Reply to Reviewer 1: H. Leijnse

General comments

Reviewer: This paper describes a method for incorporating accurate rain gauge measurements in commercial microwave link (CML) rainfall estimation through on-line parameter adjustment of the CML retrieval model. The idea of adjusting those model parameters that we know are most uncertain based on rain gauges is very appealing. This means that the accuracy of the gauges is used where it is most needed. The authors test their method on two different datasets, with different algorithm settings and different distances to the gauges used for adjustment. I think that the paper is interesting and certainly appropriate for HESS. I also have some issues that I think the authors should deal with before the paper is ready for publication. The most important of these issues are: 1) How well does the presented method work when gauges are even further away from the links (i.e., how well can this method be employed in sparsely gauged regions)? 2) The model is claimed to be linear, but this is not the case (see specific comments below). 3) The evaluations presented here are likely to be heavily influenced by the very high correlation (perfect in the case of one of the datasets) between the gauges used for adjustment and those used for validation. More specific remarks are given below.

Authors: It is very motivating for us that the reviewer acknowledges the scientific novelty of our study and its appropriateness for HESS. We also thank him for the very specific remarks, which will help us to minimize ambiguities in the presentation of the method and improve the clarity of the manuscript. Especially regarding the interpretation of the results. First, we address the general remarks. The detailed comments are then addressed in the “Specific remarks” section below each single comment. The reviewer comments refer to the line numbers and section numbers in the original manuscript, however our responses refer already to the revised manuscript. As we slightly restructured the structure of the manuscript, section numbers might differ.

1. **The distance of RGs to CMLs** represents an important limit for the use of our method. However, when RGs are far away this is limiting for any type of adjusting to ground observations, where “far” is conditional on the space-time correlation structure of rainfall. In our case, suitable distance of RGs to CMLs depends on the climatic conditions, type of rainfall (convective, frontal), the quality of CML data, and also application (requirements on time resolution). We discuss this, focusing especially on the limitations of our approach, in section 3.2 and 4.3. We discuss (p. 15, line 2–4) that already RG layouts covering areas in the range of 10–100 km^2 tend to underestimate rainfall peaks. We also suggest a potential remedy: where rain gauges are sparse, or even missing, short CMLs, which are often severely biased, could be adjusted to long CMLs, which more often behave according to wave propagation theory (p. 14, line 1–7). Although this is speculative, because we did not test it in detail, it could be because, for long CMLs, there is relatively more water volume or drops in the propagation path than for short CMLs. For short CMLs, the attenuation in the near field around the two end nodes, which is not well understood, is comparably larger. Unfortunately, although we believe that our dataset is truly unique, the RG information is not suitable for testing the method on more distant RGs. However, this does not invalidate the original goal of the presented manuscript, which is to show that adjusting CMLs by gauges is a feasible approach (even when using very straight-forward method) to improve space-time resolution of

rainfall data, especially in urban areas. That said, we are, once more thankful for the reviewer's comments. We will take special care to better reflect the limits of the presented method (see specific remark 14).

2. **The general remark to the (non)linearity of the retrieval model** is addressed in detail under the specific remark 7. In the original manuscript we did not explicitly stated that the offset parameter k_w is constrained to avoid model outputs with negative rainfall intensity. We also agree with reviewer that the model is not entirely linear, but piecewise-linear with two segments. We will clarify this in the manuscript.

3. **Regarding artefacts from high or perfect correlation between the RGs used for calibration and validation**, we are fully aware of the fact that the correlation between RGs constrains the efficiency of our approach. Despite of our effort to discuss this issue already in the initial version of the manuscript, some ambigu-ities clearly remain. The specific reviewers remarks were helpful to identify the corresponding paragraphs and improve the clarity of the text (please see remarks 9, 10, 11, and 19).

Specific comments

Q1: On p. 3, line 24 the units of are incorrect (should be mm h^{-1} km $dB^{-\beta}$).

A1: Thank you, corrected.

Q2: On p. 6, lines 10-12 it is mentioned that four links are selected. It's not clear to me what this selection was based on. I'm guessing that they were selected because these links were in (or close to) the catchment. Or were there more links in the area that were not selected. Can you provide a short statement in the paper about why these links were selected?

A2: Yes, we have selected links which correspond to the length scale of the catchment, i.e. to the reference rainfall. Thus, we have concentrated on CMLs which are shorter than two km (p. 7, lines 1-2, p. 13 lines 13–14 in the original manuscript). In our experience, this length is also the most relevant for applications in urban hydrology. Please also note that one CML was excluded from the analysis because connection was lost during the experiment. To clarify the selection we have added an additional figure in the supplementary material, which shows the map of the experimental catchment with the whole CML network of our collaborating partner, T-Mobile, as an overlay. We refer to this material in section 2.1 Experimental sites. We also added into this subsection an information about excluded CMLs due to communication outages.

Q3: Section 2.3 seems redundant to me, and its contents can simply be put in Sections 2.1.1 and 2.1.2.

A3: We have removed section 2.3. and put an information about experimental periods into sections 2.1.1 and 2.1.2 and partly also into performance assessment section now referred as 2.5.

Q4: On p.7, lines 2-3 the authors claim that using the power law of Eq.(1) could result in overfitting. However, this power-law relation has been shown to be robust and relatively insensitive to variations in raindrop size distributions. So the parameters of this relation can be safely taken from literature without fitting them within a retrieval algorithm. The key to getting good rainfall estimates is to properly take effects of a variable baseline and wetting of antennas into account. So while I can certainly understand that the authors want to use an as simple equation as possible for the analyses presented in this paper, I think that the risk of overfitting should not be stated as a reason here.

A4: Thank you for this comment. We changed the overfitting argument as suggested in comment 6, which addresses the same issue. We also changed this argument in the introduction. In addition, we slightly adjusted section 4.1 where simplified model is discussed.

Q5: On p.7, line 7 it is stated that *k* is the specific attenuation after baseline separation. It would be good to specify here which method is used for determining and separating this baseline.

A5: Agreed, we added at the end of the section 2.3 this information: "The baseline for specific attenuation *k* is assumed to be constant during each wet periods. First, we classify the data into dry and wet periods. Classification is performed according to Schleiss et al. (2010) (using a moving window of length of 15 minutes). Second, we take the 10% quantile of the total path loss values in the preceding dry weather period as the best estimate."

Q6: On p.7, line 7, I suggest stating that you can use this simplification because b is very close to 1 for the frequencies that are often used in CML networks.

A6: We added this information into introducing paragraph of the section 2.4 "For frequencies between 20-40 GHz β is relatively close to unity according to ITU (2005) between 0.95 (20 GHz, vertical polarization) and 1.19 (40 GHz, horizontal polarization)."

Q7: On p.7, lines 20-21, as first glance I didn't think that it is necessary to state how the optimization is carried out because of the linearity of Eq.(2) and the fact that aggrega-tion over time is a linear operation. Hence minimizing L in Eq.(3) is a linear regression problem that has an analytical solution (even if you force the line to go through zero). However, I'm assuming that the authors are setting resulting rainfall estimates to zero if $k < k_w$ (which would yield $R < 0$ mm h^{-1}). This effectively means that although Eq.(2) is linear, the model that the authors are using is not. It should be expressed as

$$R = \begin{cases} \alpha(k-k_w)^\beta & \textit{if } k > k_w \\ 0 & \textit{if } k \le k_w \end{cases}$$

I think that it should be clearly stated in the text that the model is effectively not linear. I also think that the implications of this nonlinearity should be discussed in the text. Furthermore, this means that the reason for using this linearized form that is stated by the authors is not valid (because they're using a nonlinear model). In fact, one could argue that Eq.(1) could be kept as a basis for the equation that is optimized, with a provision for correcting for wet antennas and baseline variations. Something like

$$R = \begin{cases} \gamma(k-k_w) & \textit{if } k > k_w \\ 0 & \textit{if } k \le k_w \end{cases}$$

where k_w includes wet antenna and baseline variation effects, and hence should then be the only parameter that is fitted (and and taken from literature).

A7: Thank you for this valuable remark. We used gradient-based optimization during the development of the technique, where we also tested other candidate models for which analytical solutions were not available. To do this in an efficient manner, we used a single software implementation.

As suggested we explicitly stated in the revised manuscript that the tuning parameter k_w (now referred as Δ) is constrained, to avoid model to produce negative rainfall intensity and expressed the equation 2 as suggested by the reviewer. We also agree with reviewer that this means that model is not effectively linear in its whole domain, but piecewise linear. To avoid misunderstanding we do not call the model "linear" anymore, but "simplified". Finally, we labeled the offset parameter Δ instead of k_w to avoid misunderstandings and to emphasize that it is a general tuning parameter, which not only compensates for signal loss due to antenna wetting. We will also modify the description of the model (2) parameters (p. 7 lines 14-21) to: "where γ [mm h^{-1} km dB^{-1}] is an empirical parameter related to raindrop attenuation and other rainfall correlated signal losses, *k* [dB km^{-1}] is a specific attenuation after baseline separation, and Δ [dB km^{-1}] is an offset parameter which corrects for wet antenna attenuation and possible bias introduced by inaccurate baseline identification. The parameter is constrained, to avoid model to produce negative rainfall intensity. The piecewise linearity of the relation makes it possible to condition the model to rainfall and attenuation data which were aggregated over relatively long intervals (e.g., hours) and at the same time predict rainfall for attenuation data sampled at high frequencies."

It should be noted that, uncertainty related to attenuation from other effects than raindrop scattering and adsorption, i.e. "baseline variation effects" (including wet antenna effect) are most probably correlated with rainfall intensity and thus the parameter cannot be uniquely optimized on its own. As stated in the section 4.1 (and also 4.2.): "The model (2) can be interpreted as a combination of linear forms of the attenuation-rainfall model (1) and WAA models". For details on why wet antenna attenuation cannot be, in our opinion, compensated by a single offset parameter please see response to comment 13.

Q8: On p.7, line 31 a description is given on how the second parameter optimization run is carried out. It is stated that this run uses the parameter distribution of the first optimization run. However, I don't understand how the first run can yield a distribution of parameters. Or is it the distribution of parameters over all time steps in the entire dataset? In that case, the method cannot be used in a real-time Setting.

A8: This is not correct. It is correct that, in our analysis, we consider an "offline" setting, where we use the whole experimental period to estimate suitable parameter ranges. Thus, to use the method in near real-time setting the parameter ranges have to be estimated from past period. The continuous adjusting of model (2) does not "look into future", it uses rainfall intensity from the time step for which the adjustment is done and past rainfall intensities.

In summary, we explicitly stated in the corrected manuscript (in section 2.5) that we assessed the method in the setting for historical rainfalls and we also discuss the potential and limitation for real-time applications in the new section 4.3 (for more details on real-time capability of our algorithm please see our reply to comment 1 of the reviewer 2).

Q9: On p.8, lines 7-12 it is stated that the effect of temporal aggregation is studied by comparing the gauge-adjusted CML rainfall product with the same gauges that were used to adjust the CML data. I expect the fact that the gauges are not dependent to have a large effect on the outcome of the analyses. Am I correct in assuming that this is only the case for the Dübendorf dataset, and that in Prague you're using the municipality gauge network as a reference? I think that the fact that the gauges in Switzerland are not independent should be discussed in the paper.

A9: Yes, this is correct. We intentionally investigated the effect of time aggregation by using the same RGs for conditioning and validation. This enables us to study the effect of rainfall time averaging on the model's performance separately (without the influence of limited RG spatial representativeness). We investigate how performance degrades with increasing aggregation interval, e.g. due to averaging out of rainfall peaks or due to temporal evolution of the model parameters.

To make this clear, we have added into the performance assessment section this information: "… we explore whether the proposed adjusting method can be used to disaggregate cumulative rainfall data, such as hourly or daily values, to one-minute data."

Details of the analysis are further discussed under comment 11.

Q10: On p.8, line 24, a reference rainfall measurement is mentioned. It is not clear to me what this reference is. It this the average of the six (p. 6 line 16) or four (Fig.1) rain gauges operated by the municipality for the Prague dataset and the rain gauges and disdrometers for the Dübendorf dataset?

A10: Thank you, we find this comment very helpful! It is important to distinguish unambiguously between rainfall used for adjusting and reference rainfall used as a "ground truth". We use the term "reference" for the rainfall to which we compare the best estimates from the adjusted CMLs. In the case of Prague, these are RGs located in the catchment, in the case of Dübendorf reference rainfall is taken as rainfall detected by the disdrometers along the CML path. In the first analysis where the effect of rainfall aggregation is investigated, we use the same RGs (resp. disdrometers) for adjusting and the same RGs as reference. We only used them at different temporal scales. In the second analysis (on Prague dataset only), where influence of RG spacing is tested, three different spatial layouts are used for adjusting, however we still use the reference RGs in the catchment for performance evaluation of the estimates from adjusted CMLs, i.e. we use same reference rainfall as in the first analysis.

To clarify this issue, we created new subsection (2.2 Rainfall data), where we moved an information about reference rainfall used for validating the results and about rainfall data used for adjusting CMLs. We also explicitly stated there, how reference rainfall is calculated. Finally, we corrected typo in the description of RG layouts (now second paragraph in the section 2.2 Rainfall data) where we we mistakenly referred to Fig. 1, left instead of middle and vice versa.

We have also restructured performance assessment section and clearly stated in its beginning (p.8, lines 21-22) that "We evaluate the adjusting method by directly comparing QPEs to reference rainfalls (Fig. 1, middle and right), both with a temporal resolution of one minute."

Q11: In Section 3.1 the authors discuss the reasons why parameter fitting for shorter intervals yield better results than for longer intervals. I don't really agree with this discussion. What effectively happens when the length of the aggregation is increased is that the CML data receive more weight in determining the temporal evolution of the rainfall signal (relative to the gauges). Because either the same gauges (Dübendorf) or a gauge dataset that is well-correlated to the gauges that are used for the parameter fitting (Prague; see top-right panel of Fig. 4) are used for verification, it is expected that the results are best if the weight of the gauges is largest (i.e., for the shortest accumulation intervals). So I don't think that you can actually draw conclusions about which accumulation interval is best suited for this method based on these analyses.

A11: In section 3.1 we do not investigate optimal temporal aggregation intervals as stated already in the performance assessment section (see comment 9). We only study, how model performance worsens with increasing aggregation interval and we try to relate it to the autocorrelation structure of rainfall. We are very much aware of the fact that shorter aggregation intervals give more weights to the gauges and therefore, the best performance has to be achieved by short intervals when same gauges are used for adjusting and evaluation. The optimal aggregation interval is investigated subsequently in section 3.2 where aggregation is used to improve spatial representativeness of RGs far away from the catchment, resp. CMLs.

In our view, this is a misunderstanding, which partly arises from the wrong cross-references to Figure 1, which is now fixed (please see also our previous response).

In addition, we added into performance assessment section a short paragraph explaining the goal of the time averaging analysis, which is "explore whether the proposed adjusting method can be used to disaggregate cumulative rainfall data, such as hourly or daily values, to one-minute data."

Q12: On p.9, lines 20-22 the authors state that using daily rainfall accumulations to fit the model parameters would minimize the effect of diurnal fluctuations in baseline level. I think the converse is true: in order to minimize the effect of diurnal fluctuations, the model parameters should be fitted on a time scale that is significantly shorter than a day so that this variability is actually captured.

A12: We agree and we have removed this statement.

Q13: On p.13, Section 4.2 the authors discuss how the distribution of the γ parameter changes with aggregation interval. This is then related to the fact that the proposed model includes the effect of wet antennas. However, this effect should be more related to the k_w parameter of the model, and not so much to γ. Of course, the two model parameters can compensate, and this would result in wider distributions of γ, but this is a purely an effect of the fitting procedure.

