Rainfall-runoff modelling using merged rainfall from radar and raingauge measurements

Nergui Nanding, Miguel Angel Rico-Ramirez and Dawei Han

Department of Civil Engineering, University of Bristol
Queens Building, University Walk, Bristol BS8 1TR, UK
(Dated: 22 July 2014)

N. Nanding

1 Introduction

Predictions of stream discharge and groundwater flow using hydrological models are often unsatisfactory due to the lack of information of spatial variability for actual rainfall fields. Conventionally, rainfall measurements from raingauges provide relatively accurate estimates at individual point locations. The true rainfall distributions can be estimated by interpolating the available raingauges data to the ungauged areas. The approximation of areal rainfall by the interpolation methods suffers of spatial sampling errors because they are representatives of only a small range around the instrument (Villarini *et al.*, 2008). Moreover, the quality of the interpolated rainfall fields decrease with the decrease of raingauge network density. A high-density raingauge network is required for more detailed areal rainfall estimates, and in many cases this is not feasible in mountainous regions or remote areas. Such a problem could be severe for tropical regions where most rainfall has convective cells with high spatial variability. However, spatially distributed rainfall with a high resolution in space and time can be estimated from weather radars.

Despite the fact that the accuracy of radar rainfall suffers from several sources of errors and uncertainties, radars are able to provide distributed precipitation fields with high spatial and temporal resolutions over large regions. On the other hand, raingauge measurements are the most reliable point measurements, but also have their own limitations on spatial representativeness. More recently, research has proven that by combining (merging) radar rainfall estimates with raingauge measurements it is possible to obtain better rainfall estimates that are also able to capture the spatial precipitation variability (Haberlandt, 2007; Krajewski, 1987). However, there is a lack of comprehensive comparisons on rainfall estimates by different merging techniques and their impact on rainfall-runoff modelling over a wide range of catchments.

In this study, the investigations were conducted on the impact of rainfall estimates by different radar-raingauge merging techniques in terms of runoff. A study catchment across Northern England is selected and modelled with a conceptual rainfall-runoff model. Hydrological applications of rainfall measurements from radar and raingauge are accumulated on hourly timescales, and therefore rainfall estimates obtained from different radar-raingauge merging techniques are incorporated into hydrological models so that direct comparison of streamflows can be explored. The main purpose of this paper is to examine whether these merged rainfall estimates are useful as input to rainfall-runoff model over large catchment areas, focusing on the improvement of rainfall estimates for runoff predictions rather than on the rainfall estimates themselves.

2 Gauge and radar observations

The study region is located in the North of England and the area is bounded by a window of approximately 250km x 200km in size. For the rainfall estimations and hydrological model setup, hydrologic and meteorological data were provided by UK Environment Agency and UK Met Office. The UK Environment Agency operates 214 telemetered tipping bucket raingauges within the study area with temporal resolution of 10 minute. The quality control of the raingauge data is performed by using a comparison with neighboring stations. The radar rainfall field is a composite product from a network of 18 C-band weather radars provided by the UK Met Office through the British Atmospheric Data Center (BADC). The composite radar data is available at a temporal resolution of 5-minute intervals with a spatial resolution of 1-km.

It is worth to note that the rainfall data from 160 raingauges are used for radar-raingauge merging techniques for the estimation of rainfall fields in the entire region and 54 raingauges are used for the assessment of the quality of these merged products (i.e. validation). The raingauge measurements and composite radar rainfall fields are accumulated on the hourly timescale for the estimation of precipitation with spatial and temporal resolutions of 1km and 1h respectively by the aforementioned radar-raingauge merging techniques. The merged precipitation field is then averaged over the catchment (see Figure 1) to compute the areal precipitation that is then used to drive a rainfall-runoff model of this catchment. In addition, the UK Met Office maintains 29 climatological stations with hourly measurements of UK weather data, which includes air temperature data that will be used to estimate potential evapotranspiration. The distribution and locations of raingauges and weather stations are shown in Figure 1.

