Reply to the Comments by Referee #2 for HESS-2018-517

We greatly appreciate the referee's insightful comments along with many helpful suggestions, which helped us to improve the quality of the manuscript. We have faithfully revised the manuscript following the referee's comments and suggestions. Please find below our item-by-item replies to the referee's comments.

<u>Major Comments:</u>

A. Event selection:

A1. The way the events are selected in this study (based on total daily rainfall amounts) has some important consequences which are not discussed enough in the paper in my opinion. We know from other studies that at mid-latitudes and in continental climates, the rainfall events that produce the largest daily accumulations are generally more widespread and persistent than the ones responsible for small-scale extremes. As a consequence, there are plenty of heavy localized rainfall events with high peak intensity but low to moderate rainfall totals that the authors do not consider in this analysis. Conversely, there are events in the sample that do not have very high peak intensity. This is not necessarily wrong but has important consequences as it heavily influences the conclusions. This needs to be discussed more in detail given that the focus of this paper is on heavy localized rainfall.

> *=> This study aims to provide spatial uncertainty information of heavy rainfall events in a general sense, not only targeting moderated/localized rainfall events (Appendix A, Page 10), given that, i) it is very common to define heavy or extreme rainfall events using a certain threshold value (e.g., Zhang et al., 2001; Zhai et al., 2005; Villarini 2012; Salack et al., 2018, etc.) and, ii) in many studies, gauge-based data are used for, e.g., remote sensing data validation or runoff modeling, with a lack of consideration about the rain type.*
>
> *Nonetheless, we agree with the referee that the way of selecting rainfall events can strongly influence quantitative results (Page 8 Lines 20-22, Page 9 Line22). This remains as a limitation of our study and open question for further study. To avoid any confusion, we have changed the title of manuscript to: "Assessment of spatial uncertainty of heavy rainfall at catchment scale using a dense gauge network"*

A2. More generally, a table summarizing the properties of the events selected for the analysis would be helpful.

> *=> Thanks for the suggestion. We added a table in Appendix A (Page 24).*

B. Spatial correlation analysis:

B1. The WEGN is a rectangle of 20x15 km which means that it favors the sampling of some particular spatial directions over others. For small distances this does not really matter as all spatial directions are sampled more or less uniformly. But as you start considering gauges separated by 15 km or more, the number of different spatial directions you can sample in your network decreases. This has important consequences when estimating a spatial autocorrelation function, especially in cases when the rainfall has a preferred direction of spatial orientation (i.e., anisotropy). The proper way to deal with this is to (a) choose an appropriate cutoff distance that limits these effects or (b) fit an anisotropic correlation model. The cutoff distance you used (going up to 25 km) is probably too large, which can result in biased model parameters. I recommend that you check this more carefully to make sure that your fitted model parameters aren't contaminated by it. Typically, I wouldn't go much further than 10-15 km in distance.

> *=> Thanks for the comment. It is true that we have a smaller number of data samples from North-South direction rainfall events at >15 km. We have re-calculated fitting models using correlation values up to and including 15 km (Page 4 Lines 24-26) and updated the figures 3 and 4 accordingly. The new figure 4 shows clearer difference in Shape factor among seasons (compared to the previous version).*

B2. The fact that you use a logarithmic transform means that zero rainfall values are excluded from the analysis. However, this could be a problem at small aggregation time scales where it is possible to observe zero rainfall at one gauge and positive values at the others. Please explain how you deal with these cases and more generally, how zeros are handled in your analysis.

> *=> We included zero rainfall values by adding +1 to the rainfall data; log(0 +1) = 0. This is now explained with more details in Sect.4 (Page 4/Line 30 ~ Page5/Line3), where we describe the correlation calculation method.*

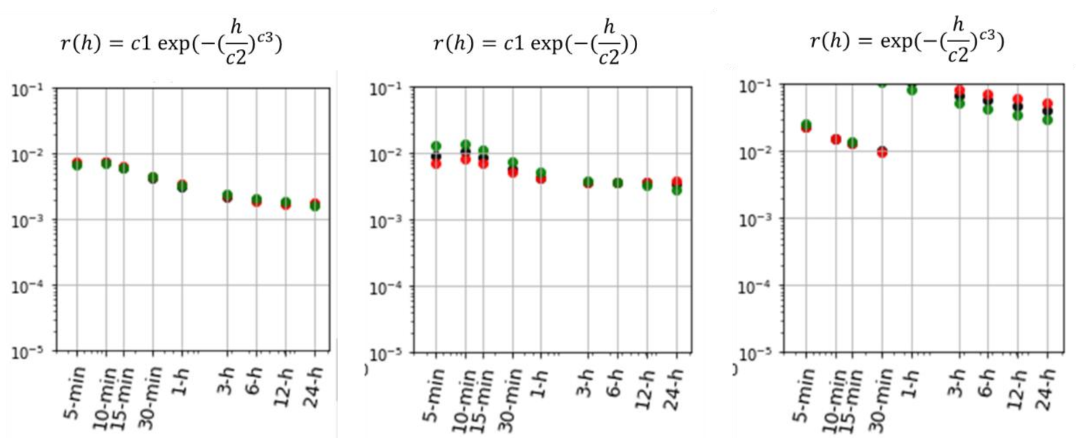
B3. Please explain how you fit your exponential correlation function to the sample points. Do you use any weights? What's the objective function you are optimizing?

> *=> We chose the parameters of fitting functions in order to minimize the sum of the squared residuals. This information is added at Page 4, Lines 29/30.*

B4. The fact that you get large yearly differences in correlation patterns (especially in winter and at 5 min resolution) might also (partially) have to do with the fact that you force an exponential model to your data without actually checking if the data comply with this model. In other words, you also need to say something about how good your model is at representing the data. Some goodness of fit statistics would be helpful for this. There is no physical justification for the exponential model you impose and other parametric fits might be equally good or better in some situations.

=> V.Svoboda et al (2014) well summarized the fitting models that are commonly used to represent spatial rainfall correlation functions; most studies adopted 3-parameters functions, while some studies used 2-parametes functions. We had compared several different forms of 2- and 3-parameters models including the models listed in V.Svoboda et al (2014) and found that the selected 3-parameters model works well across all temporal scales in terms of RMSEs of original correlations vs fitted correlations (Figure 4 is updated).

The figure below shows an example of comparing the RMSEs of the fitting model used in this study (left) and RMSEs of 2-parameter models tested (middle and right). In any cases, we observe yearly differences in correlation patterns (especially in winter at 5-min, not shown). However, it turned out that Correlation Distance can be significantly affected by the selection of the fitting model. This point will be further discussed in the following comment B5.



B5. Figure 4 shows decorrelation ranges in the order of 200-600 km. Yet the maximum range you can observe in your network is 24 km. So my questions is: how much do you trust these large range estimates? And what's the uncertainty affecting them? Please provide some form of uncertainty analysis (e.g., confidence intervals) for your parameter estimates. This would also allow you to make a more precise statement about the trend in the shape factor on p.5, line 1.

=> we have to admit that the correlation distance estimated from observation that are only available in a distance of a few kilometers (>6-hr, especially for cold season) is highly uncertain; i.e., the fitting model plays a dominant role in estimating c2 values. However, no matter what fitting model is used for obtaining the parameter values, the general behaviors of parameter like their difference among seasons, among time scales remain the same. These points are now addressed in Sec.3 (from Page 5 Line 30 & Page 9 Lines 25-28)

C. Nugget: I do not agree with your use of the word "nugget" in this paper. The nugget is NOT the value of the zero distance correlation. It's the drop in the correlation value when you go from zero distance to d>0 (i.e., the discontinuity at zero). In other words, it's not c1 but 1-c1. For example, when you say that the nugget is 0.73 to 0.98, actually, it's 0.02 to 0.27. The advantage of defining it this way is that you get a better interpretation in terms of sub-grid variability + measurement error. Large nugget = large differences at sub-grid scale. Please change and adapt the rest of the text to give the right meaning.

