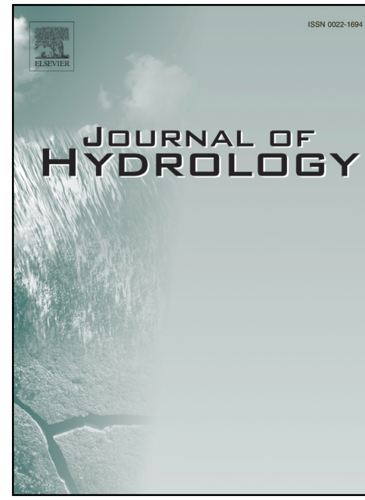


Probabilistic online runoff forecasting for urban catchments using inputs from rain gauges as well as statically and dynamically adjusted weather radar

Roland Löwe, Søren Thorndahl, Peter Steen Mikkelsen, Michael R. Rasmussen, Henrik Madsen

PII: S0022-1694(14)00212-1
DOI: http://dx.doi.org/10.1016/j.jhydrol.2014.03.027
Reference: HYDROL 19485

To appear in: *Journal of Hydrology*

Received Date: 29 November 2013
Revised Date: 21 February 2014
Accepted Date: 10 March 2014

Please cite this article as: Löwe, R., Thorndahl, S., Mikkelsen, P.S., Rasmussen, M.R., Madsen, H., Probabilistic online runoff forecasting for urban catchments using inputs from rain gauges as well as statically and dynamically adjusted weather radar, *Journal of Hydrology* (2014), doi: http://dx.doi.org/10.1016/j.jhydrol.2014.03.027

Probabilistic online runoff forecasting for urban catchments using inputs from rain gauges as well as statically and dynamically adjusted weather radar

Roland Löwe[a,*], Søren Thorndahl[c], Peter Steen Mikkelsen[b], Michael R. Rasmussen[c], Henrik Madsen[a]

[*]correspondence to:rolo@dtu.dk, +45-45253399

[a]Department of Applied Mathematics and Computer Science, Technical University of Denmark (DTU Compute), Matematiktorvet B322, Kgs. Lyngby, 2800, Denmark, rolo@dtu.dk, hmad@dtu.dk

[b]Department of Environmental Engineering, Technical University of Denmark (DTU Environment), Miljøvej B113, Kgs. Lyngby, 2800, Denmark, psmi@env.dtu.dk

[c]Department of Civil Engineering, Aalborg University, Sohngårdsholmsvej 57, Aalborg, 9000, Denmark, st@civil.aau.dk, mr@civil.aau.dk

ABSTRACT

We investigate the application of rainfall observations and forecasts from rain gauges and weather radar as input to operational urban runoff forecasting models. We apply lumped rainfall runoff models implemented in a stochastic grey-box modelling framework. Different model structures are considered that account for the spatial distribution of rainfall in different degrees of detail.

Considering two urban example catchments, we show that statically adjusted radar rainfall input improves the quality of probabilistic runoff forecasts as compared to input based on rain gauge observations, although the characteristics of these radar measurements are rather different from those on the ground. Data driven runoff forecasting models can to some extent adapt to bias of the rainfall input by model parameter calibration and state-updating. More detailed structures in these models provide improved runoff forecasts compared to the structures considering mean areal rainfall only.

A time-dynamic adjustment of the radar data to rain gauge data provides improved rainfall forecasts when compared with rainfall observations on the ground. However, dynamic adjustment reduces the potential for creating runoff forecasts and in fact also leads to reduced cross correlation between radar rainfall and runoff measurements. We conclude that evaluating the performance of radar rainfall adjustment against rain gauges may not always be adequate and that adjustment procedure and online runoff forecasting should ideally be considered as one unit.

KEYWORDS

Stochastic grey-box model, radar rainfall, radar adjustment, probabilistic forecasting, real time control, urban hydrology

Received

2014/02/21

1 INTRODUCTION

Urban catchments are typically of a spatial extent where a homogeneous distribution of rainfall over the catchment cannot be assumed. This is one of the main drivers for developing real time control (RTC) setups for urban drainage systems. The load on the sewer network is higher in some places than in others, which results in an uneven use of the available storage capacities. This suboptimal load distribution can be improved by a dynamic operation of the network. As a result, combined sewer overflows can be reduced, for example.

Real time control systems are in operation in a multitude of urban catchments (Fuchs and Beeneken, 2005; Pleau et al., 2005; Sharma et al., 2012, Seggelke et al., 2013). Classically, decision making is done on the basis of offline knowledge about the system, for example in a framework of decision rules. More recent developments incorporate an online optimization of the system that accounts for runoff forecasts (Puig et al., 2009; Vezzaro and Grum, 2012). The control setup suggested in Vezzaro and Grum (2012) makes it possible to account for forecast uncertainties in the optimization and decision making process.

In a dynamic optimisation based real time control setup, simplified rainfall runoff models that lump a bigger part of the catchment are typically applied for forecasting over short horizons of a few hours as they are fast enough to generate forecasts within seconds to minutes (for example Pleau et al., 2001, Puig et al., 2009, Vezzaro and Grum (2012)). Using highly simplified models for forecasting is also common in other fields like district heating (Nielsen and Madsen, 2006) or wind power forecasting (Giebel et al., 2011). Apart from being computationally efficient, lumped models make the application of statistical techniques such as state-updating and automated parameter calibration easier. Generating runoff forecasts in such an on-line setup is the case we consider here.

Generating runoff forecasts on-line requires rainfall inputs. For forecast horizons up to two hours, rainfall radars are currently the only means that provide the possibility to generate rainfall forecasts with a spatial and temporal resolution suitable for urban catchments. Examples of radar rainfall forecasting systems applied for quantitative online predictions in urban drainage systems are rare (Einfalt et al., 2004), but can for example be found in Einfalt et al. (1990), Kraemer et al. (2005) and Thorndahl and Rasmussen (2013).

Emmanuel et al. (2012a) discourage the direct application of the French operational weather radar product for quantitative purposes in urban hydrology. Similarly, other authors propose an adjustment of radar data to rain gauge measurements (Thorndahl et al., 2009; Villarini et al., 2010). Whereas the results of Villarini et al. (2010) suggest a constant bias between radar and rain gauge measurements during an event, other authors propose adjustment of radar measurements to gauge data also in the course of an event (Borup et al., 2009; Brown et al., 2001; Chumchean et al., 2006; Thorndahl et al., 2009, Wang et al., 2013, Wood et al., 2000). Gjertsen et al. (2003) and Goudenhoofdt and Delobbe (2009) give overviews of different methods applied in Europe.

Radar adjustment is quite usually demonstrated to be beneficial by validating adjusted radar observations against rain gauge observations (Goudenhoofdt and Delobbe, 2009, Smith et al., 2007, Thorndahl et al., 2014, Wang et al., 2013) or by generating runoff forecasts from models that were statically calibrated using rain gauge input (Borup et al., 2009, Cole and Moore, 2008, Vieux and Bedient, 2004, Wang et al., 2013). The improvement in runoff forecasting performance may however be less clear for auto-calibrated online models that can dynamically adapt to observations as well as different rainfall inputs. In such cases the skill of different quantitative precipitation estimates to describe runoff should be assessed instead. Gourley and Vieux (2005) follow this thought on a 1200 km^2 catchment to compare results of spatially variable radar adjustments against mean field bias adjustment by evaluating hydrologic simulation results with different rainfall inputs and ensembles of different model parameters. They argue that rain gauge data may not be sufficient for the validation of quantitative precipitation estimates (QPE) as they are often used in the QPE algorithm itself, because rain gauge point measurements are often inaccurate and because there are issues of different scales between rain gauges and remotely sensed rainfall. The value of time varying radar adjustments for urban online runoff forecasting is in our view unclear.

A second issue in the generation of online runoff forecasts is the required spatial resolution of the rainfall input. A multitude of studies have been performed in hydrology as to what degree of spatial model resolution is appropriate. The results from the Distributed Model Intercomparison Project (Reed et al., 2004) show in a non-urban context that conceptual models outperformed distributed models in the majority of cases. Das et al. (2008) give an overview of studies and find that generally, a higher spatial resolution does not necessarily lead to improved model performance. The authors conclude that a multitude of factors like scale of the catchment, physiographic characteristics or data availability influence model performance and that a lower, optimal limit of spatial resolution is to be expected because the model "represents spatial average behaviour". This is underlined by results obtained by the authors in predicting river discharge from a 4000 km^2 catchment using different degrees of spatial resolution of model input data.

In urban hydrology, where catchment response is generally much faster than in natural catchments and data typically available in higher resolutions, Schilling (1984) and Schilling and Fuchs (1986) find that spatial rainfall variability is the key factor for the accuracy of simulations of urban runoff and that rainfall estimation errors are amplified by the rainfall runoff models. The authors suggest the use of high resolution rainfall data and simplified models for on-line operations. Using a hydrodynamic modelling setup for an 1100 ha catchment, Schellart et al. (2011) conclude that spatial resolution of inputs should be high (in their case 1 km^2) in order to obtain a good representation of the observed flows in the sewer network. Finally, Berne et al. (2004) suggest a spatial rainfall resolution of 3 km for a 1000 ha catchment, while Emmanuel et al. (2012b) suggest 2.5 km resolution for a 600 ha catchment and Schilling (1991) suggests 1 km for on-line purposes. Studies in urban hydrology generally point in a direction where improved spatial resolution of rainfall inputs leads to improved model performance, a result which is less clear in modelling of river flows as the spatial scales considered are much larger and data more scarce. We note that previous studies in urban hydrology focused on simulation, not on the case of on-line runoff forecasting with models that adapt to observations, although similar results may be expected.

Despite the above discussed results on model performance considering different spatial resolutions of rainfall inputs, a practitioners approach to building an on-line forecast model for real time control would often be to lump the catchment upstream from a control point. Practical experience suggests that the effect of this lumping on runoff simulation quality is limited (Achleitner et al., 2007; Grum et al., 2011; Wolfs et al., 2013). Similar to previous studies in natural catchments (Das et al., 2008), we therefore consider lumped models of different spatial resolutions for runoff forecasting in urban catchments over short horizons.

Finally, runoff forecasts generated by any model are uncertain due to uncertain measurements and forecasts of the rainfall input as well as an incomplete description of the reality by the model. Achleitner et al. (2009) and Thorndahl and Rasmussen (2013) evaluate the quality of urban runoff forecasts using radar rainfall input. Acceptable forecast errors could be obtained for forecast horizons of 90 and 60 minutes, respectively. In an online setting, however, predicting also the uncertainty of runoff forecasts is of strong interest. The performance of lumped rainfall-runoff models in a stochastic grey-box layout was evaluated by Breinholt et al. (2011) and Thordarson et al. (2012) but rainfall input was assumed known. We here present an evaluation of probabilistic runoff forecast quality that can be obtained in a realistic on-line setting.

