Exploration of an adaptive merging scheme for optimal precipitation estimation over ungauged urban catchment

Sherien Fadhel, Miguel Angel Rico-Ramirez and Dawei Han

ABSTRACT

Merging rain gauge and radar data improves the accuracy of precipitation estimation for urban areas. Since the rain gauge network around the ungauged urban catchment is fixed, the relevant question relates to the optimal merging area that produces the best rainfall estimation inside the catchment. Thus, an incremental radar-gauge merging was performed by gradually increasing the distance from the centre of the study area, the number of merging gauges around it and the radar domain. The proposed adaptive merging scheme is applied to a small urban catchment in west Yorkshire, Northern England, for 118 extreme events from 2007 to 2009. The performance of the scheme is assessed using four experimental rain gauges installed inside the study area. The result shows that there is indeed an optimum radar-gauge merging area and consequently there is an optimum number of rain gauges that produce the best merged rainfall data inside the study area. Different merging methods produce different results for both classified and unclassified rainfall types. Although the scheme was applied on daily data, it is applicable to other temporal resolutions. This study has importance for other studies such as urban flooding analysis, since it provides improved rainfall estimation for ungauged urban catchments.

Key words | merging, radar, rainfall estimation, rain gauge, urban catchment

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INTRODUCTION

Pluvial flooding of urban areas is a crucial issue and should be addressed carefully since it has a large effect on the population and landscapes of cities (Houston *et al.* 2011). Heavy and localised rainfall is the main factor in this problem and the uncertainty related to it is considerable when compared with the overall uncertainty resulting from modelling and forecasting urban flooding (Golding 2009). Traditionally, rain gauges are the most direct instruments to provide rainfall measurements at individual points (Habib *et al.* 2010). Like any meteorological device, rain gauges have many sources of error, such as those due to the effects of wind, evaporation losses, wetting and splashing, siting and exposure errors (Habib *et al.* 2010). However, the most significant problem associated with rain gauges is their limited spatial coverage since they represent point rainfall measurements and are not densely available.

In contrast, weather radar can provide a better spatial and temporal coverage for the study areas with fine resolutions both in space and time. Radars with such advantages have been adopted for rainfall forecasting and real time operations in urban and rural areas (Liguori *et al.* 2012; Rico-Ramirez *et al.* 2015). However, the radar rainfall measurement has accuracy limitations since it does not measure rainfall directly, but rather the returned power from precipitation particles, which can be related to the radar reflectivity and this is then converted into an estimation of the rainfall rate. Indeed, it can be said that both

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the measured reflectivity and the radar rainfall rate are subject to errors and uncertainty (Harrison *et al.* 2009).

To overcome problems related to radar and rain gauge measurements, a diverse range of techniques to merge radar and rain gauge data have been developed and presented in the literature with different degrees of complexity ranging from simple methods, e.g. the calculation of a constant multiplicative calibration factor (Chumchean *et al.* 2006), statistical methods based on multivariate analysis (Hevesi *et al.* 1992), analysis of the probability distribution of radar-rain gauge data (Rosenfeld *et al.* 1995), geostatistical methods (Ehret *et al.* 2008; Jewell & Gaussiat 2015) and Bayesian techniques (Todini 2001).

The density of the rain gauge network has a significant impact on the performance of the rainfall merging method (Jewell & Gaussiat 2013, 2015). A denser rain gauge network produces a more precise estimation of the observed rainfall field (Ballester & Moré 2007). Recent studies related to rain gauge network density have investigated the sensitivity of the network density based on different rainfall merging methods (Villarini *et al.* 2008; Goudenhoofdt & Delobbe 2009; Nanding *et al.* 2015). The analyses show that the sensitivity of the more complex merging methods (e.g. geostatistical interpolations) is higher than that for simpler merging methods (e.g. the mean field bias corrections). Moreover, the performance of geostatistical merging improves with the increase of the network density.

Jewell & Norman (2014) developed a more refined procedure for gauge quality control to improve the gauge density used for merging by maximizing the number of gauges used for merging and at the same time reduce the error resulting from gauge measurements. It was found that the quality of the merged rainfall over a 15 minute time scale was improved.

Berndt *et al.* (2014) showed that the conditional merging (CM) method outperformed both Kriging with External Drift (KED) and indicator KED. The authors checked the performance of merged rainfall for seven cases ranging from 10 minutes to 6 hours and also included five different scenarios of rain gauge network densities, from low to high network densities. However, Jewell & Gaussiat (2015) showed that the KED method overwhelmed other geostatistical merging methods, which is the reason why KED may be adopted by the Met Office as its favoured method for real time radar-gauge merging in England and Wales.

Published studies mainly addressed the issue of merging radar and gauge data over a large domain. However, in many cases there is a lack of rain gauge network in urban areas, and there is a lack of studies assessing the performance of the rainfall merged product inside ungauged catchments. The challenge is how to select relevant rain gauges around the study area for merging. By conventional thinking, the more gauges within a fixed area, the better the results due to the increased gauge density, but in this case the situation is not so straightforward because the gauges will be outside the study area. The only way to increase the number of gauges is to increase the merging area (i.e. more gauges are included). The problem arises from the reduced relevance of the gauges if they are far away from the study area. Therefore, the increased gauges at greater distances away from the study area may not actually contribute to improving the accuracy of the merged radar-gauge rainfall over the study area. In fact, they may reduce the accuracy if the errors from those gauges are higher than the useful information gained from them. An optimal merging area should be explored and an adaptive merging area scheme is proposed.

