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Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate

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Abstract The first part of this paper demonstrated the existence of bias in GCM-derived precipitation series, downscaled using either a statistical technique (here the Statistical Downscaling Model) or dynamical method (here high resolution Regional Climate Model HadRM3) propagating to river flow estimated by a lumped hydrological model. This paper uses the same models and methods for a future time horizon (2080s) and analyses how significant these projected changes are compared to baseline natural variability in four British catchments. The UKCIP02 scenarios, which are widely used in the UK for climate change impact, are also considered. Results show that GCMs are the largest source of uncertainty in future flows. Uncertainties from downscaling techniques and emission scenarios are of similar magnitude, and generally smaller than GCM uncertainty. For catchments where hydrological modelling uncertainty is smaller than GCM variability for baseline flow, this uncertainty can be ignored for future projections, but might be significant otherwise. Predicted changes are not always significant compared to baseline variability, less than 50% of projections suggesting a significant change in monthly flow. Insignificant changes could occur due to climate variability alone and thus cannot be attributed to climate change, but are often ignored in climate change studies and could lead to misleading conclusions. Existing systematic bias in reproducing current climate does impact future projections and must, therefore, be considered when interpreting results. Changes in river flow variability, important for water management planning, can be easily assessed from simple resampling techniques applied to both baseline and future time horizons. Assessing future climate and its potential implication for river flows is a key challenge facing water resource planners. This two-part paper demonstrates that uncertainty due to hydrological and climate modelling must and can be accounted for to provide sound, scientifically-based advice to decision makers.

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1 Introduction

The establishment of long-term, strategic plans for the management and use of water resources is the responsibility of water authorities and regulatory agencies who need to build sustainable plans based on sound risk analysis. With growing concern about global warming and changing climate, the Environment Agency for England and Wales (EA) has implemented new strategies for improving the future management of water resources (Environment Agency 2001) and, along with water companies, invests in research on understanding the uncertainty in the impact of climate change on the water cycle so that results could help to build the next 25-year water resource management plan expected in 2009. However, standard methodologies to include uncertainties in potential changes and assess their impact on projected estimates have yet to be developed. One of the only tools available at present to quantify changes in water resources is through the use of climate change scenarios generated by Global Climate Models (GCM) and assuming pathways for future CO_2 emission in the atmosphere. All these climate models systematically predict that the world will become warmer as a consequence of increases in the concentrations of greenhouse gases (Le Treut 2003). With a warmer world and thus more energy available in the atmosphere, the atmospheric processes and the water cycle may be enhanced but all models predict changes varying in magnitude depending on the region of the planet and the time of the year (Trenberth 1998). The Intergovernmental Panel on Climate Change (IPCC) report on impacts (Alcamo et al. 2007) suggests that, in southern Europe in particular, changes in rainfall and temperature patterns are likely to lead to a decrease in runoff, water availability and soil moisture during the summer months, while increases in precipitation and water resources are likely in winter in the north of Europe. In the UK, the Department for Environment, Food and Rural Affairs commissioned a set of scenarios for the UK Climate Impacts Programme (UKCIP02) to provide a common reference point for assessing climate change vulnerability, impacts and adaptation in the UK (Hulme et al. 2002). These UKCIP02 scenarios, based on four future emission assumptions, show a north–west/south–east gradient in the magnitude of warming, with this increase especially pronounced in the south east in the summer. Under these scenarios, winter precipitation increases by 15–30% and summer precipitation decreases by 20–40% by 2080s. The eastern and southern parts of the UK are expected to experience the largest changes in precipitation both in winter and summer, while the smallest changes are indicated for Scotland.

There is, however, considerable uncertainty in GCM projections and the subsequent modelling of their impacts on the water resources. Prudhomme and Davies (2008) showed that hydrological uncertainty can be as large as the natural variability of the river flow regime but that in comparison, the uncertainty in mean monthly flow due to using climate simulated by different GCMs to drive the hydrological model is larger: all GCMs showing deficiencies in reproducing the current seasonal pattern of the rainfall. When using different techniques to express GCM climate output at a catchment scale, results could also diverge. The existence of potential systematic bias in the reproduction of baseline mean monthly flows by either GCM or downscaling technique needs to be considered when analysing future impacts predicted using the same techniques.

In addition, there is uncertainty in the rate and magnitude of changes in the chemical composition of the atmosphere (in terms of the greenhouse gas content) over the next 100 years, as it is closely linked to the evolution of the society. The IPCC developed a set of socio-economic projections for the future up to 2100 and the corresponding emissions of greenhouse gases (the SRES emission scenarios) in the Special Report on Emission Scenarios (IPCC 2000). The SRES scenarios are based on four storylines each describing how world population, economies and political systems may evolve. When these SRES emission scenarios are used to estimate global runoff (through GCM-derived climate and water resource modelling), they lead to differences in runoff that are relatively small compared to differences due to climate models (Arnell 2004). Many impact studies, however, only focus on scenarios from a single GCM and different SRES emission scenarios (e.g. Ashley et al. 2005; Kitoh et al. 2005; Stainforth et al. 2005), thus likely underestimating the large contribution to uncertainty arising from the climate models, shown to be significant for baseline climate (Prudhomme and Davies 2008) and known to be significant for the future. This paper will use two hydrological models (ModA and ModB) for the same four British catchments as in Prudhomme and Davies (2008) to simulate flows at the catchment outlet using catchment-average rainfall and potential evaporation outputs (Fig. 1 and Table 1). In this case, the inputs will be derived from the 30-year prediction of a future climate centred on the 2080s (from the same GCMs and downscaling techniques as for the baseline). One additional downscaling technique (factor of change) using the UKCIP02 climate scenarios is also considered. This paper provides some understanding of how uncertainty due to GCMs, downscaling techniques and emission scenarios compare with each other and with uncertainty due to hydrological modelling. It shows the importance of interpreting future projections in the context of the uncertainty derived from the modelling of river flow for the baseline time horizon.

