Improving the applicability of gauge-based radar rainfall adjustment methods to urban pluvial flood modelling and forecasting using local singularity analysis

L.-P. WANG[1], S. OCHOA-RODRIGUEZ[2], P. WILLEMS[1], C. ONOF[2]
[1]*Hydraulics Laboratory, KU Leuven, 3001, Heverlee (Leuven), Belgium (lipen.wang@bwk.kuleuven.be)*
[2]*Department of Civil and Environmental Engineering, Imperial College London, SW7 2AZ, UK*

Abstract Gauge-based radar rainfall adjustment techniques have been largely-used to improve the applicability of radar rainfall estimates to large-scale hydrological modelling. Their applicability to urban hydrology is however insufficient since these techniques were mostly developed based upon the Gaussian approximations and therefore smoothed off the so-called 'singularity' (or non-normality) that can be observed in the fine-scale rainfall structure. Overlooking the singularities could be critical because their distribution is highly consistent with that of local extreme magnitudes. This deficiency may cause tremendous errors in the subsequent urban hydrological modelling. In this paper, a methodology is proposed to incorporate an existing gauge-based radar rainfall adjustment technique with the local singularity analysis, aiming for improving the applicability of existing adjustment techniques at urban scales. Three historical storm events recorded by a flow survey campaign in 2011 in Edinburgh (UK) were selected as case study to evaluate the proposed methodology. The result suggests that the proposed 'singularity-sensitive' methodology can in general better re-construct the non-normality in local rainfall structure and at the same time preserve the advantage of the original adjustment techniques of generating unbiased estimates.

Key words Gauge-based adjustment; urban rain; singularity; fractals

INTRODUCTION

Traditionally, urban hydrological applications relied mainly upon rain gauge data as input as these provide accurate point rainfall estimates near the ground surface. 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. Thanks to the development of radar technology, weather radar has been playing an increasingly important role in urban hydrology. Radars can survey large areas and better 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. This has a tremendous effect on the subsequent hydraulic model outputs.

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 rain gauge measurements. Studies on this subject have been carried out over the last few years, though most of them focus on the hydrological applications at large scales. A couple of recent research works have examined the applicability of these adjustment techniques to urban-scale hydrological applications and concluded that these techniques can effectively reduce rainfall bias, thus leading to improvements in the reproduction of hydraulic outputs (Wang et al., 2013). However, underestimation of storm peaks can still be seen after adjustment and this is particularly significant in the case of small drainage areas and for extreme rainfall magnitudes. This may be due to the fact that the underlying adjustment techniques, mainly based upon 1st or 2nd order (statistical-) moment approximations, cannot properly cope with the non-normality observed in urban scale applications. 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 (Cheng et al., 1994; Schertzer and Lovejoy, 1987).

With the purpose of improving this aspect, a methodology has been developed which identifies the local extremes or 'singularities' of radar rainfall fields and preserves them throughout the merging process. A preliminary test of this methodology in an urban area in London (Wang and Onof, 2013a, 2013b) has demonstrated that the original Bayesian data merging technique (Todini, 2001) could be effectively improved by incorporating this singularity analysis. In this work, this incorporation has been further used to reconstruct a number of storm events observed in an urban catchment in Edinburgh during the Summer of 2011 and for which high density rainfall and flow data are available.

EXPERIMENTAL SITE AND DATA SET

As aforementioned, the proposed methodology was originally developed using the radar and raingauge data over the Maida Vale catchment (London) in June 2009. However, due to the confidential reason and lack of flow measurements, its impact on urban hydrological modelling could not be evaluated in this catchment. Therefore, in the context of this paper, the dataset of the Maida Vale catchment will be used merely for demonstrating the intermediate results in the development of the methodology, and the description of the catchment and the dataset used will not be given in this paper. For readers who are interested in the details, please find the link in (Wang and Onof, 2013b).

