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Attributing seasonal variation of daily extreme precipitation events across The Netherlands

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ABSTRACT

A recent study showed a rise in total and extreme precipitation in the Netherlands over the past century. The present study attempts to characterize and attribute the seasonal variation of daily extreme precipitation events in the Netherlands. Statistical models for extreme values were used to fit daily rainfall maxima for all months during the period 1961–2014, using data from the 231 rain gauges distributed across the country. A generalized extreme value (GEV) approach was used to determine the probability distribution of extreme values and their dependency on time and the monthly North Atlantic Oscillation (NAO) index. The non-stationary models used to represent the annual cycle of the GEV parameters assumed an invariant shape parameter and harmonic functions as location and scale parameters. The best non-stationary model was selected using Akaike's information criterion (AIC) and the log-likelihood ratio test (LRT). The results indicated that the estimates derived from the non-stationary model differed from those obtained with the aid of the stationary model, and had lower uncertainties. These non-stationary estimates were within the confidence intervals (CI) of the stationary estimates at most rain gauge stations. The non-stationary model estimated parameters with less uncertainty and with smaller CI, thus permitting more accurate representation of extreme precipitation in the Netherlands. The spatial pattern of annual mean location and scale GEV parameters was compatible with coastal, land cover (such as the wooded and heathland areas of the Veluwe region of the province of Gelderland) and orography (in the southeast of the country). The location parameter peaked over the west coast, especially on the central west coast during the summer half-year, while the centre and east of the country had the highest values during the winter half-year. The scale parameter peaked in the centre of the country during the summer, in the east in the early summer and along the west coast in the spring. The 10-year and 50-year return levels were calculated with the aid of the non-stationary model for all months. The spatial distribution of these extreme event probability clearly reflects the regional differences in the Netherlands.

1. Introduction

Precipitation is the most significant component of the water cycle for human life. Knowledge of changes in precipitation is therefore urgently needed as a basis for the planning and management of water resources in a rapidly changing world. Previous studies have reported a rise in overall precipitation and in the frequency of extreme precipitation events at higher latitudes (Anagnostopoulou and Tolika, 2012; IPCC, 2012; Karagiannidis et al., 2012; Trenberth et al., 2007). Zwiers et al. (2013) demonstrated that variations in mean precipitation can change the intensity and frequency of extreme precipitation.

Buishand et al. (2013) showed that the incidence of precipitation and extreme events has been increasing throughout the Netherlands, except in some regions in the southeast of the country, during the past years. Most analyses of precipitation events use the approach presented by Buishand and Velds (1980). This involves simulation of extreme precipitation using the Gumbel distribution for the weather station of the Royal Netherlands Meteorological Institute KNMI at De Bilt at intervals of from 5 min to 10 days during the period 1906–1977. Van Montfort and Witter (1986) used hourly data from De Bilt between 1906 and 1982, and daily data from 32 other Dutch weather stations from 1932 to 1979, to model the particular exceedances of rainfall, using the peak over threshold (POT) approach. In the last decade, Smits et al. (2004) used the long time series of rainfall data from De Bilt for the period 1906–2004 to model extreme rainfall throughout the Netherlands at intervals of from 4 h to 9 days, with the aid of the POT approach and a generalized extreme value (GEV) distribution. They concluded that the rain gauge information from De Bilt can be representative of the other regions in the Netherlands if adjusted by a correction factor (which varies from 0.93 to 1.14, depending on the area concerned).

Most previous studies (such as Wijngaard et al., 2005; Buishand et al., 2009; Overeem et al., 2009; Hanel and Buishand, 2010; Overeem

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and Buishand, 2012) applied the GEV model to climatological statistics for the Netherlands to describe the monthly and annual distribution of precipitation maxima. Regional differences in precipitation throughout the Netherlands are currently calculated on the basis of annual rainfall at De Bilt, though Diermans et al. (2005) showed that this was not appropriate for investigation of regional variability in extreme rainfall. Mudersbach and Jensen (2011) and Rust et al. (2009) calculated the seasonal dependence of precipitation on the modified location and scale parameters of the GEV distribution for explicit modelling of monthly variation. This approach explained the possible external influences on extreme precipitation events.

The North Atlantic Oscillation (NAO) is one of the major source of variability in North Atlantic region and significantly affects meteorological parameters in the Northern Hemisphere (Wakelin et al., 2003; Sienz et al., 2010). The NAO is specified by NAO index in the difference of normalized sea level pressures between the Azores and Iceland (Hurrell, 1995; Jones et al., 1997).

The GEV distribution model can be used to represent the annual precipitation cycle, while the North Atlantic Oscillation (NAO) index influences extreme precipitation events. Furthermore, the monthly variation generated by the GEV distribution model contains information about return levels (Maraun et al., 2009; Rust et al., 2009). In the present study, the variation in extreme precipitation will be assessed by the best non-stationary model for each weather station in the Netherlands, taking the impact of NAO into account. The seasonally dependent impacts of 1-day precipitation can be used for risk assessment and risk management relating to flooding, irrigation and soil erosion in the Netherlands.