> *=> We agree with the referee that "1-c1" provides a better interpretation (as does in rainfall semivariogram), however, since most studies refer to "c1" as "Nugget" (e.g., Villarini et al., 2008; Peleg et al., 2013; Tokay et al., 2014 and more; all are listed in the manuscript), we would prefer to follow convention for this parameter. Please note that we replaced "nugget" by "nugget effect" (Page 4 Line 28), "higher zero-distance correlation" by "higher c1 (smaller microscale variations)" (Page5 Line10) and "The nugget implies measurement errors […]" by "lower c1 values […], meaning larger measurement errors […]" (Page5 Line17).*

D. Areal rainfall estimates:

D1. The method used to sample the 1'000 possible combinations of gauge sub-networks is not very clear to me. Moreover, wouldn't there be a strong dependence on how the gauges are selected within the network (area of influence)? I mean, you only show graphs of accuracy as a function of the number of gauges. But obviously, having 4 gauges next to each other is not the same at all as having 4 equally spaced gauges covering the whole 20x15km area. I've read this part several times but couldn't really figure out the approach. Some further details about the approach would be helpful.

> *=> The possible range of errors in areal rainfall estimates with a fixed number of gauges (often without a consideration of gauge configuration) has been studied, e.g., to see the reliability of gauge-based ground reference for satellite data evaluation (Tian et al., 2018) or to see the influence of rain gauge density on hydrological model performance (Xu et al., 2013; references are listed in the manuscript). In this context, we provide the average and the spread of areal rainfall uncertainty as a function of gauge number, using 1,000 random combinations. Please note that we checked that the number of 1,000 is enough to represent variation of the overall estimation error; i.e., box plots are not significantly changed no matter which 1,000 combinations are selected.*
>
> *As the referee pointed out, we didn't discuss the impact of gauge configuration. To address this point, using the area of influence (the index defined in Appendix B), we selected the best and the worst configurations (100 cases, respectively) out of 1,000 combinations for each n-gauge network and calculated the error of the best and worst configurations; the results show that gauge configuration strongly determines the accuracy of areal rainfall estimates and we have addressed this point adequately in the revised manuscript, which appears in Page 6 Lines 23-27 with Fig.05-a.*

In addition, following the suggestion of the Referee #1, we also demonstrated the minimum number of gauges to meet the desired error limit, which would be interesting from the perspective of gauge network design; please see Page 6 Lines 27-31 and Fig.05-b.

Minor comments & typos:

We thank the referee for the careful reading of our manuscript.

p.2, ll.6-8 "Although relatively high-resolution data from remotely […] cannot be fully captured at the sub-pixel scale". This sentence is not clear. Please reformulate.

=> rewritten as "Gridded rainfall data from remotely sensed observations are nowadays available at high spatial resolutions. While those data sets are good alternatives to address a number of the issues relating to the scarcity of gauges, rainfall variability at sub-pixel scales can still not be fully resolved." (Page 2 Lines 7-11)

p.2, l.13 "[…] intra-pixel variability of rainfall on the performance of remote sensing" A reference to the literature is needed here.

=> references are added (Page 2 Line 17).

p.3, ll.3-7 "The accuracy of areal rainfall estimation is a long-standing issue […] high-resolution gauge data (e.g., Wood et al., 2000; Villarini et al., 2008;Ly et al., 2011)" This entire paragraph is out of context. It would be better to put it a few lines earlier in the introduction, before you mention the structure of this paper.

=> the paragraph explains the motivation of Sect.4. We would therefore prefer to leave the paragraph as it is. A sentence of "We followed the latter approach using the WEGN rainfall data." has been added to Page 3 Line 16.

p.3, ll.31-33: I'm not sure whether "wet" and "dry" seasons is really a good choice of terminology here. Wet and dry seasons are usually seen in the context of tropical climates and using them for Austria feels weird. What you have here is a continental climate, with most of the precipitation falling in the warmer months of the year. Warm and cold season would be much better choices.

=> Thank you for this comment. We have decided to follow the referee's suggestion; now "wet" and "dry" are changed to "warm" and "cold" throughout the manuscript.

p.4 ll.16-18: in this paragraph you start by saying that "we do not make a direct comparison with other studies". However, a few lines later you say that "the functions show a broad agreement with those from previous studies". I get what you wanted to say, but it's probably a good idea to reformulate the sentence to avoid the apparent contradiction here.

> *=> this sentence is modified as "[…] We therefore do not make a direct comparison of correlation values with those from other studies, yet we still observe that the behaviors of the correlation decay found in this study are in broad agreement with rainfall spatial correlation structure reported in the aforementioned studies (Page 5 /Lines 6-8).*

p. 6, ll.27-28: "+7% to +63% of increases in extreme rainfall intensities are observed depending on the considered spatial scale". Not clear what you mean by that. Please reformulate.

> *=> the sentence is rewritten as "[…] The 10-year rainfall maximum appears to be 68.4 mm/day at HR10, but 104.4mm/day at HR01; the maximum record over the entire WEGN area is 64.1 mm/day, so the ratio of the site-to-areal extreme rainfall ranges from 1.07 to 1.63 depending on the considered spatial scale." (Page 8 Lines 7-10)*

p.7, l.12 Replace "Seeing that only two operational [...]" by "Given that only two operational [...]"

> *=> replaced (Page 8 Line 29)*

p.7 l.11 "shows there to be a high dependence" English.

> *=> "shows a clear dependence" (Page 8 Line 27)*

p.7 l.13 "[…] under normal circumstances could be inadequate for particular purposes". Too vague, please reformulate.

> *=> modified as "[…] the insufficient gauge density may hamper the use of the station data to construct spatial rainfall fields in the region, especially at sub-daily scales." (Page 8 Lines 31-32)*

p.7, l.30 "statistical robust results." I don't think that you can claim this. You only have 10 years of data (which is not much for extremes) and you did not do any sensitivity analysis nor do you have any confidence intervals to prove this. Please reformulate.

=> corrected (Page 9 Line 20): "long-term records, which permits to exclusively focus on heavy rain events"

p.8, l.8 "afterword" replace by "afterward"

=> corrected (Page 10 Line11). Thanks.

Reference

Salack S, Saley AI, Zabre I, Zankli LN, Daaku EK (2018) Scales for rating heavy rainfall events in the West African Sahel. Weather Clim. Extrem , 10.1016/j.wace.2018.05.004

Villarini G (2012) Changing frequency of heavy rainfall over the central United States. J Clim, 10.1175/JCLI-D-12-00043.1

Zhai PM, Zhang XB, Wan H, Pan XH (2005) Trends in total precipitation and frequency of daily precipitation extremes over China, J Clim, 10.1175/JCLI-3318.1

Zhang X, Hogg WD, Mekis É (2001) Spatial and temporal characteristics of heavy precipitation events over Canada. J Clim, 10.1175/1520-0442(2001)014<1923:SATCOH>2.0.CO;2

Assessment of spatial uncertainty of heavy ~~local~~ rainfall at catchment scale using a dense gauge network

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Abstract. Hydrology and remote-sensing communities have made use of dense rain-gauge networks for studying rainfall uncertainty and variability. However, in most regions, these dense networks are only available at sub-pixel scales and over short periods of time. Just a few studies have applied a similar approach, i.e., employing dense gauge networks ~~, to local-scale~~ to catchment-scale areas, which limits the verification of their results in other regions. Using 10-year rainfall measurements from a network of 150 rain gauges, WegenerNet (WEGN), we assess the spatial uncertainty in observed heavy rainfall events. The WEGN network is located in southeastern Austria over an area of 20 $\mathrm{km} \times 15$ km with moderate orography. First, the spatial variability of rainfall in the region was characterised using a correlogram at daily and sub-daily scales. Differences in the spatial structure of rainfall events between ~~wet and dry~~ warm and cold seasons are apparent and we selected heavy rainfall events, the upper 10% of wettest days during the ~~wet~~ warm season, for further analyses because of their high potential for causing hazards. Secondly, we investigated the uncertainty in estimating mean areal rainfall arising from a limited gauge density. The average number of gauges required to obtain areal rainfall with errors less than 20% tends to increase roughly following a power law as the time scale decreases, while the errors can be significantly reduced by establishing regularly distributed gauges. Lastly, the impact of spatial aggregation on extreme rainfall was examined, using gridded rainfall data with horizontal grid spacings from 0.1° to 0.01°. The spatial scale dependence was clearly observed at high intensity thresholds and high temporal resolutions. Quantitative uncertainty information from this study can guide both data users and producers to estimate uncertainty in their own observational datasets, consequently leading to the sensible use of the data in relevant applications. Our findings are generalisable to moderately hilly ~~region in~~ regions at mid-latitudes, however the degree of uncertainty could be affected by regional variations, like rainfall type or topography.

