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The suitability of precipitation estimates from short CMLs for urban hydrological predictions

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Abstract

Commercial microwave links (CMLs) can provide path-integrated quantitative precipitation estimates (QPEs). Path lengths of short (< 2 km) CMLs usually well correspond to the spatial scale of urban (sub)catchments. However, QPEs derived from short CMLs are prone to be biased. Thus, it is unclear whether rainfall-runoff models can benefit from the well-fitting lengths of the short CMLs. For a small (1.3 km²) urban catchment drained by a separate sewer system and located in Prague, Czech Republic, we assess the performance of rainfall-runoff simulations executed using QPEs from CMLs of various lengths as model inputs. This is done by comparing the simulated runoffs with storm water discharges observed at the catchment outlet. Runoffs simulated using QPEs from short CMLs are very often biased and, in terms of Nash-Sutcliffe Efficiency, worse than when using long CMLs. However, the short CMLs lead to very good model performance in terms of Pearson correlation, they even outperform municipal rain gauges during heavy rainfalls. This suggest that there is valuable information about temporal dynamics of heavy rainfalls included in the QPEs from short CMLs. Yet, we show that this information is damaged when correcting the bias in the CML QPEs using a method based on adjusting the QPEs to rain gauge data.

1. Introduction

Commercial microwave links (CMLs) can provide path-integrated quantitative precipitation estimates (QPEs) derived from attenuation of radio waves by raindrops between the link end nodes. However, the raindrop-induced attenuation $A_r$ [dB] has to be separated from the total attenuation $A$ [dB], i.e. the difference between the transmitted and received signal power, since $A$ includes as well additional attenuation due to other phenomena, such as antenna wetting at the end nodes. The following relation is often used for deriving the raindrop-induced attenuation $A_r$:

$$A_r = (A - A_w - B), \quad (1)$$

where $A_w$ [dB] stands for the attenuation due to wet antenna, and $B$ [dB] for rainfall-independent “baseline” attenuation. The attenuation by raindrops $A_r$ can be related to the rainfall intensity $R$ [mm/h] using the following approximation:

$$R = a \left( \frac{A_r}{L} \right)^\beta, \quad (2)$$

where $L$ [m] is the length of a given CML, and $a$ [mm/h km$^\beta$ dB$^\beta$] and $\beta$ [-] are empirical parameters depending on CML frequency and polarization, and on drop size distribution (Olsen et al., 1978).

The raindrop-induced attenuation $A_r$ is, for a given rainfall intensity, proportional to CML length and frequency. The baseline attenuation $B$ changes with the link length as well. Since CML lengths typically range from hundreds of metres up to several kilometres, the magnitude of $A_r$ and $B$ can vary considerably. Consequently, with decreasing CML length, the relative importance of the wet antenna attenuation $A_w$ increases, as the magnitude of $A_w$ is independent of CML length, but dependent on antenna properties (e.g. shape or coating) and meteorological conditions (rainfall, wind, temperature, humidity, solar radiation). Yet, there is still a lack of understanding how the
Various physical processes contribute to $A_w$, which leads to errors when quantifying it. These errors, as a result, considerably compromise the accuracy of CML QPEs, especially for short (< circa 2 km) microwave links (e.g. Leijnse et al., 2008). On the other hand, lengths of short CMLs often correspond to spatial scales of small urban (sub)catchments. Therefore, QPEs from short links might well capture spatially variable rainfalls, and thus improve urban rainfall-runoff modelling. However, because of the systematic errors in the QPEs from short CMLs, it is unclear whether rainfall-runoff models can indeed benefit from the promising length scale of the short CMLs.

In this study, we use CML QPEs as inputs for urban rainfall-runoff modelling and investigate how different CML lengths influence the model performance. Moreover, we compare the performance of rainfall-runoff simulations executed using the CML QPEs with the model performance obtained using traditional rainfall data. The model performance is evaluated by comparing the simulated runoffs to observed stormwater discharges.

2. Material

The experimental urban catchment (Fig. 1) with the area of 1.3 km$^2$ lies in Prague-Letňany, Czech Republic, and it is drained by a separate stormwater sewer system. Approximately 35% of the catchment’s area is covered by impervious surfaces. The catchment is slightly inclined to the north, with the altitude gradually declining from roughly 280 to 250 m above the sea level. The rainfall-runoff lag time in the catchment is approximately 20 minutes.

