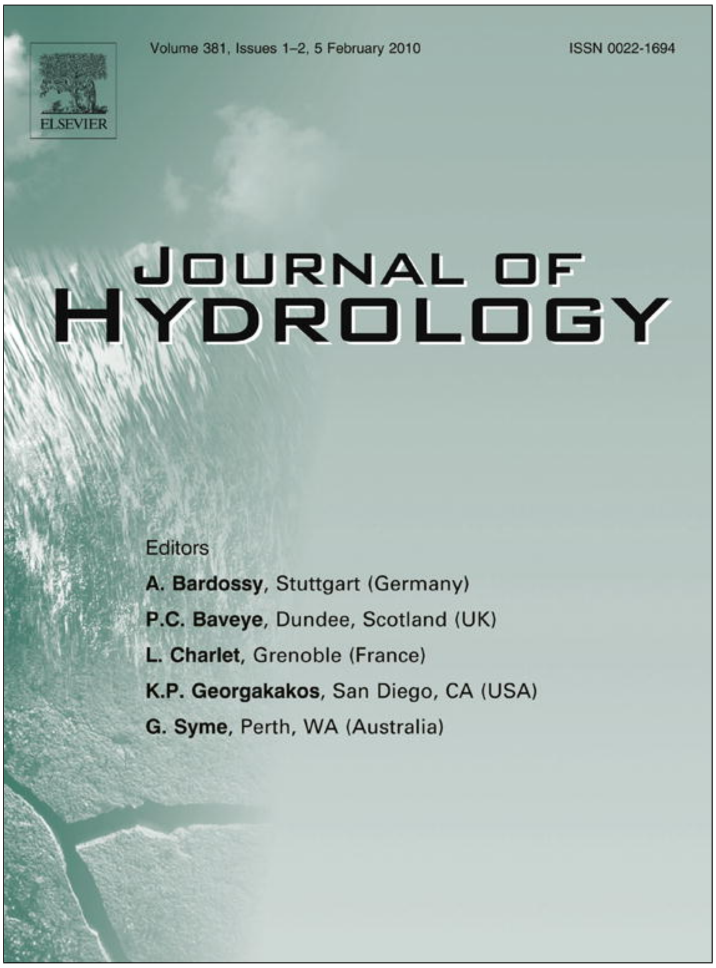
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Downscaling transient climate change using a Neyman–Scott Rectangular Pulses stochastic rainfall model

A. Burton *, H.J. Fowler, S. Blenkinsop, C.G. Kilsby

Water Resource Systems Research Laboratory, School of Civil Engineering and Geosciences, Newcastle University, UK

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SUMMARY

The future management of hydrological systems must be informed by climate change projections at relevant time horizons and at appropriate spatial scales. Furthermore, the robustness of such management decisions is dependent on both the uncertainty inherent in future climate change scenarios and the natural climate system. Addressing these needs, we present a new transient rainfall simulation methodology which combines dynamical and statistical downscaling techniques to produce transient (i.e. temporally non-stationary) climate change scenarios. This is used to generate a transient multi-model ensemble of simulated point-scale rainfall time series for 1997–2085 for the polluted Brévilles spring in Northern France. The recovery of this previously potable source may be affected by climatic changes and variability over the next few decades. The provision of locally-relevant transient climate change scenarios for use as input to hydrological models of both water quality and quantity will ultimately provide a valuable resource for planning and decision making.

Observed rainfall from 1988–2006 was characterised in terms of a set of statistics for each calendar month: the daily mean, variance, probability dry, lag-1 autocorrelation and skew, and the monthly variance. The Neyman–Scott Rectangular Pulses (NSRP) stochastic rainfall model was fitted to these observed statistics and correctly simulated both monthly statistics and extreme rainfall properties. Multiplicative change factors which quantify the change in each statistic between the periods 1961–1990 and 2071-2100 were estimated for each month and for each of 13 Regional Climate Models (RCMs) from the PRUDENCE ensemble. To produce transient climate change scenarios, pattern scaling factors were estimated and interpolated from four time-slice integrations of two General Circulation Models which condition the RCMs, ECHAM4/OPYC and HadCM3. Applying both factors to the observed statistics provided projected transient rainfall statistics (PTRS) to which piece-wise smoothly varying transient rainfall model parameterizations were fitted. These fits provided good representations of the PTRS for each RCM. An ensemble of 100 continuous daily rainfall time series, with steadily varying stochastic properties which model these projections of transient climate change, was then simulated using a new transient NSRP simulation methodology for each RCM. Together the ensembles form a 1300 member transient multi-model ensemble of rainfall time series.

The simulated transient ensemble properties were investigated, identifying RCMs giving rise to unusual behaviour. For the Brévilles, annual rainfall is projected to decrease until 2085 but the change is highly sensitive to General Circulation Model forcing; ECHAM4-driven RCMs project larger annual decreases than HadCM3/HadAM3H/P driven RCMs. All RCMs project an increase in winter rainfall and a larger summer decrease. An increase of ~10% in the 10-year return period annual maximum rainfall is projected by 2085, however both strong increasing trends and a slight decreasing trend are found for individual RCMs. Compared with transient RCMs, the new methodology provides a number of advantages: reduced biases, point scale scenarios relevant for local-scale impact studies, improved representation of natural variability and improved representation of extremes.

Introduction

Downscaling methods are typically used to resolve the mismatch of scales between coarse General Circulation Model (GCM; ~300 km grid) outputs and hydrological applications at the basin scale. These may be divided into two main types, dynamical and

* Corresponding author. Address: Water Resource Systems Research Laboratory, School of Civil Engineering and Geosciences, Cassie Building, Newcastle University NE1 7RU, UK. Tel.: +44 (0)191 222 8836; fax: +44 (0)191 222 6669.
E-mail address: aidan.burton@ncl.ac.uk (A. Burton).

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statistical downscaling, which have been reviewed in detail by Wilby and Wigley (1997) and Fowler et al. (2007). In dynamical downscaling, Regional Climate Models (RCMs) with a higher spatial resolution and a limited spatial domain are forced by boundary conditions from a GCM. However, the spatial resolution of the outputs is still too coarse for many hydrological applications, there are biases in relation to observed climate statistics and typically only one integration or a small ensemble of integrations is available. Until recently outputs have also generally been restricted to ~30-year 'time-slices'; e.g. for a control from 1961 to 1990 and for a perturbed climate from 2071 to 2100. However, climate change impacts on shorter time horizons (10–50 years) and smaller spatial scales (e.g. river catchment) are of greater relevance to water resources managers and planners.

Alternatively, a wide range of statistical downscaling methods have addressed the coarse resolution of GCM outputs by establishing empirical relationships between GCM-resolution climate variables and local climate. These methods enable climate scenarios to be generated at a much lower computational cost than dynamical downscaling, particularly where large ensembles of integrations are required. One of the simplest, the perturbation method (Prudhomme et al., 2002), applies 'change factors', calculated as the multiplicative or additive difference between the control and future GCM simulations, to observations. More sophisticated statistical downscaling methods include those based on regression models (e.g. Hellström et al., 2001), artificial neural networks (e.g. Cavazos and Hewitson, 2005), analogue methods based on empirical orthogonal functions (e.g. Zorita and von Storch, 1999), weather typing schemes (e.g. Goodess and Palutikof, 1998) and stochastic methods, including weather generators (e.g. Wilks, 1992). Stochastic methods such as weather generators confer the advantage of being able to model natural climatic variability at time scales from daily to sub-decadal and may be resampled many times to produce ensembles of projections, though variability arising from volcanism, teleconnections or sun-spot cycles is not included. They have been used to generate climate change scenarios for hydrological impacts assessment, e.g., Scibek and Allen (2006) derived change factors from a GCM and used these in conjunction with a weather generator to produce simulations for three stationary future time-slices for an aquifer in Canada. The Environment Agency Rainfall and Weather Impacts Generator (EARWIG; Kilsby et al., 2007) applies change factors for a more extensive range of statistics derived from RCM simulations and is capable of generating stationary climate change scenarios at the point scale or for river catchments in the UK. This approach has been validated against RCM simulations for the UK Climate Projections (Jones et al., 2009).

Key issues remain in the application of downscaling methods to hydrological impacts assessments. The first of these is the provision of decision-making tools for planning and management that are robust to uncertainty in future scenarios (Fowler and Wilby, 2007) such as that arising from the climate modelling process, e.g. grid resolution, process parameterisation, model physics and emissions scenario (e.g. Giorgi and Francisco, 2000; Covey et al., 2003). Some of these uncertainties have been analysed by running perturbed-physics climate model simulations in which model parameters are varied within their range of uncertainty (e.g. Murphy et al., 2004). Alternatively methods using multi-model ensembles to provide probabilistic projections of climate change have recently been developed (Allen et al., 2000; Palmer et al., 2005). However, only limited research has applied such probabilistic methods to the simulation of the impacts on hydrological systems (e.g., Wilby and Harris, 2006; Fowler et al., 2007).

A second key issue is the need to produce scenarios for time horizons that are 'impact-relevant'. Planners and managers of many hydrological systems, such as water resources and flood infrastructure, require realistic estimates of climate change for the near-future. Statistical downscaling relationships can be applied directly to transient GCM simulations (e.g. Benestad, 2002; Burlando and Rosso, 2002; Serrat-Capdevila et al., 2007) and transient RCM integrations are now becoming available through projects such as the EU-funded ENSEMBLES (Hewitt and Griggs, 2004) and UK Climate Projections (Murphy et al., 2007). However, probabilistic scenarios of climate change impacts would require a large number of computationally expensive GCM or RCM integrations, would still contain biases in relation to observations and, particularly for GCMs, require some form of downscaling for use in hydrological impact studies.

Here we address both issues with a hybrid dynamical and statistical downscaling scheme to generate a large multi-model ensemble of transient climate change rainfall scenarios with spatial and temporal scales of relevance to hydrological planners and managers. This involves the development of a new transient rainfall generator based on the EARWIG approach (Kilsby et al., 2007) which is demonstrated using projections from 13 RCM integrations from the PRUDENCE project (Christensen et al., 2007) for the Brévilles spring in northern France. Transient scenarios are of particular interest for the managers of the previously potable but now polluted Brévilles spring as they are concerned with *when* the aquifer system is likely to achieve good potable water quality status rather than considering aquifer response to a stationary time-slice future climate scenario (e.g. 2071–2100). Ultimately such analysis will not provide a precise date when this will be achieved but instead a distribution of years, where the distribution represents elements of the uncertainty arising from natural climatic variability and from climate model uncertainty.