When trying to solve the problem of estimating rainfall for an urban catchment in the case where no gauges are available inside the area, the first logical proposal would appear to be trying to find rain gauges close to the study area and perform the merging of these with the radar data. However, many questions have arisen when considering such a solution. For instance, how far away from the study area should rain gauges be included to still provide reliable merging results relative to the range of influence? What is the optimum number of rain gauges around the study area in order to provide the best merged data inside the area? Does adding more gauges far from the study area have a positive or negative impact on the merged data, i.e. is there information redundancy? In the case of classifying the rainfall into convective and stratiform storms, is the optimum distance and consequently the number of gauges outside the study area the same as for the cases without rainfall classification? What will the results be like for different merging methods?

With the aim of answering these questions, an adaptive scheme of selecting different merging areas, gauge numbers and radar domain is therefore adopted. The reason for using an adaptive merging area and an adaptive radar domain will be explained later in detail in the section describing KED below. A network of 25 gauges distributed around the study area at differing distances has been divided into four cases, with each case representing a new merging area with a different number of rain gauges. The rain gauge distribution for each case was chosen in such a way that it should surround the study area in all directions, so the study area would be almost in the middle of the merged area. The radar domain for each of the four cases of the merged areas has also been extracted from the radar network. For each case, the merging of the daily radar and the rain gauge data has been performed for extreme rainfall in the period of 1 April 2007 – 28 February 2009, by using two well known geostatistical interpolation methods: CM (Ehret *et al.* 2008), and KED (Verworn & Haberlandt 2011). The performance of the merged data is assessed using rain gauge observations inside the study area (in the real world situation, no gauges are available in the study area; those gauges are experimental gauges).

This paper is presented as follows: the methodology in the next section is divided into two sub-sections that show the geostatistical interpolation method to merge radar-gauge data and the performance assessment indicators used to analyse the results; a description of the case study area and the data used for merging; the results of the proposed method; and finally, the main findings and conclusions of this work.

METHODOLOGY

Merging of radar and rain gauge data

In this study two geostatistical interpolation methods were used for merging rain gauge and weather radar data in order to estimate the precipitation inside our study area. In addition, one geostatistical interpolation method was used for the interpolation of the validation gauges. These interpolation methods are described below.

Ordinary kriging

Ordinary kriging (OK) is one of the most widely used geostatistical methods that carry out a spatial interpolation of observations at different locations in a random field. OK is just an interpolation method, thus it cannot be used to merge radar-gauge data. However, it can be used as a benchmark to evaluate other merging methods. In this study OK is used purely for the rainfall interpolation which is briefly explained as follows.

The spatial variability of the precipitation field can be obtained by a predefined semivariogram model using rain gauge observations. In this study several semivariogram models were tested (spherical, pentaspherical, exponential, Guassian and Whittle) and it was found that the spherical model gives consistently the best results to describe the spatial variability of the gauge observations (the results are not shown here due to space constraints).

The linear combination between the rain gauge observation values $Z_G(x_i)$ and weights λ_i^{OK} at the corresponding locations x_i was used to interpolate the rainfall value $Z_{OK}(x_0)$ at the location x_0:

$$Z_{OK}(x_0) = \sum_{i=1}^{n} \lambda_i^{OK} Z_G(x_i) \tag{1}$$

where n is the number of rain gauges used for the interpolation.

The best linear unbiased estimate of the rainfall can be obtained after computing the weights and assuming a constant unknown mean across the field. More details about OK method can be found in Goovaerts (1997).

Kriging with a radar-based error correction

The kriging with a radar-based error correction (KRE), which is also known as 'CM' (Ehret *et al.* 2008) has been included in this study. A great deal of research work has adopted this method due to its simplicity and computational efficiency (Goudenhoofdt & Delobbe 2009; Pettazzi & Salsón 2012; Berndt *et al.* 2014; Mckee 2015).

The merged rainfall using this method combines the interpolated rain gauges using the OK method and the spatial variability of radar data (Ehret *et al.* 2008). The steps of CM are first to interpolate the rain gauge observations using OK to estimate the best linear unbiased rainfall field at all ungauged locations. Next, radar pixels at gauge locations are extracted from the radar rainfall field and the values at other locations are interpolated using OK. Subsequently, the deviation C between the observed and interpolated radar rainfall field is calculated from the following equation (Ehret *et al.* 2008).

$$C = \exp\left(\tan^{-1}\left[\ln\frac{R_{ORI}}{R_{ORK}}\right]\right) \tag{2}$$

where R_{ORI} is the observed radar rainfall field and R_{ORK} is the interpolated radar rainfall field using the OK method; C is equal to one at the rain gauge locations.

Finally, the deviation C is inserted into the gauge-based kriging field Z_{OK} as follows $Z_{KRE} = Z_{OK}\,C$, to obtain the merged rainfall field Z_{KRE} which has the spatial details from the radar field and at the same time maintains the features of the gauge interpolated field.

Kriging with external drift

KED is a geostatistical interpolation method, which incorporates one or more secondary variables. In this study, only one additional variable is included, which is the radar data. It follows the same scheme as in the OK, however, the additional exclusive constraint on the KED method is the adoption of the weighted sum of radar values $Z_R(x_j)$ at the gauge locations x_j to realise the interpolated radar value $Z_R(x_0)$ at the unknown point x_0 (Haberlandt 2007):

$$\sum_{j=1}^{n} \lambda_j^{KED} Z_R(x_j) = Z_R(x_0) \tag{3}$$

where λ_j^{KED} is the KED weights.

The semivariogram is fitted to a spherical model, which assumes that the rainfall field is isotropic. Further details about the KED method are available in Haberlandt (2007) and Verworn & Haberlandt (2011).