A13: We have a different opinion on this particular issue and presume this is rather a misun-derstanding caused by the unfortunate naming the offset parameter "k_w" (now Δ) of model (2) (see reply to comment 7) and its imprecise description in the original manuscript on p. 7, lines 7-9. This might create the false impression that only the offset parameter is responsible for wet antenna attenuation (WAA) correction. It is important to note that the simplified model (2) should be interpreted as "a combination of WAA model and simplified standard power-law model" (p. 7, lines 10-12). Although Overeem et al. 2011 suggest that, for their 15 minute CML data, WAA can be satisfactorily modelled as a constant, the other authors suggest more complex models. Given our theoretical understanding, these should generally depend on rainfall intensity (e.g. Kharadly et al. 2001, Leijnse et al. 2008). Indeed, we found that WAA react very dynamically on changes in rain-fall intensity. Spraying the radomes of some radios in Prague showed a substantial dynamic response. Immediately after spraying, attenuation increased by about 5 dB, decreased to 2.5 dB after 1 minute, and was almost not observable any more after 3-4 minutes (Fig. R1).

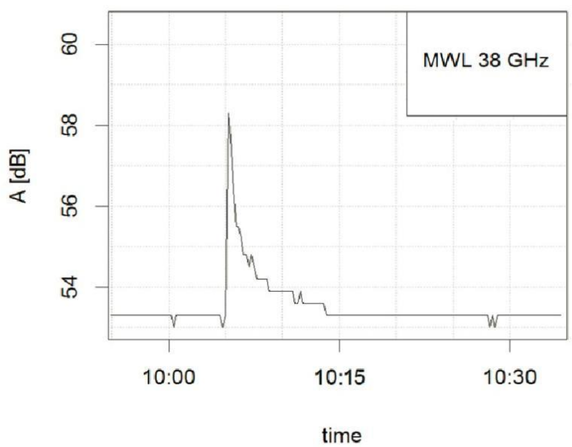

Fig. R1. Wet antenna attenuation of about 5 dB for a 38 GHz CML almost disappears within 3-4 minutes after spraying the antenna radome during dry weather.

If WAA depends on rainfall intensity, the linear approximation of any WAA model which reflects this dependence then should be affected by compensation of the offset parameter by the slope parameter. This also explains (p. 14, lines 1-3) the discrepancy between γ parameters of model (2) and α parameter of model (1) suggested by ITU (2005). Such discrepancy was already reported by Fenicia et. al (2012) "who estimated for their 23 GHz CML values of α substantially lower than values suggested by ITU (2005)" (p. 14, lines 3-4).

To clarify the nature of the simplified model (Eq. 2) and avoid misunderstanding, we labeled k_w as Δ instead. And also changed the description of the parameters when first introducing model (2). Third, we better explained that the simplified model combined linear approximations of both the rainfall retrieval model (1) and wet antenna model in section 2.4. Finally, we have also added one sentence to the end of discussion section 4.2: "Interestingly, lower values of γ parameter compared to parameter α makes even shorter CMLs relatively sensitive to rainfall and thus capable to detect even light rainfalls"

Q14: On p.13, lines 17-18 the authors state that they've found a connection between the observed systematic errors and the degree of preservation of rainfall space-time structure through averaging. I don't really see this connection, and I think this should be better explained.

A14: We explained this connection in section 3.1 p. 9 lines 11-16 of the original manuscript, and we showed in the appendix A (and figure A1 in the manuscript) how increasing the aggregation interval smoothes out rainfall peaks and smoothes out the differences between low and high intense rainfall periods. In our opinion, this smoothing of rainfall peaks most likely explains why the identification of model (2) parameters worsens with increasing aggregation intervals. Although we did not formally describe the relation between preservation of correlation patterns in aggregated rainfall and model parameter identification, we sufficiently demonstrate that this relation exist and thus we can explicitly state on p. 14 lines 23-25 that our results suggest that the underestimation of peak intensities is influenced by the preservation of autocorrelation in the aggregated rainfall (Fig. A1, in the manuscript).

Q15: On p.14, line 9 the use of CML networks in sparsely gauged regions is mentioned. However, the method presented in this paper probably won't work in sparsely gauged reasons because rain gauges located close to the links are essential (see Figures 1, 4, and 5). So I think this statement needs to be altered.

A15: Thank you for the comment. It is also discussed on p. 15 lines 9-15, however, we agree that the presented analyses rather is a proof of concept than enables us to generalize and extrapolate to different conditions, e.g. RG layout, topology, climate, weather, etc. In particular extrapolation to sparsely gauged regions has to be performed with great care. We, therefore, modified the first sentence of the Conclusion section to: "Commercial microwave links (CMLs) can improve resolution of existing rain gauge and radar networks, especially in populated areas where there are often very dense."

Q16: On p.15, line 18 it is stated that CML networks can provide rainfall data on a (sub-)kilometer scale. However, I really don't think that this will be attainable with the method presented here. This is because of the fact that the CML data are adjusted to a (point) rain gauge somewhere in the vicinity, which will effectively smooth out much of the variability captured by the individual links. So this statement should also be put into perspective.

A16: Thank you for this comment, we have considered it carefully. Nevertheless, to our opinion combined use of RGs and CMLs can provide "insight into rainfall space-time structure at (sub)minute and (sub)kilometer scale" (p. 16 lines 24-26). We have demonstrated in presented analyses that even CMLs with sub-kilometer path lengths are, after adjusting, capable to provide accurate rainfall estimates outperforming RGs used for adjusting. In our investigation we poll CMLs with approx. 10 s resolution and it is technically possible to poll CMLs at (sub)second resolution (e.g. Chwala et al. 2016), although this might also be influenced by the firmware and hardware of the radio. Moreover, the CML networks especially in city centres can be very dense, in the Prague (CZ) city centre it is up to 50 CMLs per km^2. We, therefore, think it is appropriate to conclude that CMLs can provide "insight into rainfall space-time structure at (sub)kilometer and (sub)minute scale", although we are aware of the fact that adjusting can lead to averaging of rainfall peaks etc. This is, however, also happening when adjusting weather radar rainfall data and they are commonly used to estimates rainfall space-time structure at subkilometer scale.

Q17: In Figure 1, right panel, there seem to be white letters over the figure that are partly over the disdrometers.

A17: Thank you, we have corrected this.

Q18: In Figures 2, 5, and 6 the coefficient of determination (R^2) becomes negative. It would be good to give the definition of R^2 that was used in the paper in Section 2.6 (there are different versions of R^2, some of which cannot become negative).

A18: Thank you. We used pseudo R^2 as defined by Efron (1978), i.e. it is defined identically as the Nash-Sutcliffe efficiency (NSE), a popular measure in (urban) hydrology. We have changed the label in the whole manuscript including figures to NSE to avoid misunderstanding.

Q19: In Figures 3 and 4 the slope of the regression line y = ax (i.e., with fixed offset) is given. It should be noted here that the correlation between the two variables affects this slope. The slope will always be lower with a low correlation coefficient (you can try this by switching the x- and y-axes; see also the right-hand panels of Fig.4).

A19: This is another valuable remark. We have added correlation coefficients into the legends of scatterplots in both figures (Fig. 3 and 4). The correlation coefficients on Figure 4 shows, that even CMLs adjusted to remote RGs correlate very well with reference rainfall. The slope of CML reference rainfall regression line is therefore rather influenced by systematic underestimation of rainfall peaks. In contrast to that, the correlation between RG layouts which cover larger areas and reference rainfalls are much lower (at 1 min resolution), which indeed affects the slope of regression lines. However, aggregating the RG intensities over longer intervals increases the correlation. Consequently, a longer aggregation interval improves the performance of the adjusting algorithm compared to shorter aggregation (see Fig. 5 in the manuscript: in the case of layout B2 with relatively distant RGs - the NSE of 1h ranges between 0.50-0.91 with median 0.78, whereas 5 min only achieves NSE between 0.2-0.86 with median 0.75). The areal averaging leads, however, to the smoothing out of rainfall peaks which in turn systematically affects peak rainfalls estimated from adjusted CMLs.

When we were preparing revised figure 3, we found that we presented for Prague dataset performance of CML no. 1 instead of mean of all four CMLs as stated in the figure caption. This is now corrected and figure 3 presents mean CML rainfall from all four CMLs.

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Reply to Reviewer 2: S. Thorndahl

General comments

Reviewer: The manuscript provides methods for adjusting rainfall estimates from commercial microwave links (CMLs) to rain gauges (RGs). It compares different temporal scales for adjustment and different layouts of gauge/CML systems. The work is novel and addresses very relevant issues in high resolution rainfall estimation in urban areas. It is well written and understandable and would fit well into the scope of HESS. Although not an expert in CMLs (but in radar rainfall estimation), I have some comments and suggestions which in my opinion could improve the manuscript.

Authors: First, we would like to thank reviewer for all the remarks and recommendations how to complete the manuscript and improve its clarity. Clearly, an expert on weather radars experienced in adjusting to rain gauges can give substantial advice.

Specific comments

Q1: It is unclear whether the paper aims for on-line (real-time) adjustment of CML's and thus real-time rainfall estimation or to estimate historical rainfall. Real-time adjustment would be associated with larger uncertainties.

A1: In our analysis we assess the method in the setting for historical rainfalls. However, the method does not "look into future" when continuously adjusting model (2), but uses rainfall intensity from the time point for which the adjustment is done and then from several time points in the past (p. 8, lines 9-11). Thus, method can be used with additional tuning in near real-time setting.

To have a better evidence base, we performed additional analyses where CML rainfall retrieval model is continuously adjusted based only on past data. The results of these analyses confirmed that use of the method in real-time setting leads to only slightly worse CML performance in comparison to the original analysis. We therefore explicitly stated in the section 2.5 that we assess the method in the setting for historical rainfalls and also added into section 2.4 this information: "When conditioning model (2) on historical data, parameter ranges can be set on the basis of the whole available dataset. For real-time application ranges has to be estimated from past periods." Furthermore, we added into Discussion section subsection 4.3 discussing use of the adjusting algorithm in real-time setting.

Q2: P4L31-P5L3: This is almost a conclusion of the paper. It does not belong in an introduction – but could be applied in the abstract.

A2: Thank you for this comment. In our view, this paragraph improves the intelligibility and clarity of a manuscript to i) have a very specific message and ii) convey the message to the reader. This can include explicitly stating the novelty of the work, but also concrete results. Then, a reader is not left in the dark what to expect and will not have major surprises - which are always confusing - during reading. As the abstract is too short, this info can go into the introduction. In our view, the redundancy of information-pieces (twice mentioned in the abstract and the intro) is a small price to pay for the increased clarity.

Q3: In section 2, it should be argued why two different experimental sites are used. Could the same results not have been derived using only one site – or is there an objective to compare the two sites in terms of data, layout, etc.

A3: Thank you for this comment. The reasons behind using data from two sites were distributed over the two sections 2.1.1 and 2.1.2 (differences in operational mode P5L16-17, P5L22-24, P6L1-2, or P6L12-13) and they included different reference rainfall data and power-control settings of CMLs on each of the sites. We agree that this is sub-optimal.

We have therefore briefly mention our main reason in the introductory paragraph of the section 2.1: "We analyse datasets from two different experimental sites, Dübendorf (CH) and Prague-Letnany (CZ). The dataset from Dübendorf contains detailed reference rainfall measurements along a CML path, which provide an excellent basis for investigating a rainfall from a single CML. In contrast, the areal rainfall observations from Prague are more appropriate to analyse rainfall retrieval from multiple CMLs and thus more relevant to evaluate the proposed adjusting method for common urban hydrological applications."

Q4: During the paper it is also a bit confusing where averages of CMLs are used (in Prague) and when single CMLs are used. Please be clearer on this.

A4: Thanks, we now see that this information was indeed missing in the method section (2.6 performance assessment) but was presented it in the Result section (P93-4 and P9L31-P10L3 in the old manuscript) instead. We have therefore provided this information in the new subsection 2.2 Rainfall data.

Q5: P6 bottom. It is unclear how you define an event. This is not necessarily an easy task operating with more than one rain sensor. Please clarify.

A5: The events at both experimental sites are first defined from each of the sensors and then the event periods are merged by simply increasing the duration to include the very first and the very last observation of a sensor. In the case of Dübendorf the events were defined based on disdrometer classification. In the case of Prague, events were defined from reference RG measurements. The beginning of an event is assumed to be 15 minutes before the first tip of RG and end of event 15 minutes after the last tip. In addition, the beginnings and ends of the events in Prague area were rounded (down resp. up) to full hours to ease the analysis with aggregated rainfall intensities. At both sites two rainy periods separated by shorter interval than 30 minutes are assumed to be the same event. Note, however, that adjusting is performed over whole experimental period and thus it is independent of event definition. The event definition therefore influences the performance evaluation, i.e. by the (non-)selection of events.

We have added an information about event definition into section 2.2 Rainfall data and also stressed at the beginning of this section 2.5 Performance assessment that "QPEs are adjusted over the whole experimental periods but evaluated only for rainfall events, which exceeded 5 mm in total, i.e., they are relevant for stormwater management (Table 1)."

Q6: Section 2.6. You state that you adjust on different aggregation levels ranging from 5 min to 1 day, but compare on 1 minute values. Couldn't there be reason also to compare on larger aggregation levels than 1 min. It is well known that for small rain intensities rain gauges are not very accurate. E.g. one tip of 0.1 mm per minute in a tipping bucket rain gauge corresponds to 6 mm/h. An error of +/- 6 mm/h on gauge estimates over one minute for intensities larger than 6 mm/h, it therefore not unrealistic. For smaller intensities where the intensities are estimated using the time between two tips, the intensity at minute scale might be somewhat uncertain. In a paper (Thorndahl et al. 2014) we made radar-rain gauge adjustment over different temporal scales, but also compared the results over different scales. Maybe you could find some inspiration here.

A6: Thank you for this suggestion. We used one minute reference data because this is the temporal resolution required for rainfall-runoff modeling at the scale of small urban catchments and our long-term intention is to provide rainfall data which could be used for this purpose. In the case of Dubendorf site, disdrometers are very well suited for providing rainfall data at 1 min resolution. The sampling error of tipping bucket RGs in Prague is partly reduced by calculating areal rainfall from six RGs relatively close to each other. Nevertheless, we agree that this sampling error may influence *NSE* values. We have therefore compared rainfall estimates from CML data also at other temporal scales (Fig R2, this response).

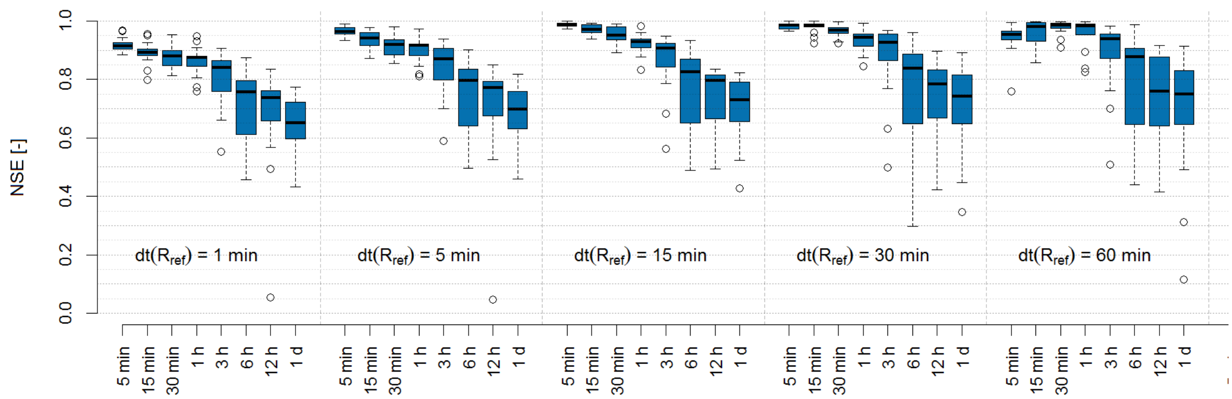

Fig. R2. Comparison of NSE for different temporal aggregations of reference rainfall. Mean of four CMLs (see figure 2 of the original manuscript) adjusted to rainfall having different aggregation intervals.