 mongolnandin@gmail.com

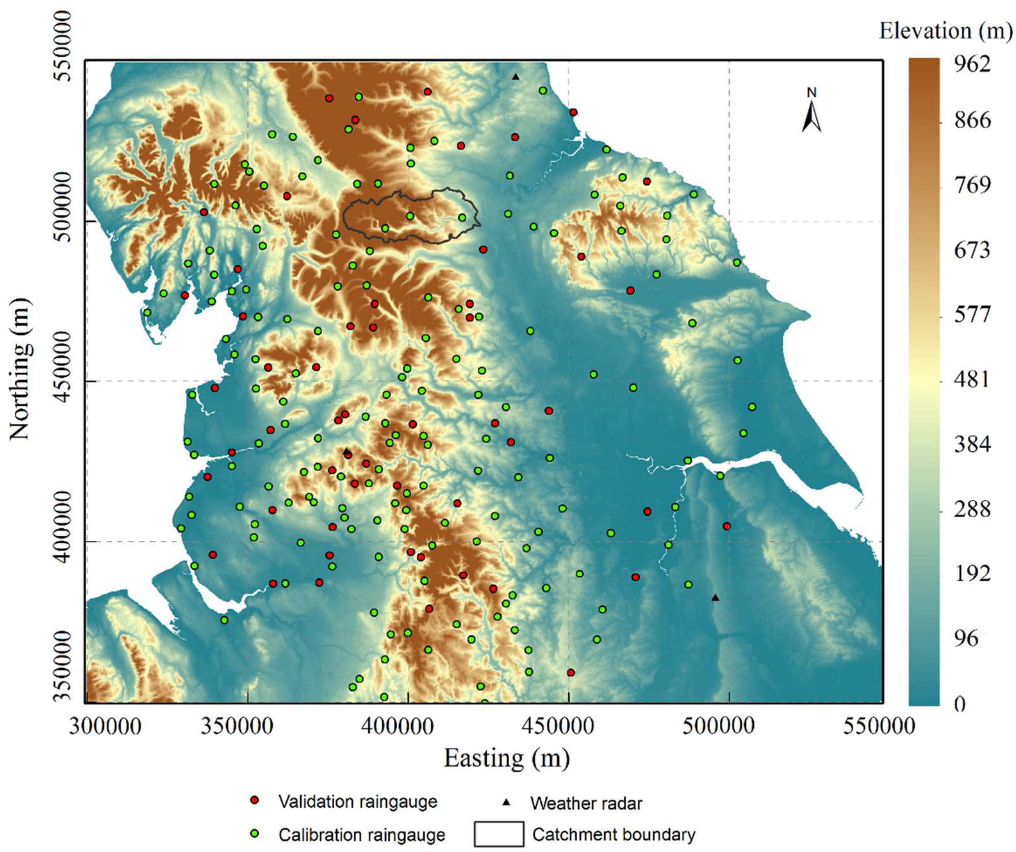

Figure 1: Map of the terrain elevation of study area, showing the locations of raingauges, weather radars and the boundary of study catchment.

3 Case study

3.1 Study catchment

The typical responsive Pennine catchment with an area of 499.4 km^2 draining the northern Yorkshire Dales, with the lower catchment in the flat Vale of York. This rural catchment is characterized by mixed geology, mainly of moderate permeability – overlain by peat in headwaters and boulder clay in lower catchments. Elevation ranges from 61 m to 709 m with an average of 358 m. The predominant land cover is grassland and horticultural area.

The areal rainfall for the calibration of the hydrological model was obtained from raingauge measurements at single point locations within the study catchment and using the Thiessen polygon method. In contrast to the raingauge measurements, the areal rainfall based on distributed rainfall fields estimated by radar-raingauge merging methods is on arithmetic averaging the values of distributed grids with a spatial resolution of 1 km^2. The brief descriptions of these radar-raingauge merging methods are presented in the next sections. Hourly air temperature was calculated as the mean of climatological stations within or near the catchment. The potential evapotranspiration was estimated by using the algorithm described in Turc (1961).

3.2 Hydrological model set up

The HBV model is a conceptual rainfall-runoff model of catchment hydrology and originally developed for use in Scandinavian catchments (Bergstrom, 1976). The model normally simulates the discharge using daily values of rainfall and air temperature and daily or monthly estimates of potential evapotranspiration, but it is also possible to use shorter time steps (i.e. hourly). It consists of different routines for snow accumulation and melt, soil moisture accounting, runoff response function and routing procedure. More detailed descriptions of the model can be found in several research papers ((Bergström, 1992; Bergström & Singh, 1995); Harlin and Kung (1992); (Seibert, 1997). The Shuffled Complex Evolution (SCE) (Duan *et al.*, 1994) as the parameterization optimization algorithm is used for the calibration of HBV model.