An alternative catchment in Portobello (Edinburgh area) was used in this paper as case study due to the completeness of rainfall and flow data. A full-scale test of rainfall estimation and the subsequent hydrological modelling was carried out in this catchment. A description of the catchment and the local monitoring data (including raingauge, flow and depth data) available and used in this study is next provided.

In addition to the local monitoring data, the experimental catchment is within the coverage of C-band radars operated by the UK Met Office. Radar rainfall estimates 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; Harrison et al., 2000).

Portobello catchment (Edinburgh, UK)

Catchment description: Portobello is a beach town located 5 km to the east of the city centre of Edinburgh, along the coast of the Firth of Forth, in Scotland (Figure 1a). 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 1b) 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 1b). Radar rainfall estimates (at 1 km and 5 min resolution) for the same period of the flow survey were obtained from the BADC.

Selected storm events

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 1.

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

Event	Date	Duration (hour)	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.

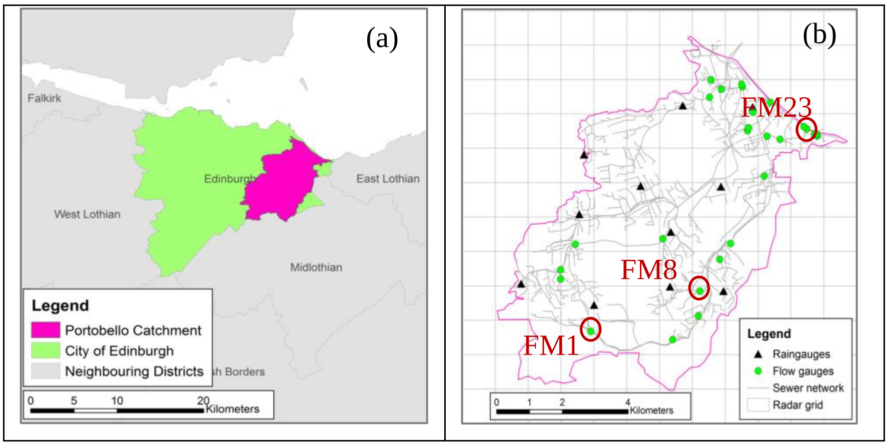

Figure 1 : Portobello catchment (a) general location; (b) sensor location, sewer network and radar grid over the catchment.

METHODOLOGY

Bayesian radar-raingauge data merging

The Bayesian data merging (BAY) is a dynamic adjustment method intended for real-time applications (Todini, 2001). It has been proven to outperform many other adjustment techniques in numerical experiments (Mazzetti and 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 (estimation) uncertainty is minimised. The key techniques used in this method include the block-kriging interpolation (BK) and the Kalman filter. The principle of the BAY method is summarised as follows.

The first step of the BAY method is, for each time step *t*, to interpolate the raingauge measurements into a synthetic rainfall field using BK interpolation (steps (a) and (c) in Figure 2). This step generates comparable areal raingauge rainfall estimates (y_t^{RG}) to the radar estimates (y_t^{RD}), based upon which a field of errors (i.e. the bias at each radar grid location: $\varepsilon_t = y_t^{\mathrm{RG}} - y_t^{\mathrm{RD}}$) can be constructed (steps (d) and (e)). The covariance of this error field can be used to represent the uncertainty of radar estimates (V_{ε_t}) and is further compared and combined with the estimation error covariance of areal raingauge rainfall estimates ($V_{\varepsilon_t^{\mathrm{RG}}}$, representing the uncertainty of raingauge estimates) that can be derived from the BK interpolation. The Kalman filter (Kalman, 1960) is employed herein (step (e)) to conduct this combination (where the radar data and the interpolated raingauge estimates respectively act as 'a priori estimate' and 'measurement' in the typical Kalman filter algorithm). The degree of 'certainty' of each type of estimates constitutes a gain value (the so-called Kalman gain, K_t) at each radar grid location, which determines the proportions of each type of estimates used to compute the merged output. As mentioned above, this gain value ensures the minimisation of the overall estimation uncertainty and is expressed as

$$K_t = V_{\varepsilon_t}(V_{\varepsilon_t} + V_{\varepsilon_t^G})^{-1},$$

and the merged output (i.e. the ‘a posteriori’ estimates in the Kalman filter) can be obtained from

$$y_t'' = y_t^{\mathrm{RD}} + K_t\left(y_t^{\mathrm{RG}} - y_t^{\mathrm{RD}}\right).$$