As can be seen from the two merging methods above, the radar values at the gauge locations should be used for the interpolation in the KRE method and as external drift in the KED method; and because all the gauges are outside the study area, the radar domain should be increased when additional surrounding gauges are included in the sphere of influence for estimating the rainfall inside the urban area, which is located at the centre of the radar domain. Thus, an adaptive radar scheme, which covers all the gauge locations, should be adopted in each merging case, rather than using a fixed radar domain, which covers only the study area. Although the merged radar-gauge rainfall field is computed for the whole adaptive merging area, only the merged rainfall that covers the study area has been extracted for each case study and the statistics were performed only over the study area.

Performance assessment

The performance of the methods has been evaluated by the comparison made between the merged rainfall estimates and the observed interpolated rainfall from the four experimental gauges located inside the study area. Those gauges are temporarily installed for research purposes only and the rainfall was interpolated over the study area using OK. The testing procedure has been conducted for extreme rainfall for the period from 1 April 2007 to 28 February 2009 covering 118 rainy days.

Several quality indicators were adopted in this study for the assessment of the results: the root mean square error (RMSE) is one of the most common indicators used for the verification:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(R_{m_i} - G_i)^2}{N}} \tag{4}$$

where R_{m_i} and G_i are the merged rainfall and the observed rain gauge data, respectively, at location i; and N is the number of data points.

The mean absolute error (MAE) is also used in this study because it is less sensitive to outlier errors:

$$MAE = \frac{\sum_{i=1}^{N}|R_{m_i} - G_i|}{N} \tag{5}$$

The Nash-Sutcliffe efficiency (NSE) is a widely used indicator in hydrological models, and here it is used to assess the predictive ability of the rainfall merging method:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(G_i - R_{m_i})^2}{\sum_{i=1}^{N}(G_i - \bar{G})^2} \tag{6}$$

where $\bar{G}$ is the mean of the rain gauge observations.

STUDY REGION AND DATA

Radar data

The urban catchment used in this study is located in West Yorkshire, Northern England, with a total drainage area of 11.06 km^2 (Liguori *et al.* 2012) (Figure 1). The composite radar data that cover the study area were provided by the UK Met Office radar network through the British Atmospheric Data Centre (BADC) with spatial and temporal resolutions of 1 km and 5 minutes, respectively. A 41 km^2 area of radar grid covers the study area. The catchment is within the coverage of three single-polarisation C-band weather radars (Hamildon Hill, High Moorsley and Ingham) located 30, 95 and 90 km, respectively, away from the study area (UK Met Office 2009). Quality control and corrections of the sources of errors relating to the radar rainfall data were implemented by the UK Met Office Nimrod System (Harrison *et al.* 2009); however, further checking and post processing for the radar data is also adopted in this research.

Firstly any gaps in the radar data were interpolated using a nowcasting model. Then, the radar data were aggregated to a daily time interval to match the time interval of the gauge. Then the daily radar data were accumulated for the entire period that covers 118 rainy days and plotted to check if there are any artefacts that need further correction. It is worth mentioning that a check has been made for an area larger than our study area in order to have a clear overview of any potential issues that may help to decide whether or not to adopt further corrections to the radar data. It is clear from Figure 2 that the partial blockage problem is still evident since there is a clear sector that appears in the area and additionally a ground clutter problem (a very large rainfall peak) appears in the left part of the area, which needed further correction. However, these problems only affected a small part of our study area. Therefore, a simplified empirical method was established to correct ground clutter pixels.

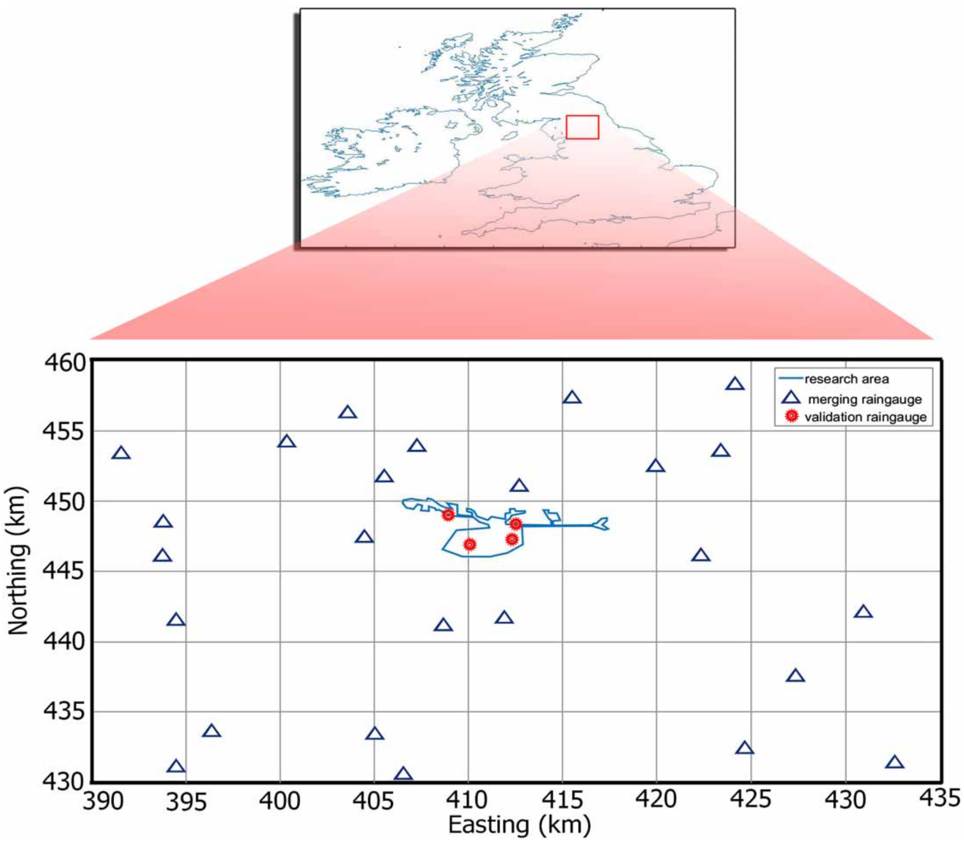

Figure 1 | Study area and location of rain gauges.

