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Downscaling transient climate change with a stochastic weather generator for the Geer catchment, Belgium

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ABSTRACT: The coarse resolution of climate models creates the need for future scenarios which are downscaled to an appropriate spatial scale. Considerable effort has been devoted to the development of downscaling methods, but a number of important issues remain to meet users' needs. These include the assessment of uncertainty for future scenarios, and the production of scenarios at time scales relevant to stakeholders. This paper describes a methodology which addresses these issues by producing a multi-model ensemble of transient climate-change scenarios. The method couples an existing stochastic rainfall model to a new, transient implementation of a weather generator, using changes projected by an ensemble of regional climate model experiments. The methodology is demonstrated by the generation of transient scenarios of daily rainfall, temperature and potential evapotranspiration for the Geer catchment in Belgium for the period 2010–2085. The utility of these scenarios is demonstrated by assessing the changes projected by the simulated time series of several temperature indices. The Geer is projected to experience a decrease in the occurrence of frost days with a corresponding shortening of the frost season and lengthening of the growing season. By examining an ensemble of transient scenarios, the range of uncertainty in these projections is assessed, but, further, it is suggested that additional information on the projected timing of specified threshold events or system responses may be provided. This could aid stakeholders in assessing the likely time scales of required interventions and adaptation responses.

KEY WORDS: Climate change · Transient scenarios · Weather generator · Downscaling · RCMs

1. INTRODUCTION

One of the fundamental difficulties with the use of climate models to assess the impact of climate change is the mismatch of scales between model output and that required by the climate impacts community. Downscaling of output from general circulation models (GCMs) is a common strategy to bridge this gap. However, despite the development and application of a wide range of dynamical (i.e. regional climate models, RCMs; Rummukainen 2010) and statistical approaches (Wilby & Wigley 1997, Fowler et al. 2007, Maraun et al. 2010), several key challenges remain for the climate change impacts community.

One of these challenges is to better represent future climate projections and associated uncertainties in a policy- and decision-making context (Smith & Stern 2011). Uncertainties in climate model projections may

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be addressed through the use of multi-model and perturbed physics ensembles (Tebaldi & Knutti 2007, Collins 2007); however, many projections are in the form of time-slice experiments, frequently for the end of the 21st century, which does not correspond with the planning horizon for many stakeholders. Although some transient RCM simulations are becoming available (e.g. Murphy et al. 2009b, Evans 2011), the large ensembles required to explore modelling uncertainty are not yet computationally feasible, and time-slice experiments are still required. Furthermore, RCM simulations contain biases when compared with climate observations (e.g. Jacob et al. 2007) and also frequently require additional statistical downscaling for local-scale climate-change impact assessments.

Downscaling with stochastic weather generators (WGs) (Wilks & Wilby 1999, Wilks 2012) is an attractive option, as it is possible to produce long or multiple realisations of synthetic weather series based on the properties of observed meteorological records. This provides the opportunity to simulate more realistic weather variability and extremes than with climate models, and to assess the uncertainty inherent in projections of future change. A framework combining the Neyman-Scott Rectangular Pulses model (NSRP; Cowpertwait 1991, Burton et al. 2008) for rainfall and the Climatic Research Unit (CRU) daily WG (Watts et al. 2004, Kilsby et al. 2007) has been used to generate local-scale state-of-the-art probabilistic projections of climate for the UK as part of the UKCP09 projections (Jones et al. 2009, Murphy et al. 2009b). Its application for the UKCP09 projections enables users to generate projections for 30-yr time-slices representing the 2020s through to the 2080s (Jones et al. 2009). The application of this framework has therefore, to date, been limited to the assessment of climate change impacts for time-slice simulations, for example, to produce projections of hydrological flow series and probabilistic estimates of changes in climate and flow statistics for UK rivers (Fowler et al. 2007, 2008, Manning et al. 2009). In contrast, Podestá et al. (2009) used a resampling-based WG which can replicate an observed low-frequency trend or a hypothetical climate trajectory (in this instance over a 25 yr period) to assess the temporal evolution of the economic sustainability of agricultural systems in the Argentine Pampas.

The integrated NSRP rainfall model and CRU WG have, however, been extended in a number of different ways. An online tool for the simulation of 5 km grid cell weather variables for 30 yr time-slices is available (Jones et al. 2009), but is limited to the UK domain. Van Vliet et al. (2012) demonstrated a further development for a catchment in the Netherlands through the application of a version of the NSRP model that simulates spatial rainfall fields. Burton et al. (2010) also describe a new framework to generate a large ensemble of time-evolving (transient) daily rainfall scenarios for the period 1997–2085 for the Brévilles spring in northern France. This used a version of the NSRP rainfall model with transient parameterisations to produce an ensemble of transient rainfall scenarios based on changes projected by 13 different RCM experiments. Alternative formulations of the NSRP model are also now being considered in the context of non-stationary simulations (Evin & Favre 2013).

Here, the Burton et al. (2010) framework is extended for the Geer catchment (Belgium) to include the addition of a new, transient implementation of the CRU WG to produce continuous, consistent daily series of precipitation, temperature and potential evapotranspiration (PET). This study therefore describes the integration of the transient NSRP with the CRU WG and its validation, and underpins the assessment of hydrological changes in the Geer described by Goderniaux et al. (2011).

2. DATA AND MODELS

2.1. The Geer catchment

The Geer catchment is located in eastern Belgium, north-west of the city of Liège, in a region characterised by intensive agriculture. It extends over approximately 480 km^2, on the left bank of the Meuse River (Fig. 1), and is important because the chalk aquifer is largely exploited for drinking water but suffers from severe nitrate contamination problems due to intensive agricultural activities. Belgium has experienced an increase in mean daily temperatures over the 20th century (Blenkinsop 2005), and, since the 1950s, there has been a significant positive trend in extreme daily temperatures (Van de Vyver 2012). Coupled with projected changes in precipitation which suggest a large decrease in summer (Goderniaux et al. 2009), the response of the hydrological system could have a significant impact on water resources for the local population.

2.2. Observed climatic data

The precipitation record at Waremme (see Fig. 1) was selected to calibrate the rainfall model, as it offers the longest continuous series of homogeneous data (1960–2004) in the Geer catchment and is also representative of average rainfall across the area. However, for subsequent modelling of climate-change impacts, such as the hydrological behaviour of the catchment, daily PET data and other variables are also needed. The CRU WG is able to provide simulated PET values but requires additional input variables (see Section 3.1) to do so. Sufficiently long series of these additional variables are not available for Waremme and so the nearby Bierset (15 km) was selected as the most appropriate weather station to use to provide representative meteorological data. In particular, this station offers a long, continuous series of temperature data that is largely contemporaneous with the Waremme precipitation record. Precipitation at the 2 locations is closely related, demonstrated by a correlation coefficient of 0.84, with mean precipitation at Bierset only slightly higher than that at Waremme (based on 7 yr of contemporaneous data). Mean monthly temperatures for the 2 locations are very similar, with differences not exceeding 0.2°C (again, based upon 7 yr of contemporaneous observations). Mean daily temperatures for the 2 locations are also very highly correlated, demonstrated by a correlation coefficient of 0.99 (0.96 after removal of the annual temperature cycle). This suggests that it is reasonable for the Waremme precipitation to be used in conjunction with the temperature at Bierset to represent the climatology of the Geer catchment.

