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Using regional climate model data to simulate historical and future river flows in northwest England

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Abstract Daily rainfall and temperature data were extracted from the multi-ensemble HadRM3H regional climate model (RCM) integrations for control (1960–1990) and future (2070–2100) time-slices. This dynamically downscaled output was bias-corrected on observed mean statistics and used as input to hydrological models calibrated for eight catchments which are critical water resources in northwest England. Simulated daily flow distributions matched observed from Q_{95} to Q_5, suggesting that RCM data can be used with some confidence to examine future changes in flow regime. Under the SRES A2 (UKCIP02 Medium-High) scenario, annual runoff is projected to increase slightly at high elevation catchments, but reduce by ~16% at lower elevations. Impacts on monthly flow distribution are significant, with summer reductions of 40–80% of 1961–90 mean flow, and winter increases of up to 20%. This changing seasonality has a large impact on low flows, with Q_{95} projected to decrease in magnitude by 40–80% in summer months, with serious consequences for water abstractions and river ecology. In contrast, high flows ($> Q_5$) are projected to increase in magnitude by up to 25%, particularly at high elevation catchments, providing an increased risk of flooding during winter months. These changes will have implications for management of water resources and ecologically important areas under the EU Water Framework Directive.

1 Introduction

A systematic increase in the global mean temperature has provided the first evidence of anthropogenic climate change (Folland et al. 2001), with global surface temperatures warming at a rate of 0.15 °C per decade since the 1970s. Hulme and Jenkins (1998) found a warming of 0.7 °C in the UK Central England Temperature record (Manley 1974; Parker et al. 1992) since the 17th century and 0.5 °C during the 20th century. Additionally, the twelve warmest years globally have occurred in the 1990s and 2000s. They are, in descending order 1998, 2005,

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2002 and 2003 (joint), 2004, 2001, 1997, 1995, 1990 and 1999 (joint), 1991 and 2000 (joint) (from http://www.cru.uea.ac.uk/cru/info/warming). However, although increases in temperature are the clearest indicator of global warming, changes to rainfall amount, variability and spatial distribution may have the largest impact upon society.

Most General Circulation Models (GCMs) predict a prominent change in rainfall over the high latitudes of the Northern Hemisphere (Giorgi et al. 2001a,b), with wetter winters and drier summers over the UK (Hulme and Jenkins 1998; Hulme et al. 2002). This is likely to lead to an overall increase in annual average rainfall (Cubasch et al. 2001). More importantly, for many sectors such as water resources, GCM results indicate increases in both the frequency and intensity of heavy rainfall events under enhanced greenhouse conditions (Hennesey et al. 1997; McGuffie et al. 1999). In the UK, it is estimated that these changes will cause a 10 to 30 percent increase in the magnitude of rainfall events up to a 50 year return period by the end of the century (Fowler et al. 2005; Ekström et al. 2005a).

One of the most significant impacts of such changes may be on hydrological processes and, particularly, river flow regimes. Changes in seasonality and an increase in low and high rainfall extremes, such as recently experienced in the droughts of the 1990s (e.g. Marsh 1996) and floods of 2000/01 (Marsh 2001), can severely affect the water balance of river basins. This will influence the rate of available water resources, as well as the frequency of flooding and ecologically damaging low-flows. Although there has been much interest in this topic, most studies have been concerned only with changes in mean climate, using the 'perturbation method' (Prudhomme et al. 2002) to alter the observed input data to a hydrological model on a monthly, seasonal or annual basis according to the future changes projected by GCMs (e.g. Arnell 1992; Arnell and Reynard 1996; Pilling and Jones 1999, 2002). However, this method allows only changes to mean flows within the historic record to be examined, without considering changes in variability (extremes) or sequences of storms and dry periods (Wood et al. 1997); but it is precisely these that will have the most effect on hydrological processes (e.g. Burlando and Rosso 2002a,b; Arnell 2003).

The acknowledged lack of reliable information given by GCMs on the potential hydrological impacts of climate change (McGuffie et al. 1999) at small spatial and temporal scales has directed research into using the synoptic-scale output of GCMs in regionally-based models (Prudhomme et al. 2002). This has led to the development of both dynamical downscaling methods, using Regional Climate Models (RCMs) embedded within GCMs, and statistical downscaling methods. Statistical downscaling methods implicitly assume a close relationship between atmospheric circulation patterns and local climatic variables such as precipitation, temperature, and potential evaporation (e.g. Brandsma and Buishand 1997; Corte-Real et al. 1998; Goodess and Palutikof 1998; Conway and Jones 1998). These relationships have been used to construct catchment scale climate change scenarios using statistical downscaling of GCM outputs such as weather circulation indices and temperature combined with stochastic rainfall modelling (e.g. Kilsby et al. 1998), rather than using rainfall directly from GCM outputs. This has allowed the simulation of time series of sufficient duration to represent the long-term variability of hydrological processes. However, the approach has been criticized as robust estimates depend on the quality and length of data used in the calibration (Wilby and Wigley 1997), modelled variations depend on the precise assumptions made in the relationship between GCM variables and local climate (Calver et al. 1999) and it is limited by the uncertain future stability of empirical current-climate relationships between circulation patterns and local weather elements (Wilby 1997; Hay et al. 2002).

Dynamical downscaling, using Regional Climate Models, provides a more appropriate scale of climatic output than GCMs for hydrological impact studies. However, this has not been widely used, and then more commonly as a driver of 'statistical downscaling' (e.g.

Pilling et al. 1999, 2002) since integrations were, until recently, too short to represent long-term variability (∼25 years) and model outputs still depend upon the veracity of GCM boundary conditions used to drive the RCM (Wilby and Wigley 1997). The recent increase in computational power has led to the development of more sophisticated and higher resolution RCMs. The Hadley Centre model developed for northern Europe, HadRM3H, is the first 'ensemble' based RCM, providing three integrations for each of the control and future scenarios of ∼30 years at a daily resolution. This is the basis of the UK Climate Impacts Project 2002 scenarios (UKCIP02) (Hulme et al. 2002) developed for the 2020s, 2050s and 2080s, providing estimated changes in mean rainfall and temperature that can be used in impact studies.

The provision of dynamically downscaled data from RCMs has led to a few studies on the use of this data as a direct input to hydrological catchment models in the US, with some success in representing historical inflows (e.g. Wilby et al. 2000; Hay et al. 2002; Hay and Clark 2003; Wood et al. 2004). Wood et al. (2004) suggest that RCM data can be used directly as input to hydrologic models after 'bias-correction', but that day-to-day variability is still underestimated (Hay et al. 2002). However, RCM simulations of current climate have not been extensively assessed (Takle et al. 1999), with most US studies using dynamical output from the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis. Hay and Clark (2003) suggest that a systematic evaluation of current RCM output is needed to provide confidence in RCM simulations as drivers of impact assessment models.

Compared to statistical downscaling, regional climate models produce more homogenous spatial patterns of climate variables such as rainfall and temperature, although this by no means suggests that they are more realistic (Cusbasch et al. 1996; Mearns et al. 1999). An investigation into rainfall simulation by HadRM3H across the UK (Fowler et al. 2005) however, found that the RCM shows reasonable skill in estimating statistical properties of extreme and mean annual rainfall in most regions during the baseline period, 1961–1990. This suggests that the HadRM3H model may be used with some confidence to estimate future changes to both mean and extreme annual rainfall distributions (Ekström et al. 2005), although some uncertainty remains over the representation of seasonal and daily precipitation distributions by the model.

This study is the first to use daily RCM data from HadRM3H directly in a hydrological impact study in the UK, as proposed by Lamb (2001). The study is part of a larger project examining the vulnerability of water resources in the northwest of the UK to climate change (Fowler et al. 2006). Therefore, although the simulation of actual gauged flows from rivers with relatively undisturbed regimes and drawn from a wider source area would provide a better test of the use of dynamically downscaled outputs of the HadRM3H model for hydrologic modelling, the analysis concentrates on six reservoired catchments (Thirlmere, Haweswater, Stocks, Longdendale, Rivington and Lake Vyrnwy) and two river abstractions (Lune and Lower Dee) in north-west England that are critical water resources within the integrated resource zone of United Utilities. It should be noted, however, that results are given only for three 'signature' catchments that also capture the characteristic response of other catchments with a similar locality or elevation.

We aim, firstly, to determine how well combining RCM data with hydrological models predicts the historic daily distribution of annual and seasonal flows in this region. Additionally, we examine the changes to mean annual runoff, seasonality of flows and the frequency of Q_5 (the flow exceeded 5% of the time) and Q_{95} (the flow exceeded 95% of the time) events that can be expected under future climate conditions.

Table 1 Characteristics of the study catchments. Rainfall, potential evapotranspiration and runoff statistics are given in millimetres as annual average for the period 1961–1990

Catchment	Area (km^2)	Average elevation (m)	Rainfall (mm)	Potential evapotranspiration (mm)	Runoff (mm) (proportion of rainfall)
Thirlmere	40.0	427	2656	468	2185 (0.82)
Haweswater	35.0	463	2466	466	2022 (0.82)
Stocks	37.0	307	1637	503	1227 (0.75)
Longdendale	76.6	417	1473	575	1029 (0.70)
Rivington	41.1	232	1203	569	852 (0.71)
Lake Vyrnwy	94.3	452	1815	518	1411 (0.77)
Lune	983.0	324	1358	510	1147 (0.84)
Lower Dee	1300.0	212	970	578	519 (0.53)

2 Catchment description and data

This section describes the datasets that have been used in the study. For the climate analysis we developed daily precipitation and potential evapotranspiration time series from observations and climate model outputs, using methods described in Sections 2.1 and 2.2 respectively. Streamflow data time series were developed from observations and derived inflow series using methods described in Section 2.1. These data were the required inputs for the hydrological analysis of Sections 4 and 5.

2.1 Study catchments and historical/observed datasets

The eight study catchments, Thirlmere, Haweswater, Stocks, Longdendale, Rivington, Lake Vyrnwy, rivers Lune and Lower Dee are critical water resources within the integrated resource zone of United Utilities, located in the northwest of England (see Fig. 1). All of the catchments except the Lune are reservoired, and receive rainfall mainly from weather systems from the westerly quadrant. This causes a seasonal flow regime, with the largest runoff during winter and spring and the minimum during summer months. All catchments are located in upland areas and have high annual average rainfall, from ∼1200 to ∼2700 mm, over 70% of which contributes to runoff in all catchments except the Lower Dee (Table 1). However, in Sections 3 and 5 results are given only for three 'signature' catchments that capture the characteristic response of other catchments in the same locality or at similar elevations. These are Haweswater (representing Haweswater and Thirlmere; high precipitation, high elevation catchments in the English Lake District), Stocks (representing Stocks, Lake Vyrnwy, and the river Lune; medium elevation, medium precipitation catchments) and the Lower Dee (representing the Lower Dee, Longdendale and Rivington; lower elevation, lower rainfall catchments that tend to be affected by rain-shadowing).