Meteorological data and climate model outputs

Observations

The Brévilles spring rises from a well instrumented hill top aquifer of ~3 km^2 located 500 m south of Buhy, about 40 km north-west of Paris in northern France (Fig. 1). Historically this spring provided drinking water but currently the water is undrinkable due to atrazine pollution caused by agricultural practices from the 1960s to the 1990s (Roulier et al., 2006). The temporal development of the spring's quality and quantity are interesting from a management perspective and may be sensitive to unsteady climate change effects. Therefore this spring was selected as a case study within the AquaTerra project (Barth et al., 2009). A 19-year daily rainfall series for the period 1988–2006 was available for a raingauge located at Buhy. This series indicates an annual rainfall of 736 mm distributed fairly uniformly throughout the year, although August is drier and December is wetter than average. In addition, the summer months from June to September have fewer wet days than other months.

Climate models

Different climate models adopt a range of physical models of processes and parameterize subgrid scale processes differently and so vary in their ability to accurately model atmospheric processes. Future projections of climatic changes are therefore subject to many sources of uncertainty. One way of partially representing these uncertainties is through the use of multi-model ensembles, as in the EuropeaN Union Fifth Framework Programme (FP5) PRUDENCE project (Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects; Christensen et al., 2007). The PRUDENCE project provides high spatial resolution (~0.5° × 0.5°) time-slice simulations of European

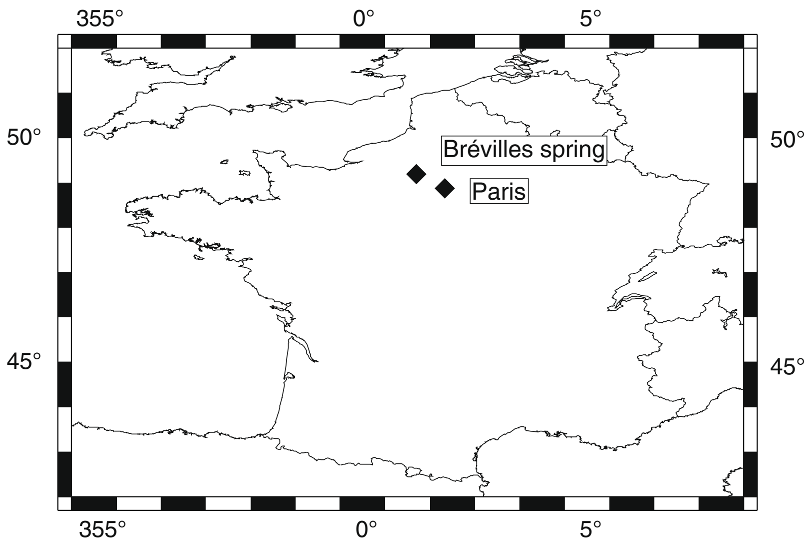

Fig. 1. The location of the Brévilles spring in northern France.

Table 1
The 13 RCMs used from the PRUDENCE project. The AquaTerra acronyms are used throughout this paper, the suffix of each denotes the driving GCM.

AquaTerra acronym	Institute	RCM	Driving GCM	PRUDENCE acronym
HIRHAM_H	DMI	HIRHAM	HadAM3H A2	HC1/HS1
HIRHAM_E	DMI	HIRHAM	ECHAM4/OPYC A2	ecctrl/ecscA2
RCAO_H	SMHI	RCAO	HadAM3H A2	HCCTL/HCA2
RCAO_E	SMHI	RCAO	ECHAM4/OPYC A2	MPICTL/MPIA2
CLM_H	GKSS	CLM	HadAM3H A2	CTL/SA2
RACMO_H	KNMI	RACMO	HadAM3H A2	HC1/HA2
METNO_H	METNO	HIRHAM	HadAM3H A2	HADCN/HADA2
HAD_P_H	HC	HadRM3P	HadRM3P A2	adeha/adhfa
CHRM_H	ETH	CHRM	HadAM3H A2	HC_CTL/HC_A2
REMO_H	MPI	REMO	HadAM3H A2	3003/3006
PROMES_H	UCM	PROMES	HadAM3H A2	control/a2
REGCM_H	ICTP	RegCM	HadAM3H A2	ref/A2
ARPEGE_H	Météo-France	Arpège	HadCM3 A2	DA9/DE6

climate for the control period, 1961-1990, and for a future scenario, 2071–2100, for a range of RCMs. These time-slice simulations represent a stationary climate over each 30-year period. Table 1 describes the 13 PRUDENCE RCMs (see also Jacob et al., 2007; and Fowler and Ekström, 2009) used here, each of which used the SRES A2 (medium–high) (Nakicenovic et al., 2000) emissions scenario used by most of the available experiments.

Each PRUDENCE RCM derives its boundary conditions from a GCM (Table 1) and so the choice of driving GCM introduces an additional layer of uncertainty in future projections. However, this representation of uncertainty is constrained by the experimental framework provided by the PRUDENCE project (Déqué et al., 2007). Boundary conditions for the RCMs are derived from what may be considered to be two different GCMs, the HadAM3H atmosphere only model (Pope et al., 2000) and the ECHAM4/OPYC coupled atmosphere–ocean model (Roeckner et al., 1996). The HadRM3P and ARPEGE RCM simulations derive boundary conditions from HadAM3P and the coupled atmosphere–ocean model HadCM3 respectively. Both HadAM3H and HadAM3P are dynamically downscaled to an intermediate resolution from the HadCM3 coupled atmosphere–ocean model and are thus closely related.

The spatial extent of the aquifer is considerably smaller than the relevant RCM grid cell, however sampling from the smallest resolution of a numerical model may be sensitive to numerical instabilities in the RCM. Therefore the time series of the daily rainfall was obtained for each RCM for the nine grid cells centred on the Brévilles spring for the control and future time-slices. Together these RCMs provide a range of alternative representations of climate change so providing a representation of the uncertainty of climate models' projections. This will be an underestimate, however, as components of the uncertainty are not included, e.g. the range of models may not fully represent the full range of possible climate changes, decadal and sub-decadal variability arising from teleconnections is not well represented and only one emissions scenario is considered.

The projected global mean temperature was also obtained from the Intergovernmental Panel on Climate Change (IPCC) data centre for four 30-year time-slices (centred on the years 1975, 2025, 2055 and 2085) extracted from transient integrations of the two GCMs for the IPCC SRES A2 emissions scenario.

Methodology

A transient Neyman–Scott Rectangular Pulses model

Stochastic rainfall models based on Poisson cluster processes represent rainfall occurrence and amount as a single continuous process and are attractive in that they represent the observed temporal clustering nature of rainfall. They have been used widely over the last 20 years following Rodriguez-Iturbe et al. (1987) and two main variants, the Neyman–Scott Rectangular Pulses (NSRP) and the Bartlett–Lewis Rectangular Pulses models, have been extensively developed and evaluated (Velghe et al., 1994; Onof et al., 2000; Burton et al., 2008).

The NSRP model is the basis for standard UK industrial urban drainage design software, regional parameterizations have been obtained for single-site applications to UK raingauges (Cowpertwait and O'Connell, 1997) and a spatial–temporal version of the model has been developed (see Cowpertwait, 1995; Burton et al., 2008). The NSRP model has been shown to realistically reproduce both daily and hourly extreme rainfall for both single-site (e.g. Cowpertwait, 1998; Kilsby et al., 2000, 2004, 2007) and multi-site investigations in Europe (Cowpertwait et al., 2002; Burton et al., 2008). For the assessment of future climate projections the NSRP model has been used in a stochastic downscaling role either (i) fitted to projected monthly rainfall statistics (e.g. Kilsby et al., 2000) or (ii) conditioned on Lamb weather types (Fowler et al., 2000, 2005). Developing the first approach, the NSRP model has been incorporated into EARWIG (Kilsby et al., 2007) which provides daily rainfall and consistent weather time series for user-selected locations and catchments in the UK for the present day and for future scenarios. It also fulfils a similar role for the UK Climate Projections 2009 climate change impact scenarios (Jones et al., 2009). A more detailed review of applications of the NSRP model is provided by Burton et al. (2008).

Here we develop a single-site transient NSRP model in which the rainfall process is conceptualised as a sequence of *storm events* consisting of temporal clusters of *raincells*. Storm time origins occur with a Poisson process and each generates a random number of raincells each with a time origin that follows the storm origin after a random time delay. Each raincell has a random rainfall intensity which remains constant throughout its random duration. Discrete daily or hourly rainfall time series may be obtained by accumulating the raincell intensities. The sampling procedures and parameters of the model's random variables are given in Table 2. Transient climate change is modelled by means of different parameterizations for each year and seasonality through the use of different parameterizations for each calendar month. A time series simulated by this model has specific dates associated with it, however, it is a projection of synthetic rainfall rather than a forecast. Such a transient simulation is limited in length to the time horizon of the RCM projections as each simulation year corresponds to a specific year in the future. Therefore, to model the climate's natural variability it is necessary to generate an ensemble consisting of a number of different realizations of the simulated transient rainfall time series. It must be noted however, that the natural variability being modelled is limited to that typically found in case study observations and does not include decadal to sub-decadal variability arising from teleconnections or sun-spot cycles or large independent influential events such as volcanism.

In contrast with the new transient scheme, the traditional single-site NSRP model uses the same set of monthly parameterizations for each year of the simulation. Consequently rainfall time series with arbitrary length may be generated for a stationary climate, i.e. the simulation date of an event does not correspond to an observation date but instead the entire time-series corresponds to the average climate of an observational period. The specific distributions used for the number of raincells in a storm and the raincell intensity may vary between applications. Detailed descriptions of the single-site NSRP model may be found in Cowpertwait (1991) and Burton et al. (2008).

Table 2
The transient NSRP model's random variables (RVs) detailing the corresponding stochastic sampling procedure, parameter and the parameter's unit.

