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

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SUMMARY

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.

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., 2013; 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 optimization 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.

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Generating runoff forecasts on-line requires rainfall inputs. For forecast horizons up to 2 h, 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, 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 min, 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 min 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 1300 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 3000 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 Fig. 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.

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 (Fig. 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 2×2 km^2. Fig. 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
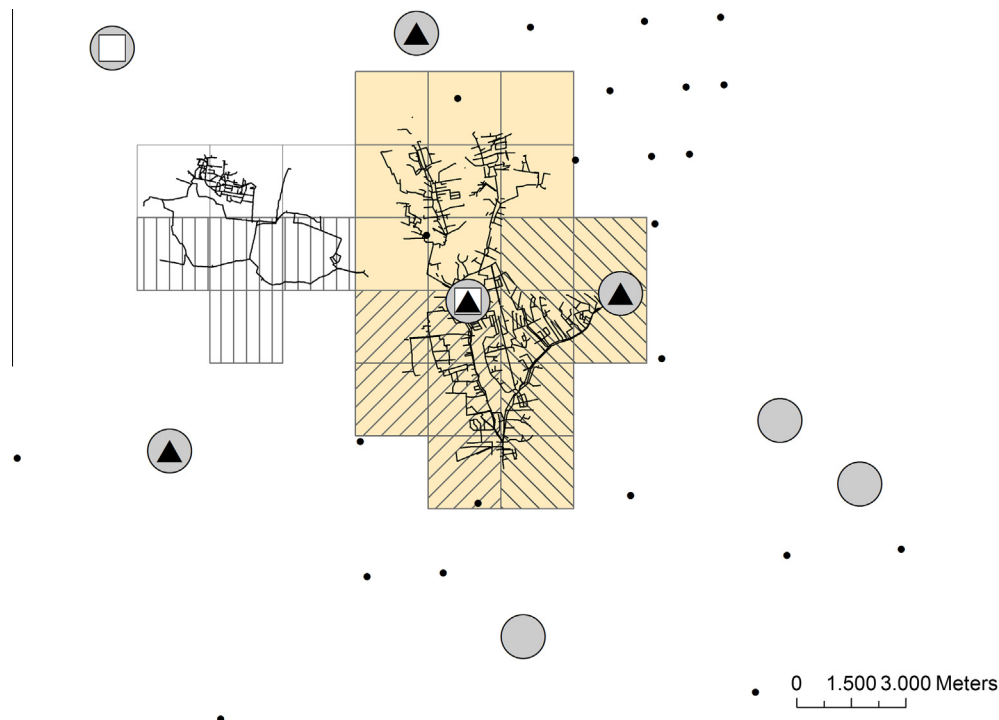

Fig. 1. Ballerup (left) and northern Damhusåen (right) catchments with C-band radar pixels (2×2 km), location of rain gauges shown as dots (large grey circles – used in radar adjustment, white rectangles – used as input to Ballerup model, black triangles – used as input to Damhusåen model, small black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

gauge observations has therefore been developed at Aalborg University and is applied here.

In the adjustment, the rain gauges marked in Fig. 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 min instead of 1 day.

When generating forecasts, the time-dynamic adjustment factor is, over a period of 120 min, 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 min.

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. Fig. 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.

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'.

$$d\begin{bmatrix} S_{1,t} \\ S_{2,t} \end{bmatrix} = \begin{bmatrix} A \cdot P + a_0 - \frac{1}{K} S_{1,t} \\ \frac{1}{K} S_{1,t} - \frac{1}{K} S_{2,t} \end{bmatrix} dt + \begin{bmatrix} \sigma_1 \cdot S_{1,t}^{\gamma_1} \\ \sigma_2 \cdot S_{2,t}^{\gamma_2} \end{bmatrix} d\omega_t$$

