

1 Downscaling future precipitation extremes to urban hydrology
2 scales using a spatio-temporal Neyman-Scott weather
3 generator

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9 **Abstract**

10 Spatio-temporal precipitation is modelled for urban application at 1-hour temporal resolution
11 on a 2 km grid using a Spatio-Temporal Neyman-Scott Rectangular Pulses weather generator
12 (WG). Precipitation time series use as input to the WG are obtained from a network of 60
13 tipping-bucket rain gauges irregularly placed in a 40 by 60 km model domain. The WG
14 simulates precipitation time series that are comparable to the observations with respect to
15 extreme precipitation statistics. The WG is used for downscaling climate change signals from
16 Regional Climate Models (RCMs) with spatial resolutions of 25 km and 8 km respectively.
17 Six different RCM simulation pairs are used to perturb the WG with climate change signals
18 resulting in six very different perturbation schemes. All perturbed WGs result in more
19 extreme precipitation at the sub-daily to multi-daily level and these extremes exhibit a much
20 more realistic spatial pattern than what is observed in RCM precipitation output. The WG
21 seems to correlate increased extreme intensities with an increased spatial extent of the
22 extremes meaning that the climate-change-perturbed extremes have a larger spatial extent
23 than those of the present climate. Overall, the WG produces robust results and is seen as a
24 reliable procedure for downscaling RCM precipitation output for use in urban hydrology.

25 **1 Introduction**

26 Pluvial flooding of urban areas is often caused by very local extreme precipitation at sub-daily
27 temporal scale (Berndtsson and Niemczynowicz, 1988, Schilling, 1991). Traditionally,
28 historical gauge measurements of precipitation at minute-scale temporal resolution are thus
29 used as input to design and analysis of urban water infrastructure (Mikkelsen et al., 1998,

1 Madsen et al., 2009, Arnbjerg-Nielsen et al., 2013). Climate change is, however, expected to
2 change the occurrence rate and magnitude of extreme events causing urban pluvial flooding
3 (Fowler and Hennessy, 1995; Larsen et al., 2009; Olsson et al., 2009, Sunyer et al., 2014), and
4 high-resolution input time series representing future climates are therefore needed. Even
5 though the overall qualitative features of precipitation are reproduced realistically by regional
6 climate models (RCMs) (Christensen and Christensen, 2007) they are not able to capture the
7 very fine-scale spatio-temporal features of precipitation satisfactorily and yield output that is
8 too spatially correlated (Tebaldi and Knutti, 2007; Gregersen et al., 2013). To overcome this,
9 either dynamic downscaling with climate models has to operate at much finer scales in order
10 to properly describe convective precipitation dynamics (Kendon et al., 2014; Mayer et al.,
11 2015) or further statistical downscaling of the climate model output has to be performed
12 (Olsson and Burlando, 2002; Wood et al., 2004; Cowpertwait, 2006; Molnar and Burlando,
13 2008; Willems et al., 2012; Sunyer et al., 2012; Arnbjerg-Nielsen et al., 2013). Fine scale
14 dynamic downscaling is computationally extremely expensive and statistical downscaling is
15 therefore often favoured (Maraun et al., 2010). Several approaches exist within statistical
16 downscaling, each with its pros and cons (Wilks and Wilby, 1999; Willems et al., 2012;
17 Arnbjerg-Nielsen et al., 2013). In the present study a stochastic weather generator (WG) is
18 used for statistical downscaling.

19 WGs can take different forms (Vrac et al., 2007; Burton et al., 2008; Arnbjerg-Nielsen and
20 Onof, 2009; Chen et al., 2010; Cowpertwait et al., 2006; 2013) but they generally work by
21 analysing observed precipitation (and possibly other weather related variables) and use the
22 obtained statistics to create artificial stochastic precipitation (or weather) time series that
23 replicate the behaviour of the observations with respect to these statistics (Maraun et al, 2010,
24 Sunyer et al., 2012). Perturbation of the WG to yield output time series representing future
25 climates is then possible by application of climate change factors calculated from output from
26 RCMs (operation at too large space-time scales) to relevant parameters of the WG (that
27 operates at the right space-time scale).

28 Several WGs exist that model precipitation as a stochastic point process where the given
29 observations are considered single realisations of an underlying precipitation process
30 (Waymire and Gupta 1981). Rodríguez-Iturbe et al. (1987a,b) developed the stochastic point
31 process models in a way to better characterise and describe the precipitation process at the
32 event level. Implementations of the stochastic point process models for spatio-temporal

1 precipitation seem to work satisfactorily at temporal resolutions down to one hour
2 (Cowpertwait and O'Connell, 1997; Burton et al., 2008; 2010a; Cowpertwait et al., 2006:
3 2013). Also, downscaling to finer resolution than one hour is inherently problematic as the
4 scaling properties change below this point (Nguyen et al., 2002; Molnar and Burlando, 2008).
5 Thus, for downscaling of extreme precipitation at sub-daily level and subsequent application
6 of climate change signals from climate models, stochastic weather generators implementing
7 stochastic point process models seem useful (Cowpertwait, 1998; Furrer and Katz, 2008;
8 Hundecha et al., 2009; Verhoest et al., 2010; Sunyer et al., 2012). The trade-off is that the
9 models do not involve rainfall movement and, hence that the spatio-temporal scale of the
10 model has to be such that rainfall movement is not the main descriptor of the spatial rainfall
11 pattern.

12 At the daily level, the Neyman-Scott Rectangular Pulses (NSRP) and the Spatio-Temporal
13 Neyman-Scott Rectangular Pulses (STNSRP) models (Burton et al., 2008; 2010a; 2010b;
14 Cowpertwait et al., 2013) have shown good skill in downscaling point precipitation extremes.
15 This applies for individual gauges (Sunyer et al., 2012) as well as for spatially averaged
16 precipitation covering large areas considered as having a uniform climate described by
17 relatively few gauges (e.g. 5 gauges for a 4000 km² basin in the Pyrenees (Burton et al.,
18 2010a) and 3 gauges used to calibrate a regional model covering a catchment of 342 km² in
19 the Basque Country (Cowpertwait et al., 2013)). This is however inadequate in urban
20 hydrology where the rainfall dynamics causing effects under study occur on much smaller
21 time and space scales.

22 In the present study, the STNSRP weather generator (WG) in the form of the software
23 package RainSim (version 3.1.1, Burton et al., (2008)) is used in a new, urban hydrology
24 context focusing on much smaller space and time scales than what has been done in previous
25 studies. Due to the limitations in scalability of both RCM model output and precipitation
26 measurements discussed above a temporal resolution of 1 hour is adopted, even though a
27 higher resolution would be preferable from an urban hydrology perspective. Hourly data from
28 60 rain gauges from a dense rain gauge network in Denmark are used to estimate parameters
29 for the WG which is used to generate synthetic precipitation data series on a regular dense
30 grid covering approximately 2400 km². The synthetic precipitation data is then evaluated with
31 respect to its applicability for urban hydrological purposes. A 1-hour temporal resolution on a
32 2 km grid is chosen as realistic and sufficient performance scales of the model for fine-scale

1 precipitation data in urban hydrology. The evaluation of the WG is done from an engineering
2 perspective with respect to its ability to reproduce rainfall features relevant for urban
3 hydrological modelling. We will thus focus on:

- 4 • the WG's ability to produce realistic extreme event intensities at point scale
- 5 • the WG's ability to reproduce the seasonal distribution of extreme events at point
6 scale
- 7 • the WG's ability to reproduce small scale spatio-temporal correlation structures
8 of the extreme events

9 This study uses the presented WG to analyse climate change in precipitation at scales
10 comparable to the observational data sets traditionally used today for urban water
11 infrastructure design and analysis. The WG is perturbed with climate change information
12 obtained from a collection of temporal high resolution RCMs. Six RCM runs using three
13 different RCMs, driven by three different GCMs and covering three different emission
14 scenarios (ranging from average to very high emissions) are included in the analysis and four
15 of the RCM runs are run as high resolution models at an 8 km grid. Finally, climate change at
16 urban scale is assessed based on the perturbed WG output.

17 **2 Data**

18 **2.1 Observational data**

19 The model area is a 40 by 60 km region covering the North-Eastern part of Zealand
20 (Denmark) including Copenhagen, see Figure 1. This study uses two different observational
21 data sets; Table 1 summarises their main characteristics.

22 The area is highly urbanised and has a dense but irregular network of rain gauges designed
23 and used for urban hydrology applications. The main observational precipitation data set,
24 SVK (abbreviation for *Spildevandskomiteen*, the Water Pollution Committee of the Society of
25 Danish Engineers) is obtained from this dense network of high-resolution tipping bucket rain
26 gauges (Jørgensen et al., 1998; Sunyer et al., 2013). Data from 60 stations that have been
27 active between 2 and 34 years in the period 1979 and 2012 are included in the analysis; see
28 Figure 1 for locations within the study area. Figure 2 shows (top) the temporal development
29 of the number of active stations, (middle) the average distance between nearest neighbouring
30 stations through the measuring period, and (bottom) shows the distribution of record lengths
31 by 2012. Generally, there has been an increase in the number of stations and a densification of

1 the network over the years. Some studies impose a minimum length of the time series to be
2 included in regionalisation studies, e.g. Madsen et al. (2009), but in this study the cross-
3 correlation is of key interest and hence all gauges are included in the analysis regardless of
4 their record length. The original data resolution is 1 min and 0.2 mm but for the present study,
5 data is aggregated to hourly time series. This data set is used to estimate most of the
6 parameters of the WG.

7 The second observational data set included in the analysis is referred to as the Climate Grid
8 Denmark (CGD) (Scharling 2012). It comprises spatially averaged daily data in a uniform 10
9 km grid for all of Denmark from 1989 to 2010 inclusive, cf. Figure 1. This data is generated
10 based on a national network of gauges with 27 gauges within the study site (Scharling 1999)
11 and is only used to estimate the spatial component in the WG.

12 **2.2 Regional climate model data**

13 Precipitation output from twelve different RCM runs representing present and future
14 condition is used in this study, see Table 2. Four of the model runs are identical to the ones
15 used by Gregersen et al. (2013), namely the two SRES A1B scenarios forcing the RCM
16 RACMO (version 2.1, Meijgaard et al., 2008) and the RCM HIRHAM (version 5, Christensen
17 et al., 2006) and their present counterparts. All RCM runs are driven by the GCM ECHAM5
18 (Roeckner et al., 2003) and are part on the ENSEMBLES project (van der Linden and
19 Mitchell, 2009). All have a spatial resolution of 25 km and a temporal output resolution of 1
20 hour. These were the ENSEMBLES runs we had available through personal contacts for the
21 present study at 1-hour resolution. The more generally available data series with only daily
22 maximum 1-hour intensity are not sufficient for the employed downscaling procedure. The
23 other eight simulations used in this study are run with the RCM HIRHAM driven by the GCM
24 EC-EARTH (Hazeleger et al., 2012) and the RCM WRF (Skamarock et al., 2005) driven by
25 the GCM NorESM (Bentsen et al., 2013). The four future simulations use the RCP 4.5 and
26 RCP 8.5 scenarios (van Vuuren et al., 2011), see Table 2. The spatial resolution of these
27 simulations is 8 km and the output frequency is again 1 hour (Fox Maule et al., 2014; Mayer
28 et al., 2015). The SRES A1B and RCP 4.5 scenarios are considered comparable moderate
29 forcing scenarios whereas the RCP 8.5 scenario is a very strong forcing scenario. All future
30 RCM runs are related to RCM runs driven by the same GCM for present conditions when
31 climate factors are calculated (Table 2).

