Improving rainfall nowcasting and urban runoff forecasting through dynamic radar-raingauge rainfall adjustment

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Abstract The insufficient accuracy of radar rainfall estimates is a major source of uncertainty in short-term quantitative precipitation forecasts (QPFs) and associated urban flood forecasts. This study looks at the possibility of improving QPFs and urban runoff forecasts through the dynamic adjustment of radar rainfall estimates based on raingauge measurements. Two commonly used techniques (Kriging with External Drift (KED) and mean field bias correction) were used to adjust radar rainfall estimates for a large area of the UK (250,000 km^2) based on raingauge data. QPFs were produced using original radar and adjusted rainfall estimates as input to a nowcasting algorithm. Runoff forecasts were generated by feeding the different QPFs into the storm-water drainage model of an urban catchment in London. The performance of the adjusted precipitation estimates and the associated forecasts was tested using local rainfall and flow records. The results show that adjustments done at too large scales cannot provide tangible improvements in rainfall estimates and associated QPFs and runoff forecasts at small scales, such as those of urban catchments. Moreover, the results suggest that the KED adjusted rainfall estimates may be unsuitable for generating QPFs, as this method damages the continuity of spatial structures between consecutive rainfall fields.
Keywords Nowcasting; pluvial flooding; flood forecasting; gauge-based adjustment; radar

INTRODUCTION

Flood risk management has historically focused on fluvial and coastal flooding. However, recent events have revealed the imminent risk imposed by urban pluvial flooding (also known as surface water flooding) and therefore the need for appropriately managing it (Pitt, 2008). In the context of urban pluvial flood risk management, good quality flood forecasts play an ever increasing role, as these would enable the successful implementation of non-structural flood risk reduction measures, such as real-time control systems and urban pluvial flood early warning systems. Nonetheless, predicting and pinpointing this type of flooding is a difficult task, due to the small spatial and temporal scales at which it occurs. Although significant work has been done in recent years aiming at improving the forecasting of this type of flooding, the uncertainties associated with the currently available forecasts are still too high, thus limiting its operational use (Golding, 2009; Parker *et al.*, 2011).

In general, the sources of uncertainty in flood forecasting can be classified as (Todini, 2004): (i) uncertainties in input measurements, mainly relating to the rainfall fields measurements; (ii) uncertainties in input forecasts, which relate to the uncertainties in the meteorological models, namely radar nowcasting or Numerical Weather Prediction models, which are used to generate Quantitative Precipitation Forecasts (QPFs); and (iii) uncertainties in hydrological models, which relate to the ability of the model to transform inputs into flows/flood forecasts (these comprise parametric uncertainty, uncertainty in model structure and solution, and uncertainty in the measurement of responses used for calibration). In the case of urban pluvial flooding, inundation occurs directly (and quickly) as a consequence of rainfall; as a result, input uncertainties (sources (i) and (ii)) usually dominate the overall uncertainty of the forecasts (Golding, 2009). In spite of this, research on uncertainty in urban drainage modelling has so far focussed on runoff and quality models (Deletic *et al.* (2011)) and little attention has been given to rainfall input uncertainty at urban scales, especially for forecasting purposes (most of this research has focused on event reconstruction, e.g. Willems (1999); Gires *et al.* (2012); Wang *et al.* (2013)).