2 Methodology

Only brief details of the rainfall-runoff models and the methods used to derive model inputs from GCM data will be given here. More details on method and data are given in Prudhomme and Davies (2008).

2.1 Natural and climate variability

Baseline and future natural climate variability were quantified by running the hydrological model (ModA) with 100 rainfall and PE series resampled from the observed series and series representative of the 2080s using the 3-month block resampling method (Prudhomme and Davies 2008). Variability due to the choice of input data and model is also quantified for baseline and future time horizons, as described in Section 3.

2.2 Hydrological modelling

2.2.1 Model description and calibration

The hydrological model used is based on the Probability Distributed Moisture model (PDM) (Moore 1985) with a probability-distributed representation of soil

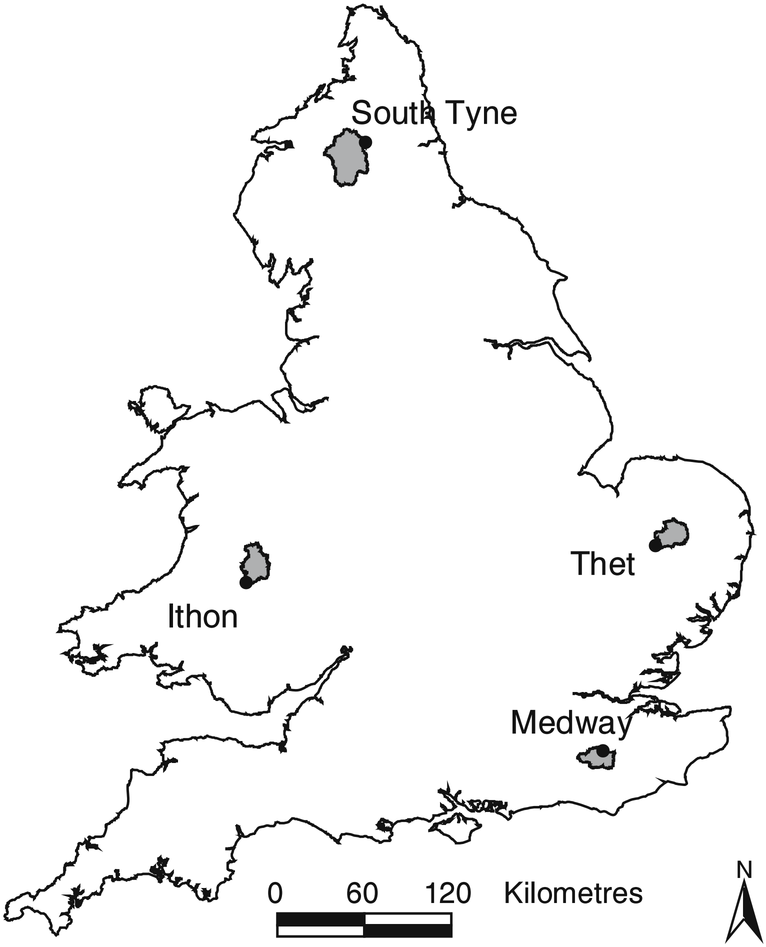


Fig. 1 The four case study catchments

storage capacities (Pareto distribution) and a second-order linear routing reservoir scheme for simulating quick and slow flow routing of effective rainfall. It includes an interception storage term and a soil moisture related drainage term, and has five free parameters for calibration (Young 2006) (Fig. 2). For ModA, the calibration was done on a 10-year period, and the parameters evaluated on an independent period (from 17 years for the Ithon to 25 years for the Medway) to insure stability of the parameters (Nash and Sutcliffe efficiency criterium for the evaluation period varies between 0.64 for the South Tyne to 0.76 for the Thet and the Ithon).

For future runs, the hydrological model is used with the parameters fitted on observed data. The underlying assumption is that the parameter set is not dependent on the climate, but strictly on the physical transformations of precipitation into stream flow, itself independent from climate. The majority of hydrological impact studies are based on similar assumptions (e.g. Booij 2005; Dibike and Coulibaly 2005; Fowler and Kilsby 2007; Maurer and Duffy 2005; Wilby 2005). There are two main reasons for this method: first, the lack of long records (climate and flow) that

Table 1 Test catchments and their characteristics under baseline climatic conditions—from Marsh and Lees (2003)

NWA ID	River	Station	Area (km^2)	Short description	BFI	Mean annual rainfall (mm)	Data record
23004	South Tyne	Haydon Bridge	751	Upland catchment draining the northern Pennines. Landuse predominantly moorland and upland pasture. Mainly Carboniferous Limestone and Millstone Grit.	0.34	1,182	1962–1997
33019	Thet	Melford Bridge	319	Predominantly chalk catchment approximately 70% overlain by boulder clay. Mainly of arable land.	0.78	625	1962–1996
40007	Medway	Chafford Weir	255	Drains from Ashdown forest. Predominantly rural. Mixed geology but mainly Ashdown Sands and Wadhurst Clay. Quite responsive regime despite significant baseflow	0.49	867	1961–1997
55016	Ithon	Dissert	358	High moorland and extensive forestry plantations on the higher ground and mixed farming in the valleys. Upper and western catchment drains Ordavician and Silurian shales and igneous complex in South East.	0.38	1,123	1968–1997