1 As in Gregersen et al. (2013), climate change is considered uniform for all land cells over
2 Denmark; this results in 87 considered grid cells for the ENSEMBLES SRES A1B
3 simulations and 648 for the RiskChange RCP 4.5 and 8.5 simulations.

4 **2.3 Weather generator data**

5 The last data set is the output from the applied weather generator (WG, described in Section
6 3). A total of 10 data sets comprising sets of 50 years' time series in the 2 km grid (as shown
7 on Figure 1) are simulated as output from the WG. These data sets are used to corroborate the
8 WG by refitting and rerunning it, evaluating the output variability and comparing the output
9 statistics to those of observations.

10 **3 Weather generator**

11 Burton et al. (2008) gives a thorough description of the weather generator and its components,
12 Burton et al. (2010a) an introduction to the application of the model and Burton et al. (2010b)
13 an introduction to incorporation of climate change into the WG; the remainder of this section
14 is, thus, only giving a brief introduction to the WG and a more in depth description of the
15 workflow associated with working with the model is given in the supplement. Generally, the
16 approach by Burton et al. (2010a) is followed with inclusion of climate change as described
17 by Burton et al. (2010b) using the software presented by Burton et al. (2008).

18 **3.1 Parameters**

19 The RainSim WG (version 3, Burton et al. (2008)) describes the spatio-temporal rain field as
20 discs of rain (rain cells) with uniform rain intensity that temporarily occur and overlap in
21 space and time to produce output that realistically describe the statistical properties of
22 precipitation. As the calibration data set consists of point observations, the time series from
23 the simulations are not grid cell averages but strictly comparable to what a gauge would have
24 measured if present in a grid point.

25 The WG parameters and their meaning and interactions are described in-depth in Burton et al.
26 (2008) where a schematic representation of the WG is also found (Burton et al., 2008: Fig. 1).
27 A uniform Poisson process governed by λ describes the storm occurrences. For each storm a
28 random number of rain cells are produced, which occur at independent time intervals after the
29 storm origin and where the time intervals follow an exponential distribution with parameter β .

1 A uniform spatial Poisson process governed by ρ describes the density of the rain cells in
2 space. The cell radii are randomly drawn from an exponential distribution described by γ , and
3 the duration and intensity of each rain cell is independent and follows an exponential
4 distribution with parameters η and ζ , respectively. The rain intensity at a given point is
5 therefore the sum of all overlapping rain cell intensities at a given time. In all, seven
6 parameters describe the WG:

- 7 • λ^{-1} , the mean waiting time between storm origins (in hours)
- 8 • β^{-1} , the mean waiting time for rain cell origins after storm origin (in hours)
- 9 • η^{-1} , the mean duration of rain cells (in hours)
- 10 • ρ , the spatial density of rainfall cell centres (cells per km²)
- 11 • ζ^{-1} , the mean intensity of the rain cells (in mm/h)
- 12 • γ^{-1} , the mean radius of the rain cells (in km)
- 13 • Φ , the non-homogeneous intensity scaling field describing how the mean
14 monthly rainfall intensity varies in space within the model area (-)

15 The non-homogeneous intensity scaling field, Φ , is a proxy for the spatial variation of mean
16 monthly precipitation and is used for relative scaling of the precipitation in space; for this
17 study it is interpolated from the CGD data set using inverse distance weighting. Regional
18 modelling of short-duration extreme precipitation for Denmark using the SVK data set has
19 shown that the only significant parameter that can explain the geographical variation of point
20 extremes statistically is the corresponding mean annual precipitation (Madsen et al., 2002;
21 2009). Thus, taking Φ as the only spatially varying parameter in the WG, and as such the only
22 parameter describing spatial differences within the WG, is considered to be an acceptable
23 approximation. The actual spatial variation of mean monthly precipitation calculated from the
24 CGD data set is considerable (see Figure 3), even though the model area is small in size and
25 relatively flat. Especially in June and July there is a clear North-South gradient with 75-80
26 mm/month in the North of the area and 55-60 mm/month in the South.

27 **3.2 Parameter estimation**

28 The parameters for RainSim (see Section 3.1) are estimated based on daily and hourly
29 statistics for each calendar month from the observed time series (SVK). The objective
30 function is adopted from Burton et al. (2010b: Eq. (2)) and the weights are chosen to best

1 reproduce features at both hourly and daily levels, as described by Burton et al. (2008; 2010a;
2 2010b). The custom weighing scheme used is constructed to support the features of rainfall
3 that are important in the context of the present study (i.e. the higher order moments are
4 assigned more weight to secure a realistic fit for the extremes, see Table 3). The statistics used
5 for fitting the WG are:

- 6 • The mean daily precipitation intensity from the individual gauges (24 hour
7 mean)
- 8 • The variance of the intensity of the daily and hourly observations from the
9 individual gauges (1 hour and 24 hour variance)
- 10 • The skewness of the intensity of the daily and hourly observations from the
11 individual gauges (1 hour and 24 hour skewness)
- 12 • The probability of dry days and of dry hours based on the observations from
13 the individual gauges and with thresholds of 1.0 and 0.1 mm respectively as
14 suggested by Burton et al. (2008).
- 15 • The lag-1 auto-correlation of the hourly precipitation intensity calculated
16 from the observations at the individual gauges
- 17 • The cross-correlation between observations of hourly precipitation intensity
18 at the individual gauges

19 The chosen weighing scheme favours the higher order moment statistics, variance and
20 skewness, over the mean as the extreme characteristics of the simulated precipitation is
21 prioritised. Furthermore, the cross-correlation and auto-correlation are given high weights to
22 ensure a realistic representation of the spatio-temporal extent of the simulated precipitation.
23 The different observation time series are furthermore weighted relative to each other
24 according to the effective length of the time series to give more weight to longer time series.
25 This is done to increase the data basis for cross-correlation analysis, utilising that a great deal
26 of the short time series are from recent years and thus overlap in time, see Figure 2.

27 The standard fitting bounds suggested by Burton et al. (2008) are applied in the fitting
28 procedure to ensure that the WG is fitted with values that are considered realistic by the
29 model developers for a Northern European climate.

1 **3.3 Perturbation of the weather generator with climate change signals**

2 The WG is perturbed with climate change signals by application of change factors, $\alpha_{i,j,k}$'s, to
3 the statistics, $Y_{i,j,k}^{Present}$'s, calculated from the SVK data set and used for the original parameter
4 estimation for present climate. In this manner new statistics are produced for future climate,
5 $Y_{i,j,k}^{Future}$'s, as (Fowler et al., 2007, Burton et al., 2010b):

$$6 \quad Y_{i,j,k}^{Future} = \alpha_{i,j,k} Y_{i,j,k}^{Present} \quad (1)$$

7 where one climate change factor, $\alpha_{i,j,k}$, is calculated for each statistic, i , for each month, j , for
8 each RCM, k . The change factors are calculated using the methodology introduced by Burton
9 et al. (2010b: Eq. 1-3) which includes transformations that ensure that the bounded statistics
10 (probabilities of dry days and hours and auto-correlation) stays within their prescribed
11 boundaries (further described in the supplement). No change factor is calculated for the cross-
12 correlation as this statistic is described poorly by the RCMs (Gregersen et al., 2013).

13 **4 Methodology**

14 **4.1 Evaluation of simulated time series**

15 The evaluation of the simulated time series will be in line with previous studies such as
16 Olsson and Burlando (2002), Cowpertwait (2006) and Molnar and Burlando (2008). This
17 implies that simulated time series are not evaluated directly against the observations with the
18 expectation of a perfect fit; the expectation is rather that the simulated series have the same
19 statistical properties as the measured precipitation. In practise this is achieved by analysis of
20 the statistics used in the fitting procedure and through analysis of statistics which are
21 independent of the fitting statistics as will be outlined in Section 4.2.

22 For evaluation of all realisations of the WG the 60 grid cells closest to the observational
23 gauges are extracted and evaluated point-wise with respect to all the fitting statistics as
24 recommended by Burton et al. (2008). Furthermore, the WG is refitted to the simulated data
25 sets to evaluate if the realisation is representative and results in model parameters that are
26 comparable to the parameters estimated from the SVK observational data set.

27 Ten realisations of the WG, named WG1 to WG10, are used in this study. The actual
28 simulation time is very short, but the process of writing data to text files for the complete grid
29 takes long time, making it a rather cumbersome approach, which limits the number of
30 realisations evaluated in this study.

1 The refitted WG data is evaluated with respect to the fitting statistics, $Y_{i,j,k}^{WG}$ for each statistic, i ,
2 for each month, j , for each WG realisation, l , through discussion of the density plots for the
3 normalized error against the SVK data set:

$$4 \quad \epsilon = \frac{Y_{i,j,l}^{WG} - Y_{i,j}^{SVK}}{Y_{i,j}^{SVK}} \quad (2)$$

5 **4.2 Evaluation of extremes**

6 Gregersen et al. (2013) compare extreme precipitation observations with RCM output. One
7 issue is the difference in absolute magnitude of the extremes, which can partly be explained
8 by the inherent difference between gridded data and point observations; another issue is the
9 spatial correlation structure of the extremes, where extremes calculated from RCM output are
10 much more spatially correlated at the sub-daily time scale. In this study, a data set simulated
11 with a WG will be considered better than using RCM data directly for the specified purpose if
12 it better resembles the observations with respect to both the absolute magnitude and the
13 spatial correlation structure of the extremes.

14 The statistics used in this study to evaluate the WG's performance with respect to simulating
15 extreme precipitation are based on the identification of independent rainfall events, as done
16 when estimating intensity-frequency-duration relationships, see e.g. Madsen et al. (2002).
17 Individual events are separated by dry periods equal to or longer than the chosen event
18 duration (i.e. 1-hour events have at least 1 hour of dry weather between them and 24-hour
19 events have at least 24 hours of dry weather between them) and the maximum averaged event
20 intensities over the chosen durations are calculated. Furthermore, the Peak over Threshold
21 (POT) approach from Mikkelsen et al. (1996) and Madsen et al. (2002) is adopted with a
22 global constant intensity threshold (i.e. Type I censoring) to define the extreme events for
23 each gauge/grid point. In this study, extreme precipitation events are evaluated for 11 distinct
24 durations of 1, 2, 3, 4, 6, 8, 12, 24, 48, 72 and 120 hours with thresholds ranging
25 (approximately log-linearly) from 7.6 to 0.34 mm/hour (the same as used by Gregersen et al.
26 (2013) for the SVK data set). Three different event-based indices of extreme precipitation are
27 evaluated as explained below.

1 4.2.1 Magnitude of extreme events

2 To evaluate the magnitude of the extreme events intensity-duration-frequency relationships
3 are calculated for all data sets. First, the return periods of extreme events extracted from an
4 observed or simulated rainfall time series is calculated using the California plotting position
5 formula:

$$6 T_m = \frac{T_{obs}}{m} \quad (3)$$

7 where T_m is the return period of the event (years) with rank m and T_{obs} is the observation
8 period (years) of the time series. T_m is obviously affected by sampling variability and is
9 biased, especially for large return periods. There are more elaborate methods to estimate T_m
10 than Eq. (3), but we use Eq. (3) here because it allows for comparing extreme value curves
11 from multiple sites (including sampling variability and spatial variability) in a straightforward
12 way.

