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Streamflow estimation for six UK catchments under future climate scenarios

K. P. Chun, H. S. Wheater and C. J. Onof

ABSTRACT

Possible changes in streamflow in response to climate variation are crucial for anthropological and ecological systems. However, estimates of precipitation under future climate scenarios are notoriously uncertain. In this article, rainfall time series are generated by the generalized linear model (GLM) approach in which stochastic time series are generated using alternative climate model output variables and potential evaporation series estimated by a temperature method. These have been input to a conceptual rainfall–runoff model (pd4-2par) to simulate the daily streamflows for six UK catchments for a set of climate scenarios using seven global circulation models (GCMs) and regional circulation models (RCMs). The performance of the combined methodology in reproducing observed streamflows is generally good. Results of future climate scenarios show significant variability between different catchments, and very large variability between different climate models. It is concluded that the GLM methodology is promising, and can readily be extended to support distributed hydrological modelling.

Key words | climate change, generalized linear model (GLM), rainfall model, rainfall–runoff model, statistical downscaling, streamflows

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INTRODUCTION

Streamflow is an essential resource for a range of societal needs, is fundamental to the functioning of aquatic and riparian ecosystems and represents a major hazard to life, property and infrastructure. It is a spatial integrator of the hydrological response of terrestrial ecosystems and has a nonlinear relationship to climate, amplifying the effects of climate variability and climate change. Changes in streamflow resulting from climatic variations are of critical importance to water resources (e.g. Harrison *et al.* 2003; Christensen *et al.* 2004; Maurer 2007) and flood risk management (e.g. Wheater 2006), as well as ecosystems (e.g. Mortsch & Quinn 1996), water quality (e.g. Mimikou *et al.* 2000) and sediments and geomorphology (e.g. Inman & Jenkins 1999). Integrated management of streamflow is needed to balance competing demands e.g. water supply, ecosystem protection and effluent dilution. Assessment of the effects of climate change therefore requires understanding of effects on streamflow variability, including high and low flow extremes, across a wide range of timescales from hours and days (in the case of floods) to months and years (for water resources).

In early studies of climate change impacts on streamflows, the main areas discussed were the characteristics of the historical data and sensitivity of hydrological systems to climate variability. For example, the trends of hydrological time series were extracted from streamflow records (e.g. Lettenmaier *et al.* 1994; McCabe & Wolock 1997; Hannaford & Marsh 2006) and the sensitivity of streamflows produced by hydrological models was assessed using hypothetical climate profiles (e.g. Nemec & Schaake 1982; Bultot *et al.* 1988). However, data uncertainty and natural climatic variability limit the potential for the detection of change (e.g. McCabe & Wolock 1997) and observed historic trends are not necessarily an only guide to the future.

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Modelling physical mechanisms can be an alternative approach to understand the limitation of the historical data and enable a projection of the non-stationary climate system. Hence, in the last few decades, climate models and specifically global circulation models (GCMs) (e.g. Manabe 1969; Bates & Meehl 1986; Bacher *et al.* 1998; Hulme *et al.* 1999; Pope *et al.* 2000) have been developed to provide an important source of information about possible climate change.

Since the Intergovernmental Panel on Climate Change (IPCC) first assessment report (Houghton *et al.* 1990), GCMs have rapidly evolved. Many studies (e.g. Stamm *et al.* 1994; Lawrence & Slingo 2004*a*,*b*) have tried to improve the performance of streamflow simulations from GCMs by employing more complex land surface hydrological parameterization schemes. However, there are still major problems in using GCM outputs directly or employing them to drive hydrological models (Wheater 2002). At the grid scales of current models (10,000 km^2), there are major issues associated with e.g. lack of representation of sub-grid scale variability of land surface properties and meteorological processes and the model outputs which represent grid-scale averages for variables such as precipitation and soil moisture which have high spatial variability. As a result, GCMs may display bias on regional scales (e.g. Maurer 2007) and the track record of reproducing observed streamflow response is generally poor (Elshamy *et al.* 2006).

In an attempt to overcome these problems, downscaling and bias-correction methods have been developed to facilitate the use of GCM outputs as direct inputs for hydrological models. Reviews concerning different methods and limitations of downscaling include e.g. Giorgi & Mearns (1991), Xu (1999) and Fowler *et al.* (2007). In general, downscaling methods are classified into one of two fundamental approaches: dynamical and statistical downscaling.

Dynamical downscaling methods are usually based on the use of regional climate models (RCMs), which generate finer resolution output over a region of interest using GCM fields as boundary conditions (e.g. Giorgi & Mearns 1991, 1999). Although RCMs should theoretically provide better feedback relationships among different physical processes within the model boundary, they are computationally intensive and have similar biases and problems to the driving GCMs because of their strong dependence upon GCM forcing.

Blenkinsop & Fowler (2007) noted the problematic outputs from six investigated RCMs and acknowledged their weakness (such as the poor capture of important precipitation processes and the difficulty of assessing the performance of the models). From the results of the PRUDENCE project, Beniston *et al.* (2007) concluded that RCMs introduce significant uncertainty in GCM downscaling. As with GCM outputs, there are difficulties in the direct use of RCM outputs in hydrological models, and hence statistical downscaling techniques have been developed in parallel with the dynamical approaches.

Based on local observations or theoretical distributions, statistical downscaling methods establish the relationship between large-scale atmospheric states and fine-scale climate variable. The delta change method is an early common statistical downscaling method (e.g. Hay *et al.* 2000) for streamflow impact assessment. The signal of change from the climate models (GCMs/RCMs) is identified using the differences or the ratios between the control and future global climate outputs. The effect is then added to the observed time series of climate variables or used to scale them.

In the US, the delta change method has been widely used to assess the sensitivity and impact of the characteristics of streamflow under different hypothetical climate-change scenarios based on GCM outputs (e.g. Gleick 1986, 1987; Lettenmaier & Gan 1990). Arnell (1992) and Arnell & Reynard (1996) applied a similar approach using conceptual hydrological models to assess the possible effects of river flows in the UK. Although the delta change method is simple, the assumption of a linear relationship in application of the method may not be realistic.

Other more complicated statistical downscaling models have been developed. For example, Wilby *et al.* (2002) downscale GCM outputs using empirical regressions between local-scale predictands and regional-scale predictors. Cavazos & Hewitson (2005) used artificial neural networks for downscaling. Ines & Hansen (2006) and Sharma *et al.* (2007) generated rainfall input for a hydrological model by bias-correction and stochastic disaggregation by gamma-gamma transformation and multiplicative shift techniques.

Among many statistical downscaling methods, Leith & Chandler (2008) applied generalized linear models (GLMs) to simulate daily rainfall using GCM outputs as regional driving forces. GLMs provide a powerful general framework for data analysis and simulation and, in their application in this context, the signal of regional change is extracted from the more reliable GCM variables and used as input to stochastic models of the daily rainfall process. Yang *et al.* (2005) also applied the GLM framework for the temporal downscaling of potential evaporation. Apart from using GCM and RCM output variables directly, the flexible GLM framework can also include large-scale climate indices such as the North Atlantic Oscillation (NAO) as predictors for rainfall simulation (Chandler & Wheater 2002).

In the work of Leith & Chandler (2008), more fully reported in Chandler (2005) and Leith (2005*a*,*b*), promising results were obtained for the disaggregation of UK rainfall. A range of GCMs and RCMs was used to evaluate the associated uncertainty. In this paper, this work is extended to represent catchment average rainfall and evaluate its effects on streamflow for six UK catchments. The methodology and data are described in Section 2. The results of possible hydrological change are presented in Section 3. The issues and other considerations of using the proposed framework to assess the change of streamflow under different climate scenarios are summarized in the last section.