Random variable	Sampling	Parameter	Unit
Storm origin time	Poisson process	λ	(1/h)
Number of raincells	Poisson RV	ν	(–)
Raincell origin delay	Exponential RV	β	(1/h)
Raincell intensity	Exponential RV	ξ	(h/mm)
Raincell duration	Exponential RV	η	(1/h)

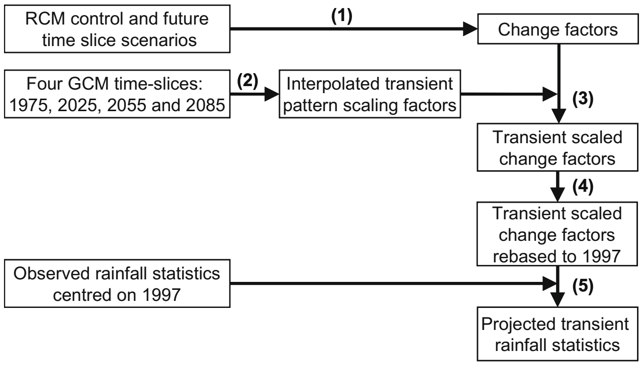

Fig. 2. Schematic summarizing the procedure used to prepare the projected transient rainfall statistics. Numbering corresponds to the steps described in the text.

Projected rainfall statistics for transient climate scenarios

Rainfall statistics derived from the observed timeseries and from the RCM control and future time-slices were combined with GCM derived global temperature projections to obtain a set of projected transient rainfall statistics (PTRS) for each calendar month using a change factor and pattern scaling approach described in this section and summarized in Fig. 2. This considerably extends the approach of Kilsby et al. (2007) which only projects statistics for discrete time-slices of a single climate model. Here, a set of six statistics were selected to characterise rainfall: the five used by Kilsby et al. (2007), daily mean, daily variance, the probability of a dry day[1] (PDD; <1 mm), daily skewness coefficient and daily lag-1 autocorrelation (AC); and one with particular relevance to groundwater applications, the variance in monthly (specifically 672 h) accumulation.

Step 1 (see Fig. 2) is based on the change factor or 'perturbation' approach (Prudhomme et al., 2002). Projected future changes to observed point rainfall statistics are assumed to be in proportion to the spatially averaged rainfall changes simulated by an RCM. Such an approach has the benefits of insensitivity to bias in RCM projections and simplicity. Change factors, $\alpha^R_{g,i}$ Eq. (1), were calculated to measure the change in each statistic, g, for each RCM, R, between the control (Con) and future (Fut) time-slices for each calendar month, i, for the grid box corresponding to the study area. Since PDD and AC can only take values on a limited range they were first transformed using the invertible transformations given by Eq. (2) (Kilsby et al., 2007) and Eq. (3) respectively before evaluating their change factors.

$$\alpha^R_{g,i} = \frac{g^R_{\mathrm{Fut},i}}{g^R_{\mathrm{Con},i}} \tag{1}$$

$$X(\mathrm{PDD}) = \frac{\mathrm{PDD}}{1-\mathrm{PDD}} \tag{2}$$

$$W(\mathrm{AC}) = \frac{1+\mathrm{AC}}{1-\mathrm{AC}} \tag{3}$$

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

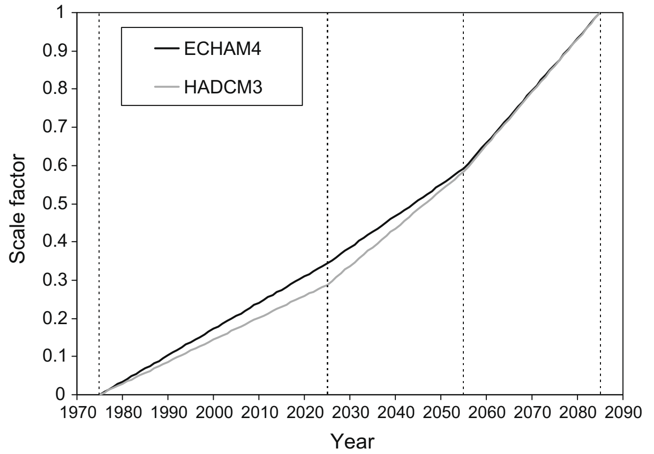

Fig. 3. Interpolated transient scale factors for the GCMs ECHAM4 and HadCM3 for 1975–2085. Vertical dashed lines show centres of the 30-year time-slices.

In numerical models the limits to process integration and numerical instabilities at the grid scale means that projections for a single RCM grid box must be treated with caution. However the RCM projections of each rainfall statistic, as used in Eq. (1), are temporal averages estimated from 30-year time-slices, which has the advantage of reduced sample variability. Change factors for the nine element grid centred on the study area were found to be spatially consistent indicating that the results from the single RCM grid box centred on the Brévilles spring was appropriate for use for this study.

Whilst the change factor approach provides estimates of how rainfall statistics might vary between the control and a specific future time-slice, to estimate transient statistics a method is required to project the likely variation during the intervening period. Pattern scaling (Santer et al., 1990; Mitchell, 2003) is in widespread use providing a pragmatic means to produce scenarios for stationary time-slices not covered by GCM/RCM simulations. Pattern scaling makes the assumption that future changes in climatic variables will occur steadily and in proportion to the projected change in global mean temperature. Mitchell (2003) and Tebaldi et al. (2004) have analysed a range of GCM experiments and found these assumptions to be generally accurate for temperature and precipitation change at seasonal and grid scales.

The pattern scaling for this study was based on the HadCM3 and ECHAM4 projections of global mean temperature, T_y^G, available for periods centred on the years 1975 (control), 2025, 2055 and 2085 (future). These were used to calculate the scale factor, SF_y^G, for each year, y, and GCM, G, according to Eq. (4). For the new transient methodology, scale factors were estimated for the intervening years by linear interpolation (step 2) to obtain a continuous set of transient scale factors (Fig. 3). ECHAM4 projects a global mean temperature increase by 2100 that is slightly greater than that for HadCM3. Therefore three results from the GCM projections of the control-future period are shown by Fig. 3: both GCMs project global temperature increase with an increasing rate; ECHAM4 has a consistently greater temperature increase than HadCM3; ECHAM4 has a slightly more evenly distributed temperature increase than HadCM3.

$$SF_y^G = \frac{T_y^G - T_{1975}^G}{T_{2085}^G - T_{1975}^G} \tag{4}$$

Pattern scaling was applied to the change factors (step 3) by assuming that the future change in rainfall statistics will be in proportion to the interpolated scale factors, Eq. (5), where $\phi_{g,y,i}^R$ are scaled change factors and $G(R)$ indicates the GCM providing lateral boundary conditions to the RCM, R (see Table 1).

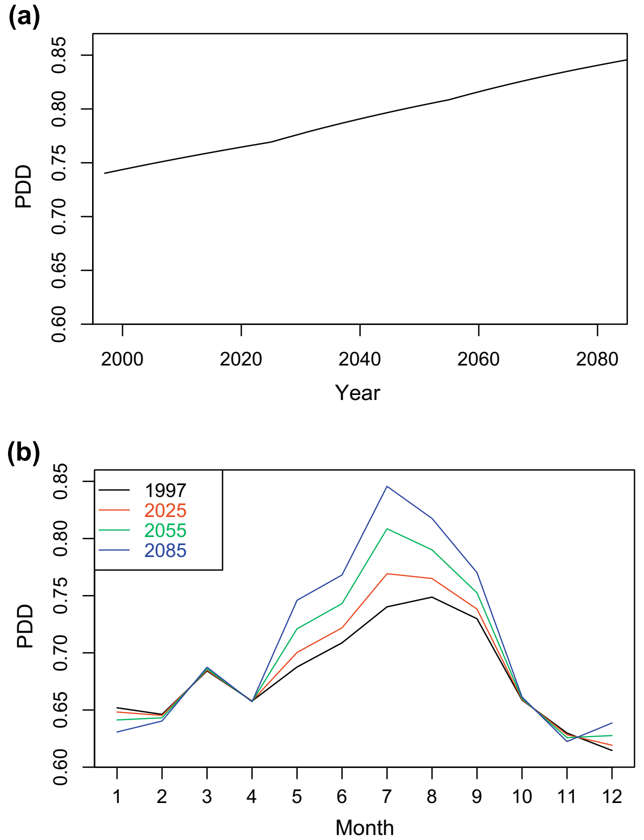

Fig. 4. The projected transient statistics for PDD based on the ARPEGE_H RCM (a) July for all years and (b) all months for selected years.

$$\phi_{g,y,i}^R = 1 + (\alpha_{g,i}^R - 1)SF_y^{G(R)} \tag{5}$$

Since the central year, $Y = 1997$, of the observed data period (1988–2006) was distinct from the centre of the control period (1961–1990) $\phi_{g,y,i}^R$ was rebased to year Y using $\phi_{g,Y,i}^R$ (step 4). Note that if observations were instead centred on the control period, $\phi_{g,Y,i}^R$ would be one. The PTRS, $g_{y,i}^{Est,R}$, were then calculated (step 5) by scaling the observed rainfall statistics, $g_{Y,i}^{Obs}$, according to the proportionality assumption stated in step 1. Eq. (6) summarizes both steps 4 and 5 algebraically. Finally, projected transient PDD and AC statistics were obtained using their inverse transformations.

$$g_{y,i}^{\mathrm{Est},R} = \frac{\phi_{g,y,i}^R}{\phi_{g,Y,i}^R} g_{Y,i}^{\mathrm{Obs}} \tag{6}$$

The PTRS then comprised the six estimated statistics for each year of the transient period, 1997–2085, for each calendar month and for each RCM. The PTRS is illustrated using the ARPEGE_H scenario projections: Fig. 4a shows the transient PDD for July; Fig. 4b shows the seasonal cycle for selected years during the transient period. It can be seen that ARPEGE_H projects a steady increase in the number of dry days in the summer (May–September) but almost no change in PDD in other months.