It can be seen that the Kalman gain is a function of the covariances of radar and raingauge (estimation) errors. When $V_{\varepsilon_t} \gg V_{\varepsilon_t^{\mathrm{RG}}}$ (or $K_t \approx 1$, i.e. radar estimates are of much higher uncertainty), the output estimates will be similar to the interpolated raingauge estimates. In contrast, when $V_{\varepsilon_t^{\mathrm{RG}}} \gg V_{\varepsilon_t}$ (or $K_t \approx 0$), the output will be similar to the radar estimates.

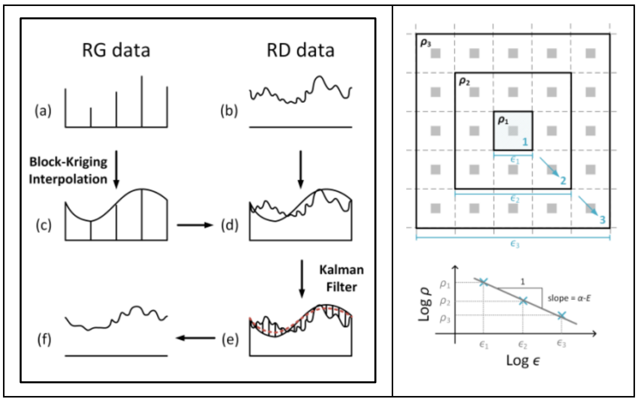

Figure 2: Schematic of the Bayesian radar-raingauge data merging (BAY) technique (left) and the local singularity analysis (right).

Local singularity analysis

The local singularity analysis is a simple yet effective method to identify the anomalies from geo-data. This method was proposed in (Cheng et al., 1994), and has been used for the estimation of geo-chemical concentration (Agterberg, 2007; Cheng and Zhao, 2011; Cheng et al., 1994). It employed the definition of the coarse Hölder exponent to identify the local scaling behaviour that follows a power-law relationship (i.e., the areal average measure increases as a power function when the area decreases; see Figure 2 (right)):

$$\rho(\mathbf{x}, \epsilon) \propto \epsilon^{\alpha(\mathbf{x})-E},$$

Where $\propto$ represents proportionality, the term $\rho(\mathbf{x}, \epsilon)$ represents the density of measure (e.g. concentration of geo-data) over a squared area with side-length ϵ centred at the location $\mathbf{x}$, $\alpha(\mathbf{x})$ is the singularity index (or the coarse Hölder exponent), and E=2 is the Euclidean dimension of a plane. By introducing a constant $c(\mathbf{x})$, one can further formulate this power-law relationship as an equation (Cheng et al., 1994):

$$\rho(\mathbf{x}, \epsilon) = c(\mathbf{x})\epsilon^{\alpha(\mathbf{x})-E}.$$

This equation constitutes a useful tool to decompose a rainfall magnitude at a given location $\mathbf{x}$ into two components (Wang et al., 2012): 1) the background (or non-singular, NS) magnitude $c(\mathbf{x})$ that is invariant as measuring scale ϵ changes and is more approximately normal than the original field, and 2) a local ‘scaling’ multiplier of which the magnitude changes according to the local singularity index $\alpha(\mathbf{x})$ and measuring scale ϵ. It can be seen that, when $\alpha(\mathbf{x}) < 2$, the rainfall magnitude will strikingly increase as the measuring scale ϵ decreases (namely local enrichment), so it is a ‘peak’ singularity. In contrast, when $\alpha(\mathbf{x}) > 2$, the rainfall magnitude decreases as ϵ decreases (i.e. local depletion), and it is therefore a ‘trough’ singularity. When $\alpha(\mathbf{x}) = 2$, there is no singularity; the rainfall magnitude within a $\epsilon \times \epsilon$ area retains the same as scale changes (i.e. $\rho(\mathbf{x}, \epsilon) = c(\mathbf{x})$).

