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Response of extreme precipitation to urbanisation over the Netherlands

Vahid Rahimpour Golroudbary*, Yijian Zeng, Chris M. Mannaerts, and Zhongbo (Bob) Su

Faculty of Geo-Information Science and Earth Observation (ITC), Department of Water Resources, University of Twente, Enschede, The Netherlands

* Correspondence to Vahid Rahimpour Golroudbary, Faculty of Geo-Information Science and Earth Observation (ITC), Department of Water Resources, University of Twente, 7514 AE, Enschede, The Netherlands. E-mail: V.rahimpourgolroudbary@utwente.nl

ABSTRACT:

Knowledge of the response of extreme precipitation to urbanisation is essential to ensure societal preparedness for the extreme events caused by climate change. To quantify this response, this study scales extreme precipitation according to temperature using the statistical quantile regression and binning methods for 231 rain gauges during period of 1985-2014. The positive 3-7% scaling rates were found at most stations. The non-stationary return levels of extreme precipitation are investigated using monthly blocks of the maximum daily precipitation, considering the dependency of precipitation on the dew point, atmospheric air temperatures and the North Atlantic Oscillation (NAO) index. Consideration of CORINE land cover types upwind of the stations in different directions classifies stations as urban and nonurban. The return levels for the maximum daily precipitation are greater over urban stations than those over non-urban stations especially after the spring months. This discrepancy was found by 5-7% larger values in August for all of the classified station types. Analysis of the intensity-duration-frequency curves for urban and non-urban precipitation in August reveals that the assumption of stationarity leads to the underestimation of precipitation extremes due to the sensitivity of extreme precipitation to the non-stationary condition. The study concludes that non-stationary models should be used to estimate the return levels of extreme precipitation by

30 considering the probable covariates such as the dew point and atmospheric air
31 temperatures. In addition to the external forces such as large-scale weather modes,
32 circulation types and temperature changes that drive extreme precipitation, urbanisation
33 could impact on extreme precipitation in the Netherlands, particularly for short-duration
34 events.

35 **Keywords:** Extreme precipitation, air temperature, nonstationarity, return levels,
36 urban impacts.

37 1. Introduction

38 Extreme precipitation events have been shown to have significant impacts on the
39 environment and society (Alfieri et al., 2015; Kundzewicz et al., 2013; Feyen et al., 2012).
40 Ample studies have demonstrated that increases in extreme precipitation events are
41 expected as the climate warms (Aalbers et al., 2017; Attema et al., 2014; Lenderink and
42 Attema, 2015). The relationship between precipitation and temperature might be affected
43 by different factors such as temperature (Westra et al., 2014), duration and type of the
44 precipitation events (Molnar et al., 2015; Panthou et al., 2014), as well as seasonality and
45 location of the precipitation occurrences (Berg et al., 2009; Wasko and Sharma, 2014).
46 Higher air temperatures increase the water vapour holding capacity of the atmosphere (6-
47 7%/°C). This increase is known as the Clausius-Clapeyron (C-C) relationship and is used
48 in many studies as a physical basis for assessing the variations in extreme precipitation
49 with the dew point and air temperatures (Allen and Ingram, 2002; Lenderink et al., 2011;
50 Min et al., 2011; Westra et al., 2014). The scaling rate of precipitation to near-surface air
51 temperature decreases with higher frequencies, while increases with the duration of
52 precipitation events (Wasko et al. 2015). Lenderink and van Meijgaard (2008) described
53 the hourly extreme precipitation in the Netherlands (i.e., the De Bilt station is taken as a
54 representative station) and found that the increase rate of extreme precipitation exceeds

55 the C-C rate. Enhancements in the dependency of extreme precipitation on the C-C rate
56 appear due to increases in latent heat driven by moisture convergence or convective
57 precipitation (Berg et al., 2013; Haerter and Berg, 2009; Lenderink and Van Meijgaard,
58 2010). Furthermore, Ali and Mishra (2017) explored the positive relationships between
59 precipitation extremes with dew point and atmospheric air temperatures and used them
60 as covariates for developing nonstationary models for understanding the extreme
61 precipitation changes under the nonstationary climate condition.

62 Consequently, evidence on the dependence of the extreme precipitation time series on
63 other factors violates the stationarity assumption to derive the existing precipitation
64 intensity–duration–frequency (IDF) curves. In recent years, updating IDF curves were
65 considered to confront precipitation extreme events in nonstationary environments (e.g.
66 Agilan and Umamahesh, 2018; Cheng et al., 2014; Cheng and Aghakouchak, 2014;
67 Mondal and Mujumdar, 2015; Salas et al., 2018; Yilmaz and Perera, 2013). For example,
68 in the direction of developing nonstationary precipitation IDF curves, Cheng and
69 Aghakouchak (2014) introduced time varying nonstationary IDF curves and found the
70 stationary assumption may lead to underestimation of extreme precipitation, and Agilan
71 and Umamahesh (2018) revealed the significance of selecting covariates to develop the
72 nonstationary models and IDF curves.

73 The incidence of extreme precipitation is increasing in the Netherlands, and several
74 studies have identified increases in mean annual precipitation and trends in extreme
75 indices due to climate change and internal variability across the Netherlands (Aalbers et
76 al., 2017; Buishand et al., 2013; Rahimpour et al., 2017). Fairly rapid urbanisation has
77 also occurred during the last several decades in the Netherlands, based on the expansion
78 of urban areas (Daniels et al., 2015b; Hazeu et al., 2011) and the increase in population
79 growth rates (e.g., 1.05% in 2015) (United Nations, 2015). Due to the lack of long-term

80 observations (i.e., precipitation, dew point and air temperatures) for Dutch cities, efforts
81 to investigate extreme precipitation in urban areas in the Netherlands have been limited.
82 Daniels et al. (2015) simulated the effects of the urban land-use type on precipitation for
83 a 4-day period in May 1999 over the Netherlands and reported that no clear local response
84 could be identified. In another study, Daniels et al. (2016) investigated the impacts of
85 land-use changes during 19 summer days from 2000 to 2010. They found that the
86 influence of the urban land-use type on precipitation is not negligible, and it caused an
87 increase in precipitation by 7-8% regarding temperature perturbation in this decade for
88 the Netherlands. Moreover, a similar result was found by Rahimpour et al. (2018) for
89 hourly extreme precipitation at local urban stations when compared to nearby rural
90 stations. These studies emphasize that variations in extreme precipitation may also occur
91 due to urbanisation and human activities that impact regional and local climates.

