Commercial microwave links instead of rain gauges: fiction or reality?

Martin Fencl, Jörg Rieckermann, Petr Sýkora, David Stránský and Vojtěch Bareš

ABSTRACT

Commercial microwave links (MWLs) were suggested about a decade ago as a new source for quantitative precipitation estimates (QPEs). Meanwhile, the theory is well understood and rainfall monitoring with MWLs is on its way to being a mature technology, with several well-documented case studies, which investigate QPEs from multiple MWLs on the mesoscale. However, the potential of MWLs to observe microscale rainfall variability, which is important for urban hydrology, has not been investigated yet. In this paper, we assess the potential of MWLs to capture the spatio-temporal rainfall dynamics over small catchments of a few square kilometres. Specifically, we investigate the influence of different MWL topologies on areal rainfall estimation, which is important for experimental design or to a priori check the feasibility of using MWLs. In a dedicated case study in Prague, Czech Republic, we collected a unique dataset of 14 MWL signals with a temporal resolution of a few seconds and compared the QPEs from the MWLs to reference rainfall from multiple rain gauges. Our results show that, although QPEs from most MWLs are probably positively biased, they capture spatio-temporal rainfall variability on the microscale very well. Thus, they have great potential to improve runoff predictions. This is especially beneficial for heavy rainfall, which is usually decisive for urban drainage design.

Key words | areal rainfall, rainfall monitoring, rainfall spatial variability, telecommunication microwave links, QPE, urban hydrology

INTRODUCTION

Rainfall is the main driver for urban runoff and thus represents a crucial input for urban hydrology. This is especially important in urban drainage modeling, because uncertainties in rainfall measurements directly propagate to the predicted runoff (Fankhauser 1997; Stransky et al. 2007). In addition, urban catchments are often impervious and have little depression storage. Thus, their runoff response is extremely sensitive to spatio-temporal rainfall dynamics on very fine temporal and spatial scales (Schilling 1991; Berne et al. 2004). Unfortunately, such theoretical requirements for rainfall monitoring are largely neglected in practice. Our experience shows that the actual state of national and regional rainfall measurement networks – and even those specifically designed for urban hydrology – is usually one order of magnitude sparser than optimal. To complete the missing spatial rainfall information, X-band radars or local area weather radars are being increasingly used. Unfortunately, radar rainfall estimates are still affected by substantial errors (Berne & Krajewski 2013), and in addition, the required high-resolution radar information is not always available. Recently, commercial microwave links (MWLs) from telecommunication networks have been suggested as a novel source of rainfall information (Messer et al. 2006; Leijnse et al. 2007), which could provide quantitative precipitation estimates (QPEs) on the radar pixel scale or at even finer resolution. MWLs are point-to-point radio systems, which connect two remote locations, mostly at line-of-sight. They usually operate at millimetre wave lengths, where rainfall drops represent a major source of signal attenuation, and can provide path-averaged QPEs.

Unfortunately, QPEs from MWLs are influenced by different systematic and random errors. Such errors have been already described, both theoretically (e.g. Berne & Uijlenhoet 2007; Zinevich et al. 2010) and by comparing

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single MWLs with reference rainfall from rain gauges (RGs) (e.g. Leijnse et al. 2007; Fenicia et al. 2012; Rieckermann et al. 2012). There have been also several attempts to reconstruct the spatial rainfall distribution from joined analysis of nearby MWLs (Zinevich et al. 2008; Goldshtein et al. 2009). However, the influence of the topology of MWL networks on the ability to capture rainfall spatio-temporal dynamics over small areas of a few square kilometres has not been reported yet. In addition, in many studies, the frequency of logged MWL signals was too coarse for urban hydrological applications (e.g. Leijnse et al. 2007; Overeem et al. 2013), and experience with high-frequency observations in tens of seconds is lacking. In this investigation, we therefore collect a unique high-resolution (in time and space) dataset from 14 MWLs. We then use the dataset to investigate the influence of different MWL topologies on the retrieved spatio-temporal rainfall dynamics over an urban catchment of a few square kilometres. Our results show that QPEs from most MWLs capture microscale rainfall variability very well. Thus, they can improve runoff predictions at virtually no cost.