Ideally, data for the period 1961–1990 should be selected to calibrate the WG to correspond with RCM control period simulations. However, although the temperature and precipitation series are continuous throughout this time, records of some of the variables required to estimate PET only commence in 1985. The CRU WG requires observed data with a duration of at least 20 yr (Watts et al. 2004) for robust calibration; thus, to ensure this could be achieved for all variables, the period 1960–2004 was used. However, this means that the total calibration period does not correspond with the RCM control period, and, consequently, a part of the change projected by the RCMs might be assumed to be present in the observed data set. This is addressed in Section 3.1, describing the calculation of change factors (CFs) from the climate model ensemble.

2.3. Regional climate models

RCM output from the European Union's Fifth Framework Programme (FP5) PRUDENCE project (Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects; Christensen et al. 2007) was used to derive projections of regional climate at a resolution of 0.5° × 0.5°. Mean daily temperature and daily total precipitation were extracted for a 3 × 3 matrix of grid cells centred on the Geer catchment for the control (1961–1990) and future (2071–2100) time-slices under the SRES A2 emissions scenario (Nakićenović et al. 2000). Such time-slice experiments are assumed to be representative of a stationary climate and here were used to derive CFs for a series of climate statistics, these, in turn, being used to perturb

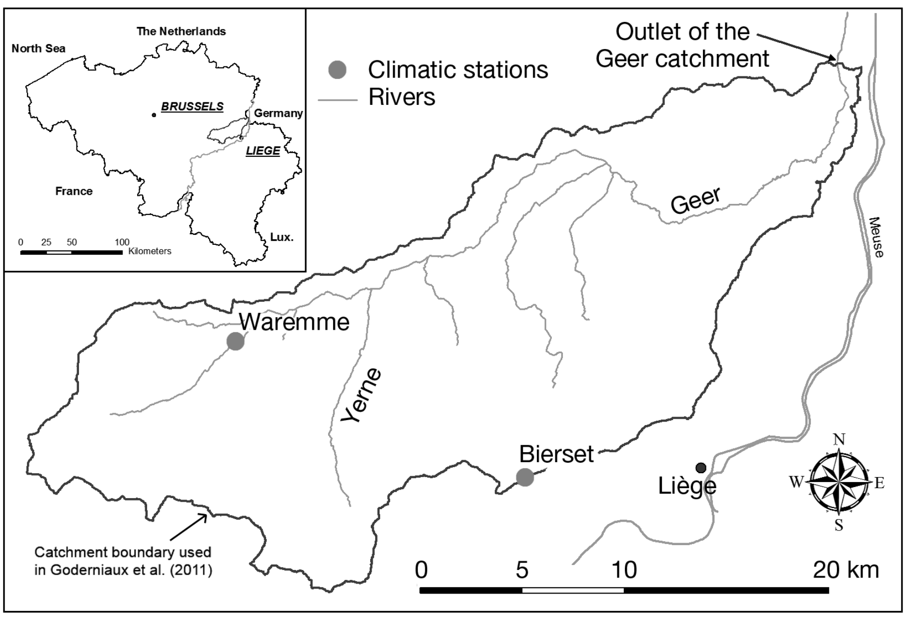

Fig. 1. Location of the Geer catchment, Belgium

Table 1. The 6 regional climate model (RCM) experiments used from the PRUDENCE project. The acronyms adopted by the AquaTerra project (Gerzabek et al. 2007) are used in this study, the suffixes E and H denoting RCMs driven by the ECHAM4/OPYC and HadAM3H/P/HadCM3 general circulation models (GCMs), respectively. DMI: Danish Meteorological Institute; SMHI: Swedish Meteorological and Hydrological Institute; HC: Met Office Hadley Centre. For further details on RCM formulations see Jacob et al. (2007)

RCM	AquaTerra acronym	Institute	Driving GCM	PRUDENCE acronyms
HIRHAM	HIRHAM_H	DMI	HadAM3H A2	HC1 / HS1
HIRHAM	HIRHAM_E	DMI	ECHAM4/OPYC A2	ecctrl / ecscA2
RCAO	RCAO_H	SMHI	HadAM3H A2	HCCTL / HCA2
RCAO	RCAO_E	SMHI	ECHAM4/OPYC A2	MPICTL / MPIA2
HadRM3P	HAD_H	HC	HadAM3P A2	adeha / adhfa
Arpège	ARPEGE_H	Météo-France	HadCM3 A2	DA9 / DE6

the stochastic rainfall model and CRU WG (see Section 3).

Here, we use the climate model ensemble shown in Table 1. The full range of uncertainty generated by the choice of GCM boundary conditions is necessarily constrained by the experimental structure provided by the PRUDENCE project (Déqué et al. 2007). In this instance further limitations are imposed by the resources available to apply the downscaled RCM scenarios to subsequent hydrological modelling. It is acknowledged that such multi-model ensembles do not sample structural uncertainties in a systematic manner, and many models also possess common components and algorithms (Collins 2007). All RCM-GCM combinations are thus not explored, and the ensemble may be considered what Tebaldi & Knutti (2007) defined as an 'ensemble of opportunity'. Nonetheless, this ensemble is the same as that used by Goderniaux et al. (2009) who employed a quantile correction approach to downscale stationary time-slice simulations. The simulations provided in the present study could, therefore, also be used to provide an indication of the uncertainty in the modelled catchment hydrological response to different climate downscaling methods (for an initial assessment see Goderniaux 2010).

3. METHODS

3.1. Calculating change factors

The widely used CF approach (Prudhomme et al. 2002, Diaz-Nieto & Wilby 2005) may be used to downscale projections from the RCM scale to that required for climate impacts assessments. This method assumes that climate models more accurately simulate relative change than absolute values, and, by applying the change simulated by climate models to observed data, it removes model bias (relative to some climatological baseline) from projections. Simple applications of CFs such as 'morphing' (e.g. Belcher et al. 2005) are frequently used but have the disadvantage that future scenarios can only follow patterns of weather previously seen in the observed record. Furthermore, a simple perturbation of the mean is unable to reflect other changes in the distribution which are important in the simulation of changes in variability and in extremes. Here, the application of CFs to the second or higher order moments of the weather statistics, to which the stochastic models are calibrated, surmounts these problems. Specifically, the method used here offers the advantages that weather sequences not previously observed may be generated and that weather variables in addition to rainfall and temperature are generated. This approach has been used within the UKCP09 probabilistic projections (Murphy et al. 2009b) and now forms part of a standard tool in the UK for climate-change impact assessments (Jones et al. 2009).