An example can be found in Figure 3 a and b of applying this local singularity analysis to the decomposition of a radar image. As compared to the original radar image (a1: RD), the spatial structure of the non-singular component $c(\mathbf{x})$ (b1: NS-RD) is found to be smoother and more symmetric. In addition, the NS-RD estimates are of better normality than the original RD data (In Figure 3 a2 and b2, it can be seen that the NS-RD estimate quantiles are highly consistent with the Normal theoretical quantiles, but this is not case for the original RD estimates, where a much longer tail at the right end of the data distribution is expected). Therefore, the NS-RD estimates may be a more suitable input than the original RD estimates for many existing data merging techniques under the Gaussian approximation.

"Singularity-Sensitive" radar-raingauge data merging

The underlying idea of the proposed methodology is to use the local singularity analysis to decompose each radar snapshot into a non-singular image and a singularity map, where the former's distribution is closer to normality and thus can be better merged with the coincidental raingauge data under the Gaussian assumption. Afterwards, the singularity map is applied back to the merged image for recovering local extreme magnitudes. In implementation, the local singularity analysis is firstly carried out in the step (b) of Figure 2 (left) to decompose the RD image, then the non-singular part (NS-RD) of the original radar image is merged with the BK raingauge estimates (steps (c)-(f)) to obtain the non-singular merged (NS-BAY) estimates, and then the singularity map is multiplied back to the merged output to finally produce the 'singularity-sensitive' merged (SIN) estimates.

An example is shown in Figure 3 to demonstrate the variations in spatial structure of each estimate. It is observed that the structure of the BAY estimates tends to be smoother than that of the SIN estimates, where the latter can better preserve the non-normality of the original RD measurements than the former and thus its pattern is relatively realistic. In addition, due to the lack of raingauge information at the middle-left area of the experimental domain, the BK and BAY techniques failed in reproducing local extreme magnitudes measured by radar at that area. This indicates that the reliability of the BK and BAY estimates is very sensitive to the number and the deployment of raingauges, and the underlying Gaussian approximation causes the BAY technique to give more credit to the 'smooth' estimates generated by the BK technique and subsequently to neglect the local peaks in the RD data. This tendency towards 'smoother' estimates in the original BAY technique can be improved using the proposed methodology and therefore the missing local information at the middle-left area in the BAY can be re-constructed in the SIN estimates.

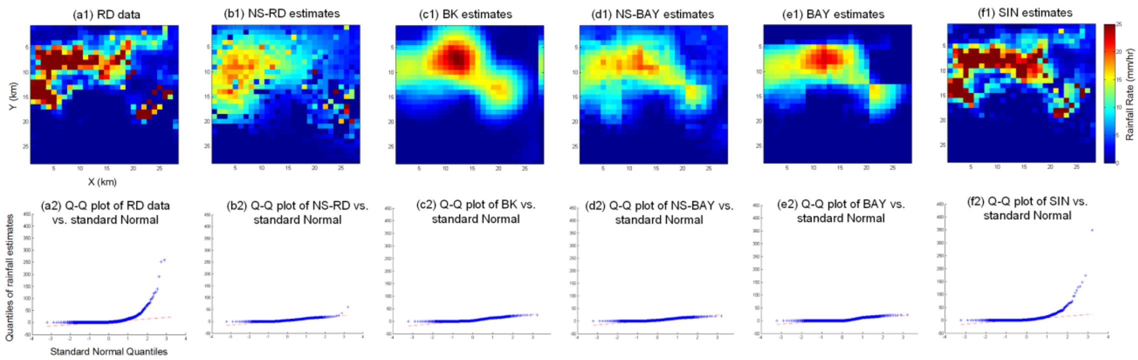

Figure 3: Snapshot images of RD (radar, a1), NS-RD (non-singular radar, b1), BK (block-kriged raingauge, c1) and NS-BAY (NS-RD merged with BK, d1), BAY (RD merged with BK, e1) and SIN (singularity-sensitive merged, f1) rainfall estimates, and the associated Q-Q plots (a2-f2) for demonstrating the degree of normality of each estimates.