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

(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 Eq. (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 Eq. (2)).
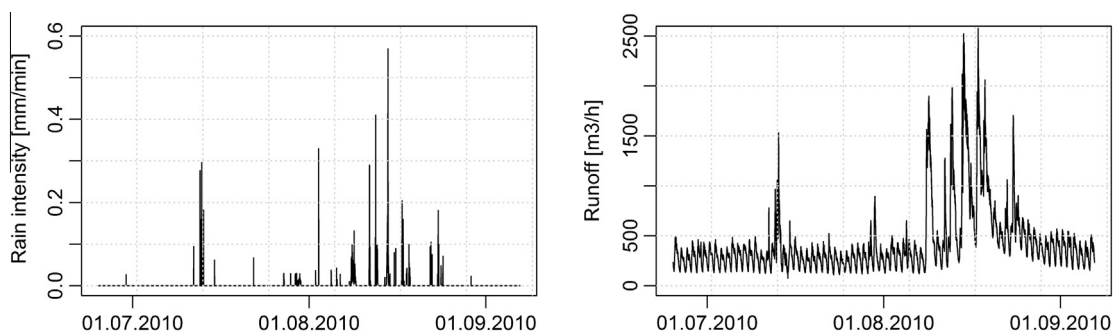

Fig. 2. Areal mean of rain gauge observations and flow measurements for the Ballerup catchment in the estimation period.

- Integrated subcatchment – for radar inputs, the catchment is divided into subcatchments (Fig. 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 Fig. 3.

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 1 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.
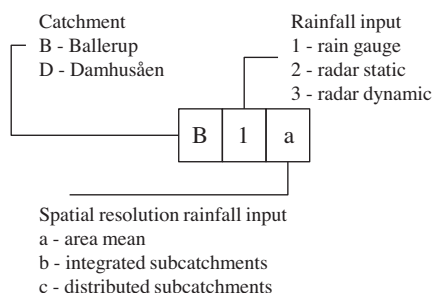

Catchment
B - Ballerup
D - Damhusåen

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

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

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 h of dry weather. Rainfall intensities below 0.2 mm/10 min 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. Fig. 4 shows the total rainfall depth and the maximum intensity together with the duration of the events.

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.

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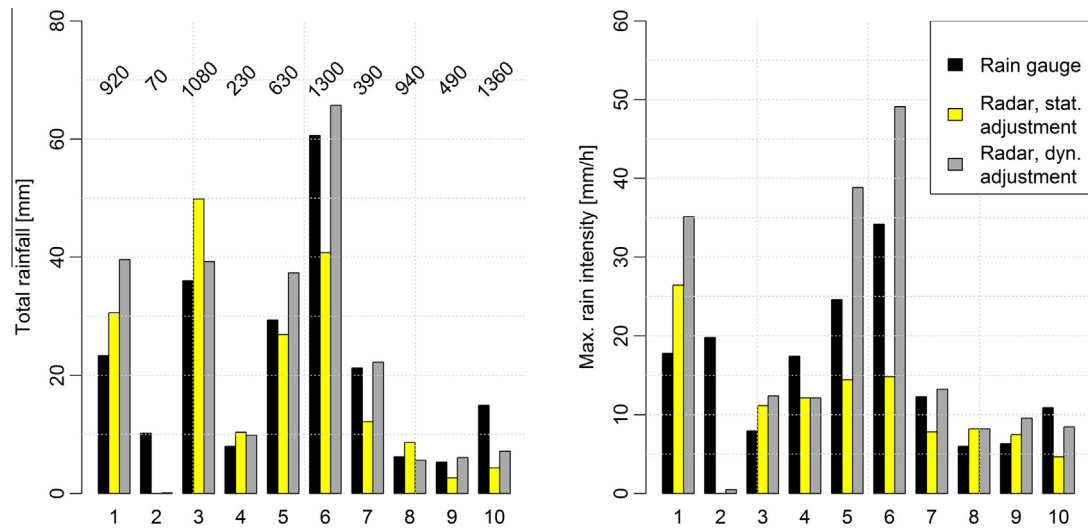
Fig. 4. Rain event depths (left) and maximum intensity (right) derived for mean areal rainfall with different rainfall measurements in the Ballerup catchment. Left plot includes label of duration of rain event (in min).
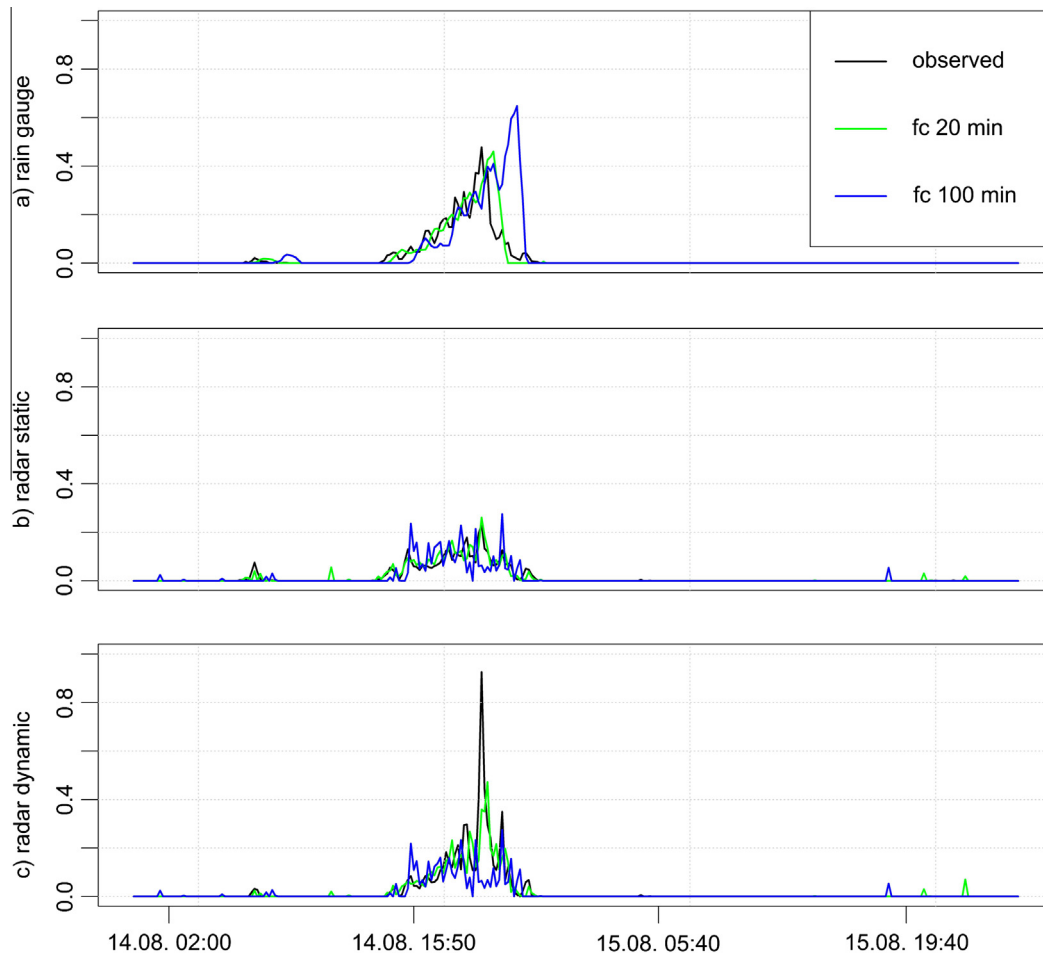