Model fitting

Following the preparation of a full set of PTRS for each RCM, the development of a methodology to obtain a parameterization of the transient NSRP rainfall model was required. A two-stage process was adopted. Firstly, a stationary (i.e. non-transient) single-site NSRP model was fitted to the observed rainfall statistics. This involved adjusting the automatic model fitting procedure to obtain the optimal match to observed rainfall by adjusting statistic weights and parameter bounds, reducing the number of fitted parameters and validating the fitted model against observed rainfall properties. Secondly time series of model parameters were obtained to represent the transient climate, using an iterative fitting procedure based on that for the initial stationary fit.

Fitting a stationary NSRP model to observations

The stationary NSRP model may be fitted automatically for each calendar month using a bounded numerical optimization of an objective function comprising a weighted sum of squared errors between a selected set of observed statistics and their equivalent analytically expected model statistics (Burton et al., 2008). However, a set of optimization weights and parameter bounds must be selected to ensure both model physicality and the optimal match of observed statistics for the application. As sub-daily observed statistics were not used the η parameter was fixed to a value of $4\,\mathrm{h}^{-1}$ (corresponding to a mean raincell duration of 15 min) to avoid over-parameterization involving the η and ξ parameters, which as a pair are only sensitive to finer time-scale data. This considerably improved the identifiably of the ξ parameter and reduced the stationary NSRP model fitting problem to four parameters. Further, the lower bound to β was set to $0.01\,\mathrm{h}^{-1}$ to limit the effect of numerical drift biases, whereby the rainfall properties of the preceding month affect the following month by means of the presence or absence of rainstorms which persist beyond the end of the month (e.g. as noted by Fowler et al. (2000) in an application of a stationary NSRP model to simulate rainfall in Yorkshire, UK). Fitting the stationary NSRP model to the observed statistics then provided a full set of monthly model parameters representing a stationary climate corresponding to the observed record.

To evaluate the model's representation of the present day climate an assessment was made of two sets of climatic diagnostics: the statistics used to calibrate the NSRP model and extreme rainfall statistics which were not used in the fitting. An ensemble of 50 synthetic 19-year stationary-climate time series was generated using a stationary NSRP generator with the parameters fitted to the observed record. Fig. 5 compares the observed monthly rainfall statistics with the corresponding fitted statistics and the distribution of the simulated statistics evaluated from the stationary-climate ensemble. The difference between each fitted and corresponding mean simulated statistic represents a combination of stochastic variability and biases in the estimation of model parameters. Since these differences are generally small compared with the variability of the model statistics then in general the observed statistics are simulated well by the stationary NSRP model.

Additionally the RCM 30-year control time-slice statistics are also shown for the grid cell representing the Brévilles, albeit for spatial average rainfall and noting that the control period is centred on 1975 and the observation on 1997. This allows an assessment of the control RCMs against the observed climate. No individual RCM was found to match all of the statistics well: the seasonality of the mean is too high with large overestimates for November–January; PDD, daily variance and skew are typically underestimated; AC is typically overestimated. However, grid square average rainfall is expected to have lower PDD, variance and skew and higher AC than point rainfall. On spatial scales of a grid square or greater such biases may not be of concern, however, biases in mean rainfall statistics will remain and for small catchments the need for downscaling is indicated.

Fig. 6 shows a comparison of daily annual maxima from the 19-year observed dataset, an ensemble of fifty 19-year observed-climate stationary NSRP simulations and the thirteen 30-year RCM control time-slice integrations using a Gumbel plot (e.g. Shaw, 1994). Since the annual maxima of the observations, NSRP simulations and RCM time series were all evaluated for discrete daily time-steps rather than for arbitrary 24 h periods, these have been multiplied by a *fixed-window* correction factor of 1.16 (Dwyer and Reed, 1995) to provide an estimate of the true 24-h maximum. This increases the absolute value of all maxima shown but not their relative values. A further correction was also applied to the RCM extremes to account for comparing spatial average extremes with point samples. Assuming a grid size of approximately $2500\,\mathrm{km}^2$ an areal reduction factor, *ARF*, of $\sim$0.864 for daily extremes is implied (see NERC, 1975; Svensson, 2007), so the RCM maxima were scaled by a factor (1/*ARF*). Each of the NSRP simulated series of extremes was ranked in the same manner as for the observed series, following the standard Gumbel plotting procedure (e.g. Shaw, 1994), and the 10th, 50th and 90th percentiles were evaluated for each return period. The extremes generated for the stationary simulation of the observed climate are seen to provide a good match to the 19 years of observed extremes, which were not used in model fitting, as well as an estimate of the sample variability. In comparison three of the RCMs appear to match the observations for some return periods whereas the majority of the RCMs are shown to underestimate the extremes.

Fitting a transient NSRP model

An initial transient NSRP model parameterisation was obtained using the same weights, parameter bounds and reduced set of parameters as used for fitting the stationary model of the observed climate. The automatic fitting scheme was used to fit the model independently to the PTRS of each month and year of the transient period (1997–2085) providing transient time series of parameters for each RCM and month. Whilst fitting an NSRP model to a single year of observations is not recommended due to sample variability, here the PTRS for each year is calculated from 19 years of observations and 30-year RCM integrations and so has an acceptable level of sample variability. Typically the transient time series of parameters closely approximate smooth curves, for example as illustrated in Fig. 7a for the ARPEGE_H RCM. Although some of the parameter time series exhibit some roughness as shown in Fig. 7b, this is of relatively small magnitude compared with the overall trend in the parameter. Kinks may also occur in the time-series when a parameter hits a bound (e.g. Fig. 7c and d) or the trend in a parameter may reverse if the fitting error of a statistic changes sign. Smooth parameterizations throughout the transient period, as typically obtained here, are desirable as these indicate that the model is not over-parameterized whereas parameterizations that are highly variable from one year to the next may produce unsteady projections in which certain years are simulated with unusual rainfall characteristics in all transient timeseries realizations.

Three different effects can affect the accuracy with which simulations of each transient year match the PTRS. Firstly, an exact match between the PTRS and the expected simulated statistics may not be achieved by the model fit. Secondly, biases between the expected and actual simulated statistics may occur, either though numerical drift (see "Fitting a stationary NSRP model to observations") or from the approximate analytical expression for PDD used in the automatic fitting (e.g. see Burton et al., 2008). Thirdly, the actual simulated statistics are a realization of the stochastic NSRP process, and so are themselves random variables subject to sampling variability.

Two refinements were therefore made to the initial transient fitting procedure to address the first two of these effects. Firstly a correction was made for biases in the mean and PDD arising from numerical drift and the approximate PDD expression. For each RCM, a separate stationary simulation of 1000 years was generated for each year in the transient period so that simulation statistics could be estimated with low sample variability. Then for each RCM and calendar month the transient-average mean and PDD

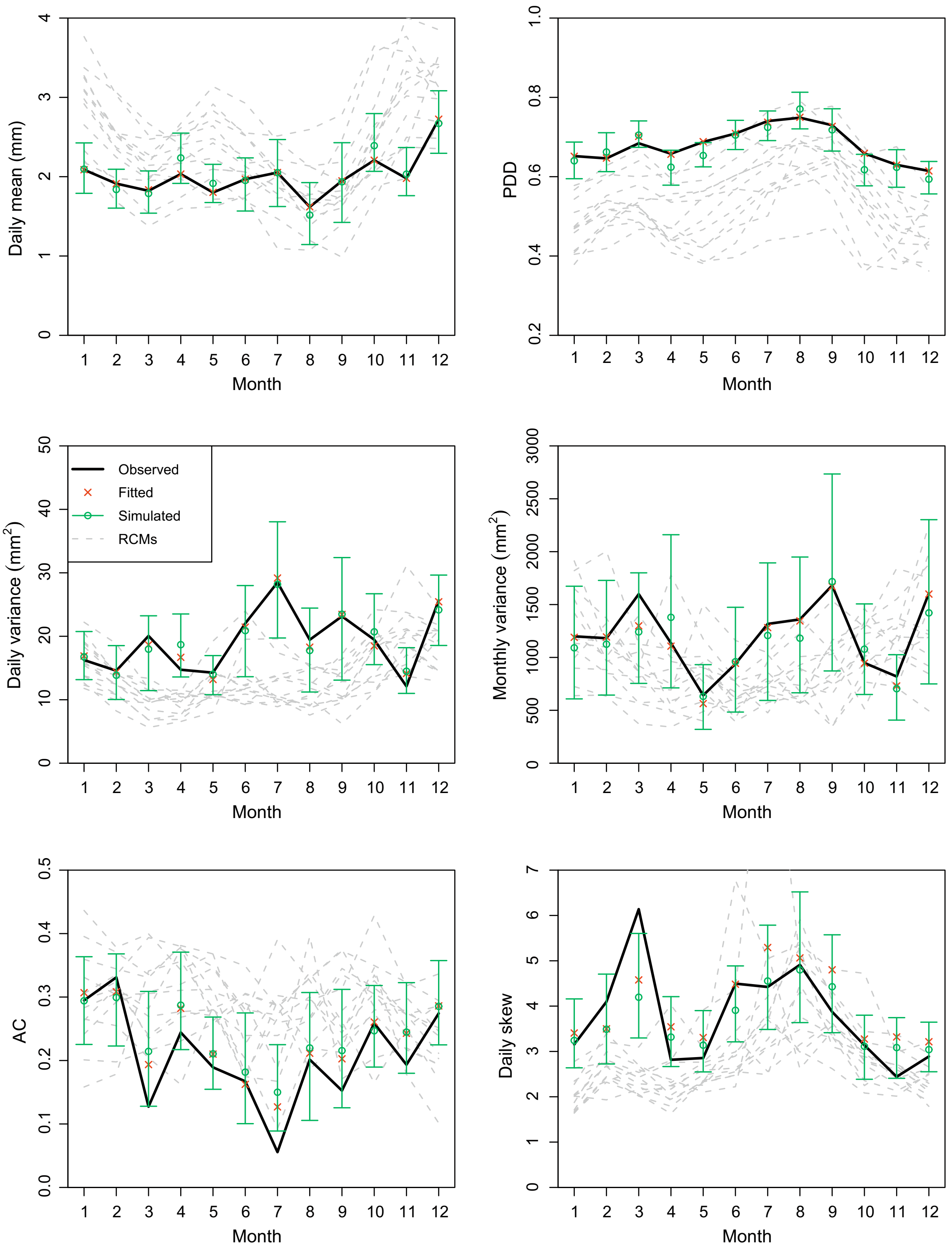

Fig. 5. Fitted (Fitted) and simulated (Simulated) monthly rainfall statistics for the rainfall model of the observed climate compared with observed statistics from 1988 to 2006 (Observed). The error bars indicate the mean and the 10th and 90th percentiles evaluated from an ensemble of 50 19-year simulations. The control time-slice statistics are also shown for each RCM (RCMs).

biases were estimated and used as an additive bias-correction to the transient projected mean and PDD statistics. This refinement was found to significantly reduce these biases even for cases when the mean or PDD statistics varied non-linearly along the transient. The second refinement involved adjusting the fitting weights to provide the best overall fit to the PTRS. The transient NSRP model parameterization for each RCM was then obtained by automatically fitting to the bias-corrected PTRS for each transient year and month in turn.

