Journal of Hydrology 402 (2011) 193–205

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Statistical precipitation downscaling for small-scale hydrological impact investigations of climate change

P. Willems [a,b,c,*], M. Vrac [c]

[a] Katholieke Universiteit Leuven, Department of Civil Engineering – Hydraulics Division, Kasteelpark Arenberg 40, BE-3001 Leuven, Belgium
[b] Vrije Universiteit Brussel, Department of Hydrology and Hydraulic Engineering, Pleinlaan 2, BE-1050 Brussel, Belgium
[c] Laboratoire des Sciences du Climat et de l'Environnement, UMR CEA-CNRS-UVSQ 1572, CE Saclay l'Orme des Merisiers, 91191 Gif-sur-Yvette, France

ARTICLE INFO

Article history:
Received 8 January 2010
Received in revised form 31 January 2011
Accepted 24 February 2011
Available online 3 April 2011
This manuscript was handled by A. Bardossy, Editor-in-Chief, with the assistance of Attilio Castellarin, Associate Editor

Keywords:
Climate change
Precipitation
Statistical downscaling
Urban drainage
Weather typing

SUMMARY

Impact investigations of climate change on urban drainage require projections to be made on short-duration precipitation extremes. The relevant time scales can be as low as 10 min, which requires strong statistical downscaling of climate model simulation results. In this research, two sets of methods have been suggested and tested based on Belgian data. The first set makes direct use of the precipitation results of the climate models. They involve computation of quantile perturbations on extreme precipitation intensities, and the tested assumption that the same perturbations hold for daily and sub-daily time scales. The second set of methods is based on weather typing, and accounts for the low accuracy of daily precipitation results in current climate modelling. In these methods, climate model outputs on pressure (atmospheric circulation) are used to obtain precipitation estimates from analogue days in the past. Different criteria for defining analogue days have been tested. The weather typing methods have been further advanced accounting for the fact that precipitation change does not only depend on change in atmospheric circulation, but also on temperature rise. Results have been investigated as changes to precipitation intensity–duration–frequency (IDF) relationships. It is shown that both the quantile-perturbation and advanced weather typing based methods allow precipitation biases in climate model simulation results to be largely corrected. Both types of methods moreover produce similar short-duration changes in precipitation extremes, which gives some credibility to the downscaled impacts. The corresponding changes in IDF statistics show that the extreme precipitation quantiles typically used for design of urban drainage systems, can increase up to 30% by the end of this century. Those changes mean that sewer surcharge or flooding would occur about twice more frequently than in the present climate (if no other environmental or management changes are accounted for). This would have a significant impact on future urban water management and planning.

1. Introduction

One of the major problems in current hydrological impact investigations of climate change is the spatial and temporal scale mismatch between the outputs of climate models (General Circulation Models or Regional Climate Models) and the small scale at which hydrological impact investigations are carried out. Up-to-date global and regional climate models produce results at spatial grid sizes in the range from 100 to 10 km, and at time steps of days to hours. Hydrological impact investigations, however, need information on climate changes at finer spatial scales (down to point scales), and for time scales as small as few minutes. Although river and urban drainage catchments most often have spatial sizes of at least few kilometers, the precipitation, temperature and evaporation inputs to hydrological models are most frequently based on point data (from meteorological stations). In terms of temporal scale, the flow in urban drainage systems has response times to precipitation in the order of magnitude of minutes. For Belgium, 10 min can be considered the shortest response time of our urban drainage systems.

In order to overcome this scale related gap between what climate models provide and what hydrological impact modelers need, statistical downscaling methods are traditionally applied. In the literature, they are usually classified in three types (Wilby et al., 1998; Nguyen et al., 2006; Fowler et al., 2007; Vrac and Naveau, 2007):

* Corresponding author at: Katholieke Universiteit Leuven, Department of Civil Engineering – Hydraulics Division, Kasteelpark Arenberg 40, BE-3001 Leuven, Belgium. Tel.: +32 16 321658; fax: +32 16 321989.

E-mail addresses: Patrick.Willems@bwk.kuleuven.be (P. Willems), mathieu.vrac@lsce.ipsl.fr (M. Vrac).

0022-1694/$ - see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.jhydrol.2011.02.030

- Transfer function approaches, trying to translate directly large-scale atmospheric information to local-scale meteorological data. In this class, some recent developments for enhanced downscaling of precipitation can be found in Vrac et al. (2007b), Dibike et al. (2008) and Olsson et al. (2004);
- Stochastic weather generators (Wilks and Wilby, 1999; Olsson et al., 2009), which are statistical models generating local-scale time series based on probability density functions whose parameters can be related to large-scale data (e.g. Vrac and Naveau, 2007); and
- Weather typing approaches, conditioning the simulation of small-scale data on so-called weather types over the region of interest (e.g. Vrac et al., 2007a).

Current literature on the development, application and testing of statistical downscaling methods, however, mostly focuses on hydrological impacts on larger river catchments and at daily time scales. These scales are rather coarse in comparison with the needs for finer scale urban drainage impact investigations (10-min and point scale). Most studies furthermore only cover one specific selected downscaling method. Given the high uncertainties involved in the downscaling process (see also the results of this paper), good practice would involve quantification of these uncertainties. Given that future climate conditions are highly uncertain, it is clear that such quantification is very difficult (which probably also explains why past studies most often did not deal with it). Instead of quantifying statistical uncertainties, it would, however, be possible to deal with scenario uncertainties. In the same way as it became common practice in climate change impact modelling to use an ensemble modelling approach using several climate model runs (several climate models, greenhouse gas emission scenarios and initial conditions), it should become common practice to apply several downscaling approaches. The latter would require an ensemble of statistical downscaling techniques and scaling assumptions to be considered.

This paper deals with the testing of statistical downscaling techniques with particular focus on small-scale hydrological impact investigations. In these investigations, the change in local precipitation is of primary importance. Uncertainties in the assessment of local scale precipitation changes mainly arise from (i) the significant uncertainties in the precipitation results from the climate models and (ii) the various assumptions underlying the downscaling process. Referring to reason (i), it is well-known that the uncertainties in the precipitation results of climate models are an order of magnitude higher in comparison with the climate model outputs on pressure (atmospheric circulation) and temperature (Hewitson, 1996; Baguis et al., 2009). This brings us to the two classes of statistical downscaling methods considered in this paper: methods that make use of the precipitation results of the climate models, and methods that do not make use of these results but are based on the more accurate climate models outputs, namely atmospheric pressure and related circulation patterns and temperature. When considering the former class (i.e., use of GCM precipitation), either the climate model precipitation results are used directly, or only the information of the precipitation changes. The precipitation changes can be represented in the form of "perturbation factors" (factor change φ), as commonly used in the so-called "Delta-approach" (Gellens and Roulin, 1998; Lettenmaier et al., 1999). When the precipitation results are biased (say with a factor φ_b), and assuming that the bias will be identical under future climate conditions, the same bias factor φ_b applies to the precipitation results under current climate conditions and the precipitation results under future climate conditions. It is clear that under these conditions the perturbation factor is not affected by the bias. Consequently, the results on the factor change (the perturbation factors) can be seen as being more accurate in comparison with the precipitation results themselves. This partly meets the above-mentioned problem on the poor accuracy of the climate model precipitation results.

The perturbation factors can be derived depending on different conditions, such as season, month of the year, time scale, precipitation intensity or exceedance probability of this intensity. The dependence on season and month is trivial given that climate conditions and their changes highly depend on the period in the year. Dependence on intensity or exceedance probability (or return period) might be relevant as well, given that changes in more extreme rain storms might differ from changes in less intense (i.e., more regular) storms. Given that intensities associated with given exceedance probabilities are called quantiles, the corresponding perturbation factors are in this paper called quantile-perturbation factors.

The second type of methods, which do not make direct use of the precipitation results of the climate models, tries to relate (small-scale) precipitation to the (climate model scale) atmospheric pressure and temperature results. This is commonly done by means of "weather typing" (e.g. Vrac and Naveau, 2007). For each time step (i.e., day) in the climate model simulation result, the atmospheric circulation pattern is identified from the climate model spatial atmospheric pressure results. The pattern is selected out of a limited set of patterns (or weather types). The local (downscaled) precipitation value for that day is taken from a local historical precipitation series, selecting the day in that series having analogue large-scale weather conditions (Zorita and von-Storch, 1998). "Analogue" means that the large-scale condition of the day to be downscaled is similar to that of 1 day in the historical dataset. This similarity can be defined through different distances or metrics, and can involve weather types (or more generally circulation data over a large region), as well as other criteria, such as season, month of the year and temperature.

Both types of statistical downscaling (SD) methods have been applied and tested in the paper. Because the hydrological impact investigations envisaged for this paper include the impacts on high runoff flows (in order to assess climate change impacts on floods), specific focus is given to the high precipitation extremes. Due to this focus, the perturbation factors (in the first type of methods) are considered in a quantile-based way. The quantile-perturbation based methods hereafter will be referred to as statistical downscaling methods type A: SD-A, whereas the methods based on weather typing are called methods type B: SD-B.