Fig. 5. Sample rainfall event in the Ballerup catchment. Part a: rain gauge observations (black, as in model B1a) and rainfall forecasts with lead times of 20 min (green) and 100 min (blue), Part b: statically adjusted radar rainfall observations and forecasts (B2a), and Part c: dynamically adjusted radar rainfall observations and forecasts (B3a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

Fig. 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.

In Fig. 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

Fig. 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 min. 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.

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 (Fig. 5).

Tables 2 and 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 51–72% of the observations included in a 90% prediction interval during rain periods. Considering the whole data period, including dry weather periods, 84–92%

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 Eq. (2).

We further identify an insufficient quantification of forecast uncertainties, in particular at the start of rain events (Fig. 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 (Tables 2 and 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
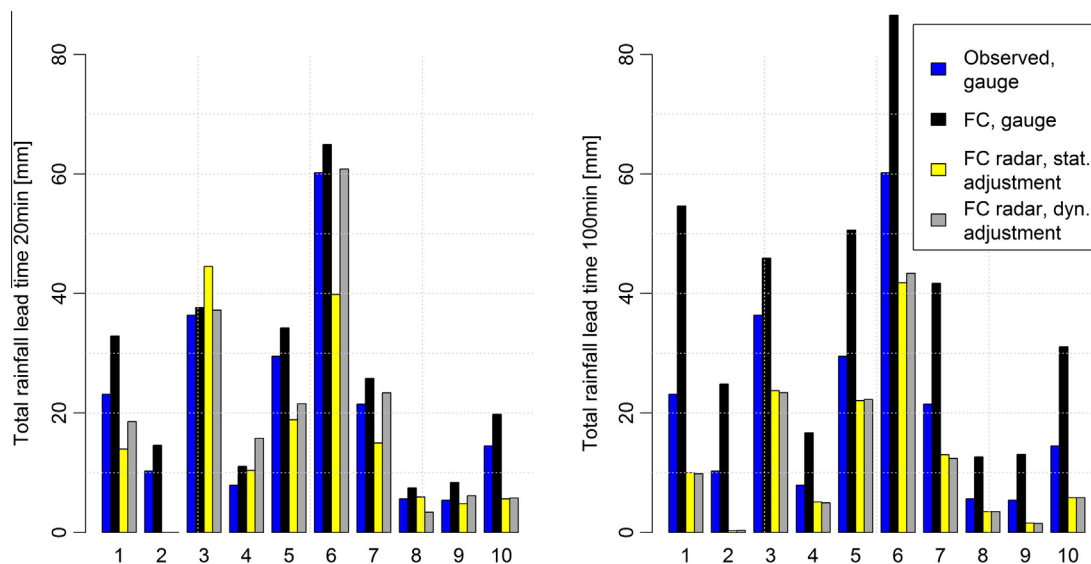

