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Impact of different sources of precipitation data on urban rainfall-runoff predictions: A comparison of rain gauges, commercial microwave links and radar

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Abstract

In this study, we investigate whether commercial microwave links (CML) can bridge the gap between rain gauge and radar. We performed a rainfall-runoff monitoring experiment with rain gauges, CMLs and weather radar in a small urbanized catchment during several months. The results of comparing rainfall data and resulting sewer flows suggest that quantitative precipitation estimates from CMLs require adjustment to local rain gauges to produce satisfactory results in a similar fashion as weather radar. In our study, CML with baseline removal and wet-antenna correction, but without adjustment, lead to substantial bias and underestimate rainfall-runoff ratios by more than 48% (Radar: ca. 40%). In contrast, adjusted CML produced results very similar to those from a dense rain gauge network and underestimated rainfall-runoff by about 11%. Further work is needed to better understand influential factors on the data quality of QPEs from CML. In addition, incentives are needed to motivate both telecommunication companies to provide CML data and weather service companies to use them in their products, i.e. commercializing information from opportunistic sensors.

1. Introduction

To control urban flooding, and reduce environmental damage of wastewater emissions, rainfall data with a high spatial resolution and a temporal resolution of less than 5min are needed (Ochoa-Rodriguez et al., 2015). In most urban areas, rain gauge networks are not dense enough and quantitative precipitation estimates (QPE) from weather radars are still inaccurate. In this study, we investigate whether commercial microwave links (CML) can bridge the gap between rain gauge and radar. A CML is a transmitter-receiver system which operates in the lower-medium GHz range and which is therefore sensitive to precipitation, and in particular, liquid rainfall (Messer et al., 2006, Fencl, Pastorek, 2018). However, despite a decade of research, still little is known on the performance of CMLs as operational rainfall sensors and, especially, how they compare to rain gauge and radar in urban drainage applications.

Therefore, we performed a comprehensive experiment to collect real-world evidence from a full-scale experiment in an urban sewershed to assess the potential of CMLs for urban drainage. The main innovation over similar studies (Pastorek et al., 2017; Stransky et al., 2018) is that we compare all sensors, including weather radar in a full-scale urban setting. In our experimental catchment in Adliswil (ZH) of about 1x3km2, we collected data from three different types of rainfall sensors, as well as runoff data in the urban drainage system. The presented results cover 35 rainfall events during the period from 8.6.2013 to 15.11.2013, where all sensors were functioning correctly.

Rain gauges: five weighing RGs of the type OTT Pluvio2 were recording rainfall with an accuracy of 0.1mm/min at a 1min timestep. The data of a sixth gauge, permanently installed at the WWTP of Adliswil failed plausibility checks and was ignored.

CML: Received signal levels (RSLs) expressed in dB from 19 CMLs were provided by the operator Salt (former ORANGE). Two of them recorded no attenuation data during the period under study. Therefore, 17 CMLs were included in further investigations. Five out of the 17 CMLs recorded data only for the beginning of the time period. The RSLs were recorded with a simple server-based script, which queried the 19 CMLs in an iterative fashion and resulted in a variable time resolution of about 3min.

Weather radar: QPEs from the Swiss weather radar network was provided by MeteoSwiss. This contains rain intensities with a spatial resolution of 1x1km2 and a temporal resolution of 2.5min. Further specifications of the radar can be found in Germann et al., 2006. As the nation weather service currently improves their processing chain and products, the information about the preprocessing of the data is probably outdated.

Sewer flow data: The runoff at the drainage point of the system was recorded during the above mentioned time period with a SIGMA 950 area-velocity meter. This data was used to calibrate the SWMM model in previous studies (Fu, 2013). In this analysis, the observed flow was only used for the identification of influencing storm type characteristics.

