different locations should only be compared while carefully considering the particular characteristics of each site. Moreover, similar to *R*, *NSE* is not very sensitive to systematic model over- or under prediction (Krause et al., 2005).

As can be seen, the assessment measures used in this study cover different aspects of the performance of the simulations and each of them has advantages and disadvantages; as such, they need to be analysed jointly.

Hydraulic outputs for the Cranbrook catchment: For this catchment only depth records from one gauge were available for the storm events under consideration. Figure 6 presents hydrographs of observed and simulated depths (with the different rainfall inputs) for the two storm events at this gauging station, which is located in the mid-stream part of the catchment. In addition, a summary of the performance measures for the simulation results associated to the different rainfall estimates is presented in Table 5.

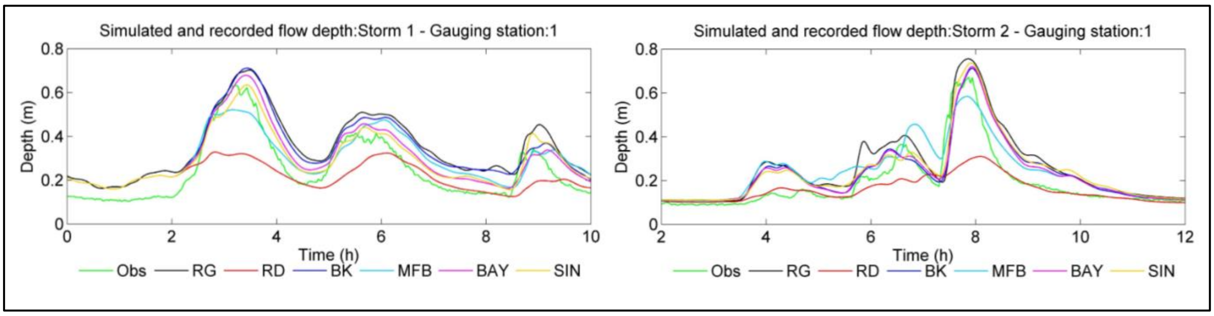

Figure 6: Comparison of observed and simulated flow depth hydrographs for different rainfall inputs at the Valentine sewer (Point A in Figure 2(b)) in the Cranbrook catchment: (left) Storm 1 and (right) Storm 2.

Table 5: Performance measures for the simulated flow depths resulting from feeding different rainfall inputs into the hydraulic model of the Cranbrook catchment. The measures were estimated based on the simulation results and on the flow depth measurements at the Valentine sewer (PointA in Figure 2(b)).

Performance Measures/ Rainfall estimates	**RG**	**RD**	**BK**	**MFB**	**BAY**	**SIN**
				Storm 1		
RE in peak depth	0.111	-0.481	0.125	-0.176	0.073	0.004
R – depth	0.874	0.618	0.881	0.814	0.913	0.902
NSE – depth	0.283	0.315	0.452	0.696	0.772	0.800
				Storm 2		
RE in peak depth	0.126	-0.538	0.061	-0.130	0.072	0.098
R – depth	0.838	0.751	0.808	0.813	0.834	0.857
NSE – depth	0.522	0.492	0.680	0.658	0.711	0.676

The most prominent feature which can be observed in the hydrographs and in Table 5 is the large underestimation of flow depths (especially peak depths) resulting from the RD rainfall input; this is further corroborated by the *RE* values (Table 5), which are largest for the RD inputs, as compared to other rainfall inputs. Nonetheless, the overall pattern of the RD-based hydrographs is in good agreement with that of the observations; in fact, the associated *R* and *NSE* associated to the RD outputs are acceptable. The large underestimation in flow depths can be explained by the large underestimation in rainfall depths and intensities exhibited by the RD rainfall estimates (see Table 3 and Figure 5). The good pattern indicates that in spite of the inaccuracy, RD estimates can well capture the spatial and temporal structure of rainfall fields.

As compared to the RD hydraulic outputs, MFB provides a considerable improvement, but it still cannot capture well the largest depth peaks observed in the two storm events. This is consistent with the rainfall statistics presented in Table 3 and Figure 5, where the MFB adjusted rainfall fields were found to underestimate rainfall peak intensities. This indicates that 1) a spatially-uniform 1-hr (sample bias) ratio is insufficient to satisfactorily characterise the spatial and temporal variability of the RG/RD biases, and 2) it is critical to capture the rainfall peak intensities in urban-scale modelling, in which the small scale dynamics of rainfall have a significant effect on the associated hydraulic outputs.

