ON THE PROPAGATION OF RAINFALL BIAS AND SPATIAL VARIABILITY THROUGH URBAN PLUVIAL FLOOD MODELLING

by

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ABSTRACT

The reliability of urban flood modelling can be largely improved if high-accuracy and fine-resolution rainfall estimates are available; however, this requires a very dense network of rainfall sensors and is usually not available due to limited budget and space. Adjustment and downscaling techniques are largely used respectively to post process the radar and rain gauge data to obtain better rainfall estimates in terms of accuracy and resolution. However, the combined application of these two types of techniques was seldom discussed in literatures, and its impact on the subsequent hydraulic modelling is unknown. This work implements a combined procedure of stochastic downscaling and gauge-based adjustment, aiming to evaluate its applicability to urban pluvial flood modelling. Unlike the adjustment process that reduces the rainfall input uncertainty (due to mean bias) through merging rainfall information from different sensors, the stochastic process of generating street-scale rainfall estimates actually causes additional uncertainty (due to spatial variability). This additional uncertainty will further propagate through hydraulic modelling and consequently affect the reliability of the resulting hydraulic outputs. The result of case study suggests that the uncertainty caused by the downscaling process could be larger than that reduced by the adjustment as the drainage area is very small.

Keywords: gauge-based adjustment, downscaling, urban pluvial flooding

1 INTRODUCTION

The reliability of urban pluvial flood forecasting/modelling largely depends on the accuracy of rainfall inputs (Golding, 2009). The rainfall events that cause this type of flooding however are of small scale and high intensity and consequently highly unpredictable. The applicability (in terms of accuracy and resolution) of operational radar rainfall products is however insufficient for urban hydrological uses. For example, the current C-band radar network (operated by the UK Met Office) produces 5-min and 1-km radar data for whole UK area. This achievement has not yet fully satisfied the requirements for urban-scale pluvial flood modelling, which in general requires higher spatial- and temporal-resolution rainfall estimates/forecasts (e.g. 1-5 min and 100-500 m, as suggested by Fabry et al. (1994)). In addition, as compared to local rain gauge measurements, substantial overestimates or underestimates of radar estimates are often observed over small-scale urban catchments (Liguori et al., 2011).

In order to tackle these two shortcomings, gauge-based adjustment and stochastic downscaling techniques have been largely used to respectively improve the accuracy and the resolution of the operational rainfall estimates (Vieux and Bedient 2004; Wang et al., 2012a; Gires et al., 2012). The former focuses on reducing the rainfall volume bias between radar and the coincidental rain gauge measurements; whilst the latter disaggregates the operational radar data to produce finer-scale rainfall details with higher spatial and temporal variability. In conventional, rainfall volume bias is regarded as the major error that causes the uncertainty of hydrological modelling (Einfalt et al., 2004), whilst the impact of spatial or temporal variability of rainfall is relatively minor and is often neglected. However, due to the highly-urbanised environment and small areas, urban catchments have proven to be sensitive to spatial and temporal variability (fluctuation) of rainfall inputs (Smith et al., 2007). The additional uncertainty caused by the downscaling process, in order to obtain higher-resolution rainfall estimates, shall not be neglected in urban hydrological modelling. Therefore, a systematic analysis of the propagation of this type of uncertainty through urban hydrological modelling is carried out in this work.

2 COMBINED RAINFALL PROCESSING PROCEDURE

A combined application of gauge-based adjustment and downscaling techniques is implemented in this work. The original 1-km and 5-min radar (Nimrod) data are first adjusted using the *in situ* rain gauge records. These adjusted 1-km radar estimates are then downscaled to street-scale (500/250/125 m) rainfall estimates, which are further used as inputs for urban flood modelling. According to the detailed review given by Wang et al. (2012b) of the state-of-the-art gauge-based adjustment techniques, the Bayesian-based merging method (Todini, 2001) is suggested to be a suitable tool for urban rainfall adjustment. For rainfall downscaling, the SD model (Semi-Deterministic cascade model) is employed, which is a discrete-in-scale cascade model developed based upon the theory of left-sided Multifractals (Mandelbrot et al., 1990) and shows promising results for urban rainfall applications (Wang et al., 2010; Liu, 2012).

2.1 Gauge-based radar rainfall adjustment

The Bayesian-based merging technique is a dynamic method intended for real-time applications (Todini, 2001; Mazzetti, 2004). The first step of the method is to, for each time step, interpolate the real time rain gauge measurements into a synthetic rainfall field using the Block Kriging (BK) interpolation method. After that, the interpolated rainfall field is merged with the coincidental radar image using the Kalman filter algorithm. The idea of the BK interpolation method is to synthesise a rainfall field whose semi-variogram curve is very similar to the semi-variogram curve empirically estimated from the associated point rainfall information, where the semi-variogram curve is a function used to characterise the degree of spatial dependence of a spatial random field (e.g. a rainfall field). In other words, the information contained in the Block-Kriged rainfall fields can reflect the spatial structure of rainfall right above the ground; this can be very useful to adjust the spatial structure observed by radar, which is at a given elevation above the ground and could be horizontally shifted by wind advection.