The downscaling approaches are calibrated and tested based on local data (including 10-min precipitation) for the main hydro-meteorological station of the Royal Meteorological Institute of Belgium at Uccle (Brussels) and a set of available climate model simulations covering that location.

Section 2 describe the data used (climate model runs and historical data). Sections 3 and 4 thereafter give an overview of the quantile-perturbation and weather typing based downscaling methods applied and evaluated in this paper. Section 5 summarizes the results and evaluates the differences, and is followed by general conclusions in Section 6.

2. Data used (climate model runs and historical data)

Use is made of global climate model simulations, specifically for the climate model grid cell covering the main meteorological station of Belgium at Uccle (Brussels). From the European ESSENCE project (http://www.knmi.nl/~sterl/Essence/), a set of 17 ensemble runs from the ECHAM5 general circulation model were provided by the Dutch Royal Meteorological Institute (KNMI). These ensemble runs are labelled as run 21 till run 37 and cover continuous simulations for the period 1950–2100 (historical forcing till

2000; A1B emission scenario of IPCC after 2000). The 17 runs differ in the initial circulation conditions. Daily sea level pressure, temperature and precipitation results have been taken from these runs. In order to investigate the climate changes, the period 1961–1990 is considered as the reference period, and the period 2071–2100 as the future climate period. Hence, climate changes in this paper refer to the changes from the 30-year reference period to the 30-year future period.

Local historical data at Uccle (10-min precipitation intensities and daily temperatures) were considered for the period 1901–2000 (100-year period, or subperiods). To obtain information on historical weather types, these station data were complemented with the daily 1.125° × 1.125° ERA40 re-analysis data on European sea level pressures (Uppala et al., 2005), for the period 1967–2000, and selected for the NorthWest-Atlantic region (15°W–25°E; 35– 65°N).

3. Quantile-perturbation based downscaling methods

The SD-A (quantile-perturbation based) methods in this paper have the common feature that precipitation quantile-perturbations are obtained per month after ranking the daily precipitation values from the climate model results in both the reference period 1961–1990 and the future period 2071–2100. Daily precipitation intensities (i.e., quantiles) having the same rank number in the future and reference periods are compared; the ratio of the precipitation quantile value in the future period over the corresponding quantile value in the reference period being the perturbation factor φ:

$$\varphi(p) = \frac{Q_f(p)}{Q_c(p)} \tag{1}$$

where $Q_f(p)$ and $Q_c(p)$ are respectively the future (2071–2100) and current (1961–1990) climate precipitation quantiles, both associated to the exceedance probability p.

The quantile-perturbation factors on daily precipitation intensities afterwards are applied to the historical Uccle series of 10-min precipitation intensities (considering the same reference period 1961–1990 or any longer period) in order to perturb this Uccle series. The perturbed Uccle series represents a modification of the historical Uccle series, to account for the expected changes (based on a specific climate model run) of the future climate conditions. All 10-min values of a given day are perturbed by the same perturbation factor for that given day.

The quantile-perturbation procedure thus basically involves the calculation of the factor change in daily precipitation for each specific month and each specific empirical probability (estimated by sorting the daily precipitation values). Suppose that the climate model control or scenario run contains n_g days in a given month; and that the historical series covers n_h days in the same month. In case the series are of the same length (cover the same years), n_g will be identical to n_h. The perturbation factors in (1) are calculated after sorting the precipitation intensities (Q_c or Q_f) of the n_g days in the climate model control and scenario runs: $Q(1) \geqslant \cdots \geqslant Q(k_g) \geqslant \cdots \geqslant Q(n_g)$. The exceedance probability p of any daily precipitation intensity $Q(k_g)$ is empirically calculated as the ratio $\left(\frac{k_g}{n_g}\right)$ of the rank number k_g over the total number of days n_g. In the same way, the historical series is sorted based on the daily precipitation intensities (Q_h): $Q_h(1) \geqslant \cdots \geqslant Q_h(k_h) \geqslant \cdots \geqslant Q_h(n_h)$. For each historical daily precipitation intensity $Q_h(k_h)$, the empirical exceedance probability is calculated as the ratio $\left(\frac{k_h}{n_h}\right)$ of the rank number k_h for that day over the length n_h of the historical series. The factor change (perturbation factor) applied to that day is based on the climate model control and scenario intensities for the same exceedance probability (in case n_g and n_h are identical):

$$\varphi\left(\frac{k_g}{n_g}\right) = \frac{Q_f\left(\frac{k_g}{n_g}\right)}{Q_c\left(\frac{k_g}{n_g}\right)} \tag{2}$$

In case n_g and n_h are different, control and scenario intensities with closest empirical exceedance probability are selected. This means that in (2) the rank number k_g will be selected such that the absolute difference $\left|\frac{k_g}{n_g} - \frac{k_h}{n_h}\right|$ is minimum for all integer values of k_g in the range $1 \leqslant k_g \leqslant n_g$, with k_h the rank number of the historical day considered.

It might happen that the historical series contains several days with identical precipitation values, e.g., in the range $i_h \leqslant k_h \leqslant j_h$. This will be mainly the case for the lower precipitation values; including the many dry days. The perturbation factors may, however, differ for these days. It therefore has to be decided which factor is applied to which day. This can be done in a random way or based on some criteria. Depending on these criteria five quantile-perturbation downscaling (SD-A) methods have been considered in this research:

- SD-A-1: a day is randomly selected (among the days in the same month and with identical precipitation quantile).
- SD-A-2: a day is selected based on four criteria, calculated for each day in the historical series and the climate model runs. They account for the precipitation conditions of the previous and next days in the series. In order of decreasing importance, these criteria have been taken by the authors as:
  C_1: the length of the previous dry spell period (if any),
  C_2: the length of the next dry spell period (if any),
  C_3: the ratio of the precipitation value for the previous time step over the value for the current time step, and
  C_4: the ratio of the precipitation value for the next time step over the value for the current time step.
  Criteria C_3 and C_4 are only considered when the precipitation value at the current time step differs from zero.

From the above, it became clear that the four criteria are only applied in case several days (in the same month) have identical precipitation value, i.e. $Q_h(i_h) = \cdots = Q_h(k_h) = \cdots = Q_h(j_h)$ for $i_h \leqslant k_h \leqslant j_h$. For each day in the historical series $Q_h(k_h)$, among the set of perturbation factors $\varphi\left(\frac{k_g}{n_g}\right)$, where $\left|\frac{k_g}{n_g} - \frac{k_h}{n_h}\right|$ is minimum for all k_h values in the range $i_h \leqslant k_h \leqslant j_h$, one factor is selected based on the four criteria C_1, C_2, C_3 and C_4. Given that each factor $\varphi\left(\frac{k_g}{n_g}\right)$ is based on a day in the climate model control run (with precipitation intensity $Q_c(k_g)$), the four criteria can be calculated based on the climate model control run for each factor. The factor is selected for which the four criteria best match the criteria obtained for the historical day considered (with precipitation intensity $Q_h(k_h)$). The best matching day is the one that has the smallest absolute difference between the criteria applied to the historical and control series. Criterion C_1 has highest priority. If this criterion is not decisive, C_2 will be tested, and so forth. This method avoids that perturbation factors valid for wet periods will be applied to days situated in dry periods, and vice versa.

Given that identical precipitation quantiles most often relate to low precipitation conditions (i.e., all the zero precipitation days), application of the four criteria avoids that a single day in a long dry spell is perturbed into a wet day; by preference this will be done just after or before another wet period. In other words: among all historical days having identical daily precipitation value the highest perturbation factor is given to the day situated in a period with wettest conditions. Correspondingly, the lowest perturbation factor, i.e., zero or close to zero, is given to days situated in driest periods. This assumption is developed from the idea that, due to climate change, long dry spells in summer might become longer (as concluded for the study region by Baguis et al. (2009)). This is, however, an assumption, which might not completely hold. Therefore, also other plausible assumptions will be considered next (cfr. the ensemble downscaling principle discussed in the introduction). The assumption applied in SD-A-2 can be seen as an assumption that leads to most dry climate change impacts (longest dry spells in summer).

- SD-A-3: In this downscaling method, another assumption is considered. It involves the highest 10-min intensity values for each day in the historical series. The assumption is made that among all days having same daily precipitation value, the day with the highest 10-min peak precipitation intensity should be given the highest perturbation factor. It leads to most extreme short duration (10 min) intensity perturbations, and is based on the observations made by Boukhris and Willems (2008) that precipitation intensities with lower exceedance probabilities might have higher perturbation factors, and that this is more likely for the shorter duration intensities. Boukhris and Willems (2008) did their analysis based on daily, weekly, monthly and seasonal time scales. During the summer season, higher perturbation factors were found for the precipitation quantiles (derived from regional climate model results) when comparing daily values with weekly values, when comparing weekly values with monthly values, etc. When these results are extrapolated to the sub-daily time scales, it is possible that 10-min precipitation quantiles have higher perturbation factors in comparison with the daily intensities.

The reduction in perturbation factors from daily to higher time scales in summer, was explained by Boukhris and Willems (2008) by the decrease of the number of wet days in that season. In the quantile-perturbation based method, changes in the number of wet days are intrinsically accounted for (some days indeed receive zero perturbation factors, by which wet days are transferred to dry days).