Due to the small spatial and temporal scales which characterise runoff processes in urban catchments, the most accurate QPFs for these areas must be achieved in the forecast horizon between 30 min and 2 hours (Einfalt *et al.*, 2004). At these short lead times, nowcasting forecasts are, in general, more suitable than NWP forecasts (Golding, 1998; Liguori *et al.*, 2012; Liguori and Rico-Ramirez, 2012). As nowcasting models are mainly based on the extrapolation of radar images, the quality of their associated forecasts largely depends on the quality of the initial radar rainfall estimates, which are subject to significant uncertainties. The main uncertainty associated to radar rainfall estimates arises from insufficient accuracy in the estimation of rain rates, particularly in the case of extreme rainfall magnitudes (Einfalt et al., 2005; Harrison et al., 2009). In order to improve the accuracy of radar rainfall estimates, it is possible to dynamically adjust them based on raingauge measurements, which provide relatively accurate point rainfall estimates near the ground. Studies on this subject have been carried out over the last few years (though most of them focus on larger scales) and encouraging results have been achieved in terms of the quality of quantitative precipitation estimates (QPEs) (e.g. Wang *et al.* (2013)). Nonetheless, the benefits of gauge-based radar rainfall adjustment in terms of QPFs suitable for urban runoff/flood forecasting have, to the author's knowledge, not yet been explored. With the purpose of giving a first step in this direction, in the present work two techniques were applied to adjust the initial radar rainfall estimates for a large area of the UK (500 km X 500 km) based on raingauge data. Afterwards, QPFs were produced by using the original radar rainfall estimates as well as the adjusted ones as input to the nowcasting model of the UK Met Office STEPS (Short Term Ensemble Prediction System, see Bowler *et al.* (2006)). The resulting QPFs were then fed into the storm-water drainage model of an urban catchment in the Greater London Area, for which local raingauge data and water depth measurements are available.

EXPERIMENTAL SITE AND DATASET

The Cranbrook catchment is located within the London Borough of Redbridge (Fig. 1b). It is predominantly urbanised and has a drainage area of 865 ha. The main water course is 5.75 km long, of which 5.69 km are culverted and have become part of the storm water drainage system, which is mainly separate. The storm water drainage system of this catchment discharges into the Roding River (Fig. 1b), which in turn discharges into the river Thames. This area has experienced several pluvial, fluvial and coincidental floodings in the past.

The above mentioned techniques were tested using two event periods: 15-18 July 2011 and 3-8 August 2011, each of which comprises several rainfall sub-events (Fig. 2), including frontal and convective ones. For the testing, two types of datasets with different domains were used: (i) radar and raingauge data covering a large area were used for generating adjusted rainfall estimates which were then used to run the nowcasting model and generate QPFs; (ii) local rainfall and hydrological data were used for calibration of the hydraulic model of the Cranbrook catchment and for assessing the performance of the adjusted QPEs and the associated QPFs and runoff forecasts. It is important to note that the local raingauge data was not used in the adjustment of radar rainfall estimates.

(i) Radar (Nimrod) data: The radar data used in this study covers an area of the UK of 500 km x 500 km size (Fig. 1c). This data was obtained from the British Atmospheric Data Centre (BADC) and corresponds to a quality-controlled multi-(C-band) radar composite product generated with the UK Met Office Nimrod system (Harrison *et al.*, 2009). This data was available at spatial and temporal resolutions of 1 km and 5 min, respectively. It was accumulated to 15 min temporal resolution, to match the resolution of raingauge rainfall data.

(ii) Raingauge data used for radar rainfall adjustment: Rainfall data with 15 min resolution from 1064 raingauges covering the same area as the radar data (Fig. 1c) was used for adjusting the radar rainfall estimates. This data was provided and quality-controlled by the UK Met Office (Georgiou and Hogg, 2012).

(iii) Local monitoring system. A real time accessible monitoring system has been maintained in the Cranbrook catchment since April 2010 and its quality has been constantly controlled by the authors of this paper. It includes three tipping bucket rain gauges, one pressure sensor for monitoring water levels at the Roding River, two sensors for water depth measurement in sewers and one sensor for water depth measurement in open channels (Fig. 1b).

MODELS

Gauge-based radar rainfall adjustment models

Over the last few years a number of methodologies have been developed for dynamically adjusting radar estimates based on raingauge data. These techniques include simple formulations such as mean field bias correction, as well as more complex formulations such as statistical approaches (e.g. Cole and Moore (2008)), geostatistical estimators (e.g. Ehret *et al.* (2008), Goudenhoofdt and Delobbe (2009)) and Bayesian methods (e.g. Todini (2001)). In this paper two of the most commonly used gauge-based adjustment methodologies will be used; these are the Kriging with External Drift (KED) and the Mean Field Bias (MFB) correction. These methodologies are widely used by meteorological services around the world (e.g. Goudenhoofdt and Delobbe (2009), Harrison *et al.* (2009)) and have proven to effectively improve the quality of quantitative precipitation estimates (QPEs). Nonetheless, these methodologies have been normally applied at large scales and their suitability for urban hydrological applications has not been analysed in detail.

