Replies to reviewer comment #1

RC C241:
Title: Temporal and spatial scaling impacts on extreme precipitation
Authors: Eggert et al.

We thank the anonymous reviewer for the insightful comments, which we feel have helped improve the clarity of the manuscript! Our point-by-point replies (blue) to the reviewer comments (black) are given below.

Reviewer #1

My only technical concern relates to the use of the "pdf overlap" metric which comes from Perkins et al (2007). Statisticians have been concerned with this problem for over six decades, with the Kullback-Leibler divergence commonly used to measure the difference between two probability distributions, and the two-sample Kolmorogov-Smirnov test being commonly used to test whether two pdfs differ. I wonder why the pdf overlap is used in place of these more traditional approaches, and whether it matters (for example, is there any potential for the pdf overlap to give misleading results, for example due to different sample sizes between pdfs etc)?

> We thank the reviewer for this comment.
> The PDF-overlap is calculated using normalized PDFs that use identical bins. All boxes with sample sizes less than 500 are excluded (this only occurred using the seasonal data in the supplement). Due to the normalization procedure the sample size should not make a difference.
> The PDF overlap after Perkins is a very intuitive way of comparing PDFs and we find that it nicely mirrors the changes found in the 99th percentile as seen in Fig 3, and is probably better known and easier to comprehend by the climate impact community which we believe will be the main target group of the paper.
>
> We included the following sentence to connect with earlier studies that use alternative measures:
> "We find that the PDF overlap mirrors the changes found in the 99th percentile (Fig. 3a). Using cumulative PDF measures as the Kolmogorov-Smirnov statistics is an alternative way of comparing PDFs."

Abstract [general]: Most of the abstract is focusing on method (what was done) and a bit more emphasis needs to be placed on results (what was found/discovered). The implications are also a bit vague for example the sentence "The resulting curve is relevant when deciding on data resolutions where statistical information in space and time is balanced" is very vague and should be made more precise.

> We rephrased the abstract with a focus on the results.

Abstract, line 2: "Risk" is commonly defined as "probability * consequences". I think here it is only the probability that is of concern?

> Yes it should have been "probability". The word "Risk" is not used anymore in the new abstract.

Abstract, line 3: “qualitatively” – why not quantitatively?

We meant to emphasis the change from stratiform to convective type extreme events by using the word “qualitatively”. But of course there is also a quantitative change. Due to the focus change of the abstract this wording is not used anymore.

The new abstract:

Convective and stratiform precipitation events have fundamentally different physical causes. Using a radar composite over Germany, this study separates these precipitation types and compares extremes at different spatial and temporal scales, ranging from 1 km to 50 km and 5 min to 6 h, respectively. Four main objectives are addressed: First, we investigate extreme precipitation intensities for convective and stratiform precipitation events at different spatial and temporal resolutions, to identify type-dependent space and time reduction factors and to analyze regional and seasonal differences over Germany. We find strong differences between the types; with up to 30% higher reduction factors for convective extremes, exceeding all other observed seasonal and regional differences within one type. Second, we investigate how the differences in reduction factors affect the contribution of each type to extreme events as a whole, again dependent on the scale and the threshold chosen. A clear shift occurs towards more convective extremes at higher resolution or higher percentiles. For horizontal resolutions of current climate model simulations, i.e. ~10 km, the temporal resolution of the data as well as the chosen threshold have profound influence on which type of extreme will be statistically dominant. Third, we compare the ratio of area to duration reduction factor for convective and stratiform events and find that convective events have lower effective advection velocities than stratiform events, and are therefore more strongly affected by spatial than by temporal aggregation. Finally, we discuss the entire precipitation distribution regarding data aggregation, and identify matching pairs of temporal and spatial resolutions where similar distributions are observed. The information is useful for planning observational networks or storing model data at different temporal and spatial scales.

Introduction

I am finding the introduction a bit underwhelming. There are a lot of great threads of ideas, and the authors have succeeded in capturing the relevant literature, but the ideas could be brought together much better and the relevance of ideas to the paper made more explicit.

For example, how is the “alarming” finding that statistical downscaling procedures assume that the empirical relationships between large and small scales hold in the future relate to the research proposed here?

Our study shows that large and small scales emphasize different events. Assuming that the empirical relationships between the scales will hold in the future would hence mean to assume that both types of events will behave similarly in the future. The different response of the different precipitation types to temperature increase is however largely discussed and we cite 4 papers to this topic.

We strongly shortened this part of the introduction since it is only indirectly related to the research presented here.

Similarly, while it is obvious that convective and stratiform rainfall would require different climate model resolution (page 2162, line 5), it’s not clear whether the space-time resolutions identified in this paper would necessarily be equivalent to the "minimal climate model resolution".

We here only talk about model output resolution. The actual calculation time step has to be much shorter and is not subject of this research. Still the space-time resolutions identified in this paper are obtained using observational data and cannot directly be translated to model resolutions. But knowing the space time relation of precipitation events will lead to the knowledge about what is statistically possible to be captured at a certain resolution. This will be a great help in order to validate and set up model and observation studies.

What is the issue with the simple power law dependence not holding generally, and is the "regime-distinction" related to the classification of convective/stratiform rainfall or is this a different issue?

We could not find a direct connection. To avoid confusion we left this issue out of the introduction.

Page 2162, paragraph 2: the need for the study could be made stronger; the importance of this question is not stresses enough. Please include more literature or other examples to explain why it is importance.

We made major changes in the introduction by shortening and emphasizing stronger on ideas directly relating to the results of the paper. The need for the study should now be made stronger.

New Introduction:

The IPCC's fifth assessment report highlights an intensification of heavy precipitation events in North America and Europe (Hartmann et al., 2013), and projects further increase of extremes as global temperatures rise (Collins et al., 2013). The study of extreme events is complex due to a strong inhomogeneity of precipitation intensities in space and time. Assessment of precipitation extremes, e.g. as defined by an intensity threshold, therefore always requires specification of the relevant spatial and temporal resolution.

Even though spatial and temporal scales are far from independent (Taylor, 1938), it is often unclear how to compare datasets directly, when their data is measured at differing resolutions. The data resolution needed by users, e.g. hydrologists or crop modelers, often differs from that at which observed or modeled data is recorded (Willems et al., 2012).

The primary societal interest in extreme precipitation lies in its hydrological implications, typically requiring statistics of precipitation extremes for the area of a given catchment or drainage system, which is not identical to that of model grid boxes or the observations.

Moreover, temporal scales relevant to flood risk vary enormously with area (Blöschl and Sivapalan, 1995; Westra et al., 2014): For catchments, hours to days are relevant (Mueller and Pfister, 2011), whereas urban drainage systems of ~ 10 km (Arnbjerg-Nielsen et al., 2013) are impacted at timescales from minutes to hours (De Toffol et al., 2009), and soil erosion can occur at even smaller scales (Mueller and Pfister, 2011).

Areal Reduction Factors (ARF) and Intensity Duration Functions (IDF) have previously been used to describe the decrease of average precipitation intensity due to spatial and temporal aggregation (Bacchi and Ranzi, 1996; Smith et al., 1994). The capability of radar data to capture the spatial structure of storms was identified as a key factor in deriving the ARFs (Bacchi and Ranzi, 1996; Arnbjerg-Nielsen et al., 2013). A general outcome was that ARFs exhibit a decay with respect to the return period (Bacchi and Ranzi, 1996; Siva- palan and Blöschl, 1998) and a dependency on the observed region, resulting from different governing rainfall generation mechanisms (Sivapalan and Blöschl, 1998).

In the current study we separate the physically different processes leading to convective and stratiform type precipitation events. Using synoptic observation data, we classify precipitation events into these two types, allowing us to analyze their aggregated statistics individually across scales.

The two types physically differ in that convection is often initiated by local radiative surface heating, resulting in a buoyantly unstable atmosphere (Houze, 1997), whereas stratiform precipitation stems from large-scale frontal systems and relatively weak and uniform up- lifting. Analyzing these two types separately regarding their intensities at different scales can e.g. be important when considering temperature changes, such as anthropogenic warming: Over large scales, the changes were found to be moderate, whereas for very small scales, it has been argued that the two processes may increase with warming (Trenberth, 1999; Trenberth et al., 2003; Trenberth, 2011; Lenderink and van Meijgaard, 2008), albeit at very differing rates (Berg et al., 2013). Using high-resolution model simulations, heavy precipitation at high temporal resolutions was suggested to increase strongly in a fu- ture climate, and a dominant contribution to extreme events to stem from convective events (Kendon et al., 2014; Muller et al., 2011; Attema et al., 2014).

In spite of their small horizontal and temporal range, convective events can cause substantial damage (Kunz, 2007; Kunz et al., 2009), e.g. through flash floods (Marchi et al., 2010).

Numerous studies have assessed the temporal and spatial characteristics of precipitation events using a storm centered, or *Lagrangian*, approach (Austin and Houze Jr., 1972; Houze Jr. and Hobbs, 1982; Moseley et al., 2013), which focuses on the storm dynam- ics, e.g. lifetime or the history of its spatial extent. Moseley et al. (2013) showed that, for Lagrangian event histories of 30 min, the convective type can produce significantly higher intensities than the stratiform type. As we here focus on potential hydrological applications and those addressing possible impact of extremes, e.g. floods, defining events over a *fixed* surface area and time period is more appropriate (Berndtsson and Niemczynowicz, 1988; Onof et al., 1996; Bacchi and Ranzi, 1996; Michele et al., 2001; Marani, 2003, 2005). The statistics thereby constitute averages over a defined space–time window within which both dry and wet sub-intervals may occur.

In this study, we analyze at which fixed temporal and spatial scales convective precipitation dominates precipitation extremes. To this end, we analyze two years of mid-latitude high-resolution radar data (5 min temporally and 1 km spatially), classified by precipitation types and separated into seasons (summer vs. winter) and geographic areas (north vs. south Germany). Analysis of these data over large spatial and temporal periods characterizes the statistical aggregation behavior in space and time. It can quantify the requirements on minimal model resolution sufficient for the proper description of the respective extremes. Revisiting the Taylor-hypothesis (Taylor, 1938), we contrast the two precipitation types, as to how resolutions in space and time can be compared. Using a resulting effective advection velocity, we give a simple means of quantifying effective temporal averaging in models, resulting from a given spatial resolution.

The structure of the article is as follows: In Sec. 2 we describe the data and methods used. Section 3 presents the results for extremes at different resolutions (Sect. 3.1) and suggests a method to compare the corresponding probability density functions (Sect. 3.2). We close with discussions and conclusions (Sect. 4).

Data and methods:

Page 2163: How many synoptic cloud observation stations were used?

222 stations in total, we included this in the text.

Synoptic cloud observations, at 222 stations, obtained from the Met Office Integrated Data Archive System (MIDAS) data base [http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas] are used to separate large-scale and convective precipitation following Berg et al. (2013).

Results:

Second paragraph, page 2165 on temporal aggregation: Just a suggestion, but could "the effect of temporal aggregation is to even out spatial variations due to large-scale flow" be illustrated using a conceptual diagram? Similar for the subsequent discussion of Taylor's hypothesis. Again, this would help expand the appeal of this paper.

We included a diagram showing the concept of the Taylor hypothesis together with the two major assumptions made in order to use this hypothesis for our analyzes (frozen in time, no variability perpendicular to the advection direction). We further rewrote parts of the chapter to better explain the concept.

Page 2159: Can you provide a more formal definition of an Areal Reduction Factor here?

We changed the definition to a more formal one.

Equation 2, page 2167: Is "x" a length scale? Can you confirm whether this is consistent with the standard definition of an ARF? [since an area is a lengthˆ2 scale].

x is the grid size hence it is a length^2 scale.

Page 2168-2169: This section would have been much more compelling with some illustrative diagrams of the "frozen turbulence" vs self-affine concepts, and how the choice of interpretation would lead to differences in space-time aggregation. This is the same issue as made in reference to the Taylor's hypothesis on page 2165, and I think that a conceptual diagram would make the results much easier to interpret.

We have rewritten parts of the chapter that describes the self-affine process to make this clearer. Also a conceptual diagram is added.

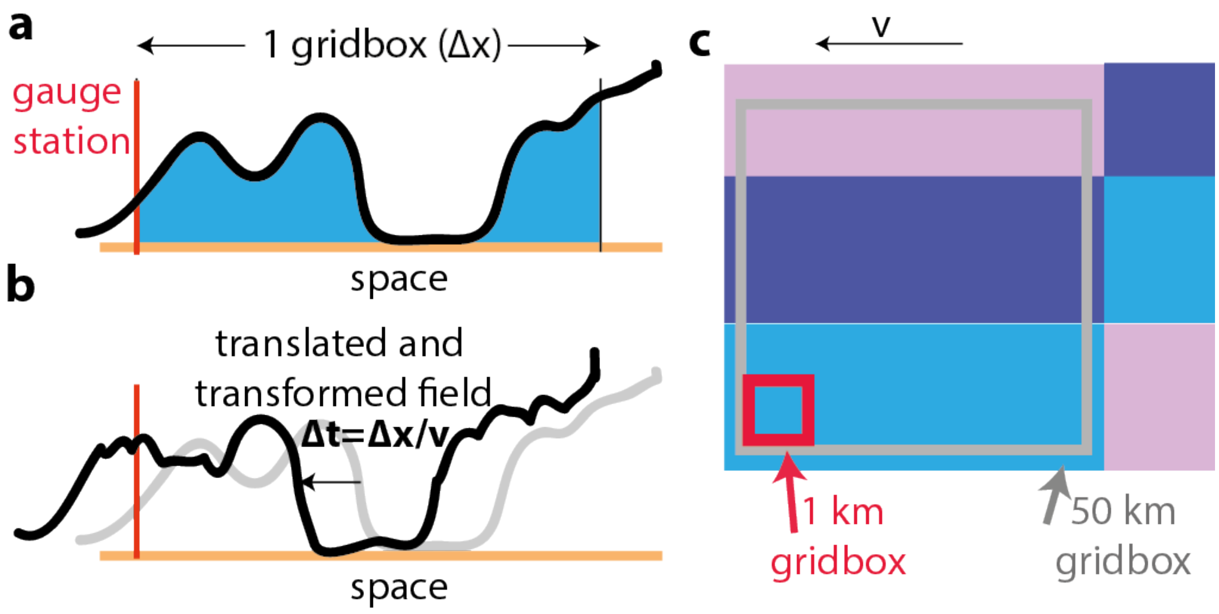

Figure 6. Schematic illustration of the Taylor hypothesis. (a) One-dimensional case, showing space, gridbox width and precipitation intensity (black curve); the location of a gauge station is marked in red. (b) Similar to (a), but illustrating how the curve may change due to small scale dynamics after a time interval $\Delta t = \Delta x/v$, with v the atmospheric advection velocity. (c) Two-dimensional inhomogeneity (different colors indicate different intensities) perpendicular to the advection direction (direction indicated by the thin arrow). Small (red) and large (gray) gridboxes as marked.

Page 2178: "the optimum temporal resolution for state of the art regional climate simulations, performed at a 11 km horizontal resolution, would be approximately 20 to 25 minutes." This to me is an extremely important practical outcome of the paper but is a bit buried here. This is the sort of thing that could be highlighted in the abstract? Similarly, the finding that different meteorological events are considered extreme depending on the threshold is an interesting finding.

We changed the abstract and the conclusions to highlight this point more clearly

Page 2159, line 3-6: this sentence was unclear, please rewrite.

we rephrased the sentence.

Assessment of precipitation extremes, e.g. as defined by an intensity threshold, is strongly scale dependent and therefore requires specification of the analyzed spatial and temporal resolution.

Page 2164: what is the role of the apostrophe in I' ? This is not defined or used elsewhere.

That is standard math nomenclature to show that it is the variable being integrated over.

Page 2176, line 20: "smoothening" should be "smoothing"

yes we changed this.

Page 2162, line 4-6: should be rephrased as a question

This sentence is not included anymore in the new introduction.

Page 2165, line 4-5: unclear, please rephrase

We rephrased the sentence:

Stratiform precipitation is more uniform in the sense that sampling over small areas yields a good description of the statistics also at larger areas of aggregation.