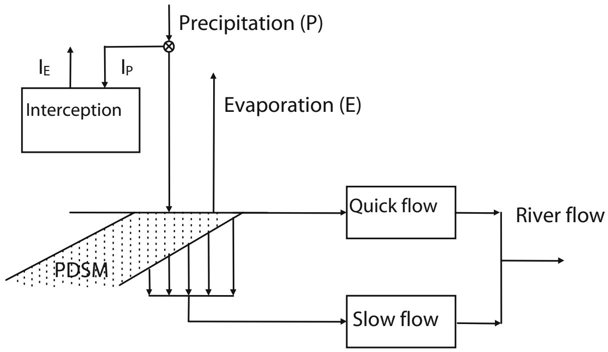


Fig. 2 Conceptual structure of the hydrological model (from (Young 2002))

would include climatic conditions similar to what may be expected in the future. This precludes the fitting of a set of parameters specific to such future conditions. Second, Niel et al. (2003) showed no evidence that non-stationarity in climate would incur parameter instability in Africa. However, more research is needed on the possible non-stationarity of model parameters in regions such as the UK.

2.2.2 Potential evapotranspiration

Potential Evapotranspiration (PE) represents the maximum water a plant could loose through evaporation and transpiration if enough water was available in the soil to the plant. PE cannot be directly measured, but modelled using other climate variables, such as temperature, wind speed and relative humidity (e.g. Penman-Montieth PE; Allen et al. 1994, 1998). Global and Regional Climate Models do not provide direct estimates of PE. This includes the UKCIP02 scenarios, which are monthly averages of the Hadley Centre's RCM model HadRM3 ensemble runs. Daily series of all variables necessary for Penman-Montieth equations were available from HadRM3 outputs, and thus daily PE series were directly derived from these outputs for the baseline and 2080s time horizons. Future PE scenarios were obtained using the "change factor" method described in detail in the following section.

2.3 Uncertainty in climate modelling

2.3.1 GCMs and downscaling techniques

The same three GCMs (HadCM3, CGCM2 and CSIRO) and downscaling techniques (SDSM and HadRM3) as used in Prudhomme and Davies (2008) are used to generate 30-years daily precipitation scenarios representative of the 2080s future time horizon. For SDSM-generated scenarios, twenty separate runs were made for each of the three GCMs using the stochastic element of the SDSM, thus providing some element of climate variability for the future time horizon (2080s). Block resampling was used to produce a total of 100 resampled series for each scenario.

2.3.2 Change factor method: the UKCIP02 scenarios

The UKCIP02 scenarios were derived using the "change factor" method, previously extensively used in climate change impact assessments (e.g. Hay et al. 2000). The UKCIP02 factors of change are derived from the outputs of the HadRM3 model and are defined as a set of monthly changes in a range of climatic variables (including temperature, precipitation, wind speed and relative humidity) (Hulme et al. 2002) here re-gridded at a 0.5° × 0.5° grid over the UK. For the 2080s time horizon, the factor of a given variable (e.g. precipitation) corresponds to the difference between future (2071–2100) and baseline (1961–1990) average monthly values, expressed in percentage of the baseline average monthly value. Future series for the 2080s time horizon were derived using the monthly UKCIP02 factors as follows:

$$X_{\text{future,day,month}} = X_{\text{baseline,day,month}} \cdot \left(1 + \frac{X_{\%\text{UKCIP02factor future,month}}}{100}\right)$$

with X, the variable of interest (e.g. rainfall, PE)

The resulting series are the same length as the observed series and have the same day-to-day variability each month. The same technique was used for PE using monthly factors derived from GCM monthly averages. The PE factors were defined by (1) computing baseline and future PE using the Penmon-Montieth equation from UKCIP02 data and (2) computing the difference between UKCIP02 PE-PM future and UKCIP02 baseline.

2.4 Uncertainty in emission scenarios

Two SRES emission scenarios were considered in this study. The A2 scenario depicts a world slow to globalise, where regional preservation is emphasised and the underlying theme is self-reliance. This scenario results in a relatively high anthropogenic forcing of the future climate (IPCC 2000). The B2 scenario represents a regional world (like A2), but with an emphasis upon achieving economic, environmental and social sustainability via local solutions (IPCC 2000). Although the global population continues to rise, the rate of increase is smaller than in the A2 scenario. A2 and B2 scenarios are the most widely used emissions assumptions in future GCM simulations, and the only SRES scenarios where daily runs from different GCMs are easily available. The A2 and B2 scenarios correspond respectively to the Medium High and Medium Low scenarios of the UKCIP02 factors. For each emission scenario, SDSM-downscaled GCM rainfall outputs are block resampled to produce 100 daily series representative of the 2080s.

2.5 Uncertainty in hydrological modelling for future time horizon

Uncertainty in hydrological modelling for future time horizons for the emission scenario A2 is considered in three ways:

1. *Model structure*. ModB (best parameter set, see Prudhomme and Davies 2008) is used with the 100 resampled rainfall and PE series representative of each of the GCM-SDSM or RCM combination for the 2080s. This is directly comparable to Section 2.3 but with a different model structure.
2. *Model parameters*. A set of near-optimal parameter sets for ModA is run with one series of rainfall and PE representative of each of the GCM-SDSM or RCM combination for the 2080s.
3. *Combined model parameters and GCM variability*. 100 random pairs were drawn from the near optimal model parameter sets and 100 resample rainfall and PE representative of each of the GCM-SDSM or RCM combination for the 2080s.

The first two tests consider individually the hydrological uncertainty transposed in a future time horizon. The relative size of uncertainty from two model structures or from model parameters can be directly compared. The third test assesses the combined hydrological model uncertainty and future climate variability compared to future climate variability alone (Section 2.3).

2.6 Reference value, indicator of change and uncertainty bands

Two ways of assessing the changes are presented and discussed.