RESULTS AND DISCUSSION

The proposed SIN methodology, as well as other gauge-based interpolation (BK) and adjustment techniques (BAY) mentioned above, was employed to reconstruct three historical storm events in Portobello (Table 1), and the resulting rainfall estimates were further used as input for hydraulic simulations. In addition, the adjusted estimates generated from a simple yet effective method, called mean-field bias correction (MFB), were also included in the comparison because it has been a widely-used correction procedure used by many meteorological services (Goudenhoofdt and Delobbe, 2009; Harrison et al., 2000). This adjustment is implemented by comparing the summations of the RG and the co-located RD grid rainfall estimates over a specific area (i.e. the Portobello catchment area in this paper) and duration (i.e. one hour) to obtain a sample bias ratio (i.e. $B = \Sigma RG/\Sigma RD$). This ratio is then multiplied back to each radar grid estimate to ensure that the mean of RD rainfall estimates is the same as (or similar to) that of the RG measurements.

In the following, features of the rainfall estimates resulting from different interpolation and adjustment techniques are firstly presented and discussed. Then, the hydraulic outputs resulting from each rainfall input are presented, inter compared and discussed. Due to space constraints, 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.

Rainfall estimates

The features of the rainfall estimates generated by different techniques were characterised by comparing them with the local RG measurements, in terms of areal average and individual-site time series. In Figure 4 (left), the result is presented of a direct comparison of areal average RG intensities versus areal average BK, RD and adjusted estimates' intensities at each time step throughout the whole Storm 1 period. As expected, BK estimates are in good agreement with RG estimates. With regards to RD estimates, it can be seen that they tend to overestimate small rainfall rates and underestimate the peak intensities. This tendency 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 to well reproduce 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 respect and its performance is especially poor at higher intensities (which are of outmost importance in the modelling and forecasting of urban pluvial flooding).

Similar comparisons were conducted at each RG location, and the associated statistics are summarised in Figure 4 (middle) and (right). The simple linear regression analysis was applied to each pair of RG measurements and the co-located grid estimates obtained from different gauge-based interpolation and adjustment techniques. The result of these regression analyses can be evaluated in terms of β (regression coefficient) an R^2 (coefficient of determination). These two statistics provide the measures of how well RG observations are replicated by the RD/BK/merged rainfall estimates at each gauging station. The R^2 measure ranges from 0 to 1, describing how much of the observed dispersion is explained by the modelled one. However, the systematic bias (under- or over-estimation) of the modelled estimates cannot be reflected by this measure. The slope of the simple linear regression analysis (i.e. β) was therefore employed to provide additional information to cope with the drawback of R^2 measures.

As expected, the BK estimates in general possess the highest R^2 values since the RD information was not taken into account (Figure 4 (right)). However, from the distribution of β values of the BK estimates, one can find that the whole box and the whiskers are below the axis of unity (Figure 4 (middle)). A similar result can be found in the BAY estimates, where high R^2 values are observed and most of the β values are below one. This indicates that both BK and BAY estimates tend to systematically underestimate the RG rainfall intensities at each gauging site. This may be caused by the underlying Gaussian approximation, which tends to smooth off some local extreme magnitudes.

The RD estimates possess the lowest R^2 and β values. This is expected because RD data provide rainfall information at a certain elevation above the ground, which is unlikely to be the same as the ground raingauge measurements. Nonetheless, a certain degree of the similarity between RD and RG estimates can be still observed. The MFB adjustment can slightly increase their similarity, but the effect is very limited since this method uses merely the mean-field estimate from the RG data but fully follows the spatial structure of RD estimates.