Daily and monthly rainfall data for the eight catchments for 1961–1990 were obtained from the British Atmospheric Data Centre (BADC) (http://www.badc.rl.ac.uk/). The data were checked for both completeness and anomalous values, such as monthly totals within daily series. Thiessen polygons were then used to determine the contributing area of each rainfall station within the catchment and construct daily catchment rainfall series for 1961–1990 in a simple weighting procedure based on contributing area. The catchment SAAR was then checked against that provided by the Flood Estimation Handbook (FEH) (IH 1999) (see Table 1), providing close matches for all catchments.

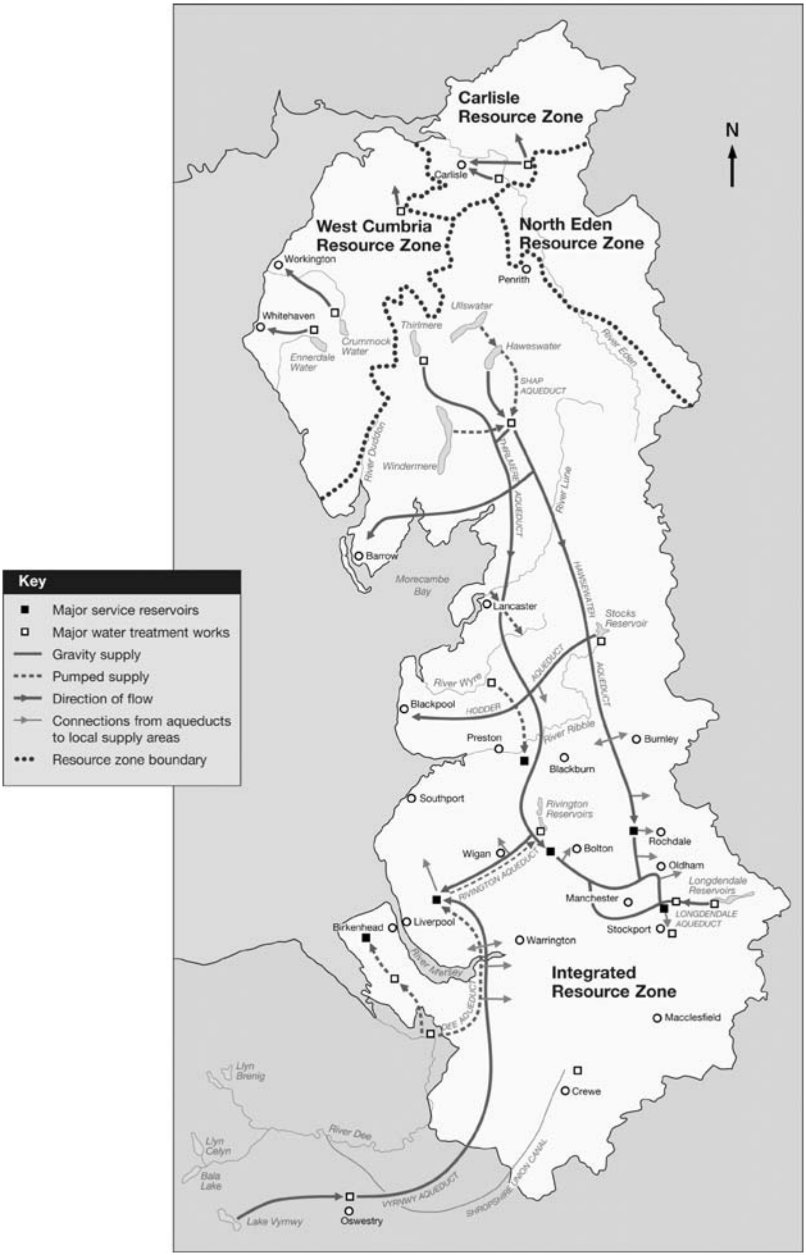

Fig. 1 The study area, showing the six north-west reservoired catchments of Thirlmere, Haweswater, Stocks, Longdendale, Rivington and Lake Vyrnwy and the rivers Lune and Dee. The white area denotes the NW integrated resource zone, with the additional water resources of Lake Vyrnwy and the river Dee lying in north Wales to the west

To estimate catchment potential evapotranspiration (PE) series, the annual MORECS (Meteorological Office Rainfall and Evaporation Calculation System) PE time series corresponding to each catchment was disaggregated to monthly values using an empirical Blaney-Criddle formula (Blaney and Criddle 1950) derived for NW England by Walsh and Kilsby (2006) and monthly 1961–1990 temperature data taken from the UKMO 5 km data set (http://www.metoffice.com/research/hadleycentre/obsdata/ukcip/index.html) (detailed in Hulme et al. 2002, his appendix 7). This was then disaggregated to give a daily series of PE (constant for each day within a particular month).

Historical daily flow series from 1961–1990 were obtained from the England and Wales Environment Agency. For reservoired catchments, these are derived inflows based on reservoir level data and represent natural channel flow to the dam wall. For groups of reservoirs, such as Longdendale and Rivington, this means to the lowest in the chain, or a flow representing the combination of all reservoirs in the group. For the two rivers, these represent naturalised flow in the river channel.

2.2 Regional climate model datasets

The HadRM3H regional climate model was developed at the Hadley Centre of the UK Meteorological Office (see Fig. 2) and derives from the HadCM3 (Gordon et al. 2000; Johns et al. 2003) global climate model. The HadRM3H integrations were used to produce the UKCIP02 climate change scenarios for the UK (Hulme et al. 2002). Boundary conditions are derived from the global atmosphere model, HadAM3H (Pope et al. 2000), which is of intermediate scale between the coarser resolution HadCM3 and HadRM3H. An ensemble of 3 integrations has been run for a reference baseline or 'control' period (1960–1990) using observed values of sea-surface temperatures (SST) and sea-ice instead of their HadCM3 modelled counterpart (Hulme et al. 2002). The ensemble members involve the same model initiated from three different points in the HadCM3 control run (Hulme et al. 2002) and have similar long-term characteristics but show significant yearly and decadal differences. An ensemble of 3 integrations has also been produced for a future period (2070–2100) based upon the IPCC A2 SRES (Special Report on Emissions Scenarios) 'storyline' (IPCC 2000) (the UKCIP02 Medium-High Emissions scenario) and driven by changes in the SST and sea-ice predicted by HadCM3 added to the observations. This combination of models gives a more realistic representation of the North Atlantic storm track compared to using a GCM alone (Hulme et al. 2002), but has the disadvantage that only the A2 SRES emissions scenario and the period 2070–2100 are simulated. Therefore, a method of pattern-scaling has been used to develop scenarios for different emissions scenarios and time-slices.

Daily rainfall data and other climate parameters were extracted from the three control and A2 SRES future integrations of HadRM3H for grid cells corresponding to the UK, shown in Fig. 2. This gave 93-years (31 years $\times$ 3) of daily data for the control and future scenarios respectively.

Control scenario data underestimates observed 1961–1990 mean rainfall in northwest England by up to 50% in some catchments, as well as over-emphasising seasonality, with wetter winters and drier summers. The standard practice for dealing with corrections to modelled climate variables is to apply factors based on the ratio of the control climatology to observed values on a grid box basis (as Durman et al. 2001). In a comparison of six downscaling methods, Wood et al. (2004) found that RCM output is not useful for hydrologic simulation purposes without a bias-correction step, although they used a more sophisticated 'quantile-based mapping' of the control scenario data onto the observed distribution for bias removal. Here, the Durman et al. (2001) approach was used and daily temperature and

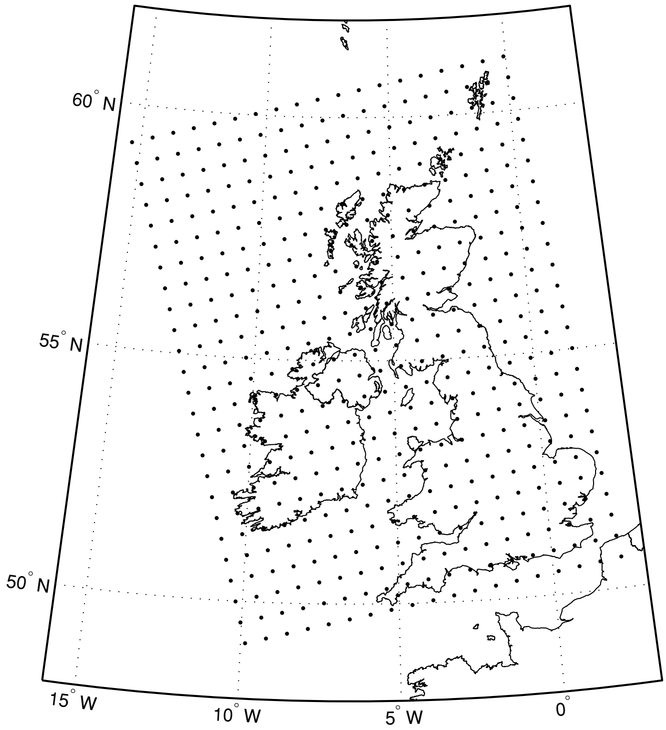

Fig. 2 HadRM3H model dataset over the UK where points denote grid box centres (reproduced from Fowler et al. 2005)

rainfall data series were 'bias-corrected' by monthly factors such that the modelled monthly average in the control climate matched the observed monthly average over the period 1961–90. The future temperature and rainfall time series were adjusted by the same factors as for the control climate. This approach provides a correction of monthly mean climate only and does not consider additional corrections to variability provided by the Wood et al. (2004) 'quantile-mapping' approach. The modification of mean monthly climate is used here to test if this correction alone is sufficient to represent statistics such as variability and skewness. Any further correction to variability such as through the use of 'quantile-mapping' would place further constraints on the correction of the future scenario, with the assumption that the rainfall distribution will be approximately the same in a future climate.

Daily potential evapotranspiration (PE) was calculated using an empirical Blaney-Criddle equation developed for NW England (Walsh and Kilsby 2006) and bias-corrected daily temperature data from HadRM3H. This method assumes that the historic 1961–1990 monthly relationship between temperature and PE can be extrapolated to a future climate. To compute daily PE the following approach was used (see Ekström et al. 2006a for more detail):

1. The coefficients of an empirical Blaney-Criddle equation were derived by Walsh and Kilsby (2006) for a northwest England catchment using a linear regression of historic temperature on PE data:

$$PE_t = p_t(\alpha T + \beta), \tag{1}$$

Table 2 Rough scaling factors for future changes in climate for the four UKCIP02 emissions scenarios and three future 30-year periods centred on the decades of the 2020s, 2050s and 2080s (taken from Hulme et al. 2002); conversion factors from the 2080s Medium-High (SRES A2 2070–2100) scenario

Time-slice	Low-emissions (SRES B1)	Medium-low-emissions (SRES B2)	Medium-high emissions (SRES A2)	High emissions (SRES A1)
2020s	0.24	0.27	0.27	0.29
2050s	0.43	0.50	0.57	0.68
2080s	0.61	0.71	1.00	1.18

where PE_t = PE estimated by Penman-Monteith formulation,
p_t = mean daily percentage (for month) of total annual daytime hours,
α = empirically derived, 0.456,
β = empirically derived, 0.416,
T = temperature in °C.