Fig. 6. Total forecasted (FC) rainfall amount for the Ballerup catchment for lead times of 20 (left) and 100 min (right) for the considered rain events, together with rainfall amount observed by rain gauges.
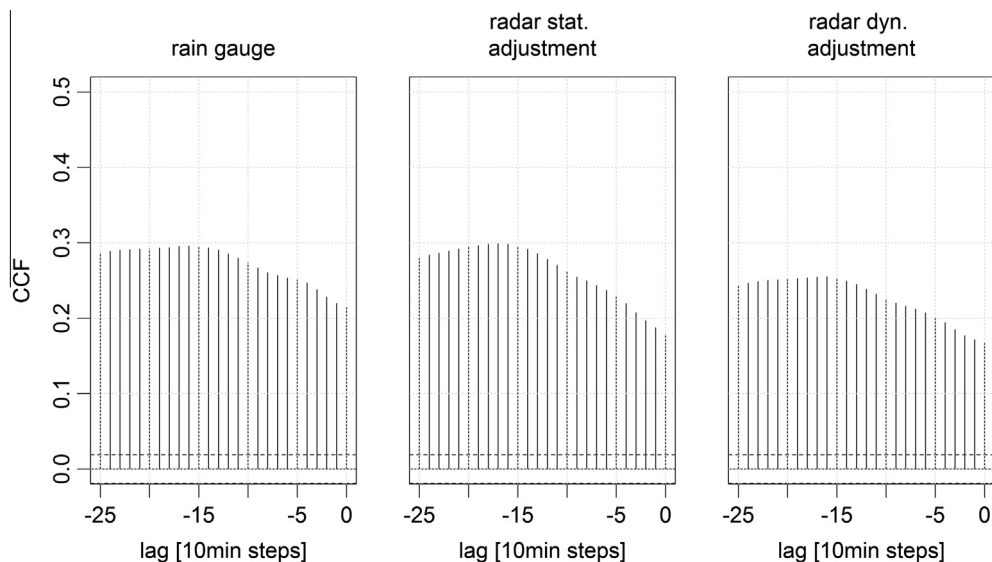
Fig. 7. Cross correlation (CCF) between runoff and catchment averaged rainfall observations in the Ballerup catchment. Rainfall observations are lagged in 10 min steps to the runoff observations.

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
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 m³ 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 (m³)	RMSE 10 (m³)
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 m³ 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 (m³)	RMSE 10 (m³)
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

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 Fig. 7).

