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Applicability of open rainfall data to event-scale urban rainfall-runoff modelling

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Abstract

Rainfall-runoff simulations in urban environments require meteorological input data with high temporal and spatial resolutions. The availability of precipitation data is constantly increasing due to the shift towards more open data sharing. However, the applicability of such data for urban runoff assessments is often unknown. Here, the feasibility of Finnish Meteorological Institute’s open rain gauge and open weather radar data as input sources was studied by conducting SWMM (Storm Water Management Model) simulations at a very small (33.5 ha) urban catchment in Helsinki, Finland. In addition to the open data sources, data were also available from two research gauges, one of them located on-site, and from a research radar. The results confirmed the importance of local precipitation measurements for urban rainfall-runoff simulations, implying the suitability of open gauge data to be largely dictated by the gauge’s distance from the catchment. Performance of open radar data with 5 min and 1 km² resolution was acceptable in terms of runoff reproduction, albeit peak flows were constantly and flow volumes usually underestimated. Gauge adjustment and advection interpolation were found to improve the quality of the radar data, and at least gauge adjustment should be performed when open radar data are used. Finally, utilizing dual-polarization capabilities of radars has a potential to improve rainfall estimates for high intensity storms although more research is still needed.
Highlights

- Open gauge and radar rainfall data as input to rainfall-runoff model are studied
- Runoff simulations are conducted at a 33.5 ha urban catchment in Helsinki, Finland
- Distance to catchment largely dictates suitability of gauge data as input source
- Open radar data may outperform gauge data 2.5 – 5 km from catchment
- Gauge correction and advection interpolation improved the radar product performance

Keywords

SWMM; urban hydrology; open data; radar; rain gauge
1. Introduction

Urban catchments are characterized by a complex mosaic of constructed surfaces, fast surface runoff generation, and a rapid storm flow response to rainfall events (Shuster et al., 2005; Sillanpää and Koivusalo, 2015). An adequate replication of catchment runoff in urban hydrological simulations therefore requires rainfall information at fine spatial and temporal resolutions (Bruni et al., 2015; Müller and Haberlandt, 2016; Schilling, 1991). The requirements become progressively more stringent with decreasing catchment area (Berne et al., 2004; Ochoa-Rodriguez et al., 2015; Segond et al., 2007).

The traditional rainfall measurement device, rain gauge, is still a frequently used data source in urban rainfall-runoff studies (e.g. Krebs et al., 2014; Notaro et al., 2013; Sun et al., 2014), as the gauges are low in cost, easily operable, and capable of providing accurate point measurements at high temporal resolutions. Meteorological offices operate national and regional rain measurement networks but unfortunately their spatial resolution is often inadequate for urban hydrological studies (Berne et al., 2004). Recently, the use of weather radar has gained in popularity (e.g. Ochoa-Rodriguez et al., 2015; Rico-Ramirez et al., 2015; Schellart et al., 2012; Smith et al., 2005; Villarini et al., 2010), mainly due to the wide spatial coverage of radar compared to the sparse rain gauge networks. In urban catchments, stormwater management practices, such as low impact development tools, are realised in small scales and therefore usable radar data must also be of high temporal and spatial resolution (Emmanuel et al., 2012; Gires et al., 2013, 2012; Wright et al., 2014). The resolution of commonly provided data products from national radar networks, consisting of mainly S- and C-band radars, is in the order of 5 min and 1 km$^2$ (Berne and Krajewski, 2013), but this may not be sufficiently high for runoff modelling in urban areas (Bruni et al., 2015; Gires et al., 2012, 2013).
The resolution requirements depend also on the storm spatial structure and therefore storm type (Emmanuel et al., 2012; Peleg et al., 2013; Shucksmith et al. 2011). In a relatively homogeneous rain field, e.g. in widespread frontal rain, the variability within a storm is relatively low, and even a coarse rain gauge network or low resolution radar data may be sufficient for most hydrological analyses. On the other hand, more heterogeneous storm types such as convective summer showers require high resolution rainfall measurements in order to capture the spatial variability of the rain field. Too coarse a gauge network may either miss the convective cells, or especially with small catchments, measure additional rain if the gauges are located outside the catchment. Radar measurements, on the other hand, suffer from sampling errors especially if the spatial resolution is coarser than the length scale of the rain feature (Shucksmith et al., 2011). This can lead to over- or underestimation of rainfall amounts. While this is a problem also for frontal storms, the conventional 1 km² radar resolution is even more restrictive for observing the small scale rainfall variability in convective events (Gires et al., 2012).

In recent years the availability of meteorological data has greatly improved due to web-services providing access to such data in a machine readable form. At the same time, changes in legislation and governmental policies are increasingly urging national agencies to openly share the data produced with public funding. In Europe, the INSPIRE directive (European Parliament, 2007) was established to create a European infrastructure for delivering integrated spatial information to all end-users. As a result of the INSPIRE directive, e.g. the Finnish Meteorological Institute (FMI) has made a large amount of continuous real-time observations, historical time-series, and model forecast data open for public use via an online service (Honkola et al., 2013).

The objective of this paper is to study the feasibility of using open rainfall data as an input source in small scale urban hydrological simulations. The open gauge and radar rainfall data
from FMI are used as an input for the urban hydrological simulation model SWMM (Huber and Dickinson, 1988; Rossman, 2015) at a very small (33.5 ha) urban catchment in Helsinki, Finland. The applicability of the open data sources is evaluated against simulation results produced with rainfall data available from two research gauges, one of them located on-site, and from one research radar. Suggestions are provided on how to improve the reliability of the data sets for stormwater flow simulations.

2. Material

2.1. Study site

The Pihlajamäki catchment (60°14'05.9"N 25°00'37.0"E) (Fig. 1) is a very small 33.5 ha urban catchment located in the city of Helsinki, Finland. It belongs to the boreal climate zone with a mean annual air temperature of 5.9 °C and a mean annual precipitation of 655 mm, with late summer and autumn months being the wettest time of the year (Pirinen et al., 2012). The rain events causing excessive runoff in urban areas of Helsinki are typically intensive convective summer showers with a short duration (Aaltonen et al., 2008).