1. Future projections are compared to baseline value (called reference flow hereafter) and variability (called natural variability in Prudhomme and Davies (2008) and representative of the 1961–1990 period).
2. Future projections are compared to baseline flow (median of simulations) and variability as reproduced by the GCM/ downscaling technique combination, whose potential bias is removed.

The percentage changes between the median baseline and future projection ranges by methods (1) and (2) are given in Table 2. Table 3 give the size of the 90% Confidence Intervals CI obtained from different scenarios runs. Figures 3, 4, 5, 6, 7 and 8 show future mean monthly flows projections (CI described by box plots, with from bottom to the 5th, 25th, 50th, 75th and 95th percentile) and can be compared with baseline natural variability (grey boxes) and baseline climate variability (hashed boxes).

Changes are only defined as significant if at least 75% of the ensemble runs are outside the 90% CI of the baseline variability range (natural variability for method 1, flow variability from hydrological modelling or GCM and downscaling combination by method 2). This is because variations smaller than expected from the current climate alone cannot be attributed as a signal of change. The threshold of 75% is a practical choice to be compared with the 68% of values comprised within plus or minus one standard deviation around the mean and 16% of values below or above one SD from the mean for a normal distribution.

3 Results

Using four test catchments across Britain, the size of the uncertainty associated with projections of river flows using different hydrological models (structure and parameters), GCMs, downscaling techniques and emission scenarios was analysed and compared with the size of uncertainty found when modelling the baseline regime (Prudhomme and Davies 2008). In particular, the paper discusses the significance and consistency in the sign and magnitude of predicted changes (using the same GCMs, downscaling methodology or emission scenarios on different catchments, or using different climate scenarios on the same catchment), changes in monthly flow variability (i.e. size of uncertainty bands), and the relative importance of hydrological modelling uncertainty compared to climate (GCM and downscaling combination) uncertainty. Results provide basic assessments on the uncertainties seemingly dominant over the others. The small number of catchments considered precludes the assessment in the skills in reproducing the river flow regime of any

Table 2 Changes in median of uncertainty bands for the 2080s time horizon for SDSM-downscaled GCMs scenarios run with the A2 SRES emission scenarios

		JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
a													
South Tyne	CCGCM2	26.03	41.58	-32.75	-35.66	-54.79	-65.74	-79.22	-85.3	-84.74	-63.52	-25.62	20.13
	CSIRO	43.86	85.95	-1.65	21.48	55.44	39.8	-25.32	-51.02	-58.42	-59.82	-42	36.01
	HadCM3	48.52	64.09	-12.32	-31.62	-48.88	-31.35	-49.12	-48.01	-53.33	-20.8	-3.03	38.88
Thet	CCGCM2	-6.23	8.46	1.91	-8.25	-14.93	-21.58	-37.5	-57.24	-71.25	-73.85	-60.96	-32.42
	CSIRO	-1.87	-4.38	20.42	38.68	96.88	97.89	43.06	-15.94	-33.75	-53.08	-41.33	-20.52
	HadCM3	-26.48	-18.43	0.00	-2.36	-9.03	-10.53	-27.78	-52.17	-71.25	-74.24	-61.73	-47.25
Medway	CCGCM2	18.1	51.94	13.33	-3.16	-6.39	16.55	35.58	10.87	-32.52	-65.17	-64.72	-10.84
	CSIRO	59.73	92.12	22.58	36.75	46.94	18.62	5.77	-15.22	-41.46	-55.43	-27.18	71.27
	HadCM3	29.7	74.89	3.48	-15.81	-25.56	-32.75	-36.54	-51.09	-73.98	-83.9	-53.12	5.96
Ithon	CCGCM2	-15.54	-4.94	-23.83	-25.63	-27.78	-52	-46.67	-63.82	-71.44	-58.43	-45.28	-23.82
	CSIRO	-17.71	-1.78	-10.74	51.52	259.73	90.18	53.1	-30.25	-40.97	-48.3	-37.86	-12.76
	HadCM3	9.32	28.06	-5.26	-5.47	13.19	16.73	-15	-55.52	-70.99	-42.86	-11.84	-2.08
b													
South Tyne	CCGCM2	10.65	15.13	-22.34	-29.36	-58.92	-67.60	-72.86	-65.88	-57.31	-27.40	14.60	13.39
	CSIRO	16.98	31.07	-8.13	-0.92	-9.50	-19.03	-28.12	-18.59	-33.79	-20.32	-10.74	22.76
	HadCM3	29.84	30.71	9.79	-19.12	-39.50	-37.59	-49.69	-33.98	-22.99	-10.19	5.22	22.55
Thet	CCGCM2	-0.99	9.45	0.00	-6.73	-15.17	-28.16	-37.50	-40.00	-47.73	-42.37	-39.20	-17.41
	CSIRO	-2.78	-13.66	-8.14	19.03	59.55	49.21	22.62	0.00	-17.19	-18.67	-26.75	-14.90
	HadCM3	4.42	9.31	18.02	2.48	-18.13	-39.72	-56.67	-68.87	-72.62	-56.41	-35.90	-11.11
Medway	CCGCM2	22.9	12.9	2.19	-10.9	-20.4	-33.7	-30.9	-32.9	-30.8	-32.6	-31.7	15.1
	CSIRO	27.9	30.2	-10.8	29.1	45.1	8.86	3.77	-1.27	-14.3	-38.7	-39.2	17.1
	HadCM3	14.5	53.2	-2.01	-22.3	-33.3	-43.4	-44.1	-55.0	-60.5	-58.3	-42.2	-7.79
Ithon	CCGCM2	13.36	17.31	-12.0	-14.4	-43.5	-41.1	-23.3	-12.7	-32.2	-27.0	-22.28	8.51
	CSIRO	7.13	11.61	1.56	57.8	60.87	10.6	13.8	22.3	-14.7	-13.5	-4.95	20.12
	HadCM3	8.09	39.79	22.6	-12.7	-31.1	-20.3	-46.2	-58.3	-47.7	-20.0	-0.77	2.80

Method 1 a: Changes expressed as percentage points from the reference value. Months with significant changes (defined when at least 75% of the scenarios where outside the natural variability 90% range) are in bold. Significant increases on hashed background, significant decrease on grey background. Framed changes signify when flow variability due to baseline GCM variability is within natural variability.

