Strong Dependence of Extreme Convective Precipitation Intensities on Gauge Network Density

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Abstract  Extreme convective precipitation on subhourly scales is notoriously misrepresented in rain gauge-based observations, but uncertainties are weakly quantified at the 1 to 30 km scale. We employ a unique observing network, the high-density WegenerNet and surrounding operational rain gauge network in southeastern Austria, to sample convective precipitation extremes at these scales. By systematically constructing lower-density networks, we explore how estimated maximum area precipitation depends on observing station density. Using subhourly to hourly temporal resolution, we find a $d^{-0.5\pm0.1}$ power law decay of the event maximum area precipitation over distances $d$ from 1 to 30 km, showing that operational gauge networks underrate extreme convective precipitation falling over small areas. Furthermore, extremes at point scale are found underestimated by operational networks by about 20%. We consider the dependencies representative for short-duration convective events over similar regions at midlatitudes and the results valuable for high-resolution climate model evaluation.

Plain Language Summary  Precipitation is commonly measured using rain gauge networks. For many applications it is relevant how much precipitation fell over a given area, which is often approximated from point-scale gauge observations. In operational networks, gauges are usually 10 km or more apart. This spacing is not sufficient to observe extreme rain intensities in summer convective events, which occur on subhourly time scales and over small areas. Sparse gauge observations lead to high uncertainty in the estimated area precipitation from such events, hampering, for example, damage risk assessments. The WegenerNet Feldbach region in southeastern Austria is one of the densest networks worldwide, with 150 rain gauges within an area of just 300 km². We use this as core network to explore how maximum area precipitation in convective events depends on the density of the gauge network. We find strong spatial dependence showing that maximum area precipitation observed at 5–6 km gauge separation distance is less than 50% of the maximum intensity observed at point scale. We demonstrate that extreme convective precipitation is underestimated in operational networks. The derived spatial dependence curves illustrate the concentrated nature of convective extremes and are valuable for evaluating climate models and interpreting rain gauge-derived precipitation data sets.

1. Introduction

Convective storms at midlatitudes cause the most intense precipitation on short time and small spatial scales (minutes to hours and meters to a few kilometers, respectively). Knowing the spatial distribution, timing, and magnitude of convective extreme precipitation is crucial to understand flash floods (Archer & Fowler, 2018; Cristiano et al., 2017; Rogelis & Werner, 2013) or debris flow initialization (Marra et al., 2016). Concurrent with socioeconomic changes, risks from such events might change as heavy convective precipitation intensifies with global warming (e.g., Ban et al., 2015; Dai et al., 2017; Prein et al., 2017; Westra et al., 2014; Ye et al., 2017).

Rain gauges deliver the only direct measurement of surface precipitation and, with data available on meteorological time scales, constitute the fundamental source and reference for precipitation studies despite inevitable uncertainties (McMillan et al., 2012; Sun et al., 2018). Often, area rather than point precipitation...
is desired, and deriving area estimates from gauge observations is a long-standing challenge in hydrometeorology. Usually, gauge data are deterministically or geostatistically interpolated (Dirks et al., 1998; Lebel & Laborde, 1988; Ly et al., 2011; Syed et al., 2003; Verworn & Haberlandt, 2011). Spatial correlation measures of gauge observations help estimating area precipitation (Ciach & Krajewski, 2006; Sivapalan & Blöschl, 1998; Sunilkumar et al., 2016; Tokay et al., 2014; Villarini et al., 2008). On small scales, however, this is a challenge because usually very few data pairs exist at small station separation distances, weakening the robustness of the estimated correlogram, semivariogram, or covariance function (Lebel & Laborde, 1988).

For coherent precipitation fields over flat terrain, interpolation yields acceptable results even in low density networks (Dingman, 2015; McMillan et al., 2012), but intense convective precipitation in the midlatitudes unfolds on smaller scales than most operational networks cover at scales of 10 km or larger. Because of the scale mismatch between point observations and precipitation process (cf. Blöschl & Sivapalan, 1995), convective extremes are poorly represented in widely applied gauge-derived precipitation grids.