MATERIAL AND METHODS

Experimental data and material

The experimental catchment is located in a suburb of Prague, Czech Republic, and has an area of about 2.3 km² (Figure 1) (Fencel et al. 2015). The experimental setup consists of 14 MWLs (MINILINK, Ericsson) operated by T-Mobile Czech Republic and three dynamically calibrated tipping bucket RGs (MR3, Meteoservis). We chose to deploy three RGs based on the suggestions by Schilling (1991), who recommends 1 RG km⁻² for most demanding urban hydrological engineering applications.

The MWLs operate at frequencies between 25 and 39 GHz and the quantization of transmitted and received signal levels (Tx and Rx) is 1 and 1/3 dB, respectively. For data logging, we designed a specific server-sided software application that actively polls selected MWLs serially using Simple Network Management Protocol commands and stores the data in an SQL database (Lhotan 2013). Each MWL is polled approximately five times per minute. The RGs have a funnel area of 500 cm² and the tipping bucket has a volume of 5 ml, i.e. one tip per minute corresponds to approximately 6 mm.h⁻¹. The experimental period was between June and October 2013. In this period, 17 rain events with total cumulative rainfall exceeding 5 mm occurred. From these, we selected 12 rain events for our analysis for which data from all the three RGs were available. The rain events are listed in Table 1. As MWL * (Figure 1) fluctuates about ±5 dB even in dry periods, we use only data from the other 13 MWLs to retrieve QPEs.

Quantitative precipitation estimates from microwave link signals

Path-averaged QPEs from MWLs are computed with a simple power law model

\[ k = a \times R^b \]  

(1)

where \( R \) (mm.h⁻¹) is the average rainfall along MWL path, \( k \) is the specific rain-induced attenuation (dB.km⁻¹), \( a \) and \( b \) are parameters that depend on (i) MWL frequency and (ii) polarization, (iii) rain drop temperature and (iv) drop size distribution (DSD) (Olsen et al. 1978). For a given frequency and polarization, they can be either (i) taken from the literature (ITU 2005), (ii) fitted to reference rainfall data or (iii)
calculated directly from reference DSD data. By transforming Equation (1), we can obtain rainfall \( R \) (mm.h\(^{-1}\)) as a function of specific attenuation \( k \) (dB.km\(^{-1}\)) and transformed model parameters (Messer et al. 2006) as follows:

\[
R = a \times k^\beta
\]

(2)

where \( \beta = b^{-1} \) and \( a = a^{-\beta} \). This inverse procedure requires the separation of the attenuation caused by rainfall from the total attenuation. The baseline is usually set based on dry weather attenuation (Leijne et al. 2007), which can be calculated as the difference between \( Tx \) and \( Rx \). The wet weather attenuation is, however, affected also by the formation of water on the surfaces of antennas during rainfall. Thus, specific rainfall attenuation \( k \) (dB.km\(^{-1}\)) can be expressed as follows:

\[
k(t) = \max \left( \frac{A_{\text{tot}}(t) - B(t) - A_w(t)}{l}, 0 \right)
\]

(3)

where \( A_{\text{tot}}(t) \) (dB) represents total attenuation at time \( t \), \( B(t) \) (dB) is baseline, \( A_w(t) \) (dB) is wet antenna attenuation and \( l \) (km) is MWL length.

MWL data pre-processing

First total MWL attenuation is calculated for each MWL and each time step from the difference between \( Rx \) and \( Tx \). The baseline for dry periods is set equal to this attenuation. For a wet period, the baseline \( B \) is linearly interpolated from the total attenuations before and after this period. A safety window of 1 h before and 6 h after rainfall is applied to eliminate potential influence of attenuation by antenna wetting \( (A_w) \). Dry and wet periods are evaluated based on RG data. The wet antenna attenuation is assumed to be constant during the whole rain event and it is set to 1.5 dB for all MWLs following the recommendation of Overeem et al. (2011). Specific attenuation \( k \) (dB.km\(^{-1}\)) is calculated according to Equation (3). As MWLs operate in two directions on two channels, specific attenuation from both channels is averaged. QPEs, as path-averaged rain rates, are calculated individually for each MWL with Equation (2) and specific parameters taken from ITU (2005). All QPEs are aggregated to 1-minute averages.