Method 2 b: Same as Method 1 but changes expressed as percentage points from median of CI due to GCM baseline variability

particular GCM or downscaling technique, but does provide a valuable indication of the potential variations in the modelled flows and changes for the same future time horizon.

3.1 GCMs uncertainty alone

All results in this section were obtained by running ModA with the GCM-derived rainfall and PE daily series obtained using the SDSM downscaling (rainfall) and change factor method (PE). Prudhomme and Davies (2008) found that baseline natural variability in the seasonal and monthly river flow pattern exists for the four test catchments and that the 90% CI can be as large as 60% (mean May flow of the Ithon).

Table 3 Confidence Bands (comprising 90% of simulations, in m^3/s) for current and 2080s time horizons from ModA best parameter set run with 100-resampled SDSM-downscaled GCMs scenarios with the A2 SRES emission scenarios

			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
a														
South Tyne	CCGCM	baseline	6.41	5.16	3.71	3.86	3.07	2.93	3.33	1.55	2.57	4.35	4.58	5.75
		2080s	**10.06**	**8.25**	3.25	2.22	1.10	0.98	0.69	1.10	1.34	3.76	**5.14**	**7.27**
	CSIRO	baseline	5.61	9.01	4.83	3.15	4.59	5.39	2.70	2.77	4.01	3.91	7.92	5.85
		2080s	**13.80**	**11.65**	**4.91**	**5.63**	4.41	4.88	2.45	**3.19**	2.44	3.26	5.65	**7.87**
	HadCM3	baseline	8.32	4.87	2.82	2.95	3.63	3.27	3.66	3.37	3.97	5.03	5.42	9.28
		2080s	**10.40**	**7.68**	**4.60**	**3.05**	1.60	1.74	2.14	**3.40**	**4.12**	4.67	**7.25**	6.62
	Nat. baseline clim. Var.		6.46	8.51	4.52	4.06	3.14	2.86	3.39	5.18	5.08	6.28	8.3	6.8
Thet	CCGCM2	baseline	0.85	0.82	0.50	0.28	0.20	0.24	0.16	0.11	0.11	0.19	0.56	0.82
		2080s	**1.34**	**1.23**	**0.57**	**0.38**	**0.21**	0.18	0.11	0.07	0.07	0.14	0.28	**0.84**
	CSIRO	baseline	1.01	0.99	0.69	0.46	0.27	0.29	0.13	0.11	0.23	0.21	0.75	0.94
		2080s	**1.03**	**1.15**	**1.27**	**1.03**	**0.91**	**0.49**	**0.23**	**0.14**	0.17	**0.24**	0.54	0.88
	HadCM3	baseline	0.74	0.72	0.47	0.48	0.39	0.49	0.49	0.42	0.34	0.35	0.53	0.46
		2080s	**0.78**	**0.88**	**0.66**	**0.49**	0.29	0.19	0.11	0.10	0.08	0.11	0.28	0.42
	Nat. baseline Clim. Var		0.73	0.84	0.41	0.41	0.28	0.22	0.17	0.22	0.39	0.64	0.86	0.8
Medway	CCGCM2	baseline	1.25	1.92	1.04	0.83	0.7	1.09	0.72	0.44	0.33	0.54	1.04	1.23
		2080s	**2.46**	**2.49**	**1.16**	0.77	0.26	0.56	0.55	0.25	0.22	0.33	0.71	**1.83**
	CSIRO	baseline	2.39	1.43	1.32	0.79	0.54	0.34	0.15	0.11	0.25	0.95	2.06	2.15
		2080s	**2.47**	**2.65**	**1.56**	**1.12**	**1.06**	**0.55**	**0.18**	**0.12**	0.18	0.66	1.36	2.1
	HadCM3	baseline	2.18	1.62	1.1	0.82	0.63	0.79	0.33	0.29	0.21	0.51	1.56	1.98
		2080s	**2.32**	**1.74**	1.09	0.57	0.18	0.13	0.07	0.05	0.04	0.17	1.39	**2.03**
	Nat. baseline Clim. Var		2.1	1.81	0.83	0.74	0.39	0.36	0.19	0.19	0.62	1.53	1.72	1.61
Ithon	CCGCM2	baseline	2.68	2.87	2.96	1.54	1.54	0.92	0.96	0.57	1.52	2.81	2.95	2.37
		2080s	**3.57**	**3.88**	1.55	1.35	0.99	0.57	0.50	**0.66**	1.03	1.54	2.14	2.12
	CSIRO	baseline	2.82	2.49	3.16	1.65	2.07	2.04	0.95	0.88	1.53	2.33	2.21	3.34
		2080s	**5.13**	**3.33**	2.49	**2.96**	**3.81**	**2.23**	**1.45**	**1.33**	**1.82**	1.72	1.78	2.83
	HadCM3	baseline	4.01	3.46	2.24	1.87	2.27	1.57	1.64	2.10	1.88	1.76	2.46	2.24
		2080s	3.66	3.43	**2.34**	**1.90**	1.11	**1.90**	0.93	1.32	0.86	1.73	**3.47**	**2.95**
	Nat. baseline Clim. Var		3.23	3.4	2.71	2.08	1.78	1.09	1.11	1.79	2.25	2.59	3.2	3.57