We find only small changes in *NSE* values when comparing CML rainfall to reference rainfall at larger temporal scales. This indicates that the analysis even at 1 min scale is not substantially influenced by random errors. Interestingly, we see a slight increase in *NSE* values for larger temporal scales of reference rainfall, although aggregation should reduce RG sampling errors. In our view, giving a larger weight to the RG data in the adjusting procedure increases the *NSE*, because the temporal scale of reference rainfall gets closer to the aggregation interval used for CML adjusting (for details see comment no. 11 of the reviewer 1). The results presented here do not, however, change our conclusions drawn in the original manuscript where we only presented the performance for 1 minute data. We therefore think it is sufficient to show only these results.

Q7: With regards to estimating area rainfall (section 2.2 and 3.2) I guess results are still compared on the minute scale and adjustment is performed on larges temporal scales. I guess this will be associated with many random errors if there is rain in one gauge and not in another? Again I suggest to also comparing e.g. hourly estimates of Rainfall.

A7: Yes, the discrepancy between rainfall measured by those RG layouts which were used for adjusting and those used for validation purposes (reference rainfall), indeed influences the performance of the adjusting procedure. Here, we reduce these errors by aggregating the RG data used for adjusting to longer intervals (up to 1 h). The performance of the procedure is then evaluated by comparing adjusted CMLs to the reference rainfall (i.e. RGs in the catchment). Thus, all rainfall observation errors which stem from RG layouts (including instrumental errors, sampling errors and limited spatial representativeness of point RG measurements) are implicitly included in the evaluation. The comparison at larger time scales would indeed reduce the sampling error in reference rainfall. However, as discussed in the reply above, their influence on the performance is small. Moreover, our adjusting procedure is only relevant where the temporal scale of reference rainfall (resp. adjusted rainfall) is finer than the aggregation interval used for CML adjusting. As we identified in our analysis that optimal aggregation intervals for the evaluated RG layouts are relatively short (15 min for layouts A1 resp. B1 and 1 h for layout B2), the comparison to e.g. hourly estimates is not useful.

Q8: Related to my comment no 4. I think it would be interesting to see a scatter plot of a single CML vs a single RG and how R^2 would depend on the range between CML and RG?

A8: Thank you for this suggestion. Unfortunately, although this might be an interesting analysis our experimental layout is not suitable for that. Each CML included in the analysis (see Fig. 1 in the manuscript) has different features (lengths, frequencies, polarizations) which considerably influences its performance in terms of rainfall estimation. The differences between single CMLs and a corresponding RG would be dominated by these differences. In our experience, the discrepancy between path integrated and point measured rainfall usually dominates the discrepancy due to different locations of the CML and the RG.

Q9: For the Dübendorf site it is unclear what you use the disdrometers for. Don’t you use the RGs for adjustment/validation? Related to the problem above, disdrometers might be more accurate for small rain intensities?!

A9: Thank you, we have modified the sentence at P5L27-28 to: "In addition, three tipping bucket RGs measure rainfall intensities which make it possible to validate the disdrometer data." Furthermore, we explain in the section 2.2 Rainfall data (P6L25-26) that “To validate the QPEs from CMLs, we use different reference rainfall information. For Dübendorf we take the mean of five disdrometers along the CML path (Fig. 1, right) and for Prague-Letnany the mean of the six RGs (Fig. 1, middle).”

Q10: P9L18-19. A likely reason for the smaller scatter on the 1 day aggregation levels might be found in the fact that all of your events (except one) have duration shorter than 1 day. Thus, for some events same results for 12 and 24 h should be expected!

A10: In our study we adjusted each CML over the whole experimental period, although it is evaluated only on events listed in the table 1. Thus for longer aggregation intervals also other events (with heights lower than 5 mm) influence the adjusting. This is also one of the reasons why CML adjusted with 12 h aggregation interval have different scatter than adjusted to 1 d aggregation interval.

We have therefore explained more clearly in the revised section 2.5 (Performance assessment) that: “CML QPEs are adjusted over whole experimental periods but evaluated only for rainfall events, which exceeded 5 mm in total and thus are relevant for stormwater management (Table 1).”

Q11: Figure 1. Please use lat/long or UTM rather than a local coordinate system.

A11: Thank you for the suggestion. We changed the coordinate system to UTM in the figure 1.

References:

Thorndahl, S., Nielsen, J.E., Rasmussen, M.R., 2014. Bias adjustment and advection interpolation of long-term high resolution radar rainfall series. Journal of Hydrology 508, 214–226. doi:10.1016/j.jhydrol.2013.10.056

Gauge-Adjusted Rainfall Estimates from Commercial Microwave Links

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Abstract. Increasing urbanization makes it more and more important to have accurate stormwater runoff predictions, especially with potentially severe weather and climatic changes on the horizon. Such stormwater predictions in turn require reliable rainfall information. Especially for urban ~~centers~~centres, the problem is that the spatial and temporal resolution of rainfall observations should be substantially higher than commonly provided by weather services with their standard rainfall monitoring networks. Commercial microwave links (CMLs) are non-traditional sensors, which have been proposed about a decade ago as a promising solution. CMLs are line-of-sight radio connections widely used by operators of mobile telecommunication networks. They are typically very dense in urban areas and can provide path-integrated rainfall observations at sub-minute resolution. Unfortunately, quantitative precipitation estimates from CMLs (QPEs) are often highly biased due to several epistemic uncertainties, which significantly limit their usability. In this manuscript we therefore suggest a novel method to reduce this bias by adjusting QPEs to existing rain gauges. The method has been specifically designed to produce reliable results even with comparably distant rain gauges or cumulative observations. This eliminates the need to install reference gauges and makes it possible to work with existing information. First, the method is tested on data from a dedicated experiment, where a CML has been specifically set up for rainfall monitoring experiments, as well as ~~many~~ operational CMLs from an existing cellular network. Second, we assess the performance for several experimental layouts of "ground truth" from RGs with different spatial and temporal resolutions. The results suggest that CMLs adjusted by RGs with a temporal aggregation of up to one hour i) provide precise high-resolution QPEs (rel. error < 7 %, ~~R^2~~ *Nash-Sutcliffe efficiency coeff.* > 0.75) and ii) that the combination of both sensor types clearly outperforms each individual monitoring system. Unfortunately, adjusting CML observations to RGs with longer aggregation intervals of up to 24 h has drawbacks. Although it ~~also~~ substantially reduces bias, it unfavourably smooth~~e~~s out rainfall peaks of high intensities, which is undesirable for stormwater management. A similar, but less severe, effect occurs due to spatial averaging when CMLs are adjusted to remote RGs. Nevertheless, even here, adjusted CMLs perform better than RGs alone. Furthermore, we provide first evidence that the joint use of multiple CMLs together with RGs also reduces bias in their QPEs. In summary, we believe that our adjustment method has great potential to improve the space-time resolution of current urban rainfall monitoring networks. Nevertheless, future work should aim to better understand the reason for the observed systematic error in QPEs from CMLs.

1 Introduction

Water-related issues are one of the major challenges of modern cities. Recently, more than 54% of World's population lives in urban areas and the number is continuously growing (United Nations, 2014). Increasing urbanization, together with undergoing weather and climatic changes stresses the importance of efficient urban water management for preventing flooding and at the same time controlling pollution and ensuring sanitation. Rainfall is ~~a~~ the main driver for many urban hydrological processes. Hence, reliable rainfall observations are crucial to informed decision making. Unfortunately, rainfall is very variable in both time and space, which makes it challenging to observe reliably. This is especially true for rainfall monitoring for urban stormwater management. Urban catchments usually consist of many small subcatchments with diverse land use characteristics. In cities, large fractions of impervious surfaces reduce the times of concentration and conduits, such as gutters, streets, etc., drain stormwater runoff very efficiently. Thus, runoff responses of urban catchments are usually very fast and greatly influenced by the spatial distribution and temporal dynamics of rainfall. Accurate predictions of rainfall-runoff, therefore, need rainfall information of high spatial and temporal resolution, which is difficult to get from point rain gauges (RGs) (Ochoa-Rodriguez et al., 2015).

~~Although the temporal resolution of RGs is adequate, t~~The spatial representativeness of point rainfall observations from RGs is, however, often limited, especially for those heavy storm events which determine the design of urban stormwater systems. At many places around the world, S-band and C-band weather radars have therefore become an integral part of operational networks of weather and hydrological services. They can capture rainfall structure at the mesoscale, however, typical spatial and temporal resolution of radar's gridded precipitation product (usually 5 minutes and 1 km^2) is too low for urban hydrological applications (Ochoa-Rodriguez et al., 2015). In addition, radars measure rainfall hundreds of meters above ground (1 or 2 km of altitude at 100 km), due to the elevation of radar beam and Earth curvature (Berne and Krajewski, 2013). Finally, local weather radars, which are capable of providing rainfall observations at sub-kilometer/minute resolution, are rarely available. In addition, the data quality of quantitative precipitation estimates from radar in the heterogeneous urban environment can be compromised by many influences from the urban topology and morphology (Tilford et al., 2002). The extensive growth of GSM and other wireless networks in the recent decade around the globe opens new perspectives to improve urban rainfall monitoring with non-traditional sensors. These are either cheap simple sensors specifically designed for rainfall sensing (e.g., Stewart et al., 2012), or other devices which are disturbed by or detect rain and hence provide indirect rainfall observations, such as commercial microwave links (CMLs).

A CML is a point-to-point radio system which connects two remote locations. A CML features radio unit and a directional antenna transmitting a radio signal from one site (near-end) to another (far-end), where the signal is received by yet another unit. CMLs are commonly used by mobile network operators as a wireless connection in their backhaul network, but also by internet providers, military, and others. CMLs transmit electromagnetic waves, therefore rainfall intensities can be retrieved in a similar fashion as for weather radars. One important difference is, however, that a radar measures power of echoes reflected by raindrops, whereas quantitative precipitation estimates from a CML (QPEs) are based on the rain-induced attenuation along its path (Atlas and Ulbrich, 1977).

Originally, the use of CMLs as rainfall sensors was suggested in the last century by Atlas and Ulbrich (1977). Interestingly, it has experienced a renaissance in the last decade with extensive growth of GSM network (Leijnse et al., 2007; Messer et al., 2006), and modern IT infrastructure, which makes it possible to actually collect data from hundreds or thousands of CMLs. First studies concentrated on algorithms for ~~spatial~~ spatial-temporal interpolation (Goldshtein et al., 2009; Overeem et al., 2013; Zinevich et al., 2008) from the joint analysis of multiple CMLs. Bianchi et al. (2013a, 2013b) have reported detection of malfunctioning RGs and improvement of radar observations by CMLs. The great potential of CMLs for ungauged regions was demonstrated by Doumounia et al. (2014). Interestingly, even though CML networks are most dense in urban areas, and thus are ideally suited for urban hydrological applications, there have been only very few investigations reported, which focus specifically on CML rainfall at the scale and resolution required for urban rainfall-runoff modeling (Fencl et al., 2013).

A CML network in urban areas is usually very dense with many short hops (< 1 km) which have the potential to capture rainfall with a high spatial resolution. On the other hand, network management systems are typically configured to monitor CML power levels once in 15 minutes, or even less often, which is insufficient for urban hydrological applications. Wang et al. (2012), however, showed that it is technically possible to poll CMLs with the sub-minute sampling frequency. Fencl et al. (2015) and Chwala et al. (2016) demonstrated the feasibility of this approach on a real network maintained by mobile operators. Unfortunately, the short CMLs are very sensitive to antenna wetting (Kharadly and Ross, 2001; Leijnse et al., 2008; Schleiss et al., 2013) which leads to substantial bias in their QPEs. Correcting this bias is, therefore, crucial for exploiting the potential of CMLs for urban hydrology.

1.1 Biased rainfall estimates from commercial microwave links

Rainfall sensing with CMLs is based on relating the level of rain-induced attenuation to the rainfall intensity integrated along the CML path. As both rainfall intensity and attenuation are moments of the drop size distribution (DSD), the relation between attenuation and rainfall can be approximated by a power law:

$$R = \alpha k^{\beta}, \tag{1}$$

where R [mm h^{-1}] is the rainfall intensity, k [dB km^{-1}] is the specific path attenuation caused by raindrops and α [mm h^{-1} km dB$^{-\beta\cancel{1}}$] and β [-] are empirical parameters depending on frequency, polarization of CML, and DSD (e.g. Olsen et al., 1978). For the frequency range of CMLs commonly used in cellular networks, the power law approximation leads to relatively low uncertainties in QPEs (Berne and Uijlenhoet, 2007), compared to the other uncertainties contributing to the specific path attenuation k Eq. (1), which are associated with microwave propagation and CML hardware (Leijnse et al., 2008; Zinevich et al., 2010). Unfortunately, the microwave path propagation is not only influenced by raindrop scattering and adsorption, but also by a variety of other phenomena such as the refractivity of air, gaseous attenuation, etc. which are often not measured directly. In addition, the additional signal power loss caused by the wetting of the antenna surfaces, the so-called wet antenna attenuation (WAA) is causing a systematic overestimation of rainfall. Several WAA models have been suggested to correct CML readings for this effect: from a simple empirically estimated offset (Overeem et al., 2011) to more complex semi-empirical models (Kharadly and Ross, 2001; Leijnse et al., 2008; Schleiss et al., 2013). Nevertheless, working with data from many hundreds of antennas, we experienced that the wetting and drying dynamics are complex processes which not only dependent on the individual antenna's material and characteristics (type and material of radome, surface coating, orientation, exposure to the wind, height over ground, etc.), but are also influenced by micro-weather and climate, such as local rainfall intensity, air humidity, wind speed and air temperature, to just name a few. Thus, it is generally difficult to correctly predict WAA for a specific CML because~~,~~ i) our mechanistic understanding is limited and ii) important input data are not available. Last, but not least, the reliability of rainfall-induced path-attenuation is also compromised by today's inaccurate radio unit hardware, which measures transmitted (*Tx*) and received (*Rx*) signal levels of radio waves with a quantization of up to 1 dB.

Such hardware-related influence factors are especially important for short CMLs. In general, CMLs shorter than 1 km could be potentially most informative for urban rainfall monitoring, because i) they could capture rainfall variability at the microscale and ii) their length corresponds with the dimensions of urban sub-catchments. Unfortunately, they are also less sensitive to rainfall, because they are comparably less attenuated by rainfall than long CMLs, simply because less scattering occurs along the short path. Consequently, they are more sensitive to hardware-related errors (WAA and radio unit accuracy) which are path-length independent and thus contribute relatively more to the specific attenuation k in Eq. (1) than the[MD1] errors associated with microwave propagation. In the future, we might have detailed models to predict hardware related errors for each of the thousand CMLs of a commercial operator's network. Up until now, the most feasible approach in our view is to compare, and possibly adjust CML estimated rainfall with ~~a~~ ground rainfall observations to identify and eliminate systematic errors in QPEs. However, to date, there is no established method how to best achieve this goal.