The catchment is located in a suburb built in 1960s and is characterized by tall concrete buildings surrounded by yards, small forested patches, and several rock outcrops. Based on a 2 × 2 m² land use raster, the catchment has a total fraction of imperviousness of 47.1%, distributed mostly between asphalt (26.4% of total catchment area), rooftops (12.9%), and rock outcrops (7.5%). Vegetated areas cover 47.4% and sand or gravel areas 5.2% of the total area. A small pond comprises 0.3% of the catchment area. The granite bedrock at the catchment is very close to the surface overlain only by a thin layer of topsoil. The catchment is located on a hill resulting in an average elevation of 32.2 m.a.s.l. (elevation range from 9.1 to 46.3 m.a.s.l.) and rather varying terrain (slope range from 0 to 54.7%) with a moderate median slope of 5.1%.
2.2. Rainfall data

Open rainfall data from two FMI products were used in the analysis. Open gauge data were available from Kumpula, 5 km south-west from the catchment (Kumpula gauge in Fig. 1). The gauge belongs to the operative weather station network of FMI (WMO-ID 02998). It is a weighing type rain gauge with a Tretyakov wind shield providing data at 10 min temporal resolution.

Radar data from a C-band radar in Vantaa (WMO-ID 02975), 8.8 km north-west from the catchment (Vantaa radar in Fig. 1) corresponds to the data released for public through the FMI Open data interface. The data were provided as rain intensity maps with a temporal resolution of 5 min and processed to a Cartesian grid with a resolution of $1 \times 1$ km$^2$. The open radar data are, due to storage constraints, available only for the past 5 days and therefore the data utilised in this study were reprocessed from archives of raw radar observations analogously to the production of the open data. As only capital area data were needed, the location of the grid differs slightly from the nationwide open data product, hence causing small differences in pixel values between the actual open data product and the product utilised here. The data have first undergone standard signal processing steps involving a) removal of the stationary targets and b) adjustment of the weakest and strongest signals according to the radar. Secondly, it has gone through the post processing steps for c) correction for the effects of the vertical profile of reflectivity (VPR), d) removal of non-meteorological targets, and e) conversion from radar reflectivity (dBZ) to rain intensity (mm/h) based on a $Z(R)$ relation $Z = 223R^{1.53}$ which Leinonen et al. (2012) derived from 5 years of disdrometer observations in Finland. Even though the Vantaa radar has a dual-
polarization capability, the dual-polarization parameters are used only for removing false echoes due to non-meteorological targets and filling the resulting gaps (Peura, 2012).

In addition to the open data, two fully automatic tipping-bucket rain gauges (Decagon ECRN-100 High Resolution Rain Gauge) recorded precipitation during the snow-free periods of 2014 and 2015. The first gauge was installed at the studied catchment (On-site rain gauge in Fig. 1) to provide reference on-site rainfall measurements, and the second gauge at the nearby Veräjämäki catchment 2.5 km south-west from the study catchment (Veräjämäki gauge in Fig. 1). The gauges reported the rainfall intensity as a number of tips (0.2 mm) per one minute (2014) or two minutes (2015). They were installed on top of low-rise kindergarten buildings to minimize interference due to vandalism and to be less prone to obstruction from the urban environment than at the street level. The gauge measurements are based on the manufacturer-provided calibration with no compensation e.g. for wind effects.

Finally, Vaisala Oyj operates a research radar in Kerava, 18 km north of the catchment (Kerava radar in Fig. 1), and provided rainfall intensity maps with a nominal resolution of 250 × 250 m². As there were several scan programs operated on the radar, the time between the scans varied from 45 s to 7 min 41 s with an average of 2 min 29 s, and the actual scan resolution varied from 1° angular and 100 m range resolution to 2° angular and 4000 m range resolution. Depending on the scan, the elevation angle varied from 0.4° to 1.0°. The data were quality controlled by removing the non-precipitating echoes followed by an absolute calibration (+1.75 dB) based on the self-consistency theory of dual-polarization radar observations (Gourley et al., 2009). A blended precipitation estimate was used based on specific differential phase shift and radar reflectivity. An estimate based on dual-polarization parameters, $R(K_{dp})$, was used in cases where hail was detected and for rain intensities exceeding 4 mm/h, while an estimate based on radar reflectivity, $R(Z_h)$, was reserved for
light precipitation. For more information regarding the use of the Kerava radar see Hickman et al. (2016).

### 2.3. Runoff data

The catchment is drained by a separate stormwater network (total length 3.4 km, pipeline density 10.2 km/km²) comprising mainly concrete pipes with diameters ranging between 0.3 m and 1.0 m (Fig. 1). The stormwater runoff was monitored at the catchment outfall using a Nivus OCM Pro ultrasound probe. The device was set up to automatically compute runoff (l/s) by measuring the water level and the water flow velocity in a 1.0 m diameter concrete stormwater sewer pipe at 1 min temporal resolution. The runoff measurements suffered from sporadic device malfunctions causing short periods of missing data and sudden jumps in the observed discharge time series, especially during peak flows. This was taken into account by only selecting events with mostly unbroken discharge time series. An additional problem was encountered with the timing of the discharge measurements, likely to be caused by the logger clock being too fast. The timing problems were only noticed near the end of the measurement campaign when it was too late to correct the timing of the past events, which left no other option but to use the observed data with possibly uncertain time stamps.

### 3. Methods

#### 3.1. Rainfall-runoff model

The US EPA Storm Water Management Model (SWMM) was selected for testing the effect of varying rainfall inputs on runoff generation. SWMM is a widely used dynamic rainfall-runoff model for simulating the quantity and quality of runoff in urban areas (Rossman, 2015). The model allows the division of the investigated area into irregularly shaped subcatchments to account for the spatial variability of land use. It consists of components describing the key hydrological processes controlling generation of runoff, which is then...
routed through a system of pipes and channels. The surface runoff at each subcatchment is simulated as a non-linear reservoir receiving inflows from precipitation as well as from adjacent subcatchments, and generating outflow while accounting for losses due to evaporation, infiltration and interception. The evaporation of ponded water was computed with the Hargreaves method, infiltration was described with the Green-Ampt approach, and the flow routing in the stormwater network was solved using the dynamic wave option.

