HIGH RESOLUTION RAINFALL MEASUREMENT AND ANALYSIS IN A SMALL URBAN CATCHMENT

by

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ABSTRACT

Rainfall data from operational radar or rain gauge networks is generally not available at a resolution smaller than $1km^2$. Due to short lead times and high percentage of impervious area, the spatial variability of rainfall becomes important when simulating flow and runoff in smaller urban catchments. In the UK there is a growing interest in modelling rainfall runoff and flooding processes at scales much smaller then $1km^2$. As high density rainfall data are scarce, statistical downscaling techniques are sometimes used to spatially downscale radar or rain gauge data, in order to include the effects of small scale rainfall variability. These downscaling techniques are, however, generally not verified against high resolution rainfall data measured on the ground. This paper describes a study where operational UK radar data has been downscaled to areas between 10 and 100 m, and compared with data from a network of 16 tipping bucket raingauges located in an urban area < $1km^2$.

Keywords: fractal, downscaling, high density raingauge network, radar rainfall, spatial variability.

1 INTRODUCTION

A correct combination of spatial and temporal resolution of rainfall input and resolution of modelled runoff surfaces is important for creating meaningful urban drainage and urban flooding models. Urban areas exhibit large spatial heterogeneities (Villarini et al., 2010). Research described in Schellart et al. (2012) compared simulated sewer flows using either C-band radar or tipping bucket rain gauge data with measured flows in a combined sewer system in the UK. The results indicated that four rain gauges situated in a $11km^2$ area could miss local heavy rainfall peaks, but that $1km^2$ resolution radar data occasionally contained considerable local errors in rainfall intensity. Neither rainfall measurement method proved accurate enough to simulate flow peaks occurring in the system, whereas it is the peak flows that are important for simulation or prediction of urban flooding and combined sewer spills. When processing radar data, the rainfall estimate is commonly calibrated by reference to rain gauge data. However, in instances where rainfall is highly spatially varied the use of a limited number of rain gauge measurements may be unrepresentative of the wider area (e.g. Ciach and Krajewski, 2006). Ciach and Krajewski (2006) describe the importance of gathering empirical evidence of small-scale spatial variability of rainfall for the validation of mathematical models that describe rainfall at different spatio-temporal scales, and the lack of rain gauge networks with inter-gauge distances less than 3-4 km. Limited research in non-urban surroundings in Europe has highlighted how spatially varied rainfall can be on a sub-kilometre scale. For example, Pedersen et al. (2010) describe two experiments placing 9 rain gauges on a 500x500m area in Denmark. They found the intra-event variability between individual rain gauge depth and mean event depth ranging between 1 – 26%.

UK Water industry papers and reports, e.g. FWR (2004) describes how detailed data and models are needed for urban rainfall run-off and flood modelling. For modelling what happens on street scales, 5 ha catchment subdivisions and 2-minute intervals have been found to be useful. However, none of the UK operational rainfall radar and rain gauge networks currently supplies rainfall data at a resolution high enough to warrant urban rainfall runoff modelling at 5ha subdivisions. More research is therefore needed on high resolution rainfall data in urban areas, and finding the optimum level of detail for both rainfall data or modelled rainfall, and urban run-off models. Statistical downscaling could be a useful tool to generate street-scale rainfall estimates based upon operational radar rainfall data (Wang et al., 2010) and to further improve the performance of the meso-scale rainfall nowcasting system in urban rainfall prediction (Liu, 2012). However, the correctness of downscaled radar rainfall estimates is usually unknown and the validation is not straightforward due to the lack of street-scale rainfall measurements. In addition, there is an inherent difference between radar and raingauge measurements in representing precipitation; the prior indicates an areal average of rainfall rates, whilst the latter represents point information. The validation therefore has to depend on the comparison of the subsequent hydrological outputs resulting from downscaled rainfall inputs (Gires et al.,2012). The rainfall-runoff process however will introduce additional uncertainty and cannot truly reflect the spatial variations in downscaled rainfall estimates.