Radar data provide valuable insights to spatial precipitation structures. Eggert et al. (2015) found that convective precipitation dominates precipitation extremes in Germany at scales below 10 km and shorter than 45 min. Over the Netherlands, 90% of summertime convective events were <7 km in cell diameters, and peak precipitation intensities declined rapidly within 5 km from the storm center (Lochbihler et al., 2017). Yet, considerable uncertainties remain in radar-derived quantitative estimates of precipitation intensities at surface level (Berne & Krajewski, 2013). In convective events and on subhourly to hourly time scales, extreme intensities are often severely underestimated (Bárdossy & Pegram, 2017; Haberlandt & Berndt, 2016; Kann et al., 2015).

In infrastructure design and climate model evaluation (Mishra et al., 2012; Tripathi & Dominguez, 2013), area reduction factors (ARFs; Ly et al., 2011), relating point to area precipitation, are often employed. Area reduction is larger in summer due to increased convective precipitation and in rare extreme events (Eggert et al., 2015; Svensson & Jones, 2010). Although characteristic differences between ARFs for convective and stratiform precipitation have long been recognized (Bell, 1976), little reliable research exists of how extreme area precipitation scales in the 1 to 10 km range. On subhourly to hourly time scales, little or no reduction is assumed over areas of 5 to 10 km² (Langousis, 2005). Again, low rain gauge density hampers a robust evaluation of ARFs (e.g., Barbero et al., 2014).

Precipitation at very small scales below 1 km can be studied in confined, campaign-type study settings (Goodrich et al., 1995; Pedersen et al., 2010; Peleg et al., 2013), and at large scales, uncertainties generally decrease. But on the 1 to 10 km scale, just below most operational rain gauge network densities and in the gray zone of climate models, extreme convective surface area precipitation is still subject to large uncertainties (Lind et al., 2016). This restrains evaluation of climate model skill to represent precipitation intensities, particularly for rare extreme events relevant to society (Prein & Gobiet, 2017; Sunyer et al., 2013). Regional climate models at comparably high spatial resolution of 6 km still show considerable negative precipitation biases in summer compared to point precipitation statistics (Olsson et al., 2014). Deeper knowledge of observational uncertainties is crucial to evaluate and interpret such simulations.

Rain gauges provide close to ground-truth precipitation observations, but very few networks with >50 gauges, densities of >0.1 gauges/1 km², and subhourly recordings required to study convective area precipitation exist around the globe (e.g., Moore et al., 2000; Singer & Michaelides, 2017; Yoon & Lee, 2017). The very high density, long-term climate station network WegenerNet Feldbach Region (WEGN) in southeastern Austria provides a unique setting with 150 gauges (density 0.5 gauges/1 km²). Here we empirically explore the dependence of event maximum area precipitation (EMAP) estimates in extreme convective storms on the observing station density to quantify observational uncertainty associated with convective extreme precipitation at the critical 1 to 30 km scale.

2. Data and Methods

2.1. Precipitation Data and Convective Events Selection
The study area of 60 km × 60 km is located in southeastern Austria (Figure 1). It is characterized by low-elevation topography except for its north-western most area. The region is considered to be climatologically homogeneous regarding synoptic patterns of heavy precipitation (Seibert et al., 2007). Precipitation observations from 170 rain gauges in the extended convective season (April–September) are used over the years from 2007 to 2015. The 11 and 9 gauges are operated by the Austrian national weather service (ZAMG)
Figure 1. Study area and rain gauge locations in southeastern Austria. ZAMG = Austrian national weather service; AHYD = Austrian hydrographic service; WEGN = WegenerNet Feldbach Region.

and the Austrian hydrographic service (AHYD), respectively. The WEGN, operated by the Wegener Center of the University of Graz, comprises 150 gauges approximately aligned on a grid with $1.4 \, \text{km} \times 1.4 \, \text{km}$ station spacing.