At the outlet of the catchment, river flow and rainfall data was available for the period from 1/1/2007 00:00 UTC to 31/12/2010 23:00 UTC. The hydrological model was run on hourly time step. The three months period between 1/7/2008 00:00 UTC and 30/9/2008 23:00 UTC, which includes 2208 time steps, is for the model warm up. The following two hydrological years between 1/10/2008 00:00 UTC and 30/9/2010 23:00 UTC, which last for 17520 time steps, is for the model calibration. Due to the availability of temperature data, the flow events from 01/06/2007 00:00 UTC to 31/08/2007 23:00 UTC were selected for model validation.

3.3 Areal rainfall

Several radar-raingauge merging techniques have been selected to estimate areal rainfall in this study, which includes Kriging with Radar-based Error correction (KRE) and Kriging with External Drift (KED). The univariate method Ordinary Kriging (OK) and simple radar adjustment method (MFB) are also included as the reference for illustrating the potential benefit of the use of radar data. It is worth to note that the topography has not been taking into account when merging radar and rainfall measurements, since the study region it is relatively flat. Details on the following radar-raingauge merging methods (KRE and KED) are available from previous research papers and only a brief description is provided here.

3.3.1 Kriging with radar-based error (KRE) correction

The KRE method is also included as part of this study due to its simplicity and computational efficiency. This method produces a rainfall field that follows a mean field of raingauge interpolation based on Kriging. At the same time, it also takes advantage of the spatial variability of radar data, which is generally representative of the true spatial pattern of rainfall. A general description of this merging method was first reported in Ehret (2003) and later also refined in Sinclair and Pegram (2005) and Ehret *et al.* (2008).

3.3.2 Kriging with external drift (KED)

Kriging with external drift (KED) is a more sophisticated geostatistical method that allows the incorporation of one or more additional variables, which are correlated with the primary variable (which are assumed to be linearly related to the expected value of the primary variable). In this study, only radar data provides the external drift term and it is important that the measurements are highly linearly correlated to the value of the primary variable (i.e. raingauge measurements). A more detailed description of the KED method is presented in Haberlandt (2007), and Verworn and Haberlandt (2011).

3.4 Comparison of streamflow

The hydrological model was calibrated by comparing the simulated flow by the model and the measured flow in the outlet of the catchment and by using statistics commonly used in hydrological studies: namely the Coefficient of determination (R^2), the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), as given below:

$$MAE = \frac{\sum_{i=1}^{N}|S_i - O_i|}{N} \qquad (2.5.1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(S_i - O_i)^2}{N}} \qquad (2.5.2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}[O_i - S_i]^2}{\sum_{i=1}^{N}[O_i - \bar{O}]^2}, \qquad (2.5.3)$$

where i indicates time step, N is the number of time steps, O indicates the observed and S simulated flow values. The bar indicates mean values. The R^2 coefficient can range from $-\infty$ to 1. A perfect estimator will have a R^2 of 1. An efficiency of 0 represents that the estimator is as accurate as the mean of the raingauge observations.

4 Results

The application of the HBV model generates the following results according to the use of different rainfall input data. The predicted hydrograph for the calibration period is shown in Figure 2. For model calibration, the peak discharge was underestimated comparing to the observed peak flow.

The calibrated model was applied to the flow event from 01/06/2007 00:00 UTC to 31/08/2007 23:00 UTC. Rainfall estimates by using different radar-raingauge merging techniques were applied into the HBV model and tested for the validation event. Table 1 presents the values of MAE, RMSE and R^2 for the model simulations for calibration and also for validation using different rainfall inputs. In terms of R^2, the model using the raingauge rainfall estimates obtains the best result with the value of 0.81, which is better than the calibration value. The results produced by the model using KRE, KED and radar rainfall inputs are also similar to the model using raingauge rainfall input, with the R^2 value of 0.80, 0.75 and 0.78, respectively. However, the stream flow predicted by the model using OK and MFB input data perform poorly with the values of R^2 less than 0.6, which could not be considered for the use of hydrological forecasting (Hansen *et al.*, 1996). The similar result have been obtained for the statistical scores of RMSE.