Figure 7 caption: “larger or equal” should be “greater than or equal to”

We changed the figure caption.

Figure 8 caption: “larger or equal” should be “greater than or equal to”

We changed the figure caption.

Replies to reviewer comment #2

RC C422:
Title: Temporal and spatial scaling impacts on extreme precipitation
Authors: Eggert et al.

We thank the anonymous reviewer for the insightful comments, which we feel have helped improve the clarity of the manuscript! Our point-by-point replies (blue) to the reviewer comments (black) are given below.

Reviewer #2

Considering that the average reader who is interested in this work (and this work has potentially many practical users) it would be nice to explain in general terms what a self-affine process is. The references mentioned deal with rather specific papers, with detailed mathematical analysis, which are not easy to read, and general information on a self-affine process was not specific enough. Finally, I understood this as a change from more linear precipitation structures at larger scales to more circular structures at small scales. If this is the case, or else, it would be nice to show this with a conceptual figure.

We have rewritten the introduction and discussion and conclusions chapter to be more accessible for the more practical users, while keeping much of the details of the results chapter for the more theoretically inclined readers. We added a general explanation of the term self-affine to the paper and also rephrased parts of the already given information in order to make the text more comprehensive. Additionally we added a conceptual figure showing the concept of the Taylor hypothesis together with the two major assumptions made in order to use this hypothesis for our analyzes (frozen in time, no variability perpendicular to the advection direction).

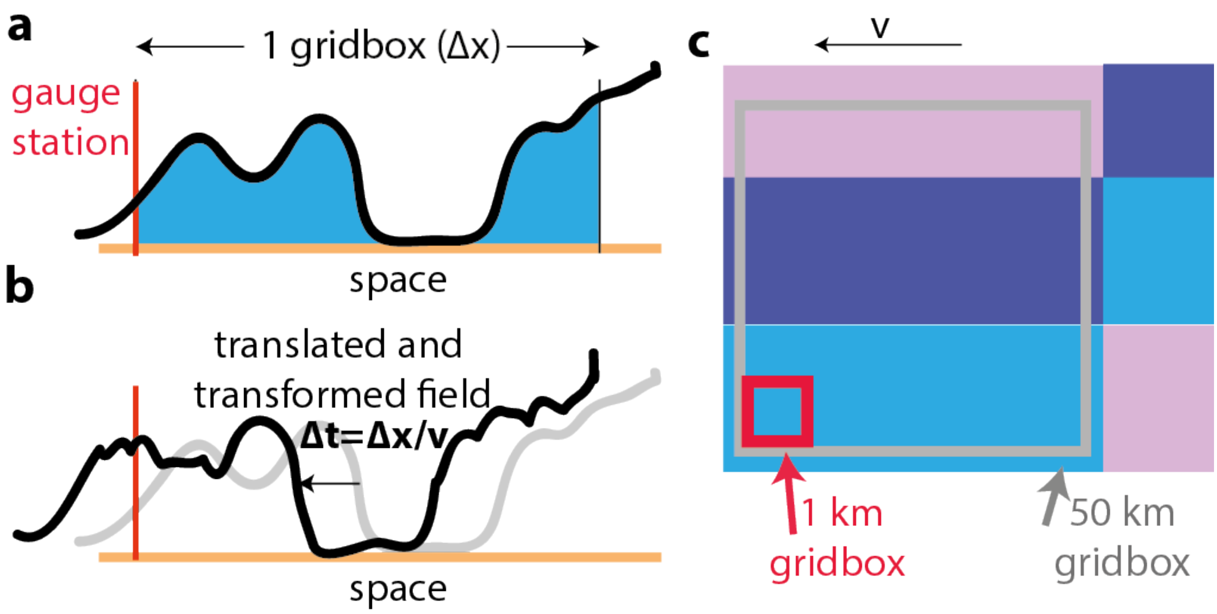

Figure 6. Schematic illustration of the Taylor hypothesis. (a) One-dimensional case, showing space, gridbox width and precipitation intensity (black curve); the location of a gauge station is marked in red. (b) Similar to (a), but illustrating how the curve may

change due to small scale dynamics after a time interval $\Delta t = \Delta x/v$, with v the atmospheric advection velocity. (c) Two-dimensional inhomogeneity (different colors indicate different intensities) perpendicular to the advection direction (direction indicated by the thin arrow). Small (red) and large (gray) gridboxes as marked.

In general I have difficulties in understanding to concept of optimal resolution, and I also do not fully understand the implications for this in term of model resolution and model output. This may be my misunderstanding, but I think the manuscript may benefit from explaining a number of points more clearly. I few points where I am puzzled are:

In the discussion, I do not see the points made at page. 2178, lines 12 to 20. I may have missed the point here, but you are arguing that the statistics of the 11 km, 5 minute output is similar to the statistics of 1 km and 25 minute output, right ? In general, there is a similarity between the statistics at different time and spatial aggregation as shown also in Figures 9 and 10. I agree to that, but I do not see the point that this implies that the combination of 11 km and 25 minutes is optimal. Optimal in the sense that it follows Eq. 6 appears a mathematical construct and I do not fully understand how these practical implications follow from this.

Also, at page 2171 line 10 you are stating that the optimal temporal resolution of stratiform events should be 3.6 times higher resolved than in the original data set to yield consistency between temporal and spatial information. I am not sure what you exactly mean by this. Somehow this goes against intuition as stratiform events are characterized by both relatively small spatial and temporal dependencies.

We understand that the word „optimal“ was not a good choice and leads to confusions. Therefore we rephrased the section and added more information to explain what we mean. We also added more detailed information on how the results should be interpreted. You are right that stratiform events are characterized by both relatively small spatial and temporal dependencies. Here we only looked at the different ratios (area reduction / duration reduction) not at absolute values.

Comparing the relevance of space compared to time aggregation. We can distinguish the behavior of spatial and temporal aggregation using two kinds of approaches (Deidda, 2000). The first approach would be to regard precipitation as a self-similar process (simple scaling). In this case the Taylor-hypothesis (Taylor, 1938) would be obeyed, and temporal variations can be reinterpreted as spatial variations that are advected over a fixed location by a large-scale flow that has a constant value over the observed temporal and spatial scales.

Following the notion of "frozen turbulence", intensity change due to spatial aggregation can then be calculated from the intensity changes that result due to temporal aggregation multiplied by a constant velocity u, i.e. $\Delta x \approx \Delta t \cdot u$. This would only hold, if precipitation extremes could be seen as objects of temporally constant characteristics that are translated by large scale advection. If we also assume spatial inhomogeneity only to occur in the advection direction, a gauge station could be used to measure the precipitation intensities that fall over an area (Fig. 6a).

The second approach would assume that the spatial and temporal aggregation behavior of precipitation extremes would behave like a self-affine process (a process where the ratio of scales is changing as one of the scales changes). In this case, the simple linear relation that connects changes due to time aggregation with changes due to spatial aggregation through an advection velocity, generally does not hold anymore (e.g. due to temporal (Fig. 6b) or spatial inhomogeneity (Fig. 6c). A multifractal analysis is needed, where in short, the "velocity" itself would become a function of the respective spatial and temporal scales. If this function is known, it is possible also for self-affine processes to connect spatial and temporal scales. Proper understanding of the relationship between spatial and temporal aggregation is e.g. crucial for precipitation downscaling and bias correction methods (Wood et al., 2004; Piani et al., 2010a, b).

Our goal here is to characterize the differences in scaling of convective and stratiform extremes: Comparing the intensity reduction due to time aggregation for the 1 km dataset (Fig. 3a, left column) with the intensity reduction that results from spatial aggregation at a temporal resolution of 5 min (bottom row), a 4 km spatial aggregation is comparable to that of spatial aggregation for roughly 15 min. Similarly, for stratiform precipitation (Fig. 4a) we find that 6 km spatial aggregation corresponds to 15 min temporally. There is hence a dependence on the precipitation type, a relation we now analyze.

Figure 7a shows for each horizontal resolution the matching temporal resolution that achieves similar intensity reduction. We describe the relation between temporal and spatial aggregation at a fixed Δx by

$$f_{\Delta x}(\Delta t)=|\ I(\Delta t,1km)-I(5min,\Delta x)\ | \qquad (4)$$

We now define $\varphi_{\Delta x}$ as the minimum value of $f_{\Delta x}$ w.r.t. Δt:

$$\varphi_{\Delta x} = \min f_{\Delta x}(\Delta t) \qquad (5)$$

The best matching time window Δt for a given Δx can be determined using the inverse function of $f_{\Delta x}$: $\Delta t = f^{-1}(\varphi)$. In practice, we determine Δt by an iterative numerical procedure, using first an interpolation between available resolutions for better approximation. The result for several high percentiles is shown for both precipitation types over Germany for the entire year on a log-log plot (Fig. 7a), i.e. straight lines represented power laws. If the Taylor-hypothesis were obeyed, the exponent would equal unity.

Within the limitations of the relatively noisy data, we find that the data represents a straight line over most of the analyzed spatial range and can be fitted to a power law function $\Delta t = a \times \Delta x^b$ with fitting parameters a and b, or by using dimensionless variables (i.e. defining $\chi \equiv \Delta x/\Delta x_0$, $\tau \equiv \Delta t/\Delta t_0$ and $\tilde{a} \equiv a\Delta x^b{}_0/\Delta t_0$), we have

$$\tau = \tilde{a}\,\chi^b\ ,) \qquad (6)$$

with fitting parameters $\tilde{a}$ and b. The parameter $\tilde{a}$ is a scaling parameter and describes the Δt_0 corresponding to Δx_0. χ^b describes how the relevance of space compared to the time aggregation changes with resolution.

In Fig. 7a and b, the best-fit for the 99th intensity percentile is shown for convective and stratiform precipitation. We find that b is similar for both types (generally between 1.17 and 1.32), a departure from unity that should be confirmed by other data sources than the radar data at hand. An exponent b > 1 indicates, that extreme precipitation is self-affine (self-similarity would require b = 1). The fractal properties of precipitation were already highlighted in earlier studies and are found to be a result of the hierarchical structure of precipitation fields (Schertzer and Lovejoy, 1987) with cells that are embedded in small mesoscale areas which in turn occur in clusters in large-scale synoptic areas Austin and Houze Jr. (1972).

Table 1 displays $\tilde{a}$ and b for the different percentiles shown in Fig. 7a (non-dimensional). We find that for convective precipitation $\tilde{a}$ is near 0.5. Within the error bars there is no obvious dependence on percentile. This is also the case for the stratiform type, besides for the 99.9th percentile, which has higher $\tilde{a}$ and lower b values.

Since the values of b are similar for both precipitation types (Table 1), the difference between the matching temporal resolution of stratiform and convective events is kept constant over the entire range of Δx analyzed. We find that the different scaling between the two precipitation types mainly results from the varying $\tilde{a}$.

Note also the kink in the observed curves in Fig. 7a at about 6 km, where a change of slope is observed. To show that this kink is a manifestation of the scale mismatch, we aggregate data spatially to 2 km (3 km for stratiform) horizontal resolution and re-plot (Fig. 7b). Due to this procedure the kink almost vanished. This test shows that aligning resolutions according to Eq. (6) allows smooth scaling.

For further analysis, and to make contact to the Taylor-hypothesis, we use the ratio of the the matching Δx and Δt to calculate the mean *effective* advection velocity, which we call v_{eff}. We define:

$$v_{eff}(\chi) \equiv \chi/\tau = \chi^{1-b}/\tilde{a}.) \qquad (7)$$

This velocity is not obviously the same as the velocity obtained by tracking algorithms, such as in (Moseley et al., 2013), as v_{eff} combines all reasons for changes caused by aggregation. The main sources for these changes are advection of the precipitation field out of the grid box, temporal inhomogeneity caused by the temporal evolution of the precipitation event (Figure 6b) and horizontal inhomogeneity perpendicular to the advection direction, that will increase the area reduction factors (Figure 6c).

Figure 7c shows v_{eff} calculated for different Δx for the 95th, 98th, 99th and 99.9th percentile, using data without seasonal distinctions over Germany. v_{eff} lies in the same range as the velocities calculated by Deidda (2000) and Moseley et al. (2013) who calculated the velocities using tracking techniques. This shows that advection is likely the major source for changes due to temporal and horizontal aggregation. Low v_{eff} for horizontal resolutions below about 2 to 4 km are again a result of the mismatch of the 5 min temporal resolution and the 1 km spatial resolution explained above.

Note the deviating value of $\tilde{a}$ for the 99.9th percentile of stratiform precipitation. This could be explained by mesoscale stratiform systems with embedded convection, i.e. systems that are somewhat intermediate between stratiform and convective events. The corresponding graph (Fig. 7c) shows intermediary behavior, connecting the curves of convective precipitation (low Δx) to those of stratiform precipitation at high Δx. Due to substantial noise at high spatial resolution it is not possible to identify if v_{eff} shows a constant behavior (b = 1) at the high resolutions, therefore the results in Zawadzki (1973) and Waymire et al. (1984) indicating the Taylor-hypothesis to hold for time scales less than 40 min can neither be confirmed nor rejected.

Realizing that v_{eff} combines all sources for changes caused by aggregation enables a simplified view on the aggregation process. In a similar way as in Deidda (2000) we can use v_{eff} to generalize the Taylor-hypothesis for a self-affine process, by using v_{eff} instead of a constant velocity to describe the relation between space and time. Following the Taylor- hypothesis we can now interpret the matching temporal and spatial scales from Figure 7a as the mean time that is needed to advect the information about the precipitation field over the matching horizontal scale (implicitly including all other sources of aggregation changes as described above). For example the typical timescale for a convective precipitation area to cross a grid box with a 10km grid-size, a typical resolution of state of the art climate models, would be about 40 min. For a stratiform precipitation event the information about the precipitation field is already captured after about 20 to 25 min. Reasons for the lower effective advection velocity might be that stratiform events are statistically more homogeneous than convective events which results in a shorter period to capture the structure of the event. Also, convective events often occur at high pressure weather conditions where low wind velocities might entail lower advection velocities.

Aggregation effects at a specific resolution will always be a combination of duration and area reduction factors. Connecting space and time scales using v_{eff} allows the association of temporal and spatial scales, shown in Fig. 7a. If, for a given spatial resolution, a larger temporal output period is used as indicated by Figure 7a, the event will on average be advected beyond the grid box area, leading to high duration reduction factors (a "smearing out").

Finally, I do not understand why a_tilde (as defined in eq 6) is not 1, since the ARF and DRF are equal at the reference resolution (1 km, 5 minutes) by construction. Does this perhaps imply that the effective resolution of the rain radar data is not 1 km and 5 minute, or that there is a mismatch between spatial and temporal scale in the radar data too. Is this what you want to say with Figure 6b? And is this also the reason why in Figure 9 the lower left point does appear to be an outlier (or is characterized by a very strong decay in pdf overlap at lower time and larger spatial resolution).

You are right, at the reference resolution of 1 km, 5 min we find that the temporal aggregation most likely lead to stronger intensity reductions than the spatial aggregation. This is what we show with Figure 7b (before 6b). The reason why in Figure 10 (before 9) the lower left point does appear to be an outlier is more likely an artifact from the data binning.

Minor points:

p 2163, l 27: I did not understand "convective together with mixed conditions"

We rephrase to make the txt more comprehensive:

For time resolutions longer than three hours, two 3 hourly time slices have to be considered. Here we classify the precipitation event as *stratiform* or *convective* only, if the type is identified at least at one of the time slices and the other time slice was not identified as the opposite type of event.

p 2165, line 26 and further. This is a nice example of explaining why these statistics are similar. But, the argument of the propagation speed should not enter the spatial averaging in this simple example since the averaged intensity over the grid cell (as long as the cell is within the grid box, and this is only where the propagation speed is important) does NOT depend on the propagation speed (at any time the area of precipitation is 10x10 km).

You are right, we corrected this example in the text. Without the propagation speed the size of the events needs to be a few hundred meters larger than the 10 km in order to have an exact match with the passage over a location example. Since this is an idealized example that uses only approximate values, we feel that the example is still valid.