The WEGN network is located over the southeast quadrant of the study domain covering an area of about $20 \, \text{km} \times 15 \, \text{km}$. Interstation distances range from 0.7 to 23.4 km. For a detailed introduction of the WEGN and its data quality control and data products generation, see Kirchengast et al. (2014) and Kabas et al. (2011). Raw precipitation amount is sampled at 5-min intervals. O et al. (2018) recently performed a thorough validation and bias estimation of the gauge data and we here use the bias-corrected WEGN level 2 version 6 precipitation data. All WEGN observations are aggregated to 10-min temporal resolution to match AHYD and ZAMG data resolution.

Summertime convective precipitation events are identified a priori. WEGN data processing automatically flags time intervals as convective based on the interstation variability of precipitation. Based on the flagged observations, convective events are classified individual events if they are separated by $\geq 5 \, \text{hr}$ of no or nonconvective precipitation. This way 429 convective events were identified, with a mean duration of 1.2 hr, and less than 1% of events longer than 5 hr. To allow for advection time over the study domain, 2 hr before and after each event are included as margins in the analysis.

To complement the WEGN classification, larger-scale synoptic conditions favoring convection were identified from ERA-Interim reanalysis data (Dee et al., 2011) using the COST Action 733 CT classification software (Philipp et al., 2016; Schiemann & Frei, 2010) and synoptic classifications issued by the Austrian weather service ZAMG. Technical details on the weather typing are provided in the supporting information Text S1.

An event detection algorithm (cf. Schroeer & Kirchengast, 2018) run over all convective days identified 98 precipitation events not flagged by WEGN over the study region. After visual validation using radar-rain gauge-blended integrated nowcasting through comprehensive analysis (INCA) nowcasting precipitation grids (Haiden et al., 2010), these were added to the sample, resulting in a total of 527 convective precipitation events $E_{1-527}$. Snapshots of two characteristic storm patterns are displayed for illustration in Figure 2.

2.2. Multi-Scale Estimation of EMAP

The spatial correlation of precipitation provides a first measure to characterize precipitation patterns. Pearson's correlation coefficient is calculated from gauge observations after Villarini et al. (2008), and root-mean-square deviation (RMSD) of precipitation (Mishra, 2013) is calculated at increasing station separation distances. For computing the RMSD, pairs of zero rainfall are omitted to avoid overestimating the spatial homogeneity of the rainfall field due to many zero-zero pairs in the network, which are naturally common in convective events. All measures are assessed for 10-min, 30-min, 1-hr, and 3-hr time integrations ($\tau$).
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Figure 2. Typical examples of sampled convective events over the study region (red square). Both events occurred after very hot days (daily max $T > 30^\circ C$) in low gradient synoptic weather conditions. Data are from the radar/rain gauge-blended integrated nowcasting through comprehensive analysis (INCA). Rain gauges are indicated as black dots. (a) Single-cell convective storm, (b) multicell convective storm.

The equations used are summarized in Table S2. Correlation analyses, however, do not measure area precipitation and are not targeted to event peak intensities. Results are sensitive to the selection of time frames and uncertainties can arise from averaging over different precipitation intensities (Wood et al., 2000).

In convective precipitation events, highest intensities and main runoff are generated by the storm core (Lochbihler et al., 2017; Syed et al., 2003). Extreme intensities are a key uncertainty in observations of convective precipitation and peaks are relevant for infrastructure design. WEGN allows us to empirically explore how estimates of gauge-derived, subhourly EMAP in extreme convective events depend on the station density.

We approach this endeavor in two steps (see Figure 3). First, subnetworks of decreasing resolution are extracted from the high-density network and second, convective area precipitation is estimated for each of the subnetworks.