A SWMM model description for the catchment was developed using a novel automated subcatchment generator presented in detail by Warsta et al. (2017). The generator first divides the investigated area into a regular $2 \times 2 \text{ m}^2$ Cartesian grid, each grid cell representing a subcatchment, i.e., a computational unit in the SWMM model. Then, the subcatchments are assigned with a land use class and corresponding parameters. The subcatchments are connected to each other and to the underlying stormwater network, and finally a SWMM input file is produced. Following the procedure of Warsta et al. (2017), the SWMM model was not explicitly calibrated for the study catchment but instead a parameter set (Set 2) calibrated for a similar small urban catchment (6.63 ha) in Lahti, Finland, available from Krebs et al. (2014) was adopted. To ensure an identical initial state of the model irrespective of the rainfall input data source, the model was run for a warm-up period of 10 days utilizing the FMI open gauge data prior to the commence of each event. The event periods were thereafter simulated using the studied input data source.

### 3.2. Studied rainfall data sets

Altogether three gauge rainfall data sources were used as an input for simulating runoff at the studied catchment (Table 1). Rainfall time series were formed utilizing the open data from the Kumpula gauge with 10 min resolution (GO in Table 1), as well as the data from the two research gauges. The research gauges were located on-site at the study catchment (GR1) and
at the nearby Veräjämäki catchment (GR2). They had a temporal resolution of 1 min (2014) and 2 min (2015). No processing of the gauge data, such as corrections for wind effects, was performed.

In addition to the gauge data sources, five radar precipitation data sources were utilized. Four of the radar data sources were produced from the open data of the FMI Vantaa radar. The first, (RO1 in Table 1), represents the open radar data with minimal processing. The only correction to the data was due to under-calibration of the radar, noticed by Hickman et al. (2016). They observed that while the radar was under-calibrated, the calibration level was however very stable. Therefore, based on a comparison with nearby FMI gauges, a constant correction factor of 1.5 was here applied to the observed radar intensities in order to bring them closer to the gauge values. A time series of the accumulated rainfall amounts at 5 min resolution was computed using the radar cell directly above the on-site gauge, i.e., assuming no drift. It was also assumed that the radar fields represent instantaneous snapshots of rainfall intensity, and that the precipitation fields remain stationary within the sampling interval.

The second radar data source (RO2 in Table 1) was created by increasing the temporal resolution of the Vantaa radar product. The assumption of field stationarity between scans has been criticized as the storm field movement between scans is not accounted for (e.g. Fabry et al., 1994; Piccolo and Chirico, 2005; Shucksmith et al., 2011). To overcome this problem, creating new intermediate fields by means of advection interpolation between the precipitation fields has been proposed as a solution with encouraging results (Fabry et al., 1994; Nielsen et al., 2014; Wang et al., 2015). Accordingly, the 5 min data from Vantaa radar were advection interpolated to a temporal resolution of 1 min using an optical flow method of Farnebäck (2003). A rainfall accumulation time series with enhanced temporal resolution for the on-site gauge cell was then produced from the interpolated fields and adjusted with the constant correction factor of 1.5.
In the third radar data source (RO3 in Table 1), the constant correction factor of the radar intensities was replaced with a time varying mean field bias (MFB) correction (Goudenhoofdt and Delobbe, 2009) to also account for the temporal variability of the radar errors due to e.g. radar calibration errors and storm characteristics. The eight nearest FMI gauges 10–50 km from the Vantaa radar were utilized to compute spatially uniform correction factors for each hour by using the available gauge-radar observation pairs where hourly accumulations exceeded 0.5 mm. The obtained correction factors were then applied to adjust the radar-measured rainfall intensities during the previous hour, and a rainfall accumulation time series for the cell above the on-site gauge was calculated with the original radar resolution of 5 min.

The last radar data source utilizing the open FMI data (RO4 in Table 1) was produced by combining the advection interpolation and MFB correction, to obtain a gauge-adjusted accumulation time series for the on-site gauge cell with 1 min temporal resolution.

Finally, the blended single- and dual-polarization precipitation estimate from the Kerava research radar was used to produce an additional radar data source (RR in Table 1). As the radar was operated using an irregular scan schedule (average time resolution 2 min 29 s), and since SWMM requires a constant time step for the input data, the intensity time series for the on-site gauge cell were regularized to a time resolution of 1 min using linear interpolation. The rainfall accumulation time series were then calculated using this nominal temporal resolution of 1 min.

|TABLE 1|

### 3.3. Event selection

Six rainfall-runoff events from 2014 and 2015 were selected for the analysis (Table 2). The first five events (E1 – E5) were selected based on availability of observed discharge data. Only short periods of missing data or data that was considered to be unreliable were allowed
during the selected events. Furthermore, rainfall data had to be available from all the input sources with only short data gaps extending over just a few time steps. The storm event durations ranged from 8 h to 32 h. The event rainfall accumulations, measured using the on-site gauge (GR1), ranged from 8.6 mm to 34.4 mm while the peak intensities ranged from 0.8 mm/10 min to 4.0 mm/10 min. Depending on the data source, Table 2 reveals a rather substantial variation between the rainfall accumulations for the same event, e.g. between RR and RO3 for E1 or between GR2 and RO1 for E4.

In addition to events E1 – E5, the most intense storm event recorded in the catchment during summer 2015 was studied. In this convective summer storm on 6 Aug 2015, GR1 observations showed 26 mm of rain with a peak intensity of 7.8 mm/10 min during a period of 1 h 40 min. The rainfall accumulations for the event varied greatly depending on the data source, from only 12.4 mm for RO2 up to 32.6 mm for GR2. Unfortunately, the flow measurement device failed to capture the event and it was therefore excluded from a closer analysis. The event is however discussed separately at the end of the Results section.

| TABLE 2 |

3.4. Performance evaluation

The different rainfall input data sources were evaluated directly by comparison against the on-site gauge (GR1) time series, as the high-resolution on-site gauge was assumed to give the most accurate rainfall information. Then each rainfall data source was used as input to the SWMM model and the simulation results were evaluated. For both evaluations, the volume error $VE$ (i.e., bias) and the Nash-Sutcliffe efficiency $NSE$ (Nash and Sutcliffe, 1970) were used as the performance measures. To enable $NSE$ computation between rainfall data sources with different temporal resolutions, all rainfall time series were aggregated to the resolution of the GO data set with the lowest studied resolution, i.e., 10 min. The aggregation was
limited to studying rainfall time series, whereas the model performance was studied at the
temporal resolution of the discharge observations and the model output, i.e., 1 min.