1 Introduction

Rainfall data are one of the most important inputs for hydrological as well as climatological studies and applications. Furthermore, fit-for-purpose information derived from rainfall data is crucial for a wider range of users, such as civil engineers, water resource managers and governments. To meet the needs of diverse user groups, rainfall observational datasets from in-situ measurement and remote sensing have been greatly enhanced in terms of both data quality and resolution (e.g., Berezowski et al., 2016; Hou et al., 2014; Keller et al., 2015; Yatagai et al., 2012). Often, rainfall data are required as areal estimates at the scale of interest, for instance, at grid or catchment scales. Point measurements from in-situ gauge observations are spatially aggregated or interpolated to estimate the areal distribution of rainfall, and hence the accuracy of areal rainfall data is highly dependent on spatiotemporal variability of rainfall events and density of observation points (Girons Lopez et al., 2015; Hofstra et al., 2010; Villarini et al., 2008; Wood et al., 2000). This limits the understanding of fine-scale rainfall processes, particularly of extreme events (Sillmann et al., 2017). ~~Although relatively higher-resolution~~ Gridded rainfall data from remotely sensed observations are nowadays available at high spatial resolutions (e.g., ~~radar provides rainfall estimates at scales of 1 km/5-min)~~1-5 km^2 for radar data or $0.1° \times 0.1°$ for satellite data). While those data sets are good alternatives to address a number of the issues relating to the scarcity of gauges, ~~still rainfall variability cannot be fully captured at the~~ rainfall variability at sub-pixel ~~scale~~ scales can still not be fully resolved (Peleg et al., 2013; Tokay et al., 2014). In addition, the quality of remotely sensed data strongly relies on gauge-based data that are used for their regional validation and correction ~~(Steiner et al., 1999)~~ (Kann et al., 2015; O et al., 2018b; Steiner et al., 1999).

Addressing the issue of spatial variability and uncertainty of rainfall has been tackled over many years with various purposes. For instance, evaluation of satellite or radar rainfall products involves investigation of ~~small-scale~~ larger-scale rainfall processes to ~~identify the effect of intra-pixel variability of rainfall on the performance of remote sensing~~ assess the ability of remote sensing in capturing the inter-pixel rainfall variability (e.g., Chaudhary et al., 2017; Dhib et al., 2017; Lockhoff et al., 2014) . On the other hand, ~~larger-scale~~ small-scale rainfall processes are of interest to ~~assess the ability of remote sensing in capturing the inter-pixel rainfall variability~~identify the effect of intra-pixel variability of rainfall on the performance of remote sensing(e.g., Ciach and Krajewski, 1999, 2006; Gebremichael and Krajewski, 2004; Habib and Krajewski, 2002; Peleg et al., 2013; Tan et al., 2018; Tokay et al., 2014). To quantify the rainfall uncertainty, observational data from ~~high-resolution~~ highly dense rain-gauge networks have been employed as a ground truth. Peleg et al. (2013) used multiple rain gauges within a radar subpixel area (4 km^2) and examined the contribution of gauge sampling error to the total radar-rainfall estimation error. Using relatively long-term gauge data (5-years), Tokay et al. (2014) analyzed the spatial correlation of rainfall for different seasons and weather systems within the footprint size of microwave satellite ~~sensor~~sensors.

A similar approach employing dense gauge networks can be adopted to diagnose the spatial variability and uncertainty of rainfall at ~~local-scale areas~~ catchment scales (e.g., 100 - 500 km^2). Such ~~a scale is~~ scales are of great interest not only for the evaluation of remotely sensed data, but also for hydrological applications like runoff modelling or gauge network design. Wood et al. (2000) examined the accuracy of areal estimates of rainfall over a 135 km^2 basin according to the HYdrological Radar EXperiment network consisting of 49 rain gauges. The network later provided a six-year rainfall dataset (from 50 gauges) for the study of Villarini et al. (2008), where a comprehensive analysis of temporal and spatial sampling uncertainties was conducted. However, most of the local areas do not have adequately dense gauge networks, which limits the comparison and verification of findings from the aforementioned studies across diverse rainfall regimes.

More recently, Schroeer et al. (2018) employed the WegenerNet Feldbach region (WEGN) and the surrounding operational rain gauge stations to sample summertime convective extreme events at sub-hourly to hourly scales and found a power law decay of the event maximum area rainfall with increasing interstation distance. In this paper, in order to contribute to the effort for better and more broadly assessing the uncertainty of rainfall at fine scales associated with the spatial variability of ~~local~~ rainfall, we employed 10-year rainfall data from ~~WegenerNet Feldbach region (WEGN)~~the WEGN, a high-density network in southeastern Austria (Kirchengast et al., 2014). The network includes 150 rain gauges deployed over an area of $\simeq 300\ \mathrm{km}^2$, approximately corresponding to one gauge per $2\ \mathrm{km}^2$. First, following previous studies (e.g., Villarini et al., 2008; Peleg et al., 2013; Tokay et al., 2014), we quantified the spatial variability of rainfall utilizing a corrologam between the gauges to understand the spatial characteristics of rainfall in the region.

Second, we investigated the uncertainty in estimating areal rainfall ~~based on~~ caused by a limited number of point observations. Given that the properties of individual rainfall events can be different from all-event averages (Ciach and Krajewski, 2006; Eggert et al., 2015), we focused on ~~potentially high-impact events~~ events with a potentially high impact, which we defined as the top 10% wettest days during the ~~wet~~ warm season. The accuracy of areal rainfall estimation is a long-standing issue, e.g., in catchment modelling because error and uncertainty in rainfall data can propagate into large variations in simulated runoff, and thus it has been dealt with in diverse manners. For instance, the influence of spatial representations of rainfall input to runoff errors has been demonstrated through modelling studies (e.g., Bárdossy and Das, 2008; Xu et al., 2013) or the error in catchment-scale areal mean rainfall has been directly quantified by employing high-resolution gauge data (e.g., Wood et al., 2000; Villarini et al., 2008; Ly et al., 2011). We followed the latter approach using the WEGN rainfall data.

Finally, we ~~assessed the impact of spatial averaging on extreme rainfall~~ compare extreme rainfall at different spatial and temporal scales using gridded rainfall fields to quantitatively assess the impact of spatial averaging on the definition of extremes. The identification of rainfall extremes based on intensity thresholds is common practice, however, the considered spatial scale of rainfall data defines different sets of extreme events (Eggert et al., 2015), potentially affecting threshold-based early warning systems (Marra et al., 2017). Although gridded datasets have been used in a range of applications like assessments of climate change impacts or evaluation of climate models, a common caveat of using the datasets in the study of extreme rainfall is that the quality of gridded rainfall data is highly constrained by the location and density of input weather station data (Hofstra et al., 2010; Prein and Gobiet, 2017). By contrast, the quasi-regular configuration of WEGN on an approximately 1.4 km x 1.4 km grid permits robust examination of the frequency and intensity of rainfall extremes at various horizontal resolutions.

Consequently, this study aims to assess spatial uncertainty of ~~local-scale rainfall~~ rainfall at catchment scale using rain gauge data, with a focus on heavy and extreme rainfall events. This paper is structured as follows. Section 2 describes WEGN rain gauge data and regional rainfall climatology. Section 3~~to Sect.~~, Sect. 4, and Sect. 5 present the results of the data analysis. We close with discussion and conclusions in Sect. 6.

2 WEGN rainfall data and regional rainfall climatology

The 10-year rainfall data (2007-2016) are obtained from the WEGN Feldbach region network in southeastern Austria (Kirchengast et al., 2014). Of 154 weather stations, 150 stations that are equipped with tipping-bucket rain gauges are used in this study (Fig. 1). ~~The gauges record rainfall~~ Raw rain gauge data are aggregated every five minutes. Errors in the rainfall data were comprehensibly analysed and corrected by O et al. (2018a). The gauges are almost uniformly spaced over an area of 20 km $\times$ 15 km with moderate topography (about 260 to 520 m asl). The inter-gauge distances range from approximately 0.7 km to 23.4 km. The gridded fields of rainfall are constructed by an inverse distance weighting (IDW) on a 200 m $\times$ 200 m Universal Transverse Mercator grid. WEGN station and gridded data products are available at www.wegenernet.org.