As would be expected, the depth hydrographs of the RG and BK (interpolated RG) are very similar. But, interestingly, in some cases the BK output is slightly closer to the observations as compared to the RG output; in fact, in terms of NSE the BK associated outputs clearly a show better performance than the RG outputs. This suggests that taking into account the spatial variability in the rainfall input (even in a simple way) could be beneficial for modelling purposes.

Lastly, the BAY and SIN outputs outperform all other simulation results, including the RG ones, both in terms of magnitude and pattern; this can be noticed visually (Figure 6), as well as from the performance measures (Table 5). In this catchment and for the storm events under consideration no large differences are observed between the BAY and SIN hydraulic outputs; however, there is a fact worth noticing. In Storm 1, the peak rainfall intensities of the BAY and SIN estimates are almost the same (Table 3), but some difference can be observed in their associated peak flow depths. In contrast, in Storm 2 the SIN estimates show a much higher rainfall peak intensity than the BAY (Table 3), but the difference in the associated flow depth outputs is very small. In both storm events the main difference between the BAY and SIN estimates was their Max/min ratios (i.e. their spatial variability). Albeit at a small scale, these results suggest that the spatial variability of rainfall fields does have an effect on the subsequent hydraulic outputs (although the effect of it is smaller than the effect of the inaccuracy or bias). This initial conclusion is further confirmed by the results obtained for the Portobello catchment, which are presented next.

Hydraulic outputs for the Portobello catchment: Due to space constraints and given the size of the Portobello catchment and the number of gauging stations for which data are available, only the results for Storm 1 are presented and discussed in detail. At the end of this section the results obtained for Storms 2 and 3 are briefly discussed and general conclusions are formulated. Results from Storm 1 were chosen as it is the most intense storm analysed for this catchment and, as such, it is the most relevant from an urban pluvial flood modelling perspective.

In Figure 7 a selection is presented of three observed vs. simulated flow and depth hydrographs from different locations within the catchment (respectively in the up-, mid- and downstream parts of the catchment) for Storm 1. In addition, in Figure 8 boxplots are presented which show the distribution of the performance measures for the simulated depths and flows at the different gauging stations for Storm 1.

From Figure 7 and Figure 8 it can be seen that, even though the cumulative RG/RD rainfall bias is very small for Storm 1 and RD accumulations are even slightly higher than RG ones (Table 4) , the RD associated hydraulic outputs consistently underestimate flow and depth peaks, with the degree of underestimation changing from location to location and possibly increasing in the direction of flows within the catchment (i.e. larger underestimations are observed in gauging locations further downstream, as compared to upstream locations). The underestimation in hydraulic outputs in spite of the small cumulative RG/RD bias can be explained by the fact that the RD estimates cannot well reproduce high rainfall rates (Figure 5). This suggests that not only is it important to get the areal total rainfall accumulations right, but getting the peak rainfall intensities correctly is also of outmost importance in order to appropriately reproduce the dynamic behaviour of the hydrological system and, in particular, the flow and depth peaks.

Similar to the results of the Cranbrook catchment, the MFB adjustment was found to provide some improvement over the original RD estimates; however, it is still insufficient to effectively reproduce peak rainfall intensities (Figure 5) and the associated flow and depth peaks (Figure 7). This confirms the fact that more dynamic adjustment radar rainfall adjustment methods which can better account for the spatial variability in the rainfall fields are required for urban-scales applications (rather than simple mean-field bias adjustments).

In general and as would be expected, the hydraulic outputs obtained with the BK interpolated estimates are very similar to the RG ones, with BK outputs sometimes performing better than the original RG ones. A striking difference between BK and RG hydraulic outputs and which is worth analysing can be observed in the hydrographs of gauging station 23 (Figure 7(middle)): it can be seen that the RG outputs largely overestimate the observed peak depth, while the simply interpolated BK rainfall input already leads to much more sound hydraulic results which are in better agreement with the observations. This confirms that accounting for the spatial variability of rainfall fields, even through simple kriging interpolation, could lead to significant benefits in the modelling.