92 Despite the need of knowledge on precipitation discrepancy between urban and non-
93 urban areas, efforts to investigate the extreme precipitation variations and its relationship
94 with surface air temperature at 1.5 m above ground, dew point temperature and
95 atmospheric air temperature at 850 hPa during the long-term period in the Netherlands
96 have been limited due to the lack of ground based meteorological observations. We
97 provide the scaling relationships between precipitation and these temperatures to develop
98 the non-stationary changes of extreme precipitation events (Barbero et al., 2018;
99 Lenderink et al., 2011; Lenderink and Meijgaard, 2009; Mishra et al., 2012). Moreover,
100 the non-stationary model is developed with another covariate (North Atlantic Oscillation
101 (NAO) index) to demonstrate the influence of annual precipitation cycle on extreme
102 precipitation events (Sienz et al., 2010; Wakelin et al., 2003). The North Atlantic
103 Oscillation (NAO) index is used to represent a large-scale mode of climate variability,
104 and it describes the variability in the North Atlantic Ocean from 80° W to 30° E and

105 between 35° N and 65° N as the normalised monthly sea-level pressure (SLP) difference
106 between stations in the Azores and Iceland (Hurrell, 1995).

107 Given the above discussion, this study presents a physically based statistical analysis
108 that assesses changes in extreme precipitation over the urban and non-urban areas in the
109 Netherlands. The study is structured as follows. Section 2 describes the datasets and
110 statistical methods used to assess the observed parameters and evaluate the non-stationary
111 models. Section 3 highlights the results of scaling and analysing extreme precipitation
112 and the differences in precipitation extremes between urban and non-urban areas. Section
113 4 presents more details underlying the results obtained in this study and suggests possible
114 mechanisms, and Section 5 gives the conclusions of this study.

115 2. Data and Methods

116 2.1. Precipitation gauges

117 Precipitation data in the Netherlands are available from the national weather institute
118 (KNMI). The network of manual rain gauges includes 325 stations
119 (<http://www.knmi.nl/nederland-nu/klimatologie/monv/reeksen>). This study considers the
120 daily validated datasets (which contain less than 1% missing data) corresponding to 231
121 rain gauges for the 30-year period extending from 1985 to 2014. The rain gauge data is
122 used mainly for scaling precipitation, developing a nonstationary model and identifying
123 the daily maximum values for each month.

124 2.2. Precipitation radar

125 The 5-minute radar-recorded precipitation on a 2.4-km grid is used when the high
126 frequency observational records at the rain gauges are unavailable. The radar-data is used
127 only for obtaining intensity-duration-frequency (IDF) curves for the selected
128 representative month. The validated (bias-corrected) radar records covering 17 years
129 (1998-2014) from the two radar stations in the Netherlands (De Bilt and Den Helder) are

130 used. The data is available and can be obtained from KNMI website
 131 ([https://data.knmi.nl/datasets/rad_nl21_rac_mfbs_5min/2.0?q=Precipitation&bbox=53.](https://data.knmi.nl/datasets/rad_nl21_rac_mfbs_5min/2.0?q=Precipitation&bbox=53.7,7.4,50.6,3.2)
 132 [7,7.4,50.6,3.2](https://data.knmi.nl/datasets/rad_nl21_rac_mfbs_5min/2.0?q=Precipitation&bbox=53.7,7.4,50.6,3.2)).

133 **2.3. Surface air temperature and dew point temperature**

134 The humidity and daily surface air temperature at a height of 1.5 m are obtained from
 135 the hourly automatic gauges without any missing data between 1985 and 2014. These
 136 data are collected by 1) a network of automatic gauges that consists of 35 stations
 137 (<http://www.knmi.nl/nederland-nu/klimatologie/daggegevens>). The dew point
 138 temperature (T_d) is derived using a formula adopted from KNMI (2000):

$$139 \quad T(^{\circ}\text{C}) = t(\text{K}) - 273.15 \quad (1)$$

$$140 \quad e_s(T) = A * e^{\left\{\frac{B*T}{T+C}\right\}} \quad \text{where } A = 6.11, B = 17.504, \text{ and } C = 241.2 \quad (2)$$

$$141 \quad e = \frac{\{e_s(T)*RH\}}{100\%} \quad (3)$$

$$142 \quad T_d = C / [\{B / (\ln e - \ln A)\} - 1] \quad (4)$$

143 where the temperature $t(\text{K})$ and relative humidity (RH) are measured directly, and the
 144 vapour pressure (e) is a consequence of the relative humidity and the saturation vapour
 145 pressure ($e_s(T)$) under the given conditions. The daily data values are extracted for 231 rain
 146 gauge locations from the 1 km resolution gridded dataset for the daily mean and maximum
 147 of the surface air temperature (T_{mean} and T_{max} , respectively) and the dew point
 148 temperature (Sluiter, 2014, 2012, 2009).

149 **2.4. Atmospheric air temperature**

150 The ERA and ECMWF datasets (i.e., the ERA-Interim reanalysis data for 1985-2014),
 151 which have a resolution of $0.125^{\circ} \times 0.125^{\circ}$, are used to provide estimates of the daily
 152 atmospheric air temperatures at 850 hPa (T_a) (see more details on
 153 <http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=pl/>) (Dee et al., 2011). To

154 avoid the effects of other factors, such as spatial differences in ground cover, on the
155 differences in air temperature, data describing the daily atmospheric air temperature at 850
156 hPa (approximately 1.5 km) produced by ECMWF are used as a covariate for understanding
157 the impacts of this quantity on precipitation. These atmospheric air temperature data (i.e., T_a)
158 from ERA-Interim are provided at T255 resolution with 60 levels up to 0.1 hPa, which is
159 adequately above the boundary layer of the atmosphere in comparison with the surface air
160 temperature.

161 **2.5.Circulation conditions**

162 To obtain atmospheric circulation conditions, the method developed by Jenkinson and
163 Collison (1977) is used to classify weather types. The Jenkinson-Collison type (JCT)
164 classification scheme reproduces the subjective Lamb weather types. In this method, the
165 circulation type is classified based on the variability in pressure around a region that
166 contains 16 grid points. A domain that is larger than the study area (3-13°E 47-58°N) is
167 used to implement the classification scheme for mean sea-level pressure from daily ERA
168 Interim data (<http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/>). The
169 cost733class software package (Philipp et al., 2016) is used to create weather types
170 corresponding to the eight prevailing wind directions, plus one unclassified type. Types
171 1 to 8 represent the wind directions (W, NW, N, NE, E, SE, S, and SW, where W = 1,
172 etc.), and 9 represents the unclassified weather type (light flow) (for more information
173 on this method, see Philipp et al., 2014).