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

2.2 Cascade downscaling

The SD model used in this work to undertake spatial downscaling was firstly proposed by Wang et al. (2010) and is constructed based upon solving the generating equation (Hentschel and Procaccia, 1983):

$$\sum_{i=1}^{b} s_i^{-\tau(q)} w_i^q = 1\,. \qquad (1)$$

This equation provides the theoretical framework to describe the multiplicative cascade process, which is widely used to simulate rainfall downscaling (Schertzer and Lovejoy 1987; Gupta and Waymire, 1993). In the equation, s_i and w_i's represent the fragmentation ratios that are respectively used to divide the scale (i.e. spatial resolution in this work) and the measure (i.e. rainfall rate) into b-adic sub-scales and sub-measures. These ratios are key parameters for the SD model and can be inversely determined by substituting the empirical $\tau(q)$ curve (obtained from real data) into Eq. (1). The $\tau(q)$ curve is the Legendre Transform of the multifractal spectrum and is highly related to the statistical moment of the dataset being investigated; it is therefore a useful tool to capture the statistical characteristics of data (Cheng and Agterberg, 1996).

Some results obtained from individual applications of these two techniques to the operational UK Met Office radar (Nimrod) data are shown in *Figure 1*. It can be seen that the original radar data (the grey dashed line in *Figure 1* (left)) are largely improved by the Bayesian-based merging technique (the orange dashed-dotted line), and the subsequent hydraulic output by using Bayesian-based adjusted rainfall estimates as input is very close to the flow depth observations (the purple round markers).

The SD model was tested in a small urban area in London (*Figure 1* (right)) to stochastically generate 1-km rainfall estimates from 8-km radar data. It can be observed that most of time the downscaled rainfall realisations (the grey area) well envelope the original 1-km radar data (the solid line) and perform sharp. This means that the SD model is able to well reproduce the statistical behaviours of rainfall observations in a small urban area.

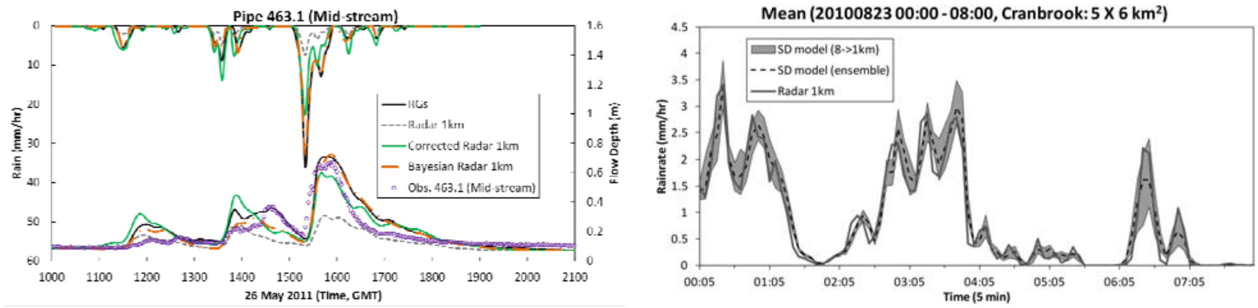

Figure 1 – Results of gauge-based adjusted rainfall estimates and the subsequent hydraulic outputs (left) and cascade-based downscaled rainfall estimates over the area of Cranbrook catchment.

3 CASE STUDY

The case study used is the Cranbrook catchment in the UK. Located in the northeast of Greater London, this catchment has a rapid response to rainfall, which is typical of densely urbanised catchments overlaying London clay. The drainage area of this catchment is approximately 900 ha.; the main water course is about 5.75 km long, of which 5.69 km are piped or culverted. Four rainfall events, crossing the Greater London area in the period of Aug 2010 – Jan 2012, were selected to assess the combined rainfall processing implemented in this work and the associated uncertainty propagation.