Monthly CFs were calculated for a set of 6 rainfall statistics for each RCM from the control and future scenario simulations. These were: daily mean, daily variance, the probability of a dry day (PDD; <1 mm)[1], daily skewness coefficient, daily lag-1 autocorrelation and variance in monthly (specifically 672 h) accumulation. The calculation of these CFs is described in detail by Burton et al. (2010), as is their use in perturbing a transient implementation of the single-site stochastic NSRP rainfall model RainSim (Burton et al. 2008). Here, further CFs are calculated for mean temperature and daily temperature variance. These CFs, α_i^R, were calculated to measure the change for

[1]The importance of clearly specified dry–day thresholds is discussed by Burton et al. (2008). The threshold used here was chosen for consistency with typical climate model analyses (e.g. Haylock et al. 2006) and the EARWIG methodology (Kilsby et al. 2007)

each RCM, R, between the control (Con) and future (Fut) scenario time-slices for each calendar month, i. For mean temperature, μ, we apply an additive CF:

$$\alpha_{\mu,i}^{R} = \mu_i^{R,\mathrm{Fut}} - \mu_i^{R,\mathrm{Con}} \tag{1}$$

and for daily temperature variance, v, we apply a multiplicative CF:

$$\alpha_{v,i}^{R} = \frac{v_i^{R,\mathrm{Fut}}}{v_i^{R,\mathrm{Con}}} \tag{2}$$

A pattern scaling method was then applied to produce transient CFs for each year from 1975 to 2085; these years represented the midpoints of the control and future scenario RCM time-slices, respectively. The method, described by Burton et al. (2010), uses scaling factors interpolated from time-slice integrations of global mean temperatures from GCMs under the assumption that changes in climatic variables will occur in proportion to the projected change in global mean temperature. Mitchell (2003) and Tebaldi et al. (2004) analysed a range of GCM experiments and found these assumptions to be generally accurate for temperature and precipitation change at seasonal and grid scales. Pattern scaling has been used to produce climate projections for the UK for multiple time-slices (Hulme et al. 2002) and has been applied to the PRUDENCE ensemble to assess changes in future flows for the River Thames in the UK (Manning et al. 2009). The pattern scaling for this study was based on projections from the GCMs HadCM3 and ECHAM4, which provide the RCM boundary conditions as described in Manning et al. (2009) and Burton et al. (2010).

Here, the observed temperature series represent a period beyond the model control simulations, and so we assume that they already incorporate a proportion of change projected by the RCMs. To reflect this difference, the transient CFs were calculated so that they express change relative to the midpoint of the period of observations, y_0 = 1982, referred to as 're-basing' by Burton et al. (2010). For μ, which has an additive CF, first the transient scaled temperature change factor, ϕ, is calculated as:

$$\phi_{\mu,y,i}^{R} = \alpha_{\mu,i}^{R}\mathrm{SF}_y^{R} \tag{3}$$

where SF_y^R is the scaling factor between 0 and 1 for each year y and for each RCM as described by Eq. (4) in Burton et al. (2010). The scaled values ϕ are then expressed relative to y_0 to obtain the final set of transient change factors ψ:

$$\psi_{\mu,y,i}^{R} = \phi_{\mu,y,i}^{R} - \phi_{\mu,y_0,i}^{R} \tag{4}$$

which may be used to provide transient estimates of future mean temperature from observations (Obs), $\mu_{i,y}^{R} = \mu_i^{Obs} + \psi_{\mu,y_0,i}^{R}$. Since v has a multiplicative CF, the same approach used for mean daily precipitation by Burton et al. (2010) was followed to produce a set of transient CFs for temperature variance, $\psi_{v,y,i}^{R}$.

This process produces a series of 8 CFs (6 for precipitation, 2 for temperature) relative to the period for which observed data is available for each calendar month and for each RCM experiment.

Numerical instabilities at the grid scale mean that projections for individual RCM grid boxes should not be used without first examining their consistency with wider regional simulations. Hence, CFs for the 3 × 3 element grid centred on the grid cell for the Geer were examined and found to be spatially homogeneous for each RCM. This indicated that those calculated for the grid cell overlying the Geer were unaffected by instabilities in the RCM simulations and were therefore appropriate for use in this study.

3.2. Generating transient climate series

The framework developed here to produce transient climate-change scenarios for the Geer is based on a 2-step process. First, to simulate daily rainfall using the transient NSRP model developed by Burton et al. (2010), and then to produce consistent simulations of additional weather variables including temperature and PET using the CRU WG.

3.2.1. Daily rainfall

Burton et al. (2008) developed a NSRP model (RainSim) to simulate rainfall at a single site, although a version capable of simulating spatial rainfall fields has subsequently been demonstrated for simpler, time-slice applications (van Vliet et al. 2012). The latter could, with further model development, be incorporated into the transient framework outlined here. However, given the relatively homogenous climate across this small catchment and that the focus of this work is the validation and application of the transient CRU WG, this approach was not deemed necessary here. Thus, we apply and extend the single-site transient framework developed by Burton et al. (2010), deriving transient daily rainfall series from the NSRP model which is re-parameterised for every month of every year, based on the application of transient CFs to the observed rainfall statistics. Here, this is used to generate an ensemble of 100 transient stochastic rainfall time series from 2010 to 2085, for each of the 6 RCM experiments.

3.2.2. Daily temperature — The CRU WG

The CRU WG uses observed relationships between site meteorological data to estimate parameters which are used to generate long time series of synthetic daily weather variables (Kilsby et al. 2007). The fundamental, primary variable is rainfall, which is produced using the stochastic NSRP model as described by Burton et al. (2008). These rainfall data are used to derive secondary variables (Table 2) using regression relationships, with further variables calculated from these. The regression equations needed for the CRU WG are calibrated with observed data for daily temperature maxima (TX) and minima (TN), precipitation (P), vapour pressure (VP), wind speed (WS) and sunshine hours (SS) using the observations described in Section 2.2. A detailed account of the operation of the CRU WG is provided in Kilsby et al. (2007). Further details of parameter adjustment for future climate scenarios and validation of the CRU WG in reproducing RCM-projected changes are provided by Kilsby et al. (2007) and Jones et al. (2009, 2011). The observed daily climate series were used to calibrate the CRU WG, which was run in 2 modes. Firstly, in a 'control' simulation mode the non-transient version of the stochastic NSRP model (Burton et al. 2008) was used to produce 100 stationary 30 yr simulations of daily rainfall possessing the same underlying statistics as the observed data. These simulations were then used to condition the CRU WG to provide corresponding additional daily weather variables which were then used to validate the performance of the models in reproducing the current characteristic climate for the Geer.

Secondly, after validation of the NSRP model and CRU WG in control mode (Section 4), the 'scenario' mode used the transient rainfall simulations to condition the CRU WG to simulate corresponding additional daily transient weather variables. This was achieved by applying the relevant transient CFs for mean temperature ($\psi^R_{v,y,i}$) and temperature variance ($\psi^R_{v,y,i}$) for each year to perturb the corresponding simulation years of the future climate. This contrasts with previous applications of the CRU WG, where it was perturbed using 1 set of monthly CFs for each RCM (or RCM variant in the case of UKCP09) for the appropriate time-slice (Jones et al. 2009).

Table 2. List of meteorological variables generated by the Climate Research Unit weather generator, CRU WG. Precipitation is generated using the Neyman-Scott Rectangular Pulses model with secondary variables derived directly from the CRU WG and used in turn to calculate further variables

Variable	Abbreviation
Primary	
Precipitation (mm)	P
Secondary	
Mean temperature (°C)	T
Daily temperature range (°C)	TR
Vapour pressure (hPa)	VP
Wind speed (m s^{-1})	WS
Sunshine duration (h)	SS
Calculated	
Relative humidity (%)	RH
Reference PET (mm d^{-1})	PET

4. MODEL VALIDATION

4.1. Validation of the rainfall simulations

Detailed accounts of fitting and validation of the rainfall model's single-site and spatial variants have been provided by Burton et al. (2008) and for the transient NSRP model by Burton et al. (2010) (Brévilles catchment, France) and Goderniaux (2010) (Geer catchment). As the focus of this study is the development of the additional transient weather variables, only a brief summary of the validation of the rainfall model for the Geer is provided here.