174 **2.6. Urban land cover**

175 The Coordination of Information on the Environment (CORINE) land cover dataset,
176 which corresponds to the year 2012 and has 44 land cover classes on a resolution of 100
177 x 100 m (EEA, 2017), is used to define urban and non-urban stations, consistent with
178 previous studies in the Netherlands (e.g., Chrysanthou et al., 2014; Daniels et al., 2014;

179 Rahimpour et al., 2017). The urban extent in this study consists of six categories: i)
 180 discontinuous urban fabric; ii) industrial or commercial units and public facilities; iii)
 181 road and rail networks and the associated land; iv) port areas and airports; v) mineral
 182 extraction sites, dump sites, and construction sites; and vi) green urban areas and sport
 183 and leisure facilities. The other types of land cover classes are defined as the non-urban
 184 extent.

185 **2.7. Scaling analysis**

186 Regression slopes are estimated using the 95th percentile of daily precipitation (P95th)
 187 associated with the changes in daily temperature on the Celsius scale (T), which is extracted
 188 at the rain gauge locations by bringing the datasets (Tmean, Tmax, Td, and Ta) to the point
 189 scale corresponding to the rain gauge stations. In previous studies, the precipitation scaling
 190 has been estimated using binned pairs of events (e.g., temperature and precipitation quantiles
 191 for each bin). Wasko and Sharma (2014) presented QR as an alternative approach to scale
 192 precipitation data in temperature. Here, the scaling is estimated directly using QR (Koenker
 193 and Bassett, 1978) and the binning method (Lenderink and van Meijgaard, 2008). For a set of
 194 data pairs (x_i, y_i) for $i = 1, 2, \dots, n$, the QR for a given percentile (p) is expressed as:

$$195 \quad y_i = \beta_0^{(p)} + \beta_1^{(p)} x_i + \varepsilon_i^{(p)} \quad (5)$$

196 where ε_i is an error term with zero mean, and the percentile (p) lies between 0 and 1. Here,
 197 y_i represents the logarithmically transformed daily precipitation, and x_i is the corresponding
 198 temperature (Tmean, Tmax, Td, or Ta). The exponential transformation for the regression
 199 coefficient $\beta_1^{(p)}$ is used to estimate the change in the regression slope ($\frac{\delta P95th}{\delta T}$ (%)) as follows
 200 (Ali and Mishra, 2017; Hardwick Jones et al., 2010; Wasko and Sharma, 2014):

$$201 \quad \frac{\delta P95th}{\delta T} (\%) = 100 * (e^{\beta_1^{(p)}} - 1) \quad (6)$$

202 The regression slope is also estimated using the binning method by Lenderink and van
203 Meijgaard (2008). In this method,

- 204 1. the observed daily events (precipitation ≥ 1 mm) for each station from 1985 to 2014
205 are paired with their corresponding predictor variable (i.e., Tmean, Tmax, Td, or
206 Ta);
- 207 2. the pairs are sorted in ascending order according to their corresponding
208 temperatures;
- 209 3. the ranked pairs are split into 20 bins at 1°C intervals such that approximately the
210 same number of events are placed in each bin;
- 211 4. the linear regressions are performed by forming a dataset for each bin based on the
212 median of their temperatures and the logarithm of the 95th percentile of
213 precipitation; and
- 214 5. the change in the regression slope ($\frac{\delta P_{95th}}{\delta T}(\%)$) is estimated by applying the
215 regression equation using the data pairs.

216 **2.8. Extreme value analysis**

217 Statistical methods can be applied to evaluate the intensities, quantitative properties
218 and distributions of extreme precipitation (Data, 2009). The generalised extreme value
219 (GEV) method is used to estimate the return levels of extreme precipitation (Coles, 2001).
220 Consecutive non-overlapping blocks are identified by applying the block maxima
221 approach to precipitation at the investigated time durations (i.e., from 5 minutes to 24
222 hours). The GEV distribution (equation 7) is determined by the location parameter (μ),
223 the scale parameter ($\sigma > 0$), and the shape parameter (ξ), which are measures of the mean,
224 spread and skewness of the distributions of extreme events in a time series (Coles, 2001).
225 Since the climate is non-stationary, the maximum likelihood (ML) method (Jenkinson,
226 1955) is selected for parameter estimation in this study (Data, 2009).

$$227 \quad F(x; \mu, \sigma, \xi) = \begin{cases} \exp\left(-\left[1 + \xi \frac{x - \mu}{\sigma}\right]^{-\frac{1}{\xi}}\right), & \xi \neq 0 \\ \exp\left(-\exp\left(-\frac{x - \mu}{\sigma}\right)\right), & \xi = 0 \end{cases} \quad (7)$$

$$228 \quad \text{where:} \quad \left[x: 1 + \xi \frac{x - \mu}{\sigma} > 0 \right], \quad \begin{cases} \mu \in \mathbb{R} \\ \sigma > 0 \\ \xi \in \mathbb{R} \end{cases}$$

229 The stationary GEV distribution assumes constant parameters without any covariates,
 230 whereas the non-stationary GEV considers the dependency of the GEV distribution on a
 231 covariate or time (Coles, 2001). In this study, the appropriate extreme value analysis,
 232 which includes non-stationary distributions, is obtained by the incorporation of
 233 covariates into the extreme distribution. The dependence of the location and scale
 234 parameters is derived by considering the covariates for each station as follows:

$$235 \quad \mu = \mu_0 + \sum_{i=1}^k \mu_i (y_i) \quad (8)$$

$$236 \quad \sigma = \sigma_0 + \sum_{i=1}^k \sigma_i (y_i) \quad (9)$$

237 where y_i represents the i th covariate, μ_0 and σ_0 represent a constant offset, and μ_i and σ_i
 238 represent a linear dependence on the covariates. The non-stationary properties of the
 239 extremes in the present study are obtained using Td, Ta and the NAO index as the
 240 covariates for the location and scale parameters, and the shape parameter is held constant.
 241 The GEV distribution parameters for the observed extreme precipitation at each station
 242 are estimated by means of ML estimation (Jenkinson, 1955). The goodness of fit for the
 243 influence of covariates is assessed using the log-likelihood ratio test (LRT) (Zhang et al.,
 244 2010) with the aid of the following equation:

$$245 \quad D=2[l^S - l^{NS}] \quad (10)$$

246 Here, l^S and l^{NS} represent the log likelihood of the stationary model and the non-
 247 stationary model, respectively. Therefore, the effect of the inclusion of the covariates on
 248 the model fit is assessed using the LRT (Zhang et al., 2010).