- SD-A-4: Idem SD-A-3, but in case in the historical series several days of identical daily precipitation quantile have identical daily and 10-min precipitation values, highest perturbation factor is given to the day with the highest previous day precipitation. This assumption leads to strongest impacts when the downscaling results are applied for sewer or urban drainage flood impact investigations. Indeed, urban drainage systems typically have response times to precipitation shorter than 1 day.
- SD-A-5: Idem SD-A-4 but switching the role that daily and 10-min precipitation intensities play: ranking is done first based on the 10-min quantiles, and for days with identical 10-min intensity highest perturbation factor is given to the day with the highest daily precipitation intensity.

The SD-A methods are illustrated in Fig. 1 based on one selected ECHAM5 run. The figure confirms that the precipitation results from climate model runs may be strongly biased (in this case overestimation in January and underestimation in October). It also shows how the historical Uccle data are perturbed in a quantile-based way, assuming that the relative precipitation differences between the control and scenario runs of the climate model are valid. Please notice that the ratios between the SD-A-4 and Uccle quantiles are different from the ECHAM5 ratios. This is due to differences in the periods considered. The ECHAM5 ratios are based on the periods 1961–1990 and 2071–2100, while the corresponding perturbation factors are applied to the full available Uccle series 1901–2000, from where the results of the subperiod 1961–1990 are selected for plotting in Fig. 1.

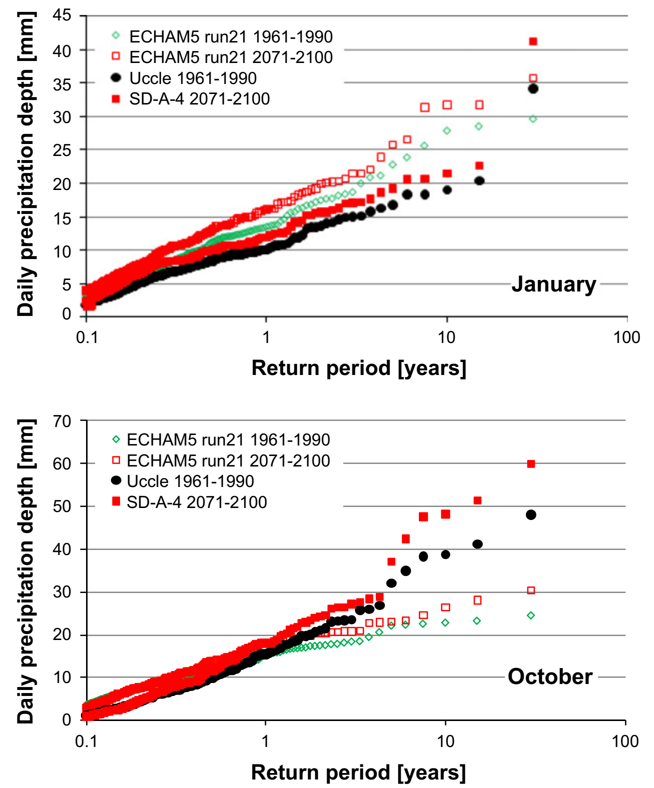

Fig. 1. Daily precipitation quantiles versus return period for the months of January and October: comparison of the precipitation results from ECHAM5 run 21 with the results of SD-A-4.

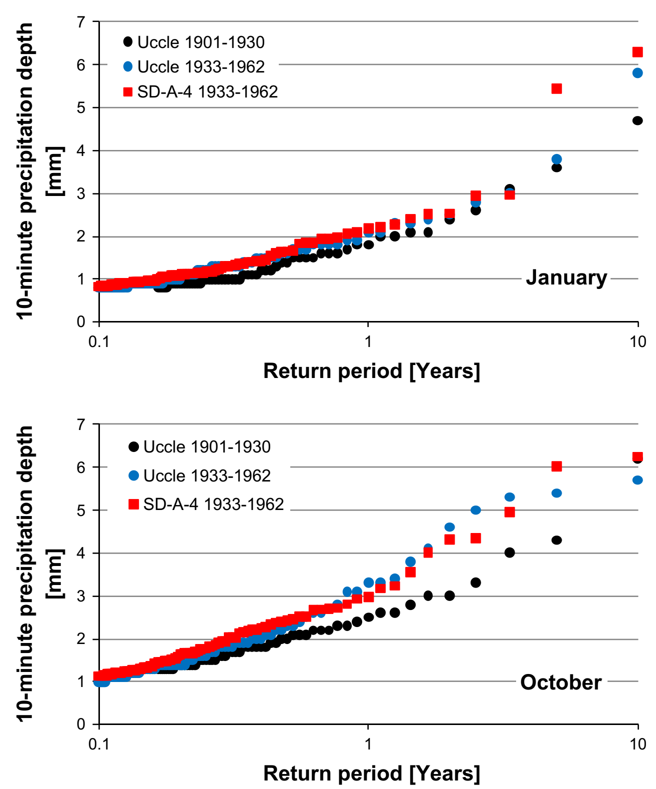

Fig. 2. Validation of the 10-min precipitation quantiles versus return period for the months of January and October: for SD-A-4 applied to the Uccle subperiods 1901–1930 (reference period) and 1933–1962 (scenario period).

The statistical downscaling involved in the SD-A methods is based on the assumption that the relative changes in 10-min intensities are identical to the changes (quantile perturbations) in daily intensities. Given that this is an important assumption, we validated this assumption by applying the SD-A methods to subperiods of the 100-year Uccle period. Fig. 2 illustrates this validation for two subperiods with clear differences in precipitation quantiles. The first subperiod (1901–1930 in Fig. 2) is taken as reference period, while the second subperiod (1933–1962) is considered as scenario period. After applying the quantile perturbations to the first subperiod, the 10-min precipitation intensities match well the observed values of the second subperiod. Same validation has been done for other subperiods and other SD-A methods. No systematic under- or overestimations have been found, which confirm the validity of the downscaling assumption underlying the SD-A methods.

Table 1
Overview of the 28 weather types of Lamb. N, E, S, W refers to the wind directions, C and A to the cyclonic and anticyclonic atmospheric patterns, U to an unclassified weather type.

Other types	Directional – hybrid types		
U	N	CN	AN
C	NE	CNE	ANE
A	E	CE	AE
	SE	CSE	ASE
	S	CS	AS
	SW	CSW	ASW
	W	CW	AW
	NW	CNW	ANW

4. Weather typing based downscaling methods

Weather types have been defined both for the historical conditions at central Belgium (zone in which the Uccle station is located) based on the ERA40 and for the ECHAM5 climate model pressure results. This has been done based on the Jenkinson–Collison classification technique by Demuzere et al. (2009), considering a set of 28 weather types (weather types of Lamb; Jones et al., 1993; see Table 1). The classification method is automated based on sea level pressure values at 16 locations in the NorthWest-Atlantic region centred around the studied location at Uccle (50°48′N en 4°20′E). From the 16 pressure values, pressure gradients and vorticity indices are computed and the weather type determined, following the Jenkinson–Collison method (Demuzere et al., 2009).

Fig. 3 shows that precipitation statistics clearly vary between these weather types and that the anticyclonic weather type occurs most frequently. Among the directional types, SW and W wind directions have the highest frequencies of occurrence in winter (ONDJFM), while for summer (AMJJAS) N and NE wind directions