2 METHODOLOGY

2.1 A very dense network of 16 rain gauges within a 1 km^2 radar pixel

The existing research on very high resolution ground rain gauge networks has been mainly carried out in non-urban areas. One problem in urban areas is finding safe and good locations for rain gauges, i.e. at a distance of twice the height away from any obstacles such as building and trees and not too close to the edge of flat roofs. A high density rain gauge network has therefore been installed at the University of Bradford campus, near the city centre of Bradford, UK. This network currently consists of 16 tipping bucket rain gauges, collocated in 8 pairs. The rain gauges have all been sited on flat roofs, or on railings at the edge of flat roofs, at locations as close as possible to the 'ideal' requirement for rain gauge siting. The distances between the pairs range between 40 m and 400 m approximately, and all rain gauges pairs are located in a single 1km^2 radar pixel of the UK Met Office operational network of C-Band radars (Nimrod). The locations of rain gauges and the coincidental 1 km^2 radar pixel are shown in *Figure 1* (A).

2.2 Scaling and interpolation

A multiscale mapping model proposed by Cheng (2005, 2008) is employed here to generate downscaled radar rainfall rates at the coincidental location of the rain gauge network. This model combines two types of information that are largely used to characterise geo-data; they are spatial dependence and singularity. The idea of the prior is to associate the variability of data values with the distances seperating them. This information can be further used to predict (or interpolate) the values at the unknown locations by linearly combining the known values (or measurements) nearby (e.g. the Kriging or IDW interpolation), which can be espressed as follows:

$$c(\mathbf{x}_0) = \sum_{\mathbf{x}_i \in \Omega(\mathbf{x}_0, \varepsilon)} \lambda_i (d(\mathbf{x}_i, \mathbf{x}_0)) c(\mathbf{x}_i)\,, \qquad (1)$$

where $c(\mathbf{x}_0)$ and $c(\mathbf{x}_\mathrm{i})$ are data values respectively at locations $\mathbf{x}_0$ and $\mathbf{x}_\mathrm{i}$, and $\lambda_\mathrm{i}(\cdot)$ is the to-be-determined weighting, which is a function of the distance between $\mathbf{x}_0$ and $\mathbf{x}_\mathrm{i}$, denoted $d(\mathbf{x}_\mathrm{i}, \mathbf{x}_0)$. However, in the process of interpolation, the singularity of values could be smoothed off in order to obtain more robust spatial association, and consequently some valuable information of local variability is removed. The singularity, in the conext of multifractals, is an index used to characterise the variation of statistical behaviour of data values as the measureing scale changes. The removal of singularity could be critical for small-scale applications (e.g. urban flood modelling) because the distribution of singularities is usually consistent with the distribution of the anomalies of singular physical processes (e.g. flooding and rainfall) that result in anomalous amounts of energy releases at a fine (spatial and temporal) scale (Cheng, 2008; Malamud et al., 1996; Schertzer and Lovejoy, 1987).

A general form of geo-data values, taking into account singularity, can be therefore expressed as follows (Cheng et al., 1994):

$$Z(\mathbf{x}, \varepsilon) = c(\mathbf{x}) \varepsilon^{\alpha(\mathbf{x}) - E}\,, \qquad (2)$$

where $c(\mathbf{x})$ is a constant data value at locations $\mathbf{x}$ (the same as the $c(\mathbf{x})$ in Eq. (1)) and is invariant as measuring scale ε changes; $\alpha(\mathbf{x})$ is the singularity index and E is the Euclinean dimension (E = 2 for plane data). When data values do not show singularity, $\alpha(\mathbf{x})$ is equal to E, and consequently the average of data values within the $\varepsilon \times \varepsilon$ area retains the same as scale changes (i.e. $Z(\mathbf{x}, \varepsilon) = c(\mathbf{x})$). By rearranging Eq. (2) and substituting it into Eq. (1), a more general interpolation relation between the unknown value at location $\mathbf{x}_0$ and its neighbourhood values can be obtained:

$$Z(\mathbf{x}_0,\varepsilon)=\sum_{\mathbf{x}_i\in\Omega(\mathbf{x}_0,\varepsilon)}\lambda_i(d(\mathbf{x}_i,\mathbf{x}_0))\varepsilon^{\alpha(\mathbf{x}_0)-\alpha(\mathbf{x}_1)}Z(\mathbf{x}_i,\varepsilon)\,,\ (3)$$

where $\alpha(\mathbf{x}_0)$ and $\alpha(\mathbf{x}_i)$ are respectively the singularity indices at locations $\mathbf{x}_0$ and $\mathbf{x}_i$.