13 Secondly, a Generalised Pareto Distribution is fitted to extremes from every single time
14 series:

$$15 z_T = z_0 + \mu \frac{1+\kappa}{\kappa} \left(1 - \left(\frac{1}{\lambda T}\right)^\kappa\right) \quad (4)$$

16 where:

- 17 • z_T is the intensity for extreme event with return period T
- 18 • z_0 is the threshold
- 19 • μ is the mean intensity of the extreme events
- 20 • λ is the mean number of extremes per year
- 21 • κ is the shape parameter
- 22 • T is the return period

23 Finally, based on $z(T)$'s intensity-duration-frequency curves are calculated for each data set.

24 For the climate change scenarios, climate factors for the intensity of the extreme events are
25 calculated as a function of the return period for different T -year event durations. This is done
26 as a simple ratio between the present and future levels for a given return period as

$$27 CF_T = \frac{z(T)^{future}}{z(T)^{present}} \quad (5)$$

1 4.2.2 Seasonality of extreme events

2 The seasonality of the extreme events is determined to further evaluate the realism of the
3 behaviour of the WG. This is done to evaluate whether the WG data set constructed with
4 individual monthly model parameters results in a realistic distribution of the extremes
5 throughout the year. The same extreme events used in the evaluation of the magnitude are
6 used in this analysis.

7 The determination is in practice performed by counting the number of extremes from the POT
8 analysis that occur within each month for the SVK and WG data sets. These are then
9 normalised and compared with a χ^2 -test (Wilks, 2011) where the normalised counts C for the
10 SVK data act as the expected values for the WG data set and where the summation is done
11 over months giving a test statistic x :

$$12 \quad x = \sum_{i=1}^{12} \frac{(C_i^{WG} - C_i^{SVK})^2}{C_i^{SVK}} \quad (6)$$

13 x then follows a χ^2 -distribution with $(12-1)(2-1) = 11$ degrees of freedom.

14 4.2.3 Unconditional Spatial Correlation of extremes

15 The Unconditional Spatial Correlation (Mikkelsen et al., 1996), ρ , between the intensities of
16 extreme events that are considered concurrent at different sites A and B is estimated. The
17 methodology follows Mikkelsen et al. (1996) with the i 'th extreme intensity Z_{Ai} measured at
18 site A being concurrent with the j 'th extreme event Z_{Bj} measured at site B if Eq. 7 is fulfilled.
19 In this framework the precipitation process is considered to generate random occurrences of
20 precipitation that are treated as correlated random variables, Z_A and Z_B , and two events are
21 considered concurrent if they are overlapping in time or at most separated by a lag time Δt ,
22 which is introduced to account for the travel time of rain storms between sites.

$$23 \quad \{Z_{Ai}, Z_{Bj}\}: \left[t_{si} - \frac{\Delta t}{2}, t_{ei} + \frac{\Delta t}{2} \right]_A \cap \left[t_{sj} - \frac{\Delta t}{2}, t_{ej} + \frac{\Delta t}{2} \right]_B \neq \emptyset \quad (7)$$

24 Here t_s 's are the start times of the events and t_e 's are the end times of events. A lag time of Δt
25 = 11 hours + the duration of the event is adopted in accordance with Gregersen et al. (2013).
26 The introduction of this lag time, in combination with lack of knowledge of the movement
27 direction of precipitation, implies that an individual event at one site can be correlated to more
28 than one event at another site.

1 The unconditional covariance is then estimated by also accounting for non-concurrent
2 extreme events at the two sites as:

$$3 \text{cov}\{Z_A, Z_B\} = \text{cov}\{E\{Z_A|U\}, E\{Z_B|U\}\} + E\{\text{cov}\{Z_A, Z_B|U\}\} \quad (8)$$

4 with U being a boolean operator taking the value of $U = 1$ if events are concurrent and $U = 0$
5 otherwise. Thus, $E\{Z|U\}$'s are not a single values, but two values for $U = 0$ and $U = 1$
6 respectively and a covariance between them can be calculated.

7 Finally, the Unconditional Spatial Correlation is obtained by division of Eq. (8) with the
8 sample standard deviations of the two sites (Mikkelsen et al., 1996):

$$9 \rho_{AB} = \frac{\text{cov}\{Z_A, Z_B\}}{\sqrt{\text{var}\{Z_A\} \text{var}\{Z_B\}}} \quad (9)$$

10 The Unconditional Spatial Correlation values are grouped together in bins where the distance
11 between the points considered are approximately the same, and an exponential model is fitted
12 to describe the Unconditional Spatial Correlation's dependence on distance between sites
13 using the e-folding distance measure as proposed by Gregersen et al. (2013).

14 **5 Results and discussion**

15 **5.1 Weather generator parameter estimation**

16 The parameter estimates (cf. Section 3.2) for the model fitted to SVK data, the parameter
17 estimates for the model refitted to the 10 realisations of the WG (WG1 – WG10) and the used
18 boundary values are given in Figure 4. All parameters values shown in Figure 4 are given in
19 the supplement. All parameters vary over the course of the year, some more smoothly than
20 others. Note that the β parameter (the parameter controlling the arrival time of cells after a
21 storm origin) is constrained at its prescribed minimum value for four months (February,
22 September, October and December). However, rain events can easily last for several days at
23 these times of the year in Denmark, and this fitting artefact is therefore considered to have
24 limited influence on those features of rainfall, which are of interest for this study. Figure 4
25 shows that all the refitted values are different and especially the β parameter does not always
26 seem to follow the same structural pattern as for the SVK data set. As β^{-1} controls the arrival
27 time of cells after storm origin it will be heavily dependent on the actual realisation of
28 weather from the WG and this is not considered to be important for the realised extreme
29 events. The ξ parameter seems to be slightly biased in the same direction for all WGs. ξ^{-1}

1 controls the mean intensity of the rain cells and the difference in fit suggests that the rain in
2 the WG data sets are slightly more intense during summer than what is seen in the SVK data
3 set. Generally, the WG data sets however represent the SVK data set well.

4 The fitting statistics (cf. section 3.1) resulting from the direct analysis of the observations
5 (SVK data set) and the simulations (WG data sets that are simulated based on fitting the WG
6 to the SVK and CGD data) are compared in Figure 5 through the normalized error (Eq. 2) and
7 directly in Table 4. Generally, the fit seems reasonable for all variables with a mean of the
8 normalized errors close to zero. For the moment statistics the WG data sets seem to have a
9 slight positive bias, and the variance and skewness distributions are also slightly positively
10 skewed (Figure 5a-e). However the WG fit are still within the bounds reported for the SVK
11 data set in Table 4. The lag-1 auto-correlation and the probabilities of dry hours seem to be
12 fitted well even though the probability of dry days also seem to have some skewness in the
13 error distribution. The probability of dry days is the only parameter that seems to differ
14 between observations and WGs, indicate that the WG concentrates the precipitation on too
15 few days. Also, it seems that none of the WG realisations performs differently than the others
16 with respect to reproduction of the fitting statistics. Hence the discrepancies observed in
17 Figure 4 do not seem to impede the use of the WGs as good proxies for observed
18 precipitation..

19 The cross correlation of the 1-hour intensities is shown in Figure 6 for each month of the year.
20 The 10 WG data sets seem to reflect the overall behaviour of the SVK data set very well and
21 also capture most of the variability seen in the SVK data set. The very low correlations
22 observed in the SVK data set for some “traces” of points, especially in March, October and
23 November, are due to some time series only overlapping for very short time periods in recent
24 years where the number of stations has increased dramatically (see Figure 2); hence the
25 correlation is depending on only very few precipitation events. There is no evidence of a
26 systematic pattern in these readings. Again, the difference between different WG realisations
27 is very limited.

28 From Figures 5 and 6 the WG fit is considered satisfactory given the complex data set used
29 and the purpose of this study. For analysis of extremes at event level this WG reproduces the
30 higher order moment statistics, which are the features expected to have the highest influence
31 on the produced extremes, well.

1 **5.2 Evaluation of extremes for present climate conditions**

2 For durations of 1 to 120 hours the extreme events are extracted from the SVK data set at
3 each gauge and from the WG data sets in each grid cell closest to the SVK observation points
4 and ranked according to return period (Eq. 3). Figure 7 shows intensity-duration-frequency
5 curves estimated for WG realisation along with the SVK data set. For both 100 and 10-year
6 events the WG data sets result in comparable extreme intensity values for all considered
7 durations well within the shown 68% confidence interval (corresponding to a one standard
8 deviation envelope) for the SVK IDF curve.

9 Figure 8 shows that the seasonal distribution of these extreme events is captured very well by
10 the considered grids from the simulated WG data sets for all considered event durations. The
11 χ^2 tests furthermore confirm that there are no significant differences between distributions for
12 the WG and the SVK data sets for all event durations.

13 Figure 9 shows the unconditional spatial correlation for the SVK and for the selected WG grid
14 points calculated according to Eq. (9) and grouped in selected bins. Table 5 furthermore
15 compares the e-folding distances based on the fitted exponential models with a set of values
16 calculated from RCM data representing a slightly larger area, taken from Gregersen et al.
17 (2013).

18 Gregersen et al. (2013) show, using data from the whole of Denmark (range 0-350 km), that
19 the spatial correlation pattern is not the same when considering output from climate models
20 compared to SVK data as the climate model output maintains too long spatial correlation
21 lengths at scales below approximately 150 km and 12 hours (see Table 5). Both Figure 9 and
22 Table 5 indicate that the WG better reproduces the spatial correlation pattern of the SVK data
23 within the spatial range (0-60 km) covered by the observations included in this study. The e-
24 folding distances computed in this study for the SVK data set are somewhat lower than the
25 ones calculated by Gregersen et al. (2013). This is a consequence of inclusion of fewer gauges
26 and, most importantly, that the time series in the SVK data set for this study have been
27 aggregated into hourly time series prior to the smoothing and POT analysis. Gregersen et al.
28 (2013) conducted the smoothing and POT analysis directly on the original time series that
29 have a one-minute resolution. The WG data sets represent the space-time features of
30 precipitation of crucial importance for urban hydrology applications much better than the

1 climate model output; the WG data set is considered realistic at this small-scale spatio-
2 temporal resolution.

3 Overall, the results show that the WG is able to realistically simulate extreme precipitation
4 statistics down to the hourly scale at a 2x2 km spatial resolution.

5 **5.3 Perturbation of the weather generator with climate change signals from** 6 **RCMs**

7 As the different realisations of the WG produce very similar output, only one 30-years
8 realisation is generated for each perturbation with climate change signals from each of the
9 RCMs. Furthermore, all grid cells are used for both present and future evaluations as no
10 comparisons are made to the observational data.

11 For each RCM run and each statistic the change factors, $\alpha_{i,j,k}$'s, are calculated. All change
12 factors and all parameters values for WG's representing future climate are given in the
13 supplement. They are primarily above 1 for the moment derived statistics (Figure 10a-e) but
14 the different RCM runs appear different. For the 24 hour mean (Figure 10a) the $\alpha_{i,j,k}$'s are
15 mostly above 1 with all RCM runs showing some months with values below 1 in an
16 unsystematic pattern. For both the 24 and 1 hour variances (Figure 10b and d) the number of
17 RCM runs and months that show a decrease is very limited and in general the variance will
18 increase for all seasons. The HIRHAM RCP 8.5 simulation differs from the other RCM runs
19 with very high $\alpha_{i,j,k}$'s for the summer months. The 24 and 1 hour skewness (Figure 10c and e)
20 show more clear seasonality than the mean and variance with higher $\alpha_{i,j,k}$'s from May to
21 September for all RCM runs clearly indicating a shift in the distribution of precipitation
22 intensities towards more extremes. Again the HIRHAM RCP 8.5 run stands out with very
23 high $\alpha_{i,j,k}$'s for the 1 hour skewness for most of the year. This means that the extreme
24 precipitation intensities are expected to be higher during summer and especially the sub-daily
25 extremes for the HIRHAM RCP 8.5 perturbation could have very high intensities as a
26 combination of a large increase in both variance and skewness will result in many severe
27 precipitation events with a high mean intensity.