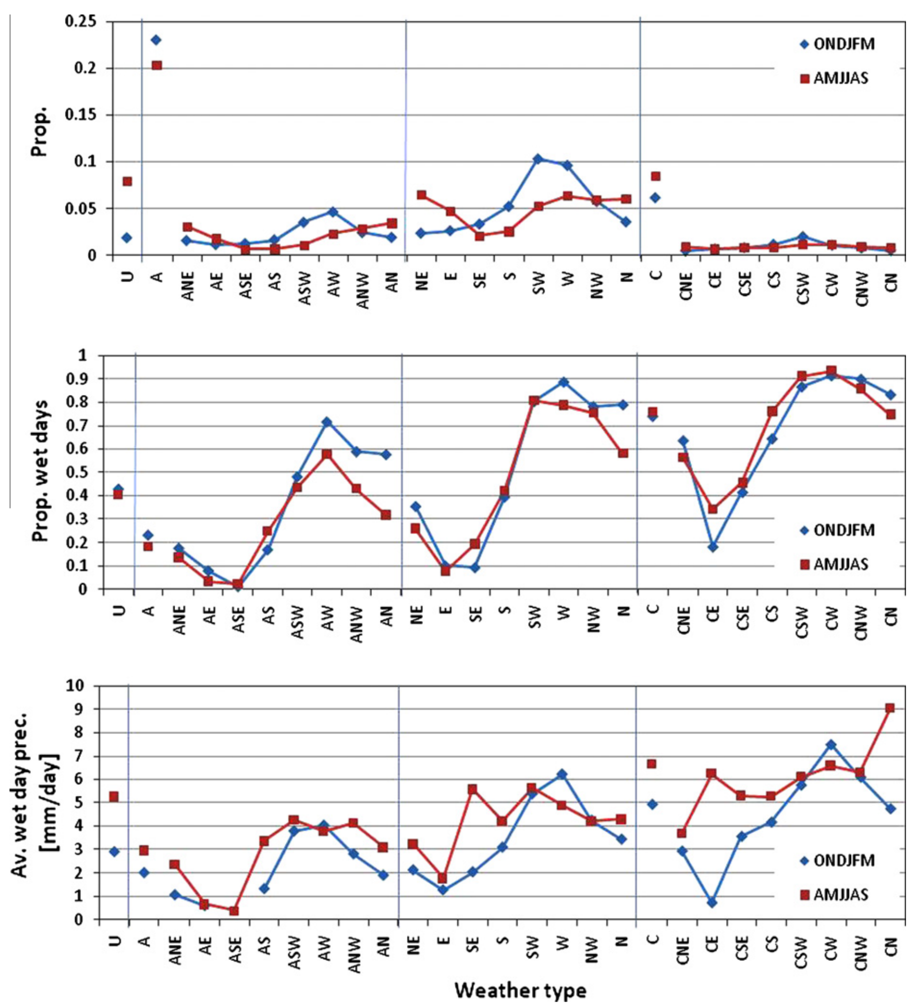

Fig. 3. Proportion of weather types (top), the proportion of wet days per weather type (middle), and the average daily wet day precipitation per weather type (bottom); for winter (ONDJFM) and summer (AMJJAS), considering daily Uccle precipitation data and Jenkinson–Collison weather typing based on ERA40 re-analysis data for the period 1967–2000.

also occur with high frequencies. Among all the directional types, the western wind directions (SW, W and NW) are associated with the highest proportions of wet days. This is valid for both winter and summer. During winter, the western wind directions also have highest average wet day precipitation values. During the cyclonic weather types, for most wind directions, the average wet day precipitation values are higher those from the non-cyclonic types. During summer, eastern and northern directions receive – in comparison with winter – higher wet day intensities. Wet days are in this research defined as days with total precipitation amounts higher than 0.3 mm.

The SD-B (weather typing based) downscaling methods use an analogue approach per month and per weather type. For each day in the climate model run a similar day is searched in the ERA-40 database (only considering days in the same month and weather type). The 10-min precipitation intensities for that day in the historical Uccle series are taken as the downscaled precipitation values. Although this can be done continuously for the full climate model simulation period (1950–2100 for the ECHAM5 runs considered here), only the results for the reference and future periods 1961–1990 and 2071–2100 are considered in this paper.

Seven SD-B approaches have been implemented depending on the method and criteria used to define similar or analogue days (based on a set of days having the same month and weather type). The following methods have been considered (Table 1):

- SD-B-1: a random day is selected; this means that no additional analogue criterion is considered next to the month and the weather type.
- SD-B-2: one additional analogue criterion is considered, based on the daily precipitation conditions. Among all days of the same month and weather type, the day with the closest empirical exceedance probability of precipitation is selected as the analogue day. The exceedance probability is considered rather than the precipitation value itself, because precipitation results of climate models might be biased from historical observations. Moreover, it is taken into account that the precipitation distribution for the future period might be shifted from the distribution in the reference period or the historical conditions. Looking for an analogue day based on the exceedance probability would not account for that distribution shift. Therefore, for each day in the future period, the exceedance probability of the precipitation is based on the distribution derived from the reference period in order to find the analogue day in the Uccle historical series. In case future climate conditions correspond with positive precipitation shifts, this would mean that for the future period more days with high precipitation values will be selected as analogue days. This approach, however, does not allow generation of future intensities higher than those in the historical dataset.

In case there are several days with identical precipitation quantile values, and thus with identical exceedance probabilities, a random day will be selected from that set.

- SD-B-3: idem SD-B-2, but further advanced in case there are several days with identical precipitation quantile values. The four additional criteria already discussed in method SD-A-2 are then considered.
- SD-B-1b, 2b, 3b: In those three variants, the three previous SD-B approaches are extended by incorporating temperature information. The extension is based on the temperature dependence

Table 2
Overview of the seven weather typing based downscaling (SD-B) methods. In case of several days with the same weather type in the same month, the resampling can be done fully random (methods SD-B-1), or based on additional criteria. The main additional criterion is based on the exceedance probability of the daily precipitation value (prec. prob. based; methods SD-B-2 and 3 and 4 and 7), the exceedance probability of the daily temperature value (temp. prob. based; method SD-B-4), or the temperature value itself (temp. based; methods SD-B-5 and 6). For some methods, additional criteria are considered depending on whether the exceedance probability is calculated based on the reference or scenario period, the 4 criteria of method SD-A-2, and (for the temp. based methods) whether the analogue day is based on the day with the closest temperature value, or a random day within a 2° or 5 °C interval. In all methods, the 10-min intensities of the analogue day are kept unchanged, except method SD-B-7 where the intensities are changed depending on the temperature change. For methods SB-B-1b and 2b and 3b, the resampling is done based on all days in the same month with the same weather type and within the same 5 °C temperature interval.

				Additional temperature based resampling criteria:		
				No additional resampling criteria		Additional resampling based on 5° temp. intervals
				No 7% prec. increase per °C temp. increase	7% prec. increase per °C temp. increase	
Resampling approach for days with identical weather type in the same month:	Random			SD-B-1		SD-B-1b
	Prec. prob. based	From reference period	No 4 criteria SD-A-2	SD-B-2		SD-B-2b
			4 criteria SD-A-2	SD-B-3		SD-B-3b
		From scenario period	4 criteria SD-A-2		SD-B-7	
	Temp. prob. based	From reference period	No 4 criteria SD-A-2	SD-B-4		
	Temp. based	4 criteria SD-A-2	Closest temp.	SD-B-5a		
			Within 2°	SD-B-5b		
			Within 5°	SD-B-5c		
		No 4 criteria SD-A-2	Closest temp.	SD-B-6a		
			Within 2°	SD-B-6b		
			Within 5°	SD-B-6c		

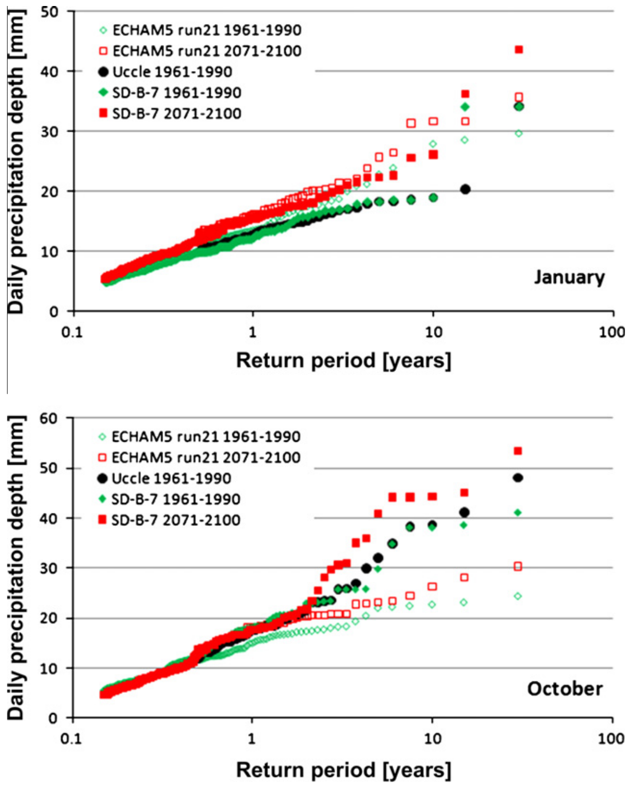

Fig. 4. Daily precipitation quantiles versus return period for the months of January and October: comparison of the precipitation results for ECHAM5 run 21 with the results of SD-B-7.

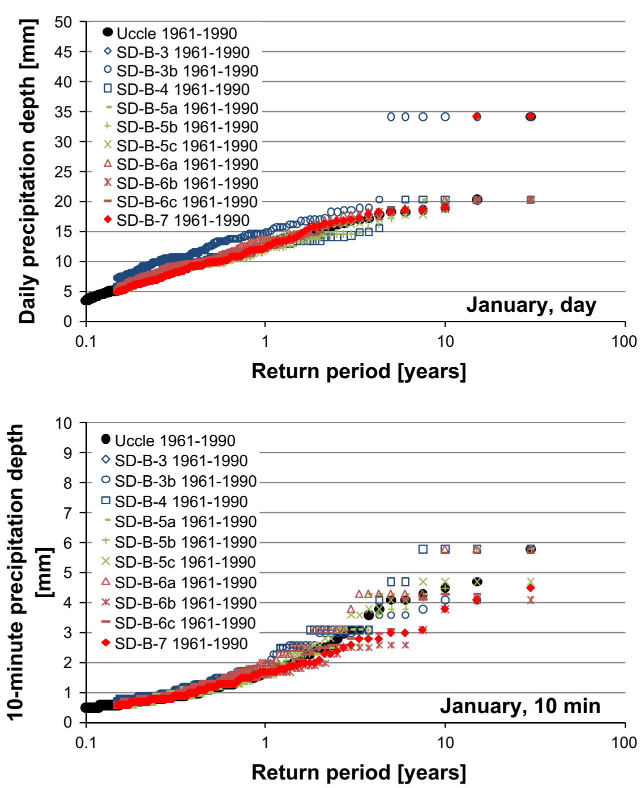

Fig. 5. Daily and 10-min precipitation quantiles versus return period for January: comparison of the Uccle data with the results of SD-B methods for ECHAM5 run 21.