249 The probability of occurrence of a severe event P is defined as the likelihood of the
 250 event happening at least one time on average in N years, so $P = \frac{1}{N}$. For a period N , the
 251 long-term return level (r_N) of the occurrence of extreme precipitation can be determined

using equation (11) (Coles, 2001). Moreover, the confidence intervals of the estimates are derived by 10^4 bootstrap samples of the observations.

$$P(x > r_N) = 1 - F(r_N; \mu, \sigma, \varepsilon) = \frac{1}{N} \quad (11)$$

3. Results

3.1. Scaling of extreme precipitation

The relationship between precipitation and air temperatures is investigated directly using data collected at rain gauges in the Netherlands. The rain gauge-based daily precipitation for a recent 30-year period extending from 1985 to 2014 is investigated using the corresponding mean and maximum surface air temperature, dew point temperature and atmospheric temperature (T_a) at 850 hPa, which are brought to the point scale of the rain gauges. The regression slopes are estimated using QR between the 95th percentile of precipitation (≥ 1 mm) and the predictors (T_{mean} , T_{max} , T_d and T_a). The binning method is performed by dividing the precipitation values into 20 temperature bins that range from 0 to 20°C and have widths of 1°C. The percentage change in the P95th precipitation quantile in each temperature bin is then estimated for each station. The trend line of the fitted linear regression reveals the relationship between precipitation and temperature as a scaling rate (i.e., $\frac{\delta P_{95th}}{\delta T}(\%)$). The robustness of the obtained change in the regression slope ($\frac{\delta P_{95th}}{\delta T}(\%)$) determined using the QR method is checked using the binning method (Figure 1). Both methods imply a positive scaling relationship for all of the investigated predictor variables for all of the stations. When the entire data set is used, QR gives more robust results, and the variability in the estimates is less than that obtained using the binning method with an equal number of bins (Wasko and Sharma, 2014). The change in the regression slopes estimated using the binning method are relatively small compared to those obtained using QR.

Figures 2(a) and 2(b) show the regression slopes between P95th and the mean and maximum daily temperature for each station. The regression slopes for the mean temperature are relatively similar to those for the maximum temperature at most of the stations. Increases in atmospheric temperature can induce more intense precipitation (Bengtsson, 2010; Wentz et al., 2007). Similar to the surface air temperature, the regression slope using T_a indicates a positive change for all of the stations (Figure 2(c)). The relationship between precipitation and T_a may provide more robust scaling rates rather than using T_{mean} and/or T_{max} , which may be influenced by diurnal variations in surface temperature in response to precipitation (Ali and Mishra, 2017). Ali et al. (2018) show a positive precipitation response to temperature for the most global stations using the binning technique (BT) or quantile regression (QR). They found a higher positive scaling with dew point temperature (median 6.1%/K) than that with surface air temperature (median 5.2%/K). The relationship between the P95th of precipitation and the dew point temperature, which represents a measure of absolute humidity, is considered instead of the surface air temperature (Figure 2(d)). Dew point temperature was used instead of surface temperature to take into account the physical linkage between the water vapour available in the atmosphere and temperature (e.g. C-C equation). The relationship between dew point temperature and precipitation was observed in greater consistency with C-C relationship (Barbero et al., 2018; Wasko et al., 2018). The regression slopes for P95th- T_d indicate greater changes than P95th- T_{mean} at most of the stations. This result reveals that changes in relative humidity become important, as does the dew point temperature. In fact, the increase in the dew point temperature is somewhat more robust than that in temperature (Attema et al., 2014). Lenderink et al. (2011) found more reliable spatial variations in the changes in the dew point temperature compared to those in the surface air temperature over Europe. As precipitation forms in clouds, T_d

301 and Ta may be the predictor variables that are most appropriately used to estimate the
302 temperature sensitivity of the P95th when compared using Tmean and Tmax.

303 **3.2. Non-stationary conditions**

304 To depict the distribution of extreme precipitation in the Netherlands, the monthly
305 maximum of the maximum daily precipitation at the De Bilt station over a 30-year period
306 is shown by a box-and-whisker plot (Figure 3(a)). Strikingly, some data points fall above
307 the whiskers, which extend to 1.5 times the inter-quartile range. Moreover, these data
308 points reflect positively skewed distributions, whereas the lower whiskers are limited to
309 the boxes.

310 The maximum average occurs between July and October, which have larger boxes
311 than the other months. Thus, it might be unrealistic to conclude that the extreme
312 precipitation variation is stationary in the Netherlands. The seasonal variability and non-
313 stationary nature of extreme precipitation are consistent with previous studies that have
314 examined the Netherlands (Buishand et al., 2013; Rahimpour et al., 2017, 2016a). The
315 seasonal precipitation changes are made obvious by the occurrence of larger boxes in the
316 box-and-whisker plots for the summer and autumn, whereas smaller boxes are seen for
317 winter and spring. Figure 3(b) demonstrates the fluctuations in the return levels
318 associated with the assessment of impacts using the covariates for the non-stationary
319 estimates (based on the annual block maxima approach) for the De Bilt station. This
320 figure shows that the return levels vary for different return periods with the variations in
321 the NAO index. With respect to study area and based on previous studies (e.g. Attema et
322 al., 2014; Buishand et al., 2013; Rahimpour et al., 2016), NAO index is identified as a
323 potential covariate to develop nonstationary models. Since daily precipitation extreme
324 relationships with Ta and Td were explored stronger than surface air temperature, we
325 used the combination (Ta and Td) as covariates for developing nonstationary models.

326 The covariates were also used separately to estimate nonstationary conditions. For
327 example change in 1 day10-year precipitation maxima was estimated under stationary
328 and nonstationary conditions using the combination of Ta and Td, only Ta and only Td
329 as the covariates. Percentage changes in precipitation maxima were found using the
330 combination of Ta and Td are larger as compared to estimations considering Ta and Td
331 separately. Furthermore, the small correlation coefficient (i.e., less than 0.5) at most
332 stations might demonstrate the necessity of using both covariates together for the sake of
333 better estimations.