To systematically generate subnetworks of predefined station separation distance $d$, we introduce the fishnet-windowed triangular mesh (FWTM) method. We increase $d$ stepwise by 1.5 km from 1.5 to 49.5 km and at each step apply a search tolerance of $s(d) = \pm 0.75$ km. As intergauge distances in a real network are never exactly the same, such a search tolerance $s$ must be applied (gray circles in Figure 3). While too low search

![Figure 3. Schematic description of the fishnet-windowed triangular mesh (FWTM) subnetwork sampling method including inverse-distance-weighted area rainfall estimation per triangle.](image-url)
tolerance decreases statistical robustness through reducing the number of station pairs, too high search tolerance leads to overlapping distance bin boundaries; we find \( s(d) = \pm 0.75 \text{ km} \) the best choice to maximize search tolerance while avoiding bin overlap.

For each \( d \), all rain gauges are paired with those neighboring gauges at distance \( d \pm s(d) \) with which they form an approximately equilateral triangle \( C \) with side length \( d \). At each distance \( d \), a total number of \( k \) triangular areas among three gauges A, B, and C with \( AB \approx BC \approx CA \approx d \) is found (\( C(d) \), Figure 3, 1a). Although rainfall cells are naturally not triangular in shape, triangles constitute the most elementary and robust way to construct an area over which mean area precipitation can be uniquely defined. Constructing equilateral triangles also eliminates issues arising from irregular rain gauge spacing.

Because of the very high density of stations in the WEGN area, triangles may spatially overlap, for example, when two gauges are so close that both qualify as edge station for a triangle at larger \( d \) (c.f. Figure 3, 1b). If both areas were kept, information is used which would not be available in a real network with separation distance \( d \). We avoid such potential biases by superimposing a regular fishnet grid with cell area \( A_{\text{rregular}}(d) \), corresponding to the area \( A_C \) of \( C(d) \) over the study domain to filter redundant triangular areas. That is, only one triangle with its center of mass closest to each fishnet cell’s center is kept. This fishnet-windowing reduces the number of triangles from \( C(d) \) to \( C(d) \) (Figure 3, 1b). We tested the sensitivity of the analysis to this filtering by shifting the fishnet’s origin in latitude and longitude, to randomize the gauges selected as edge stations, and found our results robust over the different testing scenarios (see Figure S1).

In each of the subnetworks of interstation distances \( d \in [1.5, 49.5] \), precipitation intensity \( I_{C(d)} \) over all triangular areas \( C \) is estimated as the arithmetic mean weighted by the gauge distances to the triangle’s center of mass (linear inverse-distance-weighting, IDW). Testing the sensitivity of calculations using squared IDW (exponent 2) showed little effect on the results (see Figure S1). For all convective events \( E_n \), area rainfall estimation is done for integration times \( \tau \in (10, 30, 60, 180 \text{ min}) \), obtaining time series for all triangular areas \( C(d) \) at each \( d \) and \( \tau \).

Next, we select the maximum intensity during each event in both time and space. Only the largest precipitation observation at \( \tau \) is kept: \( \max_{d} I_{C(d)} \) (temporal selection, Figure 3, 2a). Of all temporal event maxima over the study domain, we select the area with the highest estimated precipitation: \( \max_{d} I_{C(d)} \) (spatial selection). This selects the highest estimated mean area precipitation in each individual convective event \( E_n \) done for all subnetworks with the different station separation distances \( d \) (Figure 3, 2b).

Of the \( n = 527 \) convective events, extreme events are defined as those in which the maximum subhourly area intensity at \( d = 1.5 \text{ km} \) exceeds the 80th percentile (\( P_{80} \) events, Figure 3, 2c). The selected summertime convective storms always sample the most intense subdaily precipitation of the years (Schroeer & Kirchengast, 2018), so that this threshold allows analyzing a robust ensemble of extreme events.