Other approaches for modelling uncertainty in conceptual models exist and these apply Bayesian frameworks (Del Giudice et al., 2013, Kuczera et al. 2006, Renard et al., 2010), for example, GLUE (Breinholt et al., 2013, Dotto et al., 2012, Thorndahl et al., 2008) or simple output error methods (Breinholt et al., 2012). The approach presented here distinguishes itself in the explicit focus on forecasting over a multitude of horizons on a short time scale instead of describing simulation uncertainty and thus improving the capability of the model to describe reality. In addition, high computational efficiency is a focus of the presented approach.

In the following, the article first gives an introduction to the rainfall data considered as input for runoff forecasting in this study. Rainfall observations and forecasts from rain gauges and two types of C-band radar data are evaluated and compared. The types of weather radar data considered are

- temporally and spatially constant adjustment over the whole period (static adjustment)
- time-dynamic mean-field bias adjusted to rain gauge measurements in the course of an event, in addition to the static adjustment (dynamic adjustment).

The purpose of this evaluation is to demonstrate how the different rainfall measurements relate to each other and that the dynamic adjustment indeed makes the radar observations resemble the ground measurements more closely.

Subsequently, the different rainfall measurements and forecasts are considered as inputs for runoff forecasting. A quantification of probabilistic online runoff forecasting skill is provided on a 100 minute horizon. We evaluate if runoff forecasts can be improved by the different types of radar rainfall input and by an increased spatial resolution of the forecast model.

The article is structured as follows: section 2 describes the considered catchments, available rainfall measurements, the methodology for generating and evaluating stochastic runoff predictions, and the different model layouts considered. In section 3 we compare the available rainfall measurements from gauges and radar in the area, and evaluate the runoff forecast quality obtained with different rainfall inputs and model layouts. Finally, in section 4 we conclude the article.

2 Material and Methods

2.1 Catchments

Two catchments in the Copenhagen area are considered in this study. The Ballerup catchment has a total area of approximately 1,300 ha. It is mainly laid out as a separate sewer system but has a small combined part and shows strong influences from rainfall-dependent infiltration and misconnection of surface runoff to sanitary sewers (Breinholt et al., 2013).

The Damhusåen catchment is located close to Ballerup but drains to a different treatment plant. We consider the northern part of the catchment with a total area of approximately 3,000 ha. The catchment is laid out as a combined sewer system and consists of several subcatchments with a longest flow path of approximately 10 km.

An overview of the catchments can be seen in Figure 1. Flow measurements averaged over 5 min are available at the outlets of both catchments. Flow predictions are generated for both outlets and compared to the observations at 10 min resolution, where the measurements within an interval are averaged.

FIGURE 1 APPROX. HERE

2.2 Rainfall Measurements and Forecasts Using Gauges and Radar

Observations from tipping bucket rain gauges from the Danish SVK network (Jørgensen et al., 1998) are available in the considered catchments. Rainfall measurements are available at 1 min intervals and averaged to 10 min time steps (equivalent to the temporal resolution of the radar data). In the rain gauge based forecast models we use 2 and 4 gauges as input for the Ballerup and Damhusåen catchments (Figure 1). The gauges are located within or close to the catchment borders.

Rainfall forecasts are generated from the gauge measurements using a local linear trend method. A trend line is fitted to the rain gauge intensities in the past 100 min and then extrapolated over the forecast horizon.

The Danish weather service operates a C-band radar in Stevns approx. 45 km south of the considered catchments (Gill et al., 2006). Measurements from this radar were made available for this study with a resolution of 10 min and 2x2 km^2. Figure 1 shows the location of the catchments within the utilized C-band radar pixels.

We apply radar rainfall forecasts with lead times up to 100 min generated by Aalborg University using the CO-TREC algorithm (Thorndahl and Rasmussen, 2013). Corresponding to the available temporal resolution of the radar data, we apply all rainfall input data with a temporal resolution of 10 min. Considering the spatial extent of the catchments and concentration times t_c above 60 min, this resolution can be considered sufficient to capture the rainfall runoff process in the catchments. Schilling (1991) suggests a temporal resolution of the rainfall data which is between $0.2t_c$ and $0.33t_c$.

2.3 RADAR RAINFALL ADJUSTMENT

C-band radar measurements are provided as reflectivities. A direct conversion to rain intensities is commonly considered problematic. A methodology to adjust the radar measurements to gauge observations has therefore been developed at Aalborg University and is applied here.

In the adjustment, the rain gauges marked in Figure 1 are used (SVK numbers 30252, 30309, 30313, 30316, 30319, 30326, 30348 and 30386). The adjustment is performed with only 8 gauges distributed in the Copenhagen area, as one of the main objectives for using radar rainfall measurements is to derive rain intensities using as small a number of ground measurements as possible.

In a first 'static' adjustment step, the coefficients in the reflectivity (*Z*) – rain intensity (*R*) relationship are adjusted for the whole data period (see Section 2.4). The rainfall depths from all rain events at all considered rain gauges are plotted against the rainfall depths derived from the radar observations in the corresponding pixels. The *Z*-*R* coefficients are adjusted, such that the regression line between radar rainfall depths and rain gauge observations has slope 1 (Thorndahl et al., 2010). The resulting *Z*-*R* relationship is used for deriving rain intensities over the whole data period.

$$Z = 50 \cdot R^{1.8} \tag{1}$$

In a second 'dynamic' adjustment step, the radar rain intensities are again adjusted, this time at every 10 min time step (Thorndahl et al., 2014). Considering the last 4 observations, a spatially constant adjustment factor is derived, such that the radar measurements on average match the rain gauge measurements in the considered area. This is a mean field bias adjustment in the sense of Goudenhoofdt and Delobbe (2009), however, with an adjustment window of 40 minutes instead of one day.

When generating forecasts, the time-dynamic adjustment factor is, over a period of 120 minutes, linearly changed to 1 with increasing lead time. The linear transition towards zero-bias is performed because unrealistic and biased rainfall forecasts have been observed on the longer lead times when forecasting with a time-dynamic adjustment factor based on only the past 40 minutes.

2.4 Data Period

We use a summer period of 2.5 months from 25/06/2010 until 6/09/2010 for generating probabilistic runoff forecasts. Figure 2 shows rain gauge and flow observations from the Ballerup catchment for this period. We can clearly identify the diurnal dry weather variations and a number of rain events that can be considered relevant for real time control purposes. The measurements contain no major gaps in this period.

FIGURE 2 APPROX. HERE

2.5 Stochastic Flow Forecasting

2.5.1 General Model Layout

As mentioned before, we use stochastic grey-box models to generate flow forecasts for the catchments. In the basic setup we use a linear reservoir cascade of 2 storages with one rainfall input, implemented as stochastic differential equations in a state-space model layout (Breinholt et al., 2011). The model is at every time step updated to current flow observations using an extended Kalman filter (Kristensen et al., 2004).

This setup has been extensively tested for the Ballerup catchment but not for the Damhusåen catchment. The model is obviously too simple, especially for the (bigger) Damhusåen catchment. As we are mainly interested in investigating the effects of different rainfall inputs on the forecasts, we still apply this most simple setup. With respect to the magnitude of runoff forecast uncertainties, this could be considered a 'worst case scenario'.

$$d\begin{bmatrix} S_{1,t} \\ S_{2,t} \end{bmatrix} = \begin{bmatrix} A \cdot P + a_0 - \frac{1}{K} S_{1,t} \\ \frac{1}{K} S_{1,t} - \frac{1}{K} S_{2,t} \end{bmatrix} dt + \begin{bmatrix} \sigma_1 \cdot S_{1,t}^{\gamma 1} \\ \sigma_2 \cdot S_{2,t}^{\gamma 2} \end{bmatrix} d\omega_t \tag{2}$$

$$Q_k = \frac{1}{K} S_{2,k} + D_k + e_k \tag{3}$$

(2) is called the system equation, where S_1, S_2 correspond to the storage states, A to the impervious catchment area, P to the rain intensity, a_0 to the mean dry weather flow and K to the travel time constant. The uncertainty of model predictions is described in the so-called diffusion term by a Wiener process ω_t. The increments $d\omega_t$ of this process are independent and normally distributed with a standard deviation corresponding to the considered time interval dt.

The variance of the diffusion is here scaled dynamically depending on the current model states S and a scaling factor σ. Such a scaling can be problematic for the extended Kalman filtering. A Lamperti transform is therefore applied that removes the state-dependency from the diffusion term and leads to a set of transformed drift equations that equivalently describe the dynamics of the system, but have constant diffusion (Breinholt et al., 2011).

States and flow measurements are related in the observation equation (3). Q_k corresponds to the observed flow values at times k, D describes the variation of the dry weather flow using trigonometric functions and e corresponds to the observation error with standard deviation σ_e.

We refer to Kristensen et al. (2004) and Breinholt et al. (2011, 2012) for a detailed description of the modelling principles. We use the open-source software framework CTSM for the modelling process (Kristensen and Madsen, 2003).

2.5.2 Stochastic Model Layout and Rainfall Inputs

To investigate the influence of spatial resolution of rainfall inputs on the ability to create stochastic runoff forecasts, we consider the following model layouts:

- Area mean – the rainfall is assumed constant over the whole catchment and inputs from gauges or radar pixels are averaged (as shown in equation (2)).
- Integrated subcatchment – for radar inputs, the catchment is divided into subcatchments (Figure 1), an impervious area is estimated for every subcatchment, but only one storage cascade is used and all inputs are fed into the first storage. The same approach is applied for rain gauge input, but we estimate an effective area for every rain gauge and perform no assignment to subcatchments. This approach is applied for the (smaller and less complex) Ballerup catchment.

- Distributed subcatchments – every subcatchment has a cascade of 2 storages of its own and the outflows from the northern and eastern subcatchments are inputs to the western subcatchment. This approach is applied for the (bigger and more complex) Damhusåen catchment. In the simulation run with rain gauges, these are assigned to the closest subcatchment.

As a variety of rainfall inputs and model layouts are considered, in the following we denote the different simulation runs with a 3-letter identifier in accordance with Figure 3.

FIGURE 3 APPROX. HERE

2.6 Parameter Estimation

Parameters for the proposed stochastic rainfall runoff models are estimated in an automated optimization routine. Most commonly this is done by maximizing the likelihood of one-step-ahead model predictions (Breinholt et al., 2011). In an online setup, however, the models are intended to provide multistep predictions. The model identified by minimizing the error of one-step-ahead predictions may not be the best model in terms of forecasting with longer lead times.

Further, if there is strong noise on the flow observations, the model may not be identifiable. The model setup includes a Kalman filtering procedure, which means that the model states are updated to follow the observations at each time step. If the model is estimated on the basis of one-step-ahead predictions, there is a risk that the estimated model parameters simply optimize this state-updating and do not describe the physical behaviour of the system.