METHODOLOGY AND DATA

The methodology used here is to develop models of rainfall and evaporation for each of a set of catchments based on climate model outputs for contemporaneous 20th century data and to use the model to generate stochastic sequences for future climate states, based on a set of alternative GCMs and RCMs. These are then input to a set of hydrological models for assessment of impacts and the associated climate model uncertainty.

The adopted daily rainfall model is based on a two-stage process containing an occurrence model, similar to that of Gabriel & Neuman (1962) and an amounts model based on the gamma distribution. Generalized linear models (GLMs) as described by Nelder & Wedderburn (1972) are used to represent these relationships. The approach was first used for rainfall by Coe & Stern (1982) and Stern & Coe (1984) and extended by Chandler & Wheater (2002) to interpret rainfall sequences in the west of Ireland, including geophysical variables such as an index of the NAO.

Yang *et al.* (2005) also used the GLM approach to simulate multisite rainfall for UK raingauge networks. Moreover, the GLM approach has been tested in the southern hemisphere; Furrer & Katz (2007) used the GLM framework to generate weather data (including rainfall and temperature) in Argentina. The software package for fitting and simulating GLMs to daily climate sequences from a network of sites is available at http://www.homepages.ucl.ac.uk/ ~ ucakarc/work/glimclim.html (Chandler 2006).

The occurrence models take the form of a logistic regression

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i^T \beta \tag{1}$$

where p_i is the probability of rain for the ith case in the dataset; x_i^T is a transposed predictor vector and β is a coefficient vector.

The amounts models of the conditional mean daily rainfall μ_i in the gamma distribution are given by

$$\ln \mu_i = \xi_i^T \gamma \tag{2}$$

where μ_i is the mean amount of rain for the ith wet day; ξ_i^T is a transposed predictor vector and γ is a vector of coefficients.

In the initial investigation of the potential of GLMs for use in statistical downscaling, Leith & Chandler (2008) used a set of three raingauges (at Ringwood, Elmdon and Heathrow; Figure 1). This study builds on that work, and focuses on six adjacent catchments selected from a large database of gauged UK catchments developed by Young (2000) and previously used by Lee (2006) to develop a framework for regionalization of hydrological models. The locations and characteristics of the six catchments are shown in Figure 1 and Table 1. Catchment notation follows the station names and reference numbers from the UK National River Flow Archive (NRFA).

The general characteristics of the selected catchments are similar, apart from the high index of fractional urban extent of the Cole at Coleshill (28066) and relatively high

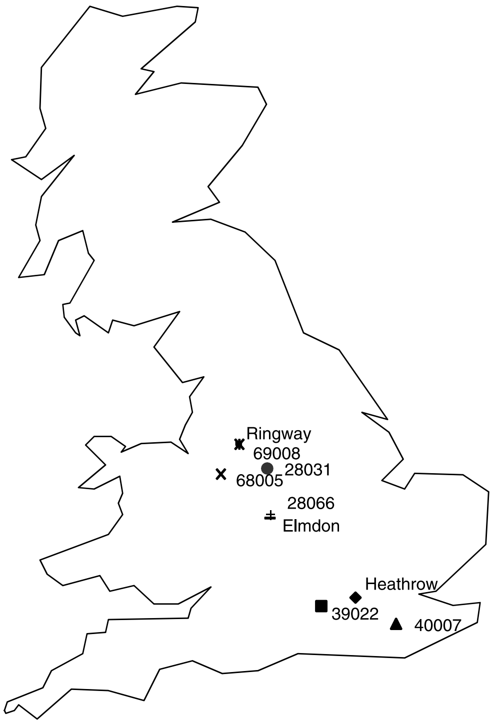

Figure 1 | Map of six catchments.

average elevation at the Manifold at Ilam (28031). The lengths of the coincident rainfall and runoff data series for the calibration and validation of hydrological models for the selected catchments are over 14 years. The available daily rainfall record lengths are between 23 and 30 years.

The climate variables for future climate scenarios are from four GCMs and three RCMs for the 2080s A2 emissions scenarios. In the A2 emission scenario, the global average temperature in 2100 is projected to be 3.9 degrees higher than the levels from 1980 to 2000 (Solomon *et al.* 2007). The details of the models are given in Table 2 and the emission scenarios are explained in Nakicenovic *et al.* (2000). GLM relationships are developed for 20th century data, based on observed rainfall and control climate variables from the US National Centres for Environmental Prediction (NCEP) reanalysis dataset (Kalnay *et al.* 1996). NCEP data enable the evaluation of the climate model performance based on contemporaneous data at the same climate model grid resolution. Data from the period 1961–1990 was available for GLM model development and simulation.

The occurrence and amount model structures (Table 3a and b) developed for catchment average rainfall are based on the work of Leith & Chandler (2008) for adjacent raingauge sites that have the same structural form. The occurrence model contains 24 parameters, of which three parameters are climate variables, eight are covariates corresponding to local daily and seasonal effects and the other twelve parameters are the autocorrelations or correlations between climate variables and covariates. Similarly, the amounts model has 14 parameters, but it only has two climate variables and a simpler autocorrelation and correlation structure. This is consistent with the assertion of Yang *et al.* (2005) that rainfall amounts are less responsive to the regional variations than rainfall occurrences. From the fitted rainfall models of six catchments, the rainfall series are simulated using pseudo-random numbers based on Marsaglia & Zaman (1991).

Apart from rainfall, potential evaporation is another principal input for conceptual hydrological models. However, there are also important methodological issues associated with the use of GCM/RCM data. In hydrological practice, the Penman-Monteith Equation (Penman 1948; Monteith 1981; Allen *et al.* 1998) is widely recognized to be

Table 1 | Summary of catchment characteristics (BFIHOST: base flow index derived using the HOST classification; NRFA: UK National River Flow Archive; PEANN: 1961–1990 standard period average annual potential evaporation; SAAR: 1941–1970 standard period average annual rainfall; URB_EXT: Flood Estimation Handbook (FEH) index of fractional urban extent)

NRFA Number	Name	Area (km^2)	Elevation (m)	SAAR (mm/yr)	PEANN (mm/yr)	Baseflow index (BFIHOST)	URB_EXT
28031	Manifold at Ilam	148.5	307.0	1,087	588	0.46	0.0023
28066	Cole at Coleshill	119.7	126.5	732	609	0.38	0.3114
39022	Loddon at Sheepbridge	176.5	94.1	757	580	0.59	0.0454
40007	Medway at Chafford Weir	252.4	108.3	852	536	0.44	0.0200
68005	Weaver at Audlem	203.1	88.5	756	588	0.50	0.0053
69008	Dean at Stanneylands	58.3	186.8	919	597	0.55	0.0346

Table 2 | Details of climate models

Model type	Institution	Model name	Reference
GCM	Canadian Centre for Climate Modelling and Analysis (CCCMA)	Cgcm2	Flato *et al.* (2000)
			Flato & Boer (2001)
GCM	Commonwealth Scientific and Industrial Research Organization (CSIRO)	csiromk2	Dix & Hunt (1998)
GCM	Max-Planck-Institute (MPI)	Echam4	Bacher *et al.* (1998)
GCM	Hadley Centre (HADLEY)	Hadcm3	Gordon *et al.* (2000)
RCM	Danish Meteorological Institute (DMI)	Hirlam	Christensen *et al.* (2001)
RCM	Swedish Meteorological and Hydrological Institute (SMHI)	Rcao	Döscher *et al.* (2002)
RCM	Hadley Centre (HCrcm)	Hadrm3p	Moberg & Jones (2004)

an accurate physically-based method to estimate potential evaporation, based on energy balance and aerodynamic principles (e.g. Lopez–Urrea *et al.* 2006).