The extreme EMAP \( I_{E_n}(d) \), called EMAP hereafter, is then adopted to be the median of the \( P_{80} \) events and is obtained for each time resolution \( \tau \): EMAP\_10, EMAP\_30, EMAP\_60, EMAP\_180. The upper and lower boundaries of the 90% confidence interval of EMAP are estimated as the \( \frac{n}{2} - \frac{1.645 \sqrt{n}}{2} \) and \( \frac{n}{2} + \frac{1.645 \sqrt{n}}{2} \) ranked values of the sample, respectively.

Finally, a two-parameter power law of the form \( I_{E_n}(d) = Bd^{-b} \) is fitted to the observed EMAP over the 1.5 to 33.0 km range (Figure 3, 2d). The chosen outer scale is considered the limit to reasonable inferences in the 60 km \( \times 60 \text{ km} \) study domain, with sampling up to \( d = 33.0 \text{ km} \) being nearly seamless despite the strict bin separation (only three bins 20.5, 22.5, and 30.5 km are not populated), whereas above, areas can no longer be seamlessly covered with triangles due to the large interstation distances combined with few stations in this large-scale domain.

### 3. Results and Discussion

Figure 4 shows rapidly decorrelating precipitation at 10-min resolution (correlation distance \( d_0 = 7.8 \text{ km} \)), which decreases for longer integration times (3 hr: \( d_0 = 26.5 \text{ km} \)). The relative RMSD of precipitation amounts between gauges (Figure 4b) increases rapidly up to around 10 to 15 km for subhourly scales and eventually levels off, while 1-hourly and 3-hourly curves increase even beyond 20 km. These short correlation distances of convective precipitation are consistent with other studies (e.g., Dzotsi et al., 2014). The results indicate...
that an operational coverage of ground observations at 7 to 10-km distance scales cannot provide reliable estimates of area precipitation on smaller spatial scales.

Figure 5 shows the maximum estimated area precipitation in extreme convective precipitation events (EMAP) depending on station separation distance (i.e., the density) of the rain gauge network. Figure 5a shows the EMAP intensity $I_{\text{area}}(d)$ relative to gauge observations $I_{\text{point}}$, which describes an empirical area reduction $I_{\text{area}}/I_{\text{point}}$.

Two measures are shown for comparison. First, theoretical ARFs, $ARF_{\text{theor}}$, are calculated from maximum point observations following Leclerc and Schaake (1972, equation given in Table S2). Among many methods of ARF calculation, this was chosen because it has repeatedly been used to evaluate precipitation in regional climate models (e.g., Mishra et al., 2012; Tripathi & Dominguez, 2013). Second, using the 20 operational ZAMG+AHYD rain gauges only, precipitation fields are interpolated onto regular grids of cell size $C(d)$ applying standard squared IDW interpolation with no further restrictions. For each $E_r(d, \tau)$, maxima are saved to obtain a best estimate of EMAP from the fixed-density operational network if no further information on the rainfall field was available.

The smallest observable area in the full network is $\sim 1 \text{ km}^2$ for a triangular area with station separation distance $\sim 1.5 \text{ km}$. At this scale, EMAP is 94% (10 and 30 min) to 85% (3 hr) of the point observation. At $d = 3 \text{ km}$, EMAP drops to 69% (3 hr) to 66% (10 min). Near operational network scales of $d = 10 \text{ km}$, the observed EMAP is 37% (3 hr) to 33% (10 min). With decreasing change rates, EMAPs reach 25% (3 hr) to 20% (10 min) at $d = 30 \text{ km}$. These results underline the small scales of extreme convective intensities, as integrating over 3 hr at 1 km scale significantly decreases observed intensities, while enlarging the area but sampling at short temporal intervals also strongly decreases the EMAP estimates.