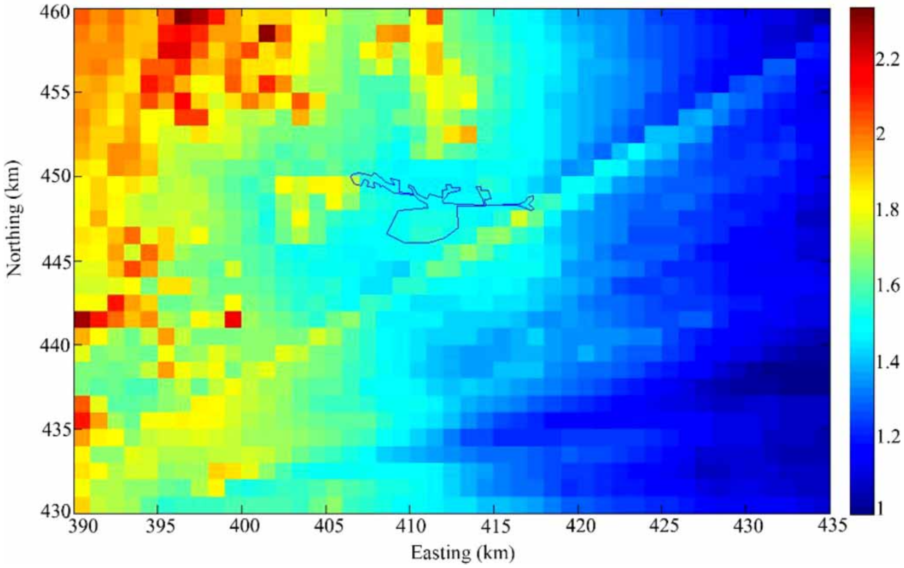

Figure 2 | Data quality check within the radar field shows partial beam blockage, and also echoes due to ground clutter.

The method consists of computing the rainfall ratio between a given pixel and the average rainfall of the surrounding pixels using a moving window of 3×3 pixels. This was done to check if the pixel at the centre of the window agrees with the average rainfall from the neighbouring pixels. If the rainfall ratio is close to 1, then this indicates there is good agreement in terms of rainfall rate. However, if the ratio is larger than a given threshold, then there is a potential problem with the pixel at the centre of the window. As such, the threshold value should be chosen with care, because a low threshold value means that many pixels will be identified as potential clutter leading to unreasonable results and important information from the original radar field could be lost. On the other hand, adopting a high threshold value means that just a few pixels will be identified as clutter and as a result the problem may still exist within the radar field. Therefore, we checked all 118 storms carefully and a trial and error procedure was adopted to choose the threshold value to ensure that only the problematic pixels were identified. For our study area, a threshold of 1.7 was good enough to identify the suspicious pixels (around 1–2 pixels in the whole region). However, this threshold will be different for other case studies since it depends on the region and storm variability. For the above correction procedure we were keen to correct only obvious outliers (e.g. very large values caused by ground clutter and other non-rainfall targets) within radar data, whose rainfall ratios were larger than the adopted threshold. The clutter pixels were identified first for the whole region using the rainfall ratio described above. Then the clutter pixels were corrected using the average rainfall of the surrounding pixels.

Rain gauge data

The daily rain gauge data were provided by the BADC. Since there were no gauges inside the study area, only the closest 25 gauges to the area were chosen to perform the proposed study of merging radar-rain gauge data (Figure 1). In order to increase the quality of the merged data, the data quality of all the gauges was checked before they were used as input data in the merging technique by using a test of spatial consistency between nearby gauges. Spatial consistency checking is utilized to distinguish outliers which are not spatially consistent with the neighbouring gauges (Kondragunta 2001). The daily time series for each gauge was compared with the nearest gauges within a maximum distance of 15 km. If there is a day that shows inconsistencies between neighbouring gauges, this is flagged up. However, since rainfall is highly variable in space and time, a rain gauge that measures rainfall amounts from a convective system does not necessarily have to be spatially consistent with its neighbours. Therefore, a convective test using radar data was adopted. The flagged days for the gauge under consideration and the neighbouring gauges were compared with the radar data (i.e. with the radar pixels where the gauges are located). If all gauges agree with the radar data within a certain threshold then the flagged days are treated as valid data. On the other hand, if the radar data disagree with the gauge under consideration, but agree with the neighbouring gauges, then those flagged days for the gauge under consideration will be considered as outliers. Thus we removed those days from the time series for that gauge. It is worth mentioning that the threshold value is an adjustable parameter and can be altered according to the location and season.

Usually the radar data are corrected using the gauge data, however in this study we adopt the radar to perform just a qualitative (but not a quantitative) check with the gauge data, which is why we compared the gauge under the test in addition to the neighbouring gauges to the radar pixels (where those gauges are located). By adopting this comparison we make sure that the radar data are more consistent with the gauges in order to adopt them for the quality check and to ensure that there is no problem within the pixel of the gauge under the test (i.e. ground clutter or attenuation, etc.). It is worth mentioning that the radar pixels that cover the location of all 25 gauges were problem free, i.e. none of those pixels reported any problems in the radar quality check, and that helped to rely on those pixels to check the quality of the gauges.