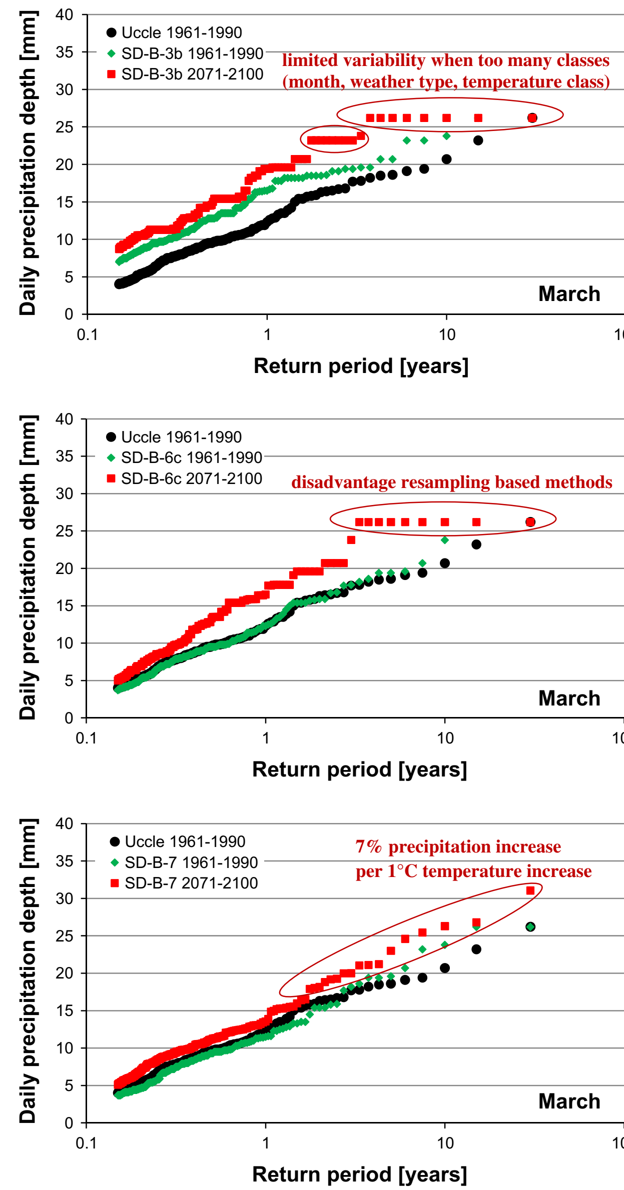

Fig. 6. Daily precipitation quantiles versus return period for March: comparison of the Uccle data with the results of SD-B-3b, 6c, 7 for ECHAM5 run 21.

of the saturation value of precipitable water in the atmosphere (known as the Clausius–Clapeyron relation: Lenderink and Van Meijgaard, 2008).

A first temperature-based downscaling method involves any of the above mentioned techniques, but after extending the classes from month and weather type to temperature intervals. Five degrees intervals are considered: (…;0], (0;5], (5;10], (10;15], (15;20], (20;25], (25;…)). These downscaling methods are labelled SD-B-1b, 2b or 3b depending on whether they follow the concept of SD-B-1, 2 or 3.

- SD-B-4: This temperature-based downscaling method looks for the analogue day having the closest temperature quantile (same method as in SD-B-2 but using temperature quantiles instead of precipitation quantiles).
- SD-B-5: This method looks for an analogue day (again among all days in the same month and with the same weather type) having the closest temperature value (or a temperature value in a given range: e.g. 2° or 5°). When different days have the same

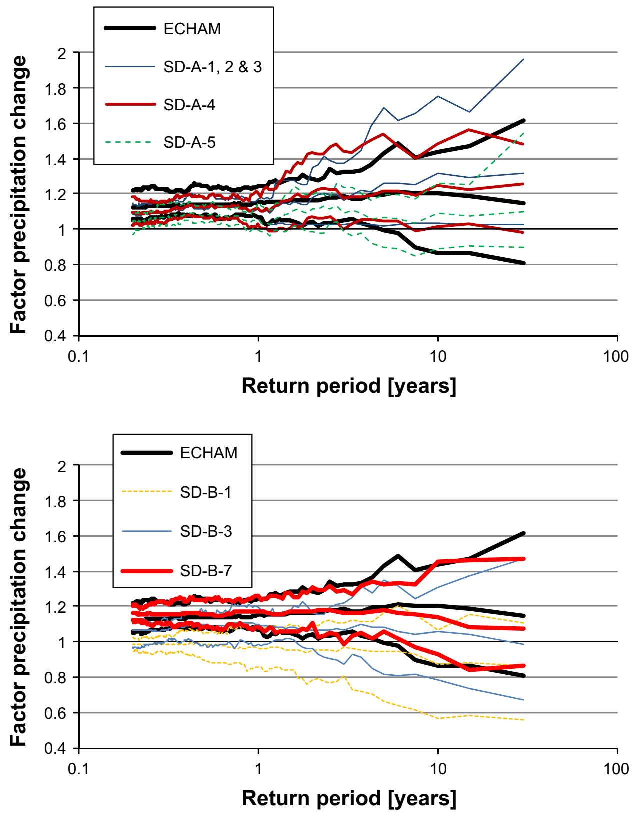

Fig. 7. Factor change in daily precipitation versus return period (whole year; minimum, mean and maximum of all 17 runs) based on ECHAM5 runs, SD-A and selected SD-B results without (SD-B-1, 3) and with (SD-B-7) temperature change.

temperature value (or have temperatures in the given range), a random day is selected. The approach based on the closest temperature is denoted SD-B-5a, while the ones based on temperature ranges SD-B-5b (2° intervals) and SD-B-5c (5° intervals).

- SD-B-6: Idem SD-B-5, but with an additional criterion to select the analogue day among different days with the same temperature value (or with temperature values in the same range): the selection will be based on precipitation exceedance probability, followed by the 4 criteria as in SD-B-3.
- SD-B-7: Idem SD-B-3, but with the analogue day based on the closest precipitation exceedance probability rather than the precipitation quantile (thus eliminating the effect of the precipitation distribution shift). This means that the exceedance probability of the precipitation is based on the distribution derived from the scenario period rather than the reference period in order to find the analogue day in the Uccle historical series. However, to compensate for the eliminated effect of the precipitation distribution shift, the Uccle precipitation values of the analogue day are increased in relation to the increase in temperature. In order to do so, the temperature of each day in the scenario period is considered; this temperature corresponds to a given probability (for the same month and weather type). For the same probability, month and weather type, the corresponding temperature rise from the control to the scenario period is calculated (temperature quantile based approach) based on the Clausius–Clapeyron relation. This relation assumes 7% increase in precipitation per 1 °C temperature increase. Work by the authors (not shown) confirmed that this also holds for the historical Uccle data and the ECHAM5 climate model results.

Methods SD-B-2 and SD-B-3 do make indirect use of the precipitation results of the climate model (daily and 10-min intensities).