First, the control mode stationary NSRP model was fitted to the observed monthly rainfall statistics as in Burton et al. (2010). Ten 100 yr simulations of this stationary model were compared with observed rainfall properties (Fig. 2), indicating a high degree of model skill. Although deviations are noted for the daily skewness coefficient and monthly variance, the range of variation displayed by the 100 yr stochastic simulations almost always includes the corresponding observed statistic value.The transient NSRP model (scenario mode) parameterisation was then obtained using the same weights, parameter bounds and reduced set of parameters as used for fitting the stationary model to the observed climate. To validate the transient parameterisation, a 1000 yr stationary-climate rainfall time series was generated separately for each year from 1976 to 2085, each corresponding to a stationary climate equivalent of the estimated transient climatic conditions of that year. Mean statistics were then calculated for each 1000 yr time series and compared with the corresponding 'target' statistics (i.e. the observed statistics perturbed by the transient CFs). Fig. 3 shows that for the RCAO_E RCM experiment the simulated mean and PDD statistics closely match the target statistics. Similar performances were noted for the other statistics and calendar months confirming the skill of the rainfall model. Following this validation, 100 equiprobable daily transient rainfall series were then generated from 2010 to 2085 for each RCM by using the corresponding transient monthly CFs.

4.2. Validation of the CRU WG: control climate

The CRU WG was validated by first examining its skill in reproducing daily weather variables and PET for the control period (Fig. 4) using a set of 100 stationary 30 yr simulations. This shows that the WG skilfully reproduces both TN and TX throughout the year, with the observed average within the 2 standard deviation (SD) range of the simulations for most periods of the year. For sunshine duration (SS) and vapour pressure (VP), the range of simulated values captures the observed mean throughout the year, with particularly close correspondence for the latter. The annual distribution of wind speed (WS) is also captured reasonably well, though it is overestimated for some half-monthly periods, whilst PET is slightly underestimated during parts of the spring and summer. Overall, the CRU WG simulations show good agreement with observed values and reproduce the annual cycles of all weather variables. Fig. 5 demonstrates that the CRU WG provides an improved representation of the mean daily temperature (T) com-

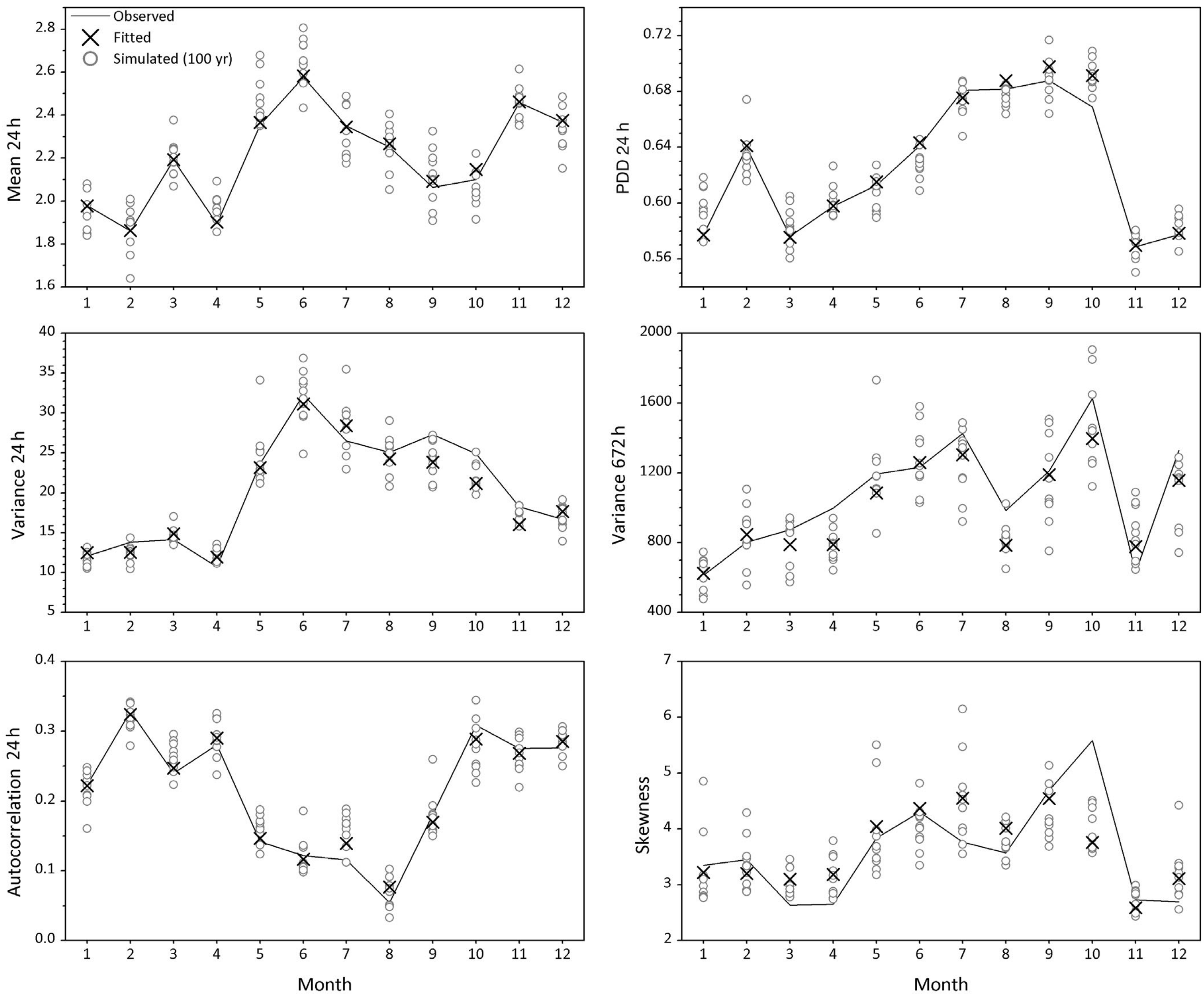

Fig. 2. Observed, fitted and simulated precipitation statistics for the Geer basin climate corresponding to the period 1961–1990. Black lines: observed data; black crosses: statistics as fitted by the stationary single-site Neyman-Scott Rectangular Pulses model after the calibration process; circles: 10 different stochastic simulations for time intervals of 100 yr under the same climate conditions as those in the observation period 1961–1990. PDD: probability of a dry day

pared with the RCM simulations. No single RCM reproduced the mean temperature well throughout the year, and the range of the RCM simulations is particularly large during summer. Relative to the observed statistics (OBS), the root-mean-squared-error (RMSE) of the mean of the 100 CRU WG half-monthly means is 0.4 compared with 1.0°C for the RCM ensemble. The CRU WG also better represents the extremes of the daily mean temperature distribution as represented by the 90th (T_{90}) and 99th (T_{99}) mean daily temperature. Both the CRU WG and the climate models perform less skilfully in simulating the extremes of the daily temperature distribution compared with the mean, as one might anticipate, but for both T_{90} and T_{99} the CRU WG performs better than each of the RCM ensemble members, in the case of the latter with a RMSE of 1.1°C compared with RCMs in the range of 1.3–3.5°C. Fig. 5 also confirms that the CRU WG simulates the daily temperature variance better than the RCM ensemble members and that overall it provides an improved representation of the climate for the Geer catchment.

4.3. Validation of the CRU WG: model perturbation

The second part of the WG validation procedure examined the perturbation of mean temperature by the CRU WG. Using temperature indices in addition to averages and SDs, Jones et al. (2011) have demonstrated that the perturbed future simulations from the CRU WG have the same statistical character as a future RCM time-slice sequence (from HadRM3), adequately representing a range of extreme indices.