2. This provides a linear regression equation for each month between PE and temperature, accounting for a radiation term, p_t, separately. There is little difference in the historic PE-Temperature relationship for different upland catchments in NW England and so this relationship was used for all catchments.
3. Daily PE for the control and future simulation of HadRM3H was estimated using bias-corrected daily temperatures from HadRM3H in the regression equation. This methodology is an improvement upon the use of climatic variables directly from the HadRM3H model in a Penman-Monteith formulation which significantly overestimates PE (Ekström et al. 2006a).

A comparison of the proportion of dry days (defined as less than 1 mm of rainfall), the daily rainfall variance, the distribution of monthly rainfall totals of the 'bias-corrected' catchment rainfall and the monthly PE series revealed little variation in neighbouring grid cells after bias-correction and therefore the nearest cell to each catchment is used in this study.

Under the future scenario a fairly uniform increase in PE is predicted throughout the year, related to the relatively uniform increase in temperature (see Figs. 3a and b). By 2070–2100, PE may increase by + 10 to + 20% in all months, with July to September showing slightly larger increases than other months.

Finally, the future scenario produced for the SRES A2 emissions scenario and 2080s (2070–2100) time-slice was pattern-scaled to provide climate change scenarios for different emissions scenarios and time-slices. To pattern-scale the other emissions scenarios (SRES B1, B2 and A1; UKCIP02 Low, Medium-Low and High emissions respectively) and time-slices (2020s 2050s and 2080s), scaling factors between the global and regional climate models have been developed by UKCIP02 to produce four scenarios matching the original SRES emissions scenarios. Time slices are then produced by taking the mean climate for periods conventionally defined as the 2020s (2011–2040), 2050s (2041–2070) and 2080s (2071–2100). Using 30 year time slices is consistent with standard meteorological practice for defining a region's 'climate'. These scaling factors are found in the UKCIP02 Scientific Report (Hulme et al. 2002, their Table 7) and reproduced in Table 2. These scaling factors were applied to the climate datasets to provide precipitation and PE datasets for the different emissions scenarios and time-slices.

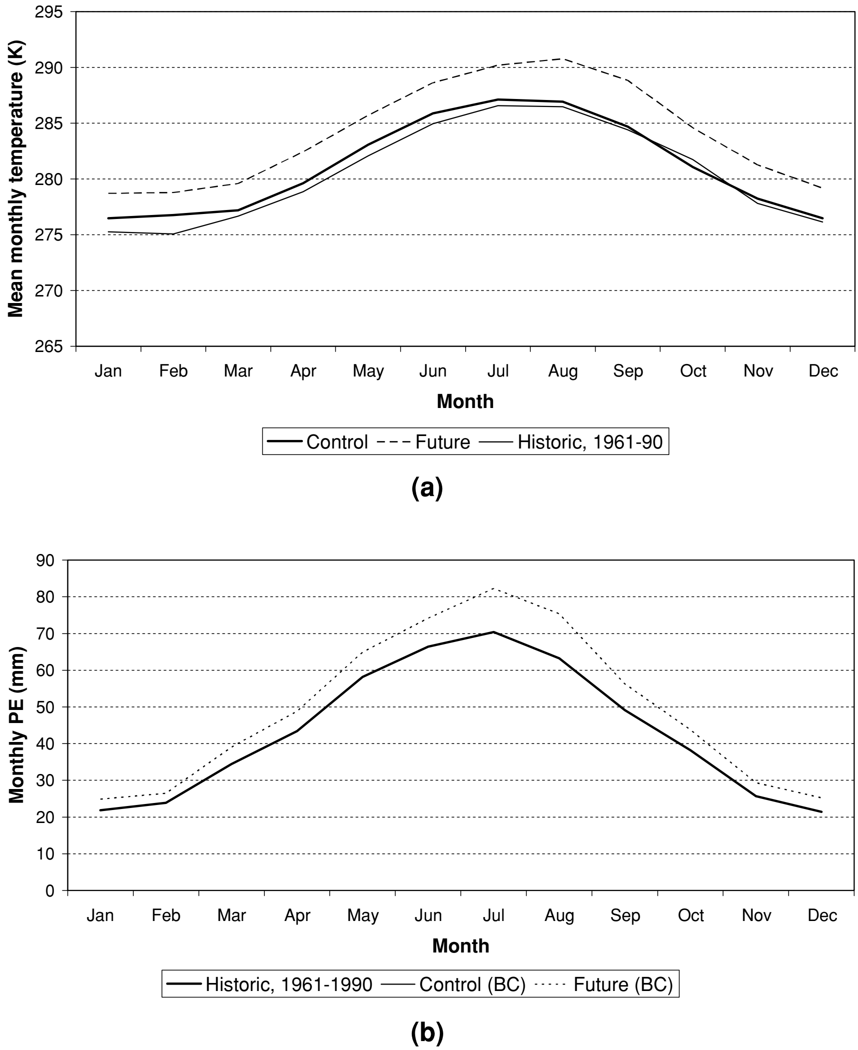

Fig. 3 (a) Mean monthly temperature (K), and (b) mean monthly PE, for historic (1961–1990), and HadRM3H control and future scenarios. BC indicates that 'bias-correction' has been used to match the observed historic series

3 Analysis of bias-corrected RCM rainfall

3.1 Comparison of observed and bias-corrected RCM control scenario data

Figures 4, 5, and 6 show a comparison of monthly mean rainfall, proportion of dry days (PD) and daily variance (VAR) respectively at the three 'signature' catchments for observed, and bias-corrected RCM control and A2 SRES future scenario data. Bias-corrected mean monthly rainfall for the control scenario perfectly matches observations (Fig. 4). The observed PD is slightly underestimated by the RCM, particularly in winter and spring months (Fig. 5).

Table 3 Comparison of basic statistical characteristics (mean, variance, lag-one autocorrelation (L1AC), skewness (Skew) and proportion dry (PD)) of daily rainfall data for historic (1961–1990) and HadRM3H control (1960–1990) and A2 SRES future (2070–2100) scenarios (corrected data) at the three 'signature' northwest catchments

Catchment	Time period	Mean (mm)	Variance $(mm)^2$	L1AC	Skew	PD
Thirlmere	Historic	7.27	165.55	0.28	3.27	0.47
	Control scenario	7.27	148.28	0.24	3.10	0.43
	Future scenario	7.60	195.33	0.24	3.34	0.47
Stocks	Historic	4.48	66.97	0.26	3.41	0.53
	Control scenario	4.48	51.05	0.23	2.85	0.44
	Future scenario	4.41	58.79	0.23	2.98	0.50
Lower Dee	Historic	2.66	20.53	0.26	3.31	0.54
	Control scenario	2.66	19.93	0.21	3.40	0.53
	Future scenario	2.43	19.11	0.21	3.35	0.59

Observed VAR is slightly underestimated by the RCM in winter and spring months, particularly at catchments with high mean annual rainfall (Fig. 6). However, given the differences in spatial resolution between point observations and bias-corrected RCM data, statistics show a surprisingly good match.

Results for a number of other rainfall statistics (mean, variance, lag-one autocorrelation coefficient (L1AC), skewness and PD) at daily, monthly and annual aggregations are shown for RCM data together with the observed counterparts in Tables 3, 4 and 5 respectively. At the daily level (Table 3), the RCM rainfall data provide a good match to the observed, with only slight underestimation of variance, PD, L1AC and skewness in the RCM series. At the monthly level (Table 4), there is underestimation of skewness and variance only at catchments with high mean annual rainfall. However, the L1AC statistic is overestimated at all catchments, suggesting greater persistence of dry or wet series of months within the RCM simulations. At the annual level (Table 5), the observed inter-annual variability is well matched by the RCM control integration. However, skewness is overestimated by the model.

Figure 7 shows the close match between RCM and observed monthly rainfall distributions at the eight catchments. Further details are given of the 99th, 95th, 75th, 50th and 40th daily rainfall percentiles in Table 5. For most catchments there is a close match between observed percentiles and those estimated from the RCM control integration, even for the highest 99th percentile. At the lowest percentile (40th) however, there is an overestimation for all catchments. This may be caused by the characteristic 'drizzle' seen in many climate models, where the PD is underestimated due to many days with very low rainfall totals. This error may propagate to cause an overestimation of low flows for the RCM control scenario when compared to the observed flow data.

Despite these small differences, bias-corrected rainfall from the RCM control integration provides a good match to the observed (1961–1990) rainfall statistics for catchments in northwest England.

3.2 Future changes in rainfall

Results from the HadRM3H SRES A2 (UKCIP02 Medium-High) 2080s future scenario indicate a substantial increase of $+$ 20 to $+30\%$ in mean monthly rainfall during winter (November to March), with a reduction of up to -50% in summer (May to September) (Fig. 4). These changes are mirrored by changes in PD, which reduces in winter and increases

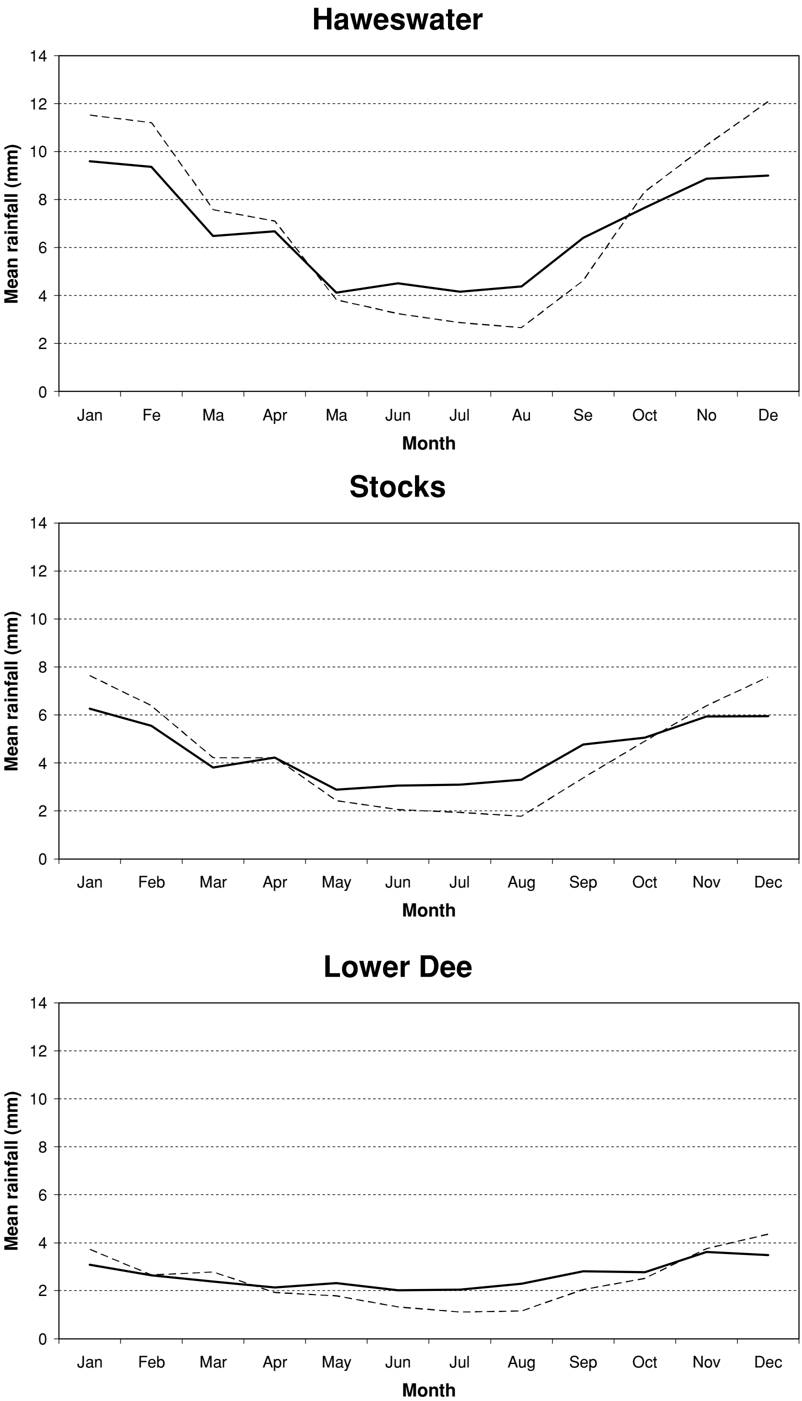

Fig. 4 Comparison of catchment monthly mean rainfall (mm) for observed data (bold line), bias-corrected HadRM3H control scenario (bold line) and bias-corrected HadRM3H future scenario (dashed line)