1.2 Adjusting rainfall estimates from commercial microwave links

As a first step, we reviewed the most relevant literature on adjusting rainfall radars. We found that i) most common adjustment methods are correcting the mean field bias of radar estimates to reference areal rainfall. The latter is usually calculated from point RG observations using a variety of interpolation methods (Smith and Krajewski, 1991), ii) the critical issue is the discrepancy between point RG observations, with a catch area of few dm^2, and areal rainfall estimated from radar measurements with pixel sizes in the order of 1 km^2, iii) this discrepancy is typically reduced by using multiple RGs and also by rainfall aggregation over longer intervals, typically one hour (Wilson and Brandes, 1979).

In this paper, we employ these findings to suggest a method for continuous adjusting of commercial CMLs to cumulative rainfall from RGs. It is intended especially for urban catchments where, according to our experience, RGs are often available, but do not provide QPEs of sufficient resolution needed e.g. for reliable rainfall-runoff modeling. The main novelty is that it is specifically tailored to the path-averaged attenuation of CMLs. Unlike radar reflectivity, this attenuation can be modelled by simplifying the power law of Eq. (1), as the β parameter of Eq. (1) is relatively close to unity.~~which makes the adjusting procedure less prone to overfitting.~~ Our results demonstrate that we can substantially reduce systematic errors from 50 % to about 7 %, which is very promising for the short CMLs in urban areas. In a fashion, our method can be viewed as a spatio~~-~~temporal disaggregation method for cumulative rain gauges based on the path-integrated high-frequent observations from CMLs. In our view, the combined use of CMLs and RGs has, therefore, a very good potential to improve the space-time resolution of current local rainfall monitoring, which is of great importance for various applications in urban hydrology. Moreover, it can contribute to our deeper understanding of rainfall behavior at the microscale and its implications for urban stormwater runoff.

The remainder of the paper is structured as follows: the Material and Methods section first describes the two experimental sites, second, presents our suggestions to simplify the power law model and, third, how it can be conditioned to local RGs. We also discuss suitable statistics for performance assessment. Then, we present the results from two experimental sites, where in total five CMLs were adjusted by cumulative rainfall during different time intervals and from several different RG layouts. Finally, we discuss our approximation of the k-R relation together with issues of model calibration and overall limitations of the adjustment approach and draw our conclusions.

2 Material & Methods

This section first describes the experimental sites, their instrumentation, and the experimental period in terms of rainfall events. Second, a simplified attenuation-rainfall model is proposed together with a procedure how to continuously adjust its parameters. Finally, we suggest suitable model evaluation procedure and statistics for performance evaluation.

2.1 Experimental sites

We analyse datasets from two different experimental sites, Dübendorf (CH) and Prague-Letnany (CZ). The dataset from Dübendorf contains detailed reference rainfall measurements along a CML path, which provide an excellent basis for investigating a rainfall from a single CML. In contrast, the areal rainfall observations from Prague are more appropriate to analyse rainfall retrieval from multiple CMLs and thus more relevant to evaluate the proposed adjusting method for common urban hydrological applications.

2.1.1 Dübendorf

The Dübendorf (CH) site represents an experiment where both CML and rainfall measurements were controlled to a high degree (Wang et al., 2012). The field campaign started in March 2011 and was maintained for more than one year. In th~~is~~e present study, we use experimental period from ~~between~~ June 2012 ~~and~~to September 2012.~~ During this period, 19 events exceeded 5 mm in total and thus are relevant for stormwater management (Table 1).~~ The experimental setup ~~It~~ consisted of a single commercial CML (MINI-LINK Ericsson) and an array of five laser precipitation disdrometers (Parsivel, OTT

Hydromet, Germany) placed along the CML path (Fig. 1, right). In addition, three tipping bucket RGs measure rainfall intensities which make~~s~~ it possible to validate the disdrometer data. The CML is a 38 GHz simple duplex dual polarized link, i.e. the CML transmits and receives both vertically and horizontally polarized radio waves in both directions (from near end to far end and vice versa). It is 1850 m long originating at Dübendorf's military airport and ending at military radar site at Wangen. The CML path is located mainly over green surfaces of the airport and agricultural land. Here, we used data from a period where the automatic transmit power control~~ (ATPC)~~, which maintains a constant received signal level (*Rx*) by adjusting the transmitted signal level (*Tx*) to minimize energy consumption and environmental radiation, was switched off. ~~In addition, to the five disdrometers, three tipping bucket RGs measure rainfall intensities which makes it possible to validate the disdrometer data.~~ For details~~, also~~ on data retrieval via SNMP and pre-processing, see Wang et al. (2012) and Schleiss et al.~~,~~ (2013).

2.1.2 Prague-Letnany

In the Prague-Letnany (CZ) site, CMLs are an integral part of the existing cellular network and their operation is fully subordinated to its primary telecommunication function. The experimental catchment Prague-Letnany is a small urban catchment. The catchment area is 2.3 km^2, being approximately 2.5 km long in SN direction and 1 km wide in WE direction (Fig. 1, middle). T-Mobile CZ, the mobile network operator which has kindly been supplying us with CML data, operates approx. 20 CMLs in the catchment (detailed view on CML network is provided in the supplementary material). The CMLs are located approx. 40 m above ground level and their network mostly follows a star-shaped design. Current *Rx* and *Tx* levels are polled from each CML via the SNMP protocol using server-sided java script and stored in a SQL database (Fencl et al., 2015). CMLs are polled in serial sequence, each approximately ~~5~~ five times per minute.

For the purposes of this study, we have selected four CMLs operating at frequencies 25, 32, and 38 GHz (Fig. 1), which were not affected by communication outages and whose lengths correspond to the length scales of the catchment and can, therefore, capture rainfall spatial variability at sub-kilometer scale. The selected CMLs are standard duplex links operated on MINI-LINK Ericsson platform with automatic transmit power control~~ATPC~~ configuration ~~(~~switched on during the whole experimental period~~)~~. The experimental period for the Prague-Letnany site was from June 2014 to October 2014.

~~"Ground truth"~~Reference rainfall observations are collected at four locations by six tipping bucket RGs (MR3, Meteoservis v. o. s., Czech Republic), two of them are collocated (Fig. 1, ~~left~~middle). Each RG is dynamically calibrated (once a year), and checked and maintained at least once a month. In addition, ~~six~~ five RGs from the operational rainfall monitoring network of the municipality are used (Fig. 1, ~~middle~~left) to test the effect of RG spatial layout on CML adjusting efficiency. These RGs are also dynamically calibrated (Stransky et al., 2007). All RGs are the same type with a catch area of 500 cm^2 and a quantization of 0.1 mm.

2.2 ~~Estimating areal rainfall from three different rain gauge layouts~~ Rainfall data

To validate the QPEs from CMLs, we use different reference rainfall information. For Dübendorf we take the mean of five disdrometers along the CML path (Fig. 1, right) and for Prague-Letnany the mean of the six RGs (Fig. 1, middle). The start of a rainfall event is set to the first observation and the end to the last observation of all sensors for a corresponding event. The minimum dry interval between events is taken to 30 minutes. In the case of Dübendorf, the events are defined based on disdrometer classification. As in Prague we use tipping bucket RGs the beginning of an event is estimated to 15 minutes before the first tip and the end to 15 minutes after the last tip. Furthermore, the beginning and end of each event in the Prague case study are rounded down to full hours for the start (and up for the end) to ease the analysis with aggregated rainfall intensities.

For the Prague case study, we also investigated in how far the limited spatial representativeness of RGs and the ~~together with~~ spatio~~-~~temporal ~~space-time rainfall peak averaging~~smoothing of peak rainfalls by the CML affect~~s~~ ~~the~~ the performance. To this aim~~performance of adjusted CMLs~~, we estimate three different ~~the~~ areal rainfalls, to which CMLs are adjusted, observed with~~from~~ three different ~~RG~~ rainfall monitoring layouts A, B1 and B2 (Fig. 1, left). The ~~L~~layout A is a single RG located inside the catchment. This is a typical configuration used by engineering companies when calibrating rainfall-runoff models of small urban catchments. Layouts B1 and B2 consist of three RGs located outside the catchment. In B1, RGs are relatively close to the catchment. They form a triangle with edge lengths of 7.0 km, 5.4 km and 2.8 km with the catchment area approximately in its center. In B2, the RGs are more distant and form a triangle with edges 11.5 km, 9.6 km and 8.2 km with the catchment closer to the NE vertices (Fig. 1, left).

~~2.3 Experimental periods~~

2.~~4~~3 Simplified attenuation-rainfall model

For frequencies between 20–40 GHz, i.e. frequencies often used by mobile network operators for shorter hops in urban areas, β parameter of equation (1) is relatively close to unity; according to ITU (2005) between 0.95 (20 GHz, vertical polarization) and 1.19 (40 GHz, horizontal polarization). To adjust CML continuously ~~in near real-time, equation (1) is especially by shorter links (less than 1÷2 km) not suitable because signal-to-noise ratio of CMLs is often low and power-law retrieval model (1) is prone to overfitting.~~

~~W~~we~~,~~ ~~therefore,~~ propose a ~~simple~~ simplified two-parameter ~~linear~~ attenuation-rainfall model which combines linear approximations of rainfall retrieval model (1) and models for wet antenna attenuation corrections (see section 4.1):~~which is intended for commercial CMLs between approx. 20–40 GHz, i.e. frequencies frequently used by mobile network operators for shorter hops in urban areas:~~

$$R = \begin{cases} \gamma(k - \Delta) & if\ k > \Delta \\ 0 & if\ k \le \Delta \end{cases} \cancel{\gamma(k - k_w)} \qquad (2)$$

where γ [mm h^{-1} km dB^{-1}] is an empirical parameter related to raindrop attenuation and other rainfall correlated signal losses, k [dB km^{-1}] is a specific attenuation after baseline separation and Δ~~k_w~~ [dB km^{-1}] is an offset parameter which corrects for wet antenna attenuation and possible bias introduced by inaccurate baseline identification. The parameter Δ is constrained, to avoid model to produce negative rainfall intensity. The piecewise linearity of the relation makes it possible to condition the model to rainfall and attenuation data which were aggregated over relatively long intervals (e.g., hours) and at the same time predict rainfall for attenuation data sampled at high frequencies.

The baseline for specific attenuation k is assumed to be constant during each wet period. First, we classify the data into dry and wet periods. Classification is performed according to Schleiss et al. (2010) using a moving window of the length of 15 minutes. Second, we take the 10% quantile of the total path loss values in the preceding dry weather period as the best estimate.

2.~~5~~ 4 Conditioning the simplified attenuation-rainfall model

First, RG rainfall intensities and CML attenuations are averaged to the same time resolution and appropriate aggregation intervals. The rainfall-attenuation model is then continuously fitted on aggregated data using moving window of N consecutive data points, i.e. for each time step i one set of model parameters (γ, Δ~~k_w~~) is identified. Only data points with non-zero rainfall are included into the calibration window as the model is designed for wet weather periods. We tested different window lengths (N = 3, 5, 10 points) and found that the optimal N in our case is five points (see section 4.1. for more details). In general, longer window (larger N) reduces sensitivity to the random noise but requires stronger stationarity of error models.

The model (2) is fitted by minimizing cost function L using a gradient method based on a quasi-Newton optimization algorithm L-BFGS-B implemented in the R language function `optim()` (Byrd et al., 1995):

$$L = \sum_{i-N+1}^{i} \left(\hat{R}_i - \tilde{R}_i\right)^2, \tag{3}$$

where $\hat{R}$ is observed aggregated RG rainfall and $\tilde{R}$ is rainfall produced by model (2). In this study, we carried out two consecutive optimization runs for each attenuation-rainfall time series. First optimization run (a) is implemented with wide parameter ranges and the second run (b) is performed with parameters constrained based on previous model realizations. For the first optimization run (a), lower limits of both parameters are set to zero. This avoids negative parameter values which do not have a physical meaning. The upper limit of the parameter γ is set to the ITU recommended value for parameter α in Eq. (1) (ITU, 2005) increased by 50 % to compensate for the effect of exponent β in Eq. (1) during heavy rainfalls. The upper limit of the parameter Δ~~k_w~~ is set proportionally to the inverse of CML length (5 dB km^{-1}), which corresponds approximately to wet antenna attenuation offsets reported by Leijnse et al.~~,~~ (2008).

New parameter ranges for optimization run (b) are estimated from parameter distribution of run (a): i) parameter values settled at upper limit are removed, as these are likely to be associated with outliers, ii) only parameters associated with a specific attenuation k > 1 dB km^{-1} are considered, iii) new parameter ranges are set from the remaining values as 5 % and 95 % quantiles.

When conditioning model (2) on historical data, parameter ranges can be set on the basis of the whole available dataset. For real-time application ranges have to be estimated from past periods.

2.~~6~~ 5 Performance assessment[MF2]

We evaluate ~~The performance of tT~~the adjusting method ~~is evaluated~~ by directly ~~comparison~~ comparing ~~of CML~~ QPEs ~~with~~ to reference rainfalls (Fig. 1, middle and right), both with a temporal resolution of one minute~~, both having a one-minute resolution~~. QPEs are adjusted over the whole experimental periods but evaluated only for rainfall events, which exceeded 5 mm in total, i.e., they are relevant for stormwater management (Table 1). The adjustment is performed in the setting for historical rainfalls. In addition, results are compared with unadjusted CMLs processed by standard models with fixed parameters. The performance of the algorithms is evaluated for each event and each single CML. In the case of Prague also mean rainfall from all four CMLs is evaluated.

2.5.1 Rainfall estimation settings

First, we explore whether the proposed adjusting method can be used to disaggregate cumulative rainfall data, such as hourly or daily values, to one--minute data.~~, is studied The effect of rainfall aggregation on CML adjusting is investigated on four CMLs from T-Mobile's network in Prague-Letnany (CZ) and one commercial CML operated for experimental purposes in Dübendorf (CH) (Fig. 1, middle and right).~~ We adjust the CML to cumulative rainfall during 5 min, 15 min, 30 min, 60 min, 3 h, 6 h, 12 h, and 1 d and evaluate the performance of retrieving one-minute rainfall data. ~~In this investigation, w~~We use the same RGs ~~used~~ for ~~CML~~ adjustment and performance ~~are also reference RGs against which CMLs are~~ evaluat~~ed~~ion (Fig. 1, middle).

Second, we investigate ~~T~~the influence of the ~~RG~~ spatial layout of RGs on CML adjusting ~~is tested on~~ on the ~~data from~~ Prague case study ~~only~~ (Fig. 1, left). We test several aggregation intervals (5 min, 15, min, 30 min, or 1 h) for each RG layout (A, B1, and B2) to identify the optimal interval which improve, on the one hand, the spatial representativeness of RG observations, but on the other hand does not substantially smooths out rainfall peaks.

Third, ~~T~~the QPEs from unadjusted CMLs are calculated using a standard power-law model (1) and wet antenna corrections with fixed parameters. The Prague CMLs are corrected for wet antenna attenuation using the constant correction as suggested by Overeem et al. (2011). The Dübendorf CML is corrected for wet antenna attenuation by a specific model suggested by Schleiss et al. (2013). Both power-law and wet antenna attenuation models are applied under two scenarios: S1) with parameters from literature (ITU, 2005; Overeem et al., 2011; Schleiss et al., 2013) and S2) with local parameters inferred from the available reference data.

2.5.2 Performance statistics

The ~~performance of the algorithms is then evaluated for each event. First, the coefficient of determination~~Nash-Sutcliffe efficiency coefficient (~~R^2~~*NSE*) is used to evaluate the ability of CMLs to capture rainfall temporal dynamics. ~~R^2~~ *NSE* is a relative measure which gives comparable results of CML performance even for events of different characteristics. Second, the systematic deviations of CMLs are assessed by plotting their QPEs against reference RGs and evaluated quantitatively by the slope of a linear regression model without intercept~~(linear trendline intersect. set to zero).~~ In addition, the relative error in cumulative rainfall is calculated for each single event as the relative difference between the QPEs and reference rainfall amounts.