Here, therefore, we provide a similar validation for the transient perturbation procedure. First, for selected years, separate 100 × 30 yr simulations of the CRU WG were performed for each RCM member using the corresponding CFs. For each future simulation, the change in mean daily temperature from the control CRU WG simulation was calculated and compared with the corresponding RCM-derived CFs. Fig. 6 (upper 2 panels) illustrates the skill of the CRU WG in perturbing the control climatology for the RCAO_E ensemble member for selected years (2055 and 2085). In each case, the CRU WG simulates the projected annual variability in the magnitude of temperature change. Throughout most of the year, the simulated change is within 2 SDs of the RCM projected change. Next, the mean monthly temperatures for the transient simulations were compared with the 'expected' means (i.e. the simulated control monthly mean plus the corresponding scaled CFs). Fig. 6 (bottom panel) demonstrates, for the months of January and July, that the transient perturbation reproduces the expected means and trajectory of change through-

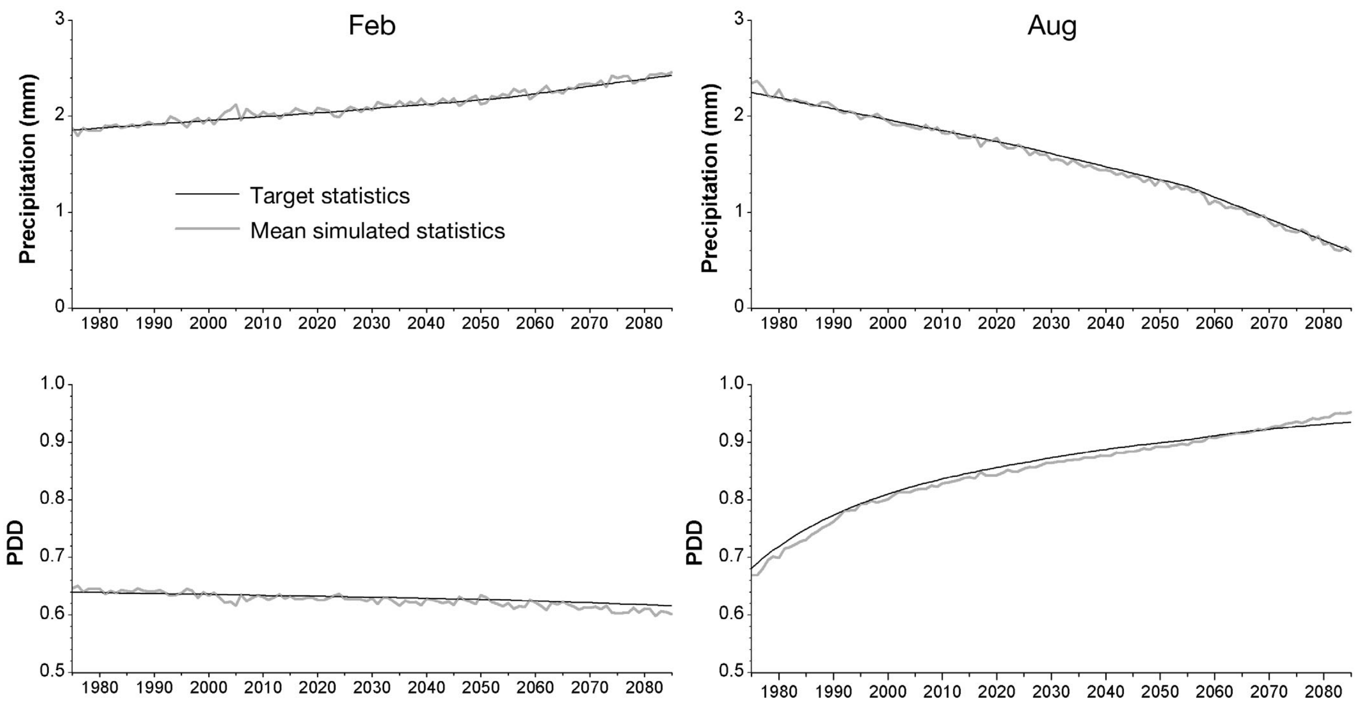

Fig. 3. Evolution of 'target' and mean simulated statistics (for successive annual simulations of 1000 yr duration) for mean daily precipitation and probability of a dry day (PDD) for the months of February and August. Results are presented using change factors derived from the regional climate model (RCM) RCAO_E