The second quality test includes comparing the zero-valued rain gauge reports with the rainfall from the neighbouring gauges. The principle behind this test is that if rainfall is reported in all neighbouring gauges (within 15 km) but the gauge under consideration reports zero rainfall, then that gauge is most likely to be malfunctioning. Following the same procedure described in the previous test, the flagged days from this test for both the gauge under consideration and the nearest gauges are compared with their corresponding radar rainfall pixels. If radar agrees with the neighbouring gauges, but disagrees with the gauge with zero rainfall, then a multiple linear regression with the neighbouring gauges is applied to correct the flagged days for the gauge under consideration.

The impact on the merged data quality when increasing the distance from the centre of the study area and the number of gauges used in the merging, was assessed using four cases of different sizes of the merging area (Table 1). For each case, in order to increase the number of rain gauges, the size of the merging area was increased to add more gauges farther afield than the ones in the previous case. The number of gauges for each case was chosen carefully to make sure that those gauges are distributed evenly around the catchment from the four directions. Also, the radar domain was increased for each case to cover the new merging area. To check the validity of the proposed method, the merged data were compared with the interpolated rainfall from the four tipping bucket gauges which were installed in the catchment from April 2007 until March 2009, with the data recorded every 2 minutes. Rain gauge data for the validation network were aggregated to a daily time scale.

Rainfall classification

The validation gauges within the urban area (see Figure 1) helped to identify the days with heavy rainfall. This resulted in identifying 118 non-continuous rainy days. Figure 3 shows the rainfall duration of these days in hours. Furthermore, each of the 118 heavy rainfall days was classified into three rainfall types: convective, stratiform and a mix between convective and stratiform precipitation. This was achieved by using the reflectivity of the original 5 min and 1 km radar data. The algorithm of Steiner *et al.* (1995) was adopted for the rainfall classification. The algorithm depends on the measured radar reflectivity to locate the convective pixels in each radar scan. The visual inspection of the observed radar data are used as further confirmation of convective pixels. Following the identification of convective pixels, the size and duration of those convective areas were analysed for each radar scan and the following procedure was adopted to classify storms.

Table 1 | Number of rain gauges and radar domain for the adaptive merging area

Case	Distance from centre of research area to the farthest gauge (km)	No. of gauges	Radar domain (km^2)
1	11.03	4	220
2	12.96	9	432
3	20.76	17	1,056
4	27.10	25	1,518

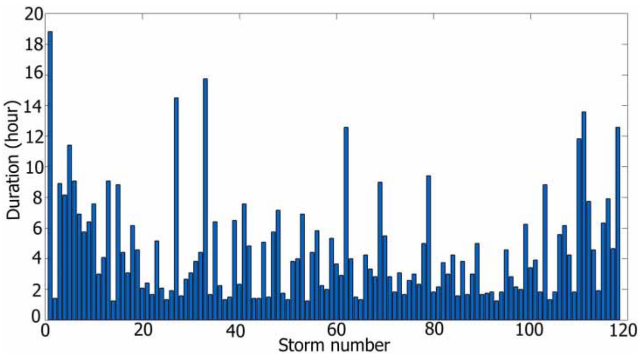

Figure 3 | Storm duration in hours for 118 days.

Unfortunately, it is not a simple task to decide the threshold value that differentiates convective from stratiform storms using only the radar reflectivity. Thus, the size of the study area was taken into account for deciding the threshold value. Since our study area was small, its size was increased in order to monitor the storm movement over time and over the area domain to be able to classify the event. Therefore, depending on the new size of the study area the following thresholds were adopted for rainfall classification: when the rain event has convective pixels that cover an area of at least 3% of the whole precipitation area for 1.15 hours or more, then that event is identified as convective. If the convective structures cover a precipitation area less than 3% of the total area, then that storm can be identified as mixed precipitation (i.e. a mix of convective and stratiform pixels). If the total precipitation area is covered by less than 1% of convective pixels, then that event is identified as stratiform. These thresholds were obtained empirically by looking at different storms that contain convective precipitation pixels. Figure 4 shows an example of the classification result of the convective pixels on 19 June 2007.

RESULTS AND DISCUSSION

First, the aggregated daily gridded radar data were compared with the interpolated gridded daily rainfall data using the four cases of gauges alone, without merging. The benchmark to assess the performance of radar and gauge data was the interpolated gridded data using the validation gauges (see Figure 1). The OK method was used for the interpolation of both validation gauges and the four cases of gauge networks.

Table 2 shows that all the performance indicators (RMSE, MAE and NSE) for the four cases of interpolated gauges were better than the gridded radar data which cover the study area. Thus it is better to merge radar data with gauges rather than using the radar alone which was already confirmed by previous studies (Goudenhoofdt & Delobbe 2009; Nanding et al. 2015).