3 Results

First, the performance of CMLs when adjusted with rainfall of different time resolution is presented. Both results from Dübendorf (CH) and Prague-Letnany (CZ) are shown (Fig. 2 and 3). Second, the influence of different RG layouts on CML adjusting is demonstrated on Prague's dataset (Fig. 4 and 5). Finally, QPEs from adjusted CMLs are compared with the application of standard attenuation-rainfall models (Fig. 6). The CML performance is in all three cases evaluated on data with ~~one~~ one-minute temporal resolution.

3.1 Influence of different aggregation intervals

The performance of CMLs adjusted by rainfalls aggregated to 5 min, 15 min, 30 min, 60 min, 3 h, 6 h, 12 h, and 1 d intervals is presented below. Relative error in cumulative rainfalls and ~~R^2~~*NSE* is shown for each link and aggregation (Fig. 2). In addition, for Prague-Letnany, the mean QPEs from all CMLs are evaluated.

It can be seen that the continuous adjustment performs well for aggregation intervals up to one hour (rel. error < 7 %, ~~R^2~~*NSE* > 75 %). CML QPEs adjusted to (sub)hourly data are associated with low systematic errors and reliable rainfall intensities over the whole range from light to heavy rainfall (Fig. 2). We only find a slight underestimation of high intense peaks (Fig. 3), which might be due to mismatch between point and path-averaged observations. The best performance is achieved when the QPEs from all CMLs are averaged. This is probably due to the reduction of random errors~~,~~ when nearly unbiased rainfall information from multiple sensors is merged. In addition, multiple CMLs cover the catchment area better than a single CML.

The performance of the adjustment algorithm substantially decreases when aggregation interval is increased from 1 h to 3 h and then further to 6 h and 12 h (Fig. 2, ~~R^2~~*NSE*). This is probably associated with the extent to which rainfall autocorrelation characteristics are preserved when aggregating rainfall data to coarser time resolution (Appendix A~~, Fig. A1~~). Hourly aggregations still seem to correspond relatively well to the temporal scale of rainfall peaks, whereas three-hour sums already often smooth~~es~~ out peak intensities by averaging them over periods ~~with~~ of low-intensity or zero rainfall (Fig. A1). This averaging probably impacts the identifiability of the parameters of the simplified model (2).

When evaluating systematic errors for each event separately its variability is increasing with increasing aggregation interval up to 12 h. Surprisingly, adjusting CMLs to daily rainfall volumes leads to less variable results, although more biased in average (Fig. 2 and 3). This might be caused by the correlation structure of rainfall, where the correlation between peak intensities is better preserved by daily than 12 hours aggregations (Appendix A, Fig. A1). ~~In addition, fluctuations of CML baseline have, according to our experience, a daily pattern and thus rainfall with daily resolution can be appropriate to minimize the effect of these fluctuations.~~

For the Dübendorf data, the method also does not perform well for long aggregation intervals > 1 h (Fig. 2 and 3). However, here the mismatch most probably stems from the different effect: antenna wetting attenuates the transmitted signal for up to six hours after rainfall has stopped (Fig. 2 in Schleiss et al., ~~(~~2013~~)~~). Aggregating these dry weather periods with increased attenuation over longer time intervals then causes substantial error in adjusted QPEs, because this process is not considered in the simplified model. Interestingly, we find that the drying times of CMLs from Prague-Letnany are considerably shorter, mostly within few minutes. The reasons for this effect are not known.

3.2 Influence of different rain gauge layouts

The performance of the algorithm for different RG layouts is evaluated on the Prague-Letnany dataset. For each layout, the rainfall was aggregated to 5 min, 15 min, 30 min, and 1 h time resolution. We found that the best performance was achieved by averaging all four short CMLs located in the catchment - for all RG layouts. The performance of single CMLs is slightly worse. The relative differences between QPEs from single CMLs and from their averages are in very similar proportions by all CMLs as when adjusting to reference rainfall (see the previous section). Therefore, only the performance of averaged QPEs from all four CMLs is presented.

Layout A: CMLs adjusted by the single RG located in the catchment measure very well both light and heavy rainfalls - with the exception of slight underestimation of high-intense peaks over 30 mm h^{-1} (Fig. 4). The median systematic error of CML QPEs corresponds to the bias of the single RG (Fig. 5). Nevertheless, adjusted CMLs clearly outperform a single RG in terms of capturing rainfall temporal dynamics. The median ~~R^2~~*NSE* of CMLs is between 0.85 and 0.87 where the highest ~~R^2~~*NSE* (0.77–0.94) is obtained for an aggregation interval of 15 min. The inter-event variability of ~~R^2~~*NSE* slightly increases for longer aggregation intervals reaching values 0.70–0.90 for 1 h. These are much higher values of ~~R^2~~*NSE* than those reached by the RG layout A alone, 0.52– 0.78 with median 0.68 (Fig. 5).

Layout B1: CMLs adjusted to three rain gauges close to the catchment perform slightly worse than CMLs adjusted by the layout A. In Fig. 4, a systematic underestimation of intense rainfalls is visible. It is most pronounced for intensities exceeding 30 mm h^{-1} and, in contrast, light rainfalls are overestimated by the CMLs. The bias in RG areal rainfall used for adjusting (evaluated for each event separately) varies substantially more than the one from the layout A. This also leads to a higher variability in the systematic error of QPEs. Interestingly, ~~R^2~~*NSE* for the CMLs (Fig. 5) is only slightly lower (median is between 0.80 and 0.84) than for CMLs adjusted by the layout A, but has a higher variability. The best performance is achieved for 15-min aggregation interval with the narrowest range of relative errors in cumulative rainfalls (-0.32–0.25) and a[MD3] ~~R^2~~*NSE* (0.68– 0.94).

Layout B2: We find that CML which are adjusted to three distant rain gauges reliably capture light and moderate rainfalls but substantially underestimate heavy rainfall peaks (Fig. 4). Systematic errors and inter-event variability are only slightly higher than for layout B1. As expected, for the distant gauges the best performance in terms of ~~R^2~~*NSE* value and its variability is achieved for longer aggregation intervals. The ~~R^2~~*NSE* for adjustment with hourly aggregation intervals ranges between 0.50–0.91 with median 0.78. The poor performance for 5 min aggregation intervals (low values of ~~R^2~~*NSE*) can be explained with both the underestimation of high intense rainfall peaks and errors in the “ground truth”, because at the spatial scale of RG layout B2 aggregation interval of 5 min is insufficient to average out discrepancies between point and areal rainfall intensity.

In summary, the optimal aggregation interval to adjust CMLs for a given catchment and RG layout increases with larger RG-CML and RG-RG distances. This is, because of time aggregation, in general, improves the spatial representativeness of point RG measurements (Villarini et al., 2008). However, computing areal rainfalls over increasingly large area also increasingly smoothes out rainfall peaks, which propagates also to CML adjusted QPEs. Therefore, CMLs adjusted to relatively distant RGs perform the worst in comparison with the other RG layouts. Considering the performance of RGs alone, the benefit of using the RGs in combination with CMLs is clearly visible (Fig. 4 and 5) even in the case of layout B2 with RGs relatively distant from the catchment. Although we can demonstrate the effect of peak averaging with our experimental data, further research is needed to adjust CMLs to remote RGs while preserving peak rainfall intensities.

3.3 QPEs from unadjusted CMLs

To demonstrate the need for an effective adjustment procedure, standard k-R power-law (1) and wet antenna attenuation models with fixed parameters were used to retrieve QPEs from unadjusted CMLs according to the state-of-the-art (Overeem et al., 2011; Schleiss et al., 2013). The results are presented for two simulation scenarios S1) model parameters taken from literature (ITU, 2005; Overeem et al., 2011; Schleiss et al., 2013), and S2) parameters obtained by fitting models to the reference dataset.

First, the results for scenario S1 show a positive bias for the QPEs from Prague-Letnany, which on average is about 50 %. This bias leads to the unsatisfactory performance of single CMLs also in terms of ~~R^2~~*NSE*. The averaging of observations from four CMLs cannot compensate for this bias and thus cannot substantially improve the ~~R^2~~*NSE*, which measures the reliability of the retrieval model. Second, the QPEs from the Dübendorf CML are much more reliable both in terms of smaller systematic deviations and a large ~~R^2~~*NSE*. In addition, variability is low, which means that it performs well even for very light and extremely heavy events. This is due to the extremely good reference data, which made it possible to tailor a custom model for wet antenna attenuation correction for this particular CML (Schleiss et al., 2013).

For scenario S2, model fitting leads to substantial reduction of bias in Prague-Letnany CML observations, in contrast to that, the bias of the Dübendorf CML remains almost unchanged. This reduction leads to a much better ~~R^2~~*NSE*. The best performance in terms of ~~R^2~~*NSE* is achieved for QPEs calculated as a mean from all Prague-Letnany CMLs. The ~~R^2~~*NSE* of Dübendorf CML is comparable to the value when scenario S1 was used (Fig. 6).

The unadjusted QPEs from Prague CMLs in scenario S1 are substantially less reliable than QPEs from any adjusted CML presented above (Fig. 2, 4, and 6). The performance of Prague CMLs treated with models with optimal parameters (S2) corresponds approximately to the CMLs adjusted with three hours cumulative rainfalls (Fig. 2) or adjusted by RG layout B2 (Fig. 4). The performance of unadjusted Dübendorf CML (for both scenarios) corresponds, similarly as in Prague-Letnany, to adjustment to an aggregation interval of 3 h (Fig. 2).

The relatively bad performance of unadjusted Prague-Letnany CMLs under scenario S1 compared to Dübendorf CML is partly caused by their short paths (1020 m, 650 m, 1400 m, and 610 m, compared to 1850 m). In addition, the automatic power control, which was switched off for the Dübendorf CML, also reduced the performance. We found that automatic power control worsens the quantization of CMLs (as *Tx* has about three times lower quantization than *Rx*) and thus one can learn less from observations about the parameters of the retrieval models, especially from short CMLs. An automatic power control as a standard feature of today's CMLs needs to be considered when modern CML networks are used for rainfall monitoring. The results, however, indicate, that combining rainfall observations from multiple unbiased (or slightly biased) CMLs reduces such random errors by averaging and thus improves QPEs for areal rainfall.

4 Discussion

The goal of this study was to suggest a procedure to adjust QPEs from CMLs to local rain gauges and to demonstrate the benefits over current retrieval methods. We obtained very promising results, with relative errors of a few percent. Although this is ~~ese are promising~~ truly encouraging, ~~results~~ we would like to discuss, first, errors associated with the piecewise linear approximation of attenuation-rainfall model Eq. (2) and WAA models~~ and~~, second, how to condition the model (2) to local RG observations and, third, the application of adjusting algorithm in (near-) real-time setting. ~~Third~~Finally, we would like to discuss limits of the proposed adjusting algorithm, e.g. regarding the preservation of peak rainfalls.

4.1 Linear approximation of the power-law retrieval model

The model (2) can be interpreted as a combination of linear forms of an attenuation-rainfall model (1) and a WAA model~~s~~. The uncertainty due to the simpler model structure of Eq. (2) is ~~comparable~~[jR4] similar especially for shorter links ~~with~~ to quantization of CML readings. To illustrate this effect, we compare the results for Eq. (1) and Eq. (2) by predicting specific attenuations for rainfall intensities from 0 to 60 mm h^{-1}. The power-law model uses the ITU parameters (ITU, 2005), the ~~linear~~ simplified model is fitted to the results of the power-law model by minimizing the maximal absolute deviation. In Fig. 7, the results for 38 GHz CML are shown, because the deviations for 38 GHz are larger than for 25 and 32 GHz due to the relatively high value of exponent beta (1.13) for vertically polarized 38 GHz CML. The deviation between the power-law model and simplified model are between ± 1.5 mm h^{-1}, which corresponds to a specific attenuation of approx. 0.5 dB km^{-1}.

The deviation between WAA models and appropriate linear approximations depend on their character. E.g. the WAA model of Overeem et al.~~,~~ (2011) is only based on a single additive parameter and is thus fully included in our model through the parameter Δk_w. Interestingly, a linear approximation of the coupled attenuation-rainfall model (1) and Kharadly's WAA model (Kharadly and Ross, 2001), which describes WAA as an exponential function of rainfall intensity, leads to considerably higher deviation (Fig. 7, middle). The deviation can be, however, substantially reduced by fitting the ~~linear~~ simplified model over a narrow range of attenuations, resp. rainfall intensities. For example, the right panel of the Fig. 7 shows two linear models fitted separately for lighter (R ≤~~<=~~ 12 mm h^{-1}) and heavier rains (R > 12 mm h^{-1}). The absolute deviation between the linear approximations and the original model is less than one third compared to the linear fit over a whole range of rainfall intensities (Fig. 7, middle).

When fitting the simplified model Eq. (2) continuously over relatively short periods, it is likely that the rainfall intensities covered by the calibration window will vary in narrow ranges resulting in relatively small errors introduced by the linear approximation. However, although the length of the calibration window reduces the effect of random errors, its optimal length also depends on the stationarity of CML errors. This stationarity ~~which in turn~~ depends on characteristics of the rain event, the CML hardware, and the local environment (see introduction). For both experimental sites, we identified the window length of five points as an acceptable compromise between window length and the temporal variability of rainfall.

4.2 Attenuation-rainfall model fitting

The time aggregation of rainfall and attenuation data smooth~~e~~s out rainfall peaks. This leads to narrower intervals of likely parameter values and especially lowers the upper bound of resulting parameter estimates. As an example, the resulting parameter distributions are shown here for the CML 2 (Prague-Letnany) when adjusted to rainfalls for different aggregation intervals (Fig. 8). The peak averaging reduces the width of the parameters distribution and thus limits the ability of the model to predict high rainfall-intensities, which are mostly associated with large values of γ. A similar tendency can be seen for spatial averaging when CMLs are adjusted based on areal rainfall estimated from RGs which cover a larger region.

The substantial difference in values of γ[jR5] ~~parameter~~ (Fig. 8) compared to ~~parameter~~ α of the model (1) suggested by the ITU (ITU, 2005) is caused by the conceptual difference between the two models: Our suggestion ~~Proposed model~~ (2) is a combination of wet antenna attenuation model and a simplified standard power-law model. ~~Such d~~Discrepancies regarding the ITU model were ~~γ was already~~ also reported by Fenicia et al. (2012), who estimated for their 23 GHz link values of α substantially lower than values suggested by ITU. Interestingly, comparably lower values of γ make even shorter CMLs relatively sensitive to rainfall and thus capable ~~to~~of detecting even light rainfalls.

4.3 Adjusting CMLs to RGs in (near-) real-time

The results sections 3.1 and 3.2 correspond to an "offline" setting, where historical rainfalls are analysed[jR6]. For practice, it would be even more valuable to have QPEs available in (near-) real-time. In our case, as the suggested model (2) does not use observations from the future ~~only uses past observations~~ (Eq. 3) and is computationally fast, it is generally real-time capable. However, suitable parameter ranges, which we here estimated from the whole dataset, would then only be available from past periods.

The ~~I~~initial investigation regarding the real-time capabilities suggests some shortcomings of the algorithm to deliver reliable results, especially at the beginning~~s~~ of rainfall events. To some degree, this is because aggregated data (e.g., hourly or daily sums) by definition arrive with a substantial delay. Interestingly, when adjusting in real-time to remote RGs with short sampling intervals the performance is comparable to the results shown in section 3.2. In our view, this is~~,~~ because the aggregation can be performed continuously. Besides retrieval algorithms, future developments towards effective real-time QPEs from CMLs should also target efficient data collection and transmission, server interoperability, data formats and strategies to deal with the continuously changing network topologies.