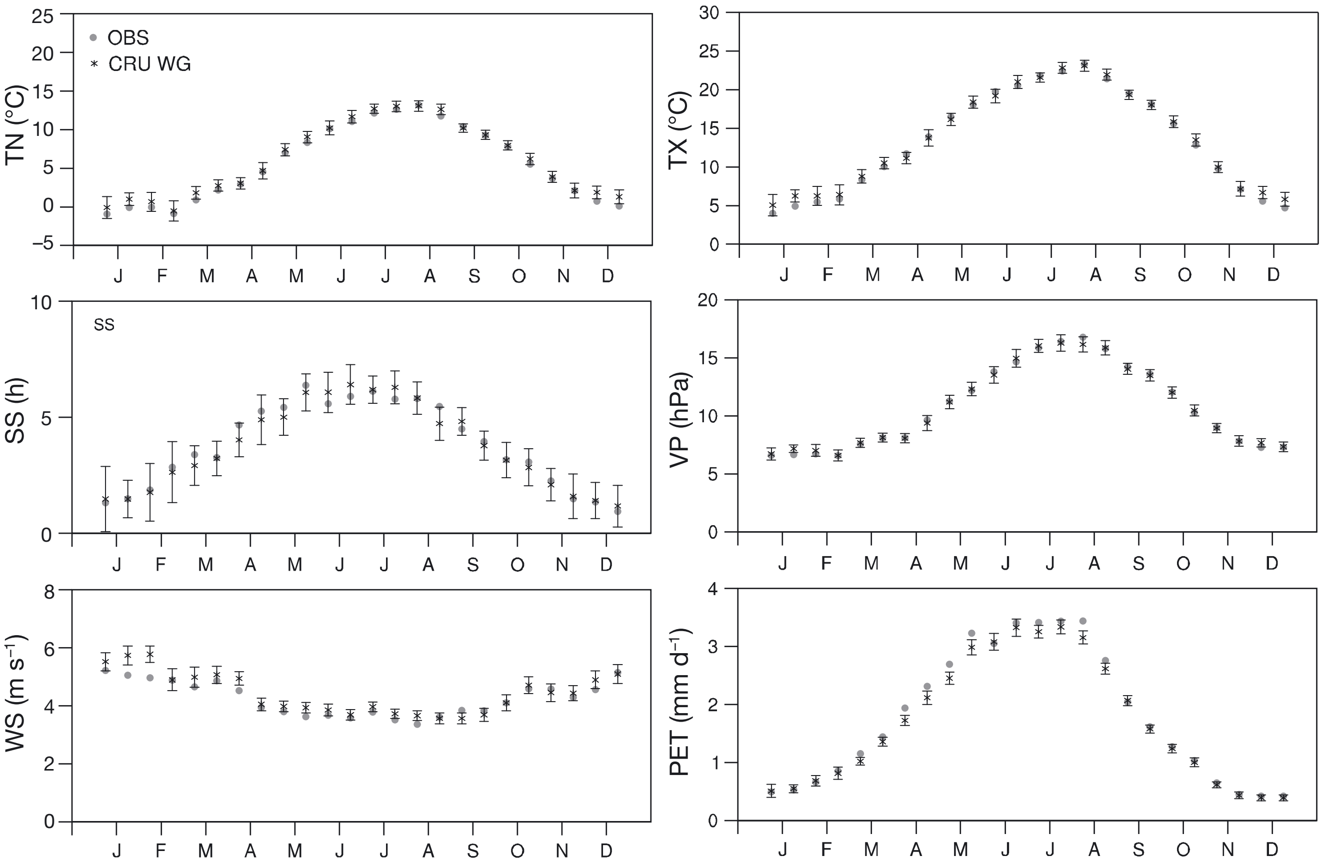

Fig. 4. Validation of the Climate Research Unit weather generator (CRU WG) control simulation (1960–2004) for minimum (TN) and maximum (TX) temperature, sunshine hours (SS), vapour pressure (VP), wind speed (WS) and potential evapotranspiration (PET). Circles: observed half-monthly means (OBS); crosses: weather generator-simulated values (CRU WG); error bars: the variability of one-hundred 30 yr-simulated series as defined by ±2 standard deviations

out the period. For some years, the difference between the expected and simulated means exceeds those observed above for the 100 × 30 yr simulations. This is probably because the transient simulations are comprised of a smaller, 100 yr ensemble simulation for individual years, and this could be addressed by increasing the ensemble size in the final transient simulations.

5. RESULTS

5.1. Transient changes in temperature indices and PET

To illustrate the application of the transient WG, 5 temperature indices were calculated for the 600 simulated daily weather series (100 WG simulations for each of the 6 RCM experiments) and assessed together with simulations of total monthly PET. These were selected as simple transient indicators of the potential impacts of climate change.

The summer days index (SDI; TX >25°C), defined by Klein Tank & Können (2003) is an indicator of hot summer days. The frost day index (FD; TN <0°C) is a widely used measure of air frosts (e.g. Frich et al. 2002), primarily sensitive to change in winter temperatures, whilst frost season length (FSL) indicates changes in the seasonal distribution of frost days by measuring the number of days from the first frost occurrence to the last based on a July to June annual cycle. The growing season length (GSL) is an important measure for agricultural applications and has been defined as starting on the last day of the first 5 d spell during which the mean temperature for each day exceeded 5°C and ending on the last 5 d spell of the year (Jones & Briffa 1995, Frich et al. 2002). However, Jones et al. (2002) suggested additional criteria due to the frequent occurrence of late frosts in areas like northwestern Europe, and therefore the first (last) 5 d spell should also occur after (before) the last (first) frost of the winter season. Finally, the total of growing degree days (GDD) has been used in a

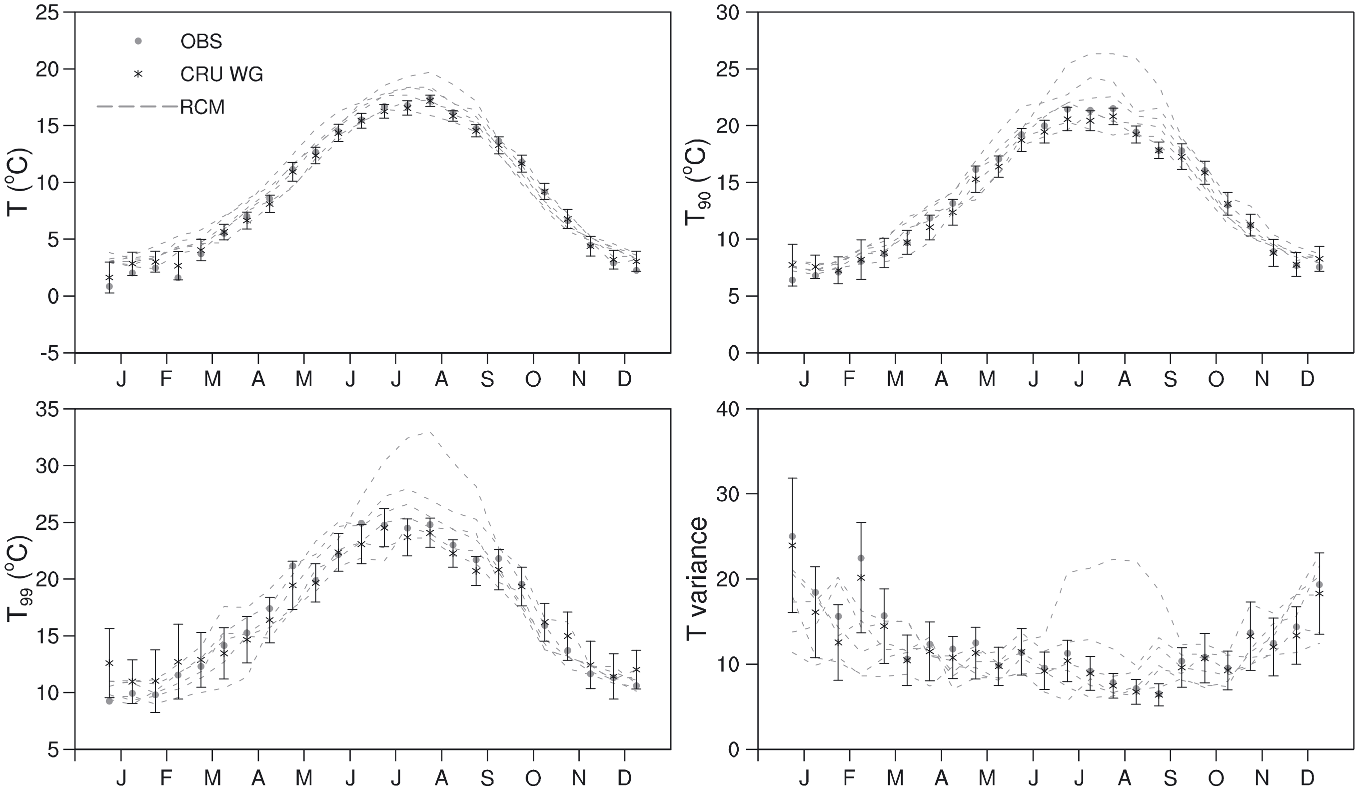

Fig. 5. Comparison of CRU WG and RCM ensemble members in simulating daily mean temperature (T), 90th and 99th percentile daily mean temperature (T_{90} and T_{99}, respectively) and daily variance. Observed statistics (OBS) are shown for comparison. CRU WG simulations here were undertaken for the period 1961–1990 for direct comparison with the RCM ensemble control experiments. Error bars: variability of one-hundred 30 yr-simulated series as defined by ±2 standard deviations

range of agronomical applications, and is calculated as the sum of all the mean daily temperatures >5°C during the growing season defined above.