However, in application to GCM/RCM data, there is large uncertainty in estimates of the driving variables. Bergström *et al.* (2001) noted the difficulty in estimating potential evaporation based on wind speed, radiation, air temperatures and humidity, and acknowledged that the hydrological components of global climate models may be inadequate for direct use because of a lack of detailed representation of natural processes. Kay *et al.* (2006*a*,*b*) used the Penman–Monteith equation with RCM outputs to estimate potential evaporation, but without validation. Also using RCM results directly, Ekstrom *et al.* (2007) noted unreasonably high potential evaporation resulting from the Penman–Monteith equation. A similar problem of using RCM output to estimate evaporation by Penman type equations was also found by Walsh & Kilsby (2007). It is concluded that the suitability of using RCM outputs directly in hydrological models is questionable and has not been rigorously validated.

Alternative approaches to the estimation of potential evaporation include temperature-based methods. These have a weaker physical basis, but have the important advantage that estimates of temperature from GCMs and RCMs are generally considered to be more robust than other climate variables. Hulme *et al.* (1999) pointed out that temperature prediction from the Hadley Centre climate models has a much higher signal-to-noise ratio than the precipitation. Oudin *et al.* (2005) proposed that temperature-based potential evaporation models are more advantageous to provide the input for hydrological models than the Penman models, based on the streamflow simulation of 308 catchments located in France, Australia and the US. Since the GCM outputs may not be adequate to support Penman-based models, it therefore appears to be reasonable to use temperature-based methods to estimate potential evaporation, while bearing in mind their potential limitations.

Following Ekstrom *et al.* (2007) and Walsh & Kilsby (2007), the adopted temperature method for estimating potential evaporation is given by the Blaney–Criddle Equation (Blaney & Criddle 1950):

$$\mathrm{PE} = p\,(0.46\,T + 8.13) \tag{3}$$

where PE is mean potential evaporation (mm/day), T is mean daily temperature (°C) for that month and p is mean daily (%) of total annual daytime hours for a particular month and latitude.

Although monthly potential evaporation is used here, it is acknowledged that different temporal scales of potential evaporation may affect overall performance of the proposed approach. Smakhtin (2001) identified evaporation as one of the fundamental factors affecting streamflow characteristics during dry periods in low flow hydrology. The uncertainty associated with potential evaporation at a different timescale and with different flow responses requires further exploration, and is the subject of ongoing work. However, only monthly potential evaporation is examined at this juncture.

The streamflows were simulated using the Matlab-based Rainfall–Runoff Modelling Toolbox (RRMT) and Monte-Carlo Analysis Toolbox (MCAT) (available at http://www3.imperial.ac.uk/ewre/research/software/toolkit). These allow rapid application of a wide range of alternative

Table 3a | Covariates used in occurrence models for daily rainfall

Components	
Constant	
Sea level pressure	1
Temperature	2
Relative humidity	3
Index	4
3I(Y[t − 1] > 0)	5
I(Y[t − 2] > 0)	6
I(Y[t − 3] > 0)	7
I(Y[t − k] > 0: k = 1 to 2)	8
Daily seasonal effect, cosine component	9
Daily seasonal effect, sine component	10
Smooth February effect	11
Ln(1 + Y[t − 1])	12
2-way interaction: covariates 2 and 9	
2-way interaction: covariates 2 and 10	
2-way interaction: covariates 2 and 11	
2-way interaction: covariates 3 and 9	
2-way interaction: covariates 3 and 10	
2-way interaction: covariates 3 and 11	
2-way interaction: covariates 1 and 5	
2-way interaction: covariates 4 and 5	
2-way interaction: covariates 4 and 6	
2-way interaction: covariates 12 and 9	
2-way interaction: covariates 12 and 10	
2-way interaction: covariates 12 and 11	

rainfall–runoff model structures and analysis of the associated parameter and output uncertainty. The adopted hydrological model structure (pd4_2par) consists of a soil moisture accounting module (pd4) based on Moore (1985) and Wagener *et al.* (2004) and a routing module (2par) composed of two parallel linear conceptual reservoirs representing fast and slow catchment responses.

Lee (2006) tested the performance of the model structure (pd4_2par) with other models and found that it provided consistent performance for a large set of UK catchments compared to alternative available lumped conceptual models. The model calibration used 10,000 parameter sets, randomly sampled from the feasible ranges of the five parameters. The calibration period is from 1986 to 1996. Parameter values were selected based on two objective functions, the modified Nash–Sutcliffe Efficiency (NSE*, Equation (4)), which is sensitive to high flow response, and the root mean squared error applied to the low flow region of the hydrograph (FSB, Equation (5)). This ensured that the adopted parameter sets for six catchments take into account both high and low flow conditions.

The modified Nash-Sutcliffe efficiency is defined as:

$$\mathrm{NSE}^{*} = 1.0 - \mathrm{NSE} = \frac{\sum_{i=1}^{N}(o_i - c_i(\theta))^2}{\sum_{i=1}^{N}(o_i - \bar{o})^2} \tag{4}$$

and the root mean squared error is defined as:

$$FSB = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(o_i - c_i(\theta))^2}}{\frac{1}{N}\sum_{i=1}^{N} o_i} \tag{5}$$

where $c_i(\theta)$ is the calculated flow at time step i using the parameter set θ and o_i is the observed flow at the time step i.

The overall framework for the streamflow simulation is summarized in Figure 2. It can be noted that the relationship between simulated rainfall and potential evaporations is based on implicit relationships between climate variables from the GCMs and RCMs, i.e. dependence has not been explicitly represented.

Table 3b | Covariates used in amount models for daily rainfall

Components	
Constant	
Sea level pressure	1
Temperature	2
5Ln(1 + Y[t − 1])	3
Ln(1 + Y[t − 2])	4
Daily seasonal effect, cosine component	5
Daily seasonal effect, sine component	6
I(Y[t − k] > 0: k = 1 to 2)	7
2-way interaction: covariates 1 and 5	
2-way interaction: covariates 1 and 6	
2-way interaction: covariates 3 and 5	
2-way interaction: covariates 3 and 6	
2-way interaction: covariates 1 and 3	
Dispersion Parameter	

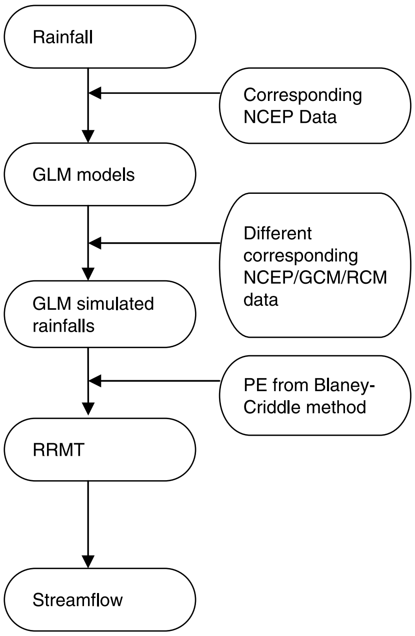

Figure 2 | Framework for streamflow impact assessment.