According to Berg et al. (2013) and Moseley et al. (2013) the average convective event has a lifetime of approximately 30 min, a spatial extent of ~ 10 km and a propagation speed of ~ 10 ms^{-1}. When using a 50 km grid box and 5 min temporal resolution, the event will move about 3 km, therefore it can be assumed that the event stays in one grid box. It will affect roughly (10x10)/(50x50)≈ 4 % of the cell at a time. When an event of ~ 10 km cross section moves over a location with ~ 10 m/s, its passage over the location would last ~ 1000 s, which is ~ 17 min, and 17/360 ≈ 5 % of the matching time interval of 6 hours.

p 2172, line 18. I thought the optimal temporal resolution is smaller (not larger) for stratiform events, which is what you get when dividing the two optimal curves.

Please see the above explanation.

Eq. 7: isn't there a root of b missing here?

Thanks for noticing, the problem in this equation is, that it should have been Xi instead of tau. We changed this in the text.

p 2178, line 14: a model resolution of 11 km does not imply that precipitation at that scale is realistically simulated as you seem to imply here.

You are correct and we did not intend to imply this; we have rewritten the sentence to make this clearer. Additionally we added more information about this subject in the discussion section and we have refrained from using the word "optimum" to avoid confusion.

Replies to reviewer comment #3

RC C440:
Title: Temporal and spatial scaling impacts on extreme precipitation
Authors: Eggert et al.

We thank the anonymous reviewer for the insightful comments, which we feel have helped improve the clarity of the manuscript! Our point-by-point replies (blue) to the reviewer comments (black) are given below.

Reviewer #3

1) Are these results generalizable? Some discussion on this is needed. The authors begin to talk about embedded convection and complex topography (important over narrow mountain ranges) but leave it hanging. A few sentences about whether the relationships shown here might/might not be expected elsewhere would be valuable. Will every region require it's own investigation? For example will the optimal pairs for Norway match those of Germany? Vietnam? UK?

> Since we only analyzed precipitation over Germany and are not aware of other similar studies that have been done at other climate zones, we can only speculate about this. We expect that the findings will depend on the mean advection velocity and also the orography might have an impact on the findings. We add this to the discussion part of the paper.

2) Abstract: the aim of the manuscript should appear in the first few sentences not at the end. Also it would be helpful to mention that current approaches, to say, regional modeling, do not account for spatial and temporal dependence in a rigorous way. Emphasize the results and their implications (see reviewer 1 comments on this).

> We rewrote the abstract in order to emphasis more on our results.

> The new abstract:
> Convective and stratiform precipitation events have fundamentally different physical causes. Using a radar composite over Germany, this study separates these precipitation types and compares extremes at different spatial and temporal scales, ranging from 1 km to 50 km and 5 min to 6 h, respectively. Four main objectives are addressed: First, we investigate extreme precipitation intensities for convective and stratiform precipitation events at different spatial and temporal resolutions, to identify type-dependent space and time reduction factors and to analyze regional and seasonal differences over Germany. We find strong differences between the types; with up to 30% higher reduction factors for convective extremes, exceeding all other observed seasonal and regional differences within one type. Second, we investigate how the differences in reduction factors affect the contribution of each type to extreme events as a whole, again dependent on the scale and the threshold chosen. A clear shift occurs towards more convective extremes at higher resolution or higher percentiles. For horizontal resolutions of current climate model simulations, i.e. ~10 km, the temporal resolution of the data as well as the chosen threshold have profound influence on which type of extreme will be statistically dominant. Third, we compare the ratio of area to duration

reduction factor for convective and stratiform events and find that convective events have lower effective advection velocities than stratiform events, and are therefore more strongly affected by spatial than by temporal aggregation. Finally, we discuss the entire precipitation distribution regarding data aggregation, and identify matching pairs of temporal and spatial resolutions where similar distributions are observed. The information is useful for planning observational networks or storing model data at different temporal and spatial scales.

3) P2159 L4-6: The sentence beginning "However, in many cases..." is vague and has phrases such as "...weather, respectively climate, models..." that do not make sense. The point this sentence is trying to make is important try to re-word and make it more precise.

We rewrote the part in the introduction.

Assessment of precipitation extremes, e.g. as defined by an intensity threshold, is strongly scale dependent and therefore requires specification of the analyzed spatial and temporal resolution.

Even though spatial and temporal scales are far from independent (Taylor, 1938), it is often unclear how to compare datasets directly, when their data is measured at differing resolutions. The data resolution needed by users, e.g. hydrologists or crop modelers, often differs from that at which observed or modeled data is recorded (Willems et al., 2012).

4) P2160 L10-14: It seems as though the authors wish to make a transition here from the discussion around the importance of, and challenges related to, distinguishing scales to a discussion on the physical processes governing convective and stratiform precipitation. If this is the case they should just say so, instead of the current, some- what clumsy transition paragraph.

We rephrased the sentence:

In the current study we separate the physically different processes leading to convective and stratiform type precipitation events. Using synoptic observation data, we classify precipitation events into these two types, allowing us to analyze their aggregated statistics individually across scales.

5) P2161 L4: This is actually a crucial motivation for the study and yet it is buried in the introduction. This should appear early on as a motivator and maybe even to kick off the nice literature review.

We rewrote the Introduction (see below)

6) P2161 L6-17: A whole paragraph on the pitfalls of statistical downscaling predictors but then it is not mentioned again. Is it relevant to the current study? If so, then describe why. If not, then place the discussion in the proper context or take it out.

The results of the study are relevant for statistical downscaling procedures since the change from convective extremes to more stratiform extremes, going to lower resolutions, will be a major pitfall of simple downscaling methods.

Since the study is not directly related to the choice of predictors, we shorten this part in the introduction.

7) Overall the introduction is a bit lacking. I suggest restructuring as follows: i) Start with the problem statement. Why is it important? Why should we care? ii) What have others done on this topic (literature review)? iii) What questions are still unanswered (cf. problem statement)? iv) Describe how is this study going to answer them. v) Structure of the paper

We have completely rewritten the introduction, taking all of the reviewer points 3 to 7 into account.

New Introduction:

The IPCC's fifth assessment report highlights an intensification of heavy precipitation events in North America and Europe (Hartmann et al., 2013), and projects further increase of extremes as global temperatures rise (Collins et al., 2013). The study of extreme events is complex due to a strong inhomogeneity of precipitation intensities in space and time. Assessment of precipitation extremes, e.g. as defined by an intensity threshold, is strongly scale dependent and therefore requires specification of the analyzed spatial and temporal resolution.

Even though spatial and temporal scales are far from independent (Taylor, 1938), it is often unclear how to compare datasets directly, when their data is measured at differing resolutions. The data resolution needed by users, e.g. hydrologists or crop modelers, often differs from that at which observed or modeled data is recorded (Willems et al., 2012).

The primary societal interest in extreme precipitation lies in its hydrological implications, typically requiring statistics of precipitation extremes for the area of a given catchment or drainage system, which is not identical to that of model grid boxes or the observations.

Moreover, temporal scales relevant to flood risk vary enormously with area (Blöschl and Sivapalan, 1995; Westra et al., 2014): For catchments, hours to days are relevant (Mueller and Pfister, 2011), whereas urban drainage systems of ~ 10 km (Arnbjerg-Nielsen et al., 2013) are impacted at timescales from minutes to hours (De Toffol et al., 2009), and soil erosion can occur at even smaller scales (Mueller and Pfister, 2011).

Areal Reduction Factors (ARF) and Intensity Duration Functions (IDF) have previously been used to describe the decrease of average precipitation intensity due to spatial and temporal aggregation (Bacchi and Ranzi, 1996; Smith et al., 1994). The capability of radar data to capture the spatial structure of storms was identified as a key factor in deriving the ARFs (Bacchi and Ranzi, 1996; Arnbjerg-Nielsen et al., 2013). A general outcome was that ARFs exhibit a decay with respect to the return period (Bacchi and Ranzi, 1996; Sivapalan and Blöschl, 1998) and a dependency on the observed region, resulting from different governing rainfall generation mechanisms (Sivapalan and Blöschl, 1998).

In the current study we separate the physically different processes leading to convective and stratiform type precipitation events. Using synoptic observation data, we classify precipitation events into these two types, allowing us to analyze their aggregated statistics individually across scales.

The two types physically differ in that convection is often initiated by local radiative surface heating, resulting in a buoyantly unstable atmosphere (Houze, 1997), whereas stratiform precipitation stems from large-scale frontal systems and relatively weak and uniform up- lifting. Analyzing these two types separately regarding their intensities at different scales can e.g. be important when considering temperature changes, such as anthropogenic warming: Over large scales, the changes were found to be moderate, whereas for very small scales, it has been argued that the two processes may increase with warming (Trenberth, 1999; Trenberth et al., 2003; Trenberth, 2011; Lenderink and van Meijgaard, 2008), albeit at very differing rates (Berg et al., 2013). Using high-resolution model simulations, heavy precipitation at high temporal resolutions was suggested to increase strongly in a future climate, and a dominant contribution to extreme events to stem from convective events (Kendon et al., 2014; Muller et al., 2011; Attema et al., 2014).

In spite of their small horizontal and temporal range, convective events can cause substantial damage (Kunz, 2007; Kunz et al., 2009), e.g. through flash floods (Marchi et al., 2010).

Numerous studies have assessed the temporal and spatial characteristics of precipitation events using a storm centered, or *Lagrangian*, approach (Austin and Houze Jr., 1972; Houze Jr. and Hobbs, 1982; Moseley et al., 2013), which focuses on the storm dynamics, e.g. lifetime or the history of its spatial extent. Moseley et al. (2013) showed that, for Lagrangian event histories of 30 min, the convective type can produce significantly higher intensities than the stratiform type. As we here focus on potential hydrological applications and those addressing possible impact of extremes, e.g. floods, defining events over a *fixed* surface area and time period is more appropriate (Berndtsson and Niemczynowicz, 1988; Onof et al., 1996; Bacchi and Ranzi, 1996; Michele et al., 2001; Marani, 2003, 2005). The statistics thereby constitute averages over a defined space–time window within which both dry and wet sub-intervals may occur.

In this study, we analyze at which fixed temporal and spatial scales convective precipitation dominates precipitation extremes. To this end, we analyze two years of mid-latitude high-resolution radar data (5 min temporally and 1 km spatially), classified by precipitation types and separated into seasons (summer vs. winter) and geographic areas (north vs. south Germany). Analysis of these data over large spatial and temporal periods characterizes the statistical aggregation behavior in space and time. It can quantify the requirements on minimal model resolution sufficient for the proper description of the respective extremes. Revisiting the Taylor-hypothesis (Taylor, 1938), we contrast the two precipitation types, as to how resolutions in space and time can be compared. Using a resulting effective advection velocity, we give a simple means of quantifying effective temporal averaging in models, resulting from a given spatial resolution.

The structure of the article is as follows: In Sec. 2 we describe the data and methods used. Section 3 presents the results for extremes at different resolutions (Sect. 3.1) and suggests a method to compare the corresponding probability density functions (Sect. 3.2). We close with discussions and conclusions (Sect. 4).

8) P2163 3rd paragraph: The procedure for time steps longer than the 3hourly cloud observations is not clear.

We rephrased this sentence:

For time resolutions longer than three hours, two 3 hourly time slices have to be considered. Here we classify the precipitation event as stratiform or convective only, if the type is identified at least at one of the time slices and the other timeslice was not identified as the opposite type of event.

9) P2175 Sec3.2: A quick question on the PDF approach. Are the sample sizes for each space-time pair roughly equivalent?

As we describe in the data section, the sample size is decreasing as 1 / dx^2 dt. They are not equivalent. Where the sample size became too small, we indicate this by "missing data" in the plots.

10) Section 4: The discussions and conclusions section, like the introduction, is lacking. The first paragraph is fine but the second should make a stronger statement about how this study sets itself apart. I suggest shortening some of the text under the main headings of this section. There is too much repetition of results and not enough interpretation and contextualization. There could be a vibrant description here of the implications these results have for future modeling studies and/or observational studies. One-way to do this is to start with a bullet list of the four major findings and their main points. Then answer the questions: What are the implications of these findings? What issues or shortcomings remain? What are some potential future research directions?

The discussion and conclusions section has been completely revised, taking the reviewer suggestions into account.

New Discussion and conclusions:

Precipitation is strongly inhomogeneous in time and space. Averaging over a specific temporal or spatial interval therefore transforms the distribution function. The resulting smoothening especially affects the extreme values, as it narrows the distribution function while preserving the mean. In this study, the focus is on how such averaging affects the two synoptically identifiable precipitation types, namely stratiform and convective extreme precipitation events. Convective events are known to produce strong, short-duration and localized precipitation while stratiform events are less bursty and cover larger areas. Using synoptic observations, we separate radar-derived high-resolution precipitation intensities conditional on events of either of these two types. Unlike other studies, we here concentrate on the different aggregation behavior of the two precipitation types at different seasons and regions of Germany.

Space-time dependency of intensity distributions. We found that convective extremes were considerably stronger in the south than in the north of Germany and also showed clear seasonal differences with the highest extremes occurring in summer. Stratiform extremes showed much more moderate differences over seasons and regions.

When aggregating data temporally or spatially, we find much stronger reduction for convective than for stratiform events (about 20 to 30 % higher). These differences are larger than seasonal or regional differences that were observed within one type. This highlights the importance of distinguishing between these two types of events for example for statistical downscaling exercises. After the type separation, only the convective extremes show clear regional and seasonal differences and only in the area reduction factors. For the convective type, the strongest intensity reductions with spatial scale were found in south Germany in summer, the lowest in north Germany in winter.

Temporal and spatial scales at which shifts occur between dominantly convective and dominantly stratiform extreme events. Depending on the spatial and temporal resolution, different meteorological events will be considered extreme. We point out that this makes it difficult to compare different studies of extremes, where these extremes were de- fined at different scales. To demonstrate this, we present the contribution of convective events to the total, as a function of data aggregation, for the 99th percentile of all precipitation events.

This information is needed to identify which space-time resolutions contain comparable information about the distribution function, including the extremes. It will further help to identify at which resolution and percentile one can expect to obtain information about convective extreme precipitation events. Besides expected seasonal and regional differences with higher contribution of convective events in summer and over south Germany, we also found a clear dependency on the scale and the threshold that is used. Over north Germany, stratiform events contribute to the 99th percentile extremes only at horizontal resolutions coarser than 12 km when the duration interval is kept constant to 5 min. For a higher threshold (99.9th percentile), convective events dominate even more strongly and convective extremes consequently prevail over even larger areas and durations. **Pairs of temporal and spatial resolutions with similar aggregation effects on the extremes.** For proper choice of model output resolution, precipitation downscaling as well as bias correction, the relation between the DRF's as compared to ARF's is important. Originating from the radar data resolution of 5 min temporally and 1 km spatially, we produced sequences of aggregation, both in space and time, yielding: (i) temporally aggregated intensities for spatial scales held fixed, (ii) spatially aggregated intensity for temporal scales held fixed. Associating the respective aggregation resolution by matching identical precipitation extremes, we yield pairs of temporal and spatial resolutions, which define a curve.

The results allow, e.g., to identify pairs (Δx, Δt) of spatial and temporal resolutions for which the decrease in extreme precipitation intensities due to temporal aggregation matches that due to horizontal aggregation. In terms of the Taylor-hypothesis, the timescales can roughly be viewed as the mean duration needed to advect the precipitation pattern by the width of a grid-box (Fig. 6).

For example; if for a given horizontal grid size a higher temporal output is used, the event will likely be advected further than the size of the grid-box, leading to strong duration reduction factors. We find that for state of the art regional climate simulations, performed at a 11 km horizontal resolution, the temporal resolution needed in order to avoid stronger duration than area reduction effects, would be approximately 20 to 25 min.

In practice, in regional climate models the temporal output is often lower than the resolution computed here. It should therefore be reconsidered why many regional models do not output at sub-hourly frequency and why often only daily averages are stored.

If a model can resolve some small scale features, e.g. deep convective extremes, information can only be preserved by outputting at the appropriate temporal resolution, information lost when using lower horizontal resolutions (Fig. 8). High temporal resolution is accessible by most models already (most models have computing time steps ~ seconds – minutes) but is not routinely output at such short periods. Recording at higher frequency would mainly affect storage space, not simulation run-time (assuming efficient I/O-handling).