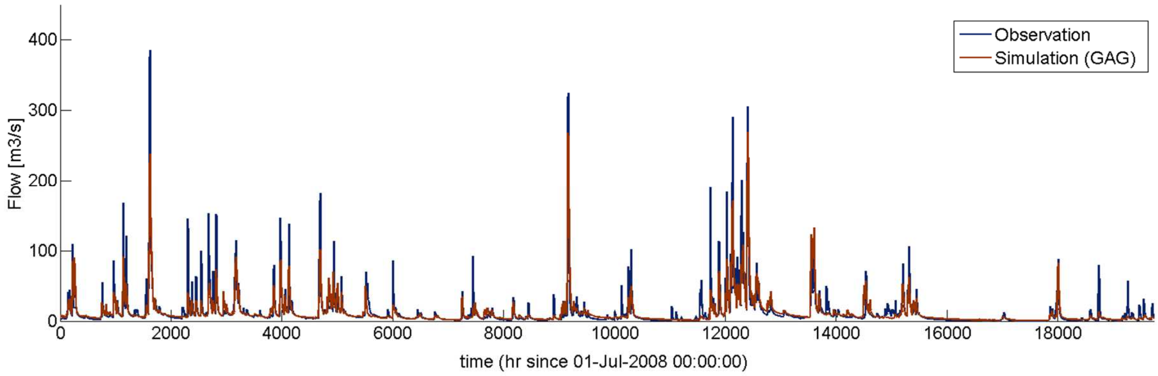

Figure 2: Comparison between observed and the HBV simulated flow for the calibration and warming up periods.

Moreover, in terms of the values of MAE, the model using raingauge merged data perform slightly better than the model using radar, MFB and KRE merged rainfall data. In overall, the result obtained by the models using radar-raingauge merged (KRE and KED) rainfall as input data perform better than the model using ORK and MFB rainfall input data. The model using the OK interpolated rainfall data is the worst in terms of all statistics.

The simulated hydrographs obtained with different input data are also compared to the observed flow, as shown in Figure 3. The model using all different rainfall input data generally underestimate the peak discharge comparing to the observed peak flow. According to the simulated hydrographs, the model using the KED rainfall input simulates the peak flow slightly better than the model using other rainfall input data. Moreover, for the simulation of base flow, the model using the KRE and KED input data shows fairly good agreement in the timing and the magnitude of the base flow. In contrast, the model using the ORK overestimates the observed base flow, but underestimate the flow peaks.

Table 1: The values of Coefficient of determination, MAE and RMSE for calibration and validation periods for different areal rainfall inputs including raingauge (GAG) and radar (RAD) rainfall.

		MAE	RMSE	R^2
Calibration	GAG	4.22	10.42	0.78
Validation	GAG	4.38	10.47	0.81
	RAD	4.85	11.29	0.78
	MFB	5.42	16.22	0.55
	ORK	9.95	16.23	0.55
	KRE	4.74	10.94	0.80
	KED	7.16	12.09	0.75

Moreover, the result of R^2 for different rainfall input data for different flow thresholds in validation period are also presented in Figure 4. The performance of the models using different rainfall inputs decreases with the increase of flow thresholds. This indicates that the models using all rainfall inputs perform poorly for simulating the high flow events. The results also indicates that the model using KED merged rainfall input data outperforms the models using other rainfall inputs data for the simulation the peak flow.