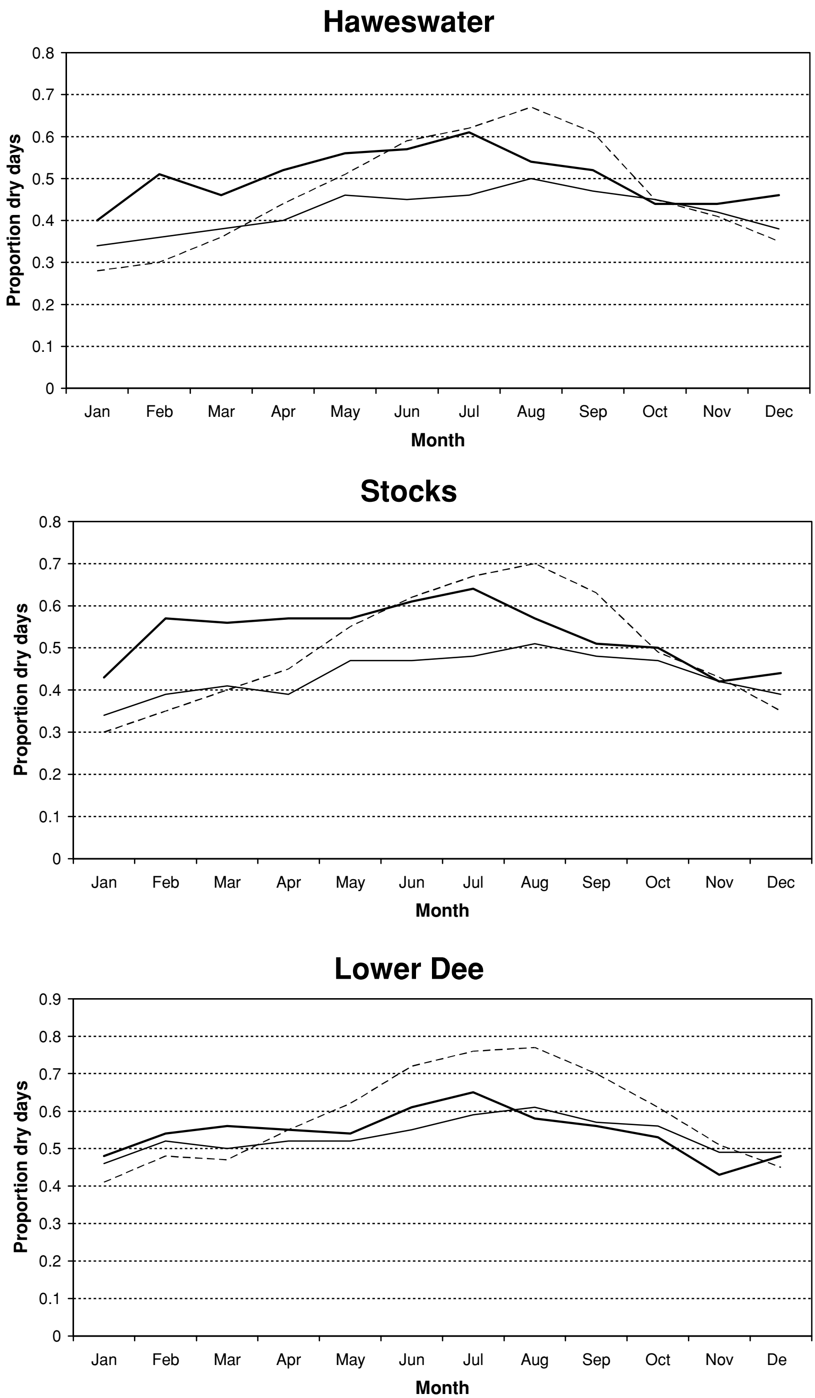

Fig. 5 Comparison of catchment proportion dry days for observed data (bold line), bias-corrected HadRM3H control scenario (line) and bias-corrected HadRM3H future scenario (dashed line)

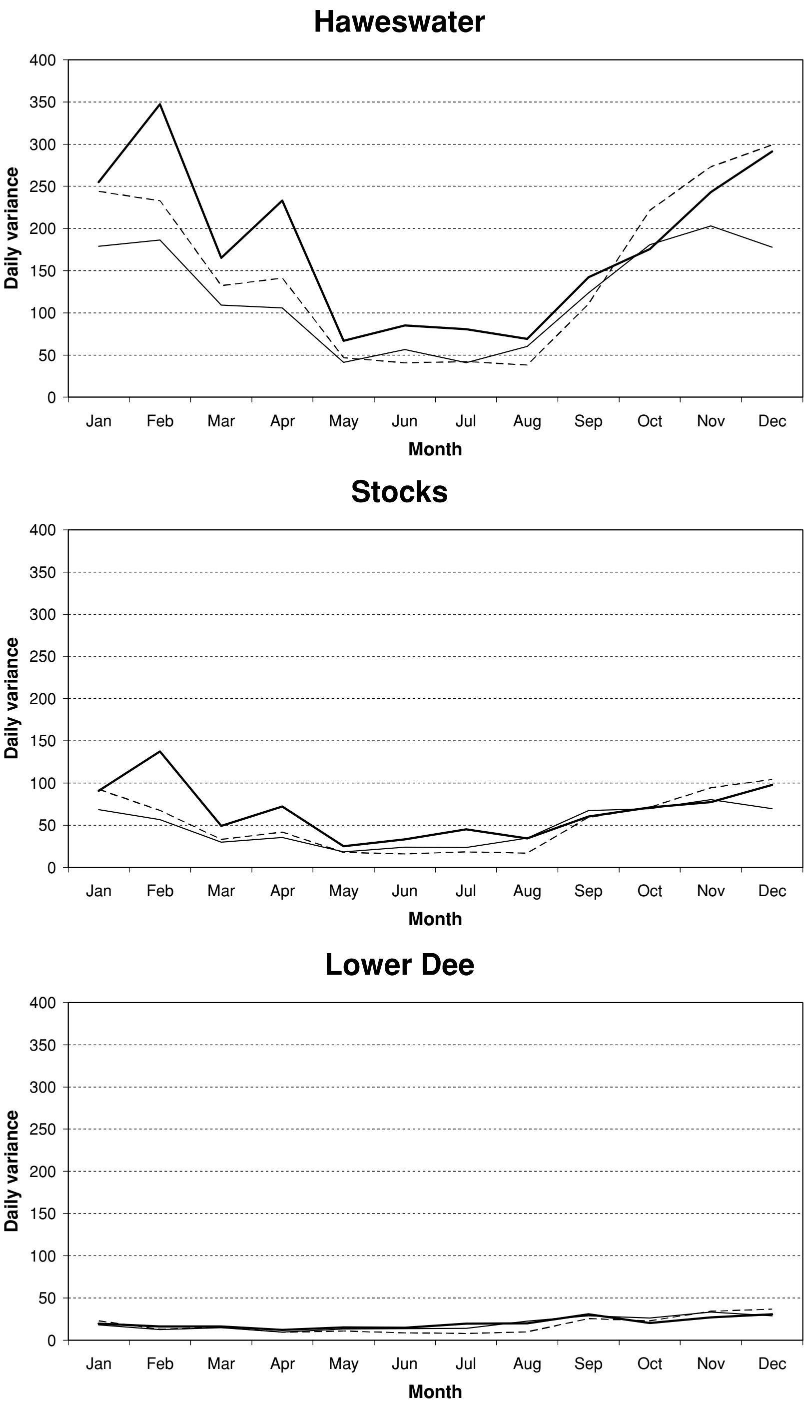

Fig. 6 Comparison of daily variance for observed rainfall data (bold line), bias-corrected HadRM3H control scenario (line) and bias-corrected HadRM3H future scenario (dashed line)

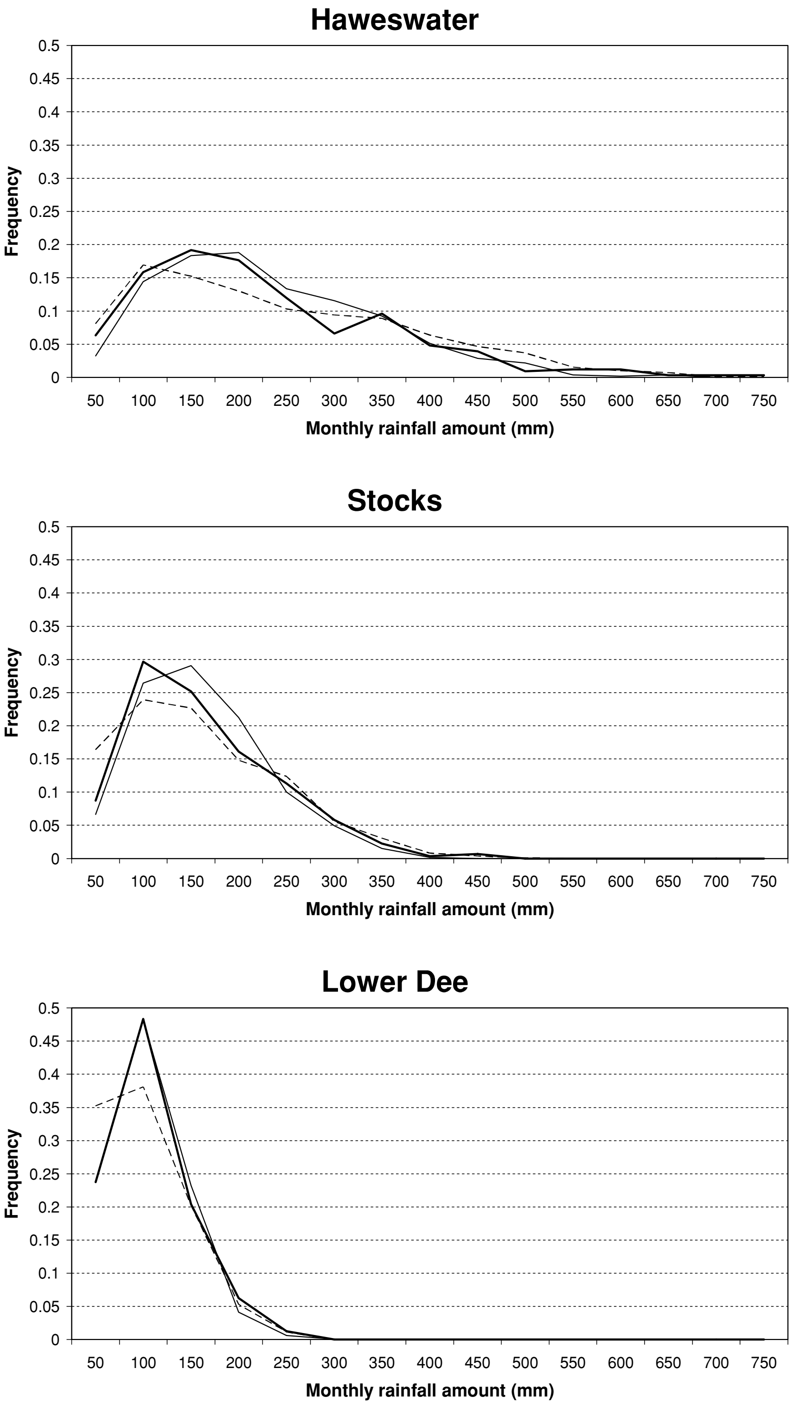

Fig. 7 Comparison of distribution of monthly rainfall totals for observed data (bold line), bias-corrected HadRM3H control scenario (line) and bias-corrected HadRM3H future scenario (dashed line)