The pairs of corresponding grid sizes and durations defines a velocity v_{eff}, which can be used to generalize the Taylor-hypothesis to the situation where temporal scales change disproportionately compared to spatial scales (self-affinity, Deidda (2000)). For constant v_{eff} as function of spatial scale, the Taylor-hypothesis would be obeyed. However, v_{eff} of convective and stratiform extreme precipitation algebraically decreases with increasing Δx with similar exponents for both precipitation types. The main scaling difference between convective and stratiform events can be described by a constant scaling factor. This scaling factor leads to about 1.75 times higher advection velocities for stratiform than for convective events. **PDF overlap.** Changes caused by temporal aggregation depend on the spatial scale of the data and vice versa. We examine these dependencies by comparing pairs of PDFs derived for different aggregation resolutions using a method developed by Perkins et al. (2007), here defined as PDF overlap.

We find that PDF changes that were observed when decreasing the temporal resolution from 5min to 2h at 50km horizontal resolution are quantitatively comparable with PDF changes when going from 5 min to 30 min at 10 km horizontal resolution or from 5 min to 10 min at 2 km horizontal resolution.

Further we show that the PDF overlap of a certain reference resolution (we chose as an example 60 min, 10 km) compared to all other aggregated resolutions, shows a ridge with values close to 1. This ridge ranges from 5 min and 25 km to 120 min at 1 km resolution for convective type events (Figure 10c) and from 5 min and 25 km to 90 min at 1 km resolution for stratiform events (Fig. 10c). These differences can be explained by the strong area reduction factors found for the convective type. The patterns found in this analysis are very similar to, the patterns found in Figs. 3 and 4 highlighting that most of the differences found in the PDF overlap are resulting from changes in the extremes.

Technical comments:

1) P2161 L27: Change to, "Here we take the perspective of an observer capturing....".

Sentence not included in the new Introduction

2) P2163 L15: Delete "single"

We deleted the word "single"

3) P2164 L4: Change from "is counted" to "are counted"

We changed "is counted" to "are counted"

4) P2170 L11: "Consider e.g. climate model simulation data". There is no need for e.g. here, change to "Consider data from a climate model simulation."

The sentence is not included anymore in the text since we reformulated parts of the chapter to make the text easier to understand.

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Temporal and spatial scaling impacts on extreme precipitation

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Abstract

~~Both in the current climate and in the light of climate change, understanding of the causes and risk of precipitation extremes is essential for protection of human life and adequate design of infrastructure. Precipitation extreme events depend qualitatively on the temporal and spatial scales at which they are measured, in part due to the distinct types of rain formation processes that dominate~~ Convective and stratiform precipitation events have fundamentally different physical causes. Using a radar composite over Germany, this study separates these precipitation types and compares extremes at different ~~scales. To capture these differences, we first filter large datasets of high-resolution radar measurements over Germany (~~spatial and temporal scales, ranging from 1 km to 50 km and 5 min ~~temporally and 1~~to 6 h, respectively. Four main objectives are addressed: First, we investigate extreme precipitation intensities for convective and stratiform precipitation events at different spatial and temporal resolutions, to identify type-dependent space and time reduction factors and to analyze regional and seasonal differences over Germany. We find strong differences between the types, with up to 30 percent higher reduction factors for convective compared to stratiform extremes, exceeding all other observed seasonal and regional differences within one type. Second, we investigate how the differences in reduction factors affect the contribution of each type to extreme events as a whole, again dependent on the scale and the threshold chosen. A clear shift occurs towards more convective extremes at higher resolution or higher percentiles. For horizontal resolutions of current climate model simulations, i.e. ~ 10 km~~spatially) using synoptic cloud observations, to distinguish convective and stratiform rain events. In a second step, for each precipitation type, the observed data are aggregated over a sequence of time intervals and spatial areas. The resulting matrix allows a detailed investigation of the resolutions at which convective or stratiform events are expected to contribute most to the extremes. We analyze where the statistics of the two types differ and discuss at which resolutions transitions occur between dominance of either of the two precipitation types. We characterize the scales at which the convective or stratiform events will dominate the statistics. For both types, we further~~

~~develop a mapping between pairs of spatially and temporally aggregated statistics. The resulting curve is relevant when deciding on data resolutions where statistical information in space and time is balanced. Our study may hence also serve as a practical guide for modelers, and for planning the space–time layout of measurement campaigns. We also describe a mapping between different pairs of resolutions, possibly relevant when working with mismatched model and observational resolutions, such as in statistical bias correction~~, the temporal resolution of the data as well as the chosen threshold have profound influence on which type of extreme will be statistically dominant. Third, we compare the ratio of area to duration reduction factor for convective and stratiform events and find that convective events have lower effective advection velocities than stratiform events, and are therefore more strongly affected by spatial than by temporal aggregation. Finally, we discuss the entire precipitation distribution regarding data aggregation, and identify matching pairs of temporal and spatial resolutions where similar distributions are observed. The information is useful for planning observational networks or storing model data at different temporal and spatial scales.

1 Introduction

The IPCC's fifth assessment report highlights an intensification of heavy precipitation events in North America and Europe (Hartmann et al., 2013), and projects further increase of extremes as global temperatures ~~increase (Collins et al., 2013) .~~

rise (Collins et al., 2013) . The study of extreme events is complex due to a ~~-~~strong inhomogeneity of precipitation intensities in ~~time and space~~ space and time. Assessment of precipitation extremes, e.g. as defined by an intensity threshold, ~~therefore always~~ is strongly scale dependent and therefore requires specification of the ~~relevant temporal and spatial resolution. However, in many cases, the~~ analyzed spatial and temporal resolution.

Even though spatial and temporal scales are far from independent (Taylor, 1938) , it is often unclear how to compare datasets directly, when their data is measured at differing resolutions. The data resolution needed by users, ~~observed by gauge stations or modeled~~

~~by weather, respectively climate, models do not match~~ e.g. hydrologists or crop modelers, often differs from that at which observed or modeled data is recorded (Willems et al., 2012).

~~For society, the primary~~ The primary societal interest in extreme precipitation lies in its hydrological implications, typically requiring statistics of precipitation extremes ~~occurring at the fixed spatial~~ for the area of a ~~-~~given catchment or drainage system~~. Specifically, small systems may be subject to flood risk when individual convective storm cells pass over them, while larger systems are less affected by convective-scale processes as the spatial average precipitation intensity remains low~~, which is not identical to that of model grid boxes or the observations.

~~Relevant scales in~~ Moreover, temporal scales relevant to flood risk vary enormously with ~~the size of the area and timescales of the processes (Blöschl and Sivapalan, 1995) . At the catchment scale, several~~ area (Blöschl and Sivapalan, 1995; Westra et al., 2014) : For catchments, hours to days are relevant ~~, depending on the catchment area~~ (Mueller and Pfister, 2011), whereas ~~, e.g.~~ urban drainage systems ~~with scales of 1 to 10~~of ~ 10 km (Arnbjerg-Nielsen et al., 2013) are ~~strongly impacted on scales~~ impacted at timescales from minutes to ~~several hours (De Toffol et al., 2009) . Even smaller temporal scales are required for research in soil erosion by water (Mueller and Pfister, 2011) . A recent review article on the physical causes and impacts of rainfall extremes on different scales has been given by Westra et al. (2014)~~ hours (De Toffol et al., 2009) , and soil erosion can occur at even smaller scales (Mueller and Pfister, 2011) .

~~The necessity of distinguishing scales, both in space and time, has been recognized in the past, captured e.g. by~~ Areal Reduction Factors (ARF) and Intensity Duration Functions (IDF) ~~. Such approaches~~ have previously been used to describe the decrease of average precipitation intensity due to spatial and temporal aggregation (Bacchi and Ranzi, 1996; Smith et al., 1994).

~~In search for adequate observational data, the~~ The capability of radar data to capture the spatial structure of storms was identified as a key factor in deriving the ARFs (Bacchi and Ranzi, 1996; Arnbjerg-Nielsen et al., 2013). A general outcome was that ARFs exhibit a decay with respect to the return period (Bacchi and Ranzi, 1996; Sivapalan and Blöschl,

1998) and a dependency on the observed region, resulting from different governing rainfall generation mechanisms (Sivapalan and Blöschl, 1998).

~~Interestingly, early attempts at capturing intensities across scales as a simple power law dependence were found not to hold generally, as shown by Marani (2003, 2005) . Instead, these papers point to a transition between an inner, a transient and an outer regime with distinct scaling: The inner regime occurs at spatial scales until around 20and temporal scales of 10 to 15while the transient regime depends on the region and season, and ends between durations of 20 to 80h. This regime-distinction was justified in terms of scale dependent memory processes.~~

In the current study we ~~recognize the fundamentally different processes in~~ separate the physically different processes leading to convective and stratiform ~~precipitation~~type precipitation events. Using synoptic observation data, we classify precipitation events into ~~convective and stratiform types. This allows us to obtain a fresh view on the aggregated statistics of these two main rain formation processes~~ these two types, allowing us to analyze their aggregated statistics individually across scales.

~~Indeed, the two types of events have different physical characteristics, with convection~~ The two types physically differ in that convection is often initiated by local radiative surface heating, resulting in a ~~-~~buoyantly unstable atmosphere (Houze, 1997)~~and stratiform precipitation stemming~~ , whereas stratiform precipitation stems from large-scale frontal systems and relatively weak and uniform up-lifting. ~~Importantly~~Analyzing these two types separately regarding their intensities at different scales can e.g. be important when considering temperature changes, such as anthropogenic warming: Over large scales, the changes were found to be moderate, whereas for very small scales, it has been argued that the two processes may ~~respond quite differently to temperature increases (Trenberth, 1999, 2011; Trenberth et al., 2003; Lenderink and van Meijgaard, 2008) . The origin of such differential response may be especially relevant for changes resulting from anthropogenic global warming . For heavy precipitation bursts, a recent study employing observed radar signals (Berg et al., 2013) backs the differential responses. Others, using model climate projections with convection permitting~~

~~simulations, point to a strong climate change signal in~~ increase with warming (Trenberth, 1999; Trenberth et al., 2003; Trenberth, 2011; Lenderink and van Meijgaard, 2008) , albeit at very differing rates (Berg et al., 2013) . Using high-resolution model simulations, heavy precipitation at high temporal resolutions ~~, and expect that a~~ was suggested to increase strongly in a future climate, and a dominant contribution to extreme events ~~will~~ to stem from convective ~~type~~ events (Kendon et al., 2014; Muller et al., 2011; Attema et al., 2014).

~~Hence, in~~ In spite of their small horizontal and temporal range, convective events ~~are often found to cause severe damages to infrastructure, such as damage to buildings (Kunz, 2007; Kunz et al., 2009) , or~~ can cause substantial damage (Kunz, 2007; Kunz et al., 2009) , e.g. through flash floods (Marchi et al., 2010).

~~The high demands of certain impact assessments regarding the temporal and spatial resolution of the data, go beyond the resolutions provided by typical regional climate models (RCM). As a result, climate change impact assessments for urban drainage systems typically make use of statistical downscaling of RCM data (Willems et al., 2012; Arnbjerg-Nielsen, 2012; Onof and Arnbjerg-Nielsen, 2009) .~~

~~Alarmingly, different climate change signals corresponding to small and large scale events may challenge the basic assumption made in statistical downscaling procedures, namely that the empirical relationships between variables at large scales and local scales, identified for the present-day climate, would hold for periods with a warmer climate than the calibration period (Maraun et al., 2010; Wilby et al., 2004) . Success then depends on the predictors chosen for the downscaling procedure and whether they are able to capture the dominant precipitation type. In most cases, only the variable itself (in this case precipitation) is employed as a predictor of sub-grid scale variability (Maraun et al., 2010) . The basic assumption would then be violated.~~

Numerous studies have assessed the temporal and spatial characteristics of precipitation events using a storm centered~~approach (Austin and Houze Jr., 1972; Houze Jr. and Hobbs, 1982; Moseley et al., 2013) or from the point of view of a fixed location or area at the surface~~

~~(Berndtsson and Niemczynowicz, 1988; Onof et al., 1996; Bacchi and Ranzi, 1996; Michele et al.~~ ~~From the storm centered, or Lagrangian~~, ~~approach the lifetime and spatial extent of the storm can be analyzed. Recently, Moseley et al. (2013) applied a rain cell tracking method on radar data in order to monitor the life cycle of convective and stratiform rain events from a Lagrangian viewpoint. That study showed thatat temporal scales~~ or *Lagrangian*, approach (Austin and Houze Jr., 1972; Houze Jr. and Hobbs, 1982; Moseley et al., 2013) , which focuses on the storm dynamics, e.g. lifetime or the history of its spatial extent. Moseley et al. (2013) showed that, for Lagrangian event histories of 30 min, ~~convective type precipitation~~ the convective type can produce significantly ~~larger~~ higher intensities than the stratiform type. ~~We here originate from an observer capturing precipitation intensity over a fixed~~As we here focus on potential hydrological applications and those addressing possible impact of extremes, e.g. floods, defining events over a *fixed* surface area and time period is more appropriate (Berndtsson and Niemczynowicz, 1988; Onof et al., 1996; Bacchi and Ranzi, 1996; Michele et al. The statistics thereby constitute averages over a defined space–time window ~~where~~ within which both dry and wet sub-intervals may occur.

~~The different spatial and temporal scaling behavior of convective and stratiform events, as well as their different physical temperature response, raises the question, at which~~ In this study, we analyze at which fixed temporal and spatial scales convective precipitation dominates ~~the heavy~~ precipitation extremes. ~~Such analysis would generate benchmarks regarding minimal climate model resolution, required for providing optimal output resolution of the respective extremes.~~

To this end, we ~~here analyze~~ analyze two years of mid-latitude high-resolution radar data (5 min temporally and 1 km spatially)~~over Germany for the years 2007–2008~~ , classified by precipitation types and separated into seasons (summer vs. winter) and geographic areas ~~of Germany. Evaluation~~ (north vs. south Germany). Analysis of these data over ~~such~~ large spatial and temporal periods ~~allows quantification of~~ characterizes the statistical aggregation behavior in ~~time and space~~space and time. It can quantify the requirements on minimal model resolution sufficient for the proper description of the respective extremes.

Revisiting the Taylor-hypothesis (Taylor, 1938) , we contrast the two precipitation types, as to how resolutions in space and time can be compared. Using a resulting effective advection velocity, we give a simple means of quantifying effective temporal averaging in models, resulting from a given spatial resolution.

The structure of the article is as follows: In ~~Sect~~Sec. 2 we describe the data and methods used. Section 3 presents the results for extremes at different resolutions (Sect. 3.1) and suggests a method to compare the corresponding probability density functions (Sect. 3.2). We close with discussions and conclusions (Sect. 4).

2 Data and methods

A Germany-wide radar composite (RADOLAN-RY) from the German Weather Service is used in this study. This data set is provided on an approximate 900 km $\times$ 900 km grid with a 1 km horizontal resolution and contains information derived from 17 radar measurement facilities (Fig. 1). The rainfall rates (R) were derived from raindrop reflectivities (Z) using the Z–R relationship (Steiner et al., 2004). The data are stored as discrete instantaneous intensities with an increasing bin size towards higher values. For the analysis, the two year time period covering 2007–2008 is considered. The data have been used (Moseley et al., 2013) and compared with gauge data previously (Berg et al., 2013).

For the current analysis, radar grid-points are aggregated in time, i. e. $\Delta t \in \{5, 10, 15, 20, 30, 45, 60, 120, 180, 240, 360\}$ min, and in space over square gridbox areas with linear dimensions $\Delta x \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 25, 50\}$ km. Aggregation includes all possible pairs $\{\Delta t, \Delta x\}$. Spatial aggregation is performed such that a coarser grid box starts at the bottom left corner of the domain and aggregates over the respective number of grid points towards the top right, with no overlap between the coarser grid boxes. As a consequence, the number of aggregated grid boxes scales $\sim 1/(\Delta t \Delta x^2)$. In cases where the original horizontal resolution cannot evenly be divided by the resolution of the coarser grid, the remaining grid points at the top and right border are not considered. This is the closest mimic of a gridded model.