A comparison of the PTRS, the fitted statistics and stationary simulation statistics for each year from 1997 to 2085 is reported here in detail for only one RCM, ARPEGE_H. Fig. 8 provides an example comparison of the transient projected, fitted and simulated statistics for ARPEGE_H in June. In this figure a 1000-year

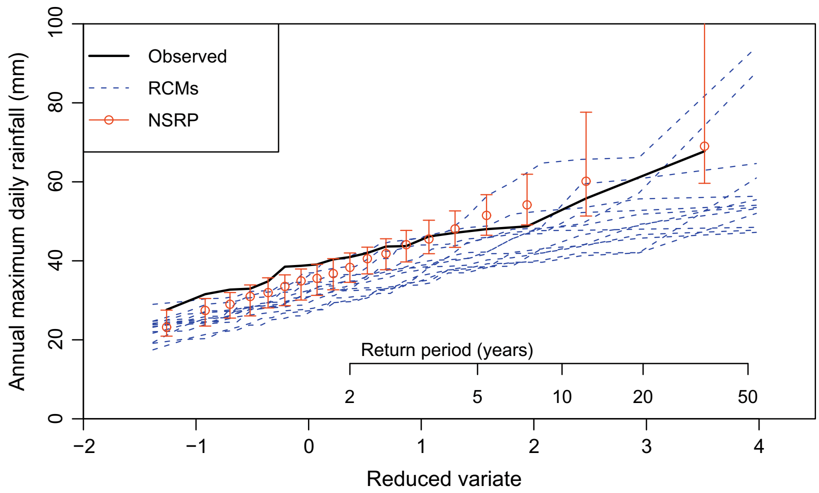

Fig. 6. Gumbel plot comparison of observed, RCM simulated and stationary NSRP simulated annual maximum 24-h rainfall. The observed data comprises a 19-year time series of extremes. The ensemble of 50 NSRP simulations of 19-years length were similarly evaluated and the estimated 10th, 50th and 90th percentiles are shown using error bars for each return period. The extremes of each of the 13 30-year RCM control period simulations have been adjusted for areal reduction and are shown with dashed lines. Reduced variate is the standard *x*-axis plotting position of a Gumbel plot.

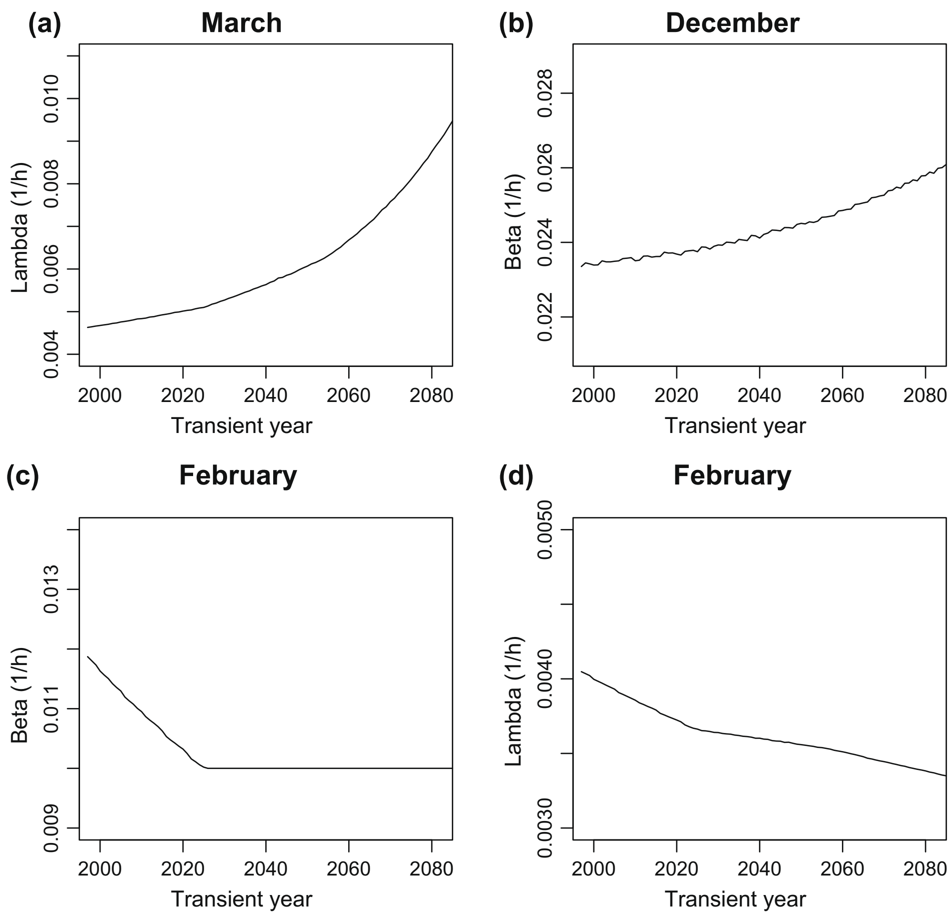

Fig. 7. Examples of (a) smooth, (b) relatively rough and (c and d) piece-wise smooth time series of transient fitted parameters for ARPEGE_H. The months and parameters illustrated are (a) Lambda for March; (b) Beta for December; (c) Beta for February, which is limited by a lower bound; and (d) Lambda in February, showing a kink caused by (c).

stationary simulation of each year in the transient is used to provide a low sample variability estimate of transient simulation properties. For the mean and PDD the model is well fitted and the bias-correction successfully removes simulation biases, although small biases remain (most notably in August and September). For the daily variance, the fitting error is small compared to the variability in the observed variance statistics but small simulation biases are noticeable in some months, consistent with the drift

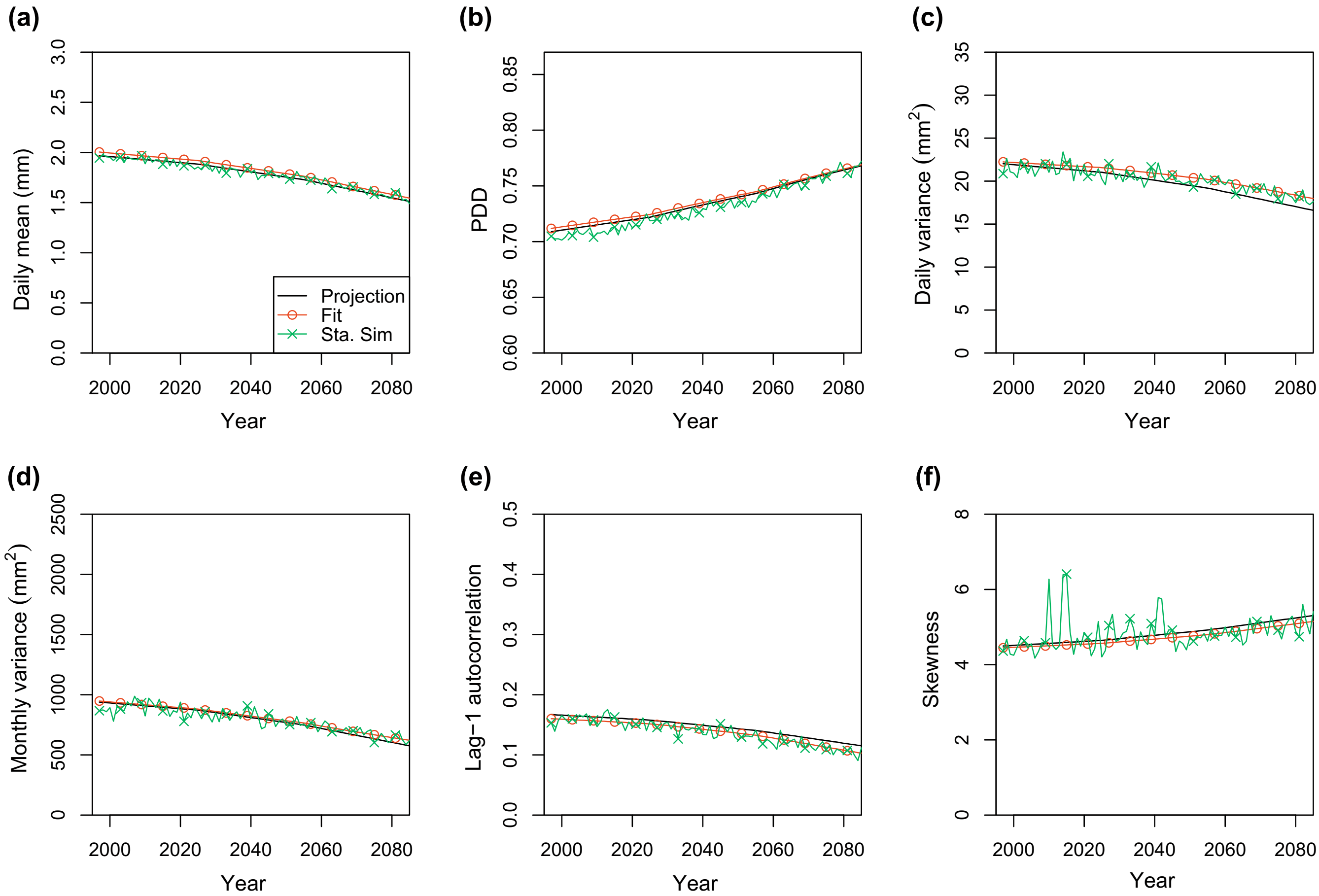

Fig. 8. Examples of the transient projected, fitted and simulated statistics for June for the ARPEGE_H RCM. Each plot presents a different statistic and shows the projected transient time series (Projection), the model fit for each individual year (Fit) and the simulated mean value of the statistic estimated from a stationary 1000-year simulation corresponding to each transient year (Sta. Sim).

bias affecting the mean. The fit to monthly variance is generally good, although in March the model under fits the high monthly variability found in the observed dataset. Biases in the simulated monthly variance are also small compared with the sampling variability of the observations. AC was fitted with the least precision of all of the statistics but has a large sampling variability. However, AC has no simulation bias, except for April in which a small bias tends to improve the simulation over the fit. For the skewness coefficient most months were fitted well compared with the underlying variability of this statistic although some under-fitting was noted in Feb and Mar and overfitting in September. The skewness coefficient is generally unbiased in the simulations. Overall the stationary simulations were found to provide good matches to the PTRS.