Table 4 Comparison of basic statistical characteristics (mean, variance, lag-one autocorrelation (L1AC) and skewness (Skew)) of daily rainfall data at a monthly aggregation for historic (1961–1990) and HadRM3H control (1960–1990) and A2 SRES future (2070–2100) scenarios (bias-corrected data) at the three 'signature' northwest catchments

Catchment	Time period	Mean (mm)	Variance (mm)^2	L1AC	Skew
Thirlmere	Historic	221.2	16828.0	0.27	0.98
	Control scenario	221.2	14518.9	0.34	0.76
	Future scenario	234.0	23636.2	0.48	0.83
Stocks	Historic	136.3	5904.5	0.25	0.82
	Control scenario	136.3	4567.9	0.34	0.66
	Future scenario	135.7	7369.9	0.49	0.77
Lower Dee	Historic	80.8	1689.0	0.12	0.90
	Control scenario	80.8	1526.2	0.18	0.74
	Future scenario	74.0	2063.3	0.41	0.82

Table 5 Comparison of basic statistical characteristics (mean, variance, lag-one autocorrelation (L1AC) and skewness (Skew)) of daily rainfall data at an annual aggregation for historic (1961–1990) and HadRM3H control (1960–1990) and A2 SRES future (2070–2100) scenarios (bias-corrected data) at the three 'signature' northwest catchments

Catchment	Time period	Mean (mm)	Variance (mm)^2	L1AC	Skew
Thirlmere	Historic	2656	151308	−0.22	−0.37
	Control scenario	2656	143401	0.03	0.13
	Future scenario	2811	124413	−0.04	−0.01
Stocks	Historic	1637	48785	0.06	0.27
	Control scenario	1637	44516	0.02	0.13
	Future scenario	1628	35674	−0.06	0.23
Lower Dee	Historic	970	14363	0.10	−0.27
	Control scenario	970	13948	0.01	0.18
	Future scenario	887	12495	0.06	0.33

in summer (Fig. 5). Moreover, daily variance is projected to increase in winter months but become slightly lower in summer months (Fig. 6). Increased rainfall variability, in conjunction with changes to mean rainfall, suggest that winter floods and summer droughts may occur more frequently than historically.

Table 5 shows that the region-wide projected seasonal changes in rainfall distribution detailed above have spatially varying impacts on annual rainfall, varying from $\sim +5\%$ to -9% for high to lower elevation catchments. Although these changes are small they may have a large impact upon runoff production.

At a daily level (Table 3), variance increases by about 30% at Haweswater but shows only small increases at other catchments. However, at a monthly level (Table 4), there is a considerable increase in variance at all catchments during the period 2070–2100, with increases from $+$ 30 to $+$ 65%. This increase reflects the enhanced seasonality of the future scenario; with significant opposite changes in summer and winter mean rainfall. At the annual level (Table 5), there is a slight reduction in variance; thus there is no indication of a similar increase in inter-annual variability.

L1AC shows a substantial increase at the monthly level (Table 4), reflecting the future enhanced 'seasonality' or persistence of dry and wet periods (seasons). However, at the daily and annual levels there is no evidence for change in L1AC. At Haweswater skewness is

Table 6 Comparison of the 99th, 95th, 75th, 50th and 40th daily rainfall percentiles for historic (1961–1990) and HadRM3 control (1960–1990) and future scenarios (2070–2100) (bias-corrected data) at the three 'signature' northwest catchments. The estimated annual future percentage change for the A2 SRES scenario (future/control) is also given

Percentile	Catchment	Observed	Control	Future	%change
99	Thirlmere	59.4	58.1	66.0	+13.6
	Stocks	38.4	33.4	35.6	+6.6
	Lower Dee	21.0	21.0	20.4	−2.8
95	Thirlmere	33.3	32.3	35.7	+10.5
	Stocks	20.5	19.1	20.5	+7.3
	Lower Dee	11.4	11.4	11.3	−0.4
75	Thirlmere	9.2	9.4	9.2	−2.1
	Stocks	5.6	5.9	5.4	−8.5
	Lower Dee	3.4	3.3	2.9	−13.3
50	Thirlmere	1.4	2.0	1.5	−25.0
	Stocks	0.7	1.5	1.1	−26.7
	Lower Dee	0.7	0.8	0.5	−36.6
40	Thirlmere	0.4	0.9	0.5	−44.4
	Stocks	0.2	0.8	0.4	−50.0
	Lower Dee	0.2	0.4	0.2	−50.0

Table 7 Description of parameters in the ADM model

Parameter	Description
W_m	Maximum water storage capacity of the soil (mm)
b	Shape parameter of the water storage capacity curve (−)
D_1	Maximum drainage rate (mm h^{-1})
D_2	Shape parameter of the drainage curve (−)
Conv	Convectivity (m s^{-1})
Diff	Diffusivity (m^2 s^{-1})

projected to increase at the daily level, possibly indicating an increase in extreme rainfall events under future climate change. However, there is increased skewness in the monthly rainfall distribution at all catchments (Table 4). Figure 7 shows the widening distribution of monthly rainfall totals under the future scenario, with an increased frequency of rainfall amounts at both tails of the distribution, and consequent reductions in the frequency of 'median' events.

More detail is given in Table 6 which compares the 99th, 95th, 75th, 50th and 40th daily rainfall percentiles from the RCM control and future integrations. The lowest percentile (40th) shows the largest change with reductions from −30 to −70%. However, there are also significant decreases projected for the present median rainfall event, with reductions of −25 to −40%. This implies that low-flow events may increase. At the upper end of the distribution, the 99th percentile changes only at high elevation catchments with projected increases of 15% for the largest events. For events exceeding the 95th percentile there are also small increases of + 1 to + 7% at other upland catchments. This has great significance for the occurrence of flood events, suggesting possible increases in most upland catchments.

4 Rainfall-runoff modelling

A simplified version of the Arno hydrologic model (Todini 1996; Franchini 1996), the ADM model, was used to translate the catchment daily rainfall and PE series into daily stream flow series. This model is partly physically based and has two distinct components: the water balance component, which models the interactions between the water content of the soil, rainfall inputs and evapotranspiration and runoff outputs; and the routing component, which transfers the runoff to the outlet of the catchment. The model requires the calibration of six parameters (Table 7). Of these, the first four are used in the water balance component calculations, with the remaining two used in the transfer function.

Among the 30 years of available derived flow, rainfall and PE data, only periods with no missing daily rainfall values and good derived inflow data (no negative values) were used in calibration and validation. Both calibration and validation periods were in excess of 5 years in length. The model was calibrated using a genetic algorithm optimisation, the shuffled complex evolution method for global optimisation (SCE-UA), developed by Duan et al. (1992), with the Nash and Sutcliffe 'efficiency' measure (CE) (Nash and Sutcliffe 1970) as the optimisation criterion. CE ranges from $-\infty$ to $+\ 1$, where CE $= 1$ means complete agreement between the observed and simulated sequences, and CE $= 0$ implies that the simulation is no better than using the mean of the observed flow series. The optimal catchment model parameters fitted during the calibration procedure, and values of CE and the water balance percentage error (WB) for both calibration and validation periods can be seen in Table 8.

The CE values are reasonable, ranging from 0.58 to 0.76, and the WB of the simulated flows is within 7% of the derived historical inflows in all cases. As a further validation, flow series were simulated for the 20-yr period 1961–1980, for comparison with the historic series. Table 9 gives a comparison of some basic statistical characteristics (mean, variance, L1AC, and skewness) of observed and simulated flows. Mean flows are slightly overestimated in most simulated series. Variance within the simulated series is underestimated at the daily level and L1AC is slightly overestimated. These result from an overestimation of low flows (Q_{95}) and an underestimation of high flows (Q_5) of about 10% by the model.

Daily flow sequences were produced for each of the eight catchments for the control and future scenarios using the bias-corrected rainfall and PE data detailed in section 2.2 as input to the calibrated catchment models. This gave 92 years of flows for both the control and future scenarios respectively, with the first year of simulated flows being discarded as a model 'warm-up'. The model parameters are used unchanged for the future impact assessment. This assumes that there are no significant changes in land use or hydrologic response for the future scenario.

5 Analysis of river flow data generated using direct RCM inputs

5.1 Comparison of flows generated using RCM and observed datasets

A comparison is made of flows generated using bias-corrected RCM data for the control scenario (1960–1990) and flows generated using the observed dataset (1961–1990). If flows derived from the RCM data satisfactorily match those simulated using the observed dataset then there can be some confidence in the use of RCM results to predict future changes in flows.