Southeastern Austria including the Feldbach region is influenced by both continental and Mediterranean climates. The region receives high amounts of rainfall during summer months. The occurrence of thunderstorms and hail is higher than in other parts of Austria (Matulla et al., 2003). Figure 2 shows average diurnal variations of rainfall and temperature over the entire network during the study period. The WEGN area is characterized by ~~hot~~ warm and wet months from May through September (hereafter "~~wet~~ warm season") and relatively cold months without much rainfall during the remaining seven months (hereafter "~~dry~~ cold season"). The average monthly rainfall is 102.8 mm in the ~~wet~~ warm season, while 48.9 mm in the ~~dry~~ cold season. The diurnal signal is more clearly seen in the ~~wet~~ warm season for both rainfall and temperature. Rainfall maxima occur in the early afternoon through midnight, shortly after maximum temperature, implying that a major contribution to the ~~wet~~ warm season rainfall is from short-duration convective events. Because diurnal heating plays an important role in triggering thermal convection, most inland regions show afternoon rainfall maxima (Dai et al., 2007).

3 Spatial variability of rainfall

The spatial structure of rainfall events is studied using the Pearson's correlation coefficient between all pairs of rain gauges. Pearson's r is the most commonly used rainfall correlation estimator (e.g., Ciach and Krajewski, 2006; Jaffrain and Berne, 2012; Peleg et a . At sub-daily and daily timescales from 5-min to 24-h (06-06 UTC), the correlation of rainfall among rain gauges is calculated for each year. One year period includes a set of ~~wet~~ warm season (May to September) and ~~dry~~ cold season (October to next April). The incomplete years (i.e., first and last years) are excluded from the calculation of all-months (May to next April), whereas the ~~wet and dry~~ warm and cold seasons have 10 annual curves each. ~~Figure 3 shows the spatial correlation of all-months, wet, and dry seasons for four selected accumulation times. Following Villarini et al. (2008), we~~ The correlation values in each period were then sorted according to the separation distance of gauge pairs and averaged into the nearest 1-km distance bins. We fitted a three-parameter exponential function to the ~~observed~~ average correlations. The ~~spatial~~ distance bins for the fitting model were taken up to and including 15 km given the network dimension, which means that rainfall data pairs were sampled uniformly for any spatial direction. The spatial correlation (r) at separation distance h is:

$$r(h) = c_1\, exp\left[-\left(\frac{h}{c_2}\right)^{c3}\right] \tag{1}$$

where $c1$ ~~is the nugget~~ represents the nugget effect, $c2$ is the correlation distance, and $c3$ is the shape factor. ~~To reduce bias in the Pearson's estimates due to non-normality of rainfall, a logarithmic transformation~~ The parameters are determined by least-squares curve fitting. Figure 3 shows the spatial correlation of all-months, warm, and cold seasons for four selected accumulation times. A logarithmic transformation ($log(x+1)$ to keep zero rainfall) is applied to the data~~(Habib et al., 2001; Jaffrain and Be~~ ~~. The function parameters tend to be sensitive to factors like rainfalltype or sample size and thus we~~ . As the transformation make rainfall data conform more closely to the normal distribution, the effects of extreme values on correlation coefficients is mitigated (Habib et al., 2001; Jaffrain and Berne, 2012). This results in slightly lower correlations (not shown), however, the overall pattern of correlation decay curves remains unaffected.

Many factors are known to affect the spatial correlation structure in rainfall. For instance, Habib et al. (2001) examined the sensitivity of correlation estimation in rainfall to sample size or extreme rainfall events and Huff and Shipp (1969) demonstrated how the rate of correlation decay varied with different rainfall types. We therefore do not make a direct comparison ~~with other studies in terms of absolute values. Nevertheless, the functions~~ of correlation values with those from other studies, yet we still observe that the behaviors of the correlation decay found in this study ~~show a~~ are in broad agreement with ~~those from previous~~ spatial rainfall correlation structures reported in the aforementioned studies. First, longer accumulation times show higher ~~zero-distance correlation (nugget~~ $c1$ (i.e., smaller microscale variations) and longer correlation distance values. Second, short-range correlation decreases rapidly with increasing separation distance, particularly at sub-hourly scales.

The ~~wet~~ warm season shows higher spatial variability of rainfall compared to the ~~dry~~ cold season, due to a higher proportion of convective events. The correlation curves of all-months show a more similar pattern with the ~~wet~~ warm season, as expected, given that most of the rainfall events are concentrated during the ~~wet~~ warm season (see Sect. 2). Tokay et al. (2014) found substantial year-to-year variations especially during autumn and spring. Similarly, WEGN rainfall shows marked interannual variability, but also during the ~~wet~~ warm season. It should be noted that the correlation functions of the ~~dry~~ cold season start with lower ~~nugget~~ $c1$ values than of the ~~wet season. The nugget implies~~ warm season, meaning larger measurement errors and microscale variability of rainfall. Because WEGN does not accurately capture solid precipitation (O et al., 2018a), since only few gauges are heated, systematic errors between neighboring gauges can be greater during the ~~dry~~ cold season, possibly yielding the low ~~nugget~~ $c1$ values.

Figure 4a-c summarizes the time dependence of the three parameters. Synthesized parameters here are obtained from the fitting function that is constructed by averaging yearly correlation values in each distance bin. Nugget effect values range from ~~0.73~~ 0.71 to 0.98 for the ~~dry~~ cold season, while from ~~0.89 to 1.00 for the wet~~ 0.85 to 0.99 for the warm season. The correlation distance of the ~~dry season is stretched up to around 200 at the 6-~~cold season at the 3-h ~~scale, while the same distance is observed~~ is nearly corresponding to the correlation distance at the 24-h scale in the ~~wet~~ warm season. The parameter values of all-months are located between those of ~~wet season and dry~~ warm season and cold season. We found that the ~~general behaviour of nugget~~ dependency of nugget effect and correlation distance on times scale is similar to the results by Villarini et al. (2008). The nugget effect parameter changes sharply at smaller timescales, while the correlation distance appears to be more sensitive for larger timescales. The shape factor of this study, however, does not show a ~~uniform~~ clear increasing or decreasing trend. This is consistent with findings from Peleg et al. (2013) and Tokay et al. (2014). We selected the three-parameter model for the function fitting, because the model shows the minimum root-mean-square error (RMSE) between observed and fitted correlation values across all time scales among the several tested models (Figure 4d). However, we also found that a two-parameter function (i.e., we set shape factor =1) is fitted comparably well and furthermore, correlation distance over large time scales decreases significantly when the two-parameter model is used. However, this model uncertainty does not affect the characteristics of the parameters including their dependence on time scale and their seasonal differences. Nonetheless, when the spatial scale of observed correlations is limited to a distance of a few kilometers (e.g., accumulation times of >6-h for warm season), the fitted correlation distances should be interpreted with caution. Interested readers may obtain a more detailed discussion of the fitting model in Svoboda et al. (2015).

4 Accuracy of areal rainfall estimation during heavy rainfall events

In this section we investigate data uncertainty associated with areal rainfall estimation. In particular, the study focuses on high-impact rainfall events. While heavy rainfall is one of the major hydrological hazards, its accurate spatial representation over an area remains a subject worthy of inquiry. Based on daily rainfall ($\geq 0.2\ \mathrm{mm\ d^{-1}}$), those days falling in the ~~upper 10th percentile during the wet~~ 90th–100th percentiles during the warm season are defined as heavy rainfall events. As a result, a total of 71 events are selected. The ~~mean~~ median of gauge-averaged accumulations is ~~31.5~~ 28.1 $\mathrm{mm\ d^{-1}}$, with a range of 19.8 $\mathrm{mm\ d^{-1}}$ to 64.1 $\mathrm{mm\ d^{-1}}$. General information on the selected events can be found in Table A1.

We assume that the mean areal rainfall of a full density network represents the "truth"~~(see also Villarini et al., 2008)~~. The areal rainfall of n-gauge networks (n = number of gauges) is calculated ~~with 1,000 possible combinations and then~~ and compared with the true rainfall ~~.~~ to quantify the accuracy of areal rainfall estimation with low-density networks (see also Villarini et al., 2008). Each n-gauge network consists of randomly selected 1,000 possible gauge combinations. The 1-gauge network has 150 cases. As shown in Fig. 5a, the average and spread of normalized ~~root-mean-square errors (NRMSEs)~~ RMSEs of areal rainfall ~~estimated from low-density networks~~ estimation tend to decrease with rising gauge number. The number of gauges required to obtain areal rainfall with NRMSEs lower than 20% is given as a function of time resolution in Fig. 5b. The curve (in black) roughly exhibits power-law behavior; 74.19 $\times t^{-0.44}$, where t is the time resolution (minute). At the daily scale, more than one gauge per 300 km^2 would be sufficient to reach ~~the $>$~~a $<$20% ~~accuracy level~~estimation error. Correspondingly, at the temporal scales of 1-h, 30-min, and 5-min, on average more than 12, 18, and 33 gauges, respectively, are needed to achieve the same level of accuracy. Villarini et al. (2008) found that four gauges are necessary at the daily scale for the same accuracy level for an area of 135 km^2. Heavy events are not explicitly considered in their study.