Due to problems with the discharge observations particularly during high flows, periods with
missing or unreliable observations were excluded from the VE and NSE performance
computations. Since especially the observed peak flows were considered unreliable, peak
time difference (PTD) and peak flow difference (PFD) were analysed by comparing the
simulation results from other input data sources to the simulation results obtained using GR1
as input data instead of the actual observed values. As with the evaluation of the rainfall time
series, the use of GR1 results as a reference was justified by the fact that high temporal
resolution rainfall data from the on-site gauge should produce runoff simulation results with
peak time and peak flow close to the real values. Still, from the simulation results (see Fig. 6
for event E4, and Figs. C1–C4 in Appendix C for other events) it is clear that also GR1
simulations tend to underestimate the peak flows, which should be taken into account when
interpreting the results.

The equations for the performance statistics are provided in Appendix A.

3.5. Lag translation of runoff observations

To overcome the problem of uncertain timing with the discharge data, the observations were
shifted in time following the proposal of Moussa (2010), who showed that low NSE values of
simulation results can be solely due to a simple lag translation of the observed hydrograph
even if the dynamics of the observations are acceptably reproduced. Therefore, a lag
translated NSE\(_T\) function was used to determine the required shifting of observations for each
of the studied events. The NSE value was computed between observations and GR1
simulations for a range of translations \(T = i\Delta t\), where \(i\) is an integer ranging from \(-20\) to \(10\),
and \(\Delta t\) is the time step of the data. Again, GR1 simulations were selected as the basis for
shifting the observations, since being located on-site, the high-temporal resolution (1–2 min) GR1 data should produce simulations with the most accurate timing. For each studied event, the lag translation producing the maximum value of NSE, $T_{max}$, was selected as the basis for shifting the observations and all the results are reported after the observations have been shifted according to the $T_{max}$ for the event.

The substantial effect that shifting the observations had on the NSE values for the studied events is demonstrated in Fig. 2. The values of the optimal lag translations are also presented.

4. Results

Fig. 3 presents the different rainfall data sets compared to the on-site gauge observations (GR1) in terms of $VE$ and NSE scores. A table of the performance statistics is given in Appendix B.

Volume errors of the off-site gauges (GR2 and GO) against GR1 observations show both over- and underestimation depending on the studied event (Fig. 3a), $VE$ varying between −21% and 29%. Only for events E3 and to lesser extent E4, the absolute $VE$ is smaller for the more distant GO than for GR2 located closer to the study catchment. Radar data sources (RR, RO1 – RO4) show a constant underestimation of rainfall amounts, $VE$ ranging from −6% for RO3 in E3 to −48% for RO1 in E4. The MFB-adjusted open radar data, RO3, for E1 is an exception with the rainfall volume overestimated by 21%, while other data sources based on the same open data underestimate the volume by −22 – −7%. RR has the most consistent performance of all data sources with $VE$ ranging from −35% to −19%.
The Nash-Sutcliffe efficiencies show the exceptionally poor performance of GR2 and GO for E4 as well as of GO for E2 and the very poor performance of GR2 for E3 (Fig. 3b). For all of these pairs, the rainfall volumes (Fig. 3a) were overestimated as well. The overestimated rainfall volume of RO3 for E1 is also characterized by the lowest NSE score amongst RO3 scores and as the lowest among the data sources for E1. The general behaviour amongst the open radar data sources is that RO1 has the poorest VE and NSE scores while the adjustments via advection interpolation and MFB correction bring the rainfall time series closer to GR1 observations.

The runoff simulation performance statistics in Fig. 4 show that, as expected, GR1 was the best input data source for the studied events. The values obtained with GR1 were constantly good with small VE (mean 10.7%; range from 0.0 to 31.6%) and high NSE (0.85; 0.76 to 0.89), compared to other data sources with worse average performance and with a greater dependence on the studied event. The performance statistics for events E1 – E5 are reported in Appendix B.

In general, the performance statistics of the runoff simulations in Fig. 4 reflect the results in Fig. 3 obtained by comparing the rainfall data sources directly. Firstly, the gauge performance deteriorated with increasing distance between the gauge and the catchment. Secondly, the poor performance of GR2 and GO for event E4 and of GO for E2 are also clearly visible in the runoff simulation results.

As with the rainfall time series, the research radar data (RR) had the most consistent behaviour as the runoff input. RR in Fig. 4 shows a constantly underestimated VE (mean −19.6%; range from −33.2% to −8.0%) and a low but somewhat reasonable NSE (0.62; 0.53 to 0.79), whereas the performance of the open radar data sources varied more from event to
The tendency of open radar data sources to underestimate flow volumes is seen in the runoff simulation results as well, however it is not as evident as when studying the rainfall directly, and the runoff volume is even overestimated for all RO data sources in event E2 and for RO3 and RO4 in E3. The advantage of advection interpolation and especially MFB correction to the open data is noticed from the $NSE$ statistics (Fig. 4b), where there is a clear trend from RO1 to RO4 for the individual events E1 to E5. Still, e.g. the overestimated rainfall with RO3 for E1 shows as an exception, but in general the corrections made RO4 the best performing radar data source.

Fig. 5 presents the peak flow difference ($PFD$) and the peak timing difference ($PTD$) computed relative to GR1 simulations. The numerical values are listed in Appendix B. Similar to other performance statistics, E4 had poor $PFD$ and $PTD$ statistics, especially when using GR2 and GO as input data, and E2 simulations performed poorly with GO data. The open radar data sources on the other hand had problems with reproducing peak flows especially for events E3 and E5.

The peak flows relative to GR1 simulations were constantly underestimated with some exceptions (Fig. 5a). Since the peak flows in GR1 simulations were often underestimated as well (Figs. C2–C4 in Appendix C), the underestimation for the other data sources was even more severe than what the $PFD$ values show. In event E3 (Fig. C3) the off-site gauge GR2 produced a simulated peak flow closest to the observation, while all other data sources, including GR1, severely underestimated the peak. This shows as an overestimation for GR2 in relation to GR1 in Fig. 5a. In event E2 (Fig. C2) heavy rainfall was detected in Kumpula (GO) but not at the study catchment, which caused the overestimated GO peak flow compared to GR1, and also explains the poor $VE$ and $NSE$ in rainfall and runoff results.
Except for E4 with largely overestimated peak flow, GR2 in general produced simulation results with peak flows closest to GR1 results. GO on the other hand suffered from large variability in peak flow simulations, and in general did not outperform the radar data sources. The radar data sources (RR, RO1 – RO4 in Fig. 5a) constantly underestimated the peak flows, with RR again having the most stable performance with the $PFD$ varying between $-39\%$ and $-19\%$ while the variation was larger for the open radar data sources. The improvements to open radar data especially due to MFB correction are again noticed when studying performance of individual events.