Although the 'areal average' behaviours of BAY and SIN estimates are similar, the SIN's 'individual-site' behaviour is very different from the BAY's. It can be found that the distribution of the R^2 values of the SIN estimates is somewhere between that of the BAY and RD estimates. This difference indicates that, as compared to the original BAY estimates, the SIN estimates inherit more features from the RD estimates. This is consistent with the underlying assumption of the SIN methodology, in which the reliability of the original RD data is improved after singularities are extracted. In addition, it can be found that the distribution of β values of SIN estimates is approximately symmetric to the axis of unity. This means no significant systematic under- or over-estimation is observed in the SIN estimates. This could be due to the process of singularity recovery of the proposed SIN methodology and the re-construction of the local extreme magnitudes (or the local singular quantities) that were smoothed off by the original BAY method.

The feature analysis of different rainfall estimates suggests that the proposed SIN methodology preserves the 'areal average' behaviour of the original BAY, but at the same time introduces more RD information into the data merging, and therefore stronger spatial and temporal variations can be found in the SIN estimates. The impact of these different features on the subsequent hydrological output is further evaluated in the following section.

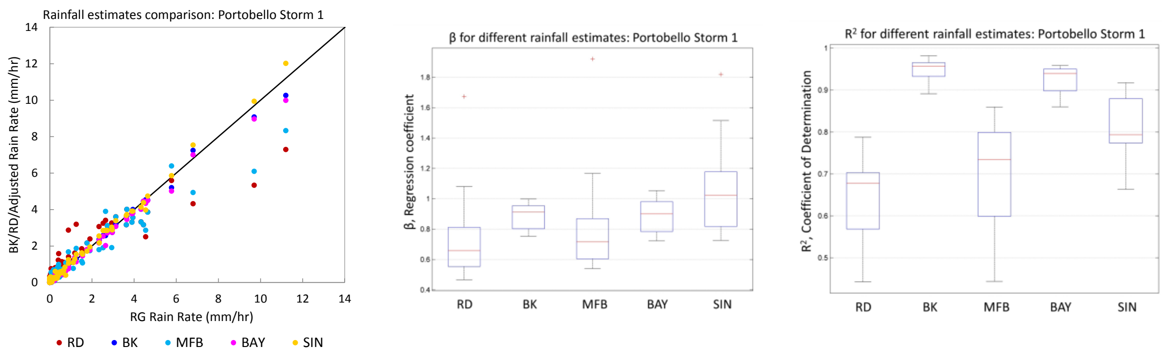

Figure 4: Comparisons of RG data and different rainfall estimates for Portobello's Storm 1: (left) Scatterplot of instantaneous areal RG vs. RD (red markers)/BK (blue)/MFB (light blue)/BAY (pink)/SIN (yellow) estimates; (middle and right) Boxplots of β an R^2 for the RG data vs. different rainfall estimates at each RG location.

Hydraulic outputs

In Figure 5 (left), 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 5 (right) boxplots are presented which show the distribution of the performance measures, i.e., Nash-Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970) and relative error (RE) in peak flow output, for the simulated depths and flows at the different gauging stations for Storm 1. The RE measure is computed by dividing the difference of the simulated and the observed flow peaks (S_{peak} - O_{peak}) by the observed one (O_{peak}). This measure gives an estimate of how well, in terms of magnitude, the simulation results can reproduce the true peak flows and 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.

From Figure 5 it can be seen that, even though the RG and RD totals are similar (RD is slightly higher) for Storm 1 (Table 1) , 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 difference of the RG and RD totals, can be explained by the fact that the RD estimates cannot well reproduce high rainfall rates (Figure 4). This suggests that not only is it important to get the areal total rainfall accumulations right, but accurately capturing the peak rainfall intensities 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.

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 4) and the associated flow and depth peaks (Figure 5 (left)). 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 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 5 (left, bottom)): 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 5 (right, bottom)), 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 5 (left, top)).

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 accumulations were larger than the RG ones (see Table 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 gauge 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 model structure, model parameters and even from errors in flow measurements.