MWL areal rainfall – MWL observation layouts

To investigate the influence of different MWL topologies on the estimated areal rainfall, we repeatedly retrieve QPEs with different observation layouts. Specifically, we evaluate 13 different layouts with 1–15 MWLs. We first evaluate each layout for all observed events. First, we assign the MWLs to either a northern (N) or southern (S) group (Figure 1). Northern/southern division reflects the predominant direction of the catchment’s rainfall runoff.

Second, we rank the MWLs in each group in ascending order according to their relative error in rainfall volume \( (V_e) \) (Equation (5)). This is convenient in practical applications, since \( V_e \) is relatively robust in regard to spatio-temporal rainfall variability (Schilling 1991). Thus, the reference is readily available, e.g. from daily cumulative rainfall published by national weather services.

After ranking, we design different observation layouts by alternately selecting MWLs from each group. Thus, the first layout only contains the least biased MWL \( (L_1 = \{1N\}) \), the second layout \( L_2 = \{1N, 1S\} \), the third layout \( L_3 = \{1N, 1S, 2N\} \) and so on. Layout \( L_{13} \) contains all 13 MWLs. Areal rainfall is calculated for each time step as arithmetic means of all the MWLs of the given layout. Not-available values are omitted.

Reference areal rainfall

Reference areal rainfall (RAR) is calculated from the three RGs. First RG data are aggregated to regular time series with 1-minute time step. The RAR over the catchment is calculated for each time step using weighted mean of all the three RGs. Weights of the RGs are in proportion to the calculated for each time step using weighted mean of all the Thiessen polygons (Figure 1, right).

Performance evaluation

We compare MWL rainfall to RAR with two different statistics: the Nash–Sutcliffe efficiency index \( (F_{NS}) \), which reflects an overall agreement of two datasets (Nash & Sutcliffe 1970), and relative error in cumulative rainfall \( (V_e) \).

\[
F_{NS} = 1 - \frac{\sum_i (R_i - \bar{R}_i)^2}{\sum_i (R_i - R_{\text{avg}})^2}
\]

(4)

\[
V_e = \frac{\sum_i (\bar{R}_i - \bar{\bar{R}})}{\sum_i R_i}
\]

(5)

\( \bar{R}_i \) (mm.h\(^{-1}\)) is RAR and \( \bar{R}_i \) (mm.h\(^{-1}\)) is the estimated rainfall at time step \( i \). \( R_{\text{avg}} \) (mm.h\(^{-1}\)) represents a RAR averaged over the evaluated period. \( V_e \) can range from \(-1\) to \( \infty \), as rain rates cannot be negative. \( F_{NS} \) can range from...
–∞ to 1, where 1 represents the perfect match and 0 indicates that the model to estimate rainfall has as much predictive power as the mean of the observations. A negative efficiency indicates that residual variance is larger than reference rainfall variance. Both statistics are calculated for all 12 events together and also for each event separately. We also calculated the same statistics for each of the three single RGs separately to compare the MWL observation layouts to common rainfall monitoring practice in urban hydrology.

**RESULTS**

In general, we find that, first, MWLs can capture microscale spatio-temporal rainfall dynamics very well (Table 2) and, second, they outperform single RGs especially during heavy rainfall. Third, the observation layout influences the accuracy of estimated areal rainfall. However, this accuracy is mainly determined by the precision of the associated MWLs. Fourth, we find that the total cumulative rainfall estimates are almost independent of MWL topology, at least in the long run, and their accuracy is usually good if the MWLs included in the layout are precise and vice versa.

**Performance of single MWLs**

The Nash–Sutcliffe efficiency index ($F_{NS}$), which reflects the short-term temporal dynamics of rainfall, ranges between –1.80 (MWL 6S) and +0.69 (3N) for single MWLs. However, based on $F_{NS}$, 5 of 12 MWLs outperform the worst performing RG, and the best MWL even outperforms the best RG (Table 2). In comparison, the relative error in total cumulative rainfall ($V_e$) is between −25 and +105% for single MWLs. The worst sensors are MWLs 7N and 6S ($V_e = 93$ and 105%), which are short and thus insensitive to low rain rates. Note, however, that light rainfall events (those with $R_{max} < 10 \text{ mm.h}^{-1}$) represent 57% of total cumulative RAR volume (Table 1).