One should note that the use of randomly selected gauge combinations only offers a rule of thumb about the required number of gauges to minimize uncertainty in areal rainfall estimates. Additionally, we wanted to see the role of gauge distribution in determining the estimation error. So we selected 'good' and 'bad' distributions, 100 cases, respectively, out of the 1,000 combinations for each n-gauge networks that ranked in the top 10% and bottom 10% based on the area-of-influence (see Appendix B). As seen in Fig 5a (red crosses), the smallest estimation error is obtained with regularly distributed gauges. In other words, a well-designed gauge network allows to meet the desired error limit with a smaller number of gauges (grey curve in Fig 5b). For example, at a 1-h scale, the 20% estimation error can be reached using uniformly distributed 8 gauges, however, the same level of accuracy cannot be guaranteed even with 23 rain gauges if their spatial configuration is not properly structured.

Additionally, the effect of gauge density on event-based rainfall statistics is assessed in Fig. 6. Daily rainfall accumulation and peak hourly rainfall of the 71 heavy daily events are recalculated using predefined sub-networks with gauges ranging from 1 to 16. The gauges are uniformly spread; the definition of the sub-networks can be found in Appendix ~~A~~B. While the sub-network with only one gauge exhibits large overestimation errors for both total and peak rainfall, employing an additional gauge already significantly reduces the degree of errors and yields underestimation error more frequently than overestimation. Note that Austrian weather service (ZAMG) has two operational stations over the actual WEGN area. Given that convective storms occur on scales of a few kilometers, low-density gauges over the region are likely to miss the core of ~~storms~~storm. On the contrary, low-density gauges ~~often~~ can also overestimate rainfall intensities by capturing only the core of ~~storms~~storm, but the magnitude and frequency of ~~the~~ these errors appear slightly less than those of the underestimation ~~error~~errors. There is no significant difference in either average error or spread of errors from more than 10 gauges, as expected from Fig. 5.

5 Impact of spatial ~~scaling~~ aggregation on extreme rainfall

We next focus on the uncertainty of area- or grid-averaged rainfall relating to ~~data spatial resolution~~spatial data resolution for the heavy rainfall events. Figure 7 compares rainfall percentiles among the gauges. Grey lines mean a 10-90th percentile range of rainfall intensities at a given percentile bin. For example, at the 30-min scale, the 99.9th percentile (the top 0.1%) rainfall intensity corresponds to roughly 45 $\mathrm{mm\,h^{-1}}$ at most gauges, while it exceeds 52 $\mathrm{mm\,h^{-1}}$ at certain gauges. It is also seen that 10% of WEGN gauges (i.e., 15 gauges) records are found to be lower than ~~40~~ 38 $\mathrm{mm\,h^{-1}}$. The upper tail of rainfall distribution shows strong spatial variation. Such point-scale extreme rainfall features will be completely missed unless there exist dense rainfall observations, or they are inherently smoothed out in gridded data.

In fact, many studies have pointed out that the use of gridded rainfall data can lead to erroneous analyses of small-scale extremes because of the limited number of point observations ~~(Hofstra et al., 2010; Tozer et al., 2012; Contractor et al., 2015; Prein and Gobi~~ (Contractor et al., 2015; Hofstra et al., 2010; Prein and Gobiet, 2017; Tozer et al., 2012). In addition to the high-resolution, the regular distribution of WEGN gauges enables generating gridded rainfall fields that are homogeneous in space, and, consequently, robustly assessing uncertainty in rare and extreme rainfall represented in the data.

We generated gridded data ~~at~~ using all 150 WEGN gauges and rescaled the data into horizontal resolutions from 0.01 to 0.1 degree (hereafter HR01 to HR10). Spatial aggregation begins from the top-left corner towards the bottom right and the remaining southern and/or eastern part of the grid is discarded (see Fig 9). HR01 corresponds to about 1.1 km and 0.8 km in latitudinal and longitudinal directions, respectively. Figure 8 shows the 99.9th and 99th percentiles of heavy rainfall intensities as a function of space-time scales. ~~HR01 clearly portrays the benefit of using dense networks to capture fine-scale extreme values, however spatial aggregation brings about the smoothing of rainfall intensities, notably~~ Although temporal aggregation more significantly alters the definition of extremes, the impact of spatial aggregation is also notable, particularly at the sub-hourly scales. The ~~decrease in~~ 5-min ~~rainfall intensity~~ extreme intensity deceases from HR01 to HR10 ~~is~~ by 30% for the 99.9th percentile while it ~~is~~ decreases by 20% for the 99th percentile.

Meanwhile, ~~the spatial scaling~~ although the spatial aggregation impact is much less pronounced at a daily scale, ~~where~~ the selected spatial scale still affects statistics of extreme areal rainfall, such as daily extreme frequency. This is shown in Fig. 9, which illustrates the occurrence of days above a selected threshold; top 5% of heavy rainfall events at HR01. The concept of the exceedance probability above thresholds is widely used in analyses of rainfall-triggered risk. ~~Several HR01 sites have experienced~~ Some HR01-scale sites appear to experience extreme rainfall more frequently than ~~others~~other part of the region. In other words, high-resolution data well-represent spatial variation and frequency of rainfall extremes, neither of which is seen in lower-resolution data. Many existing gridded datasets are not likely to fully sample such site-level extreme events owing to ~~their spatial scales being limited by sparse observation used to produce the dataset~~limited spatial resolution. The exceedance probability of extreme rainfall across spatial resolutions is given in Fig. 10. The impact of different data resolutions on extreme rainfall occurrence is pronounced in ~~the~~ both lower and upper tails. The 10-year rainfall maximum appears to be 68.4 mm/day at HR10, but 104.4 mm/day at HR01~~. Over the~~ ; the maximum record over the entire WEGN area ~~, the maximum record~~ is 64.1 mm/day~~; +7% to +63% of increases in extreme rainfall intensities are observed~~ , so the ratio of the site-to-areal extreme rainfall ranges from 1.07 to 1.63 depending on the considered spatial scale.

6 Discussion and conclusions

The understanding of spatial uncertainty in ~~local~~ heavy rainfall at fine scales has been hampered by the limited availability of suitable and reliable observational datasets. Although high-resolution radar data are often used to study small-scale rainfall variability, the use of the radar data is dubious, as indicated by Svensson and Jones (2010), owing to their indirect measurements of rain and relatively short records. In this study, we used the 10-year rainfall measurement data from the 150 rain gauges, uniformly spaced over the WEGN network in southeastern Austria. First, to quantify rainfall variability, spatial correlation between the gauge records ~~is~~ was examined. We found that the degree of ~~rainfall spatial~~ spatial rainfall variability can be substantially different not only within years (~~wet versus dry~~ warm versus cold seasons) but also between years. This implies that long-term data should be considered ~~in this light~~ to obtain comprehensive perspectives on regional rainfall variability. In fact, individual weather systems can exhibit varied spatial characteristics (Habib and Krajewski, 2002; Ciach and Krajewski, 2006; Tokay et al., 2014). In southeastern Austria, including the WEGN area, Schroeer et al. (2018) found much steeper decay in a correlogram function when only extreme summertime convective events are accounted for. Additionally, we found that during the ~~dry~~ cold season, the density of gauges is less of a concern (i.e., longer correlation distance) compared to the ~~wet~~ warm season. However, low values of ~~zero-distance correlation~~ the nugget effect parameter imply that snow ~~measurement~~ measurements during winter time ~~remains~~ remain a challenge, especially at short time scales.