RESULTS

The rainfall series simulated using the GLM approach retain the general characteristics of the observed rainfall. Figure 3(a) presents typical results for the Manifold at Ilam (28031). For each of the six catchments, the observed average daily rainfall for each month of the year is bounded by ten simulated rainfall series driven by 30 years of NCEP data. The frequency distribution of daily rainfall, generated in a single realization from the NCEP data, is also illustrated for the Manifold at Ilam (28031) in Figure 3(b). Despite a slight discrepancy in low rainfalls, the Chi-test result does not show that the distributions of the observation and the simulation are different. In general, the rainfall characteristics of the simulated rainfall are consistent with the observed data at the daily scale, and the adopted rainfall model structure should be suitable for generating rainfall series for the six catchments. Further details of the evaluation of the methodology for rainfall generation in the UK can be found in Leith (2005*a*,*b*).

Although some trade-off between optimum parameter sets for different performance criterion is expected (Wagener *et al.* 2004), the optimum parameter sets derived from the Nash–Sutcliffe efficiency and the root mean square error are similar for five out of six catchments. Apart from the Cole

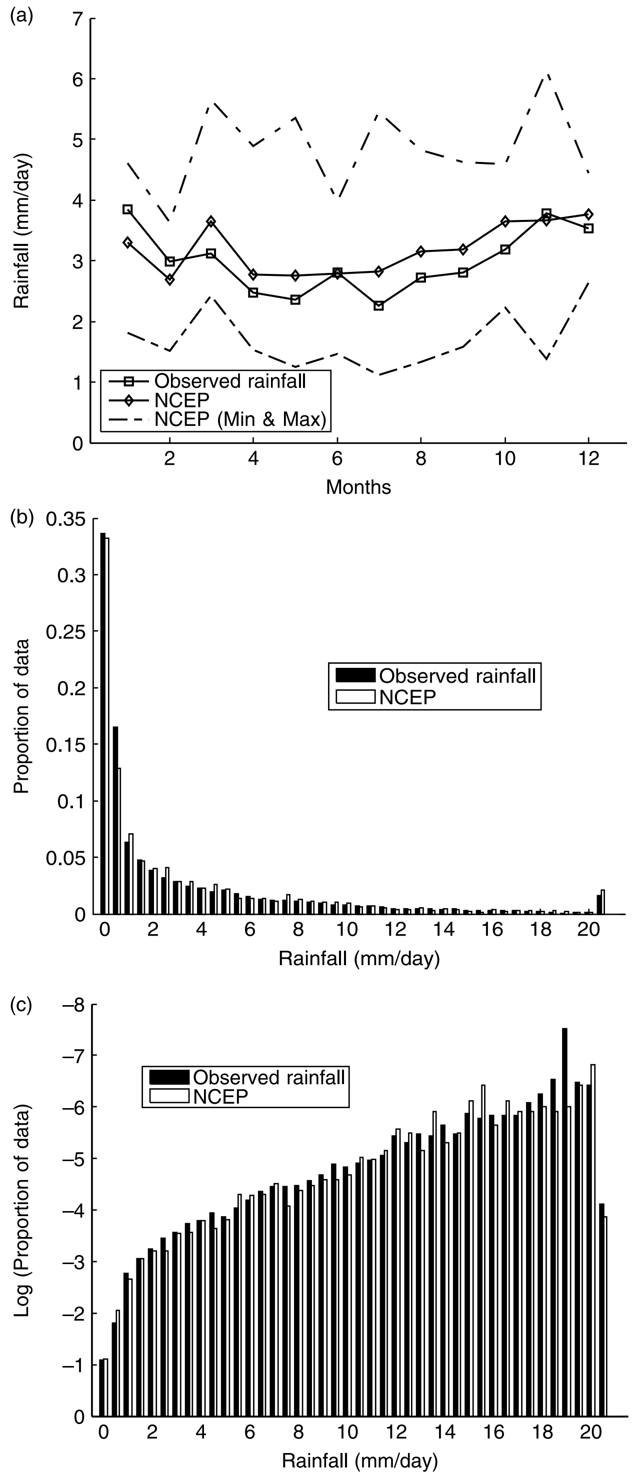

Figure 3 | Rainfall driven by NCEP using the GLM approach (a) monthly average daily rainfall for Manifold at Ilam (28031); (b) frequency distribution of daily rainfall for Manifold at Ilam (28031); (c) frequency distribution of daily rainfall for Manifold at Ilam (28031) with log-scaled frequency.

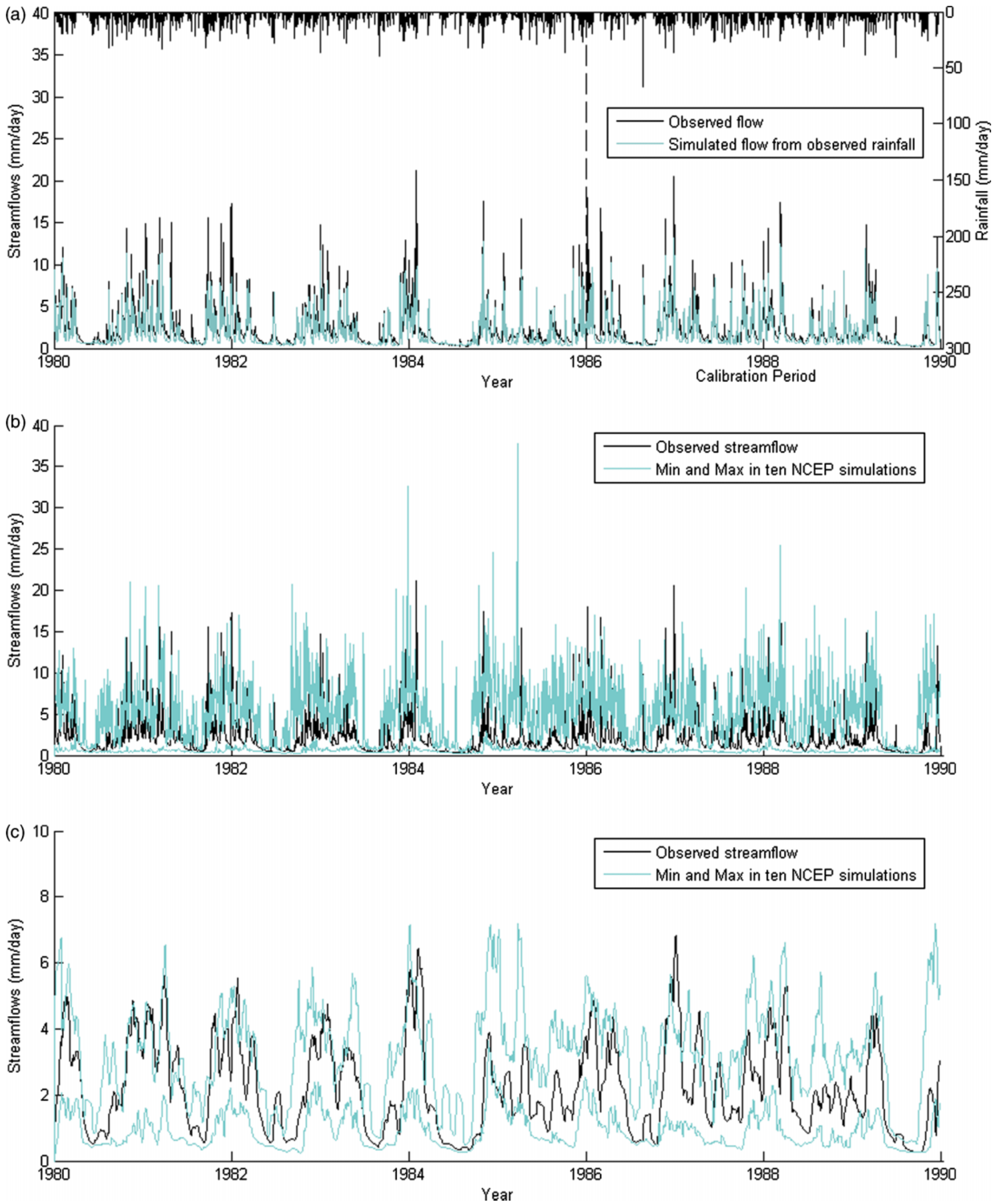

Figure 4 | (a) Daily hydrograph for Manifold at Ilam (28031) from 1980 to 1989; (b) daily simulated flow in Manifold at Ilam (28031) driven by NCEP data; (c) 30-day moving average of daily simulated flow in Manifold at Ilam (28031) driven by NCEP data.