The BAY and SIN outputs appear to be similar to the BK ones (and better than the original RD outputs), with the former (i.e. BAY and SIN) showing slightly more dynamic and realistic flow and depth patterns and with the SIN outputs performing better overall in terms of effectively reproducing peak depths and flows. The better performance of the SIN hydraulic outputs in this respect is clearly illustrated by the *RE* boxplots (Figure 8), where the median of the SIN associated *RE* for peak depths and flows is closer to zero and the dispersion of the results is smaller as compared to that of other hydraulic outputs, including the RG ones. An interesting example which also illustrates the potential benefits of the SIN method in terms of better capturing storm extremes can be found in gauging station 1: at this location the SIN methodology is the only one capable of generating a higher flow depth peak which is in better agreement with the observations (Figure 7 (top, left)).

From the results of Storm 1 it can be concluded that all adjustment methods can improve the applicability of the original RD rainfall estimates to urban hydrological applications, although the degree of improvement provided by each adjustment method is different. Overall, the BAY and SIN rainfall estimates lead to significantly better simulation results than the MFB adjusted estimates, with the SIN estimates performing particularly well at reproducing peak depths and flows.

In general, the results obtained for Storm 3 are in good agreement with those obtained for Storm 1. However, the results of Storm 2 are somehow different: in this event the RD rainfall accumulations were larger than the RG ones (RG/RD bias < 1) and the RD peak rainfall intensity was very similar to the RG one (though this was a mild storm event with maximum observed rainfall rates in general low). This led to unusual results in which at many gauging stations the RD estimates resulted in better hydraulic outputs (i.e. closer to the observations) than the original RG ones. For this event the benefits of the merged rainfall estimates as compared to the original RD estimates in terms of hydraulic outputs are not evident (some improvements are achieved in *NSE*, but these are rather minor). Nonetheless, in this as well as in the other storms, there are many sources of uncertainty affecting hydraulic outputs and it is difficult to separate the effect of rainfall inputs from that of the model structure, model parameters and even from errors in flow measurements.

While the results obtained for the Portobello catchment are promising and the merged rainfall inputs show an overall improvement over the original RD estimates, the real benefits of the merged products in a verification context are likely to become more evident once the hydraulic model is re-verified: when this is done, the modeller will be able of analysing which rainfall product appears to be more 'logical/consistent' given the recorded depths and flows and the physical characteristics of the catchment and of the sewer system. Having available a range of rainfall estimates with better spatial structure, in addition to the original RG estimates, could be a valuable resource in the verification process which could lead to improved model verification. Moreover, the analysis throughout the verification process would also provide valuable insights for further improving the adjustment methods.

In addition and as already illustrated by the results obtained for the Cranbrook catchment, the benefits of the mergering are likely to become more evident in operational conditions, when storms outside of the verification period are analysed and when data from fewer RG locations is available (when this is the case, RD becomes a necessary source of data).