We therefore here apply a parameter estimation method that minimizes the error of the probabilistic multistep flow predictions (Löwe et al., 2014). The according criterion is the continuous ranked probability score (*CRPS*). At every time step, this score measures the squared difference between the cumulative distribution function (CDF) of the forecast and the CDF of the observation, where the latter is considered as a unit step at the observed value (Gneiting et al., 2005; Gneiting, 2007).

The dry weather parameters a_0 and D of the model are assumed fixed and are estimated deterministically in a dry weather period of one week at the beginning of the considered time series. We apply a heuristic optimization algorithm described by Tolson and Shoemaker (2007) for automated parameter estimation.

2.7 On-Line Runoff Forecast Generation and Evaluation

We evaluate the quality of probabilistic forecasts of runoff volume obtained from the different models. Runoff volumes are the relevant decision variable in a real time control setup for urban drainage systems as described e.g. by Vezzaro and Grum (2012). To obtain probabilistic predictions of runoff volume, we do at every time step generate 1000 realizations of multistep flow predictions from the model equations (2) using an Euler Maruyama scheme (Kloeden and Platen, 1999). We consider forecast horizons up to 10 steps or 100 min.

In this approach, forecast uncertainties are in the on-line setting only determined by the state uncertainties, not the observation uncertainties. This is reasonable as in a real time control scheme we are not interested in the observation uncertainty. The estimated observation uncertainties are furthermore small compared to the uncertainties of the model predictions (c.f. section 3.3).

Each of the 1000 multistep flow prediction scenarios can be integrated into a runoff volume prediction. We can then analyse the distribution of these values to obtain an empirical description of the predictive distribution of runoff volumes for each horizon. We evaluate the quality of the 10-step probabilistic runoff volume predictions as compared to the observed runoff volumes for this horizon. We consider the following criteria:

- Reliability (*Rel*) – percentage of observations included in a 90% prediction interval. Ideally, this value corresponds to 90%, higher values suggest an overfitted model, lower values an unreliable model.
- Average Interval Length (*ARIL*) – average width of the 90% prediction interval relative to the observations (Jin et al., 2010).
- Continuous ranked probability score (*CRPS*) – mean squared error of the predictive runoff volume distribution for a 10-step horizon. The best forecast minimizes this value (Gneiting, 2007).
- Root mean squared error (*RMSE*) between the 50% quantile of probabilistic runoff volume predictions and the corresponding observation.

3 RESULTS AND DISCUSSION

3.1 COMPARING RADAR AND RAIN GAUGE OBSERVATIONS AND FORECASTS

In a first step, the different rainfall observations are compared. The considered data period is split into rain events. Based on the spatially averaged rain gauge observations, it is assumed that a new event starts after 10 hours of dry weather. Rainfall intensities below 0.2mm/10min are considered dry weather and we only consider events with a total rainfall sum of at least 5 mm.

Based on the above considerations, 10 rain events are identified from the averaged rain gauge observations in the Ballerup catchment and used for comparison. Figure 4 shows the total rainfall depth and the maximum intensity together with the duration of the events.

FIGURE 4 APPROX. HERE

The effect of the dynamic radar adjustment clearly varies from event to event. Yet, on average, the root mean squared error (*RMSE*) between the total areal rainfall sums measured by radar and rain gauges is reduced from 9.8 mm with the static adjustment, to 7.3 mm for the dynamic adjustment. In the Damhusåen catchment (not shown) similar results are obtained with a reduction of the *RMSE* from 11.0 mm for the static adjustment to 6.7 mm for the dynamic adjustment.

Figure 5 supports the indications from the analysis of total rainfall sums. The dynamically adjusted radar observations seem to better capture the rainfall dynamics observed on the ground. However, in both cases, the radar rainfall forecasts fail to predict the intense rainfall peak towards the end of the event. A delay is observed for the rainfall forecasts derived from the gauge measurements. This is induced by the forecast method which is based on extrapolating the observations of the last 100 min.

FIGURE 5 APPROX. HERE

Figure 6 shows the total rainfall sum for the different events derived from forecast values for a 2-step (20 min) and a 10-step (100 min) horizon. The simplistic forecast applied for the rain gauge data leads to a systematic overestimation of the total rainfall. The forecasts generated from the dynamically adjusted radar data are close to the rain gauge observations for the shorter horizon and approach the value for the statically adjusted data on the longer horizon. This is in accordance with the radar adjustment and forecasting methodology described in section 2.3.

FIGURE 6 APPROX. HERE

In Figure 4 one rain event can be identified (event 2) which is only present in the gauge measurements but not in the radar measurements for the Ballerup catchment. This deviation is a result of the gauges being located outside the catchment.

3.2 Correlation between Rainfall and Runoff Observations

Figure 7 shows the estimated cross correlation between catchment averaged rainfall observations and the measured runoff in the Ballerup catchment. For all rainfall inputs, the highest cross correlation is identified for a lag of 16 time steps or 160 minutes. The highest correlation between rainfall and runoff measurements is identified for statically adjusted radar measurements, and it is noticeably smaller for dynamically adjusted radar measurements. The same result is obtained in the Damhusåen catchment (not shown). It indicates that the type of time varying radar adjustment as described in section 2 may actually reduce the information about the runoff process that is contained in the radar rainfall time series. This is in spite of the fact that the time varying adjustment makes the radar data resemble the rainfall measurements on the ground more closely as described above.

FIGURE 7 APPROX. HERE

3.3 Probabilistic Runoff Forecasting With Different Rainfall Inputs

We consider the quality of probabilistic runoff forecasts obtained using mean areal rainfall input derived from rain gauges and weather radar (model type a). Table 1 shows the effective catchment area and the time constant estimated for the different models. We observe a tendency to estimate higher effective area values for the models with statically adjusted radar rainfall input. This is likely to be a result of the lower rain intensities in this type of input data (Figure 5).

Table 1. Estimated travel time constant (K) and impervious catchment area (A) for mean areal rainfall models (type a) with rain gauge (1) and statically (2) and

dynamically (3) adjusted radar input for Ballerup (B) and Damhusåen (D) catchments.

Model	K [h]	A [ha]
B1a	4.62	70.6
B2a	4.50	74.4
B3a	3.79	61.4
D1a	2.01	278.3
D2a	4.45	392.1
D3a	4.66	253.4

Table 2 and Table 3 summarize the runoff forecast skill of the different models averaged over all 10 events. We see that all models seem to be rather unreliable, with only 51% to 72% of the observations included in a 90% prediction interval during rain periods. Considering the whole data period, including dry weather periods, 84 to 92 % of the observations are included in a 90 % prediction interval (not shown). During dry weather periods, the flows in the sewer system are low and follow the well-defined diurnal cycle. The forecast error made by the runoff forecasting model is thus much smaller than during rain events. The uncertainty description in the model, however, accounts for dry and wet weather uncertainty in only one parameter. Uncertainties during rain events are hence forecasted too small. A solution to this problem could be to include a separate parameter for dry weather uncertainty in the diffusion term of equation (2).

We further identify an insufficient quantification of forecast uncertainties, in particular at the start of rain events (Figure 8). The reason is the state dependent uncertainty description in the model, which only leads to high forecast uncertainties for high forecast values. Ideally, the forecast uncertainty should increase already at the start of the event. This may be achieved by conditioning the forecast uncertainty on the rainfall input instead of the state values, but it is not further investigated here.

The models with statically adjusted radar rainfall input (input type 2) perform best in both catchments and all model variations in matters of *RMSE,* whereas the models with dynamically adjusted radar rainfall input result in higher *RMSE* values (Table 2 and Table 3). The forecast uncertainties for the radar based models are in most cases estimated smaller. During rain periods, this leads to a more pronounced underestimation of forecast uncertainties, resulting in some cases in a lower probabilistic forecasting skill expressed as *CRPS*.

The better quality of runoff forecasts obtained with statically adjusted radar rainfall input as compared to dynamically adjusted radar rainfall input seems to somewhat contradict the results obtained by Borup et al. (2009). The authors showed that a dynamic calibration of X-band radar rainfall measurements results in better simulations of water levels at an overflow weir than a static calibration. Apart from using a different type of radar rainfall measurements in this work, we see the main reason for the differing results in the applied type of rainfall-runoff model and the way radar forecasts are generated. A distributed simulation model was applied in the work of Borup et al. (2009). These models are typically statically calibrated to reflect observations in the sewer system based on rain gauge input. The model parameters modified during the calibration (for example impervious area, surface roughness values, pipe roughness values) do then also reflect the characteristics of rain gauge input (for example higher intensities as compared to radar rainfall measurements). Radar rainfall observations will consequently give better results the better they reflect the rainfall measurements on the ground, but different results may be obtained if the model is calibrated using radar rainfall input.

The rainfall runoff models applied in this work are data driven and fitted to the supplied input data. The rainfall input for this type of model may well be biased as compared to the “ground truth”, as the bias can be compensated for by different parameter estimates (for example the impervious catchment area) and by the state updating. The best runoff forecast will with this type of model be obtained with the rainfall input that has the highest ‘information content’ with respect to the runoff observations. This is the statically adjusted radar input in our case which is underlined by the fact that this type of rainfall measurement shows the highest cross correlation with the runoff time series.

More generally, it is interesting that the dynamically adjusted radar data appear to provide less information about the runoff time series than both, the rain gauge and the statically adjusted rainfall data. This is the case, not only for the radar rainfall forecasts, but also for the radar rainfall measurements (see the cross correlation function in Figure 7).

One likely reason is that the adjustment window of 40 minutes may be too short, leading to a nonlinear alteration of the radar data which cannot be compensated for by the automatic calibration of the rainfall-runoff model. This effect may be amplified by the fact that radar rainfall measurements are made as ‘snapshots’ every 10 minutes, while the rain gauge data used for radar adjustment are continuous over the interval. Recent works by Nielsen et al. (2014) and Thorndahl et al. (2014) suggested an interpolation of the radar data to a higher temporal resolution using an advective model and demonstrated that such processing reduces the bias as compared to rain gauge measurements. The effect of such interpolation schemes on on-line runoff forecasts needs to be investigated. In general, we suggest that the development of an adjustment methodology focuses not only on the deviation between radar rainfall estimates and rain gauges but also on the information content about the runoff time series.

Additionally, when generating rainfall forecasts, the bias between the dynamically adjusted radar forecast that is considered here and the observation on the ground changes linearly as a function of the forecast horizon. The reason is that especially in situations with sparse or very inhomogeneous rainfall within the radar range we risk adjusting the mean field based on very few radar-rain gauge pairs with very little observed rain. This might result in very small or very large adjustment factors. Applying these adjustment factors to the forecast has previously produced severe over- or underestimation of the forecasted rain. More rain gauges within the range of the radar might reduce the problem but would also reduce the added value of the radar. Generally, the non-constant bias in the rainfall forecasts introduces additional uncertainty in the runoff forecast. Improved results can likely be obtained if replacing the simple linear change of the bias factor by time series models that are fitted in a way such that the runoff forecast error is minimized.