![Fig 1: Left: Schematic layout of the studied urban catchment. Right: Location of the CMLs (with IDs denoted) and of the rain and flow gauges within the catchment. The CML central node is located close to the catchment’s centroid. Longer CMLs reach out of the catchment by several kilometres.](image_url)

We monitored 19 CMLs located in the catchment and its surroundings (Fig. 1) for a period between August 2014 and October 2016. The CMLs broadcast at 25 to 39 GHz frequencies, their lengths vary approximately from 600 to 5000 m, and they are operated by a major telecommunications service provider. The CML QPEs were retrieved at 10-s resolution (for details, see Fencl et al., 2015) and aggregated to 1-min resolution. Moreover, observations from three tipping bucket rain gauges (operated by the municipal sewer authority, each in a distance of approximately 2.5 km from the catchment) were collected at 1-min resolution during the same period. The rain gauges were manufactured by the Meteoservis company (MR3 model) and they were dynamically calibrated. They have the funnel area of 500 cm$^2$, the bucket volume 5 ml, and their single tip corresponds to approximately 0.1 mm of rainfall. In addition, we observed discharges at the stormwater drainage system outlet using an area-velocity flow metre (Triton, ADS). Uncertainty of
these measurements as quantified by standard deviations is 0.015 m for water depth and 0.05*\(v_m\) for the measured velocity \(v_m\). The temporal resolution of discharge measurements is 2 min for wet and 10 min for dry periods. Observed discharge values range approximately from 2 to 3000 l/s. The collected data set includes 67 relevant (rainfall height > 2 mm) rainfall-runoff events. Roughly 1/3 of these events are classified as heavy rainfalls (max. 10-min rainfall intensity > 12 mm/h).

3. Methods

We investigate the ability of individual CMLs to provide relevant rainfall information for urban rainfall-runoff modelling. We use the investigated rainfall data as inputs for rainfall-runoff modelling, and we evaluate the model performance by comparing the simulated runoffs with discharges observed at the stormwater drainage system outlet.

We study CML QPEs derived in the two following ways: i) by using the power law between rainfall intensity and radio signal attenuation with parameters taken from literature, and ii) by adjusting to traditional rainfall data from rain gauges. In the first approach, we apply wet antenna correction \(A_w\) from Eq. 1 as a constant offset in accordance with Overeem et al. (2011). Parameters \(\alpha\) and \(\beta\) from Eq. 2 are chosen as recommended by ITU Radiocommunication Sector (2005). In the second method, the mean of the instantaneous values of the three rain gauges, aggregated to 15-min time steps, is used for adjusting the wet antenna attenuation \(A_w\) and the parameter \(\beta\), while keeping \(\alpha\) equal to one, as proposed by Fencl et al. (2017). The baseline attenuation \((B\) from Eq. 1) is estimated in both approaches according to Fenicia et al. (2012).

Overall, there are 41 different precipitation time series used as input into the rainfall-runoff model. Firstly, we employ QPEs derived from only one CML at a time, eventually using each of the 19 CMLs. Next, we construct a time series calculated as the mean over all available CML QPEs for every time step. Thus, we construct 20 time series for each of the two methods of retrieving CML QPEs. Additionally, representing a traditional rainfall data set, the mean of three rain gauges from the permanent municipal network is used as model input. These are the same rain gauges as those used for CML adjusting (method ii), but we use the original 1-min resolution in this case. The precipitation input is always implemented as areal rainfall in the model.

To simulate the discharges at the drainage system outlet, we use an EPA-SWMM model calibrated using measurements from three rain gauges only temporarily installed in the catchment. We simulate discharges for all relevant (rainfall height over 2 mm, in total 67) rainfall-runoff events we captured during the monitoring period. The model performance is evaluated for each event using the Nash–Sutcliffe efficiency (NSE, [-]) and the Pearson correlation coefficient (PCC, [-]). Subsequently, we summarise the model performance for all 67 relevant rainfall-runoff events, and also separately only for heavy rainfalls.

4. Results

Firstly, the model performance in terms of NSE is presented. The results differ substantially for the two methods of deriving CML QPEs. The unadjusted CML QPEs (method i, Fig. 2 left) do not outperform the rain gauge data. For individual links, better NSE values (higher median, lower variability) are in general obtained for longer CMLs. However, as shown e.g. by the CML #4, this is not a universal rule. This, actually, confirms the crucial effect of the bias in CML QPEs on rainfall-runoff predictions, since, as shown by additional analyses, the worst NSE values are connected to links leading to notably overestimated (30% to 100% in median) runoff volumes. Interestingly, the CML #4 rather underestimate the runoffs. The mean over all available CMLs provides relatively good results, very similar to (but not better than) the long individual CMLs. NSE values for the adjusted CML QPEs (method ii, Fig. 2 right), when compared to the unadjusted CML data, are notably higher. The results are in general very similar to those for the rain gauges, i.e. with the median roughly between 0.5 and 0.8, and with the interquartile range between 0.4 and 0.7. About a half of the individual CMLs (including also short ones), and the mean over all CMLs as well, lead to
less variable NSE values than the rain gauges. However, only 3 CMLs, and the mean over all, lead to higher median NSE values.