334 The seasonal evolution is resolved by considering sub-annual (monthly) blocks, which
335 are sufficiently long to obtain an appropriate convergence of the probability distribution
336 functions (PDFs) of the maximum daily precipitation using the GEV model (Rahimpour
337 et al., 2016b). The suitability of one-month blocks (i.e., no significant improvement is
338 achieved through the use of two-month blocks) has been verified in our previous study
339 (Rahimpour et al., 2016b) for rain gauge stations within the Netherlands during a similar
340 period, where one-month blocks were used to estimate GEV distributions. In this respect,
341 the parameters of the GEV distribution are fitted for all of the precipitation maxima from
342 each month separately (i.e., from January, February and so on). The monthly non-
343 stationary GEV models for the precipitation maxima are estimated using three covariates
344 (i.e., Td, Ta and the NAO index) in combination with the location and scale parameters
345 at each station. They are combined as linear covariates for the location and scale
346 parameters in Equations (8) and (9), respectively. The significance of the non-stationary
347 models is tested using the LRT to assess the goodness of fit at each station. Table 1 shows
348 the percentage of the number of stations that has implications to ensure that the
349 considered nonstationary models are well founded against the stationary models. This
350 demonstrates the improvement in the non-stationary models in determining their best-fit

for parameters' distribution and shows the influence of the covariates at most of the stations for the individual months. Physically, the influence of other external factors such as geographical locations, unstable atmospheric conditions and the sea surface temperature (SST) (Attema et al., 2014; Lenderink et al., 2009) can impact the goodness of fit for non-stationary model for the stations throughout the individual months. For instance, Van Oldenborgh et al. (2009) found a significant increase in monthly SLP for winter season over the Mediterranean and decrease over Scandinavia during the last 50 years. The changes in SLP pattern caused more humid air from North sea being moved over the Netherlands. Moreover, the annual cycle of precipitation illustrates a discrepancy between the west coast and inland areas, which is mainly driven by circulation changes and increases in the sea surface temperature (SST), particularly during the summer half-year (van Haren et al., 2013).

Assessing the influence of the covariates using the non-stationary GEV models results in less uncertain estimates (i.e., with smaller confidence intervals) at most of the stations, in that they fall within the confidence intervals of those obtained using the stationary GEV models. The non-stationary GEV model at each station (as determined by considering the effects of the covariates on the location and scale parameters) is used to estimate the return levels for each month at each station. Figure 4 shows the median of the estimated return levels given different return periods and months over all of the stations in the Netherlands. This figure shows clearly that most of the occurrences of precipitation with higher values happen between July and September, and high return levels of extreme precipitation prevail in August. The average precipitation return levels during the given return periods obtained using the non-stationary models are larger than those obtained using the stationary models. These differences show that the stationary models underestimate the return levels, especially in the summer months.

3.3. Classification of station types

Considering the circulation conditions, the study makes use of the JCT scheme with nine types to classify the weather and circulation type on each day. The frequencies of daily precipitation (08-08 UTC) occurrences are investigated according to the weather types for 231 rain gauges throughout the Netherlands from 1985 to 2014. Figure 5(a) shows that the median of the precipitation events is slightly larger for the southerly and westerly weather types than those events for the easterly and northerly weather types. Although the average precipitation is fairly similar among the different weather types, the amount and number of extreme precipitation events (i.e., the upper outliers on the box-and-whisker plots) show the impacts of circulation conditions on the occurrence of extreme precipitation. Therefore, a reliable assessment of the impacts of urban areas on extreme precipitation might be obtained by considering the land-cover type upwind of each station for each wind direction.

To reach this goal, we consider the possible effects of the weather types on precipitation events by defining the urban and non-urban stations separately for each wind direction. We have taken all possibilities for wind changes. For land use, since we used only one land use map (CORINE) for the whole period, we did not analyze the seasonal changes of the land use in this study. Therefore, a rain gauge can change from being urban or non-urban station depending on the direction of the wind and the urban and nonurban classification held constant for the individual wind directions. The land cover types within 8 octants (eighths of a circle, given the 8 prevailing wind directions) surrounding each station are extracted from the CORINE dataset (Figure 5(b)). These octants extend to a distance of 20 km from each station. Depending on the wind direction, the manual rain gauges are classified as urban stations for the corresponding octant when the six aforementioned land-cover categories cover more than 25% of the entire area of

the octant; otherwise, they are classified as rural stations. Setting a threshold for defining urban land cover upwind of each station presents almost similar number of urban and non-urban stations for each wind direction. Although this approach can not select an area totally occupied with urban land use, it is helpful to distinguish areas where the overall feature includes the higher percentage of urban land cover. Therefore, the stations are classified in terms of the percentage of urban land use in the eight upwind directions and one in the whole buffer around the stations for the unclassified weather type (i.e., light flow). Throughout the study, the discrepancy between the urban and non-urban areas is evaluated by taking the difference between the average of all of the urban stations and the average of all of the non-urban stations for each wind direction.

3.4. Nonstationary return levels in urban and non-urban areas

The urban impacts on extreme precipitation are investigated using the rain gauges and the gridded datasets and by evaluating the return levels of extreme precipitation using the non-stationary models. The variations in the different return levels (i.e., 2, 5, 10 and 30-year) from January to December for the urban and non-urban stations are investigated using the non-stationary models and 30 years of historical data. Figure 6 shows that the return levels of extreme precipitation for the urban stations vary similarly to those of the non-urban stations: small values occur in winter, and large values occur in summer. The 2-year return level of daily extreme precipitation varies between 10.7 mm and 20.6 mm for the urban stations and between 10.9 mm and 19.9 mm for the non-urban stations.