Table 2. Forecast evaluation for mean areal rainfall (type a) and integrated subcatchment (type b) models with different rainfall inputs for the Ballerup catchment (B). Values are based on predicted runoff volumes in m^3 over a prediction horizon of 100 min (10 time steps) and averaged over the considered rain events. We include RMSE values for 1-step and 10-step prediction horizons.

Model	Rel [%]	ARIL [%]	CRPS	RMSE 1 [m^3]	RMSE 10 [m^3]
B1a	69%	30%	131.9	10.8	247.9
B1b	72%	30%	127.7	10.7	234.1
B2a	68%	29%	126.8	10.7	231.4
B2b	70%	30%	126.0	10.7	230.1
B3a	59%	23%	133.0	10.7	235.5
B3b	64%	27%	128.7	10.6	234.8

Table 3. Forecast evaluation for mean areal rainfall (type a) and distributed subcatchment (type c) models with different rainfall inputs for the Damhusåen catchment (D). Values are based on predicted runoff volumes in m^3 over a prediction horizon of 100 min (10 time steps) and averaged over the considered rain events. We include RMSE values for 1-step and 10-step prediction horizons.

Model	Rel [%]	ARIL [%]	CRPS	RMSE 1 [m^3]	RMSE 10 [m^3]
D1a	66%	35%	1126.3	61.2	2864.1
D1c	51%	20%	1029.5	46.9	2112.9
D2a	53%	23%	1210.6	70.2	2330.2

D2c	51%	22%	962.6	45.1	1900.9
D3a	51%	21%	1262.5	70.9	2416.0
D3c	52%	21%	1133.4	47.3	2301.3

Evaluating the probabilistic runoff forecast skill obtained for the different events (Figure 9), we see that the event with the highest volume and rain intensity (no. 6, c.f. Figure 4 and Figure 6) also leads to rather high forecast errors. We cannot identify a clear relation between event characteristics (Figure 4) and runoff forecast qualities which may be due to the small number of events considered. For event 2 the clearly lowest forecasting skill in the Ballerup catchment is observed when using rain gauge input which is a result of the gauges being located outside the catchment as discussed earlier.

FIGURE 8 APPROX. HERE

FIGURE 9 APPROX. HERE

3.4 PROBABILISTIC RUNOFF FORECASTING WITH DIFFERENT SPATIAL RESOLUTIONS

Comparing model layouts that account for the spatial distribution of rainfall observations in different degrees of detail, we can identify a trend that smaller forecast errors are obtained with more complex model structures.

Table 2 compares the runoff forecasting skills in the Ballerup catchment. For all rainfall inputs, slightly smaller *CRPS* and *RMSE* values are obtained on the 10-step horizon for the integrated subcatchment approach (model type b). The estimation of a separate effective area and using different rainfall inputs for each subcatchment, instead of averaging all inputs into a mean areal rainfall, consequently yields better results.

A similar trend can be observed in the Damhusåen catchment (Table 3). Accounting for the spatial rainfall distribution with a more complex model structure (distributed subcatchment approach - model type c) leads to a clear reduction in forecast error for all rainfall inputs. Following the discussion in Schilling and Fuchs (1986), this result was expected. Also with the slightly more complex model structure, models with statically adjusted radar input outperform those with rain gauge input and dynamically adjusted radar input (comparing models D1c, D2c and D3c in terms of *CRPS* and *RMSE*).

4 CONCLUSIONS

The quality of probabilistic on-line runoff forecasts obtained with different types of rainfall input and different conceptual model layouts that account for the spatial distribution of rainfall in varying degrees of detail was analysed. Forecasts were generated for two urban catchments with forecast horizons of up to 100 min. A number of conclusions were identified with respect to the considerations described in section 1. These are summarized here.

1) The time-dynamic adjustment of radar observations to rain gauges that is applied here makes those data resemble the rain gauge observations more closely.

2) Radar rainfall observations and forecasts can improve the skill of probabilistic runoff forecasts compared with those based on rain gauges.

3) For all considered runoff model structures, the best results are obtained with radar input that is time-statically adjusted to rain gauge observations. The time varying (dynamic) adjustment of the radar data reduces the potential for creating runoff forecasts with the stochastic grey box models. In fact, also the cross correlation between radar rainfall and runoff measurements is reduced as a result of the time varying radar adjustment.

4) Rainfall inputs for conceptual, data-driven forecasting models need not be the same as the values observed by gauges on the ground. The model can to some extent adapt to the characteristics of the input series in the parameter estimation procedure and will give the best forecasts with the rainfall input that best explains the patterns in the flow observations. In this sense, the radar is likely to provide a better spatial representation of rainfall patterns which, although biased compared with the ground observations, leads to better runoff forecasts. It is, however, important that the bias of the radar observations is not altered in a non-constant fashion. The aim of the radar adjustment should in this context be to merge rainfall information from different sources in a statistically optimal way.

5) An evaluation of radar adjustment methodologies should not only focus on the comparison with rain gauge observations but also on the final purpose for the adjusted measurements. In our case, this was runoff forecasting with data-driven

models and the radar adjustment and the runoff forecasting models should consequently be considered as a chain and coordinated.

6) Generally, rainfall runoff forecasting models will yield best results if the applied rainfall input closely resembles the input used in model calibration. Distributed simulation models are typically calibrated to resemble observations in the sewer network based on rain gauge observations. Adjusting radar data to more closely resemble the observations of rain gauges will consequently improve the results obtained with these models. Any type of model calibrated using radar rainfall observations as input may, however, yield different results.

7) The probabilistic runoff forecasts obtained with the stochastic grey-box models improve if we account for the spatial distribution of rainfall in the model. The best forecasts in the Damhusåen catchment are obtained for the distributed subcatchment approach, i.e. when splitting the catchment into 3 subcatchments that are modelled by separate, connected reservoir cascades.

8) We can identify insufficiencies in the applied models. The uncertainty description based on the model states does not allow us to capture the high forecast uncertainty at the start of a rain event. An improved model layout should be obtained by making the model uncertainty depend on the rainfall input. Further, considering also dry weather periods during parameter estimation of the models leads to unacceptably small uncertainty estimates during rain events. Either, only periods with rainfall should be considered for parameter estimation, or the model structure should be

modified to allow for proper separation between forecast uncertainties during dry and wet weather.

5 Acknowledgements

This research has been financially supported by the Danish Council for Strategic Research, Programme Commission on Sustainable Energy and Environment through the Storm- and Wastewater Informatics (SWI) project. The catchment and flow data were kindly provided by Avedøre Wastewater Services and Copenhagen Utility Company (HOFOR). We thank the Danish Weather Service (DMI) for providing data from the C-Band radar at Stevns.

6 References

Achleitner, S., Möderl, M., Rauch, W., 2007. CITY DRAIN © – An open source approach for simulation of integrated urban drainage systems. Environ. Model. Softw. 22, 1184–1195.

Achleitner, S., Fach, S., Einfalt, T., Rauch, W., 2009. Nowcasting of rainfall and of combined sewage flow in urban drainage systems. Water Sci Technol 59, 1145-1151.

Berne, A., Delrieu, G., Creutin, J.D., Obled, C., 2004. Temporal and spatial resolution of rainfall measurements required for urban hydrology. J Hydrol 299, 166-179.

Borup, M., Grum, M., Linde, J. J., Mikkelsen, P. S., 2009. Application of high resolution x-band radar data for urban runoff modelling: constant vs. dynamic calibration, 8th International Workshop on Precipitation in Urban Areas, 10-13 December, 2009, St. Moritz, Switzerland.

Breinholt, A., Thordarson, F.O., Møller, J.K., Grum, M., Mikkelsen, P.S., Madsen, H., 2011. Grey-box modelling of flow in sewer systems with state-dependent diffusion. Environmetrics 22, 946-961.

Breinholt, A., Møller, J.K., Madsen, H., Mikkelsen, P.S., 2012. A formal statistical approach to representing uncertainty in rainfall-runoff modelling with focus on residual analysis and probabilistic output evaluation - distinguishing simulation and prediction, J Hydrol, 472-473, 36-52.

Breinholt, A., Grum, M., Madsen, H., Thordarson, F.Ö., Mikkelsen, P.S., 2013. Informal uncertainty analysis (GLUE) of continuous flow simulation in a hybrid sewer system with Infiltration Inflow – consistency of containment ratios in calibration and validation? Hydrol Earth Syst Sci. 17, 4159-4176

Brown, P.E., Diggle, P.J., Lord, M.E., Young, P.C., 2001. Space–time calibration of radar rainfall data. J Roy Stat Soc C-App 50, 221-241.

Cole, S.J., Moore, R.J., 2008. Hydrological modelling using raingauge- and radar-based estimators of areal rainfall. J Hydrol 358, 159-181.

Chumchean, S., Seed, A., Sharma, A., 2006. Correcting of real-time radar rainfall bias using a Kalman filtering approach. J Hydrol 317, 123.

Das, T., Bárdossy, A., Zehe, E., He, Y., 2008. Comparison of conceptual model performance using different representations of spatial variability. J Hydrol 356, 106-118.

Del Giudice, D., Honti, M., Scheidegger, A., Albert, C., Reichert, P., Rieckermann, J., 2013. Improving uncertainty estimation in urban hydrological modeling by statistically describing bias. Hydrol Earth Syst Sci Discuss, 10, 5121–5167.

Dotto, C.B.S., Mannina, G., Kleidorfer, M., Vezzaro, L., Henrichs, M., McCarthy, D.T., Freni, G., Rauch, W., Deletic, A., 2012. Comparison of different uncertainty techniques in urban stormwater quantity and quality modelling. Water Res 46, 2545–58.

Einfalt, T., Denoeux, T., Jacquet, G., 1990. A radar rainfall forecasting method designed for hydrological purposes. J Hydrol 114, 229-244.

Einfalt, T., Arnbjerg-Nielsen, K., Golz, C., Jensen, N., Quirmbach, M., Vaes, G., Vieux, B., 2004. Towards a roadmap for use of radar rainfall data in urban drainage. J Hydrol 299, 186-202.

Emmanuel, I., Andrieu, H., Tabary, P., 2012a. Evaluation of the new French operational weather radar product for the field of urban hydrology. Atmos Res 103, 20-32.

Emmanuel, I., Andrieu, H., Leblois, E., Flahaut, B., 2012b. Temporal and spatial variability of rainfall at the urban hydrological scale. J Hydrol 430, 162-172.

Fuchs, L., Beeneken, T., 2005. Development and implementation of a real-time control strategy for the sewer system of the city of Vienna. Water Sci Technol 52, 187-194.