at Coleshill (28066), the parameter sets which have minimum root mean square error are also one of the 200 optimum parameter sets based on the Nash–Sutchliffe efficiency from 10,000 random sets. However, in the present work the final selected parameter sets are based on the optimum Nash–Sutchliffe efficiency. Further investigation of multi-objective approaches will be pursued in subsequent research.

During the calibration periods, the modified Nash–Sutchliffe efficiencies are between 0.169 and 0.332 and the root mean square errors are between 0.0394 and 0.375 for the six catchments. In Figure 4(a), the flow simulated from the conceptual model using the observed rainfall is plotted against the observed daily streamflow in the Manifold at Ilam (28031). The general characteristics of the hydrograph are reproduced by the simulated flows; and the performance of the model inside and outside of the calibration period are considered to be adequate. The bounds of the simulated flow driven by the NCEP data are given in Figure 4(b) and 4(c). Generally, the ten simulated flows driven by the NCEP data bound the observed flows. The average characteristics of the simulated and observed flows can be compared in the 30-day moving average hydrograph in Figure 4(c).

The flow frequency curves are given in Figure 5. The simulations driven by the NCEP data generally represent the observed flows adequately, although underestimation and overestimation can be observed in the Manifold at Ilam and the Cole at Coleshill respectively. Despite variation between catchments, the simulated flows are, on the whole, suitable for both high and low frequency observed flows.

In Figure 6, the mean monthly simulated daily streamflows using the observed rainfall are compared to the (shorter) observed streamflow series and to simulations based on the GLM modelled inputs using the NCEP 30 year record. Hence the performance of the calibrated

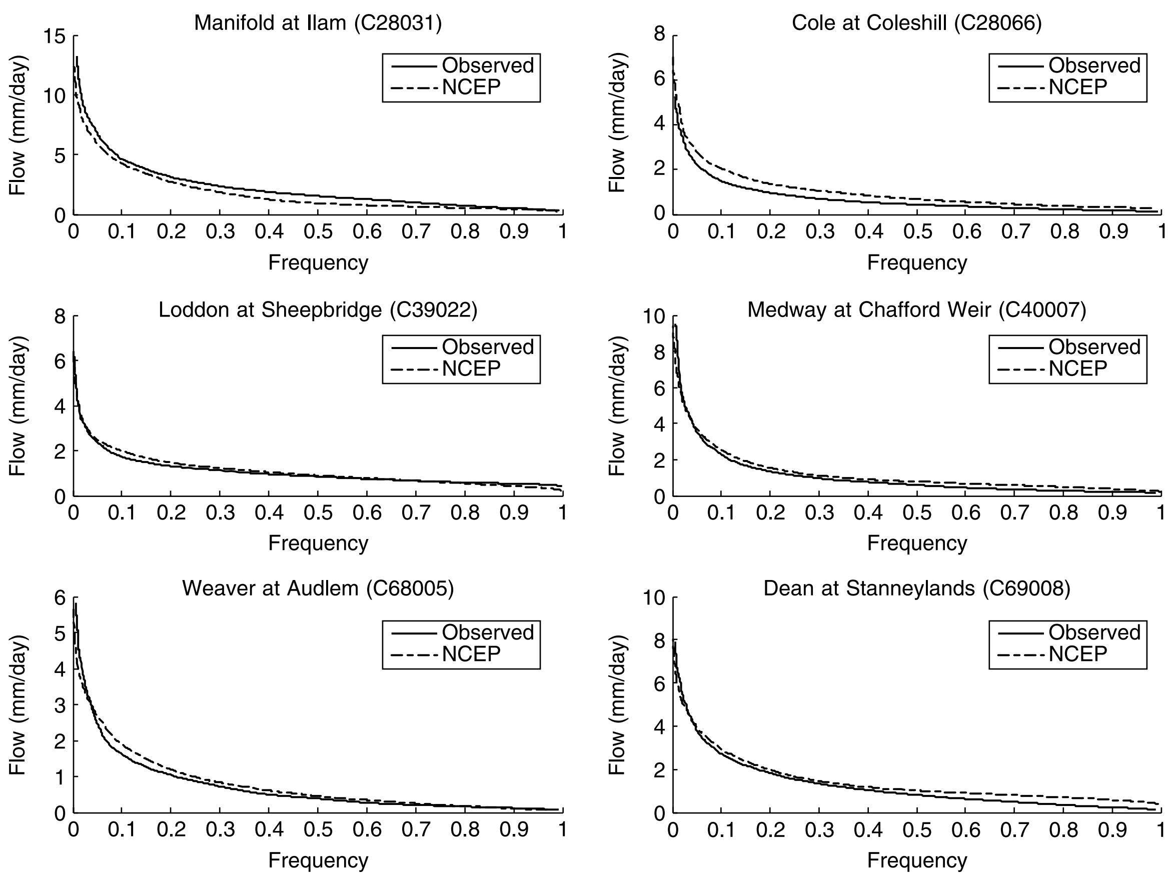

Figure 5 | Flow frequency curves of observed flows and simulated flows driven by the NCEP data (1% of the data at both ends of the curves have been removed).

rainfall–runoff models is examined, as well as the performance of the GLM methodology. The general characteristics of the averaged simulated streamflows driven by the observed rainfall are very similar to the observed streamflows, and to the simulated streamflows driven by the NCEP data. Apart from the Cole at Colehill (28066), the correlations between the observed data and the average simulations are higher than 0.9. Overall, the model is more successful at reproducing performance for the average flow in winter than for the average low flow in summer.

In Figure 7, the simulated daily streamflows in the Manifold at Ilam (28031) and the Cole at Colehill (28066) are plotted against the rainfall driven by NCEP, together with the observations. The scatter plots of the six catchments have a similar pattern. The absolute variation of streamflows grows along with the increase of rainfall. The proliferation of variations (heteroscedasticity) is related to rainfall time series and the hydrological response of the individual catchment. In general, the patterns of simulated streamflows driven by the NCEP data match the observed data of the catchments well. The consistency between the observed and simulated results shows that the streamflows should be generated adequately at a daily scale although some extreme observed points may not be captured by the simulations. Moreover, some overestimation of streamflow is noted at the Cole at Colehill (28066) and a slight underestimation is observed at the Manifold at Ilam (28031).