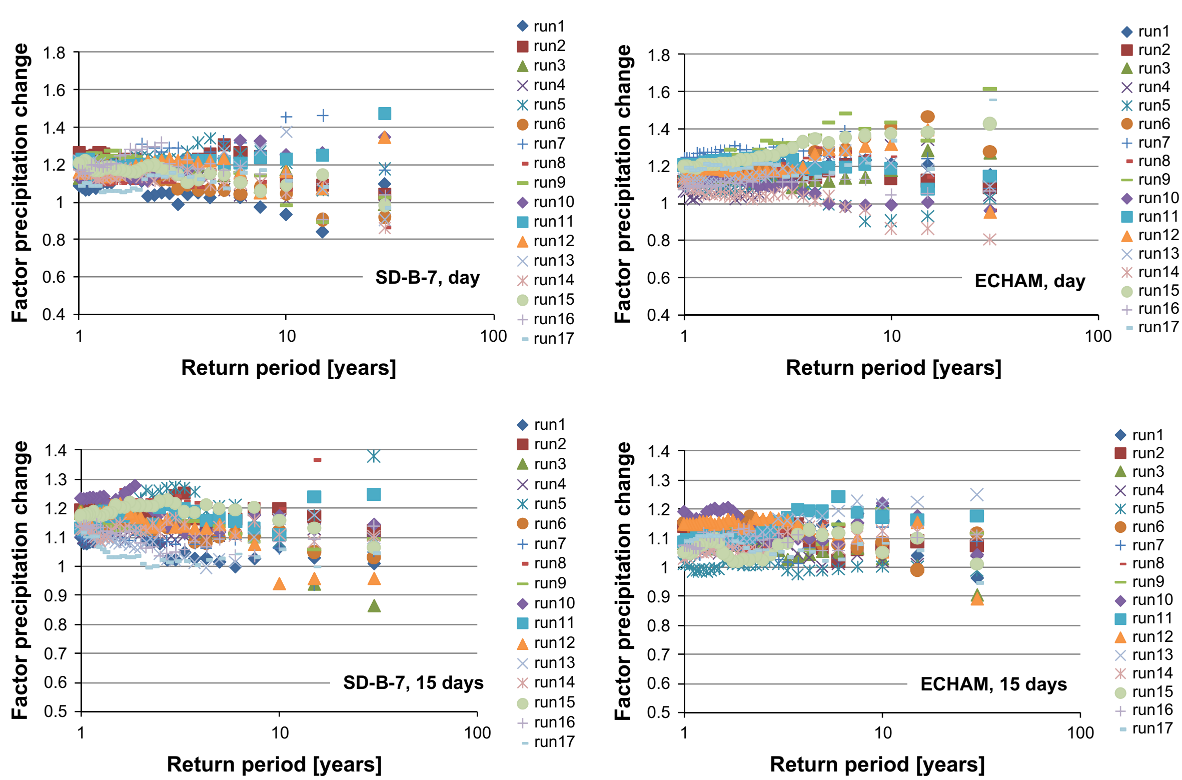

Fig. 8. Factor precipitation change versus return period for time scales of 1 day and 15 days (whole year; all 17 runs) based on ECHAM5 runs and SD-B-7 results.

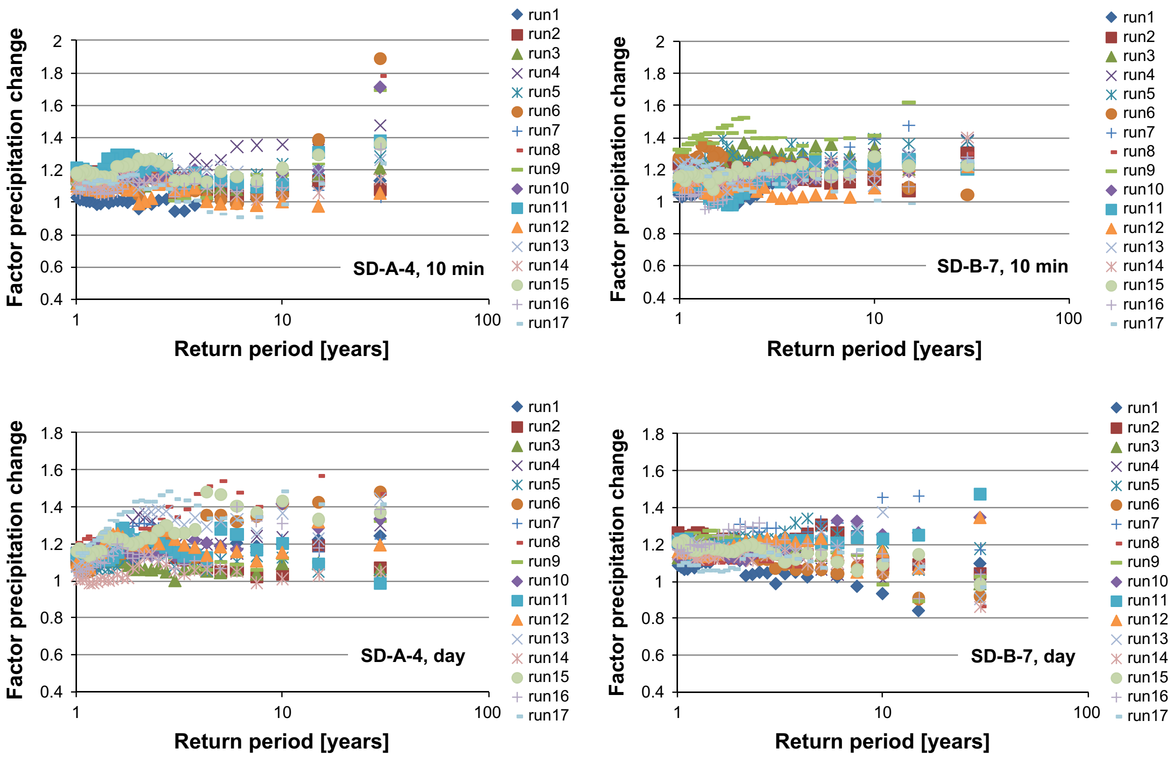

Fig. 9. Factor precipitation change versus return period for time scales of 10 min and 1 day (whole year; all 17 runs) based on SD-A-4 and SD-B-7 results.

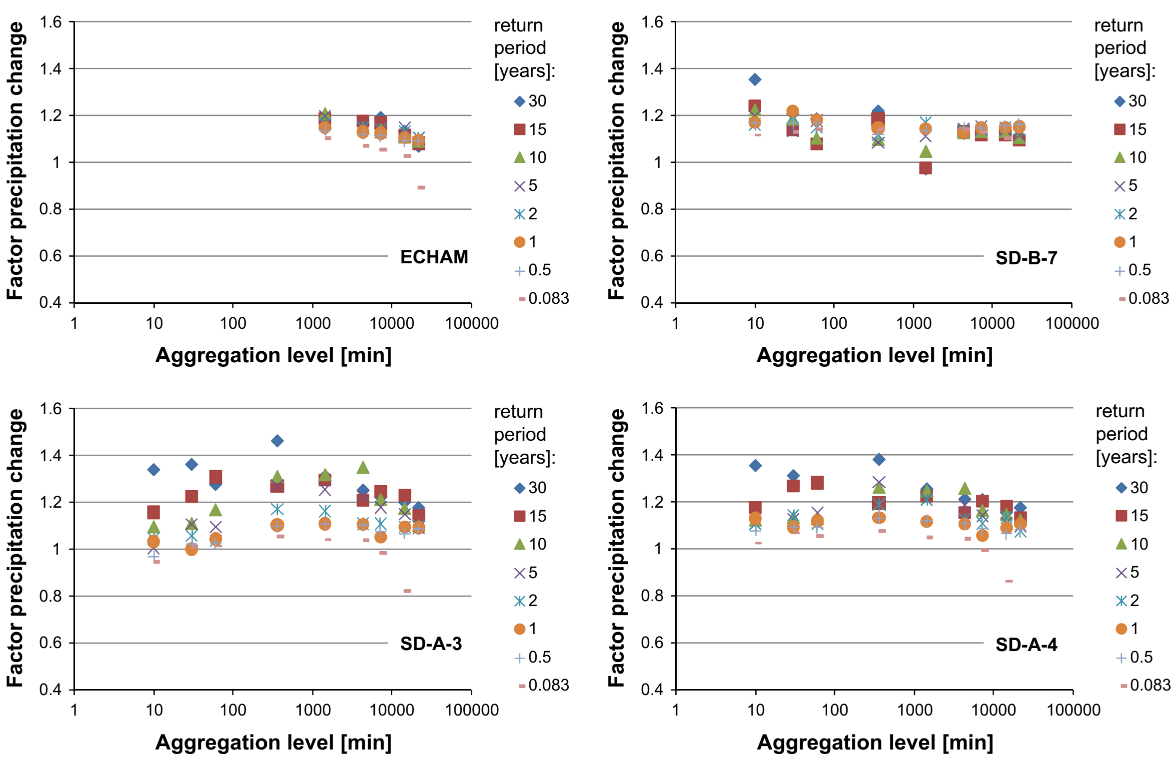

Fig. 10. Factor change in precipitation versus time scale and return period (whole year; mean of all 17 runs) based on ECHAM5 runs, SD-B-7, SD-A-3 and SD-A-4 results.

They make use of the precipitation exceedance probabilities (this means the relative rankings of the precipitation values) in the criteria for defining the analogue day. The precipitation values themselves are, however, never directly used in the weather typing

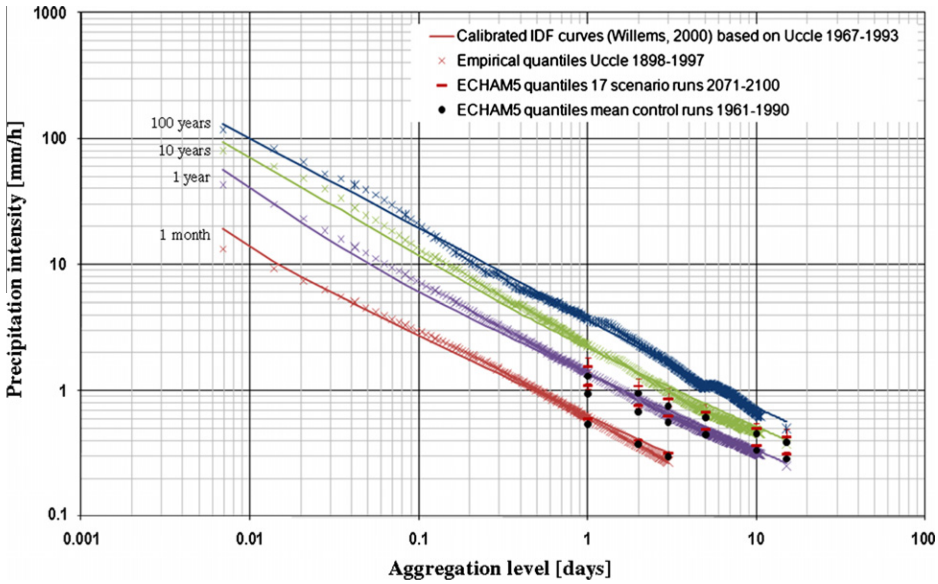

Fig. 11. Comparison of historical IDF-relationships, with the ECHAM5 simulation results (mean result of control period runs; mean, highest and lowest result of scenario period runs).

based methods. This differs from the quantile-perturbation based methods. For an overview of all downscaling methods applied, the reader is referred to Table 2.