2.3 Spatial rainfall downscaling

This integrated interpolation relation (Eq. (3)) can be further used to generate downscaled radar rainfall rates which are comparable to the coincidental raingauge data. The weighting λ_i for conducting interpolation can be determined according to the distances between the centre $\mathbf{x}_0$ of rain gauge network and the surrounding radar pixels at locations $\mathbf{x}_i$'s (see the triangular and squared markers in *Figure 1*(B)). Here, the simple IDW (inverse distance weighting) interpolation technique with power parameter equal to 2 was employed and in total 81 (i.e. 9 × 9) surrounding 1 km^2 radar pixels at locations $\mathbf{x}_i$'s were used. It is worth to clarify here that the interpolated radar rainfall estimates represent the mean rainfall rates over a 1 km^2 grid square, rather than the point rainfall rates.

The singularity indices at a given location can be estimated using Eq. (2). The mean rainfall rates within the boxes with variable sidelengthes ε's (numbered by 1-4 in *Figure 1*(A) and 1-3 in (B)) are firstly computed. The logarithms of these rates and the associated sidelengthes are then compared. If a well linear relation can be observed, that means the scaling is followed and the singularity $\alpha(\mathbf{x})$ of the dataset can be derived. Here, $\alpha(\mathbf{x}_0)$ and $\alpha(\mathbf{x}_i)$ were respectively computed using radar (scales ranging from 1 to 9 km) and rain gauge (scales ranging from 100 to 700m) rainfall values, where the mean rainfall rates of rain gauge network within the box with a given sidelength were estimated by averaging the rain gauge data within that box.

Based upon the information obtained above together with Eq. (3), the radar rainfall estimates at the centre of rain gauge network with various spatial scales can be computed.

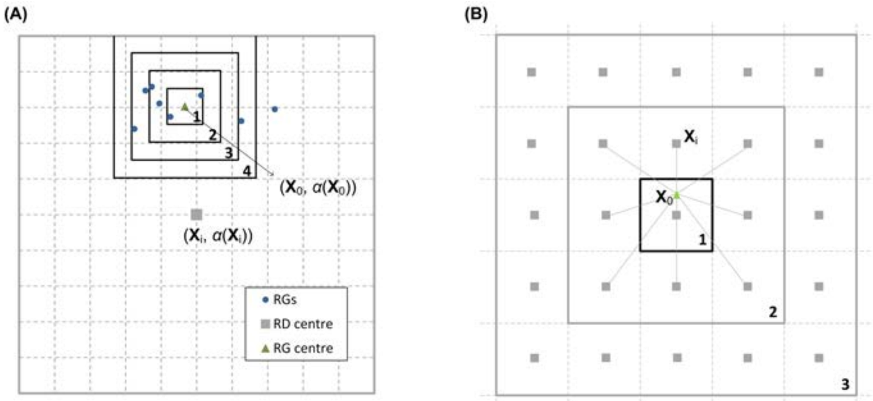

Figure 1 – Illustrations showing (A) the location setting of multi-sensor network, where the round markers represent rain gauges, the square marker is the centre of the co-located radar pixel and the triangular marker is the geometric centre of raingauge network; (B) the neighbourhood radar pixels (the squared markers are the centres of each pixel).