Each annual index was calculated for each of the 600 transient simulations. Linear regressions were fitted to each individual simulation, constrained to observed values centred on the observation period (1982). This ensured that absolute values of the projected indices derived from the regression models were evaluated relative to the observed climatology. The trends were then ranked to examine the range of projected changes. The time series associated with the multi-model ensemble median trend of each index is shown in Fig. 7 along with the range when 95% of the simulated trends is included. For SDI, the multi-model ensemble projected an increasing trend with a median of around +7 d decade^{-1}, though greater increases were projected, principally by the ECHAM-driven RCMs. The large uncertainty range in projections for these models meant that the upper bound of projections was an increasing trend of +9 d decade^{-1}, and consequently the increase in SDI projected for the 2080s by the multi-model median trend could be reached as early as the 2060s. However, the lower bound indicated a trend of just +4 d decade^{-1}, resulting in the same change as for the median ensemble member now occurring beyond 2100. Conversely, the transient simulations projected a decrease in FD, with a median trend of around –4 d decade^{-1}. Compared with SDI there was a smaller inter-model range in trends (–2.5 to –5 d decade^{-1}) due to the smaller differences in RCM-derived CFs during winter months. An associated median decrease in FSL of approximately –6 d decade^{-1} was also projected; again the change was larger for HIRHAM_E and RCAO_E, primarily due to greater projected warming in spring and autumn by these RCMs.

All models indicated an extension of the growing season, with an ensemble median trend of around +3 d decade^{-1}; however, the ensemble range indicated that the growing season length projected for the 2080s by the ensemble median trend could occur by the 2030s but also much later. For all models, therefore, a longer growing season and increasing temperature suggested that there would also be a median projected increase in GDD of around +130 degree days decade^{-1}.

Finally, changes in monthly PET totals were examined in the same way as for the temperature indices, and for brevity are summarised only for January and July (Fig. 8). Increases in summer PET were greater than those for winter, corresponding with the greater projected increase in mean summer temperatures. However, the ensemble range in projected PET, coupled with those of the temperature indices, indicated a large potential range in the timing of the hydrological response of the catchment and other potential impacts due to climate change. This makes any planning or adaptation responses difficult to assess.

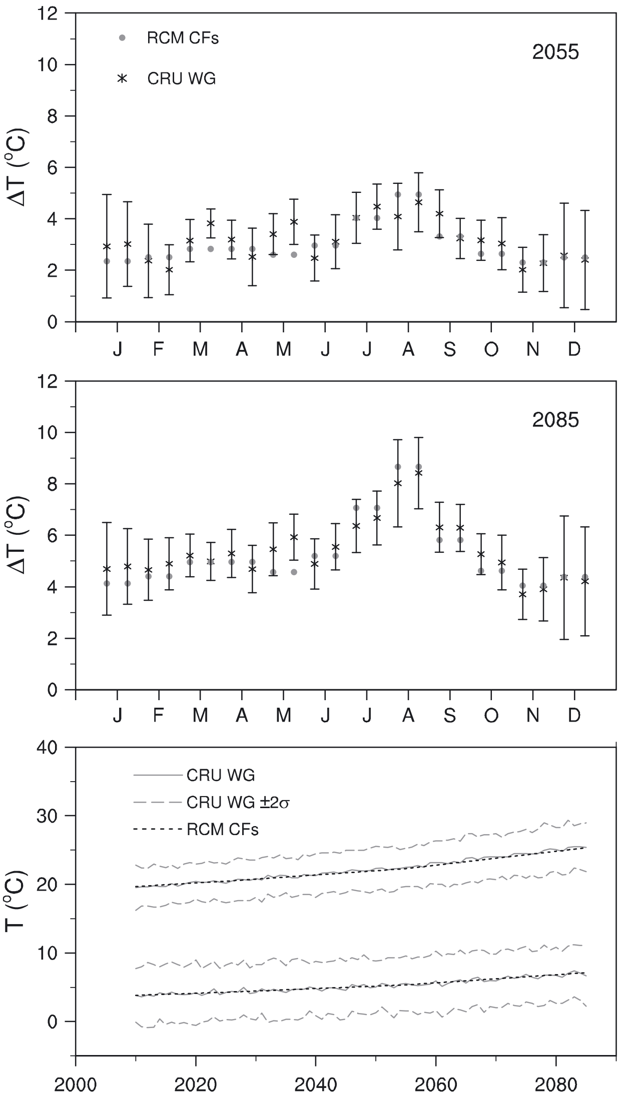

Fig. 6. Comparison of weather generator perturbation of mean temperature (T) for 2055 (upper panel) and 2085 (middle panel), with the RCM change factors (CFs) for RCAO_E. Error bars: variability of one-hundred 30-yr-simulated series as defined by ±2 standard deviations. A comparison of the transient simulations for RCAO_E throughout the whole period is also shown (lower panel)

5.2. Projected timing of climatic response

The ensemble of downscaled transient simulations offers the means to assess the uncertainty in future projections on a temporal dimension This is in contrast with an ensemble of time-slice simulations which would typically provide projections of change

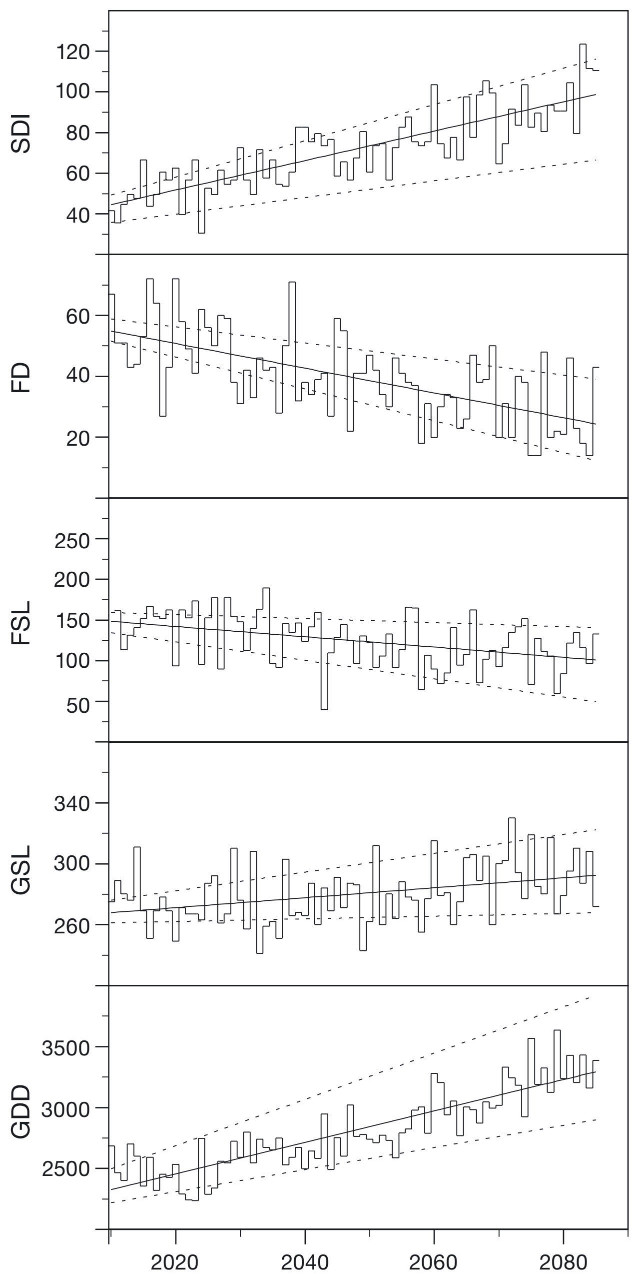

Fig. 7. Projected multi-model ensemble-median time series (stepped line) and fitted trends for each of the 5 temperature indices (SDI; summer days; FD: frost days; FSL: frost season length; GSL: growing season length; GDD: growing degree days). Solid line: median trend; upper (lower) dashed lines: 97.5th (2.5th) percentile

in a variable for a given time period with associated uncertainties. Here, a specific impact or threshold can be prescribed and a projected time scale may be estimated for it with a measure of uncertainty. For example, we pose the hypothetical question 'when could we expect to see the SDI account for 2 months of the year?', estimating the year in which each ensemble member's linear trend projects a total of 61 summer days. The resulting distribution of estimated years has a mean year of 2037 with an SD of 13.3 yr. The empirical distribution function (Fig. 9) indicates that such a change is most likely to occur in the 2020s–2030s, although the distribution has a long tail to the end of the 21st century. This distribution reflects the stochastic variability introduced by the rainfall and WGs which provides an estimate of the uncertainty associated with natural variability, in addition to the variability provided by using a climate model ensemble.