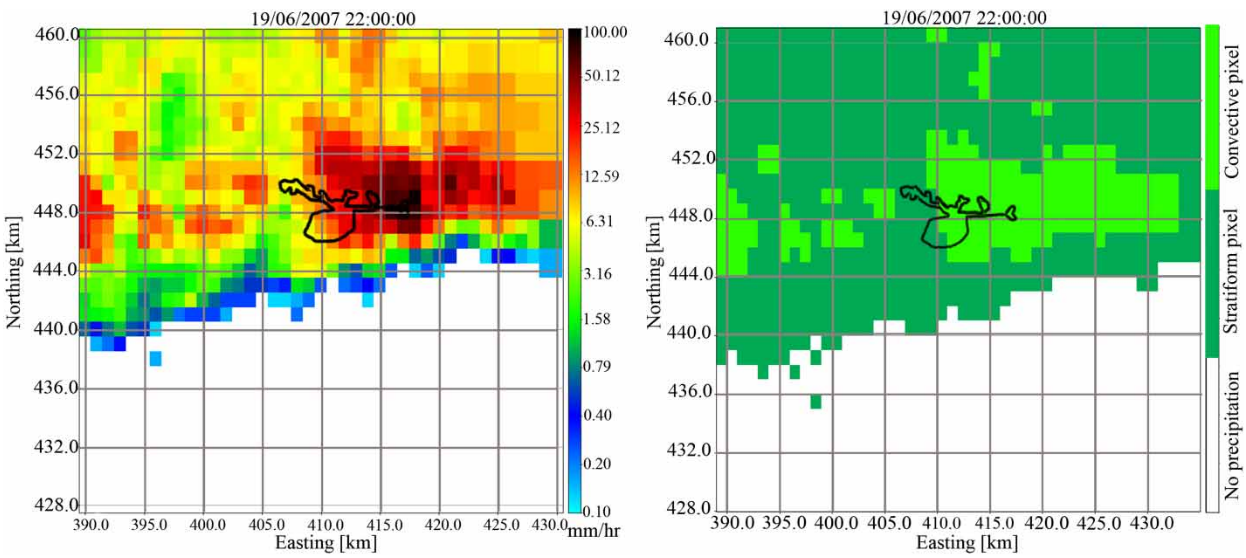

Figure 4 | Rainfall storm (left) on 19 June 2007 and classification results (right) (area identified as convective, stratiform, and no precipitation) using the pixel classification algorithm proposed by Steiner et al. (1995).

Table 2 | Performance of four cases of interpolated gauges and radar domain over the study area

		Gauge			
Performance	**Radar**	**Case 1**	**Case 2**	**Case 3**	**Case 4**
RMSE	4.563	2.875	2.832	**2.811**	2.865
MAE	3.271	2.074	2.058	**2.019**	2.063
NSE	0.666	0.867	0.871	**0.873**	0.868

It is clear from the interpolated gauge results (Table 2) that there is an optimum case (an optimum distance from the centre of the study area with an optimum number of gauges) which gives better results for the rainfall for the study area. Part of the explanation for this optimum distance is that when adding more gauges for the interpolation (in case of using gauges alone) or merging (in case of merging gauges with radar data) the distance from the centre of the study area to the farthest gauge will increase, thus the correlation will decrease (i.e. correlation error increases). On the other hand moving further away from the study area to add more gauges will reduce the sampling error (i.e. model error) produced from the interpolation or the merging methods. Thus there is an optimum distance from the study area with an optimum number of gauges which show the best interpolated or merged rainfall for the study area as shown in the schematic plot in Figure 5.

Figure 6 shows the results from the two merging methods for 118 events and for four cases of merging gauge network. It is clear from Figure 6 that the two merging methods produce consistently better results compared with the radar data. However, by comparing the results of the four merging networks to each other for both classified and unclassified storms, the first case for the KED method shows the worst dominant performance. While for the KRE method, the performances of the four cases are close to each other. Although there is a small difference between the results of the four merging cases for KRE and apart from Case 1 the results are also close for KED, there is an optimum case for each method that consistently shows better results than the other cases.

In terms of which case is the best for each merging method and which should produce the best rainfall estimate for the study area, it was found that KRE gave a different result to KED. Since KED is more sensitive to the gauge density (Goudenhoofdt & Delobbe 2009; Nanding *et al.* 2015), this shows that the third case with the maximum distance from the centre of the study area 20.76 km and 17 gauges seems the best case to adopt. However, KRE shows different results from KED, and it shows that the second case with the maximum distance 12.96 km and nine gauges is the best case to present the best rainfall data inside the study area. Thus, it is clear that various merging methods produce different results regarding which is the optimum case to present the most accurate merged rainfall for the study area, because each method has different model complexity and sensitivity to gauge density. Figure 7 shows the merged rainfall on 6 September 2008 for the two merging methods and for the four cases of merging network.

Moreover, the rainfall has been classified into three types and the two merging methods were used with each rainfall type and for the four cases of merging gauges. It was found that 52 storms were classified as stratiform; 51 storms as convective and only 15 storms were mixed (mix

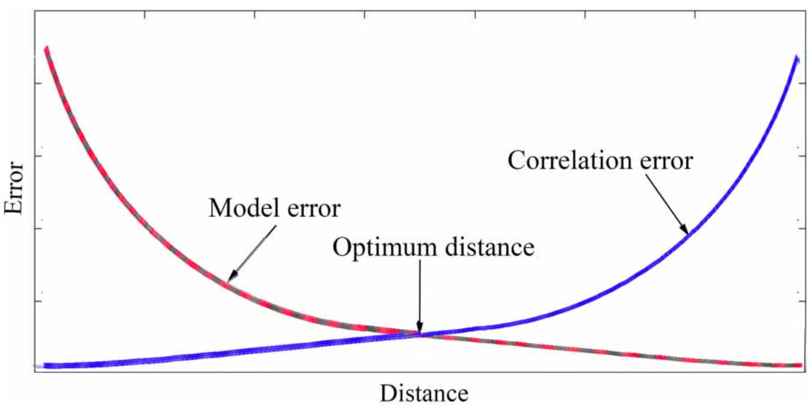

Figure 5 | Schematic plot showing the optimum distance of merging network away from the study area.