Synoptic cloud observations, at 222 stations, obtained from the Met Office Integrated Data Archive System (MIDAS) data base [http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas] are used to separate large-scale and convective precipitation following Berg et al. (2013). The locations of the stations used are shown in Fig. 1. The classification process is carried out such that first ~~,~~ a classification is made for each ~~single~~ station and each 3 hourly observation into *convective*, *stratiform*, *mixed* or *no observations*. Second, to ensure more stable conditions, the classifications are aggregated in space to quadrants over the region (see Fig. 1), such that each quadrant contains one single classification for each 3 hourly time period. The aggregated classification can only be *convective* (*stratiform*) if there are no simultaneous observations of *stratiform* (*convective*) in the quadrant. Else, the classification will be considered to be of the *mixed* type.

For the aggregated time resolutions 5 to 180 min, the precipitation is flagged as *convective*, respectively *stratiform*, according to the corresponding 3 hourly time slice. For time resolutions longer than three hours, ~~no mixing of *convective* and~~ two 3 hourly time slices have to be considered. Here we classify the precipitation event as *stratiform* ~~in the multiple time steps are allowed in the respective classes, otherwise they are classified as *mixed*. For classifications of *convective*~~ or ~~*stratiform* together with *mixed*~~*convective* ~~conditions, the classification is performed according to the following procedure: For time resolutions 240 to 360at least one time slice has to be flagged as *convective* or *stratiform*~~only, if the type is identified at least at one of the time slices and the other time slice was not identified as the opposite type of event. This procedure was found to be the best compromise between rigid classification and sufficient data availability at the coarsest averaging windows.

Next, for each averaging window, the total number of convective and stratiform *events*, i.e. single time-steps with an intensity higher than 1 mm day^{-1}, ~~is~~ are counted. To ensure that enough events for statistical analysis are present, the analysis is restricted to resolutions where at least 500 convective and 500 stratiform events were detected. All other fields will be marked as insufficient (gray squares in the Figs. 3, 4 and 8).

Discussion Paper
Discussion Paper
Discussion Paper

3 Results

3.1 Quantifying the impact of spatial and temporal aggregation on convective and stratiform precipitation extremes

Differential impact on exceedence probabilities. We define the cumulative distribution function (CDF) as the probability of precipitation intensity exceeding a given intensity I:

$$\mathrm{CDF}(\Delta t, \Delta x, I) \equiv \frac{\int_I^\infty N(\Delta t, \Delta x, I')\mathrm{d}I'}{\int_{I_0}^\infty N(\Delta t, \Delta x, I')\mathrm{d}I'}, \tag{1}$$

where $N(\Delta t, \Delta x, I)$ is the number of data aggregates to resolution Δt and Δx with averaged precipitation intensity I, and I_0 is the lower measurement cutoff. In the following, we choose $I_0 = 1\,\mathrm{mm\,day}^{-1}$ throughout. $\mathrm{CDF}(\Delta t, \Delta x, I)$ thus describes the percentiles of precipitation intensity when conditioning on wet periods. Figure 2 shows $\mathrm{CDF}(\Delta t, \Delta x, I)$ for Germany for different Δt and Δx conditional on convective and stratiform events. Note the logarithmic representation of the data, i.e. the figure focuses on the high precipitation intensities between the 99.9th percentile (10^{-1}) and the 90th percentile (10^{1}) of the distribution.

It is important to realize the effect of aggregation at varying scales: Consider first spatial aggregation (see legend in Fig. 2). Convection forms patterns with intense and localized precipitation peaks, separated spatially by regions without precipitation (Austin and Houze Jr., 1972; Moseley et al., 2013; Berg et al., 2013). Performing averages over areas of increasing size therefore yields broad variation of averages at small spatial scales but rapid decrease of variation as data is aggregated over larger areas. Stratiform precipitation ~~can be thought of as a noisy pattern overlaid some average level, and~~ is more uniform in the sense that sampling over small areas yields a good description of the statistics also at larger areas of aggregation.

Consider now temporal aggregation from an interval well below the convective life-time (e.g. $\ll 30\,\mathrm{min}$): The effect of temporal aggregation is to even out spatial variations due to the large-scale flow. This makes convection appear spatially more uniform. For stratiform precipitation, patterns are already less localized in space and temporal aggregation will change the statistics less.

We make ~~three observations~~ several observations in support of this assessment (Fig. 2)~~in support of this assessment~~: First, while convective precipitation can be much more intense (compare e.g. the solid curves in Fig. 2a vs. b) the decrease of mean intensity due to aggregation is more pronounced than for stratiform precipitation. Second, we find that the relative differences in the CDF's between the 1 and 50 km data are stronger if the data is stored at 5 min resolution than for the 360 min data. For stratiform events we find almost no differences between precipitation intensities at resolutions below 12 km for a 360 min temporal resolution. Only at the largest regions, 50 km, does the spatial aggregations clearly modify the CDF as the non-precipitating region off the boundary of the event is included. This finding suggests that, for a given time resolution, there should be an ~~adequate~~ associated horizontal resolution to store or collect data~~. Choosing higher spatial resolution would be unable to add more information to the statistics and fine-scale details are already averaged out temporally. This naturally also holds vice versa, when a spatial resolution is specified~~, i.e. a resolution that carries similar information about the distribution function.

~~Third, we highlight~~ More generally, this highlights the close match of the convective intensity CDF's when comparing two ~~different datasets~~ datasets of different resolution, namely 5 min and 50 km vs. 360 min, 1 km. For these pairs of resolutions ~~the~~ time aggregation has a similar statistical effect on precipitation intensities as does spatial aggregation.

This latter observation can be appreciated when remembering the Taylor-hypothesis of “frozen turbulence” (Taylor, 1938), stating that as the mean atmospheric flow advects eddies past a ~~station,~~ station, information about spatial variations can be gained as long as the properties of the eddies remain ~~unaltered~~frozen in time. Consider e.g. an average convective event with constant precipitation intensity over its lifetime. According to Berg et al. (2013) and Moseley et al. (2013) the average convective event has a lifetime of approximately 30 min, a spatial extent of $\sim 10\,\mathrm{km}$ and a propagation speed of $\sim 10\,\mathrm{ms}^{-1}$. When using a 50 km grid box and 5 min temporal resolution, the event will move about 3 km~~and thus affect roughly~~ ~~$\frac{10\times 13}{50\times 50} \approx 5\,\%$~~, therefore it can be assumed that the event stays in one grid box. It will affect roughly $\frac{10\times10}{50\times50}\approx 4\,\%$ of the cell at a time. When an event of $\sim 10\,\mathrm{km}$ cross section moves over a location with $\sim 10\,\mathrm{m/s}$, its passage over the location would last $\sim 1000\,\mathrm{s}$, which is $\sim 17\,\mathrm{min}$, and $\frac{17}{360}\approx 5\,\%$ of the ~~time.~~ matching time interval of 6 hours.

In the following we discuss how the actual observations depart from the approximation of the Taylor-hypothesis and how this departure is influenced by the precipitation type. In reality, there are complications such that events change intensity also on short timescales, many events can be superimposed in space and time, and the large scale flow is not constant.

To proceed, we now focus on intensity changes at a specific percentile, defined for a given combination of Δt and Δx by the inverse of Eq. (1), i.e. the intensity corresponding to a choice of exceedence probability. We will later return to the entire distribution functions in ~~Sect~~Sec. 3.2. Specifically, we now choose the 99th percentile of all detected precipitation events and refer to this percentile as *extreme precipitation*. This percentile was found to be a good compromise between the aim of focusing mainly on the high end of the intensity distributions and the need for sufficient data for the statistics. Using a percentile value as threshold to define precipitation extremes is a ~~common practicein the modeling community~~common practice.

For varying Δx and Δt, Figs. 3 and 4 show the 99th percentile of precipitation intensities for convective (termed $\hat{I}_{\mathrm{cv}}(\Delta t,\Delta x)$) and stratiform (termed $\hat{I}_{\mathrm{ls}}(\Delta t,\Delta x)$) events, respectively, for the entire region of Germany, and separated into North and South Germany, as well as for the whole year, and separated into the summer (April–September) and winter (October–March) seasons. Note that we used a ~~non linear~~ non-linear scaling for the ~~x and y axis~~ horizontal and vertical axes to better visualize the intensity changes at very high resolutions. The same plots as in Figs. 3 and 4 but with linear scales are shown in the supplementary material. In the linear case the arcs, found when connecting fields with ~~similar~~ similarly extreme intensities, become almost straight lines. Straight lines mean, that for any choice of a resolution pair, equivalent resolutions, i.e. those of similar extremes, can be obtained by ~~a simple linear transformation~~simple linear transformations.

When comparing $\hat{I}_{\text{cv}}(\Delta t, \Delta x)$ (Fig. 3) to $\hat{I}_{\text{ls}}(\Delta t, \Delta x)$ (Fig. 4), it is striking that at high temporal and spatial resolutions, the intensity $\hat{I}_{\text{ls}}$ ~~has only about a third as high intensities as~~ is only about one third of $\hat{I}_{\text{cv}}$. However, $\hat{I}_{\text{ls}}$ shows much less spatial and seasonal differences when compared to those of $\hat{I}_{\text{cv}}$. For example, the increase in intensity at the highest resolution in summer vs. winter is about 220 % for $\hat{I}_{\text{cv}}$~~and~~ , but only approximately 20 % for $\hat{I}_{\text{ls}}$. This finding is in line with the relatively weak temperature response of stratiform precipitation intensities as reported recently (Berg et al., 2013).

Regionally, South Germany exhibits higher $\hat{I}_{\text{cv}}$ in summer as compared to the North. This ~~is largely~~ may largely be due to complex orographic areas in southern Germany, e.g. the highly convectively active area of the Black Forest in southwestern Germany (Khodayar et al., 2013), but also latitudinal temperature differences and the more continental climate of the South could contribute.

The highest intensities of stratiform precipitation occur in North Germany in the months May to September. We find that for time durations lower than 3 h the highest intensities occur between June to August. For longer time durations, the highest intensities occur in the months September to November (see supplement).

Scaling behavior of convective and stratiform precipitation events. To quantify the reduction due to spatial aggregation, we define the area reduction factor ARF~~(x)~~ (Δx) as the reduction of the 99th percentile at spatial resolution x relative to ~~spatial resolution~~ the percentile (here defined as $\hat{I}_{ori}$) at the original resolution (5 min, 1 km~~,~~). Varying now the spatial resolution while keeping the temporal resolution fixed (at 5 min~~, i.e.~~), we define

$$\text{ARF}(\Delta x) \equiv 1 - \cancel{\frac{\hat{I}(5\,\text{min}, x)}{\hat{I}(5\,\text{min}, 1\,\text{km})}} \frac{\hat{I}(\Delta x)}{\hat{I}_{ori}}, \tag{2}$$

where $\hat{I}$ ~~can be either $\hat{I}_{\text{cv}}$ or $\hat{I}_{\text{ls}}$~~ and $\hat{I}_{ori}$ is shorthand for either of the precipitation types. Analogously, we define the duration reduction factor DRF~~(t) as the reduction of $\hat{I}_{\text{cv}}$ and $\hat{I}_{\text{ls}}$ due to aggregation to the temporal resolution t relative to the resolution of 5,~~ (Δt) as the intensity reduction due to temporal aggregation relative to $\hat{I}_{ori}$, while keeping the spatial resolution at 1 km, i.e.

$$\mathrm{DRF}(\Delta t) \equiv 1 - \cancel{\frac{\hat{I}(t, 1\,\mathrm{km})}{\hat{I}(5\,\mathrm{min}, 1\,\mathrm{km})}} \frac{\hat{I}(\Delta t)}{\hat{I}_{ori}} \,. \tag{3}$$

ARF and DRF are shown in Fig. 5a and b, respectively, for both precipitation types, and separately for the summer and winter ~~season~~seasons, as well as for north and south Germany. Considering $\hat{I}_{\mathrm{cv}}$, a strong intensity reduction can be seen when the ~~horizontal~~ spatial (Fig. 5a) or temporal (Fig. 5b) resolution is decreased. The reduction due to spatial aggregation shows clear seasonal and regional differences~~.~~: The lowest ARFs occur in northern Germany in winter (68 % at 50 km grid size), the highest in south Germany in summer (84 % at 50 km grid size). Temporal aggregation is nearly independent of seasonal and regional distinctions and reaches values of about 80 to 85 % at a 6 hourly resolution. The differences found between $\hat{I}_{\mathrm{cv}}$ and $\hat{I}_{\mathrm{ls}}$ are hence larger than all other seasonal or regional differences within one type.

$\hat{I}_{\mathrm{ls}}$ shows much less pronounced ARF's and DRF's. For the maximum spatial aggregation, only 52 % reduction is found in north Germany in winter. The seasonal and regional differences are smaller than for ~~the~~ $\hat{I}_{\mathrm{cv}}$ and differ only by less than 10 percentage units. Temporal aggregation shows also only small regional and seasonal differences causing DRF's of 60 to 70 %, at a temporal resolution of 6 h.

Comparing the relevance of space compared to time aggregation. We can distinguish the behavior of spatial and temporal aggregation using two kinds of approaches (Deidda, 2000). The first approach would be to regard precipitation as a self-similar process (simple scaling). In this case the Taylor-hypothesis (Taylor, 1938) would be obeyed, and temporal variations can be reinterpreted as spatial variations that are advected over a fixed location by a large-scale flow ~~, that has a constant value~~ that is constant over the observed temporal and spatial scales.

Following the notion of "frozen turbulence", intensity change due to spatial aggregation can then be calculated from the intensity changes that result due to temporal aggregation multiplied by a constant velocity u, i.e. $\Delta x \approx \Delta t \cdot u$. This would only hold, if precipitation extremes could be seen as objects of temporally constant characteristics that are translated by large scale advection. If we also assume spatial inhomogeneity only to occur in the advection direction, a gauge station could be used to measure the precipitation intensities that fall over an area (Fig. 6a).

The second approach would assume that the spatial and temporal aggregation behavior of precipitation extremes would behave like a self-affine process (a process where the ratio of scales is changing as one of the scales changes). In this case, the simple linear relation that connects changes due to time aggregation with changes due to spatial aggregation through an advection velocity, generally does not hold anymore (e.g. due to temporal (Fig. 6b) or spatial inhomogeneity (Fig. 6c)). A multifractal analysis is needed, where in short, the "velocity" itself would become a function of the respective spatial and temporal scales. ~~A proper~~ If this function is known, it is possible also for self-affine processes to connect spatial and temporal scales. Proper understanding of the relationship between spatial and temporal aggregation is e.g. crucial for precipitation downscaling and bias correction methods (Wood et al., 2004; Piani et al., 2010a, b).

Our goal here is to characterize the differences in scaling of convective and stratiform extremes: Comparing the intensity reduction due to time aggregation for the 1 km dataset (Fig. 3a, left column) with the intensity reduction that results from spatial aggregation at a temporal resolution of 5 min (bottom row), a 4 km spatial aggregation is comparable to that of spatial aggregation for roughly 15 min. Similarly, for stratiform precipitation (Fig. 4a) we find that 6 km spatial aggregation corresponds to 15 min temporally. There is hence a dependence on the precipitation type, a relation we now analyze.

Figure 7a shows for each horizontal resolution the matching temporal resolution that achieves similar intensity reduction. We describe the relation between temporal and spatial aggregation at a fixed Δx by

$$f_{\Delta x}(\Delta t) = \left| \hat{I}(\Delta t, 1\,\mathrm{km}) - \hat{I}(5\,\mathrm{min}, \Delta x) \right| , \tag{4}$$

We now define $\phi_{\Delta x}$ as the minimum value of $f_{\Delta x}$ w.r.t. Δt:

$$\phi_{\Delta x} = \min_{\Delta t} f_{\Delta x}(\Delta t)\,. \quad (5)$$

The best matching time window Δt for a given Δx can be determined using the inverse function of $f_{\Delta x}$: $\Delta t = f^{-1}(\phi)$. In practice, we determine Δt by an iterative numerical procedure, using first an interpolation between available resolutions for better approximation. The result for several high percentiles is shown for both precipitation types over Germany for the entire year on a log-log plot (Fig. 7a), i.e. straight lines represented power laws. If the Taylor-hypothesis ~~was~~ were obeyed, the exponent would equal unity.