The peak timing (Fig. 5b) was relatively close to the GR1 values for all input data sources, with some exceptions. As discussed above, the heavy rainfall caused the GO peak flow for event E2 to occur 80 minutes prior to the peak in GR1 simulations. For event E5, the FMI radar was unable to properly detect the intense rainfall producing the main peak, and therefore the reported peak for all RO data sources corresponds to the secondary peak of the event 2 h 42 min before the main peak explaining the poor $PFD$ and $PTD$ values. In E3 (Fig. C3) the RO4 peak flow occurs 2 min prior to the observed maximum flow. However, as the runoff observations for the following 11 min after the recorded maximum flow are unreliable, it is not certain if the observations actually correspond to peak flow. Advection interpolation improved the peak timing for all events except for E2 where there was no difference in peak timing between RO data sources. However, the improvements due to advection interpolation were relatively small, being largest for E1 with 8 min improvement between RO1 and RO2 and 9 min improvement between RO3 and RO4.

Performance of most rainfall data sources was poor for event E4 both when studying rainfall directly and when analysing runoff simulation results. Fig. 6 presents rainfall and runoff observations as well as runoff simulation results for E4. During event E4 convective cells with a limited areal extent hit Veräjämäki (GR2) and Kumpula (GO) but did not generate
precipitation in the studied catchment, thus explaining the additional peaks (Fig. 6b, c) and 
poor performance statistics for GR2 and GO (Figs. 3 – 5). The Kumpula (RO) and Kerava 
(RR) radars on the other hand were able to capture the first peak of the event but not the latter 
peaks, thus leading to underestimation of the flow volume (Fig. 6d – h). The advection 
interpolation and MFB correction of the open radar data did, however, help with bringing 
simulated runoff a little closer to observed values for RO2 (Fig. 6f), RO3 (Fig. 6g) and RO4 
(Fig. 6h).

Finally, the simulation results for the event of 6 Aug 2015 are presented in Fig. 7, showing 
how RR (Fig. 7d) produces a simulated hydrograph that most resembles the hydrograph 
produced using the on-site gauge (GR1, Fig. 7a) data. In addition, RR has the rainfall volume 
closest to GR1 observations (Table 2) as well as the peak flow very close to GR1 simulations 
(\(PFD \sim 7.5\%\)). GR2 has measured too much rain resulting in overestimated peak flow (\(PFD 
18.3\%\)) whereas simulations using the open gauge data (GO) underestimate the rainfall 
volume and the peak flow (\(PFD \sim 37.0\%\)). The MFB correction is again shown to be very 
useful in bringing the open radar data simulation results closer to on-site gauge simulations 
by increasing the rainfall accumulations especially during the periods of most intense rainfall 
(Table 2). The advection interpolation for this event on the other hand increased \(PFD\). Due to 
the MFB correction \(PFD\) is reduced from \(-54.2\%\) for RO1 and \(-69.6\%\) for RO2 to only \(-7.2\%\) 
for RO3 and \(-21.6\%\) for RO4.
5. Discussion

The simulations with on-site gauge rainfall data (GR1) best replicated the observed urban catchment runoff for all studied events. In agreement with previous studies (e.g. Gabellani et al., 2007; Notaro et al., 2013; Rico-Ramirez et al., 2015) the error propagation from imperfect rainfall measurements to runoff was clearly noticed as the errors present in rainfall time series (Fig. 3) were projected to runoff results (Fig. 4).

Similarly to Krebs et al. (2014), a degradation in performance was observed even with rainfall data from the gauge located only 2.5 km away from the catchment (GR2), and the performance degraded further when the open gauge data (GO) from a distance of 5 km was used (Fig. 4, Fig. 5). Especially simulation of peak flows varied substantially between the different input data sources. In general, the peaks were underestimated when compared to simulations using the on-site rainfall (GR1), but at times substantial peak flow overestimation occurred due to rainfall captured outside but not within the catchment (e.g. E4 in Fig. 6) affecting not only the peak flow but also the timing of the peak. Considering the sampling error related to using individual rain gauges (Villarini et al., 2008) the results are not surprising, since rainfall is known to vary in space even within a sub-kilometre range (Jensen and Pedersen, 2005), and especially when exploring short time periods of accumulation (Fiener and Auerswald, 2009). This is particularly true in the convective storm context, such as E4 (Fig. 6) and the event of 6 Aug 2015 (Fig. 7), emphasizing the need of local rain measurements when gauges are used.

The runoff simulation results with the open radar data (RO1) were poorer than the results obtained using the GR1 data, but generally on par with the results obtained using the off-site gauges GR2 and GO. The problems with radar data were, however, different from the gauge data. While the gauges suffered from performance varying between events, the main problem...
with RO1 simulations was the constant underestimation of peak flows leading to underestimated flow volumes for most events.

Single polarization C-band radar products, such as the open radar data studied here, are known to be prone for underestimation of high rainfall intensities due to signal attenuation (e.g. Bringi et al., 2011; Zhu et al., 2014). Furthermore, $R(Z_h)$ relations are highly uncertain and known to depend on rain type (convective vs. stratiform). Using blended single and dual polarization radar products, where rainfall is estimated using $R(Z_h)$ for low to moderate rainfall intensities and $R(K_{dp})$ for higher intensities, has been shown to improve rainfall estimates (Bringi et al., 2011; Hickman et al., 2016; Zhu and Cluckie, 2012). The blended radar product (RR) was therefore expected to outperform the single polarization RO products during intense rain events. However, the results with RR were conflicting. In general RR performed better than the open radar data without adjustments (RO1), and had the most consistent behaviour of the studied rainfall data sources except for GR1. Also, for the most intense studied event of 6 Aug 2015, RR produced simulation results closest to GR1 simulations used as a reference due to missing runoff observations (Fig. 7). However, in event E1 characterized by the second highest maximum rainfall intensity among the studied events, RR performed poorly compared to other rainfall products. This could be partly explained by the spatial (range and azimuth) and temporal resolutions of RR varying from scan to scan resulting in imprecise rainfall estimates during coarse resolution scans.