3 RESULTS

The rain gauge network in Bradford has been operational since April 2012, and up until the 21st August 2012 between 527mm and 585mm precipitation has been recorded. *Table I* provides information on the events studied and shows the range of variations in event cumulative rainfall over the campus area as recorded by the raingauges. Except for the event of 22nd June, the radar underestimates the rainfall recorded by the rain gauges. For the small high intensity rainfall event on the 21st of June, the radar did not record any rainfall at all. The downscaling was therefore only carried out for the 22nd June, 6th July and 15th August.

Table I – Details of events studied for 16 rain gauges, single radar pixel overlying campus and 81 radar pixels.

	21 Jun	22 Jun	6 Jul	7 Jul	15 Aug
Approx event duration	20 mins	24 hrs	10 hrs	25 mins	3 hrs
RGs range cum. depths (mm)	5.5 – 8.5	36.5 - 49.4	32.3 - 38.0	11.8 – 13.1	15.2 - 17.6
Overlying pixel cum. depth (mm)	0	37.7	18.9	0.7	5.8
81 pixels cum. depths range (mm)	0 – 0.2	34.6 – 62.2	15.9 – 28.3	0.1 – 1.6	5.0 – 9.9

Figure 2 shows an example of the cumulative rainfall recorded by the 16 rain gauges, as well as the 1km^2 radar pixel overlying the rain gauge network and downscaled radar data for the event of 6th July 2012. The paired rain gauges generally show very similar rainfall except for raingauges 18 and 17 which means one of these two raingauges could have suffered a temporary blockage or other random error. Filtering out these random errors will be a subject of further study. The original radar data (the dark dotted line) largely underestimes the rainfall recorded by the raingauges and can be slightly improved by interpolating the radar data at neighbourhood pixels to the centre of rain gauges (the grey dotted line); however, the interpolated radar estimates follow a very similar pattern to the original radar data This means that without taking into account local singularity the interpolated estimates still produce rainfall values that are smoothed over the 1 km^2 radar grid square. By introducing the local singularity and consequently downscaling the interpolated 1-km rainfall rates, the patterns of cumulative rainfall become more variable; for example, at time points 12:50 and 14:45, the cumulative radar rainfall values significantly increase due to the strong singularities in the radar and raingauge data. Similarly, it can be observed in *Figure 3* that at the time point 06:35 and the period of 12:30 – 13:30 the cumulative radar rainfall largely increases because of local singularites.

However, it can be found that the singularities cause discontinuity to the cumulative rainfall estimates; this could be because of the assumption that the scaling features of radar (i.e. 1 – 9 km) and rain gauge data (100 – 700 m) are comparable. In other words, the scaling beaks that may exist between two investigated scale ranges (i.e. 1 – 9 km for radar and 100 – 700 m for rain gauge data) were neglected in this paper.

4 CONCLUSIONS

The rainfall events measured over the campus exhibited significant spatial variation, between approximately 3mm and 10mm difference in event cumulative rainfall over distances < 400 m. In 4 out of 5 events studied the radar underestimated the rainfall significantly. This could partially be down to the radar 'smoothing' the rainfall over an area of 1km^2, although it does not explain all the underestimation of the radar, it is likely that other radar errors remained after the UK Met Office's quality control efforts. Downscaling of C-band radar data or high resolution rainfall measurements is likely to be necessary as input to local urban rainfall runoff and flood modelling, to prevent underestimation of the flows due to underestimation of the rainfall.