Within the limitations of the relatively noisy data, we find that the data represents a straight line over most of the analyzed spatial range and can be fitted to a power law function $\Delta t = a \times \Delta x^b$ with fitting parameters a and b, or by using dimensionless variables (i.e. defining $\chi \equiv \Delta x / \Delta x_0$, $\tau \equiv \Delta t / \Delta t_0$ and $\tilde{a} \equiv a \Delta x_0^b / \Delta t_0$), we have

$$\tau = \tilde{a}\,\chi^b\,, \quad (6)$$

with fitting parameters $\tilde{a}$ and b. The parameter $\tilde{a}$ is a scaling parameter and describes the Δt_0 corresponding to Δx_0. χ^b describes how the relevance of space compared to the time aggregation changes with resolution.

~~Consider e.g. climate model simulation data. A choice often has to be made as to the proper model output resolution, i.e. the combination of time and space intervals within which an average value of an observable (say, precipitation intensity) is produced before writing data to storage. The curve described by Eq. (6) indicates, which combination of resolutions gives consistently high information with regard to both space and time. If only higher spatial resolution is chosen without changing temporal resolution, the information gain would be relatively moderate, and vice versa for exclusive temporal resolution changes. For this reason we term values on the line $\tau = \tilde{a}\chi^b$ "optimal".~~

In Fig. 7a and b, the best-fit for the 99th intensity percentile is shown for convective and stratiform precipitation. We find that b is similar for both types (generally between 1.17

and 1.32), a departure from unity that should be confirmed by other data sources than the radar data at hand. An exponent $b > 1$ indicates, that extreme precipitation is self-affine (self-similarity would require $b = 1$). The fractal properties of precipitation were already highlighted in earlier studies and are found to be a result of the hierarchical structure of precipitation fields (Schertzer and Lovejoy, 1987) with cells that are embedded in small ~~meso-scale~~ mesoscale areas which in turn occur in clusters in large-scale synoptic areas ~~analyzed by~~ Austin and Houze Jr. (1972).

Table 1 displays $\tilde{a}$ and b for the different percentiles shown in Fig. 7a (non-dimensional). We find that for convective precipitation $\tilde{a}$ is near 0.5. Within the error bars there is no obvious dependence on percentile. ~~$\tilde{a} \sim 0.5$ indicates that temporal resolution should be approximately doubled for optimal resolution (in the sense defined above). Stratiform extreme intensities are less localized, and changes due to horizontal aggregation are lower than for the convective case. Therefore even higher temporal resolutions are required to capture intensity variations at the km scale and to create an added value compared to datasets stored on a lower horizontal resolution. For the Stratiform type we find a scaling parameter $\tilde{a} \sim 0.28$ indicating that the temporal resolution should be about 3.6 times higher resolved than in the original dataset to yield consistency between spatial and temporal information. Conversely, one could increase spatial measurement scale significantly without much loss of information~~This is also the case for the stratiform type, besides for the 99.9th percentile which has higher $\tilde{a}$ and lower b values.

Since the values of b are similar for both precipitation types (Table 1), the difference between the ~~optimum~~ matching temporal resolution of stratiform and convective events is kept constant over the entire ~~analyzed~~ range of Δx analyzed. We find that the different scaling between the two precipitation types mainly results from the varying $\tilde{a}$. ~~The *optimal* temporal resolution for stratiform events is therefore always approximately $0.49/0.28 = 1.75$ (mean values in Table 1) times the time period that would be *optimal* for convective events. Efficiency of measurement would therefore require different priorities of space and time resolution for convective and stratiform precipitation.~~

Note also the kink in the observed curves in Fig. 7a at about 6 km, where a change of slope is observed. To show that this kink is a manifestation of the scale mismatch, we aggregate data spatially to 2~~km~~ km (3 km for stratiform) horizontal resolution and re-plot (Fig. 7b). Due to this procedure the kink almost vanished. This test shows that aligning resolutions according to Eq. (6) allows smooth scaling.

For further analysis, and to make contact to the Taylor-hypothesis, we use the ratio of the the matching Δx and Δt to ~~define a ratio describing the intensity reduction due to spatial aggregation~~calculate the mean *effective* advection velocity, which we call ~~space–time ratio (ST ratio):~~ v_{eff}. We define:

$$\underline{\text{ST ratio}}\, v_{eff}(\chi) \equiv \chi/\tau = \underline{\tau}\chi^{1-b}/\tilde{a}\,. \tag{7}$$

This ~~ratio can be used to achieve approximate equivalence of spatial and temporal averaging in a similar way as in Deidda (2000) who calculated the velocities using tracking techniques. The ST ratio can now be used to generalize the Taylor-hypothesis for self-affine process, by using the ST ratio instead of a constant velocity to describe the relation between space and time. For the original Taylor-hypothesis, $b = 1$ and Eq. (7) becomes a constant.~~ effective velocity is not obviously the same as the velocity obtained by tracking algorithms, such as in (Moseley et al., 2013) , as v_{eff} combines all reasons for changes caused by aggregation. The main sources for these changes are advection of the precipitation field out of the grid box, temporal inhomogeneity caused by the temporal evolution of the precipitation event (Figure 6b) and horizontal inhomogeneities perpendicular to the advection direction, that will increase the area reduction factors (Figure 6c).

Figure 7c shows ~~the dimensional ST ratio~~ v_{eff} calculated for different Δx for the 95th, 98th, 99th and 99.9th percentile, using data without seasonal distinctions over Germany. ~~The ST ratio~~ v_{eff} lies in the same range as the velocities calculated by Deidda (2000) ~~. Low ST ratios~~ and Moseley et al. (2013) who calculated the velocities using tracking techniques. This shows that advection is likely the major source for changes due to temporal and horizontal aggregation. Low v_{eff} for horizontal resolutions ~~lower than~~ below about 2 to

4 km are again a result of the mismatch of the 5 min temporal resolution and the 1 km spatial resolution explained above.

Note the deviating value of $\tilde{a}$ for the 99.9th percentile of stratiform precipitation. This could be explained by mesoscale stratiform systems with embedded convection, i.e. systems that are somewhat intermediate between stratiform and convective events. The corresponding graph (Fig. 7c) shows intermediary behavior, connecting the curves of convective precipitation (low Δx) to those of stratiform precipitation at high Δx. Due to substantial noise at high spatial resolution it is not possible to identify if ~~the ST ratio~~ v_{eff} shows a constant behavior ($b = 1$) at the high resolutions, therefore the results in Zawadzki (1973) and Waymire et al. (1984) indicating the Taylor-hypothesis to hold for time scales less than 40 min can neither be confirmed nor rejected.

Realizing that v_{eff} combines all sources for changes caused by aggregation enables a simplified view on the aggregation process. In a similar way as in Deidda (2000) we can use v_{eff} to generalize the Taylor-hypothesis for a self-affine process, by using v_{eff} instead of a constant velocity to describe the relation between space and time. Following the Taylor-hypothesis we can now interpret the matching temporal and spatial scales from Figure 7a as the mean time that is needed to advect the information about the precipitation field over the matching horizontal scale (implicitly including all other sources of aggregation changes as described above). For example the typical timescale for a convective precipitation area to cross a grid box with a 10 km grid-size, a typical resolution of state of the art climate models, would be about 40 min. For a stratiform precipitation event the information about the precipitation field is already captured after about 20 to 25 min. Reasons for the lower effective advection velocity might be that stratiform events are statistically more homogeneous than convective events which results in a shorter period to capture the structure of the event. Also, convective events often occur at high pressure weather conditions where low wind velocities might entail lower advection velocities.

Aggregation effects at a specific resolution will always be a combination of duration and area reduction factors. Connecting space and time scales using v_{eff} allows the association of temporal and spatial scales, shown in Fig. 7a. If, for a given spatial resolution, a larger temporal output period is used as indicated by Figure 7a, the event will on average be advected beyond the grid box area, leading to high duration reduction factors (a "smearing out").

Dominance of convective vs. stratiform extremes including event occurrences. ~~Until now~~ So far we only illustrated differences in the 99th percentiles of detected convective and stratiform events with precipitation intensities above 1 mm day^{-1}, i.e. conditional probability density functions. The sample size therefore depends on the number of detections of the specific precipitation type, the resolution of the dataset and the area fraction in the detected quadrants with precipitation intensities higher than the specified threshold. Including the events without precipitation in the statistics will have a major impact on the percentile values, therefore a sensitivity analysis, performing the same analyses shown in Figs. 3 and 4 but with non conditional probability density functions was done (not shown). This demonstrated, that ~~the ST ratios are~~ v_{eff} is not strongly affected by this threshold. Naturally, due to the high number of non-precipitation-values, the high percentiles show correspondingly lower intensities. Table 2 indicates the event occurrences classified as convective or stratiform, in the 3 hourly synoptic observations.

To consider the strong variation in occurrences, e.g. concerning season, we find that also the relative occurrence frequency of the two types of events has to be accounted for. We again use the 99th percentile for all data above 1 mm day^{-1}, but now without distinction of precipitation type, for each aggregation interval, as well as for each region and season. In the following we re-define $\hat{I}$ as the corresponding intensity ~~.~~ (see Supplement for $\hat{I}$ values).

To assess the relative likelihood of a certain precipitation type to cause extreme precipitation, Fig. 8 shows the ratio of the number of convective events exceeding the intensity $\hat{I}$ vs. the total number (convective + stratiform) of events exceeding $\hat{I}$, i.e. $N_{\mathrm{cv}}(I > \hat{I})/(N_{\mathrm{cv}}(I > \hat{I}) + N_{\mathrm{ls}}(I > \hat{I}))$.

However, dominance again depends on resolution: E.g., in South Germany (all year) 80–90 % of precipitation extremes are of the convective type for the higher resolutions. Only when the data is aggregated to resolutions with grid-spacings of 25 km and more, the percentage of stratiform events becomes appreciable. Even stronger differences occur between seasons: In summer, convection dominates extremes but is of less importance in winter (less than 10 % for the aggregated datasets and less than 35 % even at the very high resolution datasets).

It is important to note that we used a percentile threshold for this analysis and the corresponding intensity threshold fluctuates with seasons. To test whether our findings simply are a consequence of overall higher intensities in summer, we also compare similar intensities for summer and winter (using the 98th percentile for summer and the 99th percentile in winter, see Fig. 8g–i and supplementary material). This revealed, that seasonal differences nonetheless prevail.

~~Sensitivity tests using~~ Fig. 9 shows the convective dominance as a function of the horizontal resolution for the 95th, 98th, 99th and 99.9th ~~percentile of precipitation intensities showed, that the~~ percentiles. The role of convective precipitation in the extremes increases with higher percentiles, and convective precipitation becomes more relevant also over larger aggregated areas and time steps (see supplementary material). ~~For example, Fig. 9 (all Germany) shows that at~~ At relatively low percentiles convective and stratiform events have the same ~~exceedence probability~~exceedance probability, but with increasing percentile convection dominates, especially at high spatial resolution.

3.2 Assessing PDF changes due to data aggregation

The results of ~~Sect~~Sec. 3.1 highlight the ~~need of choosing appropriate temporal resolution when analyzing extreme precipitation events at a specified spatial scale. Vice versa, specified spatial scales have to be matched by appropriate temporal scales . Such information may translate directly to working time and equipment costs when planning adequate measurement missions in the field. For modeling, this assessment may allow for more efficient storage of simulation data and optimal use of computing resources.~~

interdependence of spatial and temporal scales and their impact on extreme precipitation. Changing resolutions, however, modifies the entire distribution function. To give an estimate of the information loss due to the aggregation process, we adopt a measure similar to that of the Perkins skill score (Perkins et al., 2007), originally designed to validate a model against observations by assigning a skill score. Here, we use it to quantify the overlap between two intensity PDFs at different horizontal and temporal resolutions. We define the *PDF overlap* as:

$$S(\Delta t_1, \Delta x_1; \Delta t_2, \Delta x_2) \equiv \int_{I_0}^{\infty} \min(\rho_{\Delta t_1, \Delta x_1}(I), \rho_{\Delta t_2, \Delta x_2}(I))\, dI \quad (8)$$

where I is precipitation intensity, I_0 is the measurement cutoff, $\rho_{\Delta t, \Delta x}(I)$ is the normalized PDF as in Eq. (1), and $\min(\cdot,\cdot)$ gives the minimum of the two arguments. Hence, $S(\Delta t_1, \Delta x_1; \Delta t_2, \Delta x_2)$ quantifies the overlap between PDFs of aggregated data at the spatio-temporal resolutions $(\Delta t_1, \Delta x_1)$, and $(\Delta t_2, \Delta x_2)$, respectively. If the two PDFs are identical, the overlap value is 1, if there is no overlap at all, it is 0. The PDF overlap is a means of comparing not only a fixed percentile of precipitation intensity but measuring the similarity of entire distribution functions. It is hence a way to quantify our initially qualitative discussion regarding Fig. 2.

~~Figure 10 shows PDF overlap values for the~~ We aggregate convective precipitation intensities ~~aggregated over Germany~~ over Germany and present the PDF overlap in three different ways: Fig. 10a ~~-~~shows the PDF overlap between the aggregated time resolution with the corresponding 5 min data, but at fixed horizontal resolution, i.e. $S(5\,\mathrm{min}, \Delta x; \Delta t, \Delta x)$ at matrix element position $(\Delta t, \Delta x)$. For the spatially highly resolved data ($\Delta x < 7$ km), the PDF overlap degrades quickly when temporal resolution is reduced, while degradation is much slower at lower spatial resolution. In practice, if a defined spatial area, say a metropolitan region of 25 km is of interest, performing measurements at 60 min resolution may lead to a tolerable margin of error while a smaller region of 2 km would require 5 or 10 min temporal resolution for the same margin of error. The chart could hence be used to estimate the error when data is available at one resolution but another is of interest. In ~~panel~~ Fig. 10b we present an analogous analysis, but we have now fixed the temporal resolution and compare to the 1 km datasets, i.e. $S(\Delta t, 1\,\mathrm{km}; \Delta t, \Delta x)$ at matrix element position $(\Delta t, \Delta x)$. A similar pattern emerges with degradation now occurring for decreased spatial resolution.

In a third analysis (Fig. 10c) we calculate the overlap $S(60\,\mathrm{min}, 10\,\mathrm{km}; \Delta t, \Delta x)$ between aggregated data of spatio-temporal resolution (t, x) and the dataset at 60 min temporal resolution and 10 km spatial resolution. This reference point was chosen, because it is close to current state-of-the-art RCM simulation over Europe.

The plot shows a ridge with values close to 1, ranging from 5 min and 25 km to 120 min and ~~5~~1 km resolution. Apparently, all spatio-temporal resolutions along this curve produce PDFs which differ only slightly from the 5 min, 10 km aggregation. PDF overlap values quickly decrease when departing from this ridge. Comparing this ridge with the intensity decrease in the 99th percentile as illustrated in Fig. 3a we find that the PDF overlap mirrors the changes found in the 99th percentile. ~~Figure 10c is also shown as an example to demonstrate how the information from Fig. 10a and b can be combined in order to identify at which scales precipitation data stored at a certain resolution can be applied without modifying the intensities to fit to the desired scale.~~

~~In the example the 10, 60data~~ Using cumulative PDF measures as the Kolmogorov-Smirnov statistics is an alternative way of comparing PDFs. Figure 10c shows that different pairs of resolution give very similar PDFs. This can be used ~~at horizontal resolutions of about 6 to 15and shows also similar precipitation statistics at a temporal resolutionof 45. The analogous analysis is presented for stratiform precipitation in~~ when comparing datasets of different resolution. This information also proved to be useful for statistical bias correction, further analyzed in the paper (Haerter, 2015) .