The peak flow underestimation could also partly result from the large size of the radar cells ($1 \text{km}^2$) in RO products compared to the study catchment area (33.5 ha), leading to areal averaging of high and low intensity rain features inside the radar cell. These sampling errors are pronounced when the rain features are smaller than the radar spatial resolution (Shucksmith et al., 2011). As suggested by Gires et al. (2013, 2012) and Bruni et al. (2015),...
higher resolution radar data could help alleviate the problem by allowing measurement of the precipitation variability inside current resolution radar pixel cells. However, as pointed out e.g. by Einfalt et al. (2004), space-time integrated radar precipitation measurements are by nature different from point gauge measurements, and different results should be expected when such data sources are used as input in rainfall-runoff models, especially when considering a catchment as small as the one studied here.

Advection interpolation of the openly available 5 min temporal resolution radar data (RO1) into 1 min resolution (RO2) slightly improved the simulation results (Fig. 4, Fig. 5) for individual events, confirming the importance of temporal sampling in radar rainfall estimates (see e.g. Fabry et al., 1994; Piccolo and Chirico, 2005; Shucksmith et al., 2011). Similar minor improvements from using advection interpolation in urban stormflow simulations were noticed by Wang et al. (2015), who suggested to combine the interpolation with a local Bayesian gauge-based adjustment of radar estimates. Here, the gauge adjustment was implemented by means of a simpler time-varying MFB correction. Despite the simplicity of the method, MFB corrected radar data (RO3) showed improvements in the rainfall time series (Fig. 3), which were also translated into improved runoff results (Fig. 4, Fig. 5). As in Wang et al. (2015), the best results were obtained using advection interpolation together with gauge adjustment. Especially, for one of the studied events (E1) advection interpolation alone lead into underestimated rainfall, peak flow and flow volume, whereas MFB correction alone caused gross overestimation. Combining both adjustment methods yielded balanced results with very good flow volume and peak flow estimates. It is worth noting that here the MFB correction was implemented with discrete, hourly varying correction factors, although this may cause sudden jumps to the rainfall time series between consecutive hours. When needed, such jumps could be dampened by applying a moving average to smooth the factors in time. If an even more sophisticated gauge adjustment method for the FMI open radar data is
required, the recently developed method of Pulkkinen et al. (2016) could be a viable option as it was developed utilizing the Finnish radar and rain gauge networks. The method combines nonparametric density estimation, multivariate regression, and spatiotemporal Kriging interpolation, and it can explain gauge-radar discrepancies with respect to multiple factors as well as spatially non-uniform biases.

6. Conclusions

Hydrological simulations in urban areas require precipitation information at high spatial and temporal resolutions. The availability of open high-resolution meteorological data is constantly improving, as governmental policies increasingly require sharing the data compiled using public funding. In Finland, the Finnish Meteorological Institute has recently made precipitation observations publicly available through a web service. In this research, SWMM simulations of urban runoff were conducted to study the suitability of open rain gauge (10 min temporal resolution, 5.0 km away from the catchment) and weather radar (single-polarization C-band radar product, 5 min and 1 km² resolution) data as input data sources at a very small 33.5 ha urban catchment in Helsinki, Finland. The effect of the gauge distance to catchment was examined by using additional data from two research rain gauges, one located on-site and the other at a distance of 2.5 km from the catchment. Improvements to the open radar product were studied by 1) increasing the temporal resolution of the product from 5 min to 1 min via advection interpolation, 2) by adjusting the radar measurements with the nearby gauge observations using time-varying MFB correction, 3) by combining 1 and 2, and 4) by comparing the performance of the open radar products to a blended single- and dual-polarization product from a nearby research radar.

Based on the obtained results, the conclusions are summarized as follows:
The importance of local (on-site) precipitation measurements was confirmed for simulation of runoff from small urban catchments. With increasing distance between the catchment and the rainfall measurement point, the consistency between the recorded rainfall and the actual rainfall at the catchment decreases. The suitability of the open gauge data for urban rainfall-runoff modelling is therefore largely dictated by the gauge’s distance from the catchment, which again depends on the density of the operational rain gauge network.

While the off-site gauge results suffered from inconsistencies in the rainfall time series caused by the distance between the catchment and a gauge, the open radar data were prone to underestimation of the intense rainfall. Combined use of both data sources can help to provide an improved representation of rainfall, as the hourly MFB gauge-correction improved the performance of the open radar data product. The best open radar results were obtained with combined MFB correction and advection interpolation. In future, use of a gauge correction method is recommended for open radar data. Advection interpolation is a more complex method, but if there are resources to use it the results are likely to improve.

The FMI radars have dual polarization capabilities but their use at the moment is scarce. Improvements to the open radar product especially during intense rain are to be expected when the dual polarization capabilities of the radars are taken to full use. However, more research is needed as while the blended single- and dual polarization product improved the rain estimate during one high-intensity storm event, for another high-intensity event the blended estimate performed poorly.

The open data of the FMI offers interesting options for urban hydrological modelling in Finland, with implications expanding beyond the country borders. On one hand, the end-user has access to a vast pool of quality controlled meteorological information, but on the other
hand, the data requirements for runoff simulations in urban environment are stringent. The national rain gauge network is scarce, but urban hydrological assessments greatly benefit from measurements obtained at the catchment or very near to it. If the distance between the available gauge data and the catchment is large, the user probably should rather use radar data with its known problems than gauge data that may not represent the rainfall at the catchment.
Acknowledgements

This research is a part of the URCA project (The Quality and Quantity of Runoff Water in Relation to Land Use in Urbanised Catchments) and the Water JPI MUFFIN project. The funding was provided by the AKVA programme of the Academy of Finland (grants 263320, 263333, and 263335) and by Maa- ja Vesitekniikan tuki ry. The rain gauge data from Pihlajamäki and Veräjämäki and the runoff data from Pihlajamäki were collected within the URCA project by the University of Helsinki. Harri Hohti and the Finnish Meteorological Institute are acknowledged for providing the Vantaa weather radar data, which are openly available for the past 5 days via the Open data interface at https://en.ilmatieteenlaitos.fi/open-data/. The Kumpula rain gauge data is also openly available via the Open data interface. Vaisala Oyj is acknowledged for the Kerava radar data. CSC – IT Center for Science Ltd. is acknowledged for the allocation of computational resources. Labkotec Oy is acknowledged for the instrumentation of the discharge measurements. We appreciate Francesco Marra, the anonymous reviewer, and the editors for their constructive comments and criticism that improved the quality of the manuscript.
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Appendices