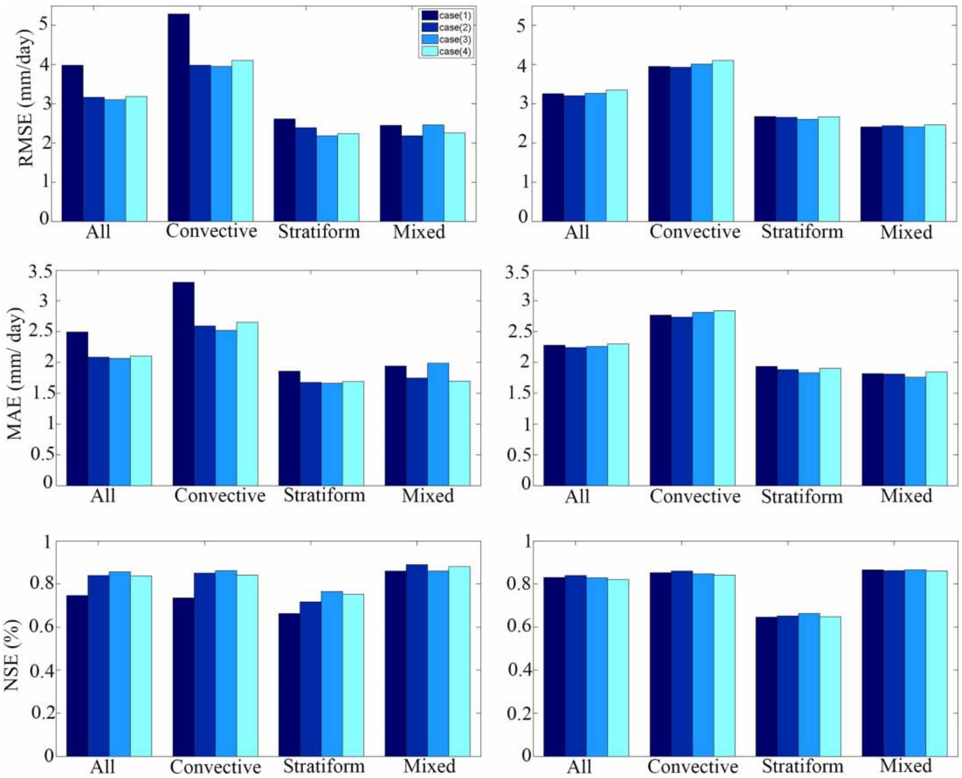

Figure 6 | Performance of the two merging methods (KED left, KRE right) for 118 days and for the four merging networks.

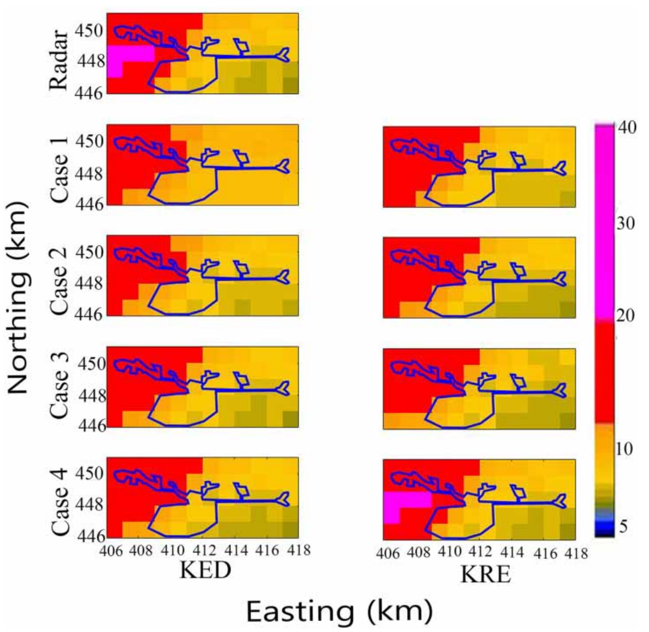

Figure 7 | Merged rainfall on 6 September 2008 for the KED merging method (left) and KRE method (right) and for the four cases of merging network. The top plot is the original radar data.

between convective and stratiform). Figure 6 shows that RMSE and MAE of both merging methods for the stratiform events are much lower than those for the convective events, which is in part due to the fact that convective events have a large spatial variability in comparison with stratiform events. However, the NSE results for the stratiform events were worse than those of convective events for both KED and KRE methods. This is due to the lower rainfall values in the stratiform events (the denominator in Equation (6) is smaller).

However, the RMSE, MAE and NSE scores for both KED and KRE methods for mixed precipitation produced conflicting results; sometimes the scores were somewhere between those obtained for convective and stratiform events, while in other cases they were better than the scores of both events. Thus, it is not possible to draw a robust conclusion regarding the mixed storms since there were only 15 cases.

In terms of which case is the most accurate for each storm type and each merging method, KRE shows that the second case – maximum distance from the centre of the study area to the farthest gauge 12.96 km and nine gauges – is preferable for convective events; while for stratiform events it is better to move farther away from the study area and to add more gauges compared with the convective scenario. Thus the third case was the optimum for the KRE and the stratiform type. Since a stratiform storm is relatively uniform over the area, gauges up to an optimum distance away are useful and contribute additional information during merging; however the convective storms are more localized and gauges far away have an apparently negative impact on the merged rainfall.

However, the KED method does produce surprising results when examining which case is the best for a given storm type. It was found that while the KED method does not seem to be so sensitive to the storm type, it is more sensitive to the gauge density, and the optimum case for merged rainfall over the study area is the third case for both stratiform and convective storms (Figure 6) which is similar to the case when the merging is performed without classification.

For the mixed storms, no conclusions can be drawn about which case is the best for both merging methods.