6. DISCUSSION AND CONCLUSIONS

This study describes a new, integrated implementation of the NSRP rainfall model and CRU WG to provide downscaled daily weather scenarios of future transient climate for the Geer catchment in Belgium. It uses a recently developed transient version of the NSRP model (Burton et al. 2010) to generate 100 transient simulations of daily rainfall for the period 2010–2085 for each member of an RCM ensemble. The simulated rainfall series are then used to condition the new, transient implementation of the CRU WG, perturbed by RCM-derived CFs, to simulate the additional weather variables.

The WG was demonstrated to successfully reproduce the observed annual cycles of minimum, mean and maximum temperatures, and was shown to offer an improvement (i.e. correction of biases) in the simulation of mean daily temperature and extremes derived directly from the RCM ensemble for the Geer. The transient perturbation of the WG was also successful in producing simulations that matched the RCM-projected trajectory of temperature change. However, in common with other downscaling methods and projections, it is unreasonable to assume that extreme events outside of the range of those previously observed can be accurately simulated in future time series.

This methodology provides a downscaled multimodel ensemble of transient climate scenarios at a daily resolution whose utility is illustrated through the analysis of daily temperature indices and simulated PET. An extension of the growing season was found, although an increase in hot days could mean a greater likelihood of heat waves and increased evapotranspiration. Given the likely decrease in summer rainfall over this part of Europe indicated by PRUDENCE and other ensembles (Christensen & Christensen 2007, Murphy et al. 2009a) and the projected regional increase in the frequency of summer droughts (Blenkinsop & Fowler 2007), increased stress could be placed upon water resources before the 2080s.

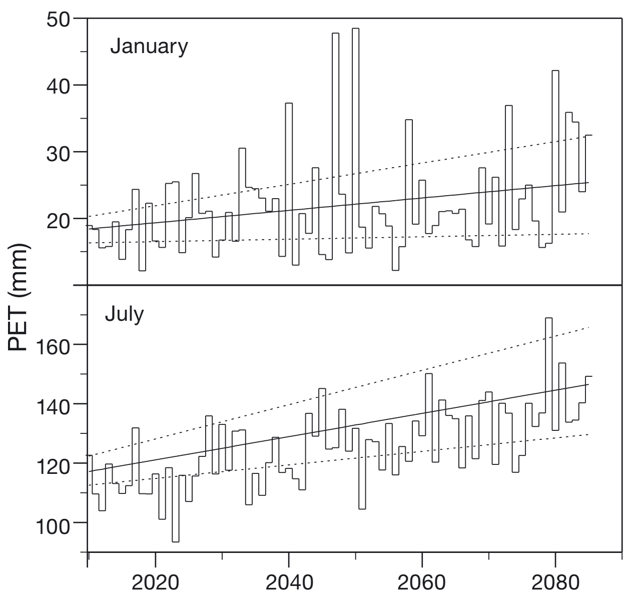

Fig. 8. Projected multi-model ensemble-median time series (stepped line) and fitted trends in potential evapotranspiration (PET) for January and July. Solid line: median trend; upper (lower) dashed lines: linear trends corresponding to the 97.5th (2.5th) percentile

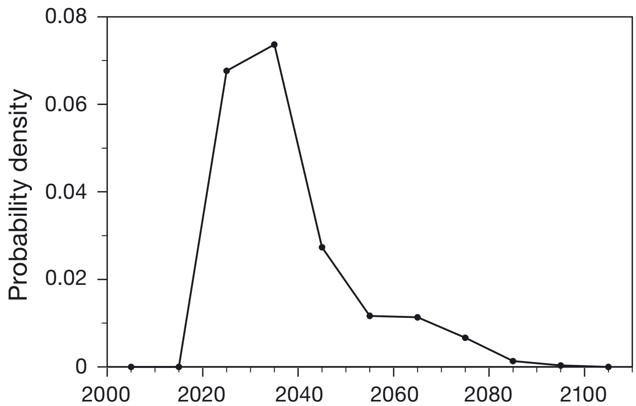

Fig. 9. Empirical density function of the projected date for an increase in the expected frequency of summer day extremes to 61 d derived from the trends of the 600 member multimodel ensemble

Although transient RCM experiments, such as those provided by the ENSEMBLES project (Hewitt & Griggs 2004) are now available, these still provide relatively small initial-condition ensembles. By using the transient simulations presented here, uncertainty in the timing of a given magnitude of climate signal may be explored. Thus, whilst RCM time-slice simulations allow the likely future change to be considered through questions like 'What will be the likely increase in temperature by 2085?', these downscaled, transient simulations provide the additional basis for the temporal evaluation of critical thresholds, such as 'By when are we likely to see a 3°C increase in mean summer temperature?' More interestingly, the time scale of required interventions or adaptation responses may be examined by coupling the climate projections with impact models, for example, using hydrological simulations. The method could therefore facilitate planning and adaptation to changes in climatic events on the shorter time scales frequently required by stakeholders. For example, changes in the occurrence of a given magnitude of an event — such as the European heat wave in the summer of 2003, which had a significant effect on agriculture regionally (the French maize grain crop fell by 30% of that in 2002; Easterling et al. 2007) and resulted in record low levels in several major European rivers (Beniston & Diaz 2004) — may require adaptation planning on time scales that end earlier than the end of the 21st century. A more detailed, policy-relevant application using the scenarios developed here is provided by Goderniaux et al. (2011), identifying when prolonged and severe drought might begin to affect stream flow rates, groundwater levels and thus abstraction from the Geer catchment.

The method described here potentially provides more useful information for the Geer catchment than that provided by Goderniaux et al. (2009), where the same RCM ensemble was used with a quantile correction method, and which was then scaled to produce stationary climate scenarios for 3 time-slices. Nonetheless, it is worth noting that by comparing the hydrological response over common periods for these 2 methods, Goderniaux (2010) indicates that the downscaling method is a relatively minor contributor of uncertainty to the projected response of this catchment to climate change relative to the contribution of climate model selection.

Although it is acknowledged that the RCM ensemble used here represents only a limited sampling of the total uncertainty space, and thus underestimates the contribution of all sources of uncertainty, this downscaling framework could be extended to larger RCM ensembles to provide a more comprehensive treatment of scenario uncertainty. Whilst the strength of this methodology lies in a transient representation of both natural variability and uncertainty in future climate projections, the former will be underestimated as the transient scenarios (including those by RCMs) do not realistically represent low-frequency variability arising from teleconnections such as the El Niño Southern Oscillation. Several authors have described potential means to improve the representation of low-frequency variability in stochastic rainfall models (e.g. Mehrotra & Sharma 2010) and WGs (e.g. Kim et al. 2012); the implementations of such techniques in transient weather generation require further investigation.

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