Likewise, similar differences between the ranges of the urban and non-urban return levels are estimated for the 5-, 10- and 30-year return levels (i.e., 15.5-30.4 mm, 18.2-31.1 mm and 21.5-54.1 mm for the urban stations and 15.5-29 mm, 18.4-36.3 mm and 22.6-51.1 mm for the non-urban stations, respectively). The differences in return levels between the urban and non-urban stations increase for larger return periods. The return

426 levels for the urban stations are 5-7% (i.e., the ratio between the difference in the return
427 levels of the urban and non-urban stations at each return period and the return levels for
428 the non-urban areas) greater than those of the non-urban stations in August throughout
429 the urban type classified as W9. The return levels of extreme precipitation are larger for
430 the urban stations than those for the non-urban stations over all of the months except
431 those between April and June. Land cover changes in the form of urbanisation are
432 modifications of surface covers in a roughly geometrical configuration (urban form) and
433 a composite of urban settlements, buildings and impervious materials. Urbanisation leads
434 to greater heat capacities and surface energy modifications in urban areas than in natural
435 surrounding areas (Oke, 1982). Changes in urban surface energy (e.g., the enhancement
436 of heat capacity and release of stored heat to the atmosphere) influence temperature, wind
437 flow and turbulent mixing. The phenomenon by which temperatures are higher in urban
438 areas than in surrounding rural or vegetated areas is known as the urban heat island (UHI)
439 effect, which is particularly predominant in clear, calm weather conditions. Similar to sea
440 breezes, urban circulation can be generated during calm-wind and fair-weather conditions,
441 during which the surrounding non-urban blows towards the warm urban region. This
442 circulation causes air to rise and can create clouds and precipitation (i.e., the warm and
443 moist air rises in the atmosphere, colliding with the overlying cooler layer of air) over or
444 downwind of the urban area. The discrepancies seen between the urban and non-urban
445 areas during the second half of the year may be partly caused by the increases in
446 temperature and convection caused by the urban heat island (UHI) effect on winter
447 precipitation (Trusilova et al., 2009, 2008).

448 **3.5. Nonstationary Intensity-duration-frequency in urban and non-urban areas**

449 To extract additional detail on the discrepancies in extreme precipitation between the
450 urban and non-urban areas, precipitation intensities, rather than quantities, are

451 investigated at short time intervals. The precipitation extremes in the Netherlands in
452 August over short time intervals ranging from 5 minutes to 24 hours are investigated
453 using 17 years (1998 to 2014) of precipitation radar data. The 5-minute radar data are
454 extracted for 231 locations (i.e., the locations of the rain gauges) in the Netherlands.
455 Furthermore, the 5-minute precipitation values are aggregated for 15, 30, 60, 120, 360,
456 720, 980, and 1440 minutes at the location of each station. The intensity is obtained by
457 dividing the precipitation amount by the duration of the period.

458 Against the current IDF curves, the non-stationary results assume that extreme
459 precipitation is expected to alter regarding climate change, which may affect the
460 reliability of infrastructure systems (Agilan and Umamahesh, 2017; Cheng et al., 2014).
461 Precipitation in the Netherlands could be influenced by the external forces from large
462 natural variability and seasonal variations (Attema and Lenderink, 2014; Rahimpour et
463 al., 2016). Therefore, the monthly IDFs regarding non-stationary climate may represent
464 a better distribution than the annual IDFs ignoring the influences of large scale
465 variabilities. In this study, the non-stationary precipitation IDF curves for August are
466 developed by using the identified covariates. Similar to the non-stationary models applied
467 to the daily rain gauge data, Td and Ta are used as covariates of the precipitation
468 intensities and applied to the extremes of the precipitation intensities. The NAO index is
469 excluded from the covariates for estimating extreme precipitation intensity in August
470 because of its negligible impact in the summer months (Haylock and Goodess, 2004).
471 Figure 7 shows the intensities at different durations and repetition times (i.e., 2, 5 and 10-
472 year return levels) averaged over the urban and non-urban stations separately. This figure
473 shows that, on average the return levels for precipitation intensities over the urban areas
474 are larger than those over the non-urban areas over all of the classified stations
475 (particularly for the urban type classified as W9). Although there is some variation in the

476 maximum daily precipitation in the urban and non-urban areas, the urban areas show the
477 highest values; in particular, the differences are clearly larger for longer return periods
478 over all of the classified urban stations. The power (polynomial) regression lines exhibit
479 similar behaviour in the urban and non-urban precipitation intensity return levels,
480 whereas they are larger in the urban areas than in the non-urban areas. The effects of
481 urban areas on extreme precipitation are clearer for shorter durations, where the urban
482 and non-urban areas display larger differences between the precipitation return levels.

483 4. Discussion

484 The scaling relationship between precipitation and temperatures is used to simplify
485 the nature of precipitation changes and understand the changes in intensity that may occur
486 in a warming climate (Lenderink et al., 2011; Lenderink and Attema, 2015). This work
487 is carried out using QR and the binning method for each individual station. Unlike the
488 binning method, QR estimates trends directly (i.e., it is unbiased with the sample
489 size), and no discretisation of the data is required (Wasko and Sharma, 2014).
490 Results obtained using the daily precipitation and temperatures (T_{mean} , T_{max} ,
491 T_d , and T_a) show similar trends in precipitation with the temperatures by both
492 binning and QR methods. However, the regression slopes ($\frac{\delta P_{95th}}{\delta T} (\%)$) estimated
493 using QR are slightly larger than those obtained using the binning method. The
494 scaling of precipitation with temperature indicates the efficacy of the dew point
495 and atmospheric air temperatures as covariates that may influence the occurrence
496 of extreme precipitation. From our understanding of the physical basis of
497 precipitation, we expect the effects of the covariates listed above to have
498 importance for the occurrence of extreme precipitation under favourable
499 atmospheric conditions. Moreover, large stratiform precipitation can change to

convective precipitation as temperature increases and dominates the extreme precipitation events (Berg et al., 2013).

The influence of atmospheric circulation conditions is studied using the JCT classification scheme for all days between 1985 and 2014. The basic statistics of precipitation are investigated separately for each weather type on each day, and the results demonstrate the dependency of variations in the frequency and intensity of precipitation on the weather types. Whereas the mean of daily precipitation is higher for the W and SW weather types, the maximum daily precipitation is associated with the light flow weather type. Although westerly winds are dominant in the Netherlands, it is unclear which weather type and circulation pattern favour extreme precipitation. Regardless of the lack of available long-term meteorological observations in urban areas in the Netherlands that can be used to assess urban micro-climates and their effects on climatic variables (i.e., precipitation), this study considers rain gauge stations as either urban and non-urban stations for the different wind directions, depending on the types of areas located upwind of the stations (see section 2). This practice helps to produce a comparable discrepancy between the urban and non-urban areas in each classified urban type and tends to produce results that are generally applicable within the country.

The seasonal variations in precipitation are relatively uniform in summer and winter (Attema and Lenderink, 2014; Buishand et al., 2013; Rahimpour, 2018), while there is a coastal gradient in spring and autumn due to the proximity of the North Sea and the influence of the NAO index (Attema et al., 2014). Moreover, extreme convective precipitation is more likely to occur in the summer months, and extreme stratiform precipitation is expected to occur in other seasons (Daniels et al., 2016; Overeem et al., 2009). Therefore, monthly data are valuable for characterising the dominant extreme precipitation. Trends in the monthly maximum precipitation that are significant at the 5%

level have been found by previous studies, indicating that precipitation displays non-stationary variations (Buishand et al., 2013; Rahimpour et al., 2017, 2016b).