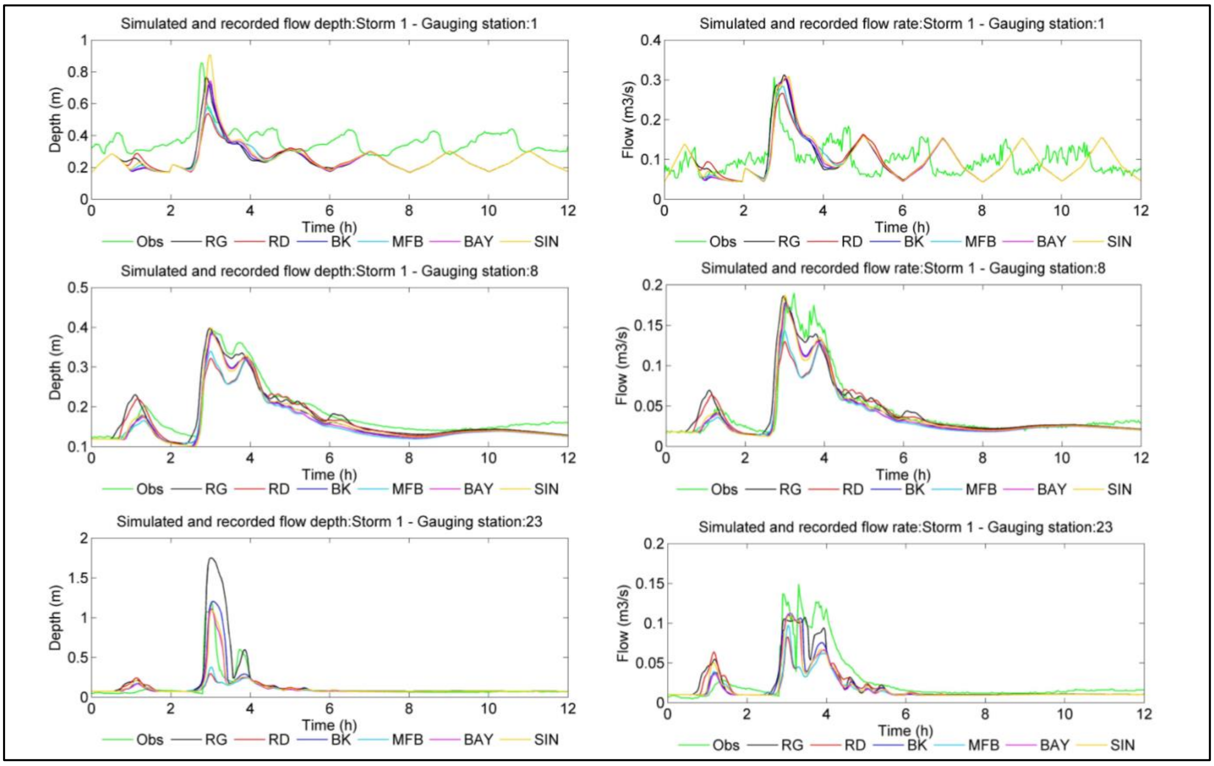

Figure 7: Comparisons of observed and simulated flow depth (left) and flow rate (right) hydrographs of Portobello's Storm 1 at three gauge stations selected from different part of the catchment (the points FM1, FM8 and FM23 in Figure 3(b)): gauge 1 (top), gauge 8 (middle) and gauge 23 (bottom).

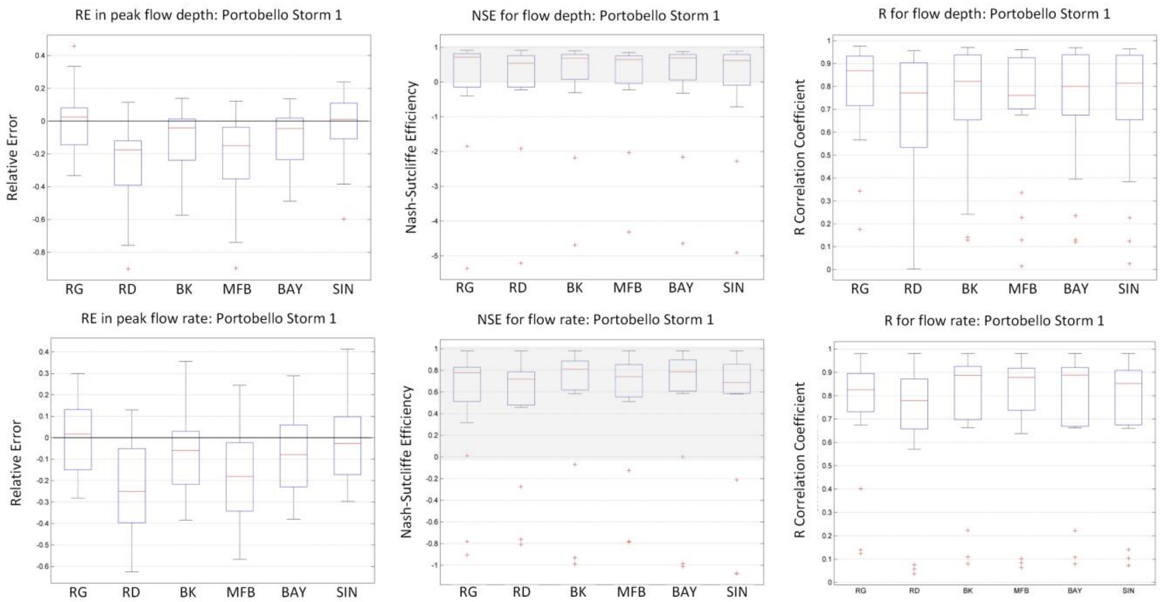

Figure 8: Boxplots of *RE* (left), *NSE* (middle) and *R* (right) for flow depths and rates simulated using different rainfall inputs for Portobello's Storm 1. The shaded areas in the *NSE* boxplots correspond to the region of positive *NSE* values (0 < *NSE* <1).