28 For the lag-1 hour auto-correlation (Figure 10h) the $\alpha_{i,j,k}$ are mostly below 1 indicating more
29 variations from one hour to the next and thus a possibility of more abrupt changes in the
30 rainfall at the hourly level. For the probability of dry days and dry hours (Figure 10f and g)
31 the pattern is less clear. The RCM simulations show some variation around 1 (approximately

1 between 0.7 and 1.7) but do not agree with respect to season of these changes or their relative
2 magnitude. This suggests that future rainfall will follow the same overall patterns as today but
3 as all RCM runs have months with $\alpha_{i,j,k}$ below 1 there will also be more severe periods since
4 the precipitation is concentrated on fewer days and hours. For instance, the peaks for the
5 WRF RCP 8.5 perturbation in August for both probability of dry days and hours (Figure 10f
6 and g) in combination with the increases in variance and skewness (Figure 10b to e) are
7 expected to result in very severe extremes as the increased rainfall amount is expected to
8 occur on fewer days. All in all, the $\alpha_{i,j,k}$'s indicate that for all RCM runs there will be more
9 rainfall on average and it will be more variable resulting in more (and more severe) extremes
10 events. This is in accordance with general findings from studies based on direct output from
11 RCMs (Christensen and Christensen, 2007; Sunyer et al., 2014).

12 **5.4 Changes in climate changed extremes from the weather generator**

13 Calculating the climate factors, CF 's (Eq. 5), from the perturbed and original WG using the T -
14 year event estimates calculated with Eq. 4 shows that despite the differences observed in the
15 $\alpha_{i,j,k}$ for the input statistics (Figure 10), the perturbation schemes based on RCM simulations
16 modelling comparable climate change (HIRHAM SRES A1B, RACMO SRES A1B,
17 HIRHAM RCP 4.5 and WRF RCP 4.5) result in similar changes to extremes after
18 downscaling with the WG (Figure 11). Clearly, and as expected from the results in Figure 10,
19 the HIRHAM RCP 8.5 perturbed WG results in a much more severe change in extreme
20 precipitation than the other perturbation schemes for both 10 and 100 year return periods. It is
21 interesting that the WG perturbed with HIRHAM SRES A1B results in a rather stable CF in
22 the range 1.35-1.55 with seemingly little dependence on return period and event duration, The
23 WGs perturbed with RACMO SRES A1B, HIRHAM RCP 4.5 and WRF RCP 4.5 show
24 similar CF values that are higher for 100-year extremes than for 10-year extremes but still not
25 depend significantly on the event duration.

26 Both the HIRHAM RCP 8.5 and WRF RCP 8.5 perturbed WGs yield CF values that depend
27 on the event duration with higher CF for short duration precipitation extremes. This indicates
28 that this high-end scenario is changing the climate more drastically than the more moderate
29 scenarios (SRES A1B and RCP 4.5) and that the observed extreme effects are not linearly
30 scalable from moderate to high end scenarios. For event durations above 48 hours the
31 different WGs yield similar CF 's, but surprisingly the high-end scenario WRF RCP 8.5

1 perturbation scheme results in the smallest CF for the long duration events. This may indicate
2 that the direct output from the RCMs underestimate the changes occurring at high spatio-
3 temporal resolutions.

4 Despite the observed differences between WGs perturbed with different RCM runs and
5 different forcing scenarios the results show an upwards change for all event durations (see
6 Figure 11). The change seems to increase with the return period with a projected change
7 factor in the order of 1.2-1.3 for $T=10$ years and 1.4-1.5 for $T=100$ years for the moderate
8 scenarios (SRES A1B and RCP 4.5). Furthermore, the RCP 8.5 scenario perturbed WG runs
9 suggest that short duration extreme events become relatively more severe compared to the
10 WG runs perturbed with the other, moderate forcing scenarios.

11 **5.5 Unconditional spatial correlation of climate changed T -year events**

12 All the perturbed WG runs produce T -year precipitation events with reasonable spatial
13 correlation structure (Figure 12, Table 6) includes calculated e-folding distances and it is
14 noteworthy that the e-folding distance for present conditions is somewhat shorter for the full
15 WG data set compared to the sub sets closest to the observations shown in Figure 9. The
16 HIRHAM RCM and WRF RCM perturbed WG runs present similar results for all event
17 durations whereas the RACMO SRES A1B perturbed WG run yield slightly larger
18 correlations lengths for the very short durations (Figure 12a). Generally, all the perturbed WG
19 runs have larger correlation lengths than for the present climate, suggesting that the WG
20 implicitly expects that more severe events on average also results in events with a larger
21 spatial extent. This behaviour has recently been observed by Kendon et al. (2014) using a
22 high resolution regional climate model (1.5 km resolution). This difference, however, is
23 limited, and in general the WG produces extremes with a spatial extent much closer to that of
24 observations than RCMs. Online Resource 1 includes an animation of extreme precipitation
25 events generated directly as output from the 25 km resolution RCM HIRHAM SRES A1B,
26 the 8 km resolution RCM HIRHAM RCP 4.5 and the 2 km WG evaluated in this study. From
27 these it is clear that the small-scale variability is much more pronounced for the WG output
28 than for the output of the RCMs, but also that the WG output lacks rainfall movement. At the
29 hourly scale this is not a problem for a catchment of the size presented in the Online Resource
30 (same as shown in Figure 1).

1 Only few apparent effects are observed with respect to choice of RCM, GCM and RCM
2 spatial resolution and it is not possible to detect any systematic patterns. The WG seems to
3 produce robust results with respect to change in extreme precipitation due to climate change
4 that are similar for similar climate forcing scenarios.

5 **6 Conclusions**

6 Precipitation time series based on high-resolution gauge measurements are presently used as
7 input to design and analysis of urban water infrastructure, and time series representing future
8 climates are needed in the future. Current RCMs operating at 25 and even 8 km spatial scales
9 however yield too spatially correlated output that poorly represents the fine-scale precipitation
10 features relevant for urban hydrology. The study indicate that statistical downscaling of
11 precipitation output from RCMs using a stochastic weather generator (WG) is therefore a
12 better solution.

13 This study demonstrates that the chosen Spatio-Temporal Neyman-Scott Rectangular Pulses
14 weather generator (WG) fitted to a dense network of 60 rain gauges in a 40 by 60 km region
15 simulates realistic extreme precipitation of relevance to urban hydrology. Output is generated
16 at the 1 hour temporal scale at a 2 km spatial grid, which is finer than what previous studies
17 using this WG have focused on. Even though urban hydrology literature claims that rain data
18 are ideally needed at a time scale of minutes, the hourly scale chosen here can still be of much
19 use when assessing climate change impacts in urban hydrology as it is much finer than what
20 regional climate models can currently provide.

21 The WG generally reproduces statistics of the observations such as mean, variance and
22 skewness of the rainfall intensity distribution well at both the hourly and daily levels. It also
23 produces realistic levels of lag-1 auto-correlation, cross-correlation between output at
24 different grid points and probabilities of dry days and hours. Evaluating the WG from an
25 urban hydrological engineering perspective yields the following conclusions:

- 26 • The extreme events of the simulated time series show realistic levels of
27 intensity as well as a reasonable spatial variability for the full 60x40 km
28 model area. Thus, the WG handles the large data set of spatially distributed
29 observational input in a robust manner.
- 30 • The seasonal distribution of the extremes are not significantly different in
31 the generated WG data sets compared to the observed SVK data set,

1 implying that the applied procedure of individual monthly model fits results
2 in a realistic seasonal behaviour of the WG.

- 3 • The spatial extent of the extreme events in the WG data set, as evidenced by
4 the unconditional spatial correlation of extremes, is close to that of the
5 observational SVK data set with e-folding distances in the same order of
6 magnitude. This is much better than what is observed for Regional Climate
7 Model (RCM) output at 25 and 8 km grid scale in previous studies.

8 This indicates that the WG is a good way to downscale spatio-temporal precipitation output
9 from RCMs to relevant urban scales and that the simulated output can be used directly as
10 input to urban hydrological models.

11 Output from six different RCM runs representing average to high emission scenarios are used
12 to perturb the WG for different possible future climate scenarios. Two have a 25 by 25 km
13 spatial resolution and four have a very high 8 by 8 km spatial resolution, and all RCM data
14 sets are available at hourly temporal resolution. A clear increase in the magnitude of extreme
15 precipitation is observed for all climate change perturbations of the WG.

16 This study highlights that different RCMs run with the same greenhouse gas emission
17 scenario can result in different precipitation output and hence different CFs for perturbation of
18 the WG. Despite these observed differences, downscaling with the WG results in similar
19 extreme precipitation behaviour for similar emission scenarios.

20 Most perturbed WGs confirm that there is a more severe climate change signal for extreme
21 events. The two WGs perturbed by the RCP 8.5 scenario show a more severe climate change
22 signal for short-duration events. However, this finding is not shared by the other emission
23 scenarios, suggesting that extreme precipitation at T -year event level is not scalable between
24 emission scenarios. The spatial correlation structure of the WG output is slightly altered by
25 the perturbation indicating a built-in correlation between intensity and spatial extent and
26 suggesting that precipitation extremes in a future climate may have larger spatial extent than
27 extremes in the present climate.

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1 Table 1 Main characteristics of the two observational data sets used in this study.

	Type of data	Spatial data resolution	Temporal data resolution	Period
SVK	Point observations	60 stations	Minute data	1979-2012
CGD	Gridded data	10 km grid	Daily data	1989-2010

2

1 Table 2 Regional Climate Model (RCM) runs from which precipitation output is used to
 2 calculate perturbations schemes for the WG used in this study. All have a temporal resolution of
 3 1 hour.

Name	RCM	GCM	Spatial resolution	Present period run	Future period run
HIRHAM SRES A1B	HIRHAM 5	ECHAM 5	25 km	1980-2009	2070-2099
RACMO SRES A1B	RACMO 2.1	ECHAM 5	25 km	1980-2009	2070-2099
HIRHAM rcp 4.5	HIRHAM 5	EC-EARTH	8 km	1981-2010	2071-2100
HIRHAM rcp 8.5	HIRHAM 5	EC-EARTH	8 km	1981-2010	2071-2100
WRF rcp 4.5	WRF 3	NorESM	8 km	1981-2010	2071-2100
WRF rcp 8.5	WRF 3	NorESM	8 km	1981-2010	2071-2100

4

- 1 Table 3 The relative weights used in the fitting procedure. *All the cross-correlations of a gauge
2 have equal weights that sum up to the value shown.

Statistic	Relative weight
24 hour mean	1
24 hour variance	3
24 hour skewness	6
1 hour variance	3
1 hour skewness	6
1 hour auto-correlation	6
1 hour Cross-correlation	6*
Probability of dry day	1
Probability of dry hour	1

3

1 Table 4 Comparison between observational (SVK) data and the simulated (WGs) statistics. Data
 2 are averaged over the full course of the year and over the full model domain. For the SVK data
 3 set the 50th percentile is reported as well as the 16th to 84th percentiles interval to emulate the
 4 empirical standard deviation. For the WGs one central 50th percentile is reported across the ten
 5 simulations.