4.~~3~~ 4 Limits of the proposed adjustment method

In our study, we focus on urban rainfall monitoring and adjust CMLs with path lengths fewer than 2 km. For these CMLs, adjusting to "ground truth" measurements with aggregation intervals up to one hour is accurate and only slightly underestimates high intense rainfall peaks. The use of rainfalls with longer aggregation intervals, e.g. from 3 h to 1 d, however, leads to systematic underestimation of high intense rainfalls and slight overestimation of low intense rainfalls (Fig. 2 and 3). We have found a connection between this systematic discrepancy and the extent to which rainfall autocorrelation is preserved in the aggregated rainfall (Fig. A1). Nevertheless, further research is needed to develop a method which would correct these systematic errors based on the spatio~~-~~temporal correlation of rainfalls in the region of interest.

The performance of the proposed adjustment method is also dependent on the spatial layout of the "ground truth" measurements. The spatial averaging, similarly as time averaging, smoothes out rainfall extremes, i.e. layouts where the RGs are further away from the CML or each other, tend to underestimate rainfall peaks. Even worse, these larger distances cause bias in the "ground truth" observations, because the probability increases that distant gauges completely miss (or hit) actual peak intensities. The optimal aggregation interval for layout B2 was 1 h, whereas the optimal interval for A and B1 was only 15 min. This is~~,~~ because longer time averaging reduces discrepancies between areal and point rainfall estimates. The factor to which high intense rainfalls are systematically underestimated corresponds quite well with the areal reduction factor reported in literature (e.g., Department of Environment National Water Council Standing Technical Committee, 1983). ~~Hydraulics Research, 1983).~~This indicates that the systematic underestimations associated with areal averaging might be reduced based on climate-specific rainfall characteristics. An interesting idea is to directly infer the spatio~~-~~temporal variability of a certain rain event from the observations of many CMLs. However, further research is needed to incorporate these features into an improved adjustment procedure.

Last, but not least, the reliability of the adjustment corresponds to the reliability of the "ground truth" observations. One possibility to ensure good reference data could be to use CMLs to eliminate gross errors, e.g. by identifying malfunctioning RGs (Bianchi et al., 2013b) and excluding them from CML adjustment. Another possibility, which should be investigated in the future, is to use longer CMLs of appropriate frequencies instead of RGs in the adjustment. As argued in section 1.~~2~~1, these long CMLs are less sensitive to hardware and environmental influence factors. Nevertheless, our personal experience after working several years with signal attenuation from many operational CMLs is that it happens rather often that CML data show erratic and seemingly random behavior and that the response to rainfall does not always correspond to a power-law relationship. While we at this time can only speculate about the reasons, it is crucial to carefully select and test those long CMLs which should serve as a reference.

5 Conclusions

Commercial microwave links (CMLs) can ~~measure rainfall in sparsely gauged regions and~~ improve the resolution of existing rain gauge and radar networks, especially in populated areas where they are often very dense. Quantitative precipitation estimates (QPEs) from CMLs as rainfall sensors are, however, affected by various uncertainties, which are still too poorly understood to build effective signal-processing algorithms based on CML observations alone. In this paper, we, therefore, suggest a generic method to adjust CML QPEs to aggregated observations from existing RGs such as 15min or hourly averages:

- Our results demonstrate that standard commercial CMLs operated by mobile network operators can be used as powerful sensors for capturing rainfall variability at (sub)minute scale. Combining the high-resolution observations from CMLs with the reliable cumulative observations from RGs enables us to derive reliable QPEs of high temporal resolution and very good spatial representativeness. Thus, our method can also be seen as a method for spatio~~-~~temporal disaggregation of cumulative RG measurements based on CML attenuation.
- We propose a simplified semi-empirical model for CML rainfall estimation which combines microwave attenuation from rain and antenna wetting into one piecewise linear relation. The model can be easily continuously adjusted to rainfall from existing RG networks in operational conditions, even though RGs may have a low spatial coverage and temporal resolution. The model is intended for short CMLs (path length ≈ 1÷2 km or less) operating at frequencies approx. between 20-40 GHz, where the model structure errors from the linearization are much smaller than other influence factors, such as for example the quantization of CML attenuation. These CMLs are crucial for capturing rainfall space-time structure at the fine scale required for urban hydrological applications.
- Our simple and robust approach performs very well for CMLs adjusted by rainfall with aggregation intervals up to one hour. Adjusting CMLs with longer aggregation intervals, however, leads to systematic underestimation of high intense rainfalls and slight overestimation of low intense rainfalls. We have found a connection between this systematic discrepancy and a degree to which autocorrelation structure is preserved in aggregated rainfall data.
- We have demonstrated on three different RG layouts that the CMLs adjusted by the RGs provide substantially better areal QPEs than the RGs alone. However, RG layouts which cover larger areas, e.g. approx.

10÷100 km^2, tend to underestimate rainfall peaks and slightly overestimate light rainfalls, which is similar to the effect observed by temporal averaging. We have found that the underestimation is proportional to the areal reduction factor reported in the literature.

- Further research towards an improved adjustment method which reduces systematic discrepancies in adjusted CML QPEs by explicitly considering space-time characteristics of rainfalls seems very promising. The rainfall space-time structure might be incorporated in the model by correction factors based on either local climatology or by directly estimating it from the response of the CML network itself. The latter seems especially interesting for ungauged regions, where longer CMLs might provide reliable reference rainfall to correct shorter CMLs.

The proposed approach overcomes one of the biggest shortcomings of commercial CMLs as rainfall sensors for practical use in the urban hydrological application: the calibration of CML rainfall estimation models to site-specific conditions.

The adjustment of CMLs to cumulative rainfall from point ground measurements has a huge potential especially for urban catchments, where the CML network is commonly very dense. The combined use of RGs and CMLs can thus greatly improve the spatial and temporal resolution of existing rainfall products and contribute to better understanding urban ~~rainfall~~ rainfall-runoff processes, which are often hampered by poor rainfall data. Moreover, the insight into rainfall space-time structures at (sub)minute and (sub)kilometer resolution can contribute to deeper understanding of rainfall behavior at the microscale.

Appendix A: Temporal rainfall aggregation

Aggregating rainfall over time reduces the discrepancies between point, path-averaged, and areal rainfall, but also smoothes out rainfall dynamics (Villarini et al., 2008) which would make it possible to better identify attenuation-rainfall model parameters. The effect of rainfall intensity averaging when increasing the aggregation interval is demonstrated on the rainfall data from our reference RGs in Prague-Letnany (CZ). The original rainfall time series with one-minute resolution (Fig. A1, top row) is aggregated over eight different integration times from five minutes (second row) to one day (bottom row). The resulting time series are compared with the original one. Only periods belonging to events listed in ~~the~~ Table 1 are selected, which restricts the analysis only to rainy periods with significant intensities. The right panel of Fig. A1 shows the correlation between entire time series (blue) and the correlation between rainfall intensity maxima of each event (red). It can be seen that the temporal aggregation up to one-hour preserves the main characteristics of rain events in Prague very well, e.g. high-intensity convective rainfalls can be recognized from low-intensity frontal rainfalls.

Competing interests

The authors declare that they have no conflict of interest.

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Table 1 – Rainfall events selected for the evaluation at Prague-Letnany site, CZ in 2014 and Dübendorf site, CH in 2011. The maximal intensity *R_max* and the total rainfall amount *H* are provided for each event. Short convective rainfalls with peak intensities up 90 mm h^{-1} and long low-intense stratiform rainfalls are included in the datasets.

Prague-Letnany, CZ				*Dübendorf, CH*			
Beginning (2014)	Duration [min]	*R_max* [mm h^{-1}]	*H* [mm]	Beginning (2011)	Duration [min]	*R_max* [mm h^{-1}]	*H* [mm]
21 Jul 15:01:00	600	19.1	13.7	13 Jul 13:55:00	330	7.7	14.0
11 Aug 01:01:00	780	5.6	7.7	17 Jul 06:30:00	620	5.5	9.2
14 Aug 14:01:00	180	38.7	5.0	19 Jul 13:55:00	430	5.5	10.5
16 Aug 13:01:00	180	24.5	5.3	23 Jul 23:30:00	225	11.2	8.2
26 Aug 21:01:00	720	5.2	8.7	27 Jul 13:30:00	90	24.0	5.2
01 Sep 13:01:00	1200	2.7	12.9	27 Jul 17:20:00	125	22.7	5.9
11 Sep 13:01:00	1560	59.7	40.5	05 Aug 18:00:00	150	76.5	18.7
14 Sep 16:01:00	240	13.5	7.3	07 Aug 05:40:00	165	14.4	5.7
21 Sep 19:01:00	420	8.6	7.3	14 Aug 23:25:00	290	19.0	9.2
13 Oct 22:01:00	600	18.2	18.1	15 Aug 11:00:00	140	92.4	20.6
16 Oct 03:01:00	420	22.7	6.6	24 Aug 16:50:00	280	9.9	10.9
21 Oct 21:01:00	300	11.4	6.3	26 Aug 23:40:00	305	8.9	12.7
22 Oct 10:01:00	420	4.8	6.5	01 Sep 03:10:00	110	54.0	5.9
				03 Sep 19:00:00	220	75.4	9.8
				04 Sep 14:40:00	360	18.2	16.3
				04 Sep 22:15:00	245	17.7	5.8
				14 Sep 02:25:00	275	13.8	8.5

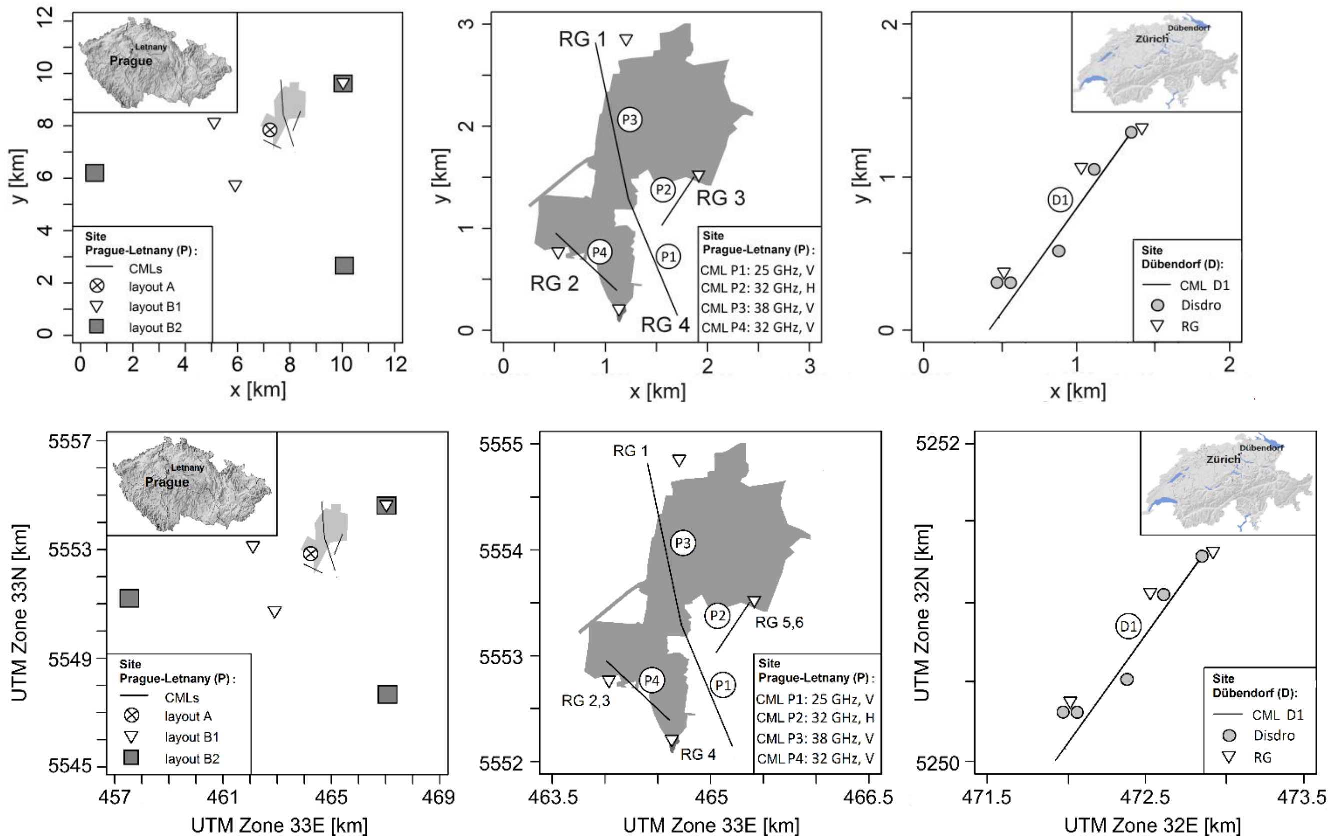
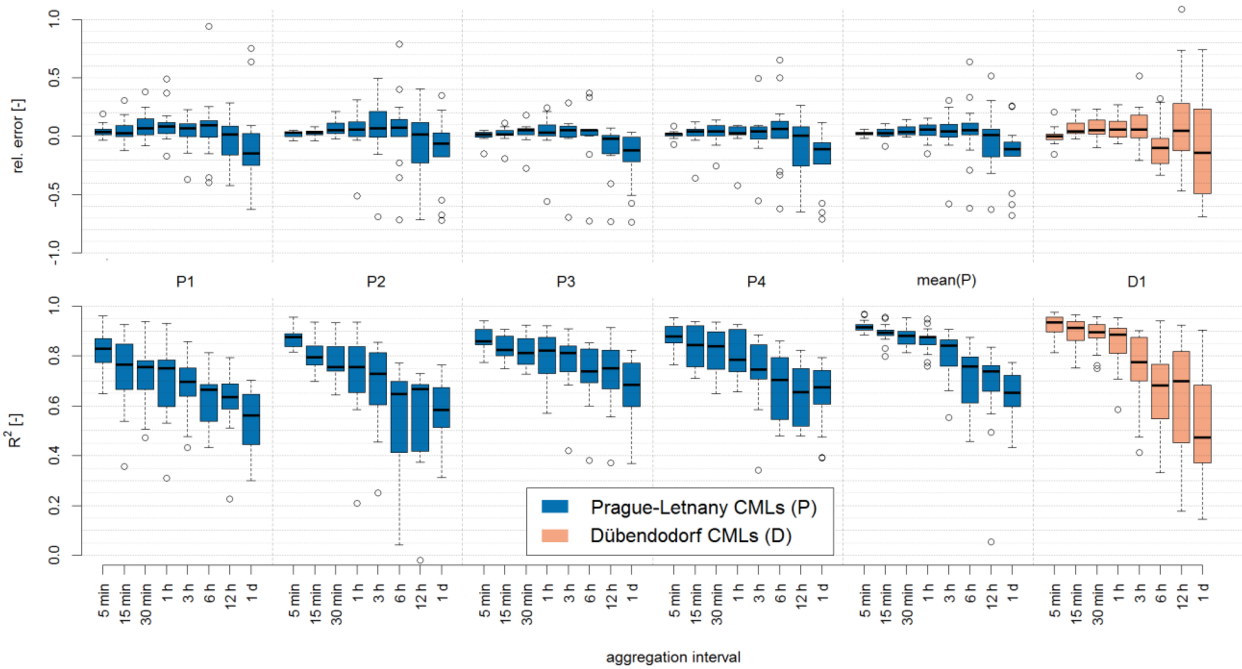


Figure 1: Experimental sites Prague-Letnany, CZ (left and middle) and Dübendorf, CH (right). Left: Overview CZ, RG layouts used for CML adjusting. Middle: Detailed view on CZ, CMLs and reference RGs. Right: Detailed view on CH, CML and the layout of reference disdrometers and RGs.