Appendix A

The performance statistics used to evaluate the rainfall data sources against GR1 observations and runoff simulation results against flow observations were the volume error (VE) (i.e., bias) (Eq. A.1) and the Nash-Sutcliffe efficiency NSE (Eq. A.2) (Nash and Sutcliffe, 1970).

\[ VE = \frac{V_{sim} - V_{obs}}{V_{obs}} \times 100 \]  \hspace{1cm} (A.1)

\[ NSE = 1 - \frac{\sum_{t=1}^{N} (Y_{t,obs} - Y_{t,sim})^2}{\sum_{t=1}^{N} (Y_{t,obs} - \bar{Y}_{obs})^2} \]  \hspace{1cm} (A.2)

where \( V_{sim} \) and \( V_{obs} \) are the simulated and observed rainfall/flow volumes, respectively,

\( Y_{t,sim} \) and \( Y_{t,obs} \) are the simulated and observed rainfall/flow values, respectively, at time \( t \),

\( \bar{Y}_{obs} \) is the observed mean rainfall/flow, and \( N \) is the number of time steps.

Peak time difference (PTD) (Eq. A.4) and peak flow difference (PFD) (Eq. A.5) are computed by comparing the simulation results using other input data sources to the runoff results obtained using GR1 as input data:

\[ PTD = t_{p,sim} - t_{p,GR1} \]  \hspace{1cm} (A.3)

\[ PFD = \frac{Q_{p,sim} - Q_{p,GR1}}{Q_{p,GR1}} \times 100 \]  \hspace{1cm} (A.4)

where \( t_{p,GR1} \) and \( t_{p,sim} \) are the simulated peak times and \( Q_{p,GR1} \) and \( Q_{p,sim} \) are the simulated peak flows. The subscript GR1 refers to the on-site gauge as the rainfall data source while \( sim \) refers to the remaining data sources used alternatively as input.
### Appendix B

Table B1. Rainfall performance statistics for the studied events (E1…E5) against the on-site gauge GR1 observations. Best data source according to each statistic is in bold.

<table>
<thead>
<tr>
<th>Event</th>
<th>Measure</th>
<th>Rainfall data source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>GR2</td>
</tr>
<tr>
<td>E1</td>
<td>VE (%)</td>
<td>-3.5</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td>0.64</td>
</tr>
<tr>
<td>E2</td>
<td>VE (%)</td>
<td>18.9</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.46</strong></td>
</tr>
<tr>
<td>E3</td>
<td>VE (%)</td>
<td>16.7</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td>0.19</td>
</tr>
<tr>
<td>E4</td>
<td>VE (%)</td>
<td>28.7</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td>-1.51</td>
</tr>
<tr>
<td>E5</td>
<td>VE (%)</td>
<td><strong>-7.0</strong></td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.87</strong></td>
</tr>
</tbody>
</table>

Table B2. Model performance statistics for the studied events (E1…E5) and studied rainfall input data sources. Best data source according to each statistic is in bold.

<table>
<thead>
<tr>
<th>Event</th>
<th>Measure</th>
<th>Rainfall data source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>GR1</td>
</tr>
<tr>
<td>E1</td>
<td>VE (%)</td>
<td><strong>0.0</strong></td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td>0.87</td>
</tr>
<tr>
<td>E2</td>
<td>VE (%)</td>
<td>31.6</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.89</strong></td>
</tr>
<tr>
<td>E3</td>
<td>VE (%)</td>
<td>11.6</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.86</strong></td>
</tr>
<tr>
<td>E4</td>
<td>VE (%)</td>
<td>9.8</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.76</strong></td>
</tr>
<tr>
<td>E5</td>
<td>VE (%)</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>NSE (-)</td>
<td><strong>0.89</strong></td>
</tr>
</tbody>
</table>
Table B3. Peak flow statistics for the studied events (E1…E5) relative to GR1 runoff simulation results. Best data source according to each statistic is in bold.

<table>
<thead>
<tr>
<th>Event</th>
<th>Measure</th>
<th>Rainfall data source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>GR2</td>
</tr>
<tr>
<td>E1</td>
<td>PF D (%)</td>
<td>−8.8</td>
</tr>
<tr>
<td></td>
<td>PTD (min)</td>
<td>−3</td>
</tr>
<tr>
<td>E2</td>
<td>PF D (%)</td>
<td><strong>−11.8</strong></td>
</tr>
<tr>
<td></td>
<td>PTD (min)</td>
<td>−1</td>
</tr>
<tr>
<td>E3</td>
<td>PF D (%)</td>
<td>26.1</td>
</tr>
<tr>
<td></td>
<td>PTD (min)</td>
<td>−11</td>
</tr>
<tr>
<td>E4</td>
<td>PF D (%)</td>
<td>282.7</td>
</tr>
<tr>
<td></td>
<td>PTD (min)</td>
<td>323</td>
</tr>
<tr>
<td>E5</td>
<td>PF D (%)</td>
<td><strong>−10.8</strong></td>
</tr>
<tr>
<td></td>
<td>PTD (min)</td>
<td>0</td>
</tr>
</tbody>
</table>
Appendix C

[FIGURE C1]
[FIGURE C2]
[FIGURE C3]
[FIGURE C4]
Table 1. Rainfall input data sources used for SWMM simulations.

<table>
<thead>
<tr>
<th>Data code</th>
<th>Distance to catchment</th>
<th>Spatial resolution</th>
<th>Temporal resolution</th>
<th>Open data</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GR1</td>
<td>On-site</td>
<td>point</td>
<td>1 – 2 min</td>
<td>no</td>
<td>On-site tipping bucket rain gauge data</td>
</tr>
<tr>
<td>GR2</td>
<td>2.5 km</td>
<td>point</td>
<td>1 – 2 min</td>
<td>no</td>
<td>Tipping bucket rain gauge data from Verääjämäki catchment</td>
</tr>
<tr>
<td>GO</td>
<td>5.0 km</td>
<td>point</td>
<td>10 min</td>
<td>yes</td>
<td>FMI weighing rain gauge data from Kumpula</td>
</tr>
<tr>
<td>RR</td>
<td>17.8 km</td>
<td>a)250 × 250 m²</td>
<td>b)2 min 29 s</td>
<td>no</td>
<td>Blended single- and dual-polarization rainfall estimate from Kerava research radar</td>
</tr>
<tr>
<td>RO1</td>
<td>8.8 km</td>
<td>a)1 × 1 km²</td>
<td>5 min</td>
<td>yes</td>
<td>FMI Vantaa radar data</td>
</tr>
<tr>
<td>RO2</td>
<td>8.8 km</td>
<td>a)1 × 1 km²</td>
<td>1 min</td>
<td>yes</td>
<td>Advection interpolated FMI Vantaa radar data</td>
</tr>
<tr>
<td>RO3</td>
<td>8.8 km</td>
<td>a)1 × 1 km²</td>
<td>5 min</td>
<td>yes</td>
<td>FMI Vantaa radar data with MFB correction</td>
</tr>
<tr>
<td>RO4</td>
<td>8.8 km</td>
<td>a)1 × 1 km²</td>
<td>1 min</td>
<td>yes</td>
<td>Advection interpolated FMI Vantaa radar data with MFB correction</td>
</tr>
</tbody>
</table>