	24 hour mean (mm/day)	24 hour variance (mm ² /day ²)	24 hour skewness (-)	1 hour variance (mm ² /hour ²)	1 hour skewness (-)	Probability of dry days (-)	Probability of dry hours (-)	Lag-1 hour auto- correlation (-)
SVK (p50 (p16- p84))	1.67 (1.09- 2.34)	12.6 (6.05- 32.9)	3.56 (2.76- 4.79)	0.117 (0.0576- 0.409)	8.93 (6.73- 15.1)	0.718 (0.667- 0.770)	0.934 (0.914- 0.947)	0.572 (0.422 - 0.654)
WGs (p50)	1.60	14.9	4.04	0.151	10.4	0.812	0.945	0.578

6

1 Table 5 e-folding distances for the SVK and WG maximum averaged intensities of extremes for
 2 1, 6, 12 and 24 hours duration, based on the fitted exponential models (cf. Figure 8) as well as
 3 for a regional climate model (HIRHAM/ECHAM) from the study by Gregersen et al. (2013) for
 4 comparison. *Values from Gregersen et al. (2013).

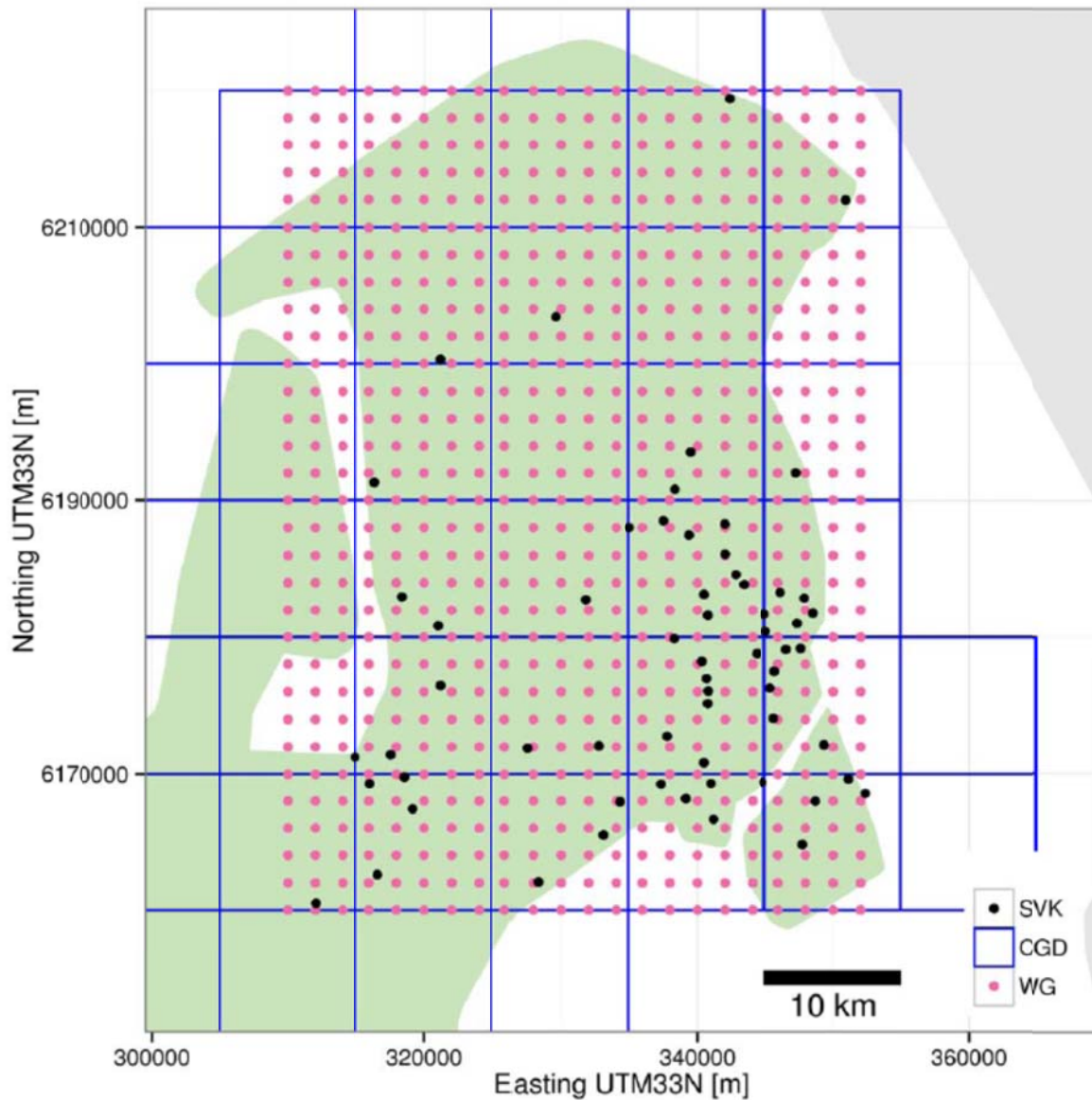
e-folding distance [km]	1 hour	6 hour	12 hour	24 hour
SVK	3.5	5.5	7.3	8.0
WGs	7.1 – 9.9	9.1 – 14	9.5 – 16	10 – 28
HIRHAM/ECHAM*	56	48	48	54

5
6

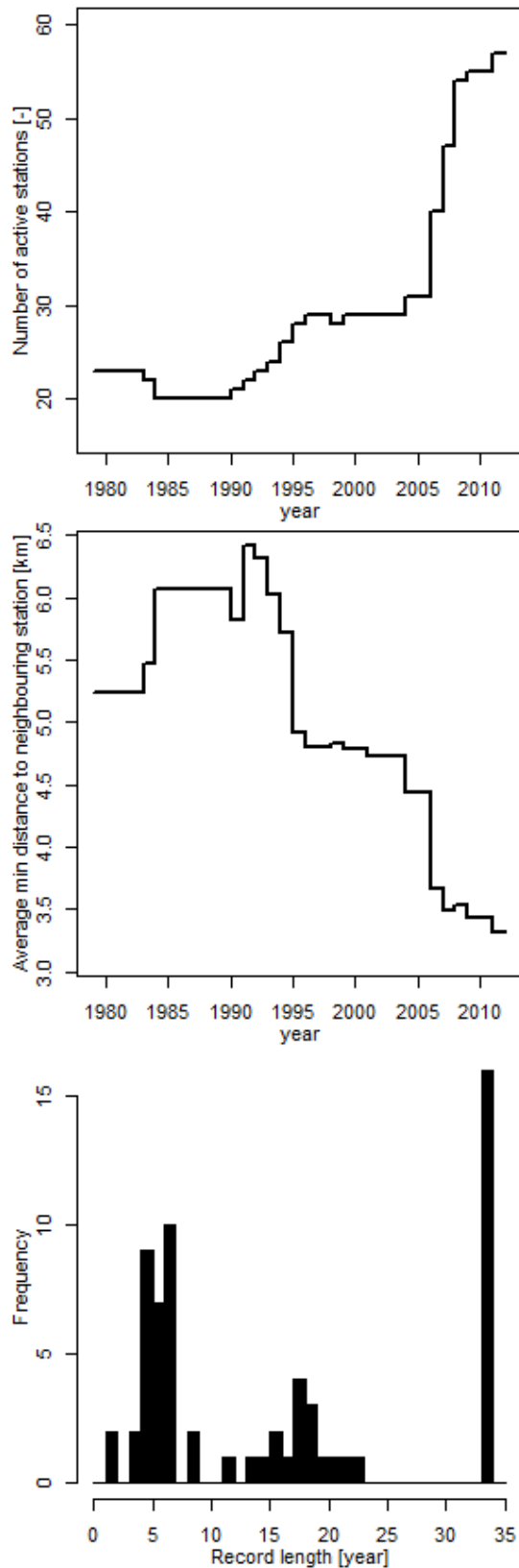
1 Table 6 e-folding distances for all aggregation periods for all WG output.

e-folding distance [km]	Aggregation period			
	1 hour	6 hour	12 hour	24 hour
WG – Present Climate	3.9	5.0	4.9	5.0
WG – HIRHAM SRES A1B	5.2	7.4	7.7	8.1
WG – RACMO SRES A1B	7.3	9.7	9.1	8.4
WG – HIRHAM rep 4.5	5.2	8.4	8.7	8.8
WG – HIRHAM rep 8.5	4.6	7.7	9.3	9.0
WG – WRF rep 4.5	5.1	9.1	9.3	11.5
WG – WRF rep 8.5	4.9	9.4	9.9	10.2