Secondly, we confirm that the 150 gauges of WEGN offer very highly accurate areal precipitation estimates. The overall uncertainty in mean areal rainfall shows ~~there to be a high~~ a clear dependence on the number of gauges and the temporal resolution considered for the estimation. ~~Seeing~~ To reach the same level of accuracy, the average number of gauge has to be increased roughly following a power law as time scale decreases. Given that only two operational meteorological stations exist over the WEGN area, the ~~accuracy of areal rainfall data obtained under normal circumstances could be inadequate for particular purposes~~insufficient gauge density may hamper the use of the station data to construct spatial rainfall fields in the region, especially at sub-daily scales. ~~We also investigated the effect of gauge density on total amount and peak hourly intensity of the daily heavy rainfall events. In the WEGN area (300)~~The accuracy of areal rainfall estimation is also significantly dependent on the spatial configuration of the network. Assuming that we have a well-distributed gauge network, it is observed that at least 2-5 gauges are required ~~for~~ in the WEGN area (300 km^2) for accurate areal rainfall estimates such that we can obtain reliable rainfall event statistics (e.g., total amount and peak hourly intensity of daily heavy rainfall events) with no significant error. More than ~~5 gauges guarantee a high accuracy of the areal rainfall estimates~~10 gauges guarantee that we can obtain constant results, regardless of number of the gauge. Our findings have implications concerning the use of sparse ~~gauge observational~~ observational gauge data, for instance, in hydrologic modeling or rainfall estimates evaluation (e.g., Syed et al., 2003; Tian et al., 2018).

Lastly, using gridded WEGN data, rainfall extremes are reproduced at multiple spatial scales; approximately from the grid resolution of regional to convective-permitting models (about 11.1 km to 1.1 km in latitudinal direction). ~~The results~~ We show how different rainfall events can be considered extreme depending on the spatial and temporal resolutions. The results also demonstrate that high-resolution gridded data provide more reliable information not only in terms of the magnitude and frequency of extremes, but also in terms of the exact location of the extremes. As a result, ~~the limited spatial scale~~ limited resolution of rainfall data can alter interpretations of rainfall statistics; extreme rainfall events at a location of interest (a $0.01° \times 0.01°$ site in our example) could occur more frequently and more intensely versus the local average. Localized information from high-resolution observation is the key ~~to~~ for developing prevention and protection plans to mitigate potential damages of extreme rainfall in an efficient and adequate way. Our results highlight the need to evaluate uncertainty in extreme statistics derived from the existing datasets for supporting data selection among available rainfall data products.

In conclusion, the WEGN network provides a unique opportunity to empirically assess spatial variability and uncertainty of surface rainfall directly based on gauge data. The network provides long-term records, of more than a decade, which ~~enable obtaining statistically robust results~~permit to exclusively focus on heavy rain events. Nonetheless, as stated in Villarini et al. (2008), there are only a few dense gauge networks on the ~~local~~ catchment scale, so the verification of findings from studies in other regions is challenging. Regional variations, such as topography or rain type, can lead to differences in the degree of rainfall variability and uncertainty (e.g., Buytaert et al., 2006; Prein and Gobiet, 2017). Therefore, some of the general conclusions of this study ~~should only be generalized~~ may only be representative for mid-latitude regions with moderate topography. In addition, more robust interpretation of the rainfall spatial structure beyond the network dimension (> 15 km) needs to be complemented by additional larger-scale gauge data. For instance, Schroeer et al. (2018) used three different scales of networks, including the WEGN, to estimate the underestimation of maximum area precipitation of extreme convective over the range of 1 km to 30 km. It should be noted that WEGN has a high flexibility in terms of providing rainfall data within various spatial scales thanks to both high-resolution and quasi-grid configuration of the gauges. In this context, WEGN will continue providing observational evidence to explore ~~small-to-local~~ local-to-catchment scale rainfall processes over the next years.

Data availability. WegenerNet data products are available at www.wegenernet.org.

Appendix A: ~~Definition of rain-gauge sub-networks~~Heavy rainfall events

~~Figure ??~~ Table A1 shows general information about the selected heavy rainfall events studied in Sect. 4 and Sect. 5. The events are corresponding to ≥90th percentile of daily rainfall (06-06 UTC) during the warm season. Peak ratio is given as a ratio of peak hourly rainfall to daily total. Rainfall in the region during the summer months is triggered by the advection of humid air masses from the Adriatic Sea. Heavy rainfall events are closely linked with local thunderstorms (Matulla et al., 2003, see also Sect. 2) . The rain type is not explicitly considered for the event selection.

Appendix B: Definition of rain-gauge sub-networks

Figure A1 shows the selection order of WEGN gauges for defining the low-density sub-networks that were used in Fig. 6 of Sect. 4. Priority consideration was given to the actual location of operational weather stations within the WEGN network; the selected gauges 1 and 2 are located nearest to the member stations of the Austrian weather service (ZAMG) and the gauges 3, 4, and 5 are nearest to the rain gauges operated by the Austrian hydrographic services (AHYD). The gauges ~~afterword~~ afterward were arbitrarily selected, ensuring a spatially uniform distribution. Normalized standard deviation of area-of-influence was used as an index for the uniformity of gauge configuration, which fluctuated between 0.37 and 0.23 with a decreasing trend as the number of the selected gauges increases. The area-of-influence is defined as follows: small grid boxes (approx. $0.01° \times 0.01°$, a total of 406 boxes) were defined over the WEGN network and each box is assigned to the nearest gauges of a given sub-network. Then, with an assumption that the most regular gauge configuration would share the same number of boxes, standard deviation of the area-of-influence of n-gauges is calculated. For instance, for the $five$-gauges sub-network, each gauge is expected to share around 80 boxes under an ideal situation. However, in this study, the five gauges share 71 to 113 boxes each, resulting in the uniformity index of 0.35. Note that this simple method does not consider the degree of centralization.

The uniformity index defined here is also used for Fig. 5 to select well- and badly-distributed n-gauge networks.

Competing interests. The authors declare that they have no conflict of interest.

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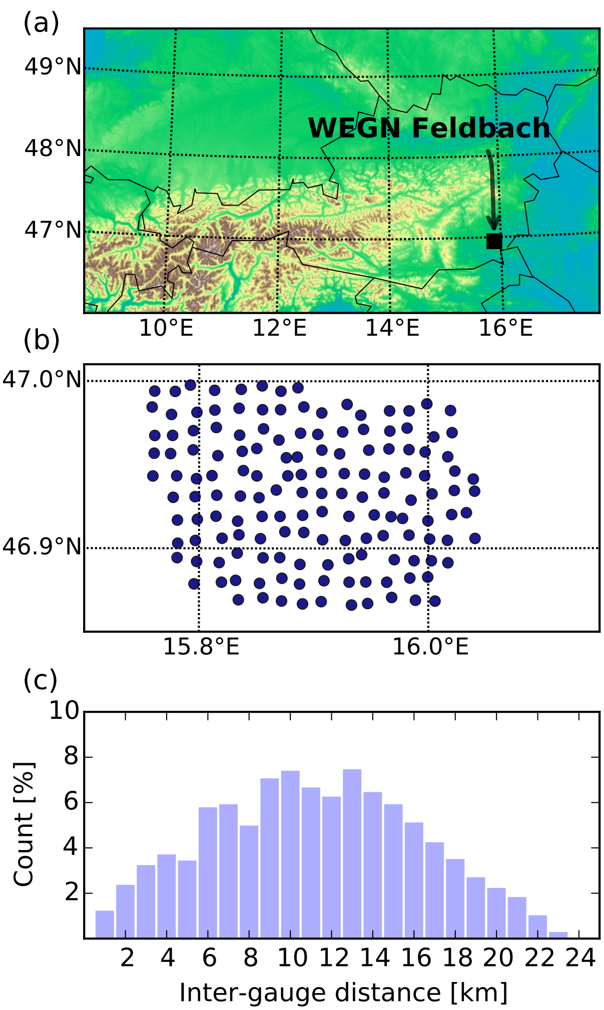

Figure 1. (a) WegenerNet Feldbach region (WEGN) network in southeastern Austria, (b) location of 150 tipping-bucket rain gauges, and (c) inter-gauge distances, rounded to the nearest 1-km bins.

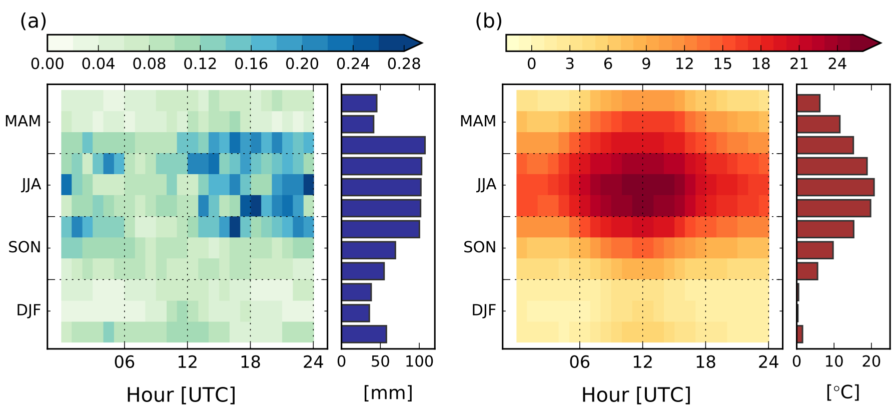

Figure 2. Diurnal cycles of (a) rainfall and (b) temperature derived from WEGN observational data.