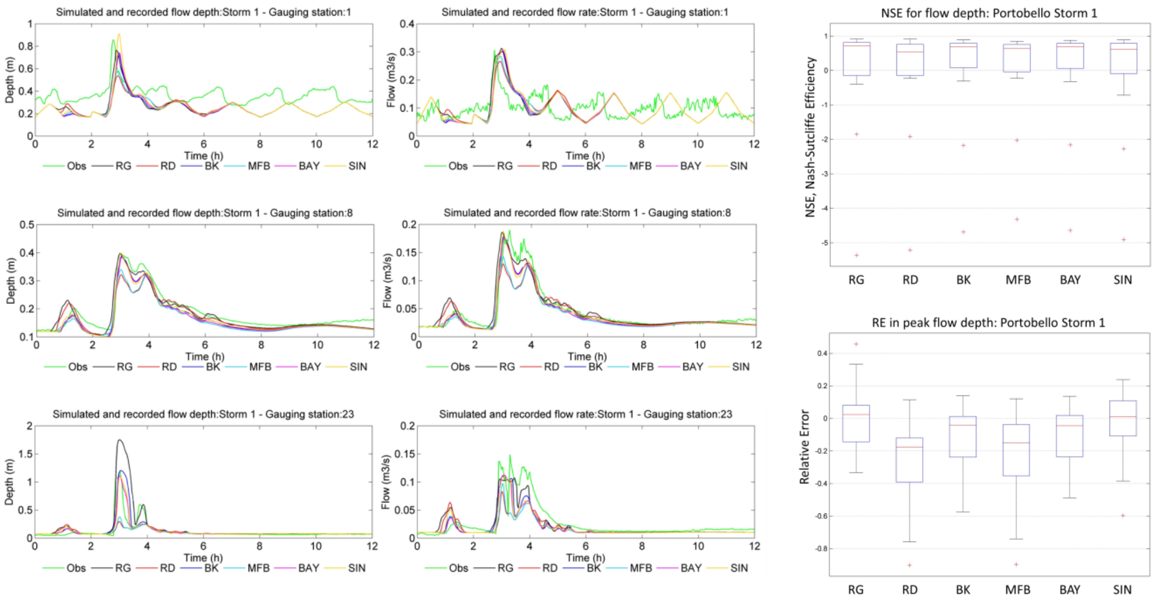

Figure 5: Comparisons of observed and simulated flow outputs for Portobello's Storm 1: (left) Flow rate and depth hydrographs at 3 gauge stations selected from different part of the catchment (from top to bottom, the points FM1, FM8 and FM23 in Figure 1 (b)); (right) Boxplots of NSE (top) and RE (bottom) for flow depths simulated using different rainfall inputs.

CONCLUSIONS

In this paper, a new gauge-based radar rainfall adjustment methodology was proposed, aiming at better merging raingauge and radar rainfall data at fine spatial and temporal scales. The proposed methodology incorporates the existing Bayesian data merging technique with the local singularity analysis. This incorporation has proven to be able to better cope with the non-normality (or singularity) in urban-scale rainfall data in this paper.

The applicability of the proposed SIN methodology to urban hydrology was tested and compared with other existing gauge-based interpolation and adjustment techniques (i.e. block-kriging (BK), mean-field bias correction (MFB) and Bayesian merging (BAY)). In terms of rainfall estimates, all adjustment methods led to areal average accumulations close to those recorded by raingauges, but only the BAY and SIN methods were capable of effectively reproducing high rainfall rates. These rates are usually poorly captured by radar, but 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. 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.

While the results are promising and the proposed SIN methodology shows great potential to be used in urban hydrological applications, the real benefits of its 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. In addition, the benefits of the SIN method are likely to become more evident in operational conditions, when storms outside the verification period are analysed and when data from fewer raingauge locations are available (when this is the case, radar becomes a necessary source of rainfall data).

ACKNOWLEDGEMENTS

The authors would like to acknowledge the support of the EU Interreg RainGain and Belgian PLURISK projects 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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