\(^a\) Cartesian grid resolution, \(^b\) Average resolution
Table 2. Summary of the selected rainfall–runoff events. Data codes for rainfall input data sources are given in Table 1.

<table>
<thead>
<tr>
<th>Event code</th>
<th>Date</th>
<th>Duration (h)</th>
<th>Rainfall depth (mm)</th>
<th>GR1 max. intensity (mm/10min)</th>
<th>Obs. runoff depth (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>20.-21.8.2014</td>
<td>14</td>
<td>34.4 33.2 28.5 23.9 32.0 27.0 41.7 31.1</td>
<td>4.0</td>
<td>10.7</td>
</tr>
<tr>
<td>E2</td>
<td>22.-23.9.2014</td>
<td>15</td>
<td>14.8 17.6 18.6 9.6 12.7 12.7 12.3 12.4</td>
<td>1.2</td>
<td>3.5</td>
</tr>
<tr>
<td>E3</td>
<td>18.-19.6.2015</td>
<td>32</td>
<td>24.0 28.0 21.0 18.3 19.8 20.0 22.5 22.4</td>
<td>0.8</td>
<td>6.6</td>
</tr>
<tr>
<td>E4</td>
<td>30.-31.7.2015</td>
<td>12</td>
<td>18.8 24.2 23.8 15.2 9.7 10.5 12.5 12.9</td>
<td>1.4</td>
<td>5.5</td>
</tr>
<tr>
<td>E5</td>
<td>6.12.2015</td>
<td>8</td>
<td>8.6 8.0 6.8 5.7 6.0 6.0 6.2 6.3</td>
<td>1.8</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td>6.8.2015</td>
<td>4</td>
<td>26.0 32.6 19.3 26.3 13.4 12.4 29.6 26.6</td>
<td>7.8</td>
<td>–</td>
</tr>
</tbody>
</table>

Abbreviations used: max. = maximum, obs. = observed.
**Figure captions**

Fig. 1. Pihlajamäki catchment. On-site rain gauge and catchment outfall are indicated by red circle and star, respectively.

Fig. 2. $NSE$ values between observed runoff and GR1 simulations for the studied events (E1…E5) with different lag translations $T$. The optimal lag translations $T_{\text{max}}$ (min) are also shown.

Fig. 3. (a) Volume error ($VE$) and (b) Nash-Sutcliffe efficiency ($NSE$) of the studied rainfall data sources computed against the on-site gauge (GR1) measurements. Values of $NSE < 0$ are shown at the lower edge of (b).

Fig. 4. Model performance statistics of runoff reproduction for the studied rainfall input data sources. (a) Volume error ($VE$) and (b) Nash-Sutcliffe efficiency ($NSE$). Values of $NSE < 0$ are shown at the lower edge of (b).

Fig. 5. (a) Peak flow difference ($PFD$) and (b) peak time difference ($PTD$) computed using GR1 simulation results as a reference. Values of $PFD > 60$ and $PTD < -20$ or $PTD > 10$ are shown at the lower and upper edges of the plots.

Fig. 6. Simulation results for E4 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4. Discarded runoff observations (18:54 – 18:57) are in grey.

Fig. 7. Simulation results for Aug 6 2015 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4. Observations have been shifted $-5$ min to maximize the $NSE$ between GR1 simulations and observations. Discarded runoff observations (02:12–02:55 and 03:03–03:14) are in grey.
Fig. C1. Simulation results for E1 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4. Discarded runoff observations (15:29–15:35, 17:33–17:39, 18:53–18:57, and 19:31–19:43) are in grey.

Fig. C2. Simulation results for E2 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4.

Fig. C3. Simulation results for E3 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4. Discarded runoff observations (13:42–13:52) are in grey.

Fig. C4. Simulation results for E5 using rainfall input data sources (a) GR1, (b) GR2, (c) GO, (d) RR, (e) RO1, (f) RO2, (g) RO3, and (h) RO4.
Figure 2

NSE (-)

-20 -15 -10 -5 0 5 10

T (min)

E1 ($T_{max} = -10$)
E2 ($T_{max} = -6$)
E3 ($T_{max} = -15$)
E4 ($T_{max} = -12$)
E5 ($T_{max} = -11$)
Figure 3

(a) VE (%)

(b) NSE (-)
Figure 4

(a) VE (%) vs. GR1, GR2, GO, RR, RO1, RO2, RO3, RO4

(b) NSE (-) vs. GR1, GR2, GO, RR, RO1, RO2, RO3, RO4
Figure 5

(a) PFD (%) vs. ROs

(b) PTD (min) vs. ROs
Figure 6

(a) GR1
(b) GR2
(c) GO
(d) RR
(e) RO1
(f) RO2
(g) RO3
(h) RO4

Observed Flow
Simulated Flow
Precipitation

Flow (l/s)

Precipitation (mm/min)

0 0.4 0.8 1.2 1.6 2

0 200 400 600 800 1000

16:00 18:00 20:00 22:00 00:00 02:00 04:00
Figure 7

- (a) GR1
- (b) GR2
- (c) GO
- (d) RR
- (e) RO1
- (f) RO2
- (g) RO3
- (h) RO4

Observed Flow
Simulated Flow
Precipitation

Flow (l/s)

Precipitation (mm/min)

01:00 02:00 03:00 04:00 05:00
0    400    800 1200 1600
0     1.5    3    4.5   6    7.5

Figure 7
Figure C1 (appendix C, figure 1)
Figure C2 (appendix C, figure 2)
Figure C3 (appendix C, figure 3)
Figure C4 (appendix C, figure 4)