2. Methods

As ground truth, we chose spatially interpolated RG data from an inverse distance weighing scheme, because its performance was superior to spatial interpolation with Thiessen polygons. The CML data were first pre-processed with a variable baseline removal and, second, antenna wetting was corrected with an empirical model suggested by (Schleiss et al., 2013). Third, a recent method to adjust CML QPEs to local rain gauges (Fencl et al., 2016). This adjustment was performed on hourly-average rain intensities to account for spatial rainfall variability and rainfall observation errors. Fourth, spatial interpolation was performed with a modified IDW algorithm (Goldshtein et al., 2009). Radar data were adjusted in a similar fashion with a simple mean field bias adjustment on hourly rain intensities. In total, we constructed four different rainfall scenarios: RG, CML, $CML_{adjusted}$ and Radar and compared the CML and Radar scenarios to the RG. To assess the impact of different sources of rainfall on urban runoff predictions, we followed the approach of (Ochoa-Rodriguez et al., 2015) and performed a sensitivity analysis to assess how different model input affects the flow predictions.

As performance metrics for rainfall, we chose Bias (as relative deviation of absolute values) and RMSE as performance measures. All rainfall scenarios were compared for a time aggregation of 15min. Performance of flow predictions was compared relative to the response of the catchment from rain gauge observations in terms of runoff volumes.

3. Results

Overall, the results from our case study for CML are promising, although adjustment to local rain gauges seems necessary for urban rainfall-runoff simulations (Figure 1). It can be seen that the unadjusted CML in our case study consistently underestimate rainfall, which is especially severe for light rainfall. Adjustment to RG data substantially reduces bias. In comparison to unadjusted radar rainfall, CML perform slightly better, which could be due to the challenging mountainous terrain. As expected, the results show an increasing precision of all instruments with increasing aggregation time (Table 1). Our results further suggest that baseline removal of CML RSLs alone is not sufficient for pre-processing, because data quality could be worse than from current weather radars (Table 1).

Regarding runoff predictions (Figure 2), it can be seen that driving the runoff model with radar rainfall leads to considerable variability and both under- and overestimates runoff. In contrast, CML data seem to generally better correspond to the RG data, e.g. by predicting less extreme flow peaks (left). Predictions with adjusted CML data (green lines) seem to show the best similarity to the predictions with spatially interpolated RG data, because unadjusted CML data seem to underestimate the runoff peaks (right).

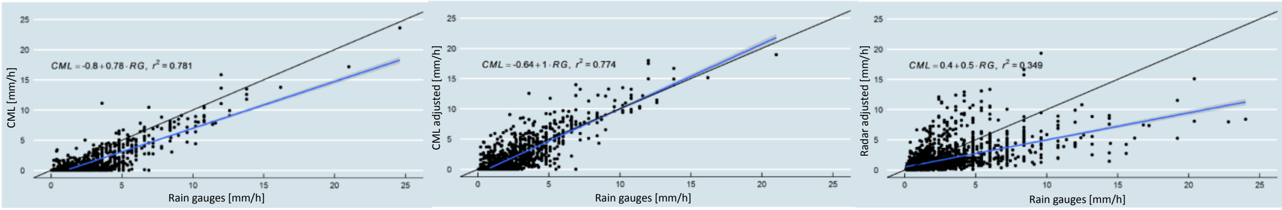

Figure 1: Comparison of unadjusted CML QPEs (left) to the RG IDW scenario for the period 8.6.2013-15.11.2013 and adjusted CML QPEs (left). Both figures show the comparison for 10min aggregated data. It can be seen that the unadjusted CML in our case study consistently underestimate rainfall, which is substantially reduced by adjustment to rain gauge data. In comparison to unadjusted radar rainfall, CML perform slightly better, maybe because they are closer to the ground.

Table 1: Quantitative rainfall analysis for increasing temporal aggregation intervals. The values represent the Bias [%] and RMSE [mm/h] in comparison to the ground truth RG IDW scenario. The high relative bias in unadjusted CML stems from a large number of relatively large deviations for small rainfall observations.