Turning now to scenarios of future climate in the Manifold at Ilam (28031) and the Cole at Colehill (28066), the simulated streamflows driven by the GCM output from the Hadley Centre model are plotted with observed data in Figure 8. The results vary in detail between catchments, but in general they show a reduction in high flows with the future streamflows lower than the observed values for the same rainfall amount (see also the discussion of flood frequency, below). This contradicts the expectation that wetter winters (Hulme *et al.* 2002) should lead to higher streamflows in the UK. Moreover, compared to observed streamflows, the variation of the predicted streamflows increases more slowly with rainfall even though the degree

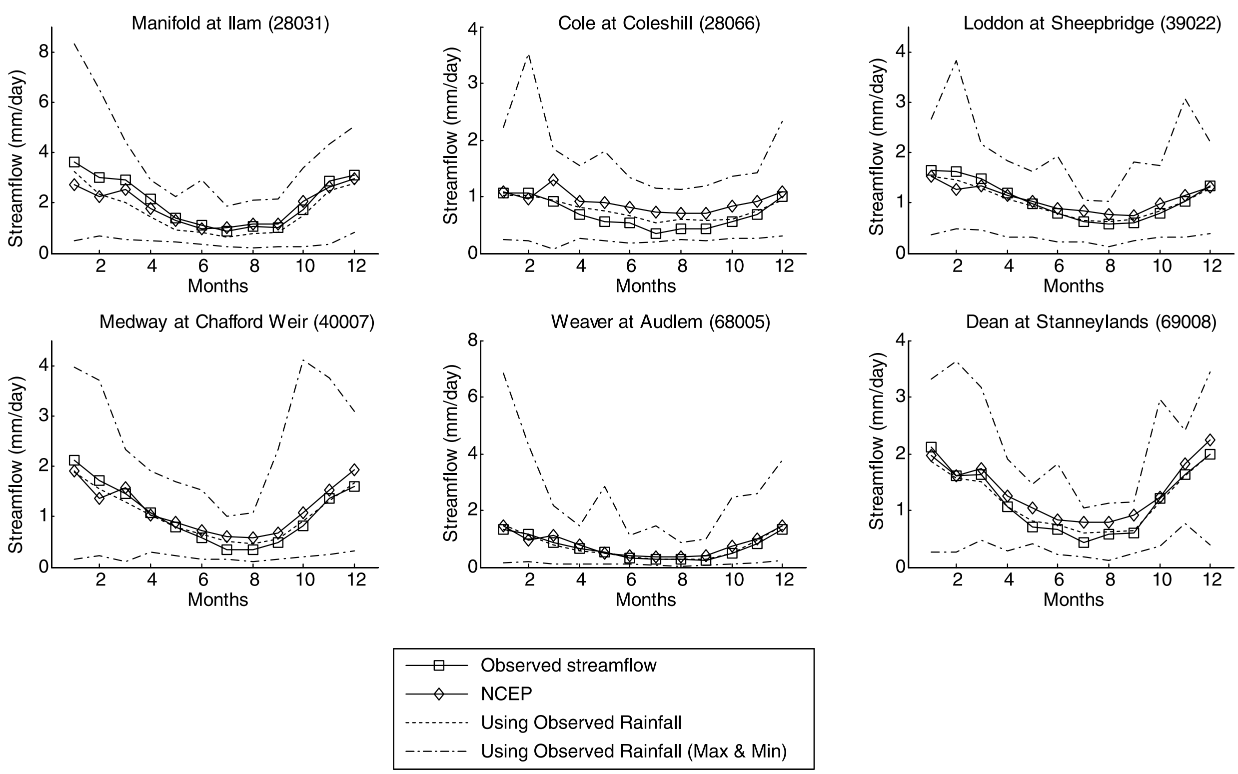

Figure 6 | Average daily observed and simulated streamflows across months of the year.

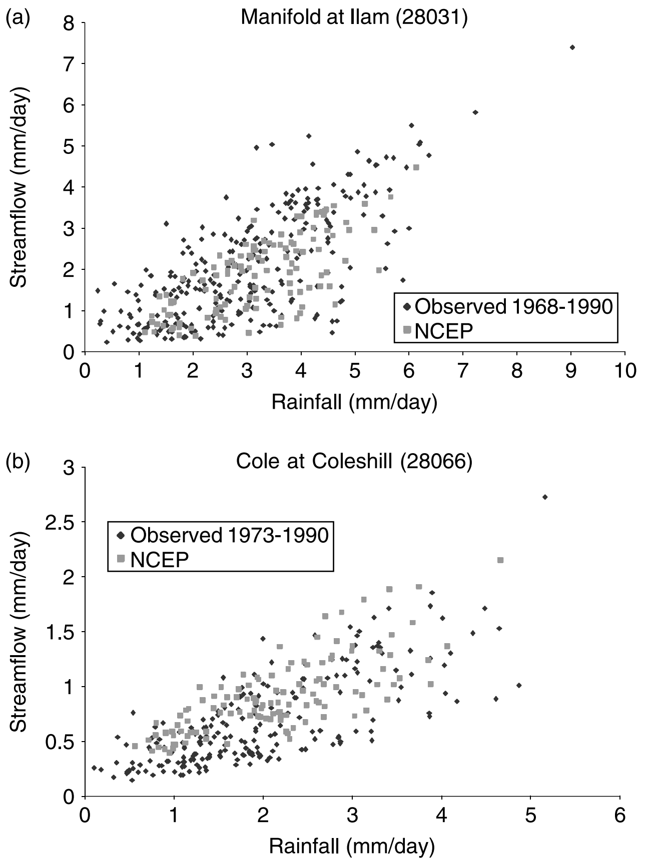

Figure 7 | Scatter plot of observed streamflows and simulated streamflows driven by NCEP data for (a) Manifold at Ilam (28031) and (b) Cole at Colehill (28066).

of the change varies between the six catchments. The varied seasonal responses of different catchments are therefore difficult to generalize and require individual quantification.

The performance of the set of GCMs and RCMs for the simulation of monthly mean daily flows is shown in Figure 9. The variability between models is extremely high, although there is a reduction in summer flows for six catchments. The seasonal variations of all the simulations are usually smoother than the observations from 1960 to 1990. The average daily future streamflows driven by all GCMs and RCMs are lower than observations in the Manifold at Ilam (28031), the Medway at Chafford Weir (40007) and the Weaver at Audlem (68005) for all months. For the other three catchments, the future streamflows driven by some GCMs and RCMs are higher than the observations in some months of the year, mainly autumn and winter. The clear message is that it is dangerous to generalize basin responses based on the output of one GCM or RCM because of the large uncertainty between models. Moreover, the possible changes in future streamflows depend not only on global climate models but also on the catchment characteristics that respond to the change in climate patterns.

Figure 10 shows the flood frequency plots from simulations generated from the different GCMs and RCMs for the Dean at Stanneylands (69008). The return periods are estimated using the Gringorten plotting position. As only the annual maximum of the streamflow time series is used to calculate the frequency curves, the frequency curves are very sensitive to the driving forces from different GCMs and RCMs, and it is difficult to generalize from the results. Moreover, the interpretation of the curves should be done with caution because of the overdispersion phenomenon noted in the GLM approach for the rainfall extremes