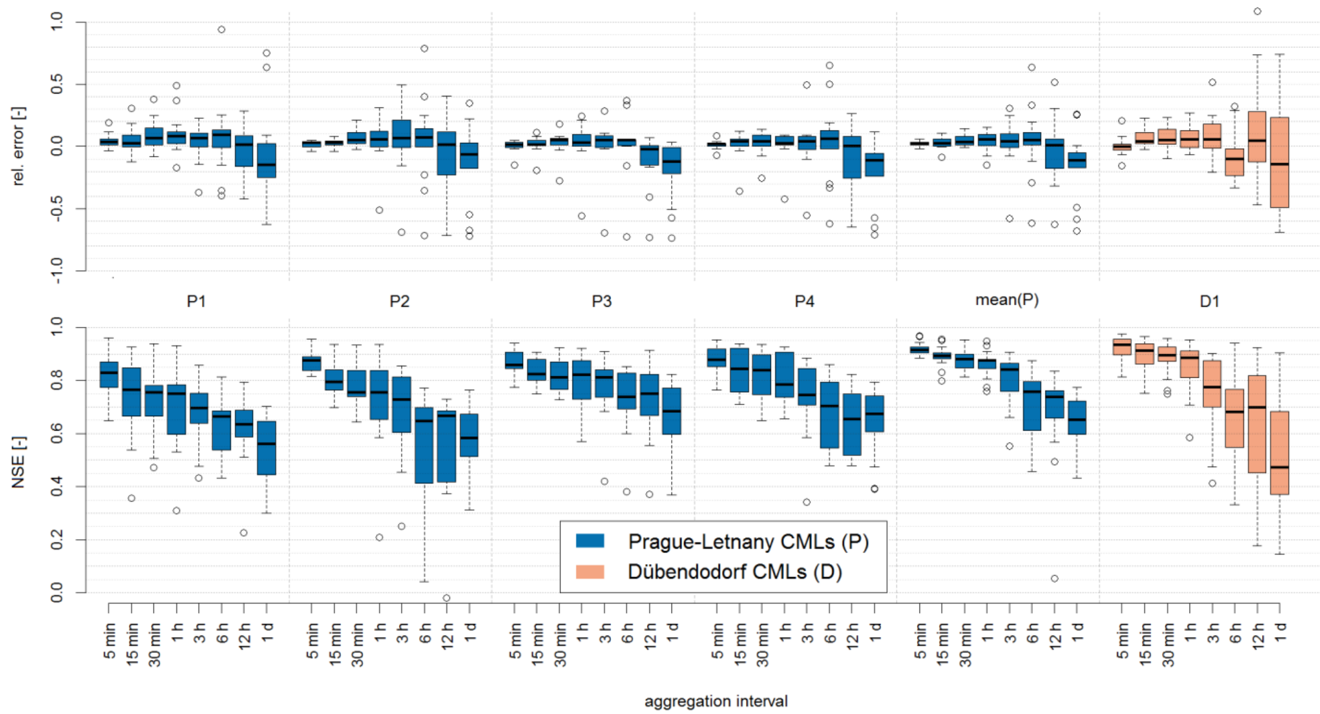


Figure 2: Relative error (top) and ~~R^2~~-NSE (bottom) in QPEs of CMLs adjusted by rainfall data of different time resolution. Each CML layout is represented by eight boxplots corresponding to QPEs adjusted by rainfall aggregated to time intervals from 5 min to 1 d. Each boxplot depicts a range of the statistics during all evaluated events. Five groups of blue boxplots (left) evaluate QPEs from single CMLs and from their average at Prague-Letnany. One group of orange boxplots (right) depicts QPEs from a single CML at Dübendorf.

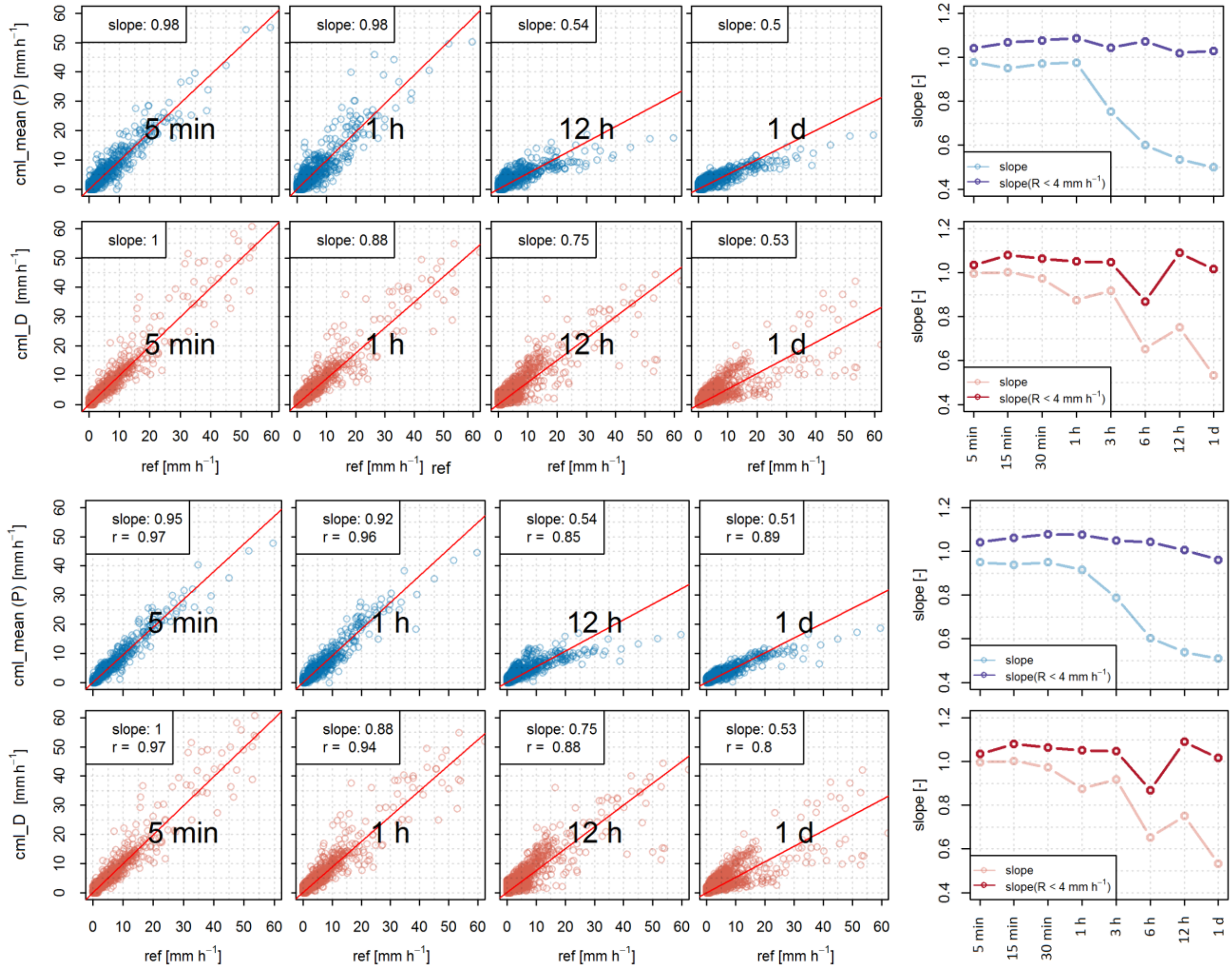
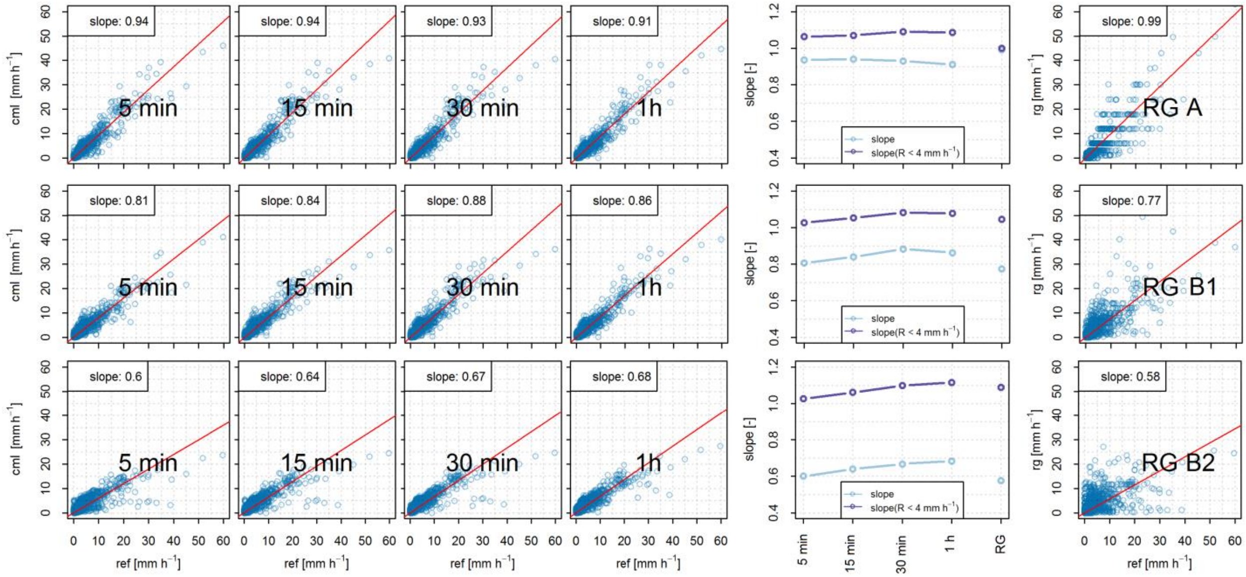


Figure 3: Comparison of CML QPEs adjusted by rainfall data of different time resolution to reference rainfall, from four averaged CMLs in Prague-Letnany (top) and one CML in Dübendorf (bottom). Scatter plots are shown only for selected aggregation intervals. Linear trendline intersects are set to zero. Slopes of trendlines for all aggregation intervals are depicted in the right panels, showing also slopes of trendlines calculated for light rainfalls (R < 4 mm h^{-1}).



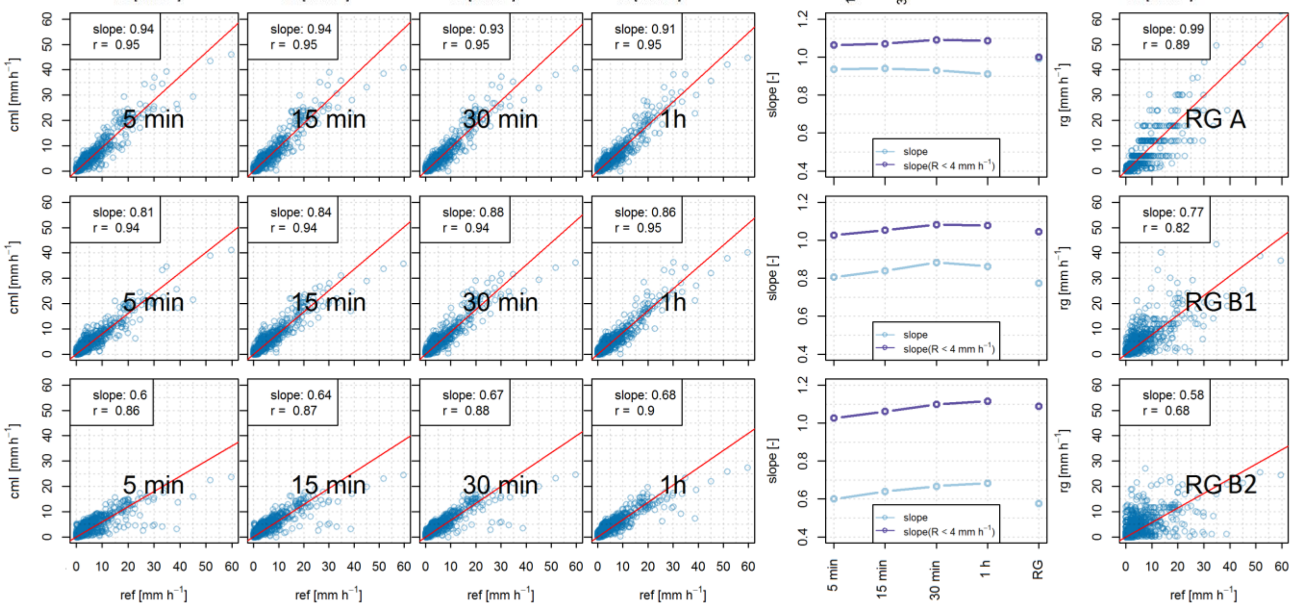


Figure 4: Comparison of mean QPEs from four CMLs to reference rainfall. CMLs are adjusted by rainfall from three different RG layouts (rows) with aggregation intervals of 5 min, 15 min, 30 min, and 1 h (four panels on the left), in addition, rainfall from the RG layouts alone is compared to the reference areal rainfall (right panel). Linear trendline intersects are set to zero. The middle panel plots the relationship between the slope of the trendlines and aggregation times as well as the slope of the RG layouts.

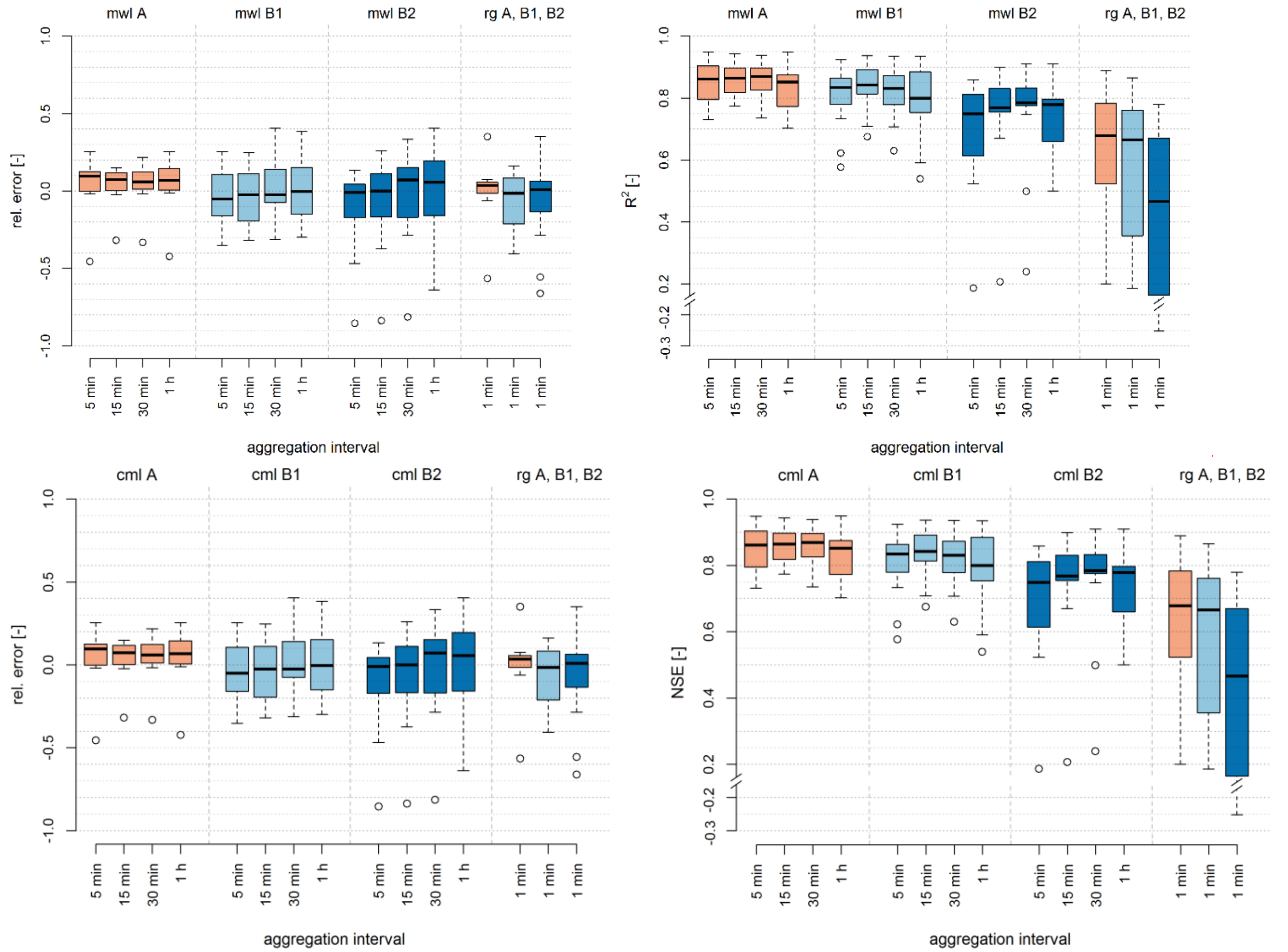


Figure 5: Relative error (left) and ~~R^2~~ NSE (right) in QPEs from CMLs when adjusted using three different RG layouts (A, B1, B2) and four different aggregation intervals (5 min, 15 min, 30 min, and 1 h). Right three boxplots in both figures correspond to RG observations of each layout when used alone without CMLs.