3.1.1 Average changes

For all catchments, projected changes in 2080s mean monthly flow are significant most of the time when compared to the reference flow (Table 2) but not all seasons or catchments show the same pattern of change. Changes are significant (hashed or grey areas) more often during autumn and less often in spring. Winter and summer do not show consistent signals with changes being significant for the majority of the scenarios for the South Tyne and Medway but not for the Thet and the Ithon. For the remaining months, shifts in mean monthly flows suggested from GCM future

Table 3 (continued)

			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
b														
South Tyne	CCGCM	baseline	0.63	0.41	0.84	1.08	1.01	0.99	0.98	0.81	1.14	1.67	2.55	2.37
		2080s	**0.91**	0.30	**1.51**	**1.47**	**1.19**	0.80	0.53	0.52	0.82	**1.74**	**3.31**	**2.38**
	CSIRO	baseline	0.62	0.44	0.94	1.07	0.69	0.78	0.92	1.12	1.79	1.22	1.96	2.41
		2080s	**0.74**	**0.47**	**1.26**	**1.21**	**1.04**	**1.02**	**1.02**	1.11	1.06	**2.03**	**2.50**	**3.32**
	HadCM3	baseline	0.27	0.35	1.29	1.21	1.00	1.14	1.40	1.54	1.01	2.60	1.96	0.89
		2080s	**0.34**	**0.42**	**1.46**	**1.44**	**1.19**	**1.34**	1.11	1.51	**1.54**	2.54	**2.77**	**1.34**
Thet	CCGCM2	baseline	0.56	0.60	0.29	0.25	0.36	0.33	0.30	0.23	0.16	0.16	0.23	0.36
		2080s	**0.78**	**0.62**	**0.42**	**0.29**	0.33	**0.34**	0.25	0.19	0.11	0.11	0.21	0.31
	CSIRO	baseline	0.57	0.63	0.41	0.26	0.38	0.42	0.33	0.26	0.21	0.19	0.27	0.35
		2080s	**0.69**	0.59	**0.44**	0.20	0.26	**0.40**	**0.39**	**0.35**	0.21	0.15	0.22	0.35
	HadCM3	baseline	0.31	0.29	0.19	0.10	0.28	0.33	0.31	0.32	0.18	0.20	0.20	0.20
		2080s	**0.37**	**0.37**	**0.33**	**0.19**	0.23	0.31	0.25	0.18	0.13	0.11	0.18	**0.28**
Medway	CCGCM2	baseline	1.36	0.97	0.28	0.56	0.76	0.66	0.47	0.37	0.42	0.30	0.14	1.00
		2080s	**2.01**	**1.00**	**0.42**	**0.75**	0.57	**0.89**	**0.64**	0.32	0.30	**0.31**	0.32	**1.19**
	CSIRO	baseline	1.00	0.23	0.33	0.77	0.71	0.68	0.37	0.31	0.48	0.48	1.14	2.17
		2080s	**1.80**	**0.57**	**0.62**	0.69	**0.76**	0.56	0.29	0.26	0.29	**0.66**	0.53	**2.37**
	HadCM3	baseline	1.25	0.31	0.35	0.52	0.70	0.47	0.38	0.37	0.31	0.37	0.60	1.72
		2080s	**1.45**	**0.96**	**0.66**	**0.84**	0.60	0.34	0.26	0.21	0.17	0.37	**0.77**	**2.12**
Ithon	CCGCM2	baseline	0.10	0.15	0.39	0.43	0.27	0.22	0.15	0.17	0.26	0.45	0.69	0.56
		2080s	**0.24**	**0.16**	**0.48**	**0.49**	**0.29**	0.14	0.14	0.14	0.19	0.39	0.67	**0.63**
	CSIRO	baseline	0.26	0.13	0.37	0.39	0.21	0.19	0.21	0.16	0.38	0.47	0.67	0.34
		2080s	0.18	0.13	**0.46**	0.16	0.14	**0.40**	**0.23**	**0.22**	0.28	0.45	0.59	**0.82**
	HadCM3	baseline	0.16	0.38	0.46	0.28	0.16	0.20	0.18	0.27	0.19	0.62	0.75	0.53
		2080s	0.06	0.25	**0.55**	**0.46**	**0.29**	**0.37**	0.17	0.18	0.17	**0.71**	**1.12**	**0.55**

simulations could occur due to natural climate variability and, therefore, should not necessarily be attributed solely to climate change.

The medians of the simulated changes show shifts from the reference flow from −85% (South Tyne, August using CGCM2) to +260% (Ithon, May using CSIRO-Mk2); the second largest increase +97.9% (Thet, June using CSIRO-Mk2). Significant decreases or increases typically start at around ±20% deviation from the reference flow (also the smallest range in baseline natural variability).