Giebel, G., Brownsword, R., Karioniotakis, G., Denhard, M., Draxl, C., 2011. The State-Of-The-Art in Short-Term Prediction of Wind Power - A Literature Overview. FP6 ANEMOS.plus deliverable.

Gill, R. S., Overgaard, S., Bøvith, T., 2006. The Danish weather radar network, 4th European Conference on Radar in Meteorology and Hydrology, 18-22 September, 2006, Barcelona, Spain.

Gjertsen, U., Salek, M., Michelson, D.B., 2003. Gauge-adjustment of radar-based precipitation estimates–a review. COST-717 Work. Doc. WDD 2.200310.

Gneiting, T., Raftery, A.E., Westveld III, A.H., Goldman, T., 2005. Calibrated probabilistic forecasting using ensemble model output statistics and minimum CRPS estimation. Mon Weather Rev 133, 1098-1118.

Gneiting, T., 2007. Strictly proper scoring rules, prediction, and estimation. J Am Stat Assoc 102, 359-378.

Goudenhoofdt, E., Delobbe, L., 2009. Evaluation of radar-gauge merging methods for quantitative precipitation estimates. Hydrol Earth Syst Sci 13, 195-203.

Gourley, J.J., Vieux, B.E., 2005. A Method for Evaluating the Accuracy of Quantitative Precipitation Estimates from a Hydrologic Modeling Perspective. J Hydrometeorol 6, 115–133.

Grum, M., Thornberg, D., Christensen, M.L., Shididi, S.A., Thirsing, C., 2011. Full-Scale Real Time Control Demonstration Project in Copenhagen's Largest Urban Drainage Catchments, Proceedings of the 12th International Conference on Urban Drainage, 11-16 Sep, Porto Alegre / Brazil.

Jin, X., Xu, C.Y., Zhang, Q., Singh, V., 2010. Parameter and modeling uncertainty simulated by GLUE and a formal Bayesian method for a conceptual hydrological model. J Hydrol 383, 147-155.

Jørgensen, H.K., Rosenørn, S., Madsen, H., Mikkelsen, P.S., 1998. Quality control of rain data used for urban runoff systems. Water Sci Technol 37(11), 113-120.

Kloeden, P.E., Platen, E., 1999. Numerical Solution of Stochastic Differential Equations. third ed., Springer, Berlin-Heidelberg-New York.

Kraemer, S., Grum, M., Verworn, H.R., Redder, A., 2005. Runoff modelling using radar data and flow measurements in a stochastic state space approach. Water Sci Technol 52, 1-8.

Kristensen N.R., Madsen H., 2003. Continuous time stochastic modelling CTSM - mathematics guide. Technical report, Technical University of Denmark, URL http://CTSM.info.

Kristensen, N.R., Madsen, H., Jørgensen, S.B., 2004. Parameter estimation in stochastic grey-box models. Automatica 40, 225–237.

Kuczera, G., Kavetski, D., Franks, S., Thyer, M., 2006. Towards a Bayesian total error analysis of conceptual rainfall-runoff models: Characterising model error using storm-dependent parameters, J Hydrol 331, 161-177.

Löwe, R., Mikkelsen, P., Madsen, H., 2014. Stochastic rainfall-runoff forecasting: parameter estimation, multi-step prediction, and evaluation of overflow risk. Stoch Environ Res Risk Assess 28, 505-516, doi 10.1007/s00477-013-0768-0.

Nielsen, H.A., Madsen, H., 2006. Modelling the heat consumption in district heating systems using a grey-box approach. Energy Build 38, 63–71.

Nielsen, J.E., Thorndahl, S., Rasmussen, M.R., 2014. A numerical method to generate high temporal resolution precipitation time series by combining weather radar measurements with a nowcast model. Atmos Res 138, 1–12, doi 10.1016/j.atmosres.2013.10.015.

Pleau, M., Pelletier, G., Lavalle, P., Bonin, R., 2001. Global predictive real-time control of Quebec Urban Communitys westerly sewer network. Water Sci Technol 43, 123-130.

Pleau, M., Colas, H., Lavallée, P., Pelletier, G., Bonin, R., 2005. Global optimal real-time control of the Quebec urban drainage system. Environ Modell Softw 20, 401-413.

Puig, V., Cembrano, G.G., Romera, J., Quevedo, J., Aznar, B., Ramón, G., Cabot, J., 2009. Predictive optimal control of sewer networks using CORAL tool: application to Riera Blanca catchment in Barcelona. Water Sci Technol 60, 869-878.

Reed, S., Koren, V., Smith, M., Zhang, Z., Moreda, F., Seo, D., DMIP Participants, 2004. Overall distributed model intercomparison project results. J Hydrol 298, 27-60.

Renard, B., Kavetski, D., Kuczera, G., Thyer, M., Franks, S., 2010: Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors, Water Resour Res 46, W05521.

Schellart, A., Shepherd, W., Saul, A., 2011. Influence of rainfall estimation error and spatial variability on sewer flow prediction at a small urban scale. Adv Water Resour 45, 65-75.

Schilling, W., 1984. Effect of spatial rainfall distribution on sewer flows. Water Sci Technol 16, 177-188.

Schilling, W., Fuchs, L., 1986. Errors in stormwater modeling-a quantitative assessment. J Hydraul Eng 112, 111-123.

Schilling, W., 1991. Rainfall data for urban hydrology: what do we need? Atmos Res 27, 5-21.

Seggelke, K., Löwe, R., Beeneken, T., Fuchs, L., 2013. Implementation of an integrated real-time control system of sewer system and WWTP in the city of Wilhelmshaven. Urban Water J 10, 330-341.

Sharma, A.K., Guildal, T., Thomsen, H.A.R., Mikkelsen, P.S., Jacobsen, B.N., 2013. Aeration tank settling and real time control as a tool to improve the hydraulic capacity and treatment efficiency during wet weather: results from 7 years' full-scale operational data. Water Sci Technol 67, 2169-2176.

Thordarson, F.O., Breinholt, A., Møller, J.K., Mikkelsen, P.S., Grum, M., Madsen, H., 2012. Uncertainty assessment of flow predictions in sewer systems using grey box models and skill score criterion. Stoch Env Res Risk A 26, 1151-1162.

Thorndahl, S., Beven, K.J., Jensen, J.B., Schaarup-Jensen, K., 2008. Event based uncertainty assessment in urban drainage modeling, applying the GLUE methodology, J Hydrol 357, 421-437.

Thorndahl, S., Rasmussen, M. R., Grum, M., Neve, S. L., 2009. Radar Based Flow and Water Level Forecasting in Sewer Systems: a Danish case study. 8th International Workshop on Precipitation in Urban Areas, 10-13 December, 2009, St. Moritz, Switzerland.

Thorndahl, S., Rasmussen, M.R., Neve, S., Poulsen, T.S., Grum, M., 2010. Vejrradarbaseret styring af spildevandsanlæg (in Danish). DCE Technical Report No. 95, Aalborg Universitet. Institut for Byggeri og Anlæg, ISSN 1901-726X.

Thorndahl, S., Rasmussen, M.R., 2013. Short-term forecasting of urban storm water runoff in real-time using extrapolated radar rainfall data. J Hydroinf 15, 214-226.

Thorndahl, S., Nielsen, J.E., Rasmussen, M.R., 2014. Bias adjustment and advection interpolation of long-term high resolution radar rainfall series. J Hydrol 508, 214-226.

Tolson, B. A., Shoemaker, C. A., 2007. Dynamically dimensioned search algorithm for computationally efficient watershed model calibration, Water Resour Res 43, W01413.

Vezzaro, L., Grum, M., 2012. A generalized Dynamic Overflow Risk Assessment (DORA) for urban drainage RTC. 9th International Conference on Urban Drainage Modelling, 3-7 September, 2012, Belgrade, Serbia.

Vieux, B.E., Bedient, P.B., 2004. Assessing urban hydrologic prediction accuracy through event reconstruction. J Hydrol 299, 217–236.

Villarini, G., Smith, J.A., Lynn Baeck, M., Sturdevant-Rees, P., Krajewski, W.F., 2010. Radar analyses of extreme rainfall and flooding in urban drainage basins. J Hydrol 381, 266-286.

Wang, L., Ochoa, S., Simões, N., Onof, C., Maksimović, Č., 2013. Radar-raingauge data combination techniques: a revision and analysis of their suitability for urban hydrology. Water Sci Technol 68, 737-747.

Wolfs, V., Villazon, M.F., Willems, P., 2013. Development of a semi-automated model identification and calibration tool for conceptual modelling of sewer systems. Water Sci. Technol. Sci. Technol. 68, 167–175.

Wood, S.J., Jones, D.A., Moore, R.J., 2000. Static and dynamic calibration of radar data for hydrological use. Hydrol Earth Syst Sci 4, 545–554.

7 Figure Captions

Figure 1. Ballerup (left) and northern Damhusåen (right) catchments with C-band radar pixels (2x2km), location of rain gauges shown as dots (large grey circles – used in radar adjustment, white rectangles – used as input to Ballerup model, black triangles – used as input to Damhusåen model, small black dots – other gauges). Different radar pixel shadings correspond to different subcatchments (c.f. section 2.5.2).

Figure 2. Areal mean of rain gauge observations and flow measurements for the Ballerup catchment in the estimation period.

Figure 3. Simulation run identifiers depending on considered catchments, rainfall input and spatial resolution.

Figure 4. Rain event depths (left) and maximum intensity (right) derived for mean areal rainfall with different rainfall measurements in the Ballerup catchment. Left plot includes label of duration of rain event (in min).

Figure 5. Sample rainfall event in the Ballerup catchment. Part a: rain gauge observations (black, as in model B1a) and rainfall forecasts with lead times of 20 min (green) and 100 min (blue), Part b: statically adjusted radar rainfall observations and forecasts (B2a), Part c: dynamically adjusted radar rainfall observations and forecasts (B3a).

Figure 6. Total forecasted (FC) rainfall amount for the Ballerup catchment for lead times of 20 (left) and 100min (right) for the considered rain events, together with rainfall amount observed by rain gauges.

Figure 7. Cross correlation (CCF) between runoff and catchment averaged rainfall observations in the Ballerup catchment. Rainfall observations are lagged in 10min steps to the runoff observations.

Figure 8. 10-step forecasts of runoff volume for event 6 in Ballerup (left, model B2a) and Damhusåen (right, model D2a) catchments together with observation (red). The shading corresponds to different prediction intervals with coverage rates from 2% to 98%.

Figure 9. Quality of probabilistic runoff forecasts for 100 min horizon (10 step) expressed as CRPS for different rain events and inputs in Ballerup (left) and Damhusåen (right) catchments.