The GEV parameters for extreme precipitation are estimated for each station at every month. The non-stationary GEV model is developed based on the dew point and atmospheric air temperatures (i.e., T_d and T_a) and a large-scale mode of climate variability (i.e., the NAO index) to demonstrate the distribution of monthly extreme precipitation and the return levels. The estimates obtained using non-stationary models fall within the confidence intervals of those obtained using stationary models at most of the stations in the Netherlands. The non-stationary increase in extreme precipitation identified in this study is in accordance with previous studies that have identified a statistically significant increasing trend in extreme precipitation in the Netherlands (Buishand et al., 2013; Overeem et al., 2008; Rahimpour et al., 2017).

The non-stationary models tend to produce more conservative estimates of the return levels of extreme precipitation. The results show that the downwind impacts of urban areas on the return levels of extreme precipitation over the country are relatively small in late spring (i.e., between April and June) and larger at other times. The exception in late spring may be caused by the suppression of shower activity (over the almost 50 km distance to the coast where most of the urban areas in the Netherlands are located) due to low sea-surface temperatures. Daniels et al. (2015a) reported that the precipitation over the coastal areas in the Netherlands in spring is almost 25% less than that over inland areas because of triggering mechanisms (air travelling over the land and planetary boundary layer growth affect cloud formation).

However, urbanisation alters the surface roughness and enhances the turbulence over urban areas (Han et al., 2014). The deeper boundary layers and temperature increases that occur in urban areas change the atmospheric water balance and enhance the water-

550 holding capacity of air (Chen and Hossain, 2016). The largest discrepancy between the
551 urban and non-urban return levels is found under light flow conditions (i.e., the urban
552 type classified as W9). Extreme precipitation events are further found to be most strongly
553 affected by urban land use in the summer months, especially August, and under the urban
554 type classified as W9, among others. It is also found that the UHI to be higher in August
555 than in other months in the Netherlands (Rahimpour et al., 2018; Wolters and Brandsma,
556 2012). The higher extreme precipitation in August is in accordance with the findings of
557 previous Dutch studies on precipitation frequency during days where convection plays a
558 relatively important role and maxima occur during the evening and near sunset (Overeem,
559 2009).

560 Intense precipitation may be caused by increases in the strength of convection due to
561 intensive UHI (Chen et al., 2015; Rahimpour et al., 2018; Yang et al., 2017). The
562 temperature discrepancy between urban and non-urban areas enhances instability
563 and convective activity over urban and areas downwind from urbanised areas (Lin
564 and Chen, 2011). Increased moisture and upward convergent movement are
565 triggered by UHI circulation patterns (Yang et al., 2017). Thus, the higher
566 temperatures in urban areas that are caused by the UHI circulation and sufficient
567 water vapour could cause more precipitation in urban areas. In this respect,
568 August is examined using high spatial resolution radar data to highlight the
569 maximum precipitation return levels for different time durations for the urban and non-
570 urban areas. The precipitation intensity return levels indicate similar occurrences for the
571 urban and non-urban stations, with more intensive events for the urban stations.

572 The better fits obtained using non-stationary models at most of the stations reveal that
573 the IDF curves derived using the stationarity assumption underestimate extreme
574 precipitation. If an IDF curve based on stationary estimates is used for designing urban

575 infrastructure, neglecting other factors and the impacts of urbanisation, the probability of
576 infrastructure failure is high due to the more extreme precipitation events that are
577 identified by the non-stationary models. In this respect, to obtain accurate IDF curves,
578 the estimation methods should be updated by considering the influence of additional
579 climate variability on extreme precipitation events.

580 The intensity-duration-frequency (IDF) curves, considering non-stationary conditions,
581 at each station are necessary for designing infrastructure and projecting future
582 precipitation return levels. It is to note that such estimates are difficult to produce, and
583 subjected to uncertainties, due to the limited numbers of long time series of precipitation
584 observations in the urban area. The differences between the urban and non-urban IDF
585 curves require more consideration of non-stationary models in projecting future extreme
586 precipitation, which requires careful choices of covariates. Understanding the physical
587 causes that underlie extreme precipitation (i.e., circulation and temperatures changes) and
588 the impacts of urbanisation on climate may assist in the development of non-stationary
589 models that can be used to produce improved assessments of the risks related to climate
590 change.

591 However, the selection of covariates is important in finding the precipitation return
592 levels. The results show that ignoring the effects of urbanisation can lead to uncertain
593 estimates of the intensity, duration and frequency of extreme precipitation events,
594 especially for short-duration precipitation. Although this study does not evaluate the
595 uncertainties of the covariates, it shows that extreme precipitation associated with
596 temperature differences between the urban and non-urban areas tend to give less
597 uncertain estimates of return levels in the future.

598 For obtaining more reliable results on precipitation discrepancy between urban and
599 non-urban areas, efforts are needed to examine the impact of bias corrections on observed

precipitation variations. The ignored undetected errors in this study (i.e. wind speed-induced errors and seasonal variations) could impact the obtained precipitation discrepancy between urban and nonurban areas. The catch efficiency of precipitation, for example, might be larger in urban areas than that of non-urban areas where urban stations surrounded by obstacles are exposed to less wind than non-urban stations in open areas. Therefore, the results could be influenced by bias corrected precipitation data regarding temperature, wind speed, drop size and snow percentage (Ding et al., 2007; Sun et al., 2013). Further, it is acknowledged that the investigated rain gauge and gridded radar datasets may not truly reveal the full micro-climate over urban areas (i.e., other factors influence urban meteorology). A larger number of meteorological stations located in Dutch cities would be needed to fully characterize these micro-climates, and these additional stations are currently unavailable. Note that the estimated precipitation return levels and IDF curves require longer-term observations in each region, and the trends in the covariates such as the NAO index may not persist in the coming years, and use of climate model simulations might enable extrapolation into the future. Therefore, care should be taken in extrapolating features seen in historical data into the future, especially for longer return periods, during which different physical causes (i.e., natural or anthropogenic forces) may influence the precipitation.