When changes are significant there is, generally but not always, an agreement amongst the GCMs regarding the direction of changes (Table 2). This is particularly true for autumn (September to October) when a significant decrease in monthly flows is suggested by all three GCMs for all catchments, extending from August to November. In winter (December to February) there is agreement in the direction and significance of changes only for the South Tyne and in February for the Medway where flow increases are projected. Spring and summer are the seasons where there are either more 'insignificant' changes or changes in different directions. For example, CSIRO-Mk2 predicts a significant increase in spring-early summer flow

Table 3 (continued)

			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
c														
South Tyne	CCGCM	baseline	6.73	6.16	3.99	3.90	2.90	2.36	2.99	1.72	2.38	3.86	5.16	6.63
		2080s	**9.95**	**7.33**	3.62	2.37	1.60	1.19	0.88	1.03	1.35	**4.07**	**5.70**	**7.87**
	CSIRO	baseline	5.25	9.03	5.12	2.64	4.56	4.80	2.44	2.76	3.75	3.87	8.10	6.54
		2080s	**14.32**	**10.74**	**5.17**	**4.98**	3.85	3.83	**2.54**	2.55	2.88	2.99	5.45	**8.08**
	HadCM3	baseline	8.66	4.40	3.03	2.66	3.40	3.26	3.67	3.34	4.07	4.56	4.93	9.32
		2080s	**10.25**	**7.58**	**4.41**	**3.47**	2.06	2.35	2.35	3.19	3.86	4.33	**7.45**	7.52
Thet	CCGCM2	baseline	0.87	0.89	0.57	0.42	0.44	0.46	0.36	0.26	0.21	0.28	0.42	0.60
		2080s	**0.88**	**1.20**	**0.71**	**0.54**	0.38	0.40	0.25	0.19	0.12	0.16	0.35	**0.62**
	CSIRO	baseline	0.85	0.99	0.65	0.55	0.47	0.60	0.43	0.33	0.33	0.25	0.51	0.78
		2080s	**1.09**	0.83	**0.84**	**0.93**	**0.67**	**0.63**	**0.49**	**0.37**	0.27	0.24	0.36	0.65
	HadCM3	baseline	0.59	0.61	0.41	0.42	0.42	0.54	0.55	0.55	0.42	0.39	0.45	0.39
		2080s	**0.68**	**0.68**	**0.61**	0.42	0.36	0.36	0.28	0.24	0.15	0.15	0.26	**0.42**
Medway	CCGCM2	baseline	1.79	2.17	0.90	0.90	0.86	1.16	1.05	0.68	0.51	0.76	0.87	1.29
		2080s	**2.72**	**2.49**	**1.07**	**1.03**	0.70	1.00	0.65	0.46	0.40	0.55	0.69	**1.68**
	CSIRO	baseline	1.78	1.44	1.17	1.06	0.86	0.74	0.39	0.34	0.62	1.04	2.23	2.71
		2080s	**2.87**	**2.66**	**1.72**	**1.31**	**1.27**	0.67	0.36	0.30	0.42	0.98	1.27	**3.39**
	HadCM3	baseline	2.67	1.68	1.08	0.82	1.06	0.95	0.56	0.50	0.36	0.64	1.08	1.94
		2080s	2.24	**1.95**	1.05	0.77	0.57	0.39	0.30	0.26	0.21	0.38	**1.35**	1.77
Ithon	CCGCM2	baseline	2.40	2.85	2.35	1.18	1.43	0.86	0.80	0.55	1.63	2.41	3.15	2.11
		2080s	**3.24**	**3.42**	1.48	**1.48**	1.10	0.68	0.47	**0.59**	0.98	1.46	2.18	2.08
	CSIRO	baseline	2.86	3.03	3.02	1.65	2.06	1.82	0.93	0.72	1.45	2.40	2.11	3.54
		2080s	**4.95**	**3.21**	2.58	**3.00**	**2.90**	**2.09**	**1.36**	**1.16**	**1.76**	1.51	1.67	3.13
	HadCM3	baseline	4.76	3.25	2.21	1.88	2.25	1.28	1.40	2.13	1.99	1.82	2.77	2.34
		2080s	**5.19**	2.80	2.12	1.61	1.13	**1.98**	1.00	1.53	0.76	1.64	**3.14**	**2.43**

Model parameters uncertainty only a: Months with greater 2080s future variability compared to their respective baseline are in bold.

GCM variability only b: Same as model parameters uncertainty only but for simulations with ModA near optimal model parameter sets run with one SDSM-downscaled GCMs scenarios with the A2 SRES emission scenarios. Months with greater 2080s future variability compared to their respective baseline are in bold, hashed area highlight hydrological variability greater than the variability due to GCM variability alone for the corresponding time horizon (model parameters uncertainty only)

Combined model parameter undertainty and GCM variability c: Same as model parameters uncertainty only but for simulations combining model parameter uncertainty and GCM variability (SDSM-downscaled GCMs scenarios with the A2 SRES emission scenarios). Months with greater 2080s future variability compared to their respective baseline are in bold, hashed (grey) areas highlight hydrological variability more than 10% (20%) greater than the variability due to GCM variability alone for the corresponding time horizon (model parameters uncertainty only)

for all four catchments, while CGCM2 and HadCM3 indicate either a significant decrease or changes within the natural variability. The inconsistency in projected changes from different GCMs highlights the uncertainty surrounding future climate change simulations and the potential misleading conclusions if only one GCM scenario is considered for impact studies.