Summary of main findings from the analysis of hydraulic outputs: Based on the analysis of the hydraulic outputs for the two experimental catchments, the following main conclusions can be drawn:

- In general, all adjustment methods showed their ability to improve the applicability of the original RD rainfall estimates to urban hydrological applications, although the degree of improvement provided by each adjustment method is different.
- The MFB adjustment appears to be insufficient for satisfactorily correcting the errors in RD estimates and this is evident in the associated hydraulic outputs, which fail to properly reproduce peak depths and flows. This suggests that more dynamic and spatially varying adjustment methods are required for urban hydrological applications.
- Overall, the BAY and SIN rainfall estimates lead to significantly better simulation results than the MFB adjusted estimates and the original RD estimates, with the SIN estimates performing particularly well at reproducing peak depths and flows.
- Although the BK estimates do not entail any adjustment and correspond to a simple interpolation of the point RG estimates, they showed to lead to improvements in hydraulic outputs as compared to using RG point estimats as input to models. This demonstrates the benefits of accounting for the spatial variability of rainfall fields, even if it is in a simple way.
- The benefits of using merged rainfall estimates as input to urban drainage models are clearly evident in an operational context, such as the one analysed in the Cranbrook catchment. In this case, the BAY and SIN merged estimates led to simulation results even better than those obtained when using point RG estimates as input.
- In a verification context (i.e. Portobello catchment), the merged estimates also performed in general better than original RD estimates, but the real benefit of the merged products is likely to become more evident when the models are re-verified. It is expected that having available merged rainfall estimates with better accuracy and spatial description of rainfall fields could lead to improved model verification (as compared to the verification that can be achieved when using solely RG or RD data as input).

5. GENERAL CONCLUSIONS AND OUTLOOK

On the whole, the three adjustment techniques tested in this study (i.e. Mean-field Bias (MFB) adjustment, Bayesian merging (BAY) and singularity-sensitive Bayesian (SIN)) proved to improve the applicability of radar rainfall estimates to urban hydrological applications. In terms of rainfall estimates, all adjustment methods led to areal average accumulations close to those recorded by raingauges, but only the Bayesian methods, especially the singularity-sensitive one, were capable of effectively reproducing high rainfall rates, which are the ones usually poorly captured by radar and which are of outmost importance in order to properly reproduce flow peaks in the drainage system. Accordingly, in terms of hydraulic outputs, all merged rainfall products in general led to better results than the original radar (Nimrod) estimates, but the Bayesian-based methods, in particular the SIN one, led to significantly better reproduction of the systems' dynamics as compared to the MFB adjusted estimates. In some cases, particularly when storms events different from those used in the model verification are analysed, the BAY and SIN merged estimates led to better hydraulic results than the original point RG estimates.

While the results are encouraging, further testing is necessary in order to better assess the benefits of the merging methods, identify their shortcomings and improve them accordingly. Particular aspects which will soon be investigated are: (i) the possibility of using merged rainfall estimates for model verification purposes; (ii) the impact of the density of raingauges on the quality of the different merged rainfall estimates; (iii) the sensitivity of the SIN methodology to the 'degree of singularity' which is extracted from the original radar rainfall field and applied back afterwards.

6. ACKNOWLEDGEMENTS

The authors would like to acknowledge the support of the European Union's Interreg IVB NWE Programme to the RainGain project, of which this research is part. The authors would also like to thank the UK Met Office and the BADC (British Atmospheric Data Centre) for providing Nimrod (radar) data, Innovyze for providing the InfoWorks CS software and Dr Cinzia Mazzetti and Prof Ezio Todini for making freely available to us the RAINMUSIC software package for meteorological data processing.

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