Figs. 4 and 5 illustrate (same example as Fig. 1) through the comparison between the SD-B based downscaled climate model control run and the historical Uccle data, the (good) quality of the downscaling procedure. After comparison of the SD-B based downscaled climate model scenario run with the SD-B based downscaled control run, the climate change effects could be evaluated.

5. Comparison and evaluation of downscaling results

The proposed downscaling methods have been implemented based on the results of each of the 17 ECHAM5 runs. The quantile perturbations derived from these runs were, for the SD-A methods, applied to the full historical Uccle series (1901–2000) of 10-min precipitation intensities. For the SD-B methods, analogue days were defined for each day in the ECHAM5 series, selected from the Uccle historical subseries 1967–2000. The latter period had to be restricted to the period of re-analysis data available for weather type classification. The downscaling results for the reference subperiod 1961–1990 are hereafter analyzed in order to evaluate and compare the different downscaling methods and results. The historical observations for that subperiod are taken as reference data, while the perturbed series represent future conditions for 2071–2100. Comparisons are made of the precipitation changes (from the reference to the future period) at time scales of 10 min, 30 min, 1 h, 6 h, 1 day, 3 days, 7 days, 15 days and 30 days, and as a function of return period. This means that changes in precipitation/duration/frequency (IDF) relationships are studied. Special focus is given to the high precipitation extremes (given their importance in hydrological climate change impact investigations).

Fig. 5 shows for the reference period and one selected month the comparison of daily and 10-min precipitation quantiles between different SD-B methods. While interpreting these results, distinction should be made between the methods SD-B-1, 2 and 3, which do not make use of temperature information, and the other methods, which do. In the latter set of methods, methods SD-B-4, 5 and 6 are entirely based on resampling (but temperature used as parameter in the resampling procedure), while method SD-B-7 combines resampling with precipitation intensity increase due to temperature rise. From the analysis shown in Fig. 5, but extended to the whole range of time scales between 10 min and 15 days, and to all 17 ensemble runs, it becomes clear that method SD-B-7 outperforms the other SD-B methods. As illustrated in Fig. 6, this is because method SD-B-7 allows precipitation quantiles to be higher than the highest historical observation. Fig. 6 moreover makes clear that one should avoid too many resampling classes. In case the resampling is based on classes per month, per weather type and also per temperature interval (i.e., SD-B-3b in Fig. 6), the number of historical days in each class becomes too limited, hence limiting the sampling variability.

Next to the intercomparison between the methods SD-B, the climate change effects have been compared with those of the methods SD-A, and with the direct ECHAM5 precipitation outputs. Fig. 7 shows the changes in daily precipitation quantiles (minimum, mean and maximum change for all 17 ensemble runs) versus return period. The figure indicates that the methods SD-B-1, 2 and 3 have low quantile perturbations when compared with the ECHAM5 results and the SD-A methods. This suggests that changes in atmospheric circulation patterns do not fully explain the changes in precipitation quantiles (as we expect from the climate model precipitation results). When the change in temperature is incorporated, the changes in precipitation quantiles become stronger and similar to the ECAHM5 runs and SD-A quantile perturbations. When interpreting Fig. 7, one has to be aware, however, that the SD-B based precipitation changes do not need to be close to the ones derived from the ECHAM5 precipitation results. They indeed correspond to different approaches: dynamic versus statistical downscaling. However, the lower precipitation changes compared to the ECHAM5 and SD-A results combined with the findings that precipitation change depends on temperature, suggests that the weather typing methods improve the quality of the downscaling if they are advanced by incorporating temperature dependence in the precipitation change. When the different SD-A methods are compared, method SD-A-5 underestimates the ECHAM5 based precipitation changes, while method SD-A-4 slightly outperforms the other SD-A methods.

In Fig. 8, changes in daily and 15-day precipitation quantiles are compared between the ECHAM5 runs and the SD-B-7 method, for all empirical return periods higher than 1 year. Same comparison is shown in Fig. 9 for 10-min and daily precipitation quantiles between SD-A-4 and SD-B-7. Although the quantile perturbations of the different method differ, Figs. 7–9 show that they cover a similar range.

When the dependency between quantile perturbations and time scale is further analyzed (Fig. 10), it is shown that the methods SD-A and SD-B-7 lead to perturbations which for time scales smaller than 1 day are equal or slightly higher than the ones for the daily time scale. The increase is more significant for the higher return periods.

Figs. 11 and 12 extend the analysis to the comparison of the changes in IDF-relationships. Precipitation extremes extracted from the ECHAM5-runs systematically underestimate the corresponding values obtained from the historical IDF-relationships at Uccle (based on the 10-min precipitation intensities for the period 1967–1993, and published in Willems, 2000; Fig. 11). The underestimations are strongest for the daily time scale and reduce towards the larger time scales. After application of the SD methods, the precipitation bias is almost completely removed (Fig. 12). The SD methods, moreover, obtain unbiased precipitation statistics for time scales smaller than 1 day.

Next to the mean of the downscaling results based on the control runs, Figs. 11 and 12 also show the shifts in precipitation quantiles between the control and scenario runs (mean, highest and lowest of the 17 ensemble runs). After application of these shifts (based on the SD-B-7 method) to the historical IDF-curves, Fig. 13 shows that the intensity versus duration curve of a 1-month

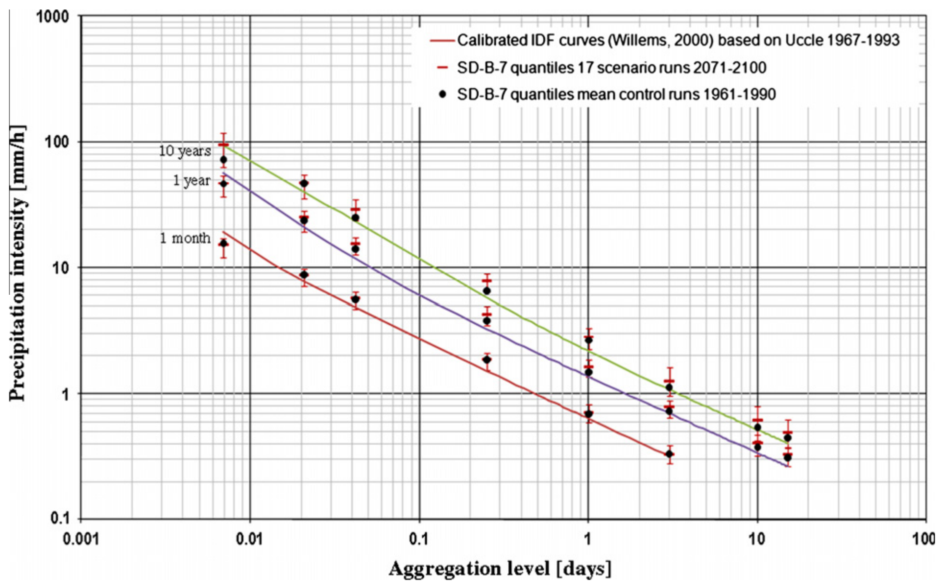

Fig. 12. Comparison of historical IDF-relationships with SD-B-7 downscaling results (mean result of control period runs; mean, highest and lowest result of scenario period runs).

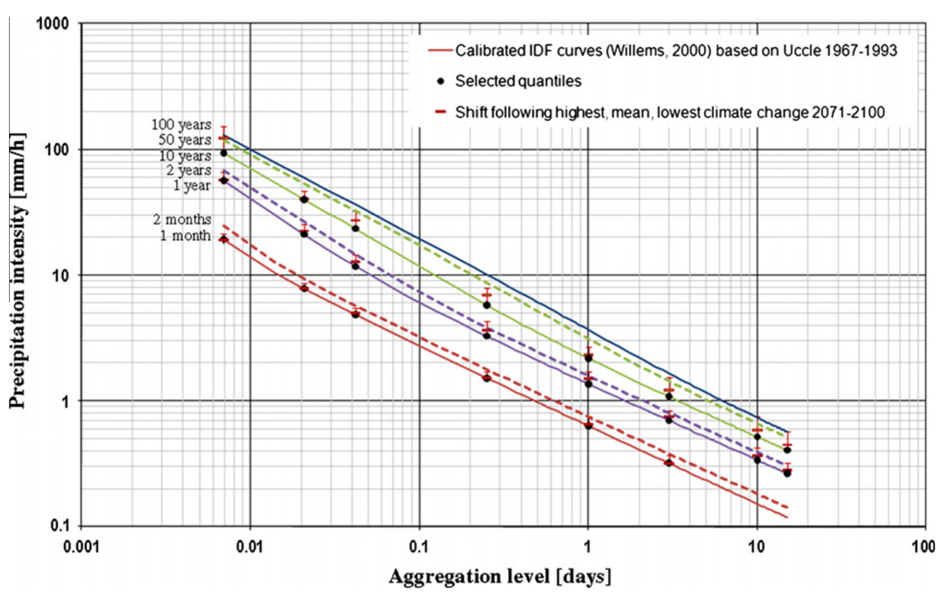

Fig. 13. Change in IDF-relationships based on mean, highest and lowest SD-B-7 downscaling result.

return period after shifting for the highest change comes close to the intensity versus duration curve of a 1.5-month return period. This means that for such highest change in precipitation design quantiles, a 1.5-month return period design value becomes a 1-month return period. In a similar way, a 2-year return period becomes approximately 1-year; a 100-year return period becomes a 10-year value. Note that all calculations in this paper are for the future scenario period 2071–2100.