Kriging with External Drift (KED). KED is a simple method to include external variables in the estimation process. Similarly to the ordinary kriging (OK), the KED constitutes a linear estimator: $Z^*_{KED}(x_0) = \sum_{i=1}^{n}\left(\lambda_i^{KED} \cdot Z_G(x_i)\right)$, where the KED estimate, $Z^*_{KED}(x_0)$, is the linear combination of known values (i.e. the observations from a network of n raingauges), $Z_G(x_i)$, with the weights λ_i^{KED}. However, the estimation of the KED weights, λ_i^{KED}, is different from that of the OK weights. In KED an additional constraint is applied to include the external variables (in this case, the co-located radar grid values, $Z_R(x_i)$): $Z_R(x_0) = \sum_{i=1}^{n}\left(\lambda_i^{KED} \cdot Z_R(x_i)\right)$. This new constraint will introduce the variability of radar data into the estimation of the KED weights and consequently in the interpolation process of raingauge data. The KED code used in this study was developed and implemented at the UK Met Office and is based on the approach used by Velasco-Forero et al. (2009), using the Fourier transform of the radar data to generate the non-parametric variogram.

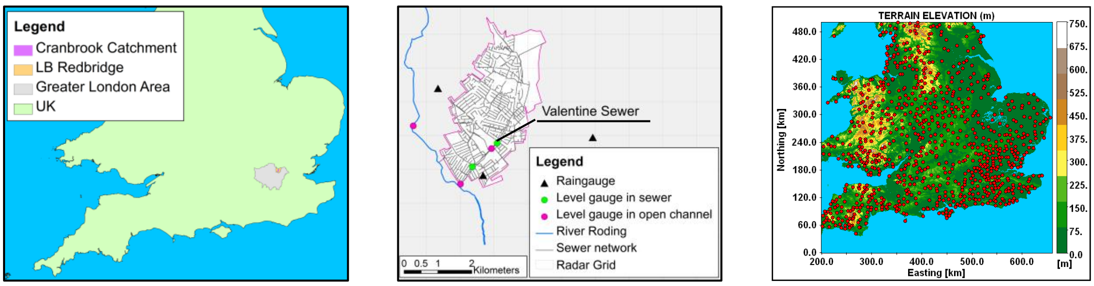
Mean field bias correction (MFB). The MFB was computed by B=ΣG/ΣR, where G and R represent the raingauge and radar measurements, respectively, at a particular location. The summation is carried out using all raingauges available within the radar domain and also using a moving window that takes into account the last 3h of rainfall data to simulate real-time operation. The adjusted radar rainfall (R') is calculated by multiplying the bias (B) obtained at a particular time step by the original rainfall field (R), that is, R' = B.R.

Nowcasting model

The nowcasting system employed is the deterministic part of the Short-Term Ensemble Prediction System (STEPS) developed by the UK Met Office and the Australian Bureau of Meteorology. This nowcasting system is based on spectral decomposition (Seed, 2003) with the incorporation of the optical flow equation (Bowler *et al.*, 2004). The STEPS model blends radar-based forecasts with NWP forecasts in order to produce better forecasts. However, in this paper only the radar-based deterministic nowcasts produced by STEPS are used. The nowcasting model was setup to run at 1 km spatial resolution and 15 min temporal resolution. Moreover, the nowcasting model was setup to produce 6 h forecasts initialised every 60 min.

Storm water drainage model of the study area

A model of the sewer system of the Cranbrook catchment was setup in InfoWorks CS and was verified in 2011 (Fig. 1b). The model comprises 1763 nodes and 1816 pipes. Rainfall is applied through subcatchments which are connected to nodes; each subcatchment is split into different surface types and the NewUK model is used to estimate runoff at each subcatchment. The flow in the sewers is simulated based on the full Saint-Venant equations.