For stratiform precipitation (Fig. 11~~. The PDF overlap now~~), the analogous PDF overlap degrades more slowly compared to convective precipitation. ~~The change in PDF overlap due to temporal aggregation is shown in Fig. 11a.~~ For example, at a 50 km grid size we find that twice the temporal aggregation can be tolerated as compared to convective precipitation when a given PDF overlap is demanded (Fig. 11a). Similar conclusions hold for the degradation as function of horizontal resolution (Fig. 11b). Starting at about 20 min we again find that the Δx can be increased to about twice the value for convective events to achieve the same PDF overlap value. For the overlap $S(60\,\mathrm{min}, 10\,\mathrm{km}; \Delta t, \Delta x)$, shown in Fig. 11c, the lower sensitivity to resolution changes for stratiform precipitation translates to a substantial widening of the ~~red~~ red-shaded area near the ridge, indicating much lower errors of estimating extremes at unavailable resolutions when stratiform precipitation is concerned, compare to the case for convective precipitation (Fig. 10c). Performing measurements over extended regions can already serve as a reasonable predictor of more local extremes. We also find that due to the different area and duration reduction factors of stratiform and convective type events, the ridge with values close to 1 is shifting. For the stratiform type we find that this ridge ranges from 5 min and 25 km to 90 min and 1 km resolution.

4 Discussion and conclusions

Precipitation is strongly inhomogeneous in time and space. Averaging ~~in space or time~~ over a specific temporal or spatial interval therefore transforms the distribution function. The resulting smoothening especially affects the extreme values, as it narrows the distribution function while preserving the mean. In this study, the focus is on how such averaging affects the two synoptically identifiable precipitation types, namely stratiform and convective ~~precipitation~~extreme precipitation events. Convective events are known to produce strong, short-duration and localized precipitation ~~events~~ while stratiform events are ~~more homogeneous.~~

~~We separate high-resolution~~ less bursty and cover larger areas. Using synoptic observations, we separate radar-derived ~~precipitation intensities into convective and stratiform events , using synoptic observations and define extreme precipitation as the 99th percentile of the distribution function~~high-resolution precipitation intensities conditional on events of either of these two types. Unlike other studies, we here concentrate on the different aggregation behavior of the two precipitation types at different seasons and regions of Germany. Althogh we have not analyzed this behavior in other regions and climate zones, we expect that the findings will depend on the mean advection velocity and also the orography might have an impact on results.

~~**Convection more sensitive to regions and seasons.** We make basic general observations regarding seasons and regions: Convective extremes were found to be markedly stronger in summer than in winter, an effect possibly explained by previously noted strong temperature response of that type (Berg et al., 2013) . We also note a regional gradient, with convective extremes~~ **Space-time dependency of intensity distributions.** We found that convective extremes were considerably stronger in the south than in the north of Germany ~~in summer. This is largely due to the convectively active Black Forest region, but may also be a consequence of higher summer temperatures in the south. Stratiform extremes showed seasonal and regional differences of about 20~~and also showed clear seasonal differences with the highest ~~values occurring in northern Germany. We then characterize intensity reduction due to temporal and spatial aggregation of extreme precipitation events . Spatially, convective extremes again~~ extremes occurring in summer. Stratiform extremes showed much more moderate differences over seasons and regions.

When aggregating data temporally or spatially, we find much stronger reduction for convective than for stratiform events (about 20 to 30 % higher). These differences are larger than seasonal or regional differences that were observed within one type. This highlights the importance of distinguishing between these two types of events for example for statistical downscaling exercises. After the type separation, only the convective extremes show clear regional and seasonal differences ~~: Strongest~~ and only in the area reduction factors. For the convective type, the strongest intensity reductions with spatial scale were found in south Germany in summer, the lowest in north Germany in winter. ~~Stratiform extremesshow smaller regional and seasonal differences in the reduction behavior~~

Temporal and spatial scales at which shifts occur between dominantly convective and dominantly stratiform extreme events. Depending on the spatial and temporal resolution, different meteorological events will be considered extreme. We point out that this makes it difficult to compare different studies of extremes, where these extremes were defined at different scales. To demonstrate this, we present the contribution of convective events to the total, as a function of data aggregation, for the 99th percentile of all precipitation events.

This information is needed to identify which space-time resolutions contain comparable information about the distribution function, including the extremes. It will further help to identify at which resolution and percentile one can expect to obtain information about convective extreme precipitation events. Besides expected seasonal and regional differences with higher contribution of convective events in summer and over south Germany, we also found a clear dependency on the scale and the threshold that is used. Over north Germany, stratiform events contribute to the 99th percentile extremes only at horizontal resolutions coarser than 12 km when the duration interval is kept constant to 5 min. For a higher threshold (99.9th percentile), convective events dominate even more strongly and convective extremes consequently prevail over even larger areas and durations.

~~Optimal pairs~~ Pairs of temporal and spatial resolutions with similar aggregation effects on the extremes. For proper choice of model output resolution, precipitation downscaling as well as bias correction, the relation between the ~~DRF'~~ DRF999s as compared to ~~ARF'~~ ARF999s is important. Originating from the radar data resolution of ~~5~~5 min temporally and ~~1~~1 km spatially, we produced sequences of aggregation, both in space and time, yielding: (i) temporally aggregated intensities for spatial scales held fixed, (ii) spatially ~~aggregates~~ aggregated intensity for temporal scales held fixed. Associating the respective aggregation resolution by matching ~~the corresponding~~ identical precipitation extremes, we yield pairs of temporal and spatial resolutions, which ~~then define a curve. We show how this curve can be used to generalize the Taylor-hypothesis to the situation where temporal scales change disproportionately with spatial scales. The result~~ define a curve.

The results allow, e.g.~~allow data analysts~~ , to identify pairs (Δx, Δt) of spatial and temporal resolutions for which the decrease in extreme precipitation intensities due to temporal aggregation matches that due to horizontal aggregation. ~~Departing from the points on the graph (Fig. 7) would give only moderately increased statistical information. Interestingly, the slopes of the curves of convective and stratiform events are similar; the main scaling difference between convective and stratiform events can be described by a scaling factor.~~

~~We find that in order to attain the *optimal* resolution, convective events require about 1.75 times higher horizontal resolutions at a given temporal scale than stratiform events.~~

~~Equivalently, the graph can be recast into the ratio between corresponding grid sizes and durations (which we term ST ratio). For constant ratio as function of spatial scale, the~~ In terms of the Taylor-hypothesis~~would be obeyed. However, the ST ratio of convective and stratiform extreme precipitation algebraically decreases with increasing Δx with similar exponents for both precipitation types.~~

~~In practice, in regional climate models the temporal output is often lower than the *optimum*resolution computed here. For example, the *optimum*temporal resolution~~ , the timescales can roughly be viewed as the mean duration needed to advect the precipitation pattern by the width of a grid-box (Fig. 6).

For example, if for a given horizontal grid size a larger temporal output interval is used, the event will likely be advected further than the size of the grid-box, leading to strong duration reduction factors. We find that for state of the art regional climate simulations, performed at a 11 km horizontal resolution, the temporal resolution needed in order to avoid stronger duration than area reduction effects, would be approximately 20 to 25 min. ~~Many regional models however~~

In practice, in regional climate models the temporal output is often lower than the resolution computed here. It should therefore be reconsidered why many regional models do not output at sub-hourly frequency and why often only daily averages are stored. ~~A higher temporal output would be advisable since this information~~

If a model can resolve some small scale features, e.g. convective extremes, information can only be preserved by outputting at the appropriate temporal resolution, while information gets lost when using lower horizontal resolutions (Fig. 8). High temporal resolution is accessible by ~~the model~~ most models already (most models have computing time steps $\sim$ seconds – minutes) ~~and recording~~ but is not routinely output at such short periods. Recording at higher frequency would mainly ~~effect~~ affect storage space, not simulation run-time (assuming efficient I/O-handling).

~~**Inclusion of dry events.**~~ ~~The different aggregation behavior of~~ The pairs of corresponding grid sizes and durations defines a velocity v_{eff}, which can be used to generalize the Taylor-hypothesis to the situation where temporal scales change disproportionately compared to spatial scales (self-affinity, Deidda (2000)). For constant v_{eff} as function of spatial scale, the Taylor-hypothesis would be obeyed. However, v_{eff} of convective and ~~stratiform events means that the probability that an extreme precipitation event being of the convective type changes with the resolution of the data. If an intensity threshold, for example the 99th percentile, is used in a study to identify extreme events, all events lower than this threshold will be filtered out. Depending on the resolution of the dataset used in the analyses, different meteorological events will be considered as extreme. Using the 99th percentile of all precipitation events, we analyze the contribution of convective events to the total as a function of data aggregation. Knowledge of this ratio is needed for example to compare climate signals of extreme precipitation, that were calculated at different resolutions. This ratio changes with resolution, season and regions of Germany. In summer and at high resolution, essentially all precipitation extremes are of the convective type. Over north Germany stratiform events contribute only at horizontal resolutions coarser than 12when the duration interval is kept constant to 5. For a higher threshold (99.9th percentile), convective eventsagain dominate more strongly and convective extremes consequently prevail over even larger areas and durations~~stratiform extreme precipitation algebraically decreases with increasing Δx with similar exponents for both precipitation types. The main scaling difference between convective and stratiform events can be described by a constant scaling factor. This scaling factor leads to about 1.75 times higher advection velocities for stratiform than for convective events.

PDF overlap. Changes caused by temporal aggregation depend on the spatial scale of the data and vice versa. ~~To~~ We examine these dependencies ~~, we compare~~ by comparing pairs of PDFs derived for different aggregation resolutions using a ~~-~~method developed by ~~Perkins et al. (2007) . This leads to practical application as to choosing appropriate resolutions in time (space)when a domain of given area (time interval) is specified. For example : If measuring precipitation data at one pair of resolutions, our results indicate other~~

~~pairs of resolutionsthat could be derived from models and should yield similar statistical distribution functions.This may be relevant for statistical bias correction~~Perkins et al. (2007), here defined as PDF overlap.

We find that PDF changes that were observed when decreasing the temporal resolution from 5 min to 2 h at 50 km horizontal resolution are quantitatively comparable with PDF changes when going from 5 min to 30 min at 10 km horizontal resolution or from 5 min to 10 min at 2 km horizontal resolution.

Further we show that the PDF overlap of a certain reference resolution (we chose as an example 60 min, 10 km) compared to all other aggregated resolutions, shows a ridge with values close to 1. This ridge ranges from 5 min and 25 km to 120 min at 1 km resolution for convective type events (Figure 10c) and from 5 min and 25 km to 90 min at 1 km resolution for stratiform events (Fig. 10c). These differences can be explained by the strong area reduction factors found for the convective type. The patterns found in this analysis are very similar to, the patterns found in Figs. 3 and 4 highlighting that most of the differences found in the PDF overlap are resulting from changes in the extrems.

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Table 1. Estimation of the exponents b and the pre-factors ã for the different ~~convection~~ precipitation types and percentiles together with the standard deviation of the parameter estimate. * Excluding the 99.9th percentile.

precipitation type	percentile	$\tilde{a}$	b
convective	95th	0.51 $\pm$ 0.05	1.17 $\pm$ 0.03
	98th	0.45 $\pm$ 0.03	1.25 $\pm$ 0.02
	99th	0.43 $\pm$ 0.04	1.27 $\pm$ 0.02
	99.9th	0.55 $\pm$ 0.01	1.24 $\pm$ 0.01
	mean	0.49 $\pm$ 0.03	1.23 $\pm$ 0.02
stratiform	95th	0.20 $\pm$ 0.04	1.32 $\pm$ 0.06
	98th	0.35 $\pm$ 0.03	1.18 $\pm$ 0.02
	99th	0.28 $\pm$ 0.02	1.24 $\pm$ 0.02
	99.9th	0.76 $\pm$ 0.03	0.96 $\pm$ 0.01
	mean*	0.28 $\pm$ 0.03	1.25 $\pm$ 0.03

Table 2. Occurrence of convective and stratiform events. Number of quadrants of Germany classified as convective (C) or stratiform (S) in the 3 hourly synoptic observations. The maximum possible values for the two years and for all four quadrants is 23360. This number reduces by about half for the seasonal data, and again by half for the sub-regions of Germany.

area	type	year	summer	winter
all	S	1358	206	1152
all	C	1537	1270	267
north	S	761	103	658
north	C	741	590	151
south	S	597	103	494
south	C	796	680	116

Figure 1. Data used in the analysis. Map of Germany with the synoptic stations (red crosses) and the radar locations and approximate range (gray circles). Dashed black lines indicate the division of the domain into quadrants.

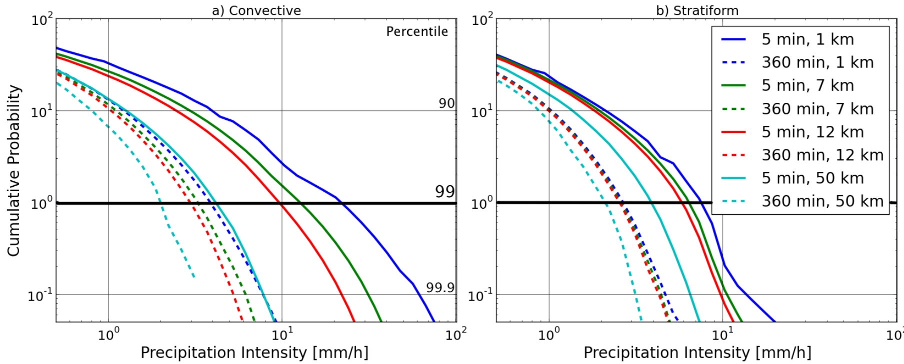

Figure 2. Cumulative probability density functions of precipitation intensities. All of Germany for the years 2007–2008, aggregated at different horizontal and temporal resolutions. **(a)** convective events; **(b)** stratiform events.

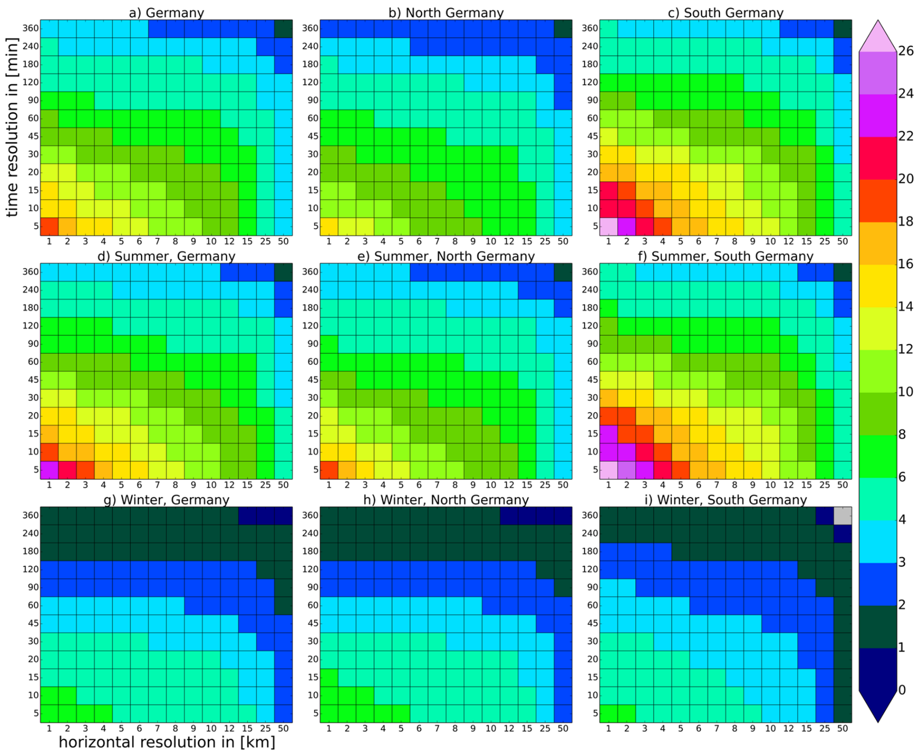

Figure 3. Convective extremes as function of resolution. The 99th percentile of convective precipitation intensities, aggregated over different parts of Germany for the years 2007–2008, on different horizontal (horizontal axis) and temporal (vertical axis) resolutions: Entire year **(a–c)**, summer season **(d–f)** and winter season **(g–i)**. All of Germany **(a, d, g)**, North Germany **(b, e, h)**, South Germany **(c, f, i)**; Intensities given in $\mathrm{mm\,h^{-1}}$.