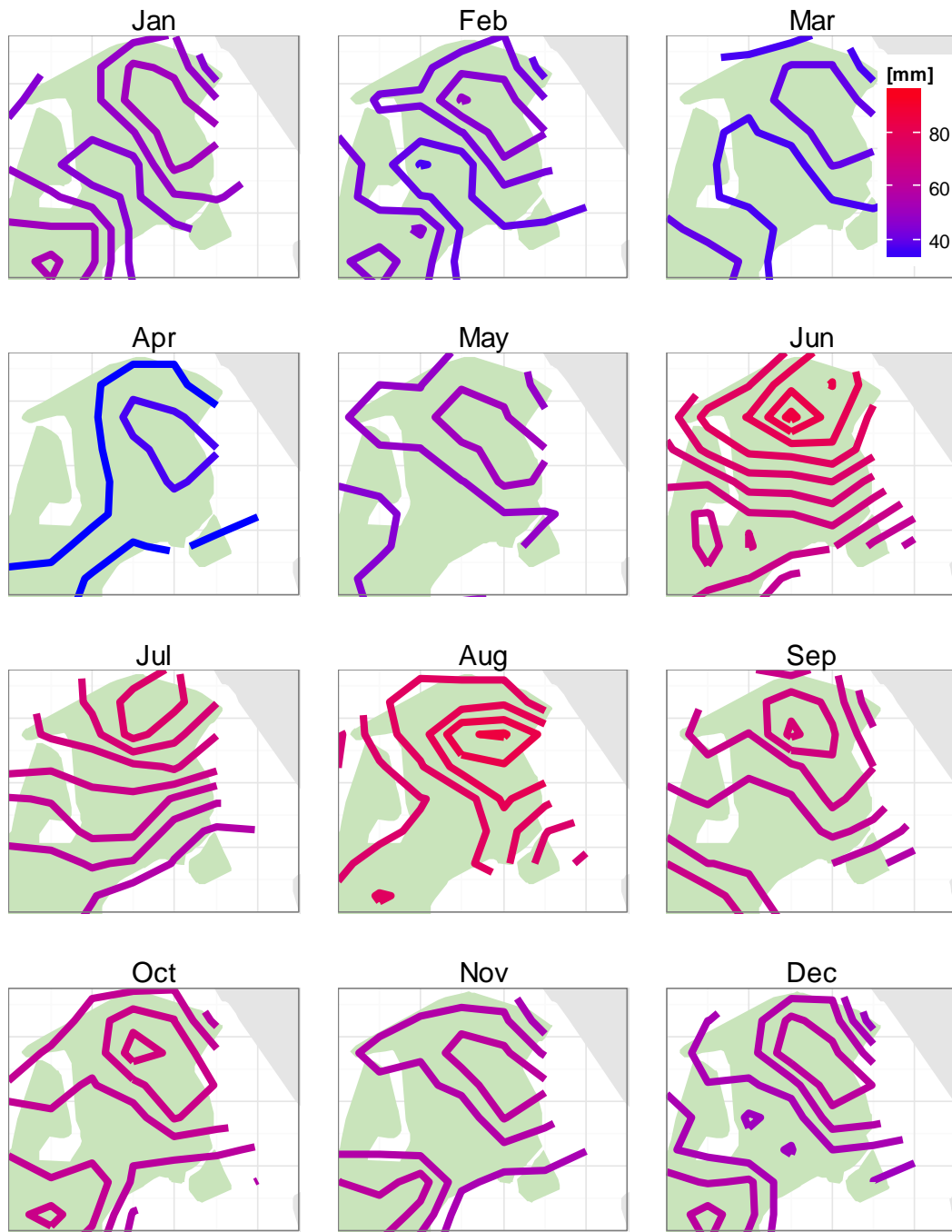
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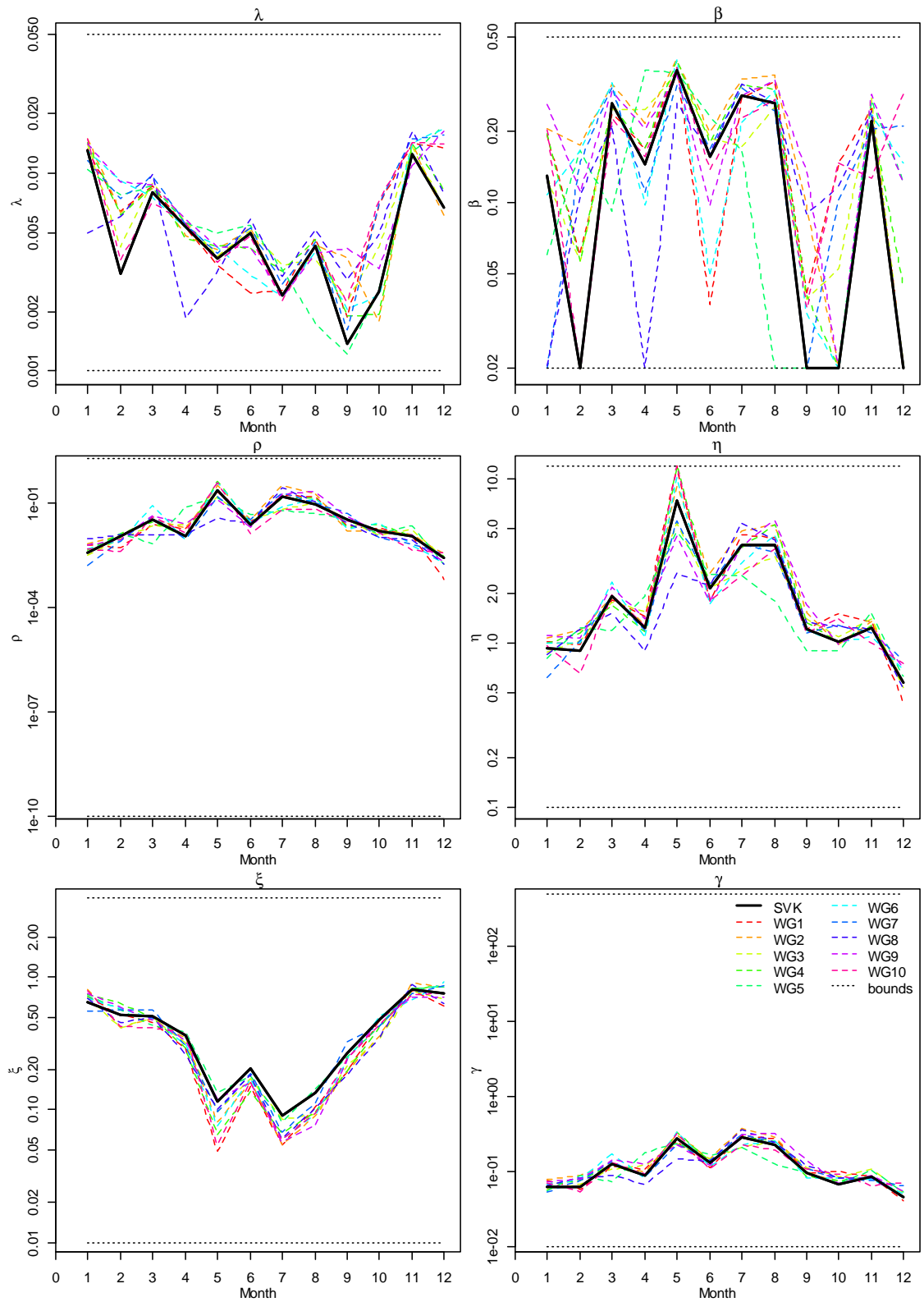
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 2 Figure 1 Locations of the rain gauges (SVK), the gridded data set (CGD) and extent of the
 3 modelled grid (WG) in the North-Eastern part of Zealand (Denmark) including Copenhagen in
 4 the South-Eastern part of the map where the concentration of SVK gauges is highest.



1
 2 Figure 2 Temporal development in (top) the number of stations in the SVK data set and (middle)
 3 the average distance between closest neighbouring stations, and (bottom) the distribution of
 4 record lengths.



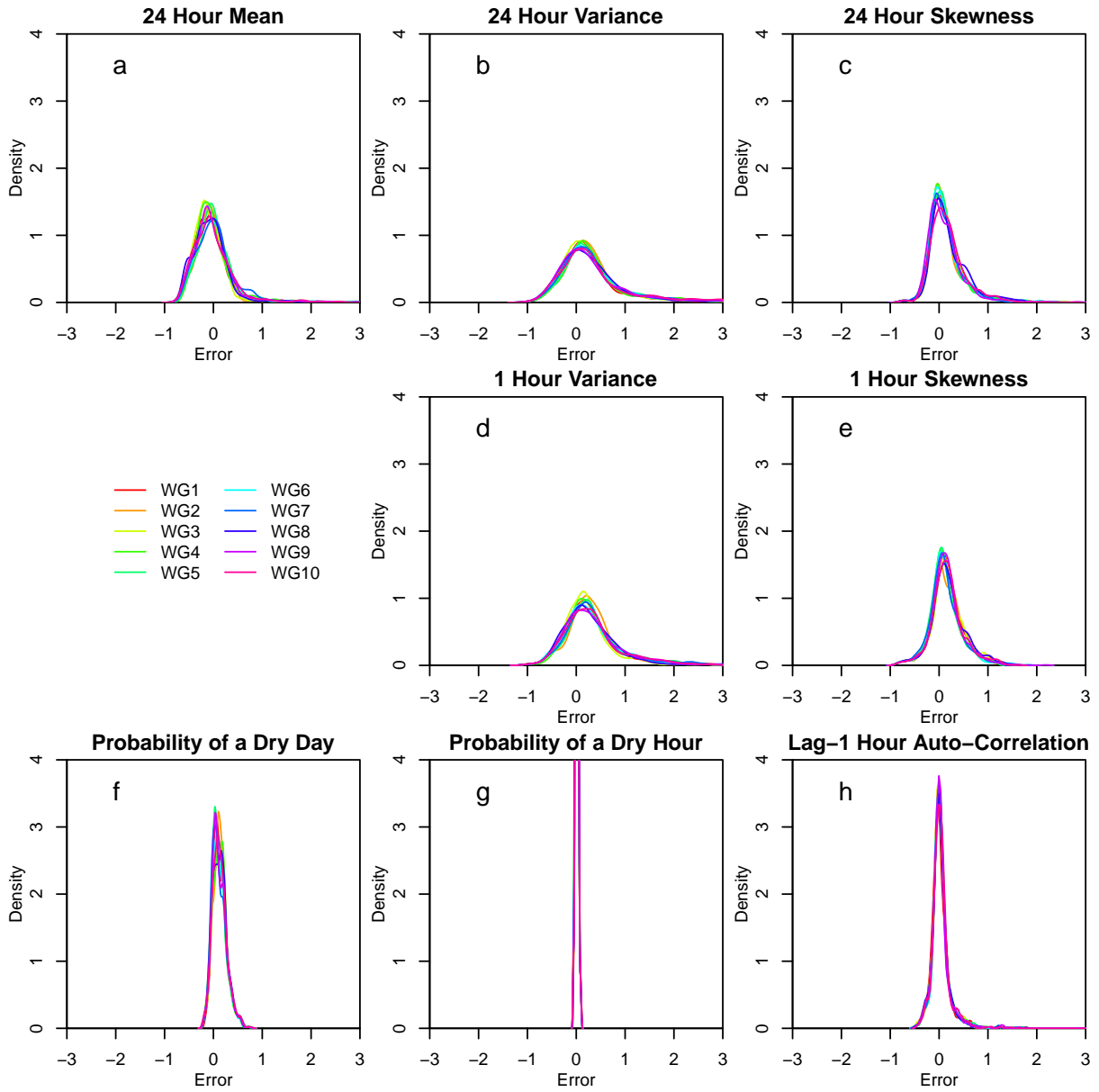
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 2 Figure 3 Spatial variation of the mean monthly precipitation calculated from the CGD data set
 3 for the model area. Isohyets are 3 mm between.



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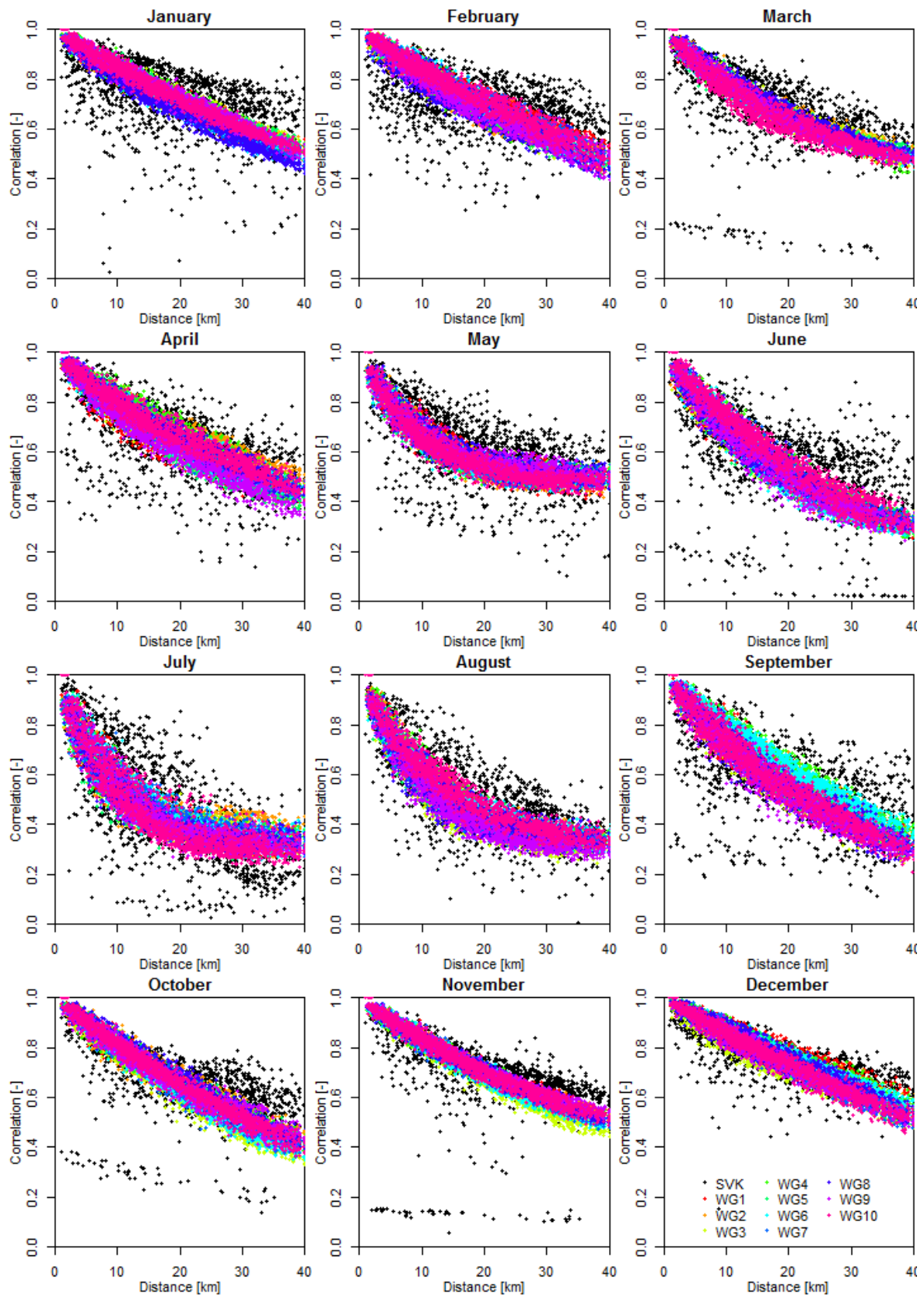
2 Figure 4 Monthly variation of the model parameters estimated from the SVK data set and from
 3 the simulated 10 WG data sets. Upper and lower fitting bounds are shown in light grey.