One likely reason is that the adjustment window of 40 min 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 min, 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
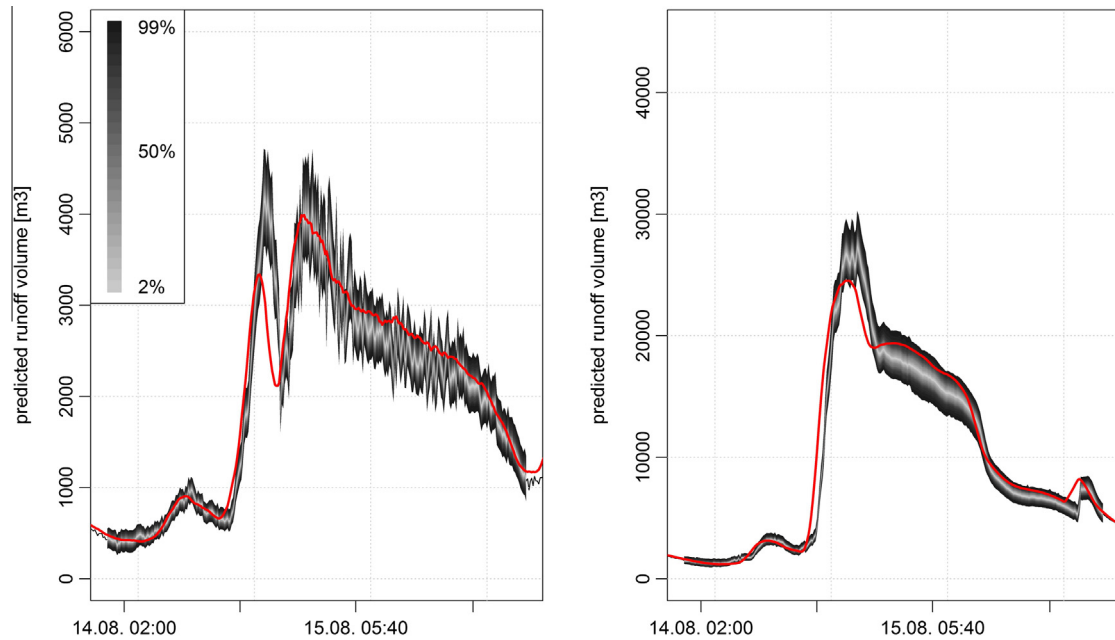
Fig. 8. 10-Step forecasts of runoff volume for event 6 in Ballerup (left, model B2a) and Damhusåen (right, model D2a) catchments together with observation (red). The shading corresponds to different prediction intervals with coverage rates from 2% to 98%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

Evaluating the probabilistic runoff forecast skill obtained for the different events (Fig. 9), we see that the event with the highest vol-

ume and rain intensity (No. 6, c.f. Figs. 4 and 6) also leads to rather high forecast errors. We cannot identify a clear relation between event characteristics (Fig. 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.

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
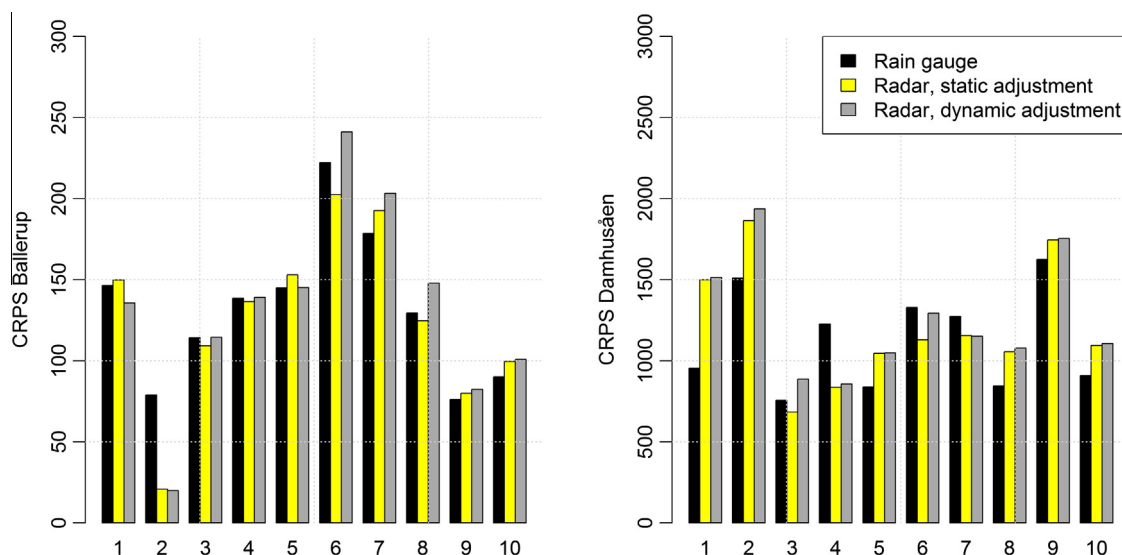

Fig. 9. Quality of probabilistic runoff forecasts for 100 min horizon (10 step) expressed as CRPS for different rain events and inputs in Ballerup (left) and Damhusåen (right) catchments.

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.

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