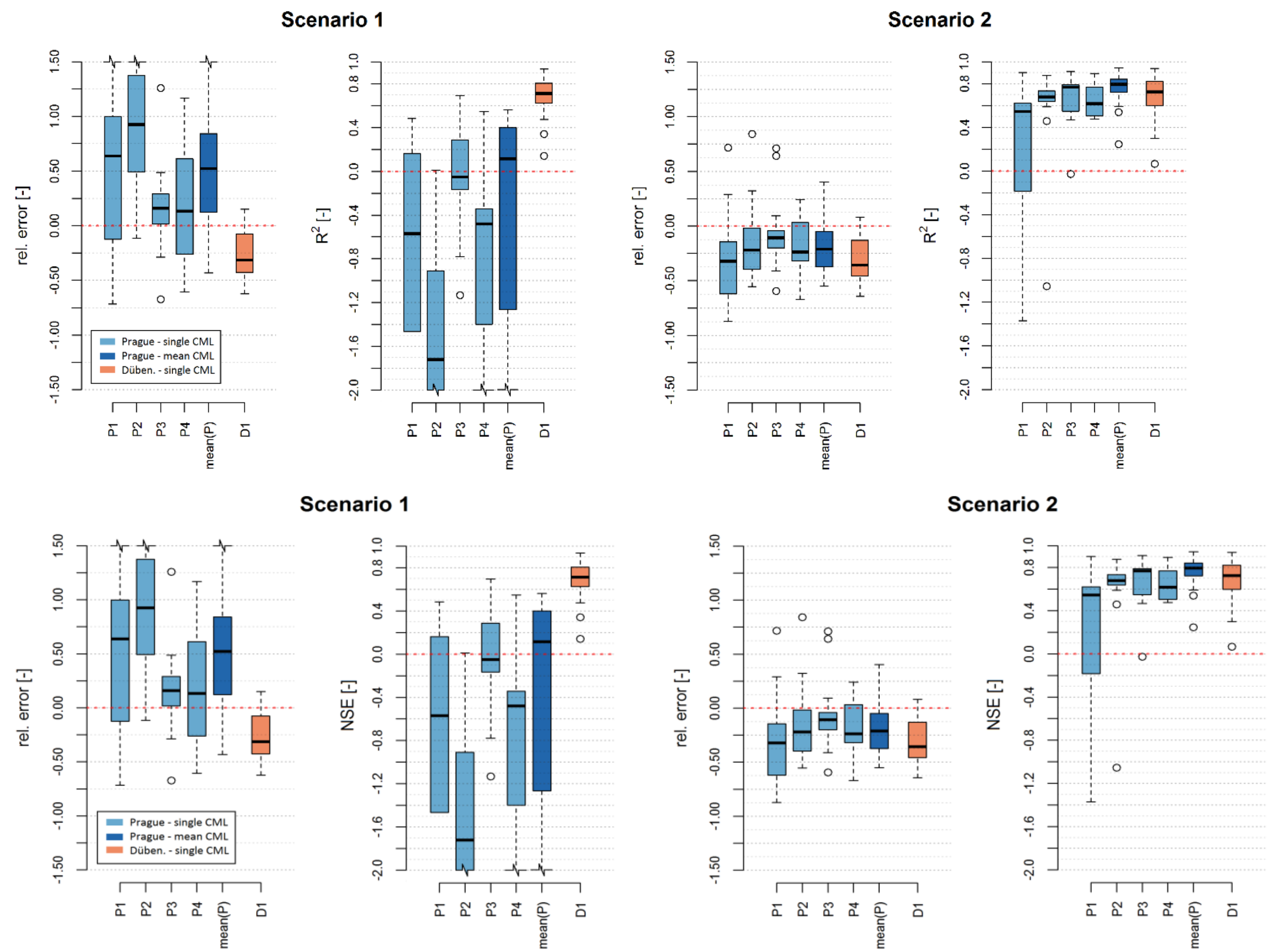


Figure 6: Relative error and R^2-NSE in QPEs of unadjusted CMLs evaluated for all events. Each boxplot depicts one CML (resp. CML mean). Scenario 1: QPEs based on models with parameters from the literature. Scenario 2: QPEs based on models with optimal parameters. It can be seen that choosing parameter values for the retrieval model from literature leads to large positive bias (scenario 1, rel. error). Conditioning the model on observations leads to a negative bias, albeit with reduced variance. Both do not achieve the virtually unbiased observations obtained with our adjustment method, with are an order of magnitude lower (Fig. 2). The comparably good performance of the CML D1 is due to an exceptional ground truth which enabled a custom-made wet antenna correction.

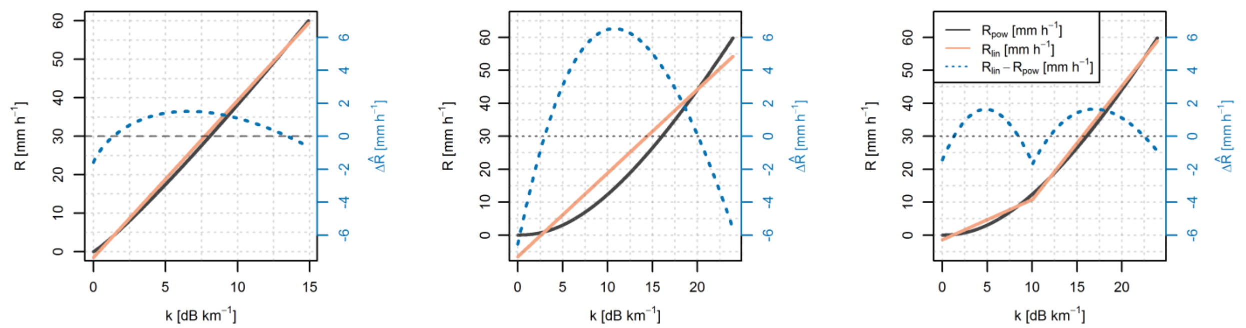


Figure 7: Performance of linear approximation of k-R models for vertically polarized 38 GHz CML in terms of rainfall intensity. Left: Linear approximation (red) of the power-law model (black). The blue dashed line shows the resulting model structure errors. Middle: Linear approximation of power-law model coupled with Kharadly's wet antenna attenuation model. Right: Power-law model combined with Kharadly's wet antenna attenuation model approximated by two linear models fitted separately for light (R ≤~~<=~~ 12 mm h^{-1}) and heavy rainfall events (R > 12 mm h^{-1}).

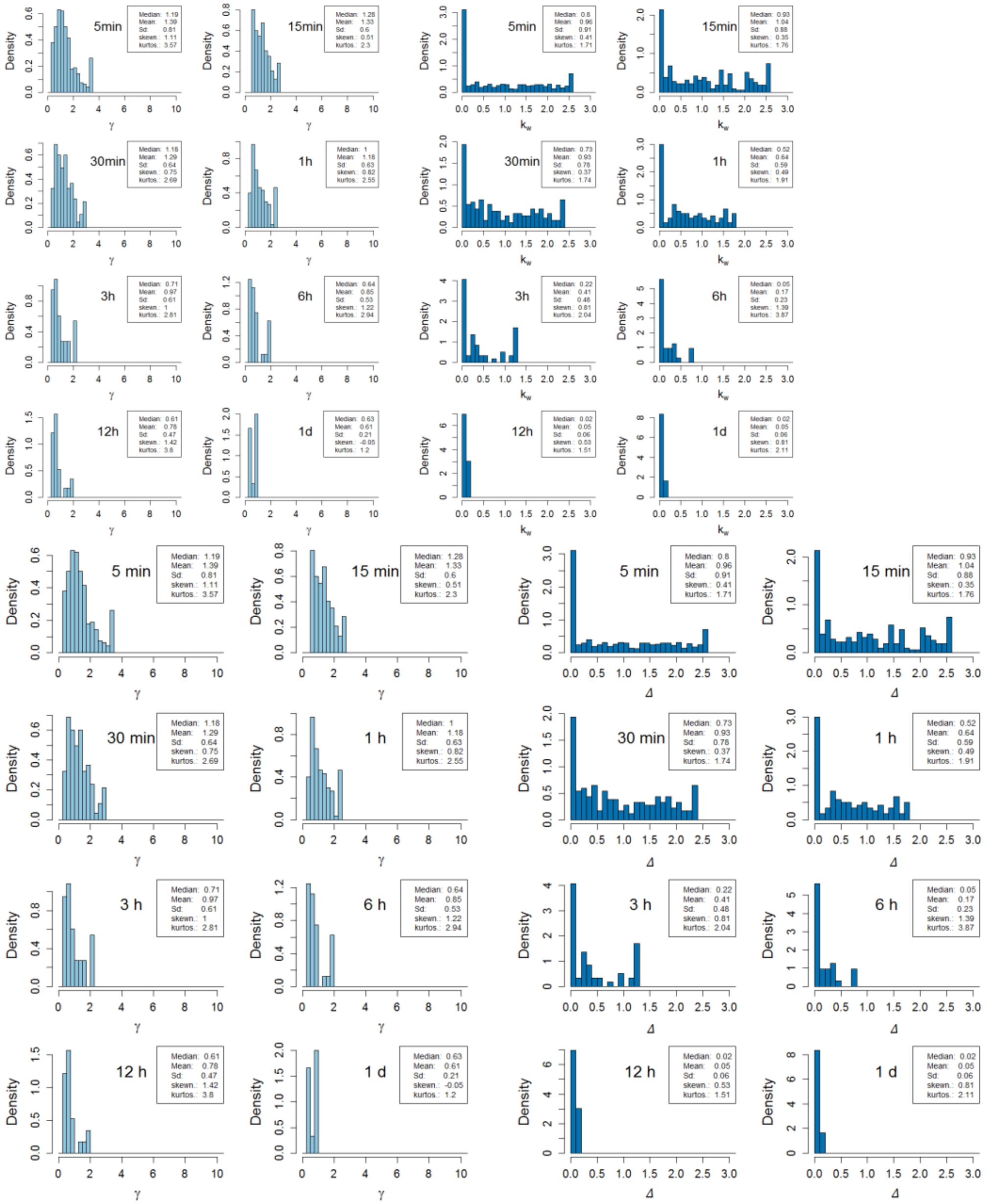


Figure 8: Parameters γ and Δ~~k_w~~ of the model (2) fitted for the CML 2 (32 GHz, horizontally polarized) using rainfall data of different aggregation intervals. Each histogram corresponds to the distribution of one parameter optimized on data of a given aggregation interval. Only parameters associated with model realizations with a specific attenuation larger than 1 dB km^{-1} are depicted by the histograms.

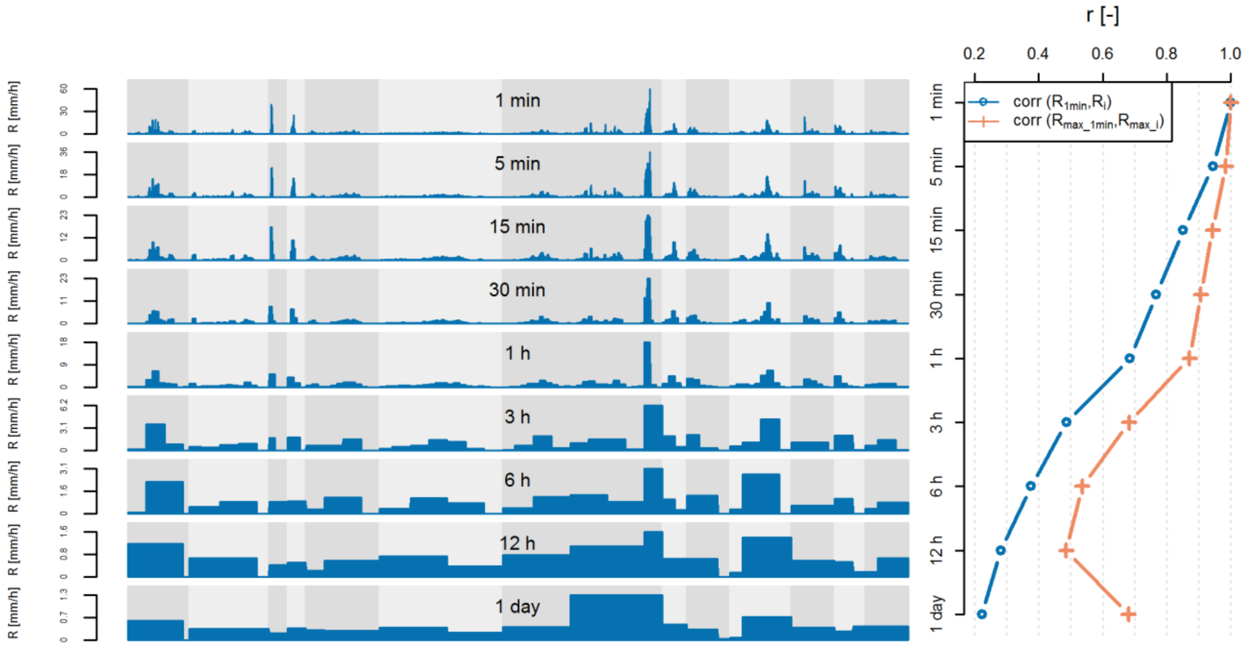


Figure A1: Rainfall peaks smoothed out by longer aggregation intervals, here shown for the case study in Prague (CZ). Left: Merged time series of thirteen events aggregated to time steps from 1 min to 1 d. Vertical stripes indicate individual events. Note how the range of the y-axis decreases from the top to the bottom row. Right: Correlation between time series with 1 min resolution and the other time series of different resolutions (blue) and correlation between peak intensities of events derived from rainfall data with 1 min resolution and peak intensities derived from aggregated rainfall data (red).