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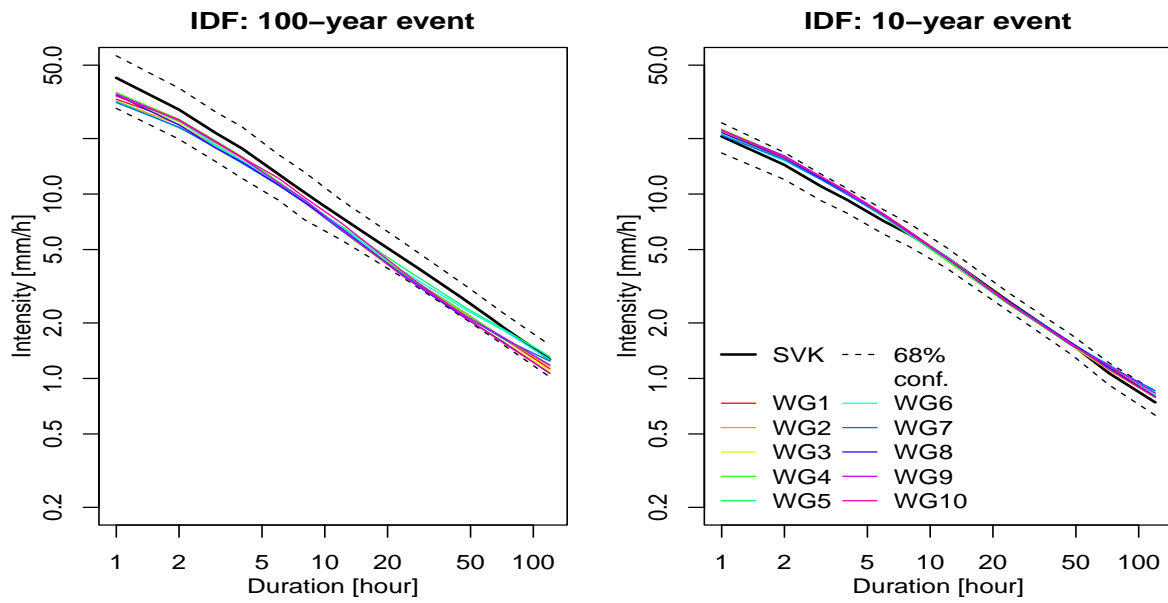
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3 Figure 5 Density plots for the normalized error between the WG and the SVK data sets for each
4 considered statistic ($i = [1..8]$) for all months ($j = [1..12]$) for all WG realisations ($l = [1:10]$).



1

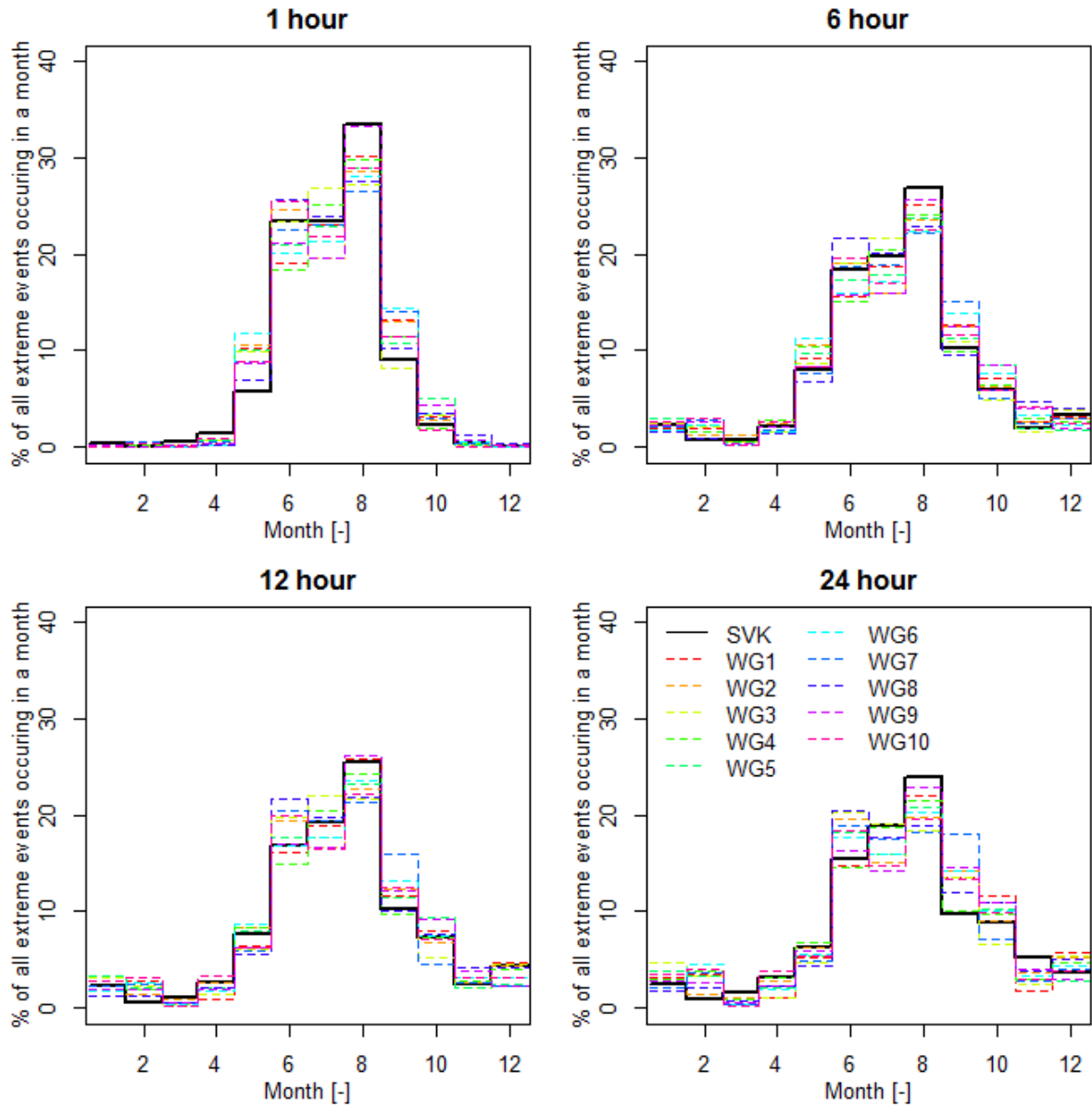
2 Figure 6 Variation of cross-correlation of the 1 hour intensity with distance between pairs of
 3 gauges in the SVK data set (black dots) and grid points in the WG data set (coloured dots).



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2 Figure 7 Mean intensity-duration-frequency curves for 100 and 10 year return periods calculated
 3 from the SVK data set and for all 10 WG realisations. 68% confidence interval for the SVK data
 4 set.