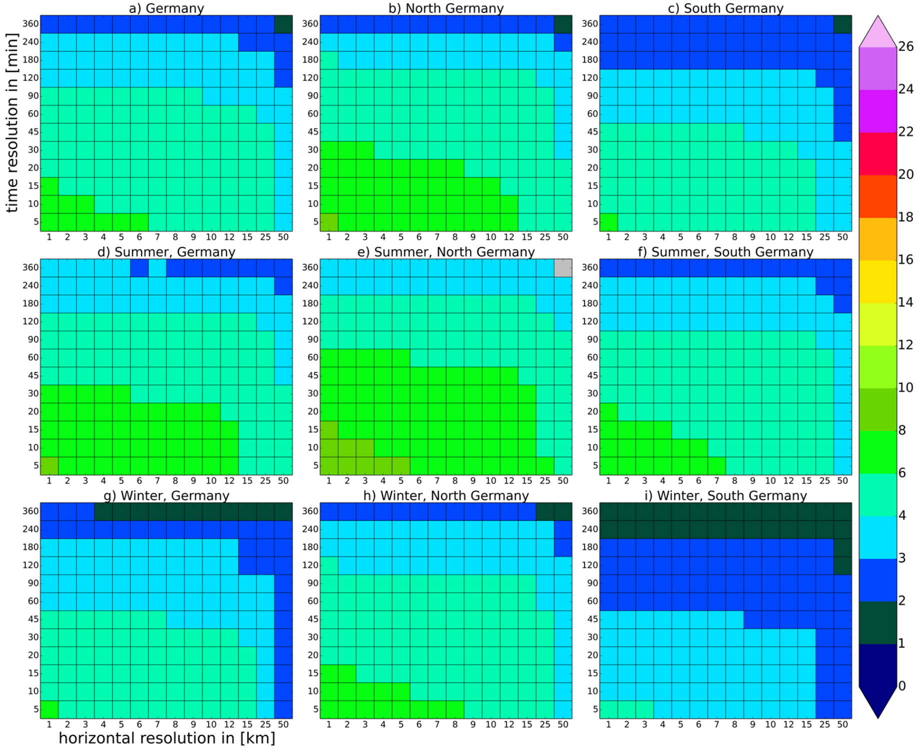

Figure 4. Stratiform extremes as function of resolution. Otherwise similar to Fig. 3.

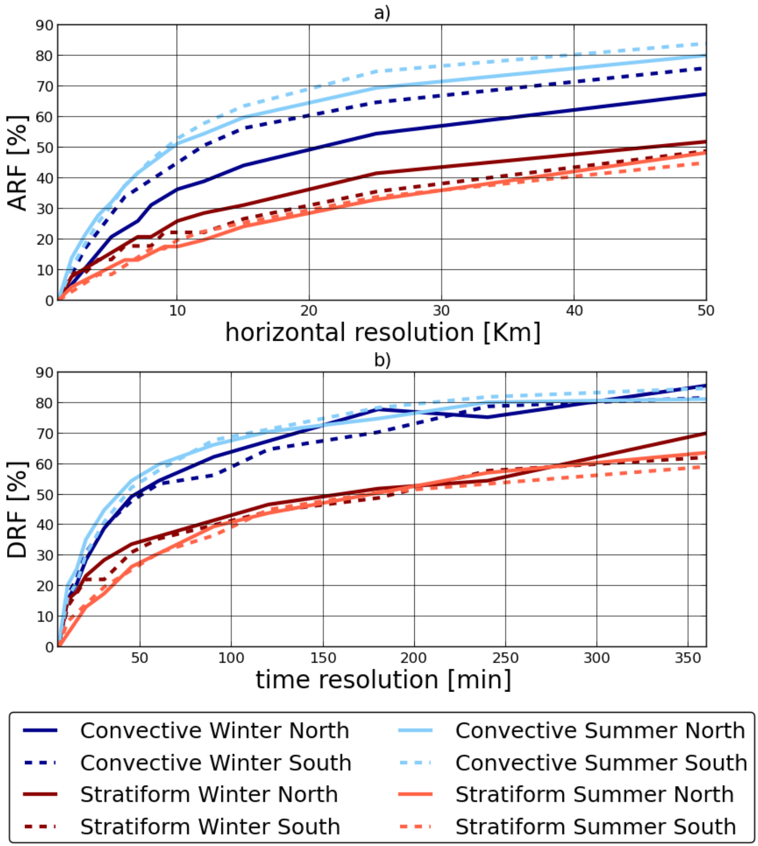

Figure 5. Area and duration reduction factors. (a) area reduction factors at 5 min temporal resolution. **(b)** duration reduction factors (DRF) for 1 km × 1 km spatial resolution in percent, for convective (blue) and stratiform (red) precipitation. Data shown for the summer and winter seasons and north and south Germany.

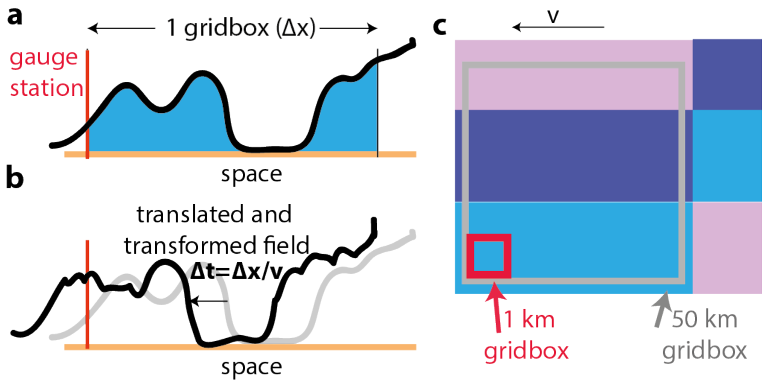

Figure 6. ~~**Consistent spatial and temporal resolutions.** Δt derived using Eq.~~ **Schematic illustration of the Taylor hypothesis. (a)** One-dimensional case, showing space, gridbox width and precipitation intensity (~~5~~black curve)~~for different values~~; the location of ~~Δx for convective (blue) and stratiform (~~a gauge station is marked in red. **(b)** Similar to (a)~~precipitation extremes at the 95th~~, ~~98th~~but illustrating how the curve may change due to small scale dynamics after a time interval $\Delta t = \Delta x / v$, ~~99th and 99.9th percentiles. Black lines are least square fit of $\Delta t = a \times \Delta x^b$~~ with v the ~~fitting parameters a and b for the 99th percentile~~atmospheric advection velocity. ~~Errorbars~~ **(c)** Two-dimensional inhomogenities (different colors indicate different intensities) perpendicular to the ~~standard deviation of parameter estimates. Gray lines show $\Delta t \sim \Delta x$ and $\Delta t \sim \Delta x^2$, respectively. **(a)** Initial resolutions $\Delta t_0 = 5$, $\Delta x_0 = 1$. **(b)** $\Delta t_0 = 5$, and aggregated spatial resolutions $\Delta x_0 = 2$~~advection direction (~~convective~~direction indicated by the thin arrow)~~and $\Delta x_0 = 3$~~. Small (~~stratiform~~red) ~~. **(c)** ST ratio~~ and large (~~Eq. 7~~gray) ~~for both precipitation types for Germany over the entire year~~gridboxes as marked.

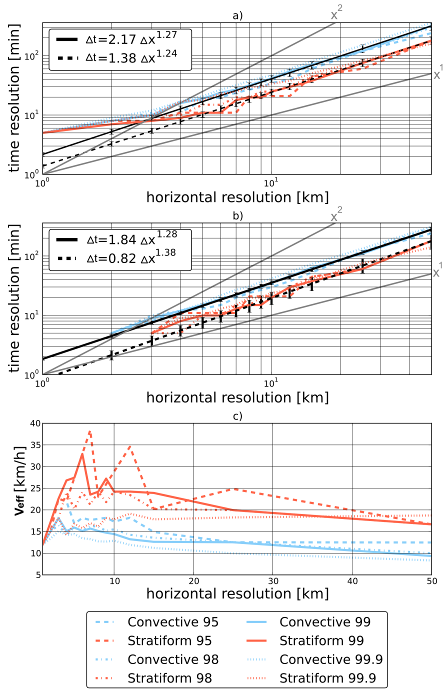

Figure 7. Consistent spatial and temporal resolutions. Δt derived using Eq. (5) for different values of Δx for convective (blue) and stratiform (red) precipitation extremes at the 95th, 98th, 99th and 99.9th percentiles. Black lines are least square fit of $\Delta t = a \times \Delta x^b$ with the fitting parameters a and b for the 99th percentile. Errorbars indicate the standard deviation of parameter estimates. Gray lines show $\Delta t \sim \Delta x$ and $\Delta t \sim \Delta x^2$, respectively. **(a)** Initial resolutions $\Delta t_0 = 5$ min, $\Delta x_0 = 1$ km. **(b)** $\Delta t_0 = 5$ min, and aggregated spatial resolutions $\Delta x_0 = 2$ km (convective) and $\Delta x_0 = 3$ km (stratiform). **(c)** v_{eff} (Eq. 7) for both precipitation types for Germany over the entire year.

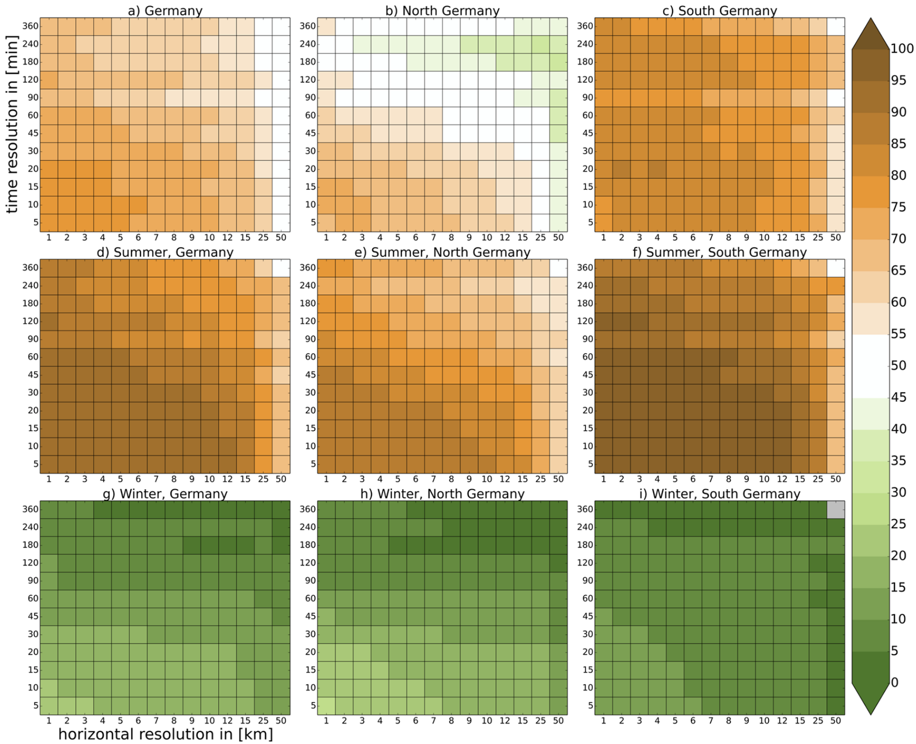

Figure 8. Convective dominance as function of resolution including dry periods. The ratio of the number of convective precipitation events with precipitation intensities ~~larger~~ greater than or equal to the threshold intensity. Threshold intensity is defined as the 99th percentile of total precipitation intensities over the different parts of Germany for the years 2007–2008. Panels otherwise as in Fig. 3.

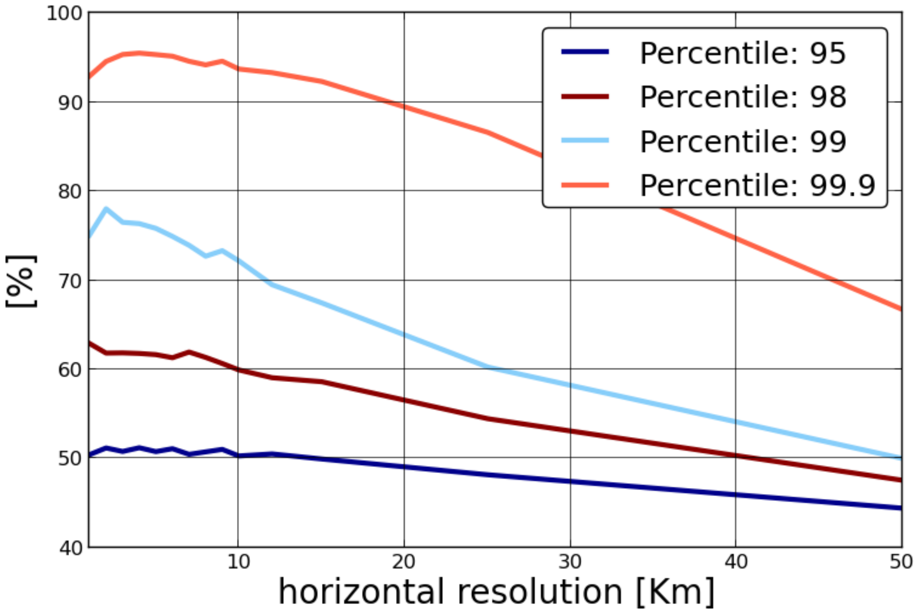

Figure 9. Convective dominance vs. horizontal resolution. The ratio of the number of convective precipitation events with precipitation intensities ~~larger~~ greater than or equal to the labeled percentile of total precipitation intensities over entire Germany for the years 2007–2008. The data is aggregated to 5 min temporal and different horizontal resolutions.

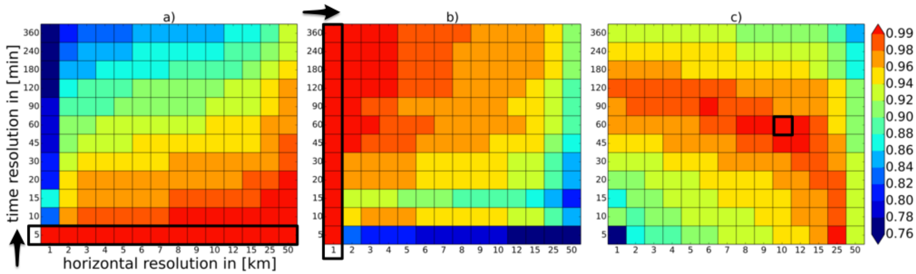

Figure 10. PDF overlap for convective precipitation intensity. All of Germany for the years 2007–2008, aggregated to different horizontal (horizontal axis) and temporal (vertical axis) resolutions. **(a)** PDF overlap of each horizontal resolution between every temporal resolution and the 5 min data. **(b)** PDF overlap of each temporal resolution between every horizontal resolution and the 1 km data. **(c)** PDF overlap of each horizontal and temporal resolution compared to the 10 km, 60 min data.

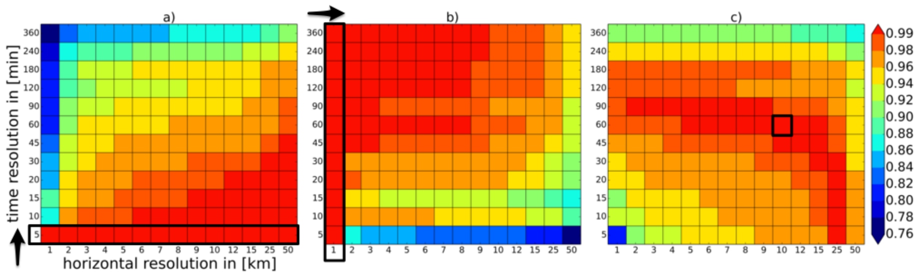

Figure 11. PDF overlap of stratiform precipitation intensity. Otherwise similar to Fig. 10.