Sensor		1 min	5 min	10 min	1 h
CML	Bias [%]	96	94	94	93
	RMSE [mm/h]	2.7	1.9	1.5	0.9
CML $_{adjusted}$	Bias [%]	34	33	32	31
	RMSE [mm/h]	2.9	2	1.5	0.6
Radar	Bias [%]	59	59	59	59
	RMSE [mm/h]	3.2	2.5	2.1	1.3

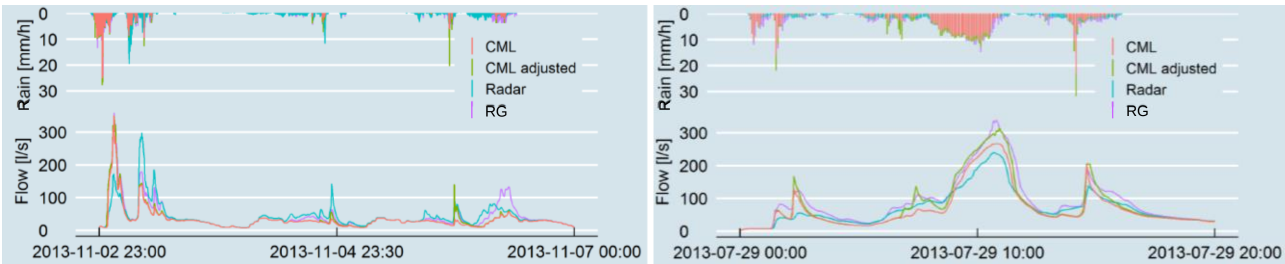

Fig 2: Comparison of predicted rainfall runoff for the urban catchment in Adliswil (ZH) and different rainfall information for event 31 (left) and event 10 (right). It can be seen that driving the runoff model with radar rainfall leads to considerable variability and both under- and overestimates runoff. In contrast, CML data seem to better correspond to the RG data, e.g. by predicting less extreme flow peaks. Predictions with adjusted CML data (green lines) seem to show more similarity to the predictions with spatially interpolated RG data than without adjustment and from radar.

Table 2: Quantitative analysis of runoff predictions. Rainfall and runoff represent the total sums for the entire period. Differences to the RG are smallest for the adjusted CML observations. Comparisons with synthetic block rain demonstrate that the SWMM model introduces additional uncertainty, because runoff formation and overflows depend on the rainfall input.

Sensor	Rainfall [mm]	Runoff [l]	Runoff/Rainfall	Diff. to RG [%]
RG	33582	480860	14.3	0
CML	17383	368264	21.2	48
CML adj	25579	406000	15.9	11
Radar	21055	424196	20.1	41
Synthetic rain	4320	39873	9.2	-

This is also reflected in analysing general rainfall and runoff volumes (Table 2). It can be seen that adjusted CML closer correspond to the runoff-to-rainfall ratio of the RGs than the other data sources. Unfortunately, the interpretation of the result of the rainfall-runoff model is not straight forward, because the system response fundamentally depends on the rainfall input, i.e. runoff formation and losses due to overflows distort the picture. This is illustrated by comparison to a synthetic 12h-block rainfall with an intensity of 6mm (Table 2, last row).

4. Discussion

In this study, we analyzed the results from a comprehensive monitoring campaign of urban rainfall-runoff regarding the using the observations from CML in urban drainage simulations. Our results from 35 observed rain events suggest that CML data which are only processed with baseline removal and wet antenna correction still contain considerable deviations to ground truth rain gauge measurements.