**Performance of different MWL observation layouts**

Layouts with multiple MWLs show a relatively stable performance regarding capturing rainfall spatio-temporal dynamics, and even the worst layout ($L_1$) outperforms the worst performing RG with regard to $F_{NS}$ (Figure 2). Interestingly, the greatest improvement of $F_{NS}$ occurs for $L_2$, which includes 1S that has a relatively low $F_{NS}$ score (Table 2). This is, probably, because 1S points in the opposite direction to 1N and thus increases the coverage of the whole catchment. The best performing layout ($L_3$) with five MWLs ($F_{NS} = 0.69$) outperforms even the best RG (Figure 2). This is partly because in this topology the MWL with the best performance ($F_{NS} = 0.68$) occurs (Figure 2).

Regarding the monitoring of heavy rainfall, the layout with five MWLs has also the highest $F_{NS}$ score (0.72) (Figure 2, right). However, further increasing the number of MWLs does not result in a gain of information regarding $F_{NS}$. In our view, it is still remarkable that layouts with more than five MWLs outperform even the best performing single RG.

Finally, we find that layouts with relatively more MWLs show an increase in $V_e$. In our view, this does not necessarily indicate bad data quality, but merely arises from the choice of the performance statistic, the ranking based on total $V_e$ and our approach to design the observation layouts. As almost all the MWLs overestimate total rainfall volume, they cannot compensate for the bias in this statistic.

<table>
<thead>
<tr>
<th>North</th>
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<td>ID</td>
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<td>1N</td>
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<td>5.8</td>
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<td>3N</td>
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<tr>
<td>7N</td>
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DISCUSSION

The overall results show that the quality of QPEs from multiple MWLs depends both on the observation layout and on the performance of single MWLs included in the layout. Although we used simple methods to estimate MWL rainfall and we did not calibrate the MWL rainfall estimation model, the resulting MWL rainfall dynamics corresponded very well to the reference one.

First, we briefly discuss important influence factors and how they depend on the observed rainfall characteristics and the performance statistics used in the analysis. On the one hand, MWL precision is crucial when evaluating the ability of MWLs to capture long-term cumulative rainfall ($V_e$). On the other hand, a certain observation layout influences considerably the ability of MWLs to capture rainfall spatio-temporal dynamics ($F_{NS}$). Interestingly, when only evaluating heavy convective events (Figure 2, right), the RGs only poorly capture the high-spatio-temporal variability of those events. Even if we assume, for simplicity, that the RGs provide unbiased point QPEs, this leads to substantial errors in the rainfall estimates but also to difficulties in detecting rain-induced attenuation, i.e. identifying the baseline during dry weather. Improper determination of rain-induced attenuation results in biased QPEs. In addition, further bias is probably introduced due to an inaccurate model for wet antenna attenuation, which was assumed to be constant for all MWLs (1.5 dB) during all rain events. In our view, the bias of MWLs could be decreased by local calibration of Equation (3) for each MWL, if reference rainfall is available. Also, more advanced baseline separation methods (e.g. Reller 2011) and wet antenna models (e.g. Schleiss et al. 2013) could be used. However, it is not well understood how dry weather attenuation is related to the other than rain-induced attenuation during wet weather. During wet weather, the propagation and backscattering of microwaves in the area of a specific MWL, with its building envelopes, roofs, etc., can be very different from those in dry weather.