Table 8 Fitted catchment models: parameter values and Nash and Sutcliffe 'efficiency' (CE) and water balance (WB) statistics for the calibration and validation periods

	Thirlmere	Haweswater	Stocks	Longdendale	Rivington	Lake Vyrnwy	Lune	Lower Dee
Parameters								
Wm	133.63	179.82	85.74	134.43	116.61	125.95	96.575	299.987
B	0.49	0.85	0.13	0.23	0.17	0.17	0	0.009
D1	2.51	2.07	1.13	0.50	0.79	1.53	0.955	0.444
D2	2.00	2.00	2.70	3.50	4.59	2.98	3.738	8.517
Conv	0.94	0.94	1.00	0.91	0.91	0.55	0.501	0.503
Diff	2007.71	2052.15	5327.30	1950.53	2032.82	4346.64	1078.566	1184.681
Model Statistics								
Calibration CE	0.75	0.64	0.74	0.67	0.66	0.67	0.72	0.63
WB	1.04	1.02	1.07	1.01	1.05	1.00	1	1.06
Validation CE	0.76	0.65	0.61	0.58	0.65	0.67	0.68	0.63
WB	1.05	0.97	1.00	0.97	1.02	1.02	0.97	1.01

Table 9 Comparison of basic statistical characteristics (mean, variance, lag-one autocorrelation (L1AC) and skewness (Skew)) of daily streamflow data for historic (1961–1980), simulated (1961–1980) and HadRM3H control (1960–1990) and SRES A2 future (2070–2100) scenario (using bias-corrected rainfall and temperature data) at the three 'signature' northwest catchments

Catchment	Time period	Mean (cumecs)	Variance (cumecs^2)	L1AC	Skew
Thirlmere	Historic	2.77	15.97	0.52	4.16
	Simulated	2.87	14.12	0.56	4.31
	Control scenario	3.22	13.54	0.61	3.59
	Future scenario	3.32	18.34	0.58	3.95
Stocks	Historic	1.44	5.43	0.49	3.81
	Simulated	1.54	5.02	0.59	4.93
	Control scenario	1.69	3.27	0.65	3.74
	Future scenario	1.63	3.91	0.65	3.47
Lower Dee	Historic	21.70	666.67	0.76	3.07
	Simulated	22.42	448.77	0.92	2.78
	Control scenario	24.05	468.79	0.89	3.74
	Future scenario	20.12	520.92	0.93	2.44

Control scenario flows slightly overestimate the simulated flows at all catchments (Table 9). At most catchments this is less than 2%, but at catchments with high annual rainfall (Thirlmere, Haweswater and Lake Vyrnwy) the overestimate is as much as 10%. This probably results from the overestimation of low daily rainfall amounts (less than 1 mm) in the control scenario, thus causing an overestimation of low flows (Q_{95} and below), with the resultant aggregation greatly increasing the water balance. This effect may therefore be more noticeable for catchments with higher annual rainfalls.

Control scenario flows slightly underestimate the variance of simulated flows (Table 9). This results from the underestimation of daily rainfall variance in the RCM data. L1AC is slightly overestimated in the control scenario flows (Table 9), causing greater flow persistence compared to simulated flows. Skewness is underestimated at Haweswater, but is well matched elsewhere. A comparison of the distribution of daily flows in the form of flow duration curves was made (not shown). At all catchments the flow distribution is well matched from Q_{95} (the flow exceeded 95% of the time) to Q_5 (the flow exceeded 5% of the time).

These results suggest that any errors come from the rainfall-runoff model and not from the direct use of RCM data to simulate historic flows. This suggests that RCM data can be used with some confidence to examine future predicted changes in the flow regime.

5.2 Future changes in average annual and monthly runoff

The average annual runoff from a catchment gives a strong indication of resource availability. Table 9 shows the average annual runoff for the control and SRES A2 future scenario; with an increase at Haweswater of $\sim +3\%$ for the future scenario resulting from a $\sim +5\%$ increase in annual rainfall. However, annual runoff is projected to decrease by ~4% at Stocks and ~16% at the lower Dee by 2070–2100; the amplification of precipitation reductions through additional PE losses is greater for low elevation catchments with lower mean annual rainfall.

The monthly distribution of runoff is perhaps more important to water resource managers than the annual total. Figure 8 gives the monthly percentage change in runoff between the control and future simulations at the three 'signature' catchments, showing results for three different time-slices (the 2020s, 2050s and 2080s) and the A2 SRES scenario, with

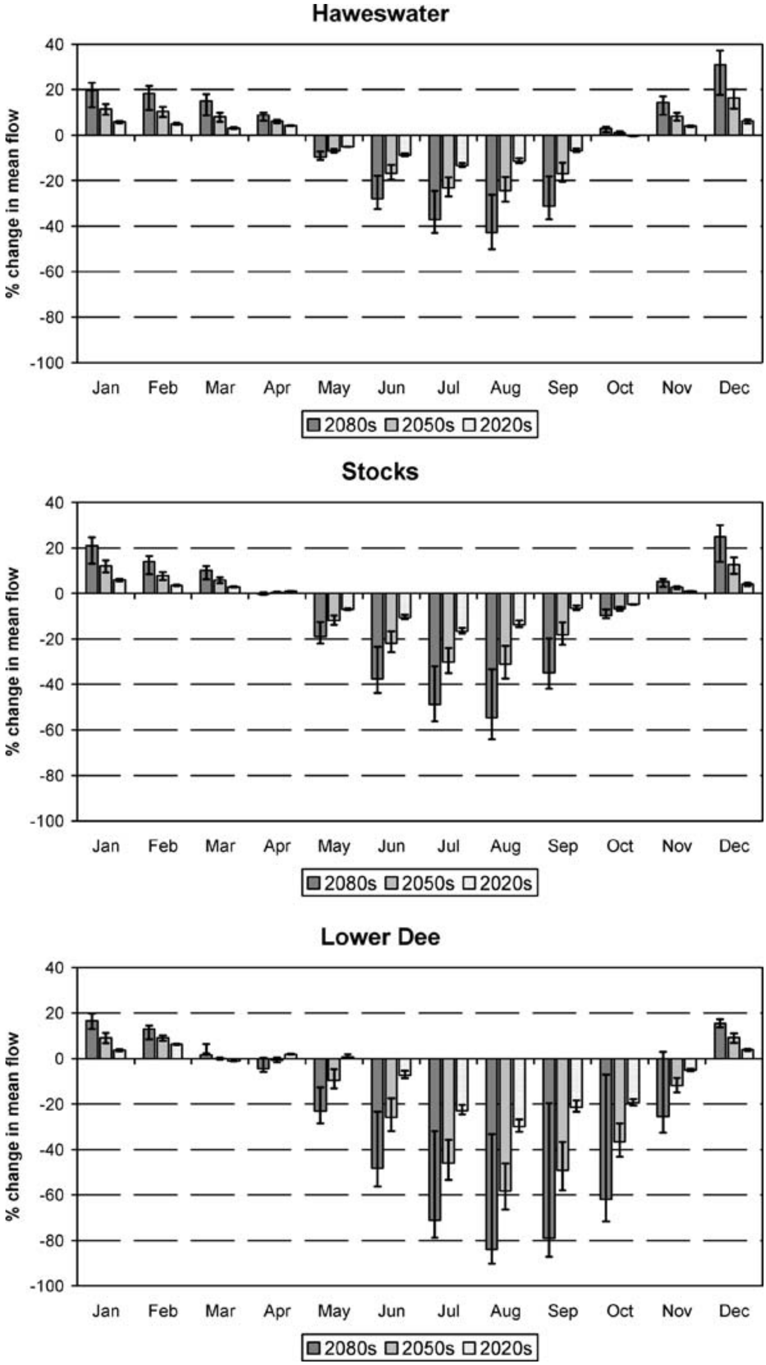

Fig. 8 Percentage change in mean monthly streamflow between the HadRM3H control and future scenarios for the 2020s, 2050s and 2080s time-slices. Results shown are for the SRES A2 (UKCIP02 Medium-High) emissions scenario, but uncertainty bounds are given for the SRES A1 and B1 (UKCIP02 High and Low) emissions scenarios

uncertainty bounds provided by the lowest and highest estimates from the other emissions scenarios (A1, B1 and B2). The largest percentage change is during the month of August, with reductions ranging from −40% to −80% for high to lower elevation catchments for the HadRM3H 2080s A2 SRES scenario. The pattern of change is similar for all time-slices, with the magnitude of change and the associated uncertainty increasing from the 2020s to the 2080s. All catchments show streamflow reductions during May to September, with lower elevation catchments also showing streamflow reductions in October and the Lower Dee showing reductions from April to November (Fig. 8).

At the present time upland catchments, which provide most of the UK's surface water resources, show a fine balance between summer rainfall and PE. This study suggests that large projected decreases in summer rainfall coupled to increases in summer PE may tip the balance and lead to large deficits in summer streamflow at all upland catchments in northwest England. Additionally, most catchments show streamflow deficits in autumn. Under future climate change, autumn rainfall may be used to replenish soil moisture stores depleted during the drier summers rather than to generate immediate streamflow. However, results for the Lower Dee suggest that lower elevation catchments may show the largest reductions in mean annual and summer flows.

Winter streamflow shows a large increase however, with December increases from $\sim +20$ to $+30\%$ in all catchments, except the Lower Dee for the 2080s A2 SRES scenario (Fig. 8). Winter streamflow increases under all emissions scenarios and for all time-slices, but is largest for the highest emissions scenario and 2080s time-slice. At Haweswater this increase provides enough surplus runoff in winter months to counter the summer deficit and increase annual runoff. However, elsewhere projected future summer deficits are larger than winter surpluses.

5.3 Future change in Q_{95} and Q_5 flows

Table 9 shows a comparison of both daily variance and the skewness of the annual daily flow distribution for the HadRM3H control and future scenarios. Annually, daily variance is projected to increase at all catchments, but skewness increases only at Haweswater. However, the change in daily flow variance and skewness on a monthly basis is more complex (Figs. 9 and 10). During the 2020s summer streamflow variance increases, but by the 2050s variance decreases substantially and further decreases by the 2080s. Winter streamflow variance shows a decrease during the 2020s, but then increases steadily until the 2080s. Interestingly, skewness shows an increase in summer and autumn, suggesting an increasingly variable flow regime with an increase in the frequency of extreme flow events. In winter there are small increases in skewness, suggesting a small increase in flooding, but the increases are substantially smaller than those in summer.

Low flows, and particularly the Q_{95} flow (the flow exceeded 95% of the time), are of great practical importance for licensing abstractions and ecological concerns. Figure 11 shows the large estimated change in the magnitude of Q_{95} flows at all catchments, with reductions of at least ~40% in all summer months, with relatively small uncertainty in estimation and large impacts as early as the 2020s. In lower elevation catchments reductions of up to 90% are projected, with low flows extending out to as late as November. This suggests a greatly increased frequency of flows below the present Q_{95} value, with serious consequences for river ecology and summer river abstractions for water supply. This concurs with conclusions by other research, e.g. Arnell (2003) who found that climate change had a greater impact on low flows than on mean flows and that the largest impacts occurred at upland catchments when