(a) (b) (c)

Figure 1. (a) Location of Cranbrook catchment; (b) Local sensors and sewer network; (c) Radar domain and raingauges used for adjustment and running the nowcasting model.

RESULTS AND DISCUSSION

Precipitation estimates: Fig. 2 shows that the original radar (Nimrod) captured the temporal profile of the rainfall over the Cranbrook area well, but largely underestimated the rainfall depth that fell over the catchment during the event periods under consideration. It can also be seen that the adjusted rainfall estimates (KED and bias-adjusted) do not produce a significant improvement over the original radar data. The magnitude and temporal profile of the mean bias adjusted estimates are nearly the same as those of the original radar estimates. The KED adjusted rainfall presents a slightly different temporal pattern; however, its magnitude is very close to that of the original radar data. The fact that no significant improvement was obtained through adjustment can be explained by the large scale at which both adjustment techniques were applied, with a single mean field bias (MFB) ratio and a single variogram (in the case of KED) used for representing the rainfall association over the entire domain (500 km x 500 km). In this way, the spatial variability of the bias was disregarded, which led to deficient corrections and inaccurate areal precipitation estimates at small urban scales. Analyses of the radar data indicated that the Cranbrook catchment is located in an area subject to radar beam blockage, which may explain part of the underestimation of radar rainfall. Nonetheless, previous studies for the same area have proven that in spite of the beam blockage, it is possible to obtain accurate gauge-based adjusted radar rainfall estimates for this small catchment, by applying adjustment methods at smaller domains (Wang *et al*., 2013). These results suggest that when gauge-based adjustment is to be done for large areas, it is important to preserve the local characteristics of rainfall; this may be achieved by splitting the domain into smaller regions and performing the adjustment over the resulting sub-regions. This may however lead to new problems which must be investigated, such as increased computational times and the presence of ‘artefacts’ at the boundaries between the sub-regions.

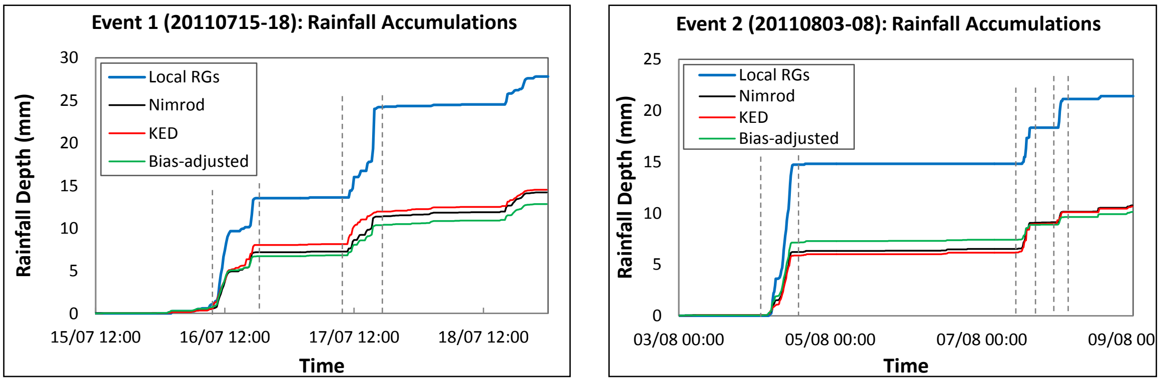


Figure 2. Average cumulative rainfall estimates (QPEs) over the Cranbrook area as recorded by the original radar product (Nimrod), gauge-based adjusted radar estimates obtained with KED and mean field bias adjustment techniques, and local raingauges.