Between $d = 1.5 \text{ km}$ and $d = 35 \text{ km}$ (areas from 1 to 500 km$^2$, respectively), the observed EMAP decays at a rate well approximated by a two-parameter power law $I_r(d) = Bd^b$, with an exponent $b$ (dimensionless) and a reference intensity $B$ (in intensity units), the latter describing the reference EMAP at a distance $d$ (in units [km]) of 1 km. We find exponents $b \approx -0.5(\pm0.1)$ up to the hourly time scale, that is, a decrease by 50% from 1 to 5 km, and a lower but not significantly different $b \approx -0.45(\pm0.1)$ at $\tau = 3 \text{ hr}$. All parameters are given in Figure 5, parameter uncertainties are provided in Table S4.

The $ARF_{\text{theor}}$ used in climate model evaluation studies decreases at a much lower rate to 80–90% within the first 10 km, to reach constant values of 50–75% at 20 to 30 km. This underlines that properties of convective extremes are not sufficiently considered by such ARFs, as emphasized also by Wright et al. (2014),
Figure 5. Observed (marker symbols) and power law fits (continuous lines) of EMAP intensities in extreme convective precipitation events observed at interstation distances \( d \) for different integration times: 10 min (dark red), 30 min (red), 1 hr (orange), 3 hr (yellow). EMAP point observations are also indicated (circles at distance zero). (a) EMAP relative to the point observation scale, ARF after Leclerc and Schaeck (1972; dashed bicolored lines) and estimates from ZAMG + AHYD operational gauge interpolation only (thin dashed colored lines) are shown for comparison; (b) Absolute EMAP intensities [mm/hr] in the high-density WegenerNet Feldbach Region (markers and heavy lines) and low density ZAMG + AHYD operational network (light dashed lines), respectively; (c) EMAP converted to the rainwater flux per area. (d–f) Shaded areas show the magnitude of the 90% confidence intervals around the corresponding EMAP estimates in (a), (b), and (c), shown in separate panels to avoid graphical confusion in (a), (b), and (c). The legend in (b) is valid also for panel (a). Boxes show parameters of the power law fits. \( x \) axis scales of distances \( d \) in (a) and (b) are consistent in scale with the \( x \) axis of (c), showing the corresponding areas between three gauges at distance \( d \). EMAP = event maximum area precipitation; ARF = area reduction factor; ZAMG = Austrian national weather service; AHYD = Austrian hydrographic service.
who explored storm-centered, event-based radar estimates of area reduction down to hourly scales in North Carolina, United States, demonstrating underestimation of reduction by the traditional U.S. Weather Bureau method.

The estimates from interpolated rainfall grids lie in between estimates from ARF$_{pore}$ and the empirically sampled EMAPs. The 80th percentile of point precipitation sampled from the operational network is 17–25% lower than in the ensemble including WEGN stations, showing that operational network sampling underestimates the magnitude of extreme point rainfall. However, from $d = 3$ km, extreme area estimates from the operational network are 12% to 50% larger than estimates from the FWTM network sampling. This indicates that the area of maximum precipitation intensity is overestimated in the operational network, because no area precipitation estimate of such magnitude is observed for the same event despite sampling with much denser networks (station separation distances of 1.5 to 9 km). A potential reason for this is the radial estimation around the rain gauge, leading to characteristic bull’s eye effects around local maxima. This statement is only robust for $d$ smaller than 7–10 km, because at larger $d$, the operational station density exceeds that of the less dense FWTM subnetworks.

Figure 5b shows EMAP intensities in WEGN and operational station network in millimeter per hour. EMAP curves of different time integrations stay separated over $d$. The 10-min intensities are highest even over large areas. Hence, peak precipitation rates in convective storms are usually not sustained for 30 min or longer, 30-min extreme rates are not sustained over 1 hr, and so forth. This is substantiated by the usually short duration of events at individual station locations (median: 1.5 hr, interquartile range: 0.9 to 2.6 hr).