The modelling of urban drainage system requires measurements and forecasts of precipitation with high spatial and temporal resolutions (Liguori *et al.* 2012). In this study, the only available 5 min data are from radar. Since the radar data are prone to different types of errors (Harrison *et al.* 2009), thus the daily merged rainfall from the optimum merged scheme could be used to adjust the 5 min radar data. First, the ratio between the daily merged data at all pixels over the study area to the corresponding original daily radar data is calculated. Then this daily ratio is applied to the original 5 min radar data at each pixel. Figure 8 shows that the corrected 5 min radar data over the study area are lower than the corresponding original 5 min data on 9 January 2008 at 21:20:00. That indicates the original daily radar data were higher than the corresponding gauge data for that day, thus merging the two former datasets produced lower rainfall amounts than the original daily radar data. As a result, the ratio between the merged rainfall and the original daily radar data reduced the 5 min data after correction.

Although we applied our method for a daily time scale due to the data availability, it is also applicable for fine temporal resolutions (hourly or 15 min). However, we believe that the optimum merged scheme will be different for various temporal resolutions. The correlation between radar-gauge datasets would have a major effect on the sphere of influence for merging rainfall. The radar-gauge correlation increases as temporal length increases (Berndt *et al.* 2014), because as the data are accumulated from short to longer time scales, the differences between the two datasets will decrease. In addition, the data for short time scales are influenced more by noise than the corresponding longer scales. Thus, it is logical to expect different results regarding the optimum merging scheme at different temporal resolutions.

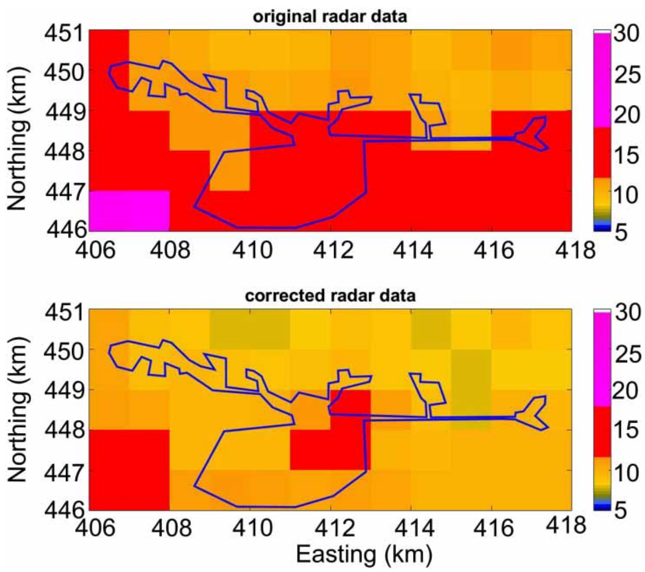

Figure 8 | Original 5 min radar data (top) and corrected 5 min radar data (bottom) on 9 January 2008 at 21:20:00.

CONCLUSIONS

Rainfall estimation over a small urban area is a challenge because there are usually no rain gauges installed in such small catchments. In addition, most gauges are of a daily type, which are poor in terms of temporal resolution for urban system modelling. Conversely, weather radars have much better spatial and temporal resolutions, but they suffer from various error sources. Merging these two sources of data has the potential to provide the best rainfall estimation over small urban areas. In this study an adaptive merging scheme has been proposed by increasing the size of the merging area to add additional rain gauges and conduct the merging incrementally with the larger radar domain. The two geostatistical merging methods employed and tested were: (i) KED and (ii) CM for different sizes of merging areas (i.e. different numbers of rain gauges and a new radar domain for each case). The merged rainfall fields over the urban catchment were evaluated using several key statistics for heavy rainfall with and without storm classification using four validation gauges inside the catchment.

The results indicate that the quality of the merged data for the research area improves with an increasing distance from the centre of the study area and number of gauges up to a certain limit; it then deteriorates when the distance and gauge numbers are further increased beyond that limit. Also, the result shows that different merging methods produce different results regarding the optimum distance and optimum number of gauges. The KED method shows that going farther away from the centre of the study area to add more gauges than the best case in the KRE method produces the most promising rainfall estimate for the study area. Furthermore, when the rainfall is classified into stratiform, convective, or mixed, the KED merging method showed that it was not affected by the storm type and it was sensitive to the gauge density. Thus, the optimum merged scheme was the same for the classified and unclassified rainfall (17 gauges). However, the KRE method showed that it was sensitive to the storm type and using a larger area (17 gauges) improves the merged rainfall for stratiform events. Convective events need fewer and closer gauges (nine gauges) from the study area than stratiform events to produce the best merged rainfall product.

Moreover, we propose a method to correct the 5 min radar data by using the optimum merged rainfall and the raw daily radar data, since the only available 5 min data in our case is from radar. However, we believe that our method is applicable with both fine and coarse temporal resolutions. Thus, the result from this study is of important and practical value for other studies, e.g. hydrological modelling to analyse flooding in urban areas. Also, it may help to improve rainfall nowcasting and forecasting for areas lacking in gauge records since the method provides the best rainfall estimation for those areas.

This study proves the existence of an optimum merging scheme, although the analysis is only concentrated in a particular urban area, so clearly more cases should be explored in different catchments and climatic conditions. Further research is required to examine the untackled questions: for example, how will different rain gauge network densities around the study area affect the result? What will the results show for both long- and short-term verifications? What would the KED and KRE performances be for a dynamic merging scheme by using the optimum merging area for different storm types?

In this study, there are four experimental rain gauges in the study area. In the real world cases, the study area is unlikely to have rain gauges and temporary rain gauges would be needed. Questions will arise about how many and how long those temporary rain gauges should be installed to determine the optimal merging area. Even more interestingly, is it possible to extrapolate the findings from the study sites to a wide range of other sites. It is hoped that this study will stimulate the community to explore such questions further.

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