When scaling precipitation on temperatures for local scales, the influences of different mechanisms such as the regional and seasonal precipitation variations should be considered (Schroeer and Kirchengast, 2017). Precipitation dependency on local temperature can be found in regions such as the Netherlands with enough moisture availability (Lenderink and van Meijgaard, 2008; Westra et al., 2014). It is to note that local temperature and global mean temperature usually scales linearly. However, connecting scaling relationships for local temperature and precipitation could be a

625 controversial issue (IPCC, 2014) where different factors involved (e.g. thermodynamic
626 effects (Barbero et al., 2017) and dynamic factors (Drobinski et al., 2018)). Furthermore,
627 changes in the temporal resolution of extreme precipitation and the covariates may
628 cause changes in the scaling rate and the estimated return levels. Sub-daily and hourly
629 long-term data could provide more valuable information for obtaining robust assessments
630 of the sensitivity of the scaling relationship between extreme precipitation and desirable
631 predictor variables, such as the dew point temperature. For instance, Barbero et al.
632 (2017) reported that the response of precipitation to temperature at an hourly
633 resolution is better than that at a daily resolution. Furthermore, other factors, such as
634 the types and sizes of cloud condensation nuclei (Drobinski et al., 2016) and the
635 geographical characteristics of stations (Mishra et al., 2012; Wasko et al., 2016) can
636 also affect extreme precipitation.

637 5. Conclusions

638 Knowledge of the impacts of climate warming and urbanisation on the observed trends
639 in extreme precipitation can lead to improved estimates for the return levels of extreme
640 precipitation. This study considers the factors that likely influence extreme precipitation
641 and extends existing statistical approaches by scaling extreme precipitation and
642 examining non-stationary models that consider covariates (i.e., the dew point and air
643 temperatures). The investigation of the appropriate covariates is done through
644 applying QR and the binning method to precipitation and temperature datasets
645 covering the Netherlands. Since the scaling of precipitation with increasing
646 temperature is positive, the results suggest that the dew point and atmospheric
647 temperatures are appropriate covariates for extreme precipitation. A linear
648 combination of the dew point and the atmospheric temperature at the 850-hPa level, as
649 well as the NAO index, which represents a large-scale influence mode, are applied to

650 estimate the monthly precipitation return levels for different return periods. The study
651 shows that presuming a non-stationary climate could lead to improved estimates of
652 precipitation return levels where the stationary models underestimate the precipitation
653 return levels.

654 The study makes use of the JCT with nine types to classify weather and circulation
655 types. The dependence of precipitation on circulation conditions leads to the
656 classification of stations as urban and non-urban areas based on their upwind land-use
657 types for each wind direction to investigate the response of extreme precipitation to
658 alternative land-cover types. The maximum daily precipitation for each month is
659 compared between the stations in the regions downwind of urban areas (i.e., urban
660 stations) and the other stations (i.e., non-urban stations). The results reveal that the
661 frequency and intensity of extreme precipitation are higher in urban areas than in non-
662 urban areas. August has the highest return level and frequency for maximum daily
663 precipitation throughout the year. The urban type classified as W9 (light flow conditions)
664 demonstrates the magnitude of the differences between the urban and non-urban
665 precipitation return levels. This study concludes that, apart from large-scale climate
666 changes, increases in extreme precipitation can be induced by urbanisation. Due to
667 land use and urban climate change, the use of non-stationary models is advised to
668 produce improved estimates of precipitation return levels and to project the
669 frequency and intensity of precipitation in the future.

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929 Table 1. Percentage of stations (%) present the goodness of fit for the stationary (S) and
 930 non-stationary (NS) models. The goodness of fit was assessed using the log-likelihood
 931 ratio test (LRT).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
S	12	8	12	19	13	7	12	14	8	16	10	12
NS	88	92	88	81	87	93	88	86	92	84	90	88

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Figure. 1. Regression slopes ($\frac{\delta P_{95th}}{\delta T}$ (%)) for 231 rain gauge stations (red circles) obtained from quantile regression (QR) and binning method (BT). Panel (a) to panel (d) show precipitation relationship with mean, maximum, dew point and atmospheric temperatures, respectively. The one-one line is shown by grey solid line.

Figure 2. Estimated regression slopes ($\frac{\delta P95th}{\delta T}$ (%)) for the 231 rain gauge stations in the Netherlands obtained from the mean surface temperature (Tmean), maximum surface temperature (Tmax), atmospheric temperature at 850 hPa pressure level (Ta) and dew point temperature (Td).

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Figure 3. (a): Box-and-whisker plot of the maximum daily precipitation and the extended inter-quartile range (i.e., the whiskers extend to 1.5 times the inter-quartile range) for the De Bilt station during 1985-2014. The outlying data points are indicated by black dots. The median of the daily maximum precipitation is displayed by the black solid line shaded in the 95% confidence interval. The dashed and dot-dashed lines show the 0.25 and 0.75 quantiles. (b): The GEV model is fitted to determine the influences of the NAO index on annual maximum daily precipitation in De Bilt from 1985 to 2014. The dashed black, dotted blue, solid red, solid green, and solid blue lines depict the annual maxima, the NAO index, and the 2-, 10- and 30-year return level. This diagnostic plot shows that the 2-year return level approximates the median of the GEV distribution.

Figure 4. Monthly return level for the maximum daily precipitation (median of all rain gauge stations) vs. the return period from the stationary models (dotted lines) and the non-stationary models (solid lines) in the Netherlands from 1985 to 2014.

Figure 5. (a) Variations in precipitation ≥ 1 mm among the nine weather types during 1985-2014. (b) Locations of rain gauge stations (blue closed circles) and areas of urban land cover (grey shading) in the Netherlands (EEA, 2017). The eighth of a circle with a radius of 20 km radius for the southwesterly geostrophic wind direction (W8) is for the De Bilt station.

Figure 6. Two-, 5-, 10- and 30-year return levels derived using non-stationary models median over urban (red lines) and non-urban (blue lines) rain gauge stations in the Netherlands from January to December. Panels (a) to (i) reflect the stations classified as W1 to W9 due to the land use types upwind of the stations.

Figure 7. Precipitation intensity return levels for 2-, 5- and 10-year return periods for nine stations classified as urban and non-urban for August within the Netherlands. The estimates are obtained using the non-stationary assumption at each station and averaged over the urban and non-urban stations. The regression lines for the urban (red) and non-urban (blue) stations are indicated by power-law trend lines. Panels (a) to (i) reflect the stations classified as W1 to W9 due to the land use types upwind of the stations.