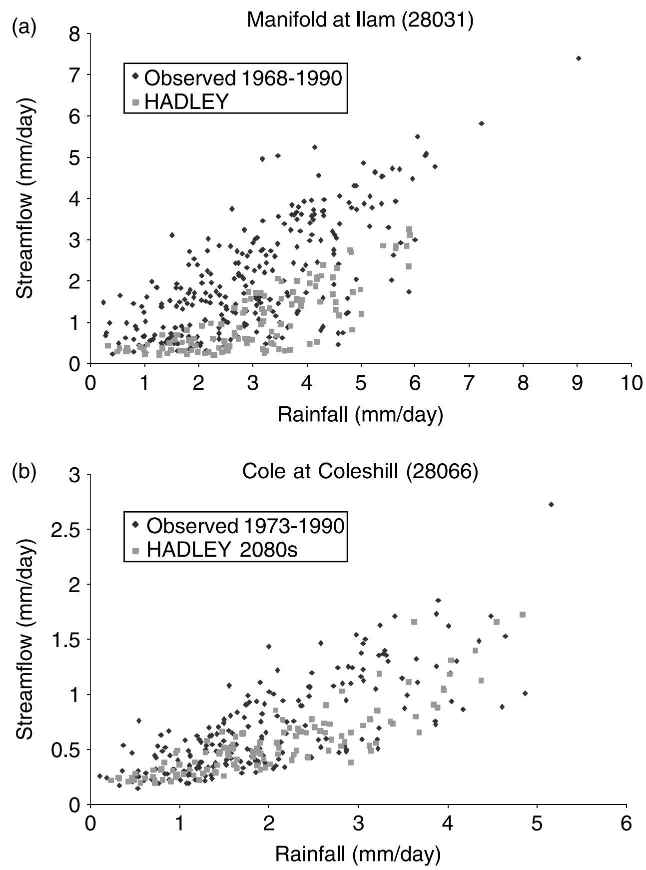

Figure 8 | Scatter plot of observed streamflow and simulated streamflows driven by GCM data from Hadley centre for (a) Manifold at Ilam (28031) and (b) Cole at Colehill (28066).

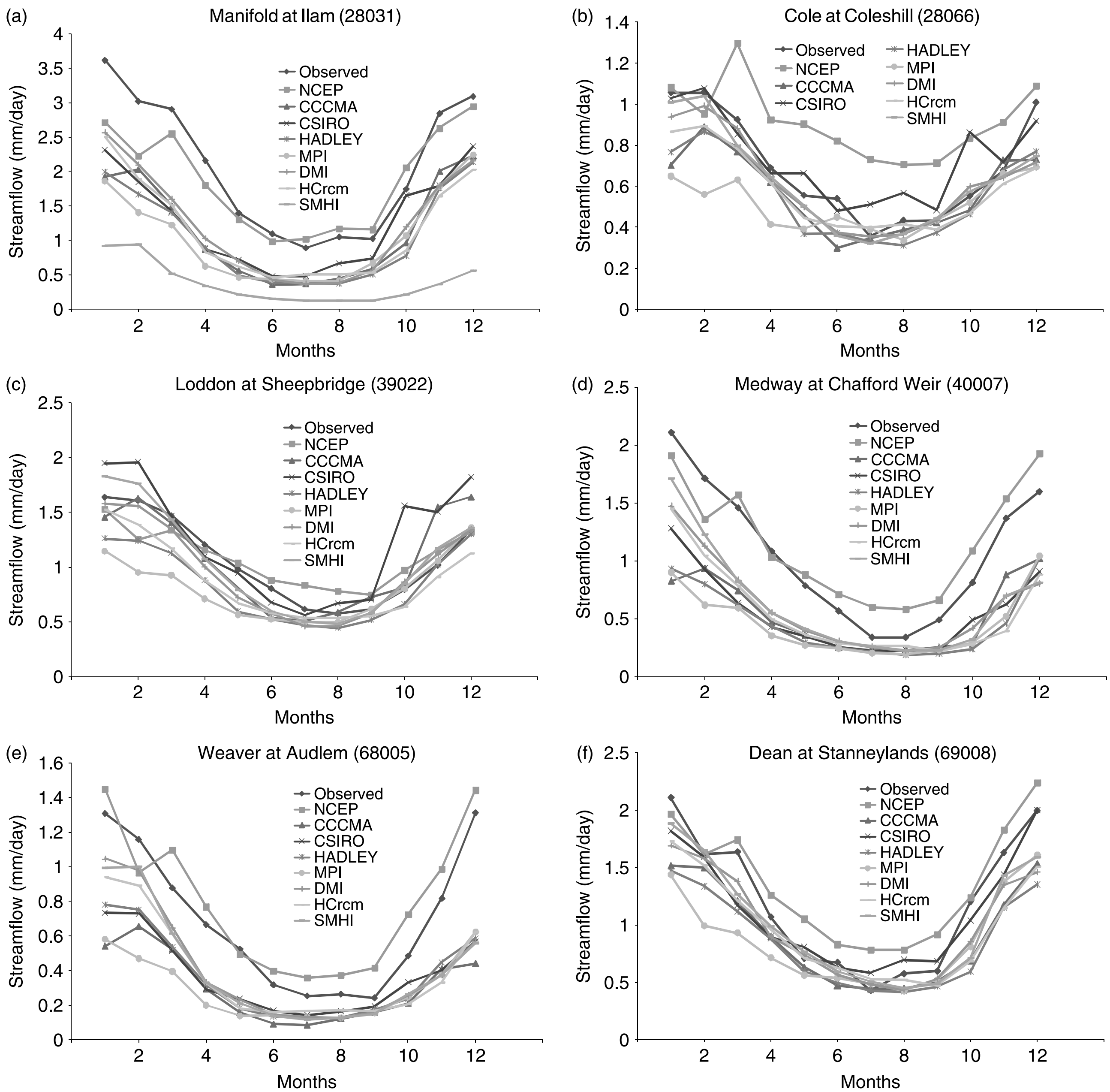

Figure 9 | Average daily streamflows driven by GCMs and RCMs using GLM approach.

(Furrer & Katz 2007). The annual maximum subsets of streamflow are prone to lower signal to noise ratio than full time series. However, the results are interesting, showing a tendency to increased flood flows at high return periods that is not evident from the mean monthly flows of Figure 9(f).

Although the results of the frequency curves driven by different GCMs and RCMs may not be coherent, the changes of flood characteristics of a specific catchment may be interpreted in more detail by looking at particular GCMs or RCMs for a specific catchment. In Figure 11, flood frequency curves for the Loddon at Sheepbridge (39022), the Medway at Chafford Weir (40007) and the Weaver at Audlem (68005) are derived from observations and the output from the Hadley Centre RCM (Hadrm3p).

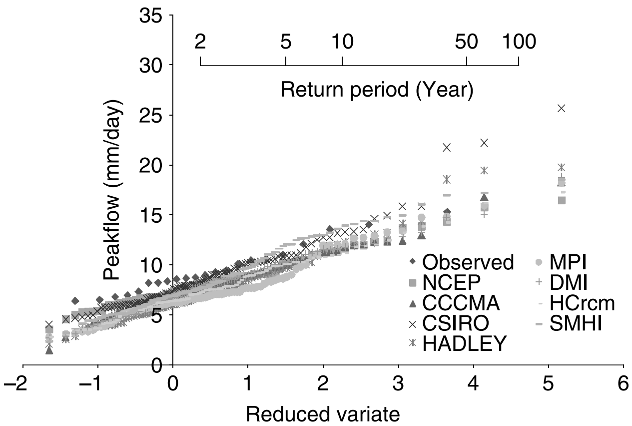

Figure 10 | Frequency curves of Dean at Stanneylands (69008) driven by GCMs and RCMs.

The changes in the characteristic of flood frequency are different for each of the three catchments. Generally, all the catchments have lower future annual peak flow for a return period of less than 10 years. However, for the higher return periods (e.g. 50 years), some catchments (e.g. 68005) may expect higher future peak flow. For the catchments (e.g. 39022, 40007) which are not expected to have higher future peak flow, the difference between future and present streamflows is expected to be smaller for the higher return periods.