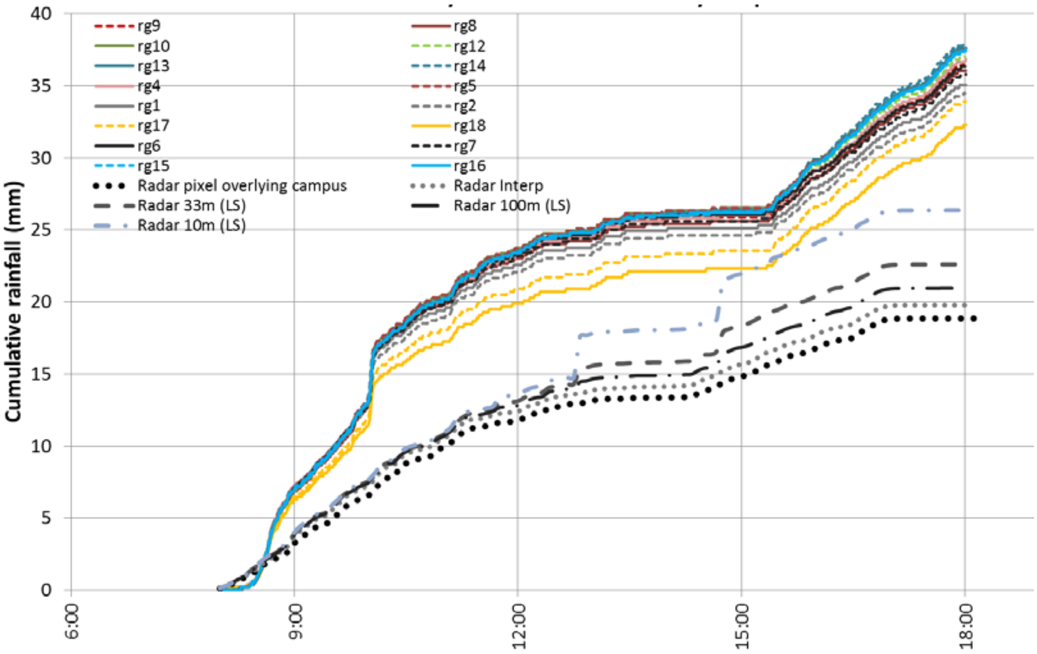

Figure 2 – Rainfall measured by the 16 rain gauges and the 1km^2 radar pixel overlying the campus and downscaled rainfall data, 6th July 2012.

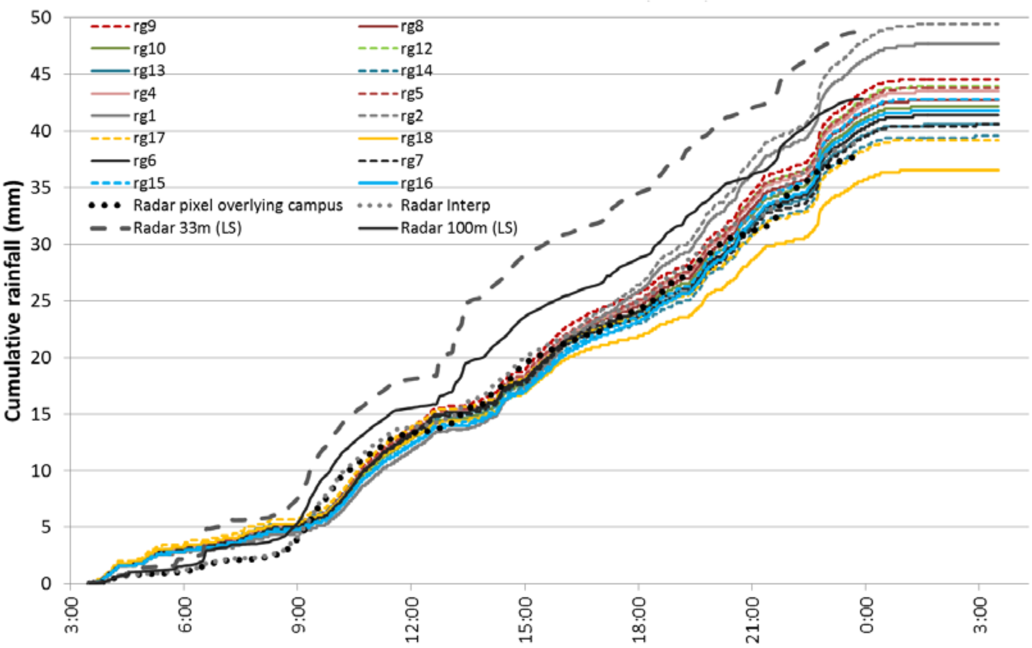

Figure 3 – Rainfall measured by the 16 rain gauges and the 1km^2 radar pixel overlying the campus and downscaled rainfall data, 22nd June 2012.

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