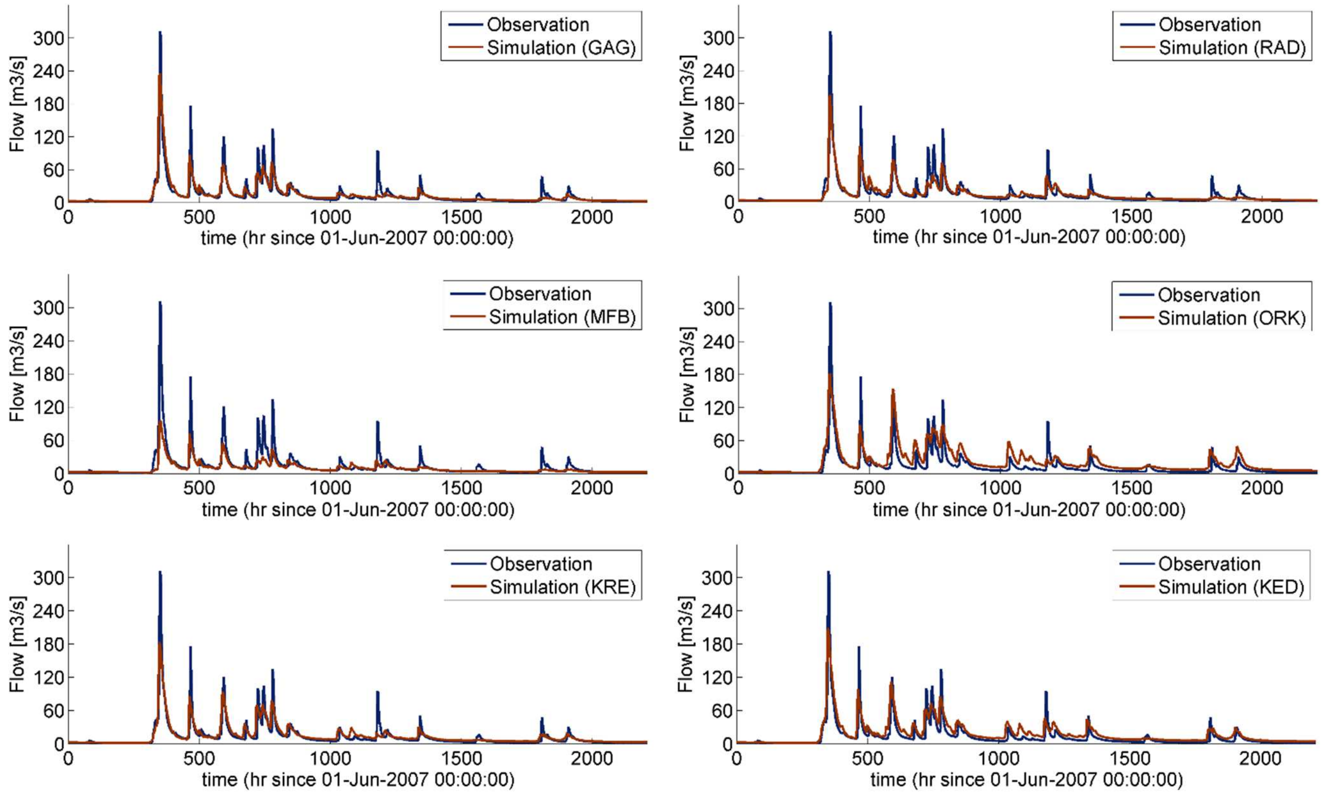

Figure 3: Comparison between observed and the HBV simulated flow by using different input rainfall inputs data including raingauge (GAG) and radar (RAD) in the validation period.

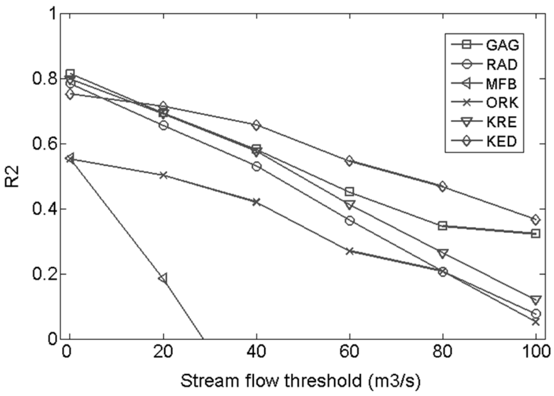

Figure 4: The behaviour of the Coefficient of determination (R2) for different inputs data for different flow thresholds in the validation period.