CONCLUSIONS

The results (Figure 6) show that the streamflows simulated from the adopted framework using the rainfall series simulated by the GLMs are capable of representing the properties of observed flows even although slight overestimation may be observed in the Cole at Colehill (28066) and the Dean at Stanneylands (69008) during the middle months (i.e. June, July and August) of the year. Generally, the rainfall generated from the GLM approach driven by GCMs or RCMs appears to be appropriate to provide the input for hydrological models under climate change scenarios despite some underestimated rainfall extremes. Compared to similar studies (e.g. Kay *et al.* 2006*a*,*b*; Fowler & Kilsby 2007) using RCM rainfall as input to their hydrological models, the GLM approach appears to be able to provide a more suitable, bias-corrected and adequately scaled rainfall time series.

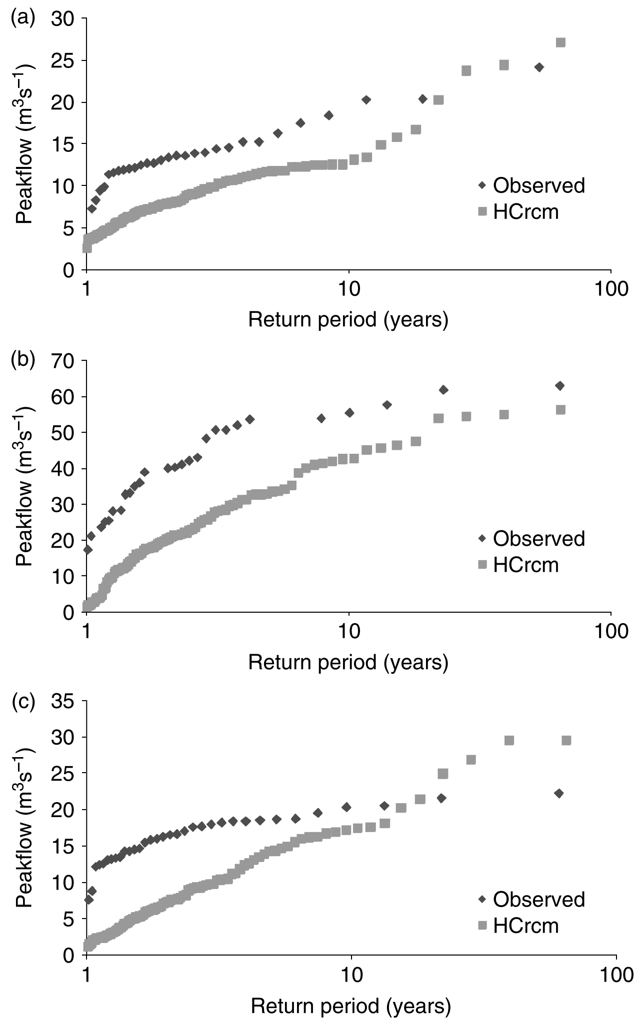

Figure 11 | Frequency curves of (a) Loddon at Sheepbridge (39022); (b) Medway at Chafford Weir (40007) and (c) Weaver at Audlem (68005) driven by HCrcm.

For the six catchments, only one rainfall model structure is used. Even though Frost *et al.* (2006) noted that elevations of catchments should affect the rainfall model structure in the GLM approach, the rainfall from the adopted model structure is still adequate for the six catchments with average elevations between 88.5 m and 310 m. The result supports the assertion of Leith (2005*a*,*b*) that her proposed GLM rainfall model structure should be robust and is transferable for other catchments in the UK.

GCMs and RCMs introduce different uncertainty to the simulated rainfall (Leith 2005*a*,*b*), and this uncertainty transfers to the streamflows simulated by the hydrological models. The uncertainty due to GCMs or RCMs in the streamflows can be quantified by the comparison of the results from different GCMs and RCMs. However, most streamflow studies (e.g. Kay *et al.* 2006*a*,*b*; Fowler & Kilsby 2007) can only include a limited number of GCMs or RCMs because the land surface scheme is difficult to transfer from one model to another using a dynamic approach. In comparison, the proposed GLM approach provides a flexible alternative way to generate streamflows by using outputs from several different GCMs or RCMs. The uncertainty of daily streamflows resulting from various global climate models can be assessed.

Apart from the uncertainty associated with GCMs and RCMs, there are other sources of uncertainty and certain issues requiring further attention. The GLM approach, using output variables of climate states from GCMs and RCMs to drive stochastic models of daily rainfall, appears to be a suitable method for the generation of rainfall time series for hydrological modelling of future climate scenarios. However, the robustness of the model depends on the appropriateness of the model structure and parameters for the future rainfall distribution, bearing in mind that 20th century relationships between climate variables and precipitation are assumed to be applicable to 21st century scenarios. The rainfall model structure (Chandler 2005; Leith 2005*a*,*b*) was used successfully for the six catchments, which suggests that it is transferable to similar catchments in the UK. The GLM methodology also has the potential to generate spatial rainfall fields. This aspect was not evaluated here, but is of potential importance for larger catchments and requires evaluation.

The estimation of potential evaporation for future climate scenarios is problematic. Combination methods have a strong physical basis but the derivation of input variables from GCMs is associated with high uncertainty. Potential evaporation based on temperature methods has inevitable limitations, but can provide practical estimates, as demonstrated here. However, despite the very good performance of the average daily simulated streamflows for current climate, the robustness of the models for estimating potential evaporation in hydrological impact studies should be further studied.

The adopted conceptual rainfall-runoff model has previously been applied successfully to different UK catchments. It is a lumped model, however, and therefore cannot be expected to represent large catchments well, or catchments where there is significant heterogeneity. For example, it can be noted that the Cole at Coleshill (28066) may have different high and low flow responses and is the most urbanized of the six catchments studied here, which may be the reason for the poorer model performance. The examined catchments represent a limited set, mainly lowland, and the methodology could usefully be applied to a larger set of catchments and catchment types.

An important limitation of the work is that the model structure and the parameters in the rainfall–runoff models are assumed to be invariant under different climatic states. This is a crude first approximation, as changes can be expected e.g. to soils, vegetation and anthropogenic influences (e.g. Feddema & Freire 2001; Holman 2006). Also, Jones *et al.* (2006) identified that the change of runoff against the variation of evaporation and rainfall is model specific. Clearly there is much work required to examine such effects further.

Another limitation of the adopted approach is that the rainfall–runoff models are offline models. As a result, the rainfall–runoff models can only employ the information from GCMs or RCMs but not provide feedback to them. This is likely to lead to inconsistency between e.g. modelled soil moisture and runoff within the GCM/RCM algorithms, and the proposed off-line approach.

Turning to the results themselves, the properties of simulated average streamflows were shown to correspond well to the characteristics of the observed streamflows, which gives confidence in the combined performance of the methods used. The clear messages from the work are the following.

(a) The characteristics of the projected future streamflows driven by different GCMs and RCMs depend strongly on the hydrological response of different basins.

(b) The variability in response between alternative GCMs and RCMs is large. However, it is noted that the uncertainty and sensitivity are higher for the simulated annual extremes than average streamflows. Although the possible change of the extremes of streamflow series may be deduced, the uncertainty of the results should be further quantified.

Finally, it is noted that the adopted framework can generate higher resolution streamflows using finer rainfall and potential evaporation time series. As discussed above, the GLMs can be used to generate spatial rainfall fields (see e.g. Yang *et al.* 2005) – an important capability, which has not been used here. Daily rainfall data from GLMs can be disaggregated to hourly rainfall series (Segond *et al.* 2006). Therefore, spatially distributed streamflow simulation for climate impact studies (e.g. ecological and water quality projects) should be feasible using the proposed framework.

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