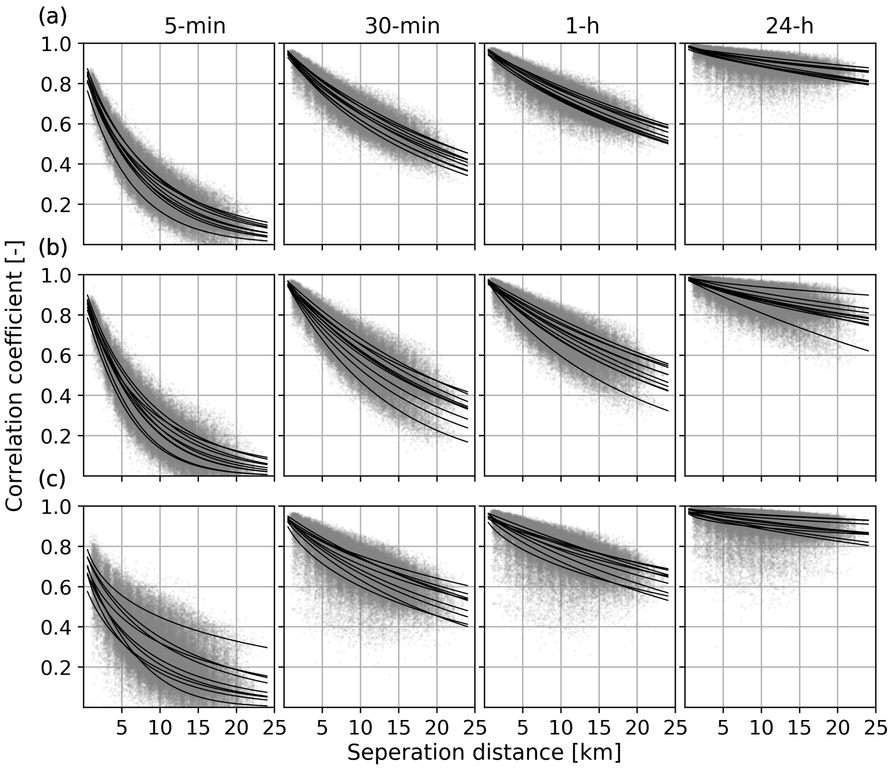

Figure 3. Spatial correlation of rainfall among rain gauges for (a) all-months, (b) ~~wet~~ warm season, and (c) ~~dry~~ cold season. Four selected accumulation times are shown. Each solid line represents a fitted exponential function for each year.

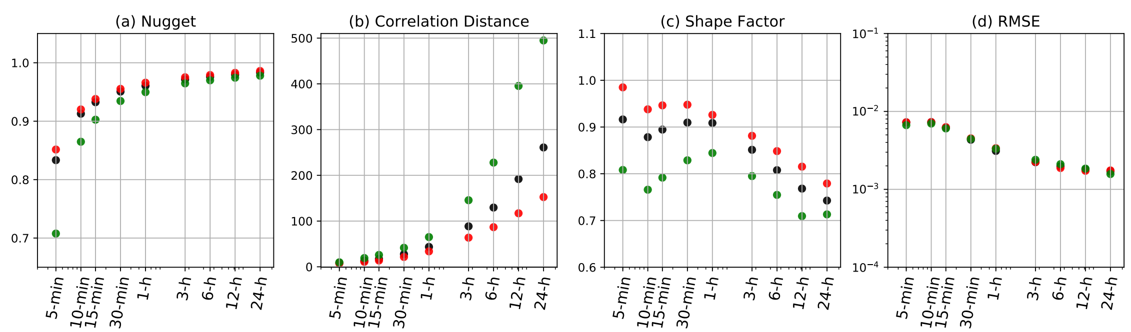

Figure 4. Dependence of (a) nugget effect, (b) correlation distance, and (c) shape factor of the fitted exponential functions on timescale. (d) shows RMSE of fitted correlation values compared to observed values (red: ~~wet~~ warm season, green: ~~dry~~ cold season, black: all-months).

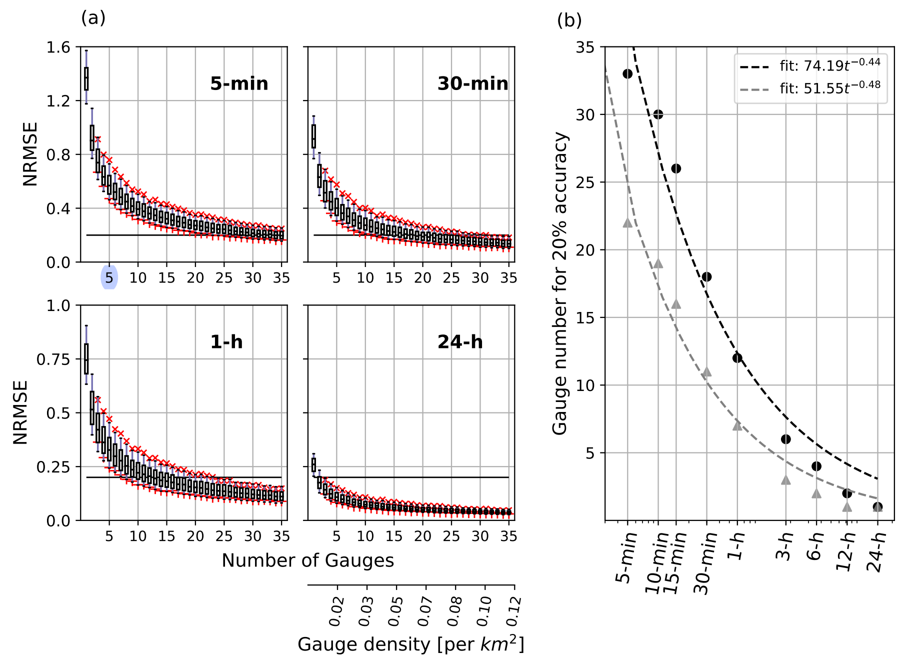

Figure 5. Dependence of the accuracy of areal rainfall estimates on the number of gauges during heavy rainfall. Normalised RMSEs (NRMSEs) of 1,000 different gauge combinations are used to assess the accuracy for each n-gauge network. (a) Four selected time accumulation are shown. Box plots display the median, 25th and 75th percentiles of NRMSE distribution, and whiskers extend to the 10th and 90th percentiles. Red crosses and Xs show the median NRMSE for good and bad gauge configurations; 100 cases are selected, respectively, for each of the 1,000 combinations. (b) The average and minimum number of gauges (black and gray, respectively) required to obtain areal rainfall estimates with an ~~normalized RMSE~~ NRMSE $< 20\%$.

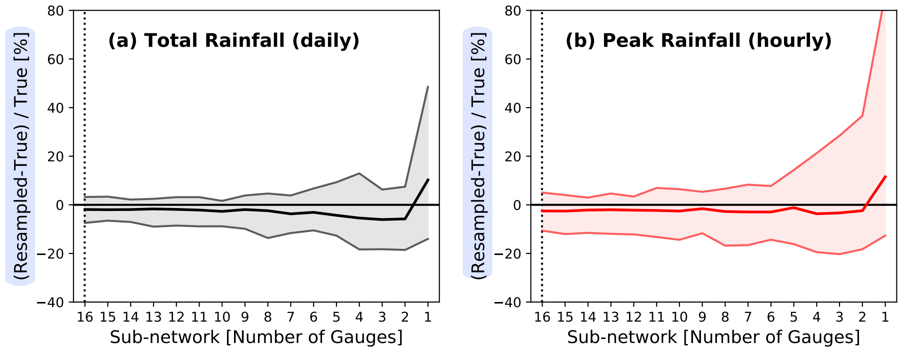

Figure 6. Dependence of the accuracy of (a) daily rainfall and (b) hourly peak intensity on the number of gauges. 71 heavy rain events are considered. The y axis displays the ~~ratio of~~ relative difference between resampled ~~rainfall to~~ and true rainfall. Resampled rainfall is calculated from n-gauge sub-networks, while true rainfall is calculated using the full density WEGN network. The thick lines show the median and the shaded areas show the 10th to 90th percentile spread.