![Boxplots of NSE values, summarised for all available rainfall-runoff events, obtained using the unadjusted CML QPEs (method I, left) and the CML QPEs adjusted to rain gauges (method ii, right). Note the different scale of the y axes.](image1)

![Boxplots of PCC values, summarised only for heavy events, obtained using the unadjusted CML QPEs (method i) and the CML QPEs adjusted to rain gauges (method ii) respectively. Right: Scatterplot of PCC for the mean over all unadjusted CML QPEs (x axis) and for the rain gauges (y axis) with colour-coded max. 10-min rainfall intensities of the individual events.](image2)

Fig 2: Boxplots of NSE values, summarised for all available rainfall-runoff events, obtained using the unadjusted CML QPEs (method I, left) and the CML QPEs adjusted to rain gauges (method ii, right). Note the different scale of the y axes.

Fig 3: Left and Middle: Boxplots of PCC values, summarised only for heavy events, obtained using the unadjusted CML QPEs (method i) and the CML QPEs adjusted to rain gauges (method ii) respectively. Right: Scatterplot of PCC for the mean over all unadjusted CML QPEs (x axis) and for the rain gauges (y axis) with colour-coded max. 10-min rainfall intensities of the individual events.

The model performance in terms of PCC, which is insensitive to linear bias, is different than when quantified by NSE. When summarised for all available rainfall-runoff events, there is no clear systematic difference between short and long CMLs. For the unadjusted QPEs, the PCC values are relatively low when compared to the rain gauges, with medians between 0.7 and 0.9. Lower (and more variable) PCC values are associated to CMLs which systematically underestimate runoff volumes (due to negative bias in the QPEs), e.g. CML #4. Adjusting to rain gauges improves the results, mainly their variability, but the values are not higher than for the rain gauges used alone.

Interestingly, the performance as quantified by PCC is rather different when summarised only for heavy rainfalls. Most notably, the unadjusted CML QPEs (Fig. 3 left) lead now to higher PCC values (medians between 0.85 and 0.95). The relation between the rainfall intensity and the PCC performance is, for the mean over all unadjusted CML QPEs and for the rain gauges, visualised in the Fig. 3 (right). The mean over all CMLs leads to the best PCC values by far. Several individual CMLs, as well, lead to higher PCC than the rain gauges. The best results are reached using relatively short CMLs located in the western part of the catchment (#3, #6, #7, #8). Individual links
differ especially in the variability of the PCC values. The high variability is connected to longer CMLs reaching eastwards out of the catchment (#9, #11, #13, #14, #17 and #18) and to those which tend to underestimate runoff volumes (#4, #10 and #19). For the CML QPEs adjusted to the rain gauges (Fig. 3 middle), the PCC values are in median, and predominantly also in variability, similar to the values obtained when using only the rain gauge data. When compared to the unadjusted QPEs, the short CMLs (and the mean over all CMLs) lead in general to worse results, and the long links to better ones.

5. Conclusions

The value of QPEs from short CMLs has been demonstrated when evaluating the urban rainfall-runoff simulations using the PCC metric (which is insensitive to linear bias) and when analysing only heavy rainfalls. In this case, the unadjusted QPEs from short individual CMLs can lead to remarkably high PCC values. Interestingly, even better PCC values (best from all the examined rainfall data) can be obtained by using combined rainfall information from all available CMLs. Next, we have shown that the high bias, common especially in QPEs from short CMLs, negatively affects the rainfall-runoff model performance as quantified by the NSE metric. Adjusting the CML QPEs to rain gauge data can improve this performance, however, it is still not substantially better than for the rain gauges used alone. Furthermore, adjusting to rain gauges worsens the model performance in terms of the PCC metric for heavy events. This suggests that there is valuable information about temporal dynamics of heavy rainfalls included in the QPEs from short CMLs, but the method of removing the bias by adjusting the QPEs to rain gauges, as a side effect, damages this information. Therefore, further research should focus on improving the methodology for bias reduction, potentially not using only additional rainfall data, but also runoff measurements.

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References