The estimated EMAP intensities are finally converted to units of total rainwater flux per area (i.e., EMAP intensities are multiplied by the area over which the EMAP is calculated (Figure 5c)). This leans toward hydrological applications and illustrates the magnitude of maximum total rainwater volume precipitating over the given areas in extreme convective storms. One may view this as catchment water influx estimates, while actual runoff water fluxes will clearly depend on factors such as topography, land cover, and soil properties.

4. Summary and Conclusions

We showed that EMAP in extreme convective storms occurs over small areas; hence, the EMAP estimation depends on the density of any observing station network. The results here are based on 9 years of precipitation observations from the very dense WegenerNet rain gauge network (WEGN) and surrounding stations of operational networks (ZAMG and AHYD).

We found a power law decay of observed EMAP with increasing interstation distance $d$ of the rain gauges over 1 to 35 km and areas of 1 to 500 km$^2$, respectively, following $d^{-0.5(0.1)}$, which corresponds to a decay of $\sim50\%$ from 1 to 5 km distance. Extremes at the point scale (the rain gauge location), however, stay well below the values extrapolated to the point from the power law for small (1 km scale) distances. This indicates that the spatial extent of the most extreme intensity in convective storm cells (i.e., the area over which there would be no EMAP reduction from the point location) is smaller than 1 km$^2$ but clearly not zero, that is, needs to be addressed at subkilometer scale (e.g., Pedersen et al., 2010).

When deriving areas of maximum precipitation from interpolation of the operational network only, a simple interpolation method such as IDW results in overestimating the area affected by most extreme precipitation intensities at scales below the operational resolution. The presented scaling rates can assist in choosing interpolation parameters, for example, when adjusting the power value of IDW to precipitation type for confining the range of influence as suggested by Kann et al. (2015).

Irrespective of interpolation, the frequency of extreme peak precipitation is significantly undersampled in the operational network. While the maximum point-scale intensities recorded in both data sets are of similar magnitude, the distribution of extreme intensities in convective events shows significant differences, with the 80th percentile being approximately 20% lower when sampled from ZAMG-AHYD as compared to WEGN.

Unadjusted traditional ARFs strongly underestimate area reduction of convective extremes on small scales, since storm type differences are not explicitly considered (Pavlovic et al., 2016). Extremes at point scale are caused by different storm types than extremes at larger scales (Eggert et al., 2015). Comparative studies show that applying unadjusted ARF methods (e.g., review by Svensson & Jones, 2010) may significantly overestimate or underestimate area rainfall and that storm-centered, radar-based approaches better capture area...
reduction in thunderstorm environments (Mineo et al., 2018; Wright et al., 2014). Advantages and drawbacks of ARF methods should thus not only be carefully considered in engineering but also in evaluating climate models.

Our empirically substantiated spatial scaling can serve as a reference for improved evaluations of convective storm types in climatologically similar regions, that is, in warm temperate, fully humid, and warm summer climates at midlatitudes, such as most of Central Europe and southeastern parts of United States, Australia, or South-America (e.g., Kottek et al., 2006).

Radar data will further grow in quality and relevance for precipitation observation but rain gauges remain the primary source for ground-truth reference data sets. Most data sets of past climate rely on gauge data alone, and insufficient coverage by ground stations is responsible for persisting uncertainty. Our study quantified part of these uncertainties for summertime convective precipitation events at midlatitudes.

Peak area precipitation in convective events decays on spatial scales much smaller than operational network interstation distances, leading to severe underestimation at scales below 10 km, which can conversely result in interpolating too low intensity over too large areas. With growing evidence that midlatitude convective precipitation extremes are intensifying with climate change (e.g., Barbero et al., 2017; Dai et al., 2017; Fischer & Knutti, 2016; Ye et al., 2017), it is increasingly relevant to interpret and evaluate climate model and gauge-derived precipitation intensities at kilometer-scales. By providing a fundamental scaling dependence of convective extreme area precipitation on station density derived from high-quality, ground-truth gauge observations, our results can assist these tasks.

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