The transient rainfall parameterizations were similarly evaluated for the other 12 RCMs. Whilst the details of the quality of the fits and the stationary simulations differed, the characteristics of the transient time series of parameters, fitted statistics and 1000-year stationary-simulated statistics were found to be broadly similar to those for ARPEGE_H and for all RCMs provided good fits to the PTRS.

Results

For each RCM an ensemble of 100 transient NSRP daily simulations were generated for the time period from 1997 to 2085 using the appropriate transient rainfall parameterization. This produced a multi-model ensemble consisting of a total of 1300 transient simulations. Whilst the simulated time series' values correspond to specific dates, the values themselves are realizations of stochastic projections and so represent possible future events rather than forecasts.

Validation of the ensemble of transient simulations

The multi-model transient ensemble statistics were compared with the relevant PTRS and the transient fitted statistics to evaluate whether simulations were accurately representing the temporal changes in the PTRS. First, statistics of the transient simulations were evaluated for each RCM, ensemble member, year in the transient series and calendar month. The 10th, 25th, 75th and 90th percentiles across each ensemble were then evaluated for each case of RCM, statistic, transient year and month. Fig. 9 shows the time series of these percentiles compared with the corresponding PTRS for ARPEGE_H for January and July, which represent one of the best and one of the worst monthly fits to the PTRS. The skewness coefficient and monthly variance cannot be compared with the PTRS in the manner used in Fig. 9, and are therefore excluded, as the former is biased by sample size and the latter cannot be estimated from a single month's data.

Fig. 9 shows that the percentiles estimated from the 100-member ensembles are highly variable as expected for a single year's data. In most cases the quartiles also indicate considerable variability when compared with the fitting and simulation biases; for example the magnitude of the bias-correction of the daily mean and the PDD statistics is relatively minor compared to the

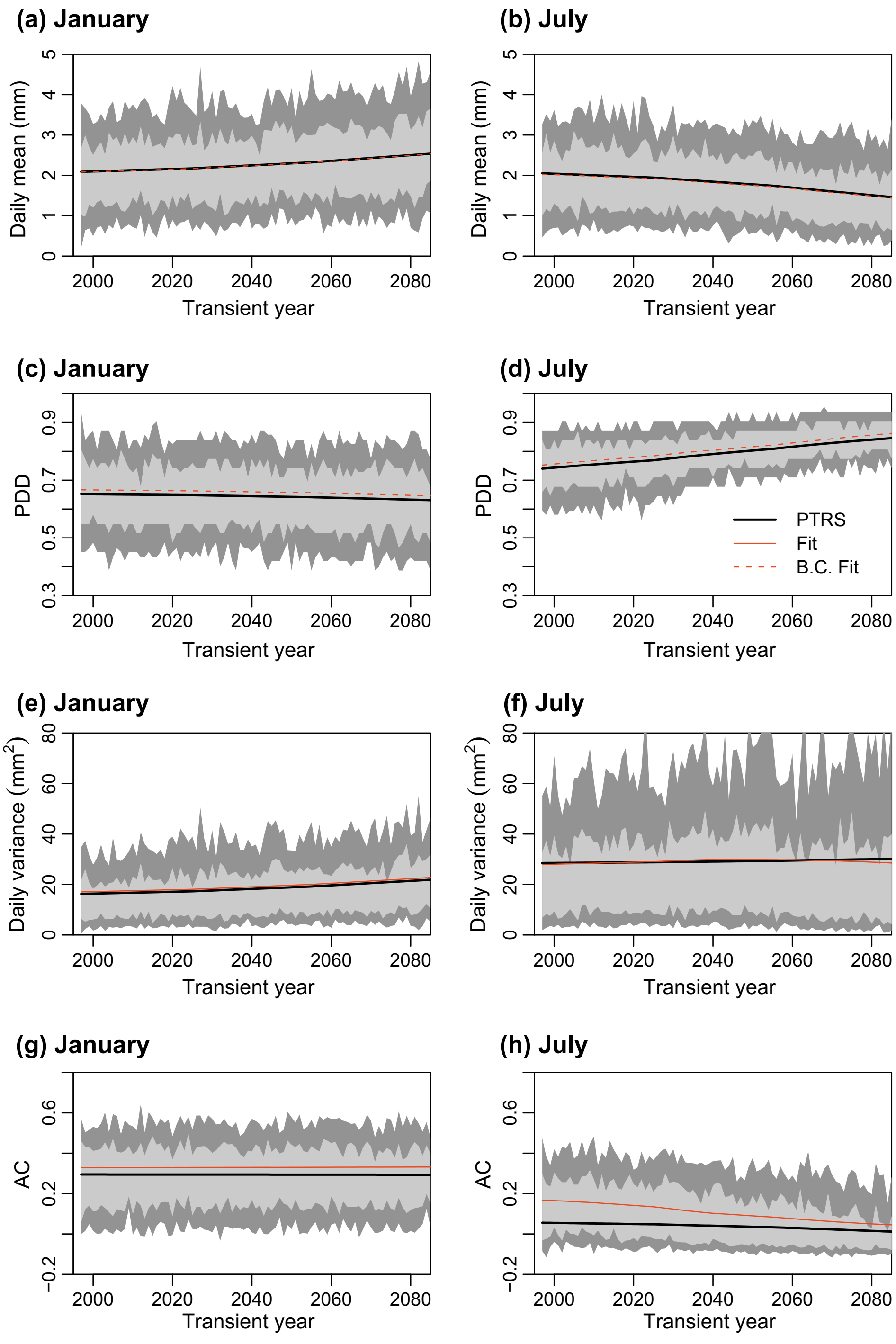

Fig. 9. Time series of ensemble-percentiles of statistics of the simulated transient time series for January and July for the ARPEGE_H RCM. Shaded areas indicate the inter-quartile range (light grey) and the 10th–90th percentile range (darker grey). These are compared with the PTRS and where appropriate either the fitted transient statistics (Fit) or the fit to the bias-corrected transient statistics (B.C. Fit).

stochastic variability in the ensemble simulation. For most cases the simulated statistics lie close to the means of the distributions and the quantiles appear to follow the PTRS in a smooth and temporally consistent manner. However, Fig. 9f and h illustrate cases for ARPEGE_H where simulation biases vary throughout the transient period, which may slightly bias projections for this month.

The other 12 RCMs were also analysed across all months and statistics. Overall the fits appear to be reasonable representations of the PTRS for each RCM and to provide a reasonable representation of the trends in the PTRS. Exceptions tend to be of relatively small magnitude compared with the ensemble variability of the simulated transient time series.

Assessment of simulated future changes in rainfall

The utility of the multi-model ensemble of simulated transient rainfall time series ultimately arises from its use as input to a groundwater quantity and water quality model for the Brévilles, enabling the production of probabilistic transient hydrological scenarios which allow the impacts of future changes in climate

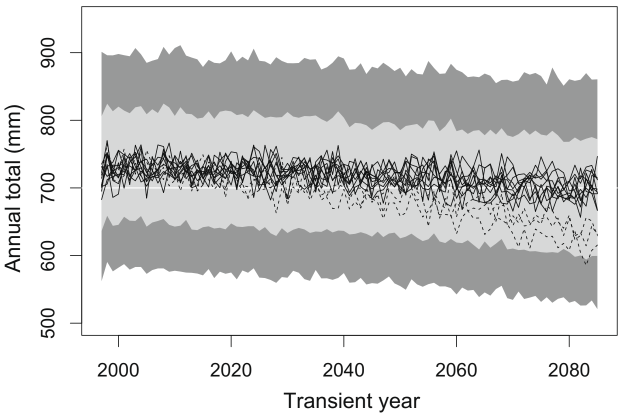

Fig. 10. The multi-model ensemble variation of the transient-simulated annual total rainfall. Shaded areas indicate the inter-quartile range (light grey) and the 10th–90th percentile range (darker grey). Time series of the simulated median annual totals for each RCM are indicated as black lines, except for HIRHAM_E, HAD_P_H and RCAO_E which are distinguished by dashed lines. The 700 mm white gridline is included for visual reference.

to be evaluated. However, in this section simple illustrative analyses of the projected changes to rainfall and the associated uncertainties in those projections are detailed.

First, the multi-model ensemble of simulated annual rainfall was examined and is shown in Fig. 10. For each year the 10th, 25th, 75th and 90th multi-model ensemble-percentiles are shown. Additionally the transient time series of the 50th percentile of annual rainfall corresponding to each RCM is also shown. Whilst most RCMs were found to project a small decrease in annual rainfall over the simulated transient period, three were found to project a much stronger decrease (HIRHAM_E, HAD_P_H and RCAO_E). Fig. 10 also shows that the variability of annual totals is projected to remain largely unchanged.