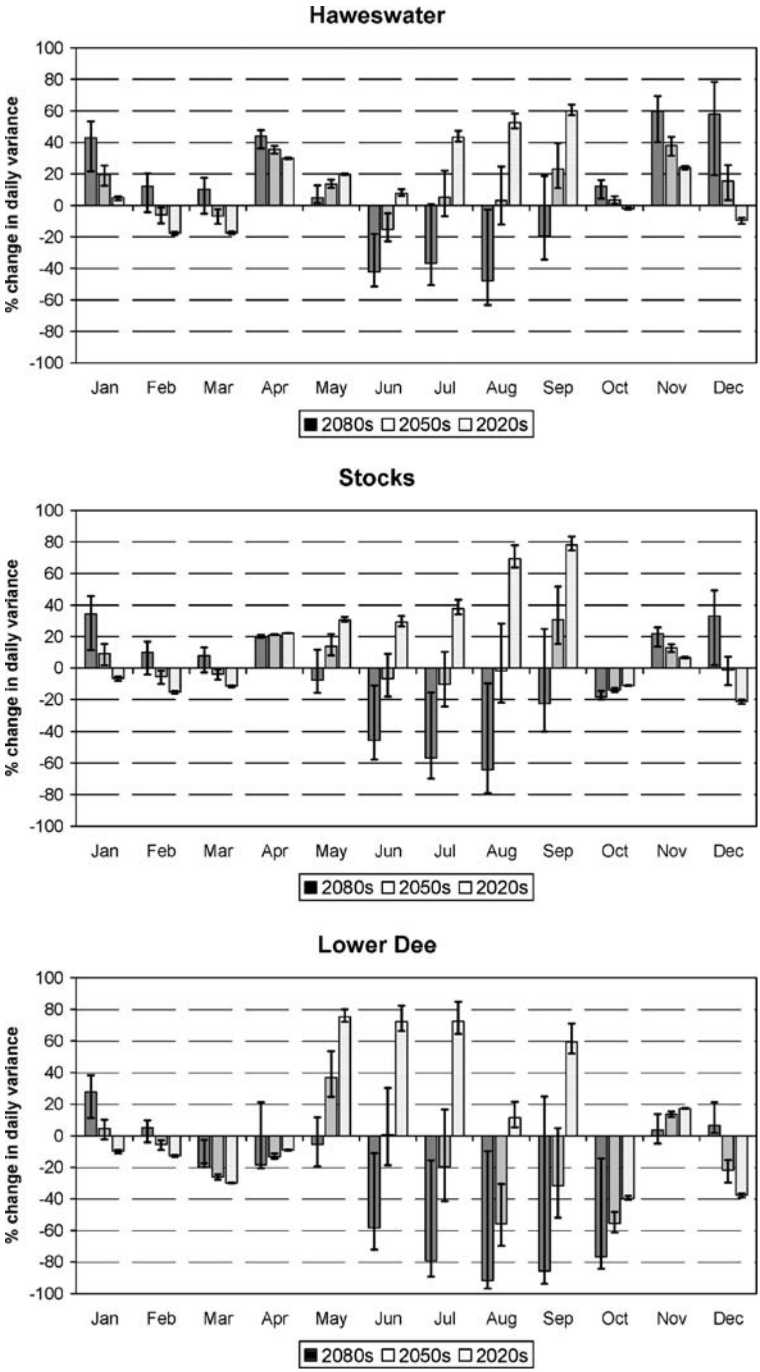

Fig. 9 Percentage change in daily streamflow variance between the HadRM3H control and future scenarios for the 2020s, 2050s and 2080s time-slices. Results shown are for the SRES A2 (UKCIP02 Medium-High) emissions scenario, but uncertainty bounds are given for the SRES A1 and B1 (UKCIP02 High and Low) emissions scenarios

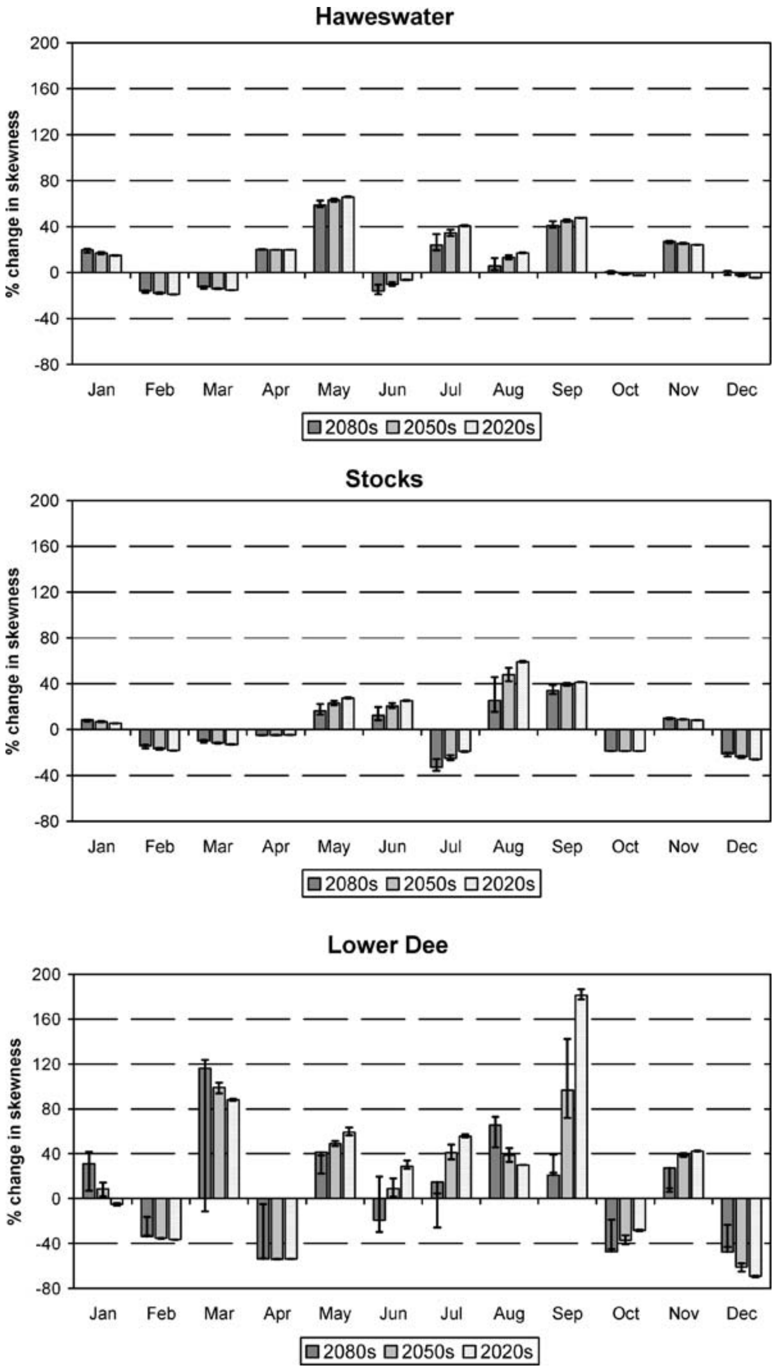

Fig. 10 Percentage change in daily streamflow skewness between the HadRM3H control and future scenarios for the 2020s, 2050s and 2080s time-slices. Results shown are for the SRES A2 (UKCIP02 Medium-High) emissions scenario, but uncertainty bounds are given for the SRES A1 and B1 (UKCIP02 High and Low) emissions scenarios

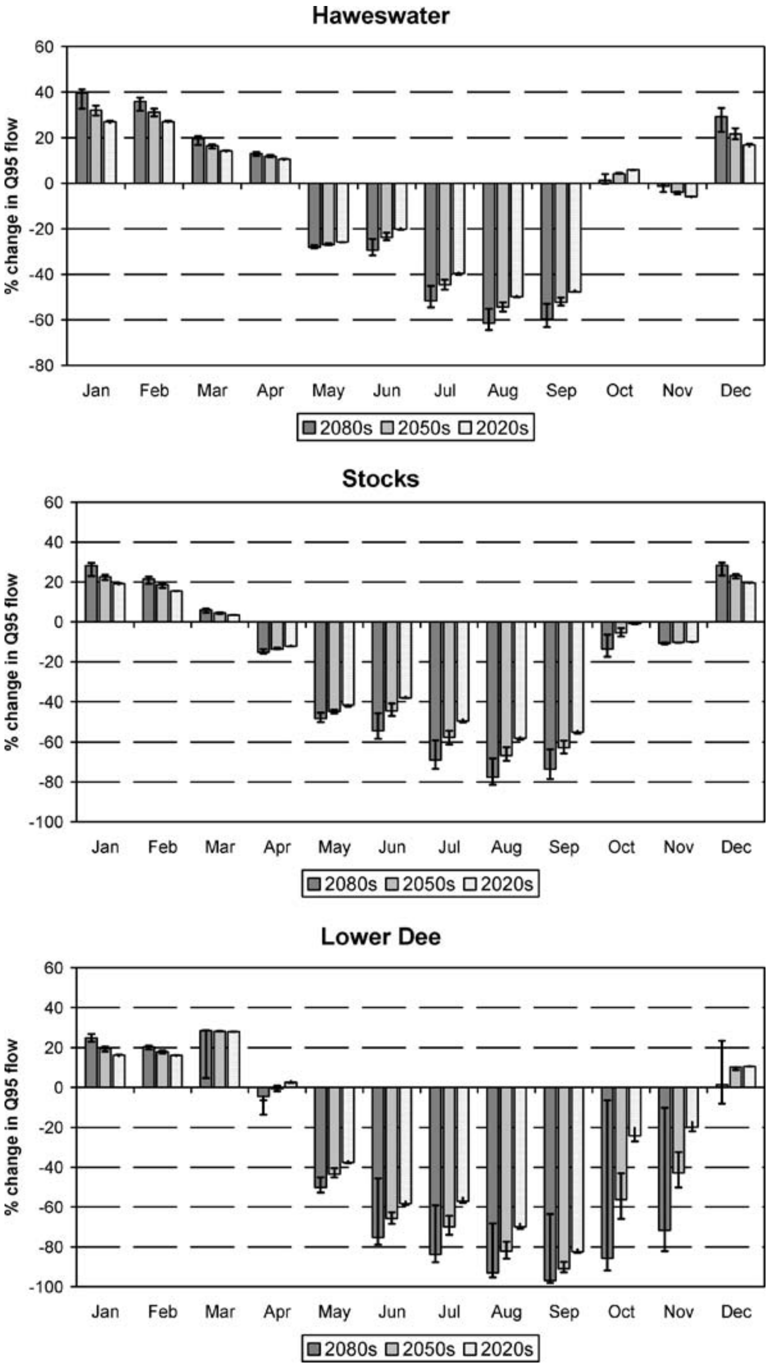

Fig. 11 Percentage change in the Q_{95} flow between the HadRM3H control and future scenarios for the 2020s, 2050s and 2080s time-slices. Results shown are for the SRES A2 (UKCIP02 Medium-High) emissions scenario, but uncertainty bounds are given for the SRES A1 and B1 (UKCIP02 High and Low) emissions scenarios