5 Conclusions

The application of rainfall estimates by different merging techniques on rainfall-runoff modelling in a large catchment has been analysed. Results given in this study suggest that the rainfall fields estimated by radar-raingauge merging methods (KRE and KED) provide suitable results that indicate that radar-gauge merging techniques can be used as input to the rainfall-runoff modelling in this catchment using an hourly time step. In terms of the statistical scores of MAE, RMSE and R^2, the application of rainfall estimates by radar-raingauge methods can relatively improve the HBV model performance. Moreover, the visual inspection of hydrographs indicates that the models using all rainfall inputs underestimate the peak discharge comparing to the observed peak flow. However, the results indicates that the model using KED merged rainfall input data outperforms the models using other rainfall inputs data for the simulation the peak flow. According to the hydrographs, the models using KRE and KED rainfall estimates perform better than the models using simple MFB and only raingauge based interpolated (ORK) areal rainfall inputs in terms of magnitude and timing of stream discharge.

Despite the fact that the accuracy of radar rainfall suffers from several sources of errors and uncertainties, radars are able to provide distributed precipitation fields with high spatial and temporal resolutions over large regions. On the other hand, raingauge measurements are the most reliable point measurements, but also have their own limitations on spatial representativeness. It is possible that the better information for hydrological applications will be the merging of radar and raingauge data. However, the application of rainfall estimates by combining radar and raingauge data in hydrological modelling need further investigation and development for different characteristics of catchments, hydrological models and temporal resolutions of data inputs.

Acknowledgement

The authors would like to thank the UK Met Office and the Environment Agency for providing the radar and raingauge data respectively. The first author wishes to acknowledge the partially support of the Bristol Alumni Foundations in the form of Postgraduate Travel Grants, which enabled me to attend this conference. The suggestions and advices of our colleagues are also gratefully acknowledged.

References

Bergstrom, S. Development and application of a conceptual runoff model for Scandinavian catchments. 1976.

Bergström, S. 1992. *The HBV model: Its structure and applications*: Swedish Meteorological and Hydrological Institute.

Bergström, S., & Singh, V. The HBV model. [Computer models of watershed hydrology.]. 1995. 443-476.

Duan, Q., Sorooshian, S., & Gupta, V. K. Optimal use of the SCE-UA global optimization method for calibrating watershed models. [Journal of hydrology]. 1994. *158*(3). 265-284.

Ehret, U. 2003. *Rainfall and flood nowcasting in small catchments using weather radar*: Eigenverlag des Instituts für Wasserbau an der Universität Stuttgart.

Ehret, U., Götzinger, J., Bárdossy, A., & Pegram, G. G. Radar‐based flood forecasting in small catchments, exemplified by the Goldersbach catchment, Germany. [International Journal of River Basin Management]. 2008. *6*(4). 323-329.

Haberlandt, U. Geostatistical interpolation of hourly precipitation from rain gauges and radar for a large-scale extreme rainfall event. [Journal of Hydrology]. 2007. *332*(1-2). 144-157.

Hansen, D., Ye, W., Jakeman, A., Cooke, R., & Sharma, P. Analysis of the effect of rainfall and streamflow data quality and catchment dynamics on streamflow prediction using the rainfall-runoff model IHACRES. [Environmental Software]. 1996. *11*(1). 193-202.

Harlin, J., & Kung, C.-S. Parameter uncertainty and simulation of design floods in Sweden. [Journal of hydrology]. 1992. *137*(1). 209-230.

Krajewski, W. F. Cokriging radar-rainfall and rain-gauge data. [Journal of Geophysical Research-Atmospheres]. 1987. *92*(D8). 9571-9580.

Seibert, J. Estimation of parameter uncertainty in the HBV model. [Nordic Hydrology]. 1997. *28*(4). 247-262.

Sinclair, S., & Pegram, G. Combining radar and rain gauge rainfall estimates using conditional merging. [Atmospheric Science Letters]. 2005. *6*(1). 19-22.

Turc, L. Evaluation des besoins en eau d'irrigation, évapotranspiration potentielle. [Ann. agron]. 1961. *12*(1). 13-49.

Verworn, A., & Haberlandt, U. Spatial interpolation of hourly rainfall—Effect of additional information, variogram inference and storm properties. [Hydrology and Earth System Sciences]. 2011. *15*(2). 569-584.

Villarini, G., Mandapaka, P. V., Krajewski, W. F., & Moore, R. J. Rainfall and sampling uncertainties: A rain gauge perspective. [Journal of Geophysical Research: Atmospheres (1984–2012)]. 2008. *113*(D11).