Future changes in rainfall are not expected to be evenly distributed throughout the year and therefore linear trends in annual and seasonal rainfall were evaluated for all 13 RCM ensembles (Table 3) which in most cases were significant at the 5% level. Comparison of the annual trend with the PTRS confirmed that these were consistent. All of the RCMs project decreasing trends in annual rainfall, decreasing trends in summer rainfall and increasing trends in winter rainfall (of a smaller magnitude than the summer decreases). In autumn most models project a decrease which is typically smaller than the increase in winter rainfall. Projections for spring are split as to whether the trend is increasing or decreasing. RCAO_E shows the largest decreasing trend in spring and summer, HAD_P_H and HIRHAM_E the smallest winter increases, HAD_P_H the largest decreasing autumn trend and HIRHAM_E the second largest decreasing spring trend. Consequently, these three RCMs project the greatest decreases in annual rainfall seen in Table 3 and Fig. 10. It is also interesting to note that the annual trends are strongly affected by the driving GCM whereby RCMs taking boundary conditions from ECHAM4 project larger decreases in annual and spring rainfall than the corresponding HadAM3H forced RCMs. The unusual behaviour of the HAD_P_H model may perhaps relate to forcing by the HadAM3P GCM in contrast with the other RCMs in the HadCM3 group. These annual and seasonal analyses provide an example of how the multi-model approach can represent a range of alternative projections arising from a range of alternative dynamical downscaling schemes and driving GCM boundary conditions.

Summer and winter trends in daily mean and PDD are shown in Fig. 11. In summer the multi-model ensemble projects a decrease in mean rainfall throughout the period (with the rate of decrease becoming larger through time) whereas for winter there is an increasing trend (with the rate increasing through time) in mean rainfall which is of a slightly smaller magnitude than the summer decrease (compare Fig. 11a and b). Outlying behaviour by RCAO_E, HAD_P_H, HIRHAM_E and ARPEGE as described in Table 3 is also shown in Fig. 11. In summer the multi-model ensemble projects a ~10% increase in the PDD. RCAO_E again follows a distinct trajectory, projecting a much greater increase in the PDD than the other RCMs. This change contributes to two-thirds of the 59% decrease in mean summer rainfall described in Table 3 for this RCM, by decreasing the number of wet days. For the winter season, most RCMs indicate a decrease in PDD of around 8% (with the rate increasing through time), which corresponds to an increase in winter mean rainfall of approximately 0.4 mm/year. This accounts for most of the change to winter mean rainfall described in Table 3 for the majority of RCMs. RCAO_E, HAD_P_H, HIRHAM_E and ARPEGE_H are exceptional in that they show little change in winter PDD as well as the smallest winter increase in mean rainfall (Table 3). Therefore, the increase in winter mean rainfall in these models must arise mainly from an increase in the wet day rainfall amount.

Although changes to mean climate are of interest, the most significant hydrological impacts are likely to be associated with changes in extreme events. Analyses of rainfall intensities in

Table 3

The fitted linear trends in the simulated annual and seasonal total rainfall for each RCM's ensemble. The standard error of each trend is roughly 0.05 mm/year for the annual trends and up to 0.03 mm/year for the seasonal trends. All trends are significant at the 5% level except in MAM for four of the RCMs (omitted). The mean, minimum and maximum of the annual and seasonal trends over the RCM multi-model ensemble are indicated. The mean observed annual and seasonal rainfall totals are provided for reference.

RCM	Annual (mm/y)	MAM (mm/y)	JJA (mm/y)	SON (mm/y)	DJF (mm/y)
PROMES_H	−0.16	0.11	−0.53	−0.25	0.49
ARPEGE_H	−0.18	−0.09	−0.44	0.07	0.28
REMO_H	−0.21	0.16	−0.55	−0.30	0.49
REGCM_H	−0.30		−0.65	−0.14	0.46
CLM_H	−0.31	0.09	−0.70	−0.25	0.54
RACMO_H	−0.42		−0.78	−0.18	0.48
HIRHAM_H	−0.45		−0.58	−0.33	0.43
CHRM_H	−0.46	0.05	−0.82	−0.26	0.57
METNO_H	−0.53		−0.72	−0.30	0.43
RCAO_H	−0.55	0.15	−0.90	−0.27	0.46
HIRHAM_E	−1.01	−0.25	−0.64	−0.31	0.20
HAD_P_H	−1.06	−0.05	−0.70	−0.52	0.20
RCAO_E	−1.46	−0.46	−1.15	−0.29	0.42
Mean	−0.55	−0.01	−0.70	−0.26	0.42
Min	−1.46	−0.46	−1.15	−0.52	0.20
Max	−0.16	0.16	−0.44	0.07	0.57
Observed (mm)	736	173	173	186	203

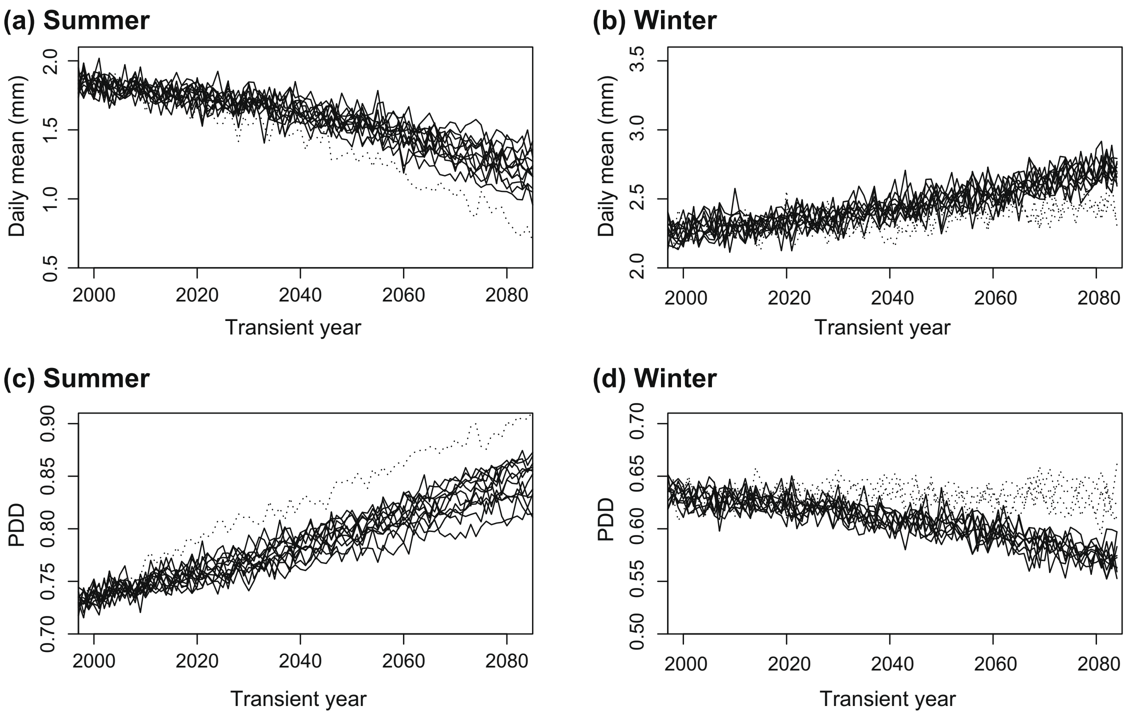

Fig. 11. The transient time series of the ensemble-mean (a) daily mean, summer (JJA), (b) daily mean, winter (DJF), (c) PDD, summer, and (d) PDD, winter, statistics for each RCM. Outlying RCMs are distinguished by dotted lines: (a) RCAO_E; (b) HIRHAM_E, HAD_P_H and ARPEGE_H; (c) RCAO_E; and (d) HIRHAM_E, HAD_P_H, RCAO_E and ARPEGE_H.

observed data on global (e.g. Frich et al., 2002) and regional scales (e.g. Fowler and Kilsby, 2003) indicate that the high latitudes of the northern Hemisphere are currently experiencing a trend towards increased rainfall and enhanced variability, particularly in winter. Such a trend is likely to continue into the future as GCMs indicate that enhanced greenhouse conditions will result in increases in the frequency and intensity of heavy rainfall (e.g. Giorgi et al., 2001; Tebaldi et al., 2006).

To assess whether RCM changes in heavy rainfall were consistent with downscaled projections, a stationary climate comparison was made of the projected proportion change in the median annual 24-h maximum rainfall between the control and the future scenarios for each RCM and between downscaled stationary NSRP simulations corresponding to each scenario. The RCMs were found to project a mean increase of 11% compared with the mean downscaled projection of a 6% increase. These estimates are both statistically significant compared with a no-change hypothesis though indistinguishable from each other at the 95% confidence level, although the projections of change are highly variable (RCM and downscaled projections of change have ranges of 35% and 16% respectively).

The likely transient changes in extreme rainfall for the Brévilles spring were assessed by evaluating the annual maximum daily rainfall for each year and for each simulated time series in the transient 100-member ensemble for each RCM. The 10-year return period 24-h event was estimated for each RCM and year as the mean of the 10th and 11th ranked maxima across the ensemble multiplied by the fixed window correction factor. This provided a time series of 10-year return period events for each RCM's ensemble to each of which linear and quadratic regression fits were made, each constrained to the 1997 value. Table 4 shows the coefficient of the linear fit, a_1, and the rate of change of the quadratic fit, a_2, where these were significant at the 5% level. Fig. 12 also shows the fitted quadratic trends, demonstrating the range of projected changes and identifying models with outlying behaviour.

Table 4
Coefficients of trends fitted to the simulated ensemble of the 10-year return period annual maximum 24-h rainfall event for each RCM. The coefficient a_1 is for a linear trend and the coefficient a_2 is the rate of change of a quadratic trend. Only trends significant at the 5% level are shown.

Model	a_1 (mm/year)	a_2 (mm/year^2)
HAD_P_H	−0.018	
PROMES_H		
HIRHAM_H	0.030	
METNO_H	0.062	
ARPEGE_H	0.071	
RCAO_H	0.073	
CLM_H	0.082	
HIRHAM_E	0.084	
REMO_H	0.090	
CHRM_H	0.091	−0.0017
RCAO_E	0.096	
RACMO_H	0.099	0.0023
REGCM_H	0.188	0.0035

REGCM_H was found to project the largest increasing trend in extreme rainfall, which is projected to increase with an increasing rate over the 1997–2085 period. The models projecting the least change were PROMES_H for which no trend can be discerned, HIRHAM_H which shows a small linear increase and HAD_P_H which is the only model to project a decreasing trend in extreme rainfall. The remaining nine RCM 100-member ensembles all project similar increases of ~10%.