This corresponds to the results of Fencl et al. (2016), where bias was also present despite of pre-processing with baseline removal and wet antenna correction. In a similar fashion, Pastorek et. al. 2017 showed that a model driven with adjusted CML better reproduced observed rainfall-runoff than a single local rain gauge, probably because of better spatial representativeness. In that sense, the comparably high temporal resolution of CML could provide the necessary information to disaggregate cumulative rainfall measurements from local point gauges in time and space. Deriving QPEs with a high temporal resolution only by means of digital signal processing or machine learning (Ostrometzky et al., 2015) seem challenging, among other things because a proper ground truth, i.e. verified 5min data from dense RG networks, is more often than not lacking. If it is present, it might also be affected by errors.

In our view, although our experimental study dates back several years, the data quality of the CML was rather well in comparison to more recent studies. This was, because today telecommunication providers usually operate their CMLs with Automatic Gain Control (AGC), which was not the case in our study. This means that in addition to the varying RSLs, signal attenuation is also affected by varying input gains, which often only have a resolution of 1 dB (Wang et al., 2012). Thus, adjusting to cumulative ground truth observations from rain gauges has even greater potential.

Regarding the chosen methodology, an alternative approach could have been to use the individual rainfall and runoff observation to calibrate the model for each rain event or scenario of input data. This brings two complications with respect to the choice of appropriate error models and the choice of performance metrics. First, the involved errors might not only be different for each sensor, but for each event, and second, the SWMM model is very flexible and can easily be overfitted to optimally match a set of output observations. Instead of analyzing the variability of the model output, i.e. flow, to different inputs, one possible alternative could be to augment the SWMM model with a component for rainfall errors, e.g. rainfall multipliers or stochastic processes (Del Giudice et al., 2016), and directly estimate its magnitude for each input. This, however, probably requires additional assumptions on model parameters and structural deficits.

In the future, we will further analyze our collected data regarding the benefit of different pre-processing methods and the advantage of combining single RGs with CML observations. This means that we will construct more rainfall scenarios, such as comparing CML to results from single RGs, combining CMLs with radar and identifying CMLs which do not provide much information on local rainfall, e.g. because they cover several kilometers.

Further work is also needed to better understand the influential factors on CML data quality, such as dynamics of signal loss during rain (Fencl et al., 2018). In addition, influencing factors, such as antenna wetting, or a changing scattering behavior of the urban areas during rain, e.g. from wet surfaces, are still unknown. In the future, we will therefore perform exploratory data analysis on our data to investigate the role of rainfall characteristics on observation results, such as duration of the storm event, the average and maximum intensities during the event or the season to possibly explain the remaining variability.

Last, but not least, it is important to work on incentives on both ends of the involved stakeholders. First, incentives are needed to motivate telecommunication companies to provide their data, e.g. commercialize the information through weather data brokers. Second, it requires work on the demand side, e.g. to convince national meteorological services to work with data from opportunistic sensors, such as CMLs or citizen-science personal weather stations.

5. Conclusions

To better assess urban drainage performance, more detailed rainfall information is needed. In this study, we investigate whether commercial microwave links (CML) can bridge the gap between point measurements from rain gauges on the ground and spatially resolved radar data. Based on our analysis of experimental data from 35 rain events we conclude that, first, despite their limitations, rain gauges still provide the reference measurement equipment for urban rainfall runoff studies. Unfortunately, the rainfall process is so highly variable on relevant temporal and spatial scales that even with 5 gauges placed on 6km2, considerable variability remains and it is necessary to work with aggregated data. Second, CML data contain indeed substantial information on rainfall, especially in urban settings where the density of antennas is high. As their received signal levels usually have a high temporal resolution, they can nicely complement cumulative rainfall measurement and be used to disaggregate hourly or even daily measurements. Our results suggest that quantitative precipitation estimates from CML which are only processed with baseline removal and wet antenna correction still contain considerable deviations to ground truth rain gauge measurements. Runoff predictions from unadjusted CMLs are heavily biased in comparison to those from rain gauges. It is currently too little understood what the influential factors on received signal levels from operational CMLs are. Further, experimental data are needed to better distinguish signal attenuation from rainfall along the CML from equipment or environmental factors.

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