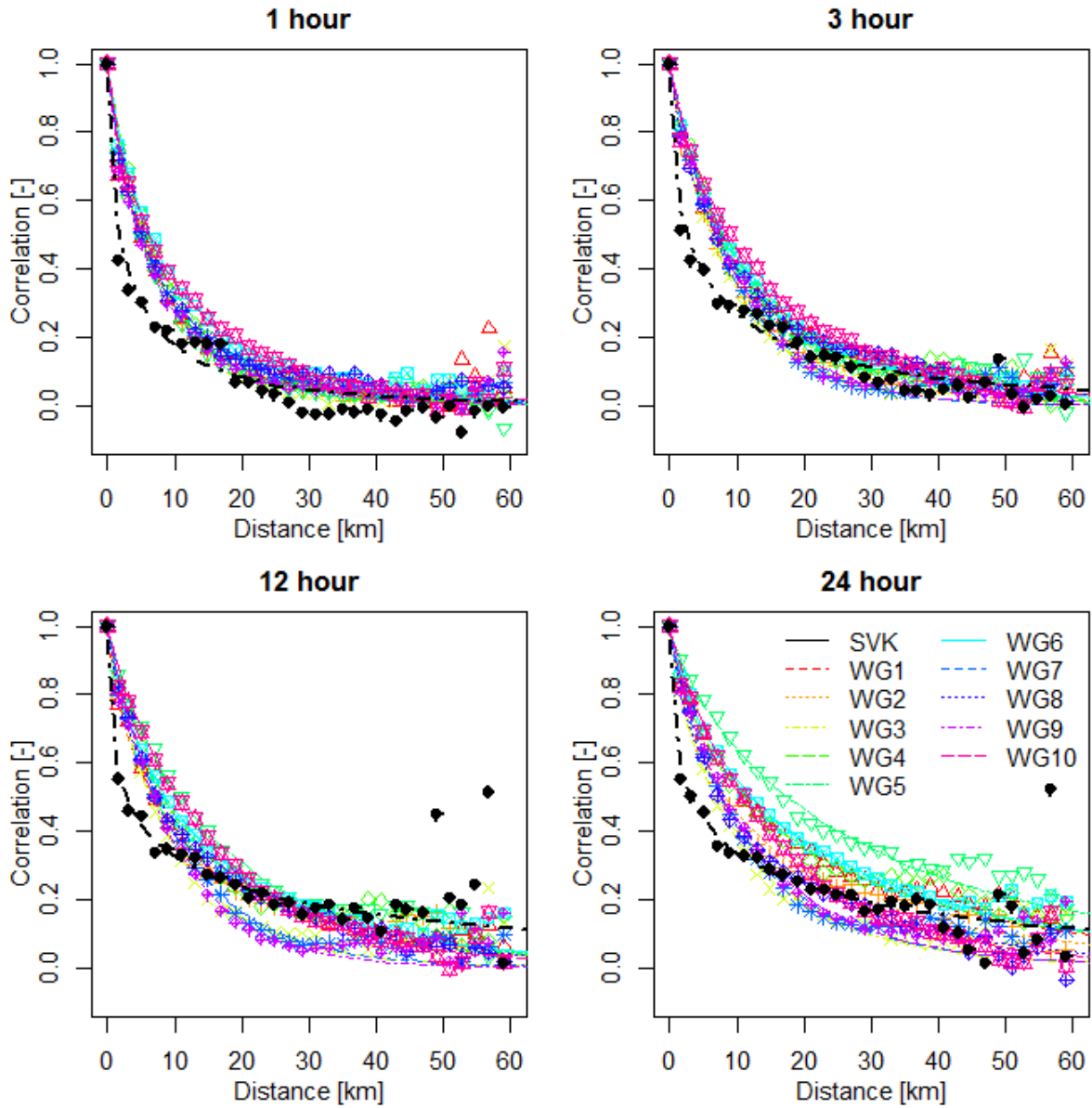
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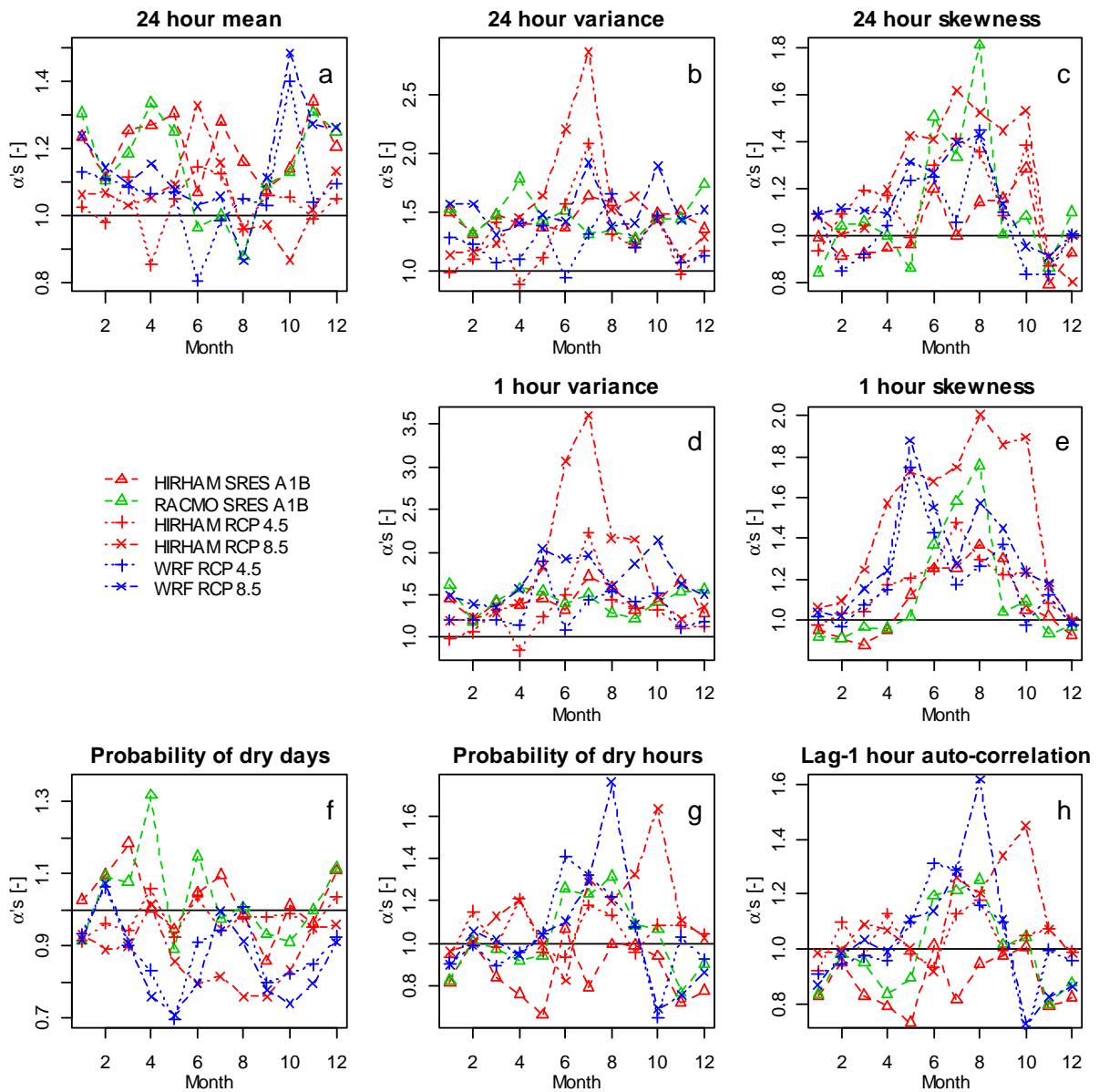
3 Figure 8 Monthly variation for 1, 6, 12 and 24-hour durations of the frequency of extreme events
4 in the SVK and WG data sets.

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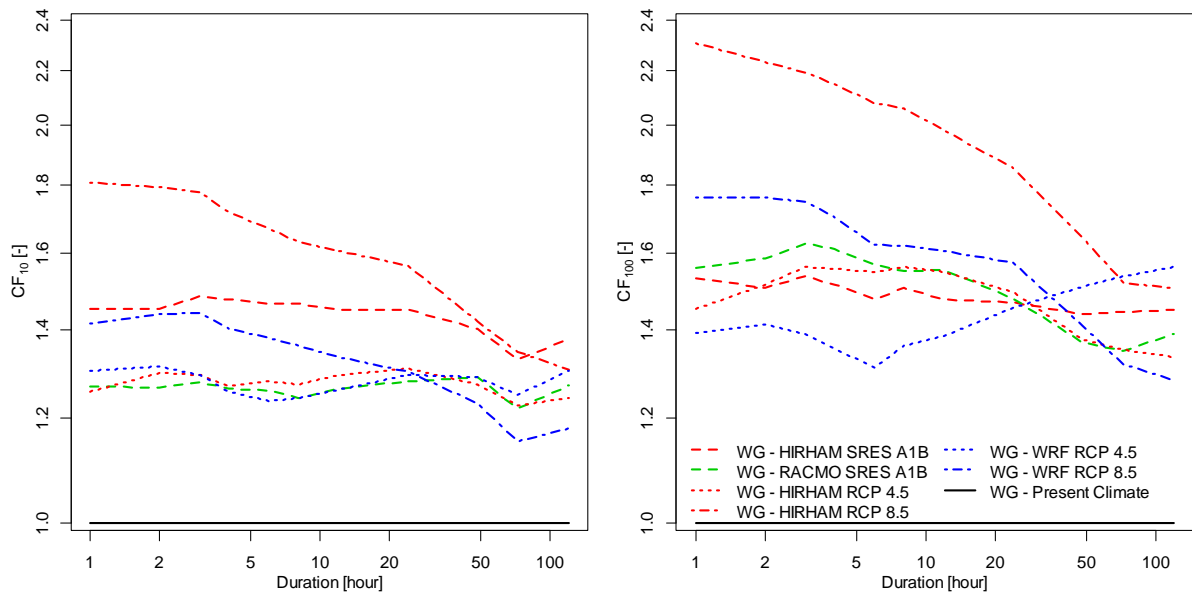
3 Figure 9 Unconditional spatial correlation for the SVK and WG data sets, calculated from
4 maximum averaged intensities of extreme events for 1, 6, 12 and 24 hours duration. Fitted
5 exponential models that highlight overall tendencies are shown.



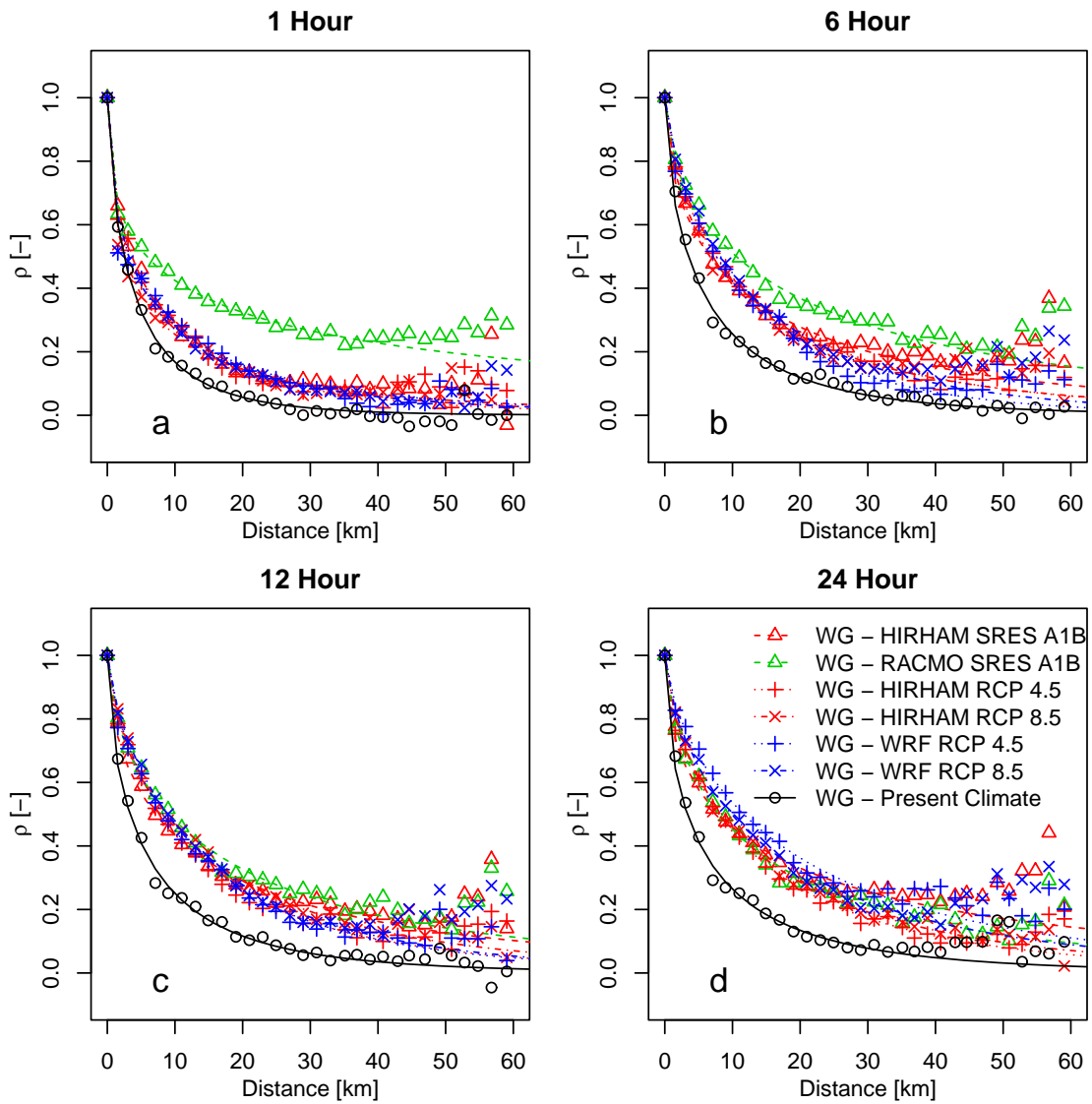
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2 Figure 10 Change factors, α 's, calculated on a monthly basis for each statistic and each RCM.

3 Each set of α 's from an RCM act as a perturbation scheme for the WG.



1
 2 Figure 11 Climate factors for different return periods for the different perturbed WG runs. $T=10$
 3 years (left) and $T=100$ years (right).



1
 2 Figure 12 The unconditional spatial correlation of all T -year events for perturbed WG output for
 3 event durations of 1, 6, 12 and 24 hours.