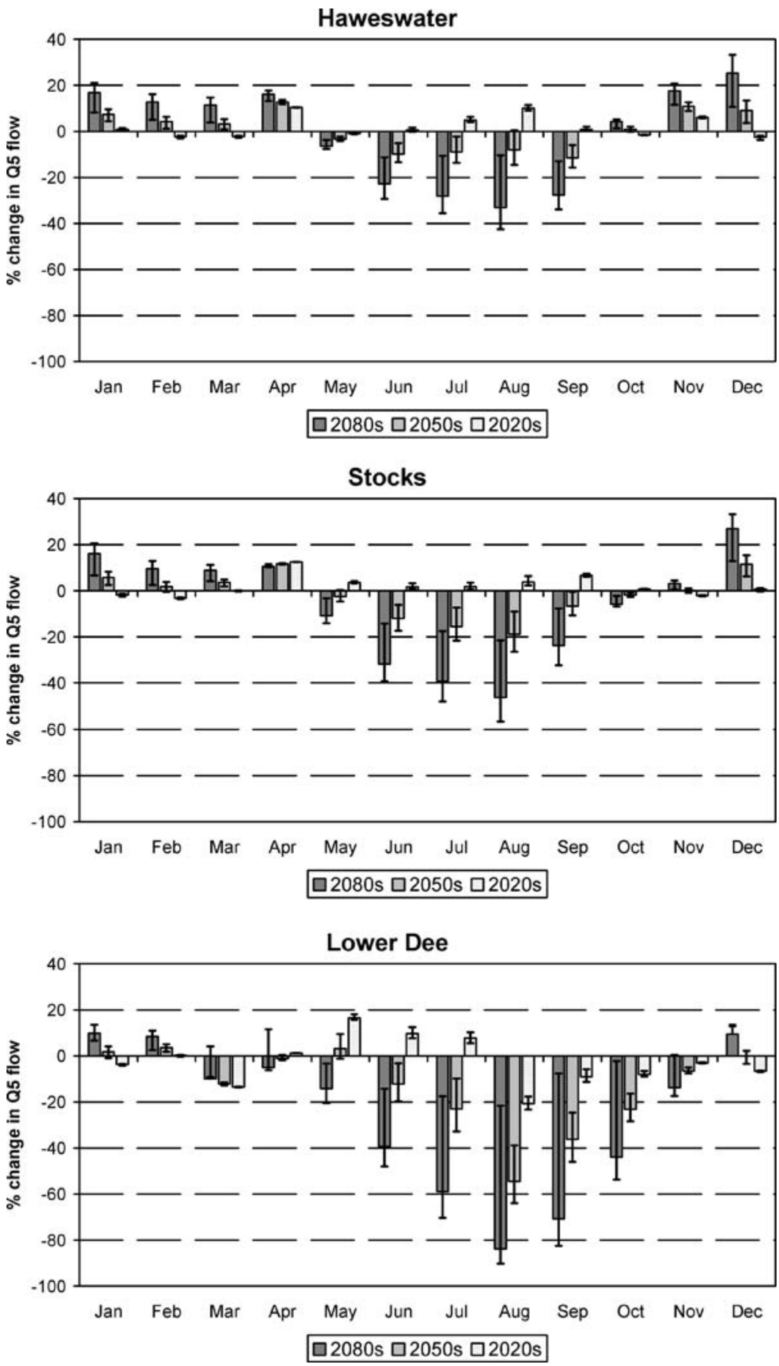

Fig. 12 Percentage change in the Q_5 flow between the HadRM3H control and future scenarios for the 2020s, 2050s and 2080s time-slices. Results shown are for the SRES A2 (UKCIP02 Medium-High) emissions scenario, but uncertainty bounds are given for the SRES A1 and B1 (UKCIP02 High and Low) emissions scenarios

using the UKCIP98 (Hulme and Jenkins 1998) scenarios. Here, we suggest that similar, if not greater, reductions in the Q_{95} flow will also occur in lower elevation catchments.

There are increases in high flows, measured by the Q_5 flow (the flow exceeded 5% of the time), at all catchments during winter but reductions in summer, except in the 2020s. In lower elevation catchments the increases are smaller ($\sim +5$ to $+10\%$) but at Haweswater there is a significant increase in the Q_5 event magnitude of $+5$ to $+25\%$, with increases from October to April by the 2080s. This suggests that the size of winter flood events will increase under future climate conditions, but most significantly in the highest elevation catchments. This concurs with research by Prudhomme et al. (2002, 2003) who found that the SRES-98 climate scenarios produced an increase in the magnitude and frequency of flooding over the UK.

6 Discussion and conclusions

The primary aim of this study was to determine if RCM data can be combined with hydrological models to simulate the historic distribution of annual and seasonal river flows in the UK. Downscaling, either statistical or dynamical, of GCM output is necessary as GCM data are too coarse to represent regional climate variations at the scale required for environmental impact assessment. The main advantage of the use of dynamical downscaling, or RCMs, is their ability to respond in a physically consistent way to external forcings (Wilby et al. 2000). Most statistical downscaling methods assume that the local climate variable is simply a function of synoptic forcing or atmospheric circulation. However, in an RCM all vertical levels of the atmosphere are considered to impact upon local climate (Mearns et al. 1999), and should therefore be more physically realistic.

The most important conclusion from this study is that, if RCM data are to be used directly as input to hydrologic models, there is a need for bias-correction of all input data series on a monthly basis. Hydrologic simulation is sensitive to biases in the mean and spatial distribution of precipitation and temperature at the monthly level (Wood et al. 2004). In the HadRM3H model control climate for the northwest of England, there are consistent biases in the simulation of mean rainfall, seasonality and variability. Bias-correction is necessary to correct both the absolute magnitude of precipitation amount and the seasonality to observations, and therefore produce realistic runoff series when input to a hydrologic model, as also noted by Hay et al. (2002) and Wood et al. (2004). However, the bias-correction scheme used here corrects only the mean monthly magnitude, and does not correct for the underestimation of rainfall variability at the daily level in the HadRM3H control scenario. The Wood et al. (2004) ‘quantile-mapping’ bias-correction scheme does address biases in climate model variability. However, the use of this type of correction method assumes that the rainfall distribution will be the same in the future as in the control climate. Using simple monthly mean climate corrections, we were able to provide reasonable estimates of the observed climatic variability within the control climate without resorting to the use of ‘quantile-mapping’ and the assumption that probability distributions used to correct climate model bias will remain stable over time. Therefore, this method was preferred, even though it provided a small underestimate of variability.

The results of this investigation into the use of RCM data to assess the impacts of climate change on the northwest England integrated resource zone therefore suggest that (1) bias-corrected RCM control scenario data can be used to represent observed precipitation and temperature series in northwest England, despite the difference in spatial resolution between the two datasets; (2) using bias-corrected RCM data as input to hydrologic models results in a slight overestimate of observed mean annual runoff at catchments with high mean annual precipitation but matches the observed daily flow distribution well, suggesting that RCM data can be used with some confidence to examine future changes in flow regime; (3) the HadRM3H future scenario (2070–2100, SRES A2) indicates increases in winter precipitation of $+20$ to $+30\%$ and summer reductions of up to 50%, and similar change in daily variance; (4) change in annual rainfall range from slight increases, $\sim+5\%$, at the northernmost catchments, to reductions of up to 9% at lower elevation catchments, coupled with an increase in PE throughout the year of $+10$ to $+20\%$; (5) annual runoff at Thirlmere and Haweswater increases by $\sim+3\%$, but lower elevation catchments show large reductions in mean annual runoff of up to 16% by the 2080s; (6) monthly changes are larger, with summer reductions from -40 to -80% of present flows and largest at lower elevations, and winter runoff increasing by $\sim+20\%$. However, many catchments also show reductions in autumn and spring, which are critical recharge periods. New water resources or management strategies may be needed to counter these effects, which will have a significant impact upon river ecological management; (7) changes in low and high flows, Q_{95} and Q_5, are substantial. Summer Q_{95} is projected to decrease by ~-40 to -80%, with the largest increases at lower elevations. Low flows below the present Q_{95} value are expected to increase in frequency, with consequences for both river ecology and summer water supply abstractions. High flows are also projected to increase, with the winter Q_5 flow increasing in all catchments but with the largest increases of up to 25% in the uplands by the 2080s. This will increase the frequency of winter fluvial flooding and spilling from reservoirs under climate change.

There are some caveats to this modelling approach. Firstly, although rainfall in the northwest of England is well matched by the RCM after bias-correction, we would not expect rainfall in other regions of the UK to be as accurately simulated. Assessment of the control climate of HadRM3H (Fowler et al. 2005; Fowler and Kilsby 2004) suggests that both mean and extreme annual rainfall statistics are better reproduced in the north than the south of England. Indeed, extreme rainfall at 1 and 2-day durations is significantly underestimated by HadRM3H in the south of England (Fowler et al. 2005). Similarly, drought events (prolonged low rainfall amounts) are overestimated in the south of the UK, particularly in southeast England (Fowler and Kilsby 2004). Therefore, the direct use of bias-corrected RCM data in these regions may not provide the same success in representing observed series as found in the northwest region. However, the fact that RCM output can be used to directly simulate accurate flow distributions in the northwest of England (an area of complex orography) suggests that the model has a good downscaling ability as it is able to resolve the non-trivial pattern of precipitation climate in this region.

It is also important to examine the uncertainty in projected changes (Ekström et al. 2005). Here we present results for an impact study assessing a single climate change emissions scenario, the SRES A2 scenario (IPCC 2000), from a single model, HadRM3H and a single time-slice, 2070–2100, with pattern-scaling used to produce results for other emission scenarios and time-slices. This selection results from the substantial computational cost associated with the double-nesting method used to produce the HadRM3H outputs. The experimental design adopted for the UKCIP02 scenarios utilises a hierarchy of climate models (as explained in Section 2.2 and Hulme et al. 2002). The coupled ocean-atmosphere HadCM3 experiments provide the boundary conditions to drive a high resolution ($\sim$120 km) model of the global atmosphere, HadAM3H, and the output from these time-slice experiments (run over the period 2070–2100) provide boundary conditions to drive the high-resolution ($\sim$50 km) regional model, HadRM3H. This double-nesting approach improves the quality of the simulated European climate, particularly the position of the major storm tracks but has the disadvantage that only the A2 SRES emissions scenario and the period 2070–2100 are simulated.

Uncertainty in climate change projections may result from many different sources: future emissions, model parameterisation and natural climate variability being just a few. This study does not examine uncertainties associated with modelling the climate system response to climate change, or model parameterisation as the HadRM3H integrations were the only available high resolution simulations of future UK climate for the new IPCC SRES emissions scenarios. Pattern-scaling, from the SRES A2 2070–2100 scenario, is used to provide estimates of change for different time-slices (2010–2040; the '2020s', and 2040–2070; the '2050s) and different emission scenarios (SRES A1, B2 and B1; respectively the High, Medium-Low and Low scenarios from UKCIP02). This is based on the assumption of linearity between change in regional rainfall and temperature and global temperature change. Further detail is given in Hulme et al. (2002). This also allows us to quantify the uncertainty associated with the chosen emissions scenario, A2. The A2 scenario applied in the HadRM3H integrations is near the centre of the range of the IPCC estimates in terms of mean global temperature change (Johns et al. 2003); here we provide upper and lower uncertainty bounds on changes in streamflow based on the highest and lowest estimates obtained from the different emission scenarios.

Further work in this area concentrates on whole system modelling and the inclusion of uncertainty estimates. A water resource system model is used to assess the performance of the entire IRZ, including pipe capacity and treatment work size restrictions, and evaluated with reference to the imposed demand for the both the control and future climate change scenarios (Fowler and Kilsby 2006), thus defining a conjunctive use element (as Wood et al. 1997; Lettenmaier et al. 1999). Alternative operating scenarios for the water resource system and uncertainties in future demand will also be investigated to provide information on optimal system management under future climate change. Uncertainty will be addressed by the use of a methodology first developed by Wigley and Raper (2001), and further advanced by Ekstrom et al. (2006b) for northwest England. This combines probability distribution functions (PDFs) for global temperature increase (Wigley and Raper 2001) and for scaling variables, such as the change in regional temperature or precipitation per degree of global annual average temperature change, to produce a probability distribution for regional temperature and precipitation. This can then be combined with Monte Carlo simulation techniques to assess uncertainty in the estimates of climate change produced using only one scenario. In this way, we hope to provide an improved methodology for the robust assessment of the impacts of climate change on water resource systems.

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