These results are of direct use in urban drainage engineering. IDF-relationships are indeed most commonly used to obtain precipitation statistics to support the design of sewer systems. From the analysis of Fig. 13, it can be concluded that when a sewer system is currently designed (avoiding sewer surcharge, or flooding) for a 2-year return period, sewer surcharge or flooding might occur approximately twice more frequently for the same system design. It also would mean that – to get identical surcharge or flood safety levels – design storms have to be adjusted, or design storms with lower return periods have to be used for the design (assuming of course that no other changes, i.e., land use or water management and planning, need to be accounted for).

6. Conclusions

Methods for statistical downscaling (from daily down to 10-min time scales) of precipitation series and statistics have been tested based on ECHAM5 global climate model results and ground station data at Uccle (Belgium). Quantile-perturbation based methods, which make direct use of the precipitation results of the climate model, have been compared with weather typing based methods. It was found that the changes in weather type frequencies cannot entirely explain the changes in precipitation intensities. Therefore, the weather typing method was advanced after implementation of additional increases in precipitation intensities depending on temperature changes (based on the Clausius–Clapeyron relation). When this method is applied to obtain statistically downscaled short-duration (down to 10 min) precipitation intensities from the daily climate model simulation results of atmospheric pressure and temperature, changes in precipitation intensities become similar to the changes derived from the direct use of the climate model precipitation results. The underestimation in the precipitation changes for the weather typing method thus could be removed by the temperature correction. After this correction, both downscaling procedures lead to close results.

The downscaling procedures are useful for urban water engineering design and flood risk estimation applications. The results for Uccle show that precipitation design statistics need to be revised or future changes in return periods taken into account. For the climate scenario with highest increase in summer precipitation extremes by 2071–2100 (among the 17 ECHAM5 ensemble runs, based on method SD-B-7, but similar for SD-A-4), the precipitation intensities for a return period of 2 years have to be increased by 27% (shifting of the IDF-curve by a factor 1.27). For the same scenario, precipitation intensities for a return period of 10 years have to be increased by 50%. This means that a 2-year return period design rainfall would occur twice that often by 2071–2100: the return period of that design value would decrease from 2 years to about 1 year. For the same case, a 5-year return period would reduce to about 2.5 years. Given that most urban drainage systems are currently designed for return periods of street flooding in this range, sewer system floods would occur – for the most pessimistic of the 17 ensemble runs considered – about twice that often in the future.

When considering these "pessimistic" impact results, water engineers also have to be aware of the high uncertainties in the future projections and related impacts. Indeed, impacts range from approximately zero precipitation change up to the "pessimistic" changes given above. The impact ranges would further widen if more climate models, including regional ones, would be considered. The ensemble modelling approach based on a large set of climate model simulations, however, only covers part of the total uncertainty. This paper confirmed that the choice of the downscaling methods introduces additional uncertainty. Therefore, the authors recommend extending the ensemble approach incorporating a range of potential downscaling methods. Some of the downscaling methods outperform others, as was shown in this paper based on comparisons with historical data and after evaluation of the consistency of the precipitation changes as function of time scale and return period. The "best" methods (SD-A-4 and SD-B-7 in this research) would form a reduced ensemble that can be applied in hydrological impact investigations. The range of hydrological impact results then would provide information on the scenario uncertainties due to the use of different climate models, different greenhouse gas emission scenarios, and (discussed in this paper) different downscaling procedures and related assumptions.

Acknowledgements

The research has been supported by a travel fund by the National Fund for Scientific Research – Flanders (F.W.O.-Flanders), Belgium. The ECHAM5 runs have been made available by Andreas Sterl of the Dutch Royal Meteorological Institute (KNMI), while the historical Uccle series were provided by the Royal Meteorological Institute of Belgium. The ERA40 based weather classifications for Belgium have been derived by Mathias Demuzere and Nicole van Lipzig of the Department of Earth and Environmental Sciences of K.U.Leuven.

References

Baguis, P., Roulin, E., Willems, P., Ntegeka, V., 2009. Climate change scenarios for precipitation and potential evapotranspiration over central Belgium. Theor. Appl. Climatol.. doi:10.1007/s00704-009-0146-5.

Boukhris, O., Willems, P., 2008. Climate change impact on hydrological extremes along rivers in Belgium. In: Samuels et al. (Eds.), Flood Risk Management: Research and Practice. Taylor & Francis Group, London, pp. 1083–1091.

Demuzere, M., Werner, M., van Lipzig, N.P.M., Roeckner, E., 2009. An analysis of present and future ECHAM5 pressure fields using a classification of circulation patterns. Int. J. Climatol. 29 (12), 1796–1810.

Dibike, Y.B., Gachon, P., St-Hilaire, A., Ouarda, T.B.M.J., Nguyen, V.T.V., 2008. Uncertainty analysis of statistically downscaled temperature and precipitation regimes in Northern Canada. Theor. Appl. Climatol. 91, 149–170.

Fowler, H.J., Blenkinsopa, S., Tebaldi, C., 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modeling. Int. J. Climatol. 27, 1547–1578.

Gellens, D., Roulin, E., 1998. Streamflow response of Belgian catchments to IPCC climate change scenarios. J. Hydrol. 210, 242–258.

Hewitson, B., 1996. Climate downscaling: techniques and application. Climate Res. 7, 88–95.

Jones, P.D., Hulme, M., Briffa, K.R., 1993. A comparison of Lamb circulation types with an objective classification scheme. Int. J. Climatol. 13, 655–663.

Lenderink, G., Van Meijgaard, E., 2008. Increase in hourly precipitation extremes beyond expectations from temperature changes. Nat. Geosci. 1, 511–514.

Lettenmaier, D.P., Wood, A.W., Palmer, R.N., Wood, E.F., Stakhiv, E.Z., 1999. Water resources implications of global warming: a US regional perspective. Climate Change 43, 537–579.

Nguyen, V.T.V., Nguyen, T.D., Gachon, P., 2006. On the linkage of large-scale climate variability with local characteristics of daily precipitation and temperature extremes: an evaluation of statistical downscaling methods. Adv. Geosci. (WSPC/SPI-B368) 4 (16), 1–9.

Olsson, J., Uvo, C.B., Jinno, K., Kawamura, A., Nishiyama, K., Koreeda, N., Nakashima, T., Morita, O., 2004. Neural networks for rainfall forecasting by atmospheric downscaling. J. Hydrol. Eng. 9 (1–12). doi:10.1061/(ASCE)1084-0699(2004)9:1(1).

Olsson, J., Berggren, K., Olofsson, M., Viklander, M., 2009. Applying climate model precipitation scenarios for urban hydrological assessment: a case study in Kalmar City, Sweden. Atmos. Res. 92, 364–375.

Uppala et al., 2005. The ERA-40 re-analysis. Quart. J. Roy. Meteorol. Soc. 131, 2961–3012.

Vrac, M., Naveau, P., 2007. Stochastic downscaling of precipitation: from dry events to heavy rainfalls. Water Resour. Res. 43, W07402. doi:10.1029/2006WR005308.

Vrac, M., Stein, M., Hayhoe, K., 2007a. Statistical downscaling of precipitation through nonhomogeneous stochastic weather typing. Climate Res. 34, 169–184.
Vrac, M., Marbaix, P., Peillard, D., Naveau, P., 2007b. Non-linear statistical downscaling of present and LGM precipitation and temperatures over Europe. Climate Past 3, 669–682.
Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J., Wilks, D.S., 1998. Statistical downscaling of general circulation model output: a comparison of methods. Water Resour. Res. 34, 2995–3008.
Wilks, D.S., Wilby, R.L., 1999. The weather generation game: a review of stochastic weather models. Prog. Phys. Geogr. 23, 329–357.
Willems, P., 2000. Compound IDF-relationships of extreme precipitation for two seasons and two storm types. J. Hydrol. 233, 189–205.
Zorita, E., von-Storch, H., 1998. The analog method as a simple statistical downscaling technique: comparison with more complicated methods. J. Climate 12, 2474–2489.