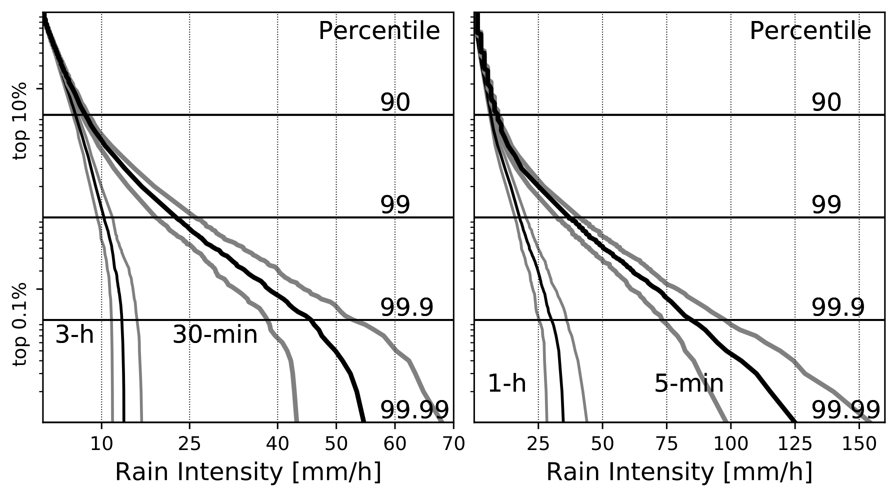

Figure 7. Distribution of gauge-level rainfall intensities corresponding to given percentile thresholds during heavy rainfall events. Four time scales are selected. Black lines show median values, gray lines show a 10th-90th percentile range among the gauges at a given threshold bin.

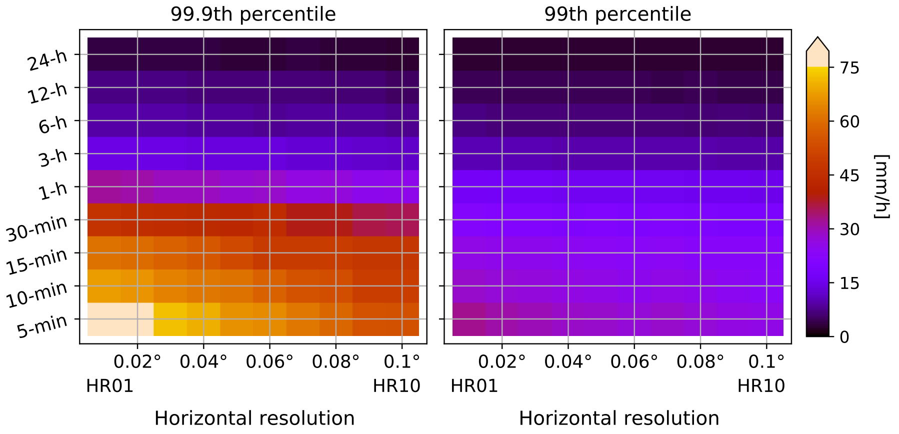

Figure 8. 99.9th and 99th percentiles of rainfall intensities derived from gridded rainfall fields with different spatial and temporal scales.

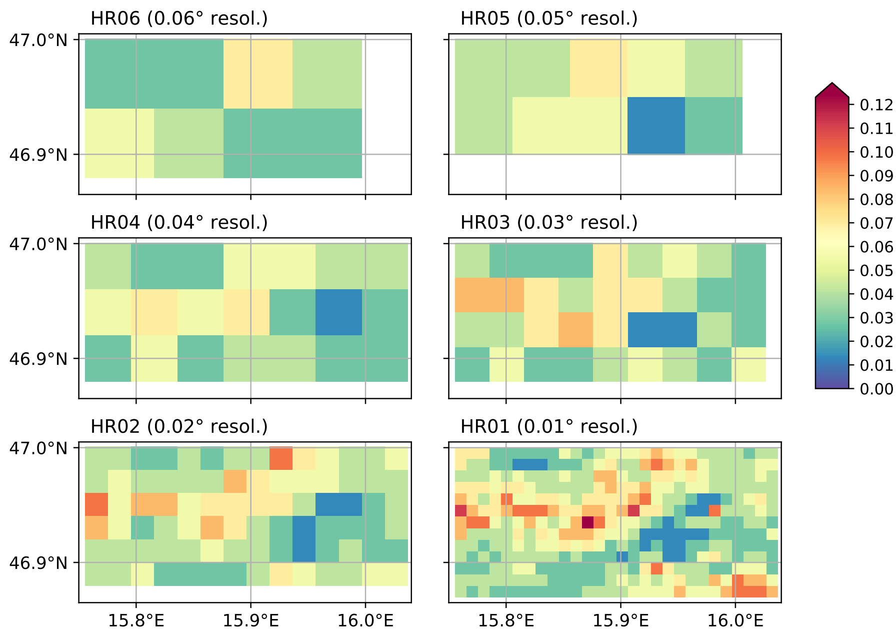

Figure 9. Occurrence of extreme events ($\geq$ 95th percentile of rainfall intensity during heavy rainfall events at HR01) at different horizontal grid spacing.

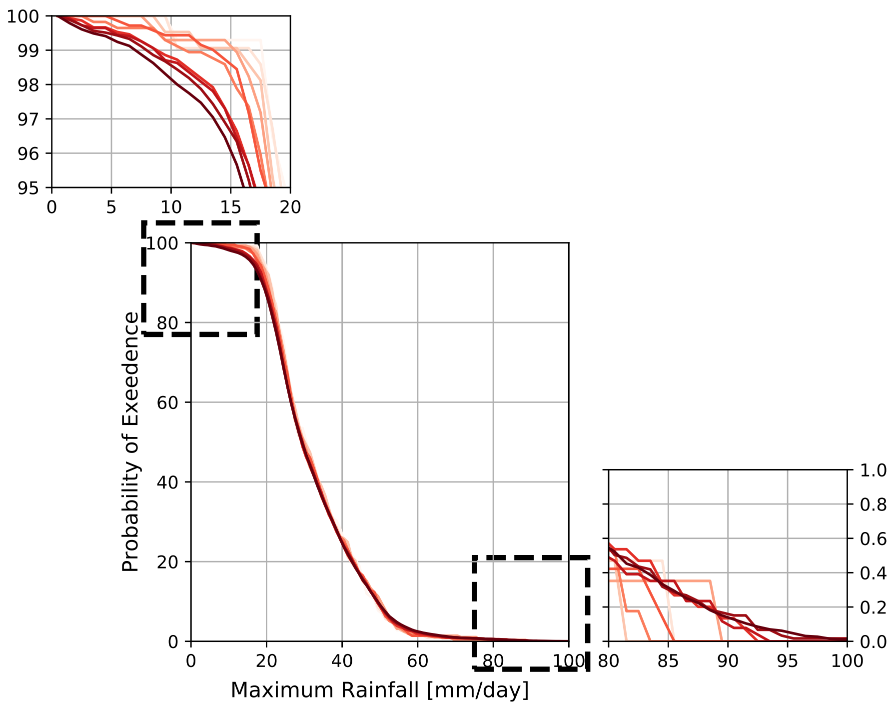

Figure 10. Probability of occurrence of heavy rainfall for different horizontal resolutions. Darker red represents higher horizontal resolution (from 0.1° to 0.01°).

Table A1. Information of selected heavy rainfall events

	Min	Median	Max
Total rainfall ($\mathrm{mm\,d^{-1}}$)	19.8	28.1	64.1
Peak hourly rainfall ($\mathrm{mm\,h^{-1}}$)	2.6	8.6	26.2
Peak ratio	7.8	25.4	91.0
Duration (h)	2.0	9.5	22.5

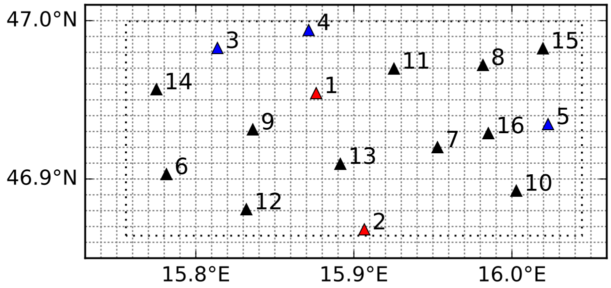

Figure A1. Selected WEGN gauges for Fig. 6. The gauges nearest to operational weather stations of the ZAMG and AHYD are in red and blue, respectively.