Figure1

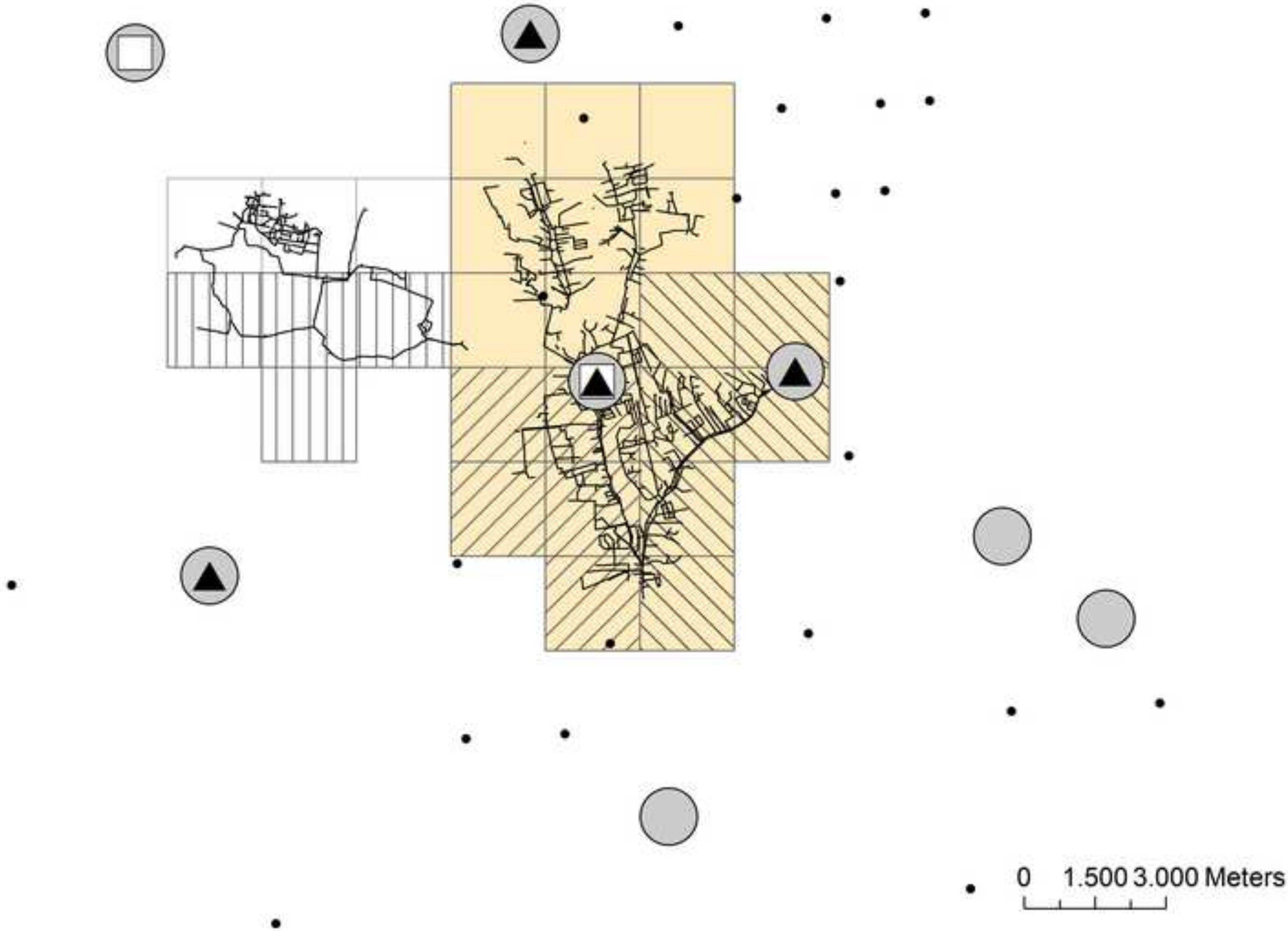


Figure2

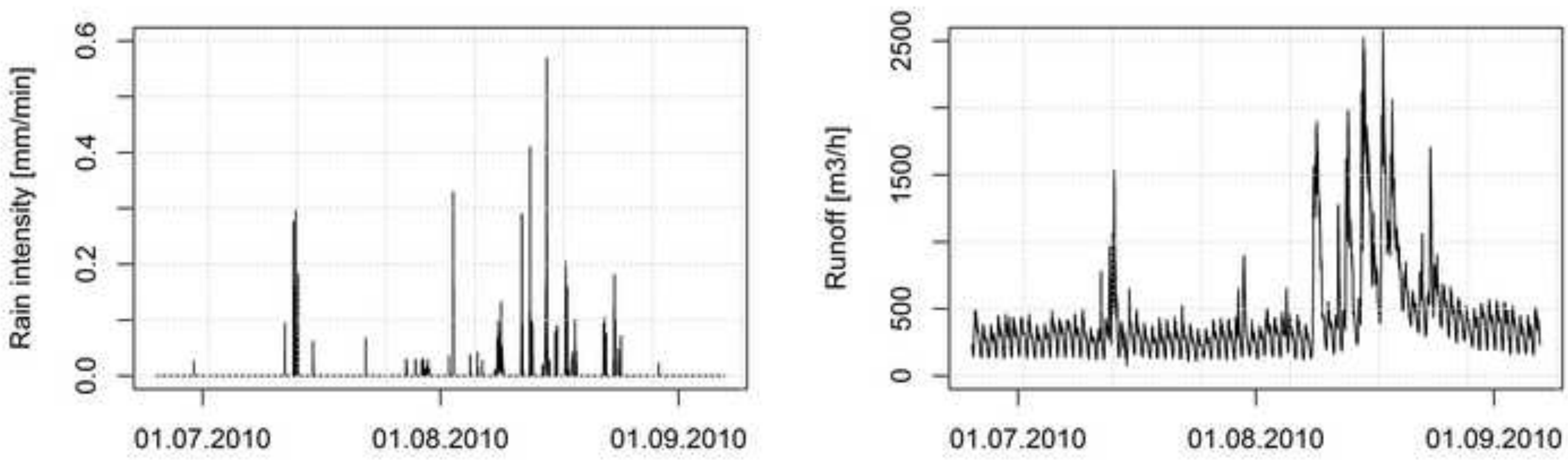

Rain intensity [mm/min]
0.0
0.2
0.4
0.6
01.07.2010
01.08.2010
01.09.2010
Runoff [m3/h]
0
500
1500
2500
01.07.2010
01.08.2010
01.09.2010

Figure3

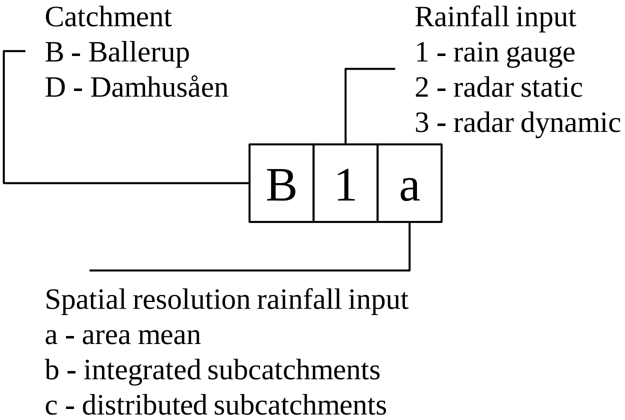
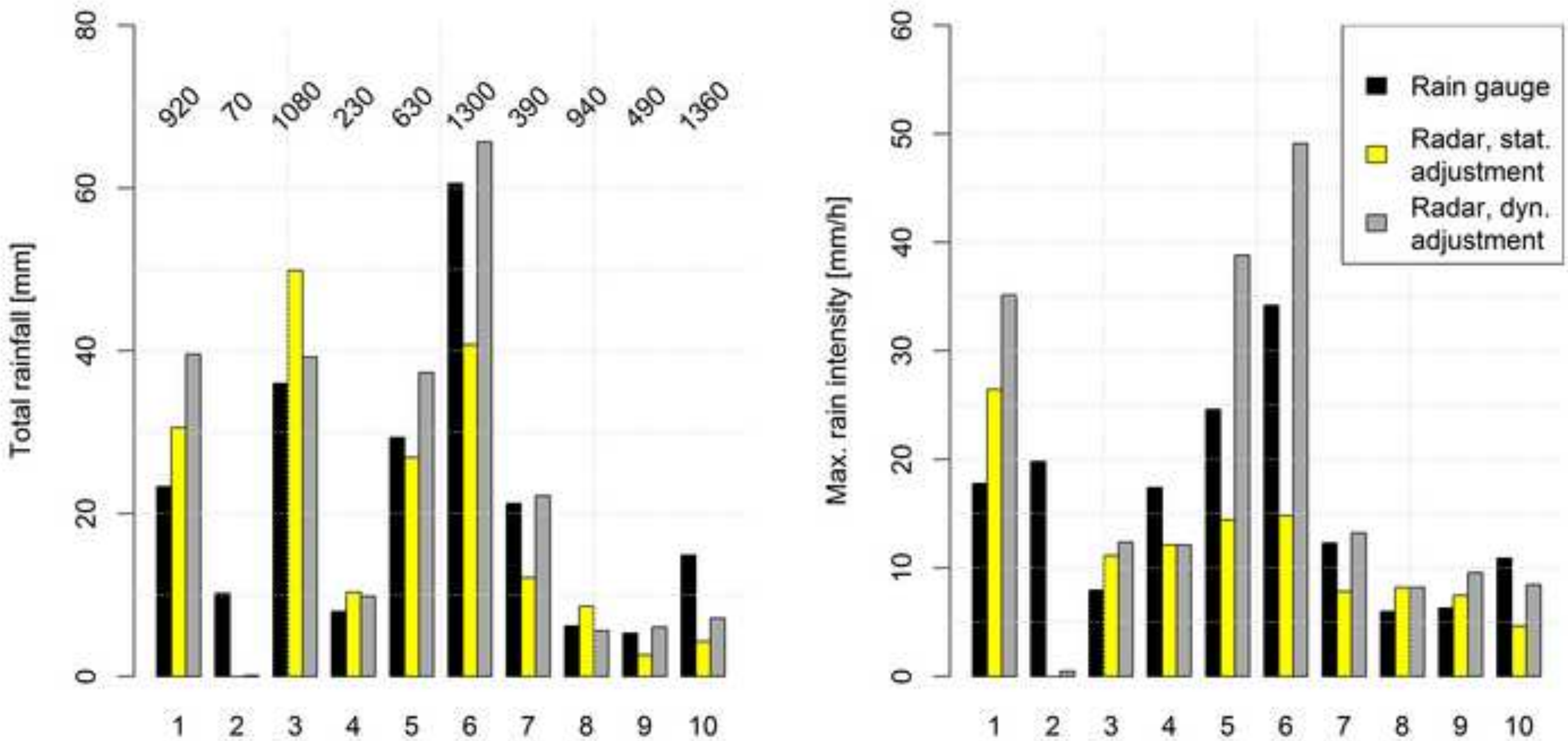