3.1 Measures

A measure is defined, based upon the proportion of uncertainty of hydraulic outputs resulting from rainfall downscaling to that reduced by the bias adjustment, to quantify their contributions:

$$r(s,t) = \frac{U_{downscaled}(s,t)}{U_{adjusted}(t)}, \tag{2}$$

where $U_{downscaled}$ (s, t) and $U_{adjusted}$ (t) represents the downscaling and adjustment uncertainty components; they are respectively obtained from the following two dimensionless measures:

$$U_{downscaled}(s,t) = \frac{F_{\max}(s,t) - F_{\min}(s,t)}{F_{adjusted}(t)} \times 100, \tag{3}$$

and

$$U_{adjusted}(t) = \frac{\left|F_{adjusted}(t) - F_{unadjusted}(t)\right|}{F_{adjusted}(t)} \times 100, \tag{4}$$

where $F_{\max}$ (s, t) and $F_{\min}$ (s, t) are respectively the maximum and minimum flow depths resulting from the stochastically downscaled rainfall estimates at the scale s and time step t; $F_{adjusted}$ (t) and $F_{unadjusted}$ (t) are adjusted and original 1-km radar rainfall estimates.

3.2 Results and discussion

The propagation of $r(s, t)$ can be observed in *Table I*, which provides variation of the mean and max of $r(s, t)$ based upon an event basis. The mean of $r(s, t)$ in general decreases from up- to down-stream. This means that the impact of the downscaling process on flow simulation decreases from up- to down-stream (as drainage areas increase). However, it can be observed (in the 03/01/2012 and 05-06/06/2011 events) that for the case of very small drainage areas the uncertainty caused by the downscaling process exceeds that reduced by the adjustment.

In addition, it can be seen that the values in the "Max" columns of *Table I* are in general larger than those in the "Mean" columns (except for the 03/01/2012 event). This means that, for the time points where the maximal adjustments were applied, the uncertainty caused by the downscaling process could increase more than usual. This is critical because, for radar rainfall estimates, the values that require larger adjustments are usually the peak or extreme values; this may dominate the performance of the subsequent hydraulic simulations.

Table I – Summary statistics of the defined measure $r(s, t)$ at three selected pipes (pipe 1455.1, 463.1 and 307.1, respectively located at the up-, mid- and down- streams of the Cranbrook catchment) for the selected four events.

Event	Scale (1 km - *s*)	Up-stream (1455.1) (A* ≈ 57 ha.)		Mid-stream (463.1) (A ≈ 480 ha.)		Down-stream (307.1) (A ≈ 775 ha.)	
		Mean	Max†	Mean	Max	Mean	Max
23/08/2011	1 km – 500 m	37.74	59.68	13.42	46.10	10.81	31.52
	1 km – 250 m	43.89	103.03	16.23	62.82	12.50	31.34
	1 km – 125 m	37.59	62.32	17.34	52.21	11.63	20.00
26/05/2011	1 km – 500 m	47.66	67.35	24.04	56.59	21.61	32.89
	1 km – 250 m	53.14	76.62	30.79	73.13	28.45	36.78
	1 km – 125 m	64.14	72.34	28.28	60.35	24.53	39.98
05-06/06/2011	1 km – 500 m	105.47	113.33	49.09	57.43	33.28	39.78
	1 km – 250 m	135.40	190.98	60.53	70.27	41.57	44.85
	1 km – 125 m	170.46	219.50	72.26	98.61	46.49	62.45
03/01/2012	1 km – 500 m	100.15	93.73	31.18	18.87	19.76	16.75
	1 km – 250 m	118.29	105.62	37.31	25.74	24.72	19.17
	1 km – 125 m	124.20	102.58	32.54	17.72	19.95	13.35

† "Max" item represents the $r(s, t)$ when maximum $U_{adjusted}(t)$ occurs at each event
* "A" represents drainage area (in ha.)

4 CONCLUSIONS

In this paper, a combination of downscaling and adjustment techniques was carried out, which is a new rainfall processing procedure aiming to improve the suitability of the operational rainfall estimates for urban pluvial flood modelling. Two interesting major findings are summarised as follows:

1. Impact of rainfall downscaling on flow simulation decreases from up- to down-stream. This indicates that the impact of the uncertainty caused by the downscaling process could be smoothed off when drainage areas increase; however this also means, for very small catchments, the uncertainty may dominate the performance of the subsequent hydraulic simulations. Therefore, it will not be ignored in urban hydrological applications.
2. The combination of the adjustment and downscaling processes introduces additional uncertainty. This could be due to the difference of the background theories of these two techniques or insufficient rain gauge information. To reduce this additional uncertainty, new processing techniques are necessary to have a better theoretical connection between these two processes; in addition, rain gauge data over larger areas can also improve the estimation of the parameters for the downscaling process.

In order to tackle the additional uncertainty introduced by the combination of two proposed techniques, a study of the variation of scaling features of adjusted and unadjusted rainfall estimates could usefully be conducted to understand the impact of the adjustment process upon downscaled rainfall estimates.

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