Precipitation forecasts (QPFs): Fig. 3a shows the performance of QPFs (obtained with different rainfall inputs) versus lead time. From this figure three main observations can be made: (1) in general, the Nimrod and bias-adjusted associated QPFs exhibit a similar behaviour, while the KED QPFs show a somehow different pattern. This is because the bias-adjusted QPEs correspond to a simple scaling of Nimrod QPEs, without altering its spatial or temporal structure. (2) In terms of quantitative performance (as measured by the relative error), all QPFs perform poorly, even at short lead times. This can be explained by the underestimation of rainfall depths observed in the QPEs used as input for the nowcasting model (Fig. 2). (3) In terms of correlation, the Nimrod and bias-adjusted associated QPFs show a better and consistent performance, with high correlation values at short lead times and lower values as the lead time increases. The good performance in terms or correlation can be explained by the fact that in spite of underestimating rainfall depths, radar can well capture the temporal and spatial structure of rainfall fields and therefore the pattern of the associated forecast correlates well to that of the observations. KED QPFs show a somehow inconsistent behaviour in terms of correlation, with particularly lower values at the shortest lead times; this is more evident in the first event, when the KED QPFs pattern is nearly opposite to that exhibited by the Nimrod and bias-adjusted QPFs.

Flow depth forecasts: Fig. 3b shows the performance of the flow depth forecasts (obtained by feeding the different QPFs into the storm water drainage model of the Cranbrook catchment) versus lead time. Consistent with the analysis above, it can be noted that the Nimrod and bias-adjusted associated forecasts exhibit similar patterns, which are generally opposite to those of the KED forecasts. In general, the Nimrod and bias-adjusted forecasts' patterns appear to be normal and consistent (i.e. better performance at short-lead times, which decreases as lead time increases), in contrast to those of the KED associated forecasts. This observation is consistent with Fig. 3c, where the similarity and better performance of the Nimrod and bias-adjusted associated forecasts are evident. The inconsistent behaviour of QPFs and flow depth forecasts resulting from KED inputs can be explained by the fact that the KED adjustment method does not take into account the temporal correlation of the radar rainfall field; therefore, the adjustment affects the rain field in the time domain. Consequently, the nowcasting model is not able to properly capture the movement the storm.