Catchment
B - Ballerup
D - Damhusåen
Rainfall input
1 - rain gauge
2 - radar static
3 - radar dynamic
B
1
a
Spatial resolution rainfall input
a - area mean
b - integrated subcatchments
c - distributed subcatchments

Figure4



Total rainfall [mm]
0
20
40
60
80
920
70
1080
230
630
1300
390
940
490
1360
1
2
3
4
5
6
7
8
9
10
Max. rain intensity [mm/h]
0
10
20
30
40
50
60
Rain gauge
Radar, stat. adjustment
Radar, dyn. adjustment

Figure5

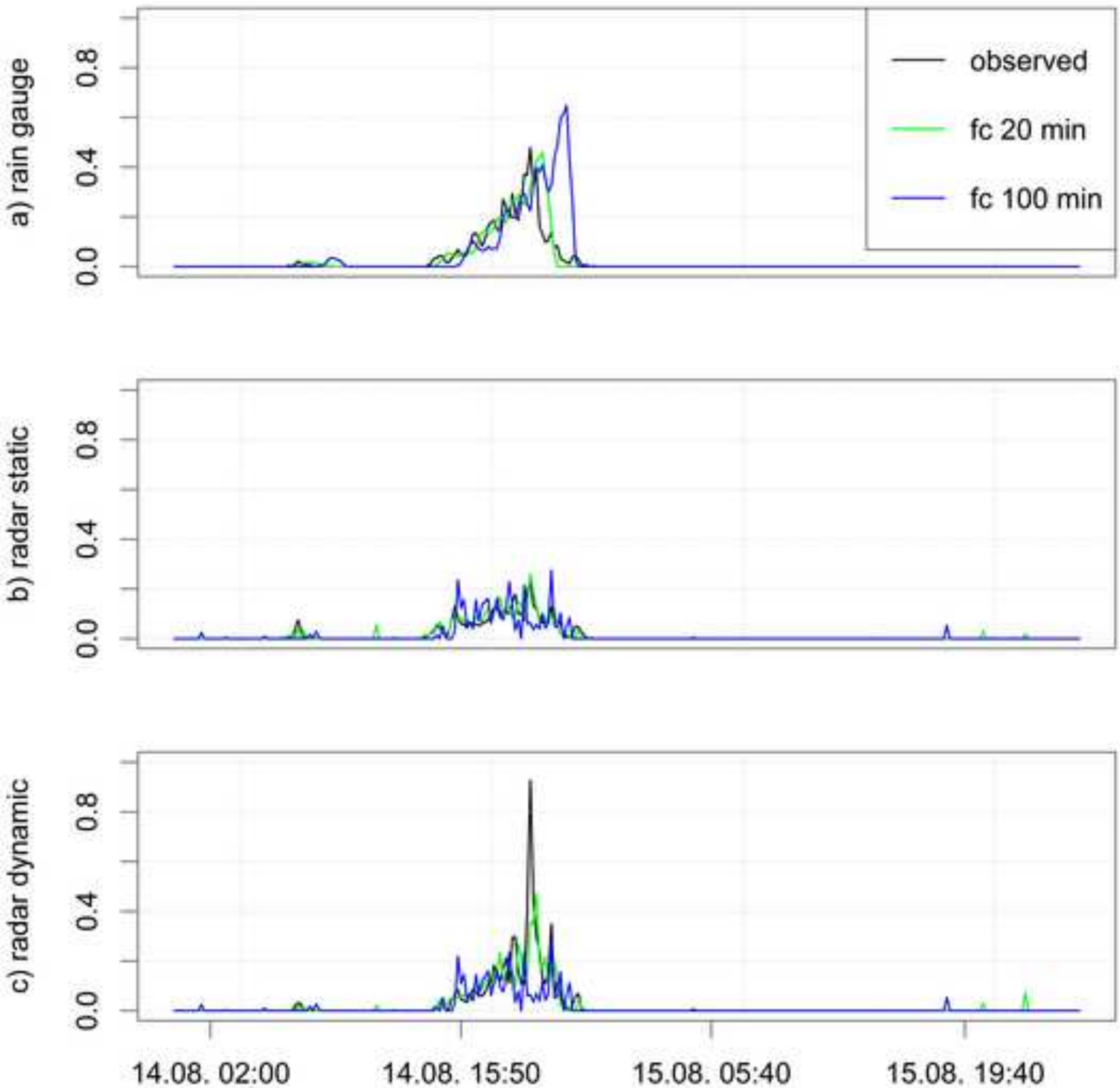

observed
fc 20 min
fc 100 min
a) rain gauge
b) radar static
c) radar dynamic
0.0
0.4
0.8
14.08. 02:00
14.08. 15:50
15.08. 05:40
15.08. 19:40

Figure6

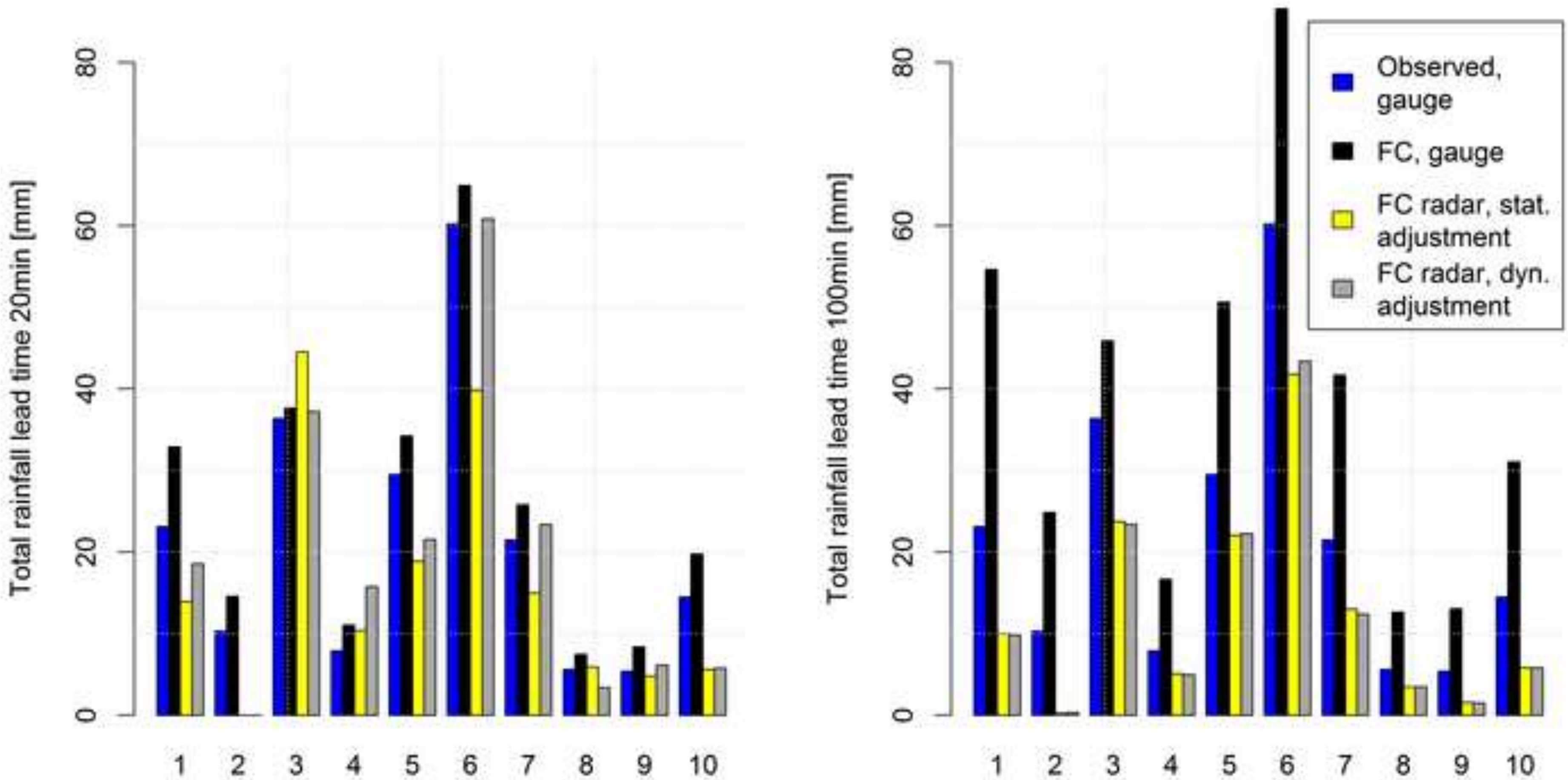

Total rainfall lead time 20min [mm]
Total rainfall lead time 100min [mm]
0
20
40
60
80
1
2
3
4
5
6
7
8
9
10
Observed, gauge
FC, gauge
FC radar, stat. adjustment
FC radar, dyn. adjustment