Second, it is important to discuss signal quality and pre-processing techniques. We find that a quantization of $Tx$ of 1 dB, which corresponds for short MWLs (e.g. 6S or 7N) to a rainfall rate of about 7 mm.h$^{-1}$, is related to relatively poor performance of single MWLs with regard to $V_e$ (Table 2). This leads not only to high random noise in the rainfall estimates but also to difficulties in detecting rain-induced attenuation, i.e. identifying the baseline during dry weather. Improper determination of rain-induced attenuation results in biased QPEs. In addition, further bias is probably introduced due to an inaccurate model for wet antenna attenuation, which was assumed to be constant for all MWLs (1.5 dB) during all rain events. In our view, the bias of MWLs could be decreased by local calibration of Equation (3) for each MWL, if reference rainfall is available. Also, more advanced baseline separation methods (e.g. Reller 2011) and wet antenna models (e.g. Schleiss et al. 2013) could be used. However, it is not well understood how dry weather attenuation is related to the other than rain-induced attenuation during wet weather. During wet weather, the propagation and backscattering of microwaves in the area of a specific MWL, with its building envelopes, roofs, etc., can be very different from those in dry weather.

Third, we find that selection of a suitable MWL layout for rainfall estimation is always a tradeoff between having (i) only a few, but precise, MWLs and thus limited coverage of the area, or (ii) many MWLs that cover the area better but also include imprecise MWLs which provide less accurate QPEs. In our case study, we considerably improved the results by eliminating those MWLs, which showed (i) logging problems due to missing observations of $Rx$ and $Tx$, or (ii) logging problems due to constant records of $Rx$ and $Tx$ during wet periods, or (iii) short-term random peaks of several dB of $Rx$ or $Tx$ (often only one or a few highly biased single
records), or (iv) significant $R_x$ or $T_x$ fluctuations during both dry and wet weather. In an extreme case, we found an MWL with fluctuations of more than $\pm 5$ dB over the whole experimental period. So far, we identified these behaviors by visual inspection of the data, which would be difficult for hundreds or thousands of MWL signals. Therefore, more advanced data validation procedures are needed to further improve QPEs with MWLs. Ideally, this should be possible a priori, without the need for reference measurements, which are often long and expensive.

Finally, the results of analysis are based on reference rainfall from only three tipping bucket RGs. Although we made special effort to dynamically calibrate the RGs and rainfall from only three tipping bucket RGs. Although we do not change the general conclusions of this paper.

The observation layout of a given MWL network influences the accuracy of estimated areal rainfall and that this accuracy is substantially influenced by the precision of single MWLs included in the layout. Therefore, one major conclusion is that the MWLs used to derive QPEs should be selected very carefully. In our case study, even layouts with just a single MWL can capture areal rainfall very well, which is probably generally the case where the length of an MWL corresponds to the length-scale of the catchment and the spatial scale of the rain cells. Therefore, we expect that only a few very precise MWLs deliver the most accurate areal QPEs. If no information on the quality of certain MWLs is available yet, the best QPE is the mean of all available MWLs. Finally, the results of this study show that uncalibrated rainfall estimates from MWLs overestimate rainfall. Nevertheless, they capture microscale rainfall spatio-temporal variability much better than RGs and can therefore greatly improve runoff simulations. This is especially beneficial for heavy rainfall, which usually determines the design and cost of urban drainage infrastructure.

CONCLUSIONS

Our analysis shows that QPEs from MWL networks can very well complement single RG measurements. For urban hydrology, the biggest benefit is probably information on the spatial rainfall variability, which can greatly improve areal rainfall estimation, especially during heavy rainfall. We demonstrated that the observation layout of a given MWL network influences the accuracy of estimated areal rainfall and that this accuracy is substantially influenced by the precision of single MWLs included in the layout. Therefore, one major conclusion is that the MWLs used to derive QPEs should be selected very carefully. In our case study, even layouts with just a single MWL can capture areal rainfall very well, which is probably generally the case where the length of an MWL corresponds to the length-scale of the catchment and the spatial scale of the rain cells. Therefore, we expect that only a few very precise MWLs deliver the most accurate areal QPEs. If no information on the quality of certain MWLs is available yet, the best QPE is the mean of all available MWLs. Finally, the results of this study show that uncalibrated rainfall estimates from MWLs overestimate rainfall. Nevertheless, they capture microscale rainfall spatio-temporal variability much better than RGs and can therefore greatly improve runoff simulations. This is especially beneficial for heavy rainfall, which usually determines the design and cost of urban drainage infrastructure.

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