This analysis provides an example of an assessment of transient and future climate that cannot be carried out using RCM integrations alone because of biases and short time-slice integrations. In this case the analysis uses the stochastic conceptualisation of rainfall embodied in the NSRP model (validated against the observed data) to downscale the RCM projections to the local scale required for impact studies. Furthermore, the multi-model, ensemble and

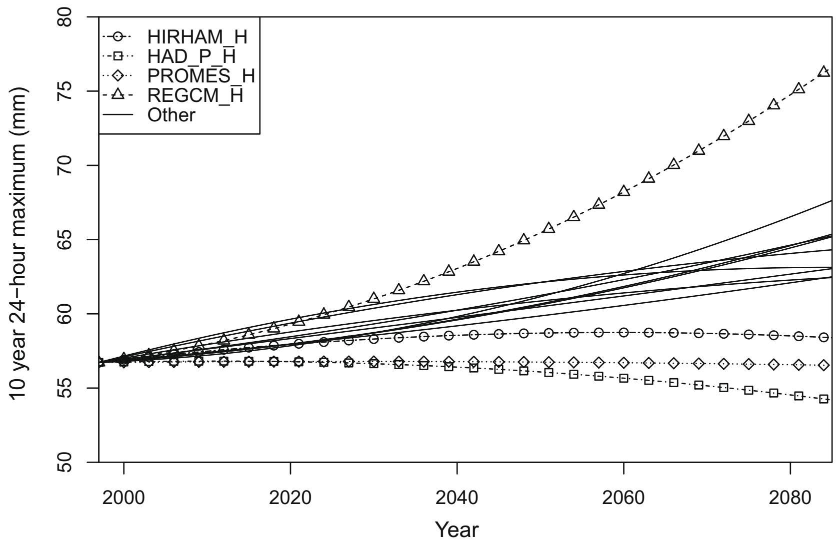

Fig. 12. Quadratic curves fitted to the 24-h 10-year return period event time series estimated from each RCM's transient downscaled ensemble time series. Models exhibiting outlying behaviours are identified in the legend.

transient nature of the synthetic datasets include relevant elements that represent the alternative dynamical downscaling schemes of the various RCMs, alternative future realizations and time varying future projections respectively.

Discussion and conclusions

Despite the large number of studies applying downscaling methods to climate models for use in hydrological impacts assessments policy makers and practitioners are not currently provided with the necessary tools to allow effective robust decision making over appropriate time-horizons (Fowler and Wilby, 2007). Future climate scenarios are required that represent future climate uncertainty at the planning and decision making time scales of policy makers which account for the transient nature of climate change effects.

We have sought to address these issues by developing a new methodology to generate a large multi-model stochastic ensemble of transient climate scenarios for the Brévilles spring in northern France. Whilst the ensemble provides some very short term projections, these are stochastic realizations of possible future weather rather than forecasts. The methodology provides several benefits. It is a computationally efficient hybrid dynamical–statistical downscaling methodology which avoids the computational burden of a transient dynamical downscaling approach and may be automated easily. A number of additional advantages are also demonstrated: (i) reduced biases compared with Regional Climate Model (RCM) simulations; (ii) relevance to the point scale, needed for local impact assessments, rather than the RCM grid cell; (iii) a representation of uncertainty, arising from natural variability by means of a large ensemble of stochastic simulations whereas RCM ensembles are currently limited to about three members; (iv) a representation of the structural uncertainty of future climate models through the use of a multi-model approach to account for alternative projections of climate change; and (v) improved simulation of extremes compared to most RCM simulations. Such a transient ensemble allows the evaluation of the probability of an event or impact by a certain future date or the estimation of a date by which an event or impact becomes likely. It also provides the basis for continuous modelling and assessment of the future temporal development of hydrological systems rather than limiting such analysis to comparisons arising from discrete scenarios.

The new methodology considerably extends and updates an approach used in the EARWIG weather generator (Kilsby et al., 2007), which can produce only stationary climate scenarios for four UKCIP02 time-slices for the UK. A multi-model approach was adopted whereby 13 RCMs from the PRUDENCE project provided an up-to-date range of alternative climate change projections. Novel sets of projected transient rainfall statistics were estimated, through the application of change factor and pattern scaling approaches to observed rainfall statistics, one set representing the transient climate projected for each RCM. A transient NSRP rainfall model was developed in which model parameterization was allowed to vary by year, to represent transient climate change, and calendar month, to represent seasonality. In contrast the stationary NSRP model (e.g. Burton et al., 2008) could represent seasonality but reused the parameter set for each simulated year thus providing a stationary-climate simulation. After fitting, the new model is able to generate continuous stochastic simulations representing both seasonal and transient effects for the projected transient period 1987-2085. Repeated transient stochastic simulations were used to generate an ensemble of 100 transient rainfall time series based on each of the RCMs. Together the multi-model ensemble comprised 1300 simulations and provides a representation of the uncertainty associated with future projections.

A simple evaluation of the downscaled transient rainfall projections was carried out. Seasonal analysis of trends derived from the ensemble of each RCM indicated a decrease (with increasing magnitude) in summer rainfall, a smaller magnitude increase in winter rainfall (with an increasing rate) and typically a decrease in autumn rainfall. The overall balance of these trends was for a slight decrease in annual rainfall. The frequency of rainfall, as measured by the number of wet days, also appears to increase in winter (with an increasing rate) and decrease in summer and was found to contribute significantly to seasonal rainfall totals. Change in annual rainfall also appears to be highly sensitive to the choice of driving GCM, with ECHAM4-driven RCMs projecting larger annual decreases than RCMs driven by HadCM3/HadAM3H/P. 10-year return period daily extremes estimated from the ensemble of each RCM indicated a likely increase of $\sim$10% by 2085 although the trends of individual RCMs ranged from an increasing trend of twice this magnitude to a decreasing trend. These findings are broadly consistent with results reported in the literature (e.g. Tebaldi et al., 2006; Giorgi et al., 2001).

For management of the Brévilles aquifer the most useful evaluation of climatic changes based on the multi-model ensemble will derive from a transient groundwater water quantity and quality assessment using a hydrological model. To support such studies daily time series of temperature and potential evapotranspiration need to be estimated that are consistent with the ensemble of rainfall time series. For this purpose a weather generator is required, such as the Climatic Research Unit's daily weather generator (Jones and Salmon, 1995; Watts et al., 2004) a second component of the EARWIG system (Kilsby et al., 2007). Together ensembles of rainfall, temperature and potential evapotranspiration may then be used as input to a hydrological water quantity and quality model of the aquifer supplying the Brévilles spring.

The new methodology makes the assumptions that changes in spatial rainfall as modelled by the RCMs will reflect changes in rainfall observed at a single raingauge and that these changes will vary steadily and in proportion with global mean temperature. The fitting precision or the simulation biases of the NSRP model may vary throughout the transient period which may lead to transient variation in the simulated time series in addition to projected changes in the PTRS. However, the main properties of the projected transient scenarios are broadly reproduced by the transient parameterizations.

Whilst the strength of the new methodology lies in representing both natural variability and uncertainty in future climate projections, this representation underestimates the full contribution of all sources of uncertainty which will affect projections of both the magnitude and the timing of climatic changes. The natural variability will be underestimated because the transient scenarios do not realistically represent decadal and sub-decadal variability arising from naturally occurring teleconnections such as the El Niño Southern Oscillation nor the effects of volcanic activity which can produce significant effects on global rainfall and temperature patterns. However, transient RCM integrations do not realistically represent decadal and sub-decadal variability either so this situation cannot be improved upon using the currently available RCMs and ensembles. Here the EARWIG approach (Kilsby et al., 2007) was extended by deriving change factors from single runs of each of the 13 PRUDENCE RCMs which were conditioned on two GCMs. It should be noted that these RCMs provide an ensemble of opportunity rather than describing the full range of future climate possibilities and so may underestimate the full range of uncertainty in climate response to global warming. Furthermore in this study only a single, medium–high, CO_2 emissions scenario was selected due to the experimental design of the PRUDENCE project, future studies could also include the effects of other emissions scenarios as suitably large ensembles become available.

The 19-year observed time series is subject to natural variation and so uncertainty due to sampling variability is also attached to the monthly values of each statistic. Whilst characterisation of this uncertainty is beyond the scope of this paper it should be considered when interpreting results derived from this simulated dataset. In contrast, long observed time series, say over 100 years in length, would already include a component of climatic change. Thus the implicit assumption that the observations represent a stationary climate would become invalid. An interesting extension of the approach reported here would therefore be to devise the means to fit a rainfall model to a climatically non-stationary observed record.

The new transient NSRP model has a large number of parameters, 4296 (i.e. four parameters per month per transient year plus two bias-corrections per month), which may make this model appear over-parameterized. However, the model is fitted to 6408 PTRS (six per month per transient year), the transient time series of model parameters is smooth and the correct modelling of observed extreme rainfall statistics which were not used in model parameterization provide evidence that the model is not over-parameterized.

Whilst the new methodology is based on time-slice projections from a GCM/RCM pair, transient RCM integrations are now becoming available through projects such as the EU-funded ENSEMBLES (Hewitt and Griggs, 2004) and UK Climate Projections (Murphy et al., 2007). Similar to current RCM results, such transient integrations may not comprise large ensembles to represent climatic variability (due to computational expense), they may underestimate extremes and they may exhibit biases in rainfall statistics. Therefore a major benefit of the methodology presented here is that such limitations are addressed and the methodology easily adapted. As transient RCM projections become available change factors may be evaluated directly from the transient RCMs thereby eliminating the need for pattern scaling.

The introduction of a downscaling step between RCM outputs and hydrological modelling adds complexity. Simpler models or even omitting the downscaling step altogether should therefore be considered as alternatives with respect to the ultimate hydrological application. Multiplicative bias-correction of RCM integrations cannot correct the frequency of wet days nor the modelling of extremes and cannot simulate events beyond those already found in the observational record or the RCM time-slices (limiting the representation of natural variability). However, the methodology presented here is relatively simple for the range of advantages it presents and in addition it also leads to a number of potential extensions not demonstrated here: relevance to a broad range of hydrological applications at smaller spatial scales, the simulation of rainfall at sub-daily time steps and the simulation of spatial rainfall fields.

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