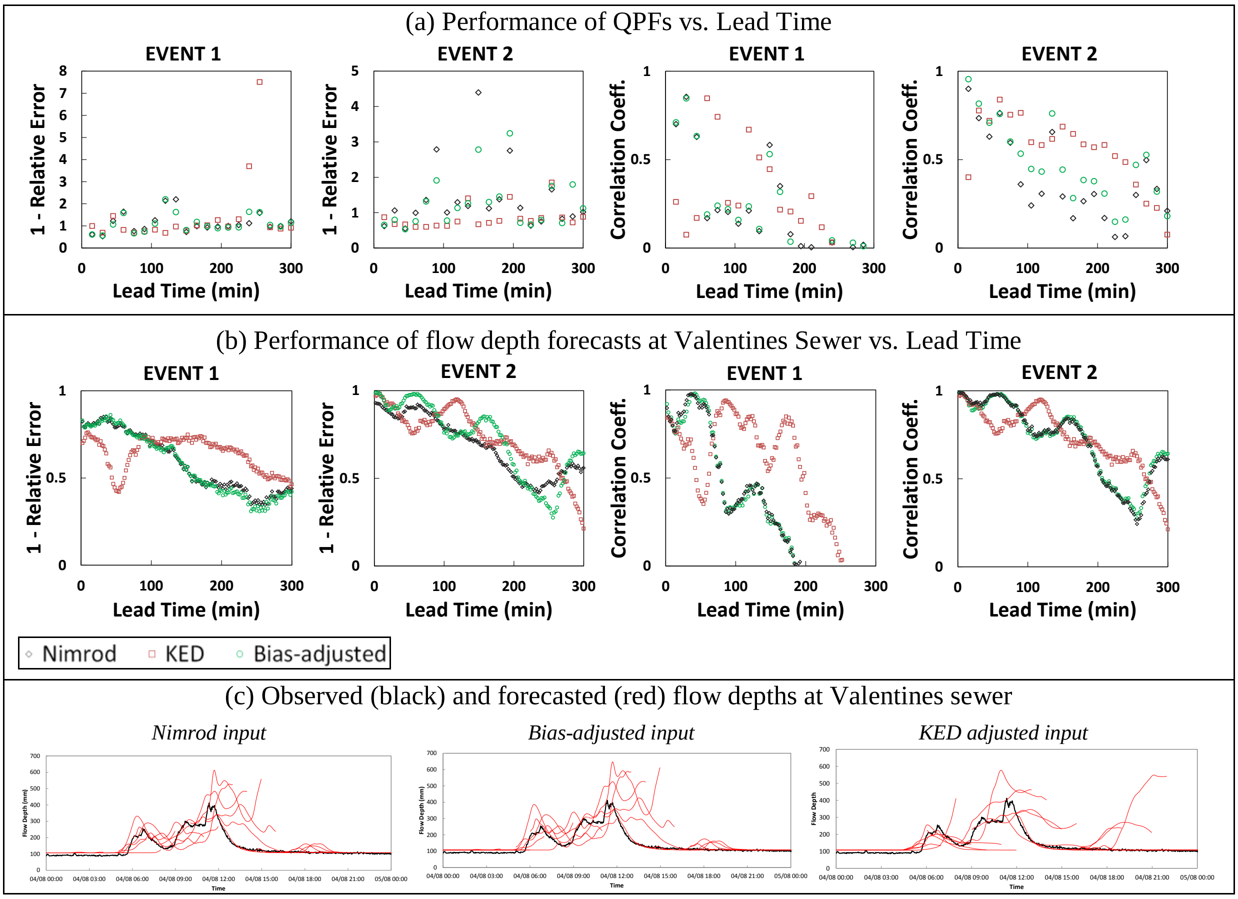


Figure 3. Performance of QPFs and associated flow depth forecasts obtained with different rainfall inputs.

CONCLUSIONS AND OUTLOOK

This study looked at the possibility of improving quantitative precipitation forecasts (QPFs) and urban runoff forecasts through the dynamic adjustment of radar rainfall estimates based on raingauge measurements. Two adjustment techniques were analysed, namely mean field bias adjustment and Kriging with External Drift (KED); QPFs and associated runoff forecasts were generated using the original and the adjusted radar rainfall estimates as input. In terms of quantitative precipitation estimates (QPEs), the results showed that the adjustment methods under consideration could not improve QPEs at small scales (such as those of urban catchments); this is due to the fact that the adjustment was done for a large domain (500 km x 500 km), without considering the spatial variability of radar-raingauge bias. To overcome this problem, the domain could be split into smaller regions and the adjustment could be done at each sub-region. Given that none of the adjustment methods tested in this study produced significant improvements to QPEs, the associated QPFs and runoff forecasts were of poor quality in terms of magnitude; nonetheless, the analysis of the correlation of QPFs versus lead time provided some relevant insights about the suitability of the two adjustment methods for improving QPEs which are suitable for generation of QPFs and runoff forecasts (this is perhaps the most important finding of this study). In general, the pattern exhibited by QPFs generated from original radar and mean bias adjusted radar appeared to be normal and consistent (i.e. better performance was observed at short-lead times and it decreased as lead time increased); in contrast, the QPFs generated from KED adjusted radar data showed inconsistent patters. This can be explained by the fact that the KED adjustment method does not take into account the temporal correlation of the radar rainfall field; therefore, the adjustment affects the rain field in the time domain. Consequently, the nowcasting model is not able to properly capture the movement of the storm. This suggests that the KED adjustment method may not be appropriate for generating rainfall forecasts and that adjustment methods which can preserve the temporal and spatial structure of the original radar data should be used when QPEs are to be used for forecasting purposes. Work is underway to confirm these initial findings. Based on these findings, dynamic adjustment techniques and ways of applying them will be sought, which can provide tangible improvements in QPEs, QPFs and urban runoff forecasts; this will constitute a major contribution towards the improved management of urban drainage systems and urban pluvial flood risk.

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