This paper examines three statistical approaches (the use of block maxima, a stationary model and a non-stationary model) to the modelling of the annual cycle. The non-stationary models for monthly maxima were determined separately for each of the 231 rain gauges in the Netherlands. The non-stationary GEV models used harmonic functions for the location and scale parameter, together with an invariant shape parameter. Section 2 describes how daily precipitation data records are obtained, and explains the methodology for determining the best non-stationary model for estimation of the statistical parameters. Section 3 presents details of the estimated parameters, the pattern of monthly return levels and the return levels of annual maxima determined with their aid. The results obtained with the optimal non-stationary model, the various spatial patterns and the physical interpretation of the discrepancies between them are discussed in Section 4. Finally, conclusions are presented in Section 5.

2. Materials and methods

2.1. Precipitation dataset

Rain gauges cover the Netherlands with a spatial resolution of 10 km. The precipitation is recorded daily, and datasets are quality-controlled and validated by KNMI. These long-term data with less than 1% missing data were reviewed and the gaps in them filled by use of the ECAD (European Climate Assessment & Dataset) datasets (Klein Tank et al., 2002). There is only a negligible difference between the corrected dataset and the original quality-controlled and homogenized dataset as far as the detection and attribution of extreme precipitation in the Netherlands is concerned (Buishand et al., 2013). Further information about the operations of KNMI (largely in Dutch, with an English summary) is available at http://www.knmi.nl/nederland-nu/klimatologie/monv/reeksen. In the present study, the index of a monthly maximum of 1-day precipitation (P1) was calculated for all 231 stations during the 54-year period 1961–2014. This index has been selected as it has a significant impact on human life and is often used to estimate the probability of rare extreme precipitation events, and for the purposes of infrastructure design (Min et al., 2011; Sillmann et al., 2013).

2.2. Methodology

Extreme value theory (EVT) was used to evaluate data on rare precipitation events. In accordance with the block maxima method in EVT, the sample under study is divided into consecutive non-overlapping blocks, and the maximum value in each block is identified. Monthly and annual blocks were defined in the present study. The block maxima are used to determine the probability distribution of the precipitation. The standard GEV model is then employed to fit the parameters and hence to determine the frequency and intensity of extreme precipitation events.

Regarding the EVT assumptions, we consider n random variable sequence (X_1, X_2, ..., X_n), which are independent and identically distributed (iid). A physical process for n time unit M_n=max (X_1, X_2, ..., X_n), conform to a common probability distribution. In this study the M_n represent the annual maxima or monthly maxima for the n number of monthly or annual blocks of daily precipitation (X_i), respectively. The block size needs to be chosen carefully, as the reliability of the estimate of the distribution factor is strongly related to the length of the precipitation series and their sequences. Eq. (1) regarding the Fisher-Tippett theorem can be used to estimate the distribution of M_n for a given precipitation dataset:

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

where: $[x\colon 1+\mathcal{E}\frac{x-\mu}{\sigma}>0]$, $\begin{cases} \mu\in R \\ \sigma>0 \\ \mathcal{E}\in R \end{cases}$

The location parameter (μ) defines the position of maximum precipitation, and the spread of the distribution is represented by the scale parameter $(\sigma>0)$. The shape parameter ($\mathcal{E}$) is important to represent the very rare occurrences which termed with return period more than 100 years, and can define the extreme value distribution types as follows:

$\mathcal{E}$=0 (Gumbel distribution) an exponential reduction of the infinite upper tail.

(Fréchet-type) a slow reduction of the longer infinite upper tail.

$\mathcal{E}>0$ (Weibull-type) a shorter finite upper tail, depicting the occurrence of very rare events.

The Gumbel distribution is equal to $F(x)=e^{-1}\approx 0.37$ if $x=\mu$ in the above equation.

The L-moment method (Hosking, 1990) and maximum likelihood (MLL) estimation (Jenkinson, 1955) can be used to estimate the distribution parameters when there is a sufficiently large body of data on extreme events. The MLL method is the preferable approach in the present study (Data, 2009), especially when the climate is non-stationary.

The non-stationary properties of extreme precipitation could be calculated by considering the dependence of the GEV distribution on a covariate or time. The non-stationary extreme value in Eq. (2) described by Coles (2001) includes the independent variable (such as precipitation) and the time-dependent parameters (such as location, scale and shape):

$$G(x;\mu(t),\sigma(t),\mathcal{E}(t))=exp\left(-\left[1+\mathcal{E}(t)\frac{x-\mu(t)}{\sigma(t)}\right]^{-\frac{1}{\mathcal{E}(t)}}\right) \quad (2)$$

Consequently, the constant GEV parameters μ (or σ or $\mathcal{E}$) are replaced by the new parameters, μ_0 and μ_1 (or the corresponding parameters for σ and $\mathcal{E}$) (Maraun et al., 2009). For instance, the parameter dependence for location is derived from the primary analysis of observed time series in Eq. (3). The μ_0 presents a constant offset and μ_1 represents a linear dependence on a time-dependent function C(t).

$$\mu=\mu(t)=\mu_0+\mu_1.\,C(t)\,, \qquad t=(1,\ 2,\ \ldots,\ n) \quad (3)$$

In Eq. (3), $C(t)$ can denote a time function that reflects a parametric trend or influence of an observed time series of extreme events that called