Figure7

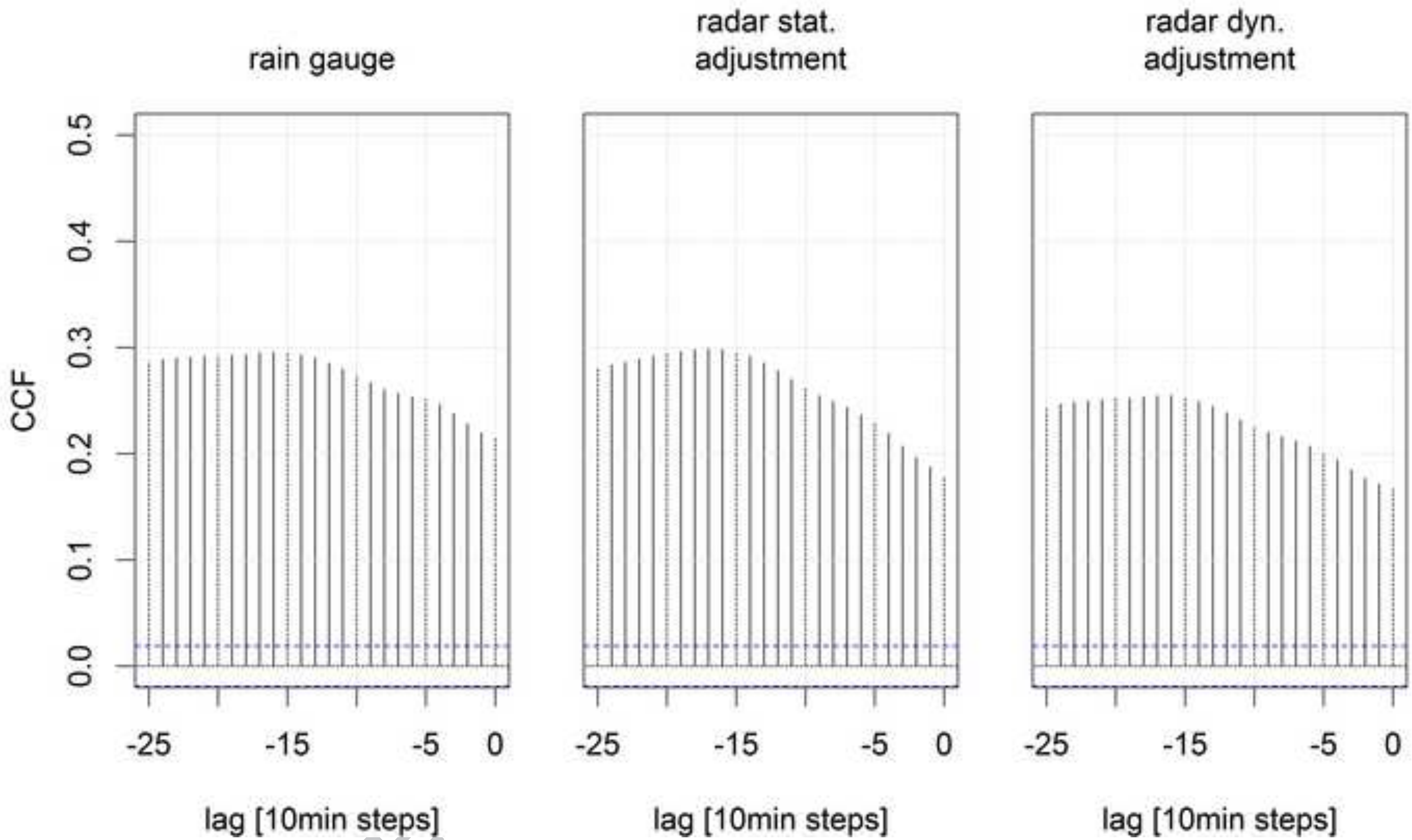

rain gauge
radar stat. adjustment
radar dyn. adjustment
CCF
0.0
0.1
0.2
0.3
0.4
0.5
-25
-15
-5
0
lag [10min steps]
lag [10min steps]
lag [10min steps]

Figure8

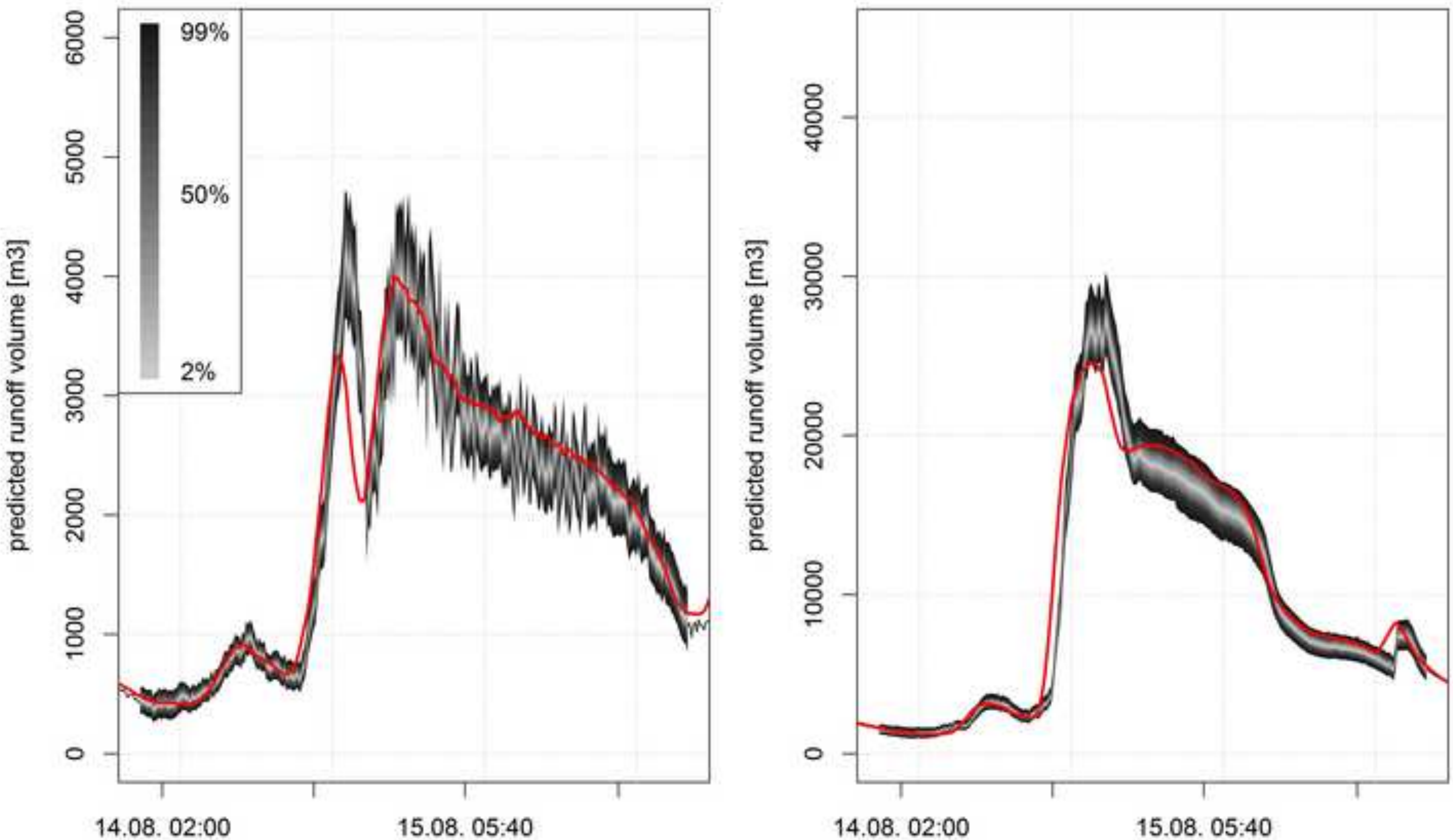
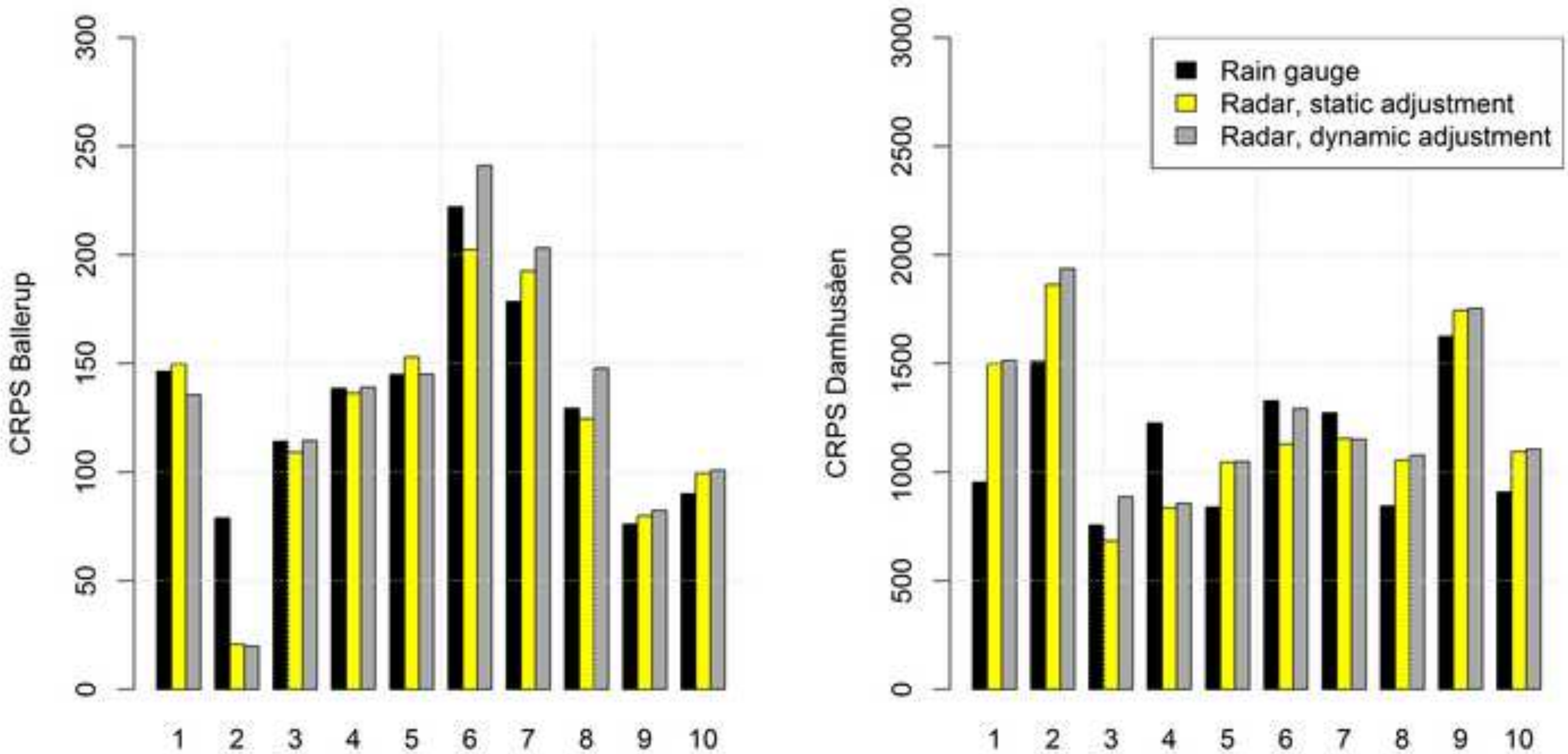

99%
50%
2%
predicted runoff volume [m3]
0
1000
2000
3000
4000
5000
6000
14.08. 02:00
15.08. 05:40
predicted runoff volume [m3]
0
10000
20000
30000
40000
14.08. 02:00
15.08. 05:40

Figure9



CRPS Ballerup
0
50
100
150
200
250
300
1 2 3 4 5 6 7 8 9 10
CRPS Damhusåen
0
500
1000
1500
2000
2500
3000
1 2 3 4 5 6 7 8 9 10
Rain gauge
Radar, static adjustment
Radar, dynamic adjustment

8 HIGHLIGHTS

- Rainfall nowcasts from rain gauges and 2 types of adjusted radar data are compared
- Probabilistic runoff forecasts are generated in 2 urban catchments in an on-line mode
- Time-statically adjusted radar data as model input yield best runoff forecasts
- Radar adjustment and online runoff forecast should be considered as a whole
- Improved spatial resolution in on-line rainfall runoff models improves forecasts