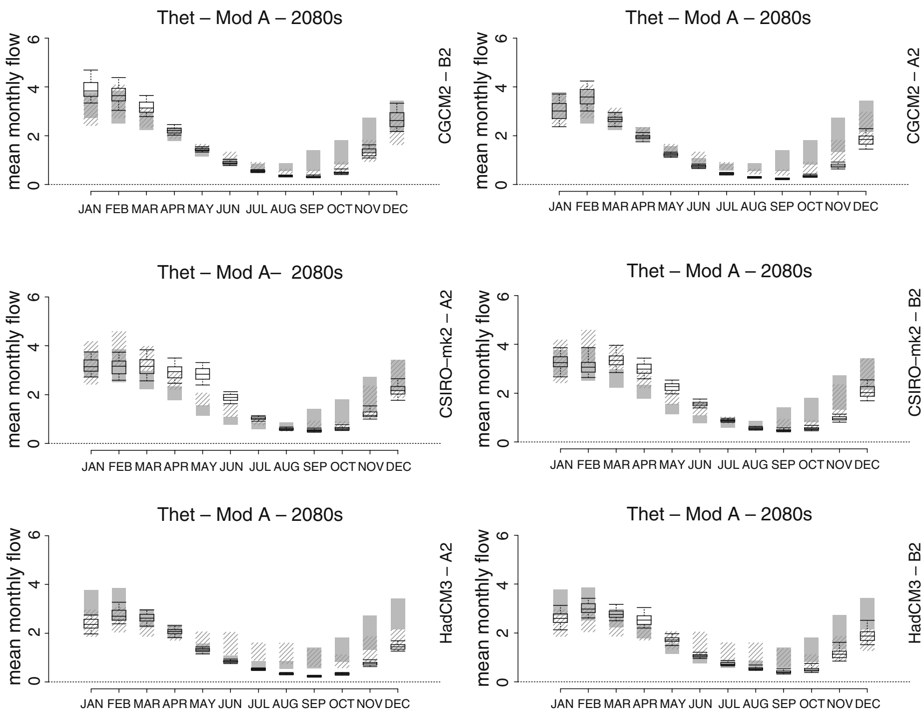


Fig. 3 Thet—uncertainty in 2080s mean month flows due to emission scenarios A2 (*left*) and B2 (*right*) for CGCM2 (*top*), CSIRO-Mk2 (*middle*) and HadCM3 (*bottom*) SDSM-downscaled. *Whisker boxes* show *from top to bottom* the 95th, 75th, 50th, 25th and 5th quantiles of simulated flow, *grey boxes* the range of natural variability, *hashed areas* show the range of GCM baseline variability

When comparing flow simulated from future GCM simulations to those from baseline GCM simulations (Table 2), the bias due to the poor reproduction of the climate and river flow regime by the GCM/downscaling method combination is removed, assuming it remains similar for both time horizons. The number of significant changes (at least 75% of the future CI is outside the 5–95% baseline CI for that GCM) decreases to just over 50% of all the monthly flows (from 28% for the Ithon to 64% for the Medway), and for an individual GCM, changes are significant for 2 months [South Tyne, CSIRO; Ithon, CGCM2] up to 9 months [South Tyne, CGCM2; Medway, HadCM3] per year.

The proportion of the year with significant changes remains similar than that found when the bias is not removed for the Thet and the Medway but is lower for the South Tyne and the Ithon, mainly due to fewer significant changes in later summer and autumn. This is consistent with significant bias found in the modelling of late summer-autumn baseline by most GCMs (see Prudhomme and Davies 2008). Significant changes usually occur during the same season and have the same sign but are generally of smaller magnitude. Medians of changes show shifts from median of GCM baseline from −72.9% (South Tyne, July using CGCM2) to 60.9% (Ithon, May CSIRO-Mk2); the second largest change is of 59.5% (Thet, May with CSIRO-Mk2). Although of a different magnitude, the greatest changes also occur for the same months and GCMs as indicated when results are compared with the reference

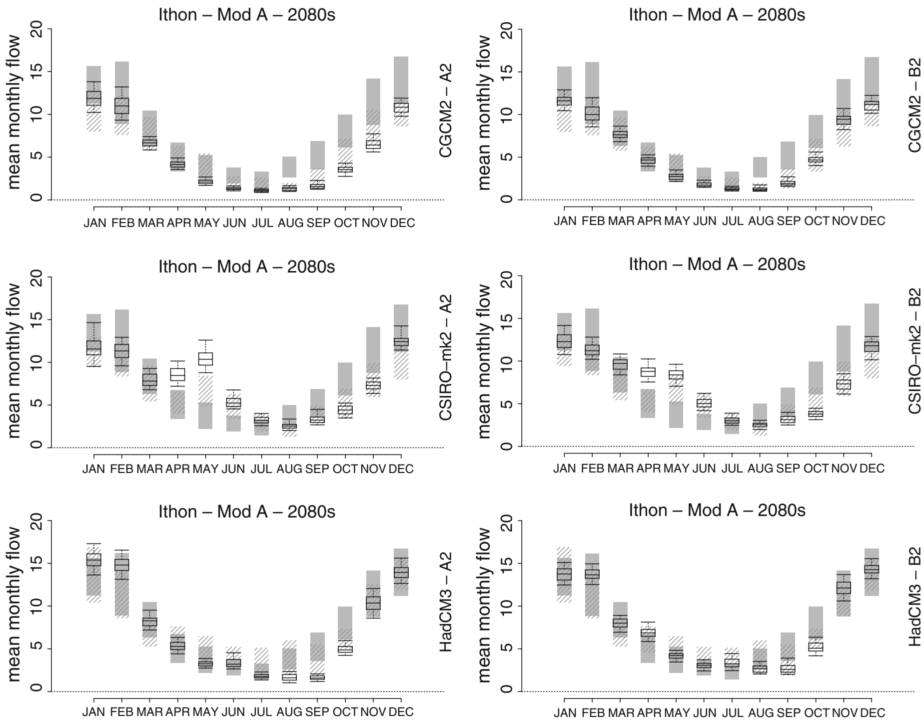


Fig. 4 Ithon—as Fig. 3

flow (bias not removed). The number of months when all GCMs show significant changes of the same sign (i.e. consistency in the signal) is reduced from 5 (South Tyne), 4 (Medway) and 3 (Thet and Ithon) to respectively 1, 2, 0 and 0. Conversely, the number of months with inconsistent significant changes from different GCM slightly increases for all catchments.

Both methods consistently suggest significant increase in winter flow from most GCM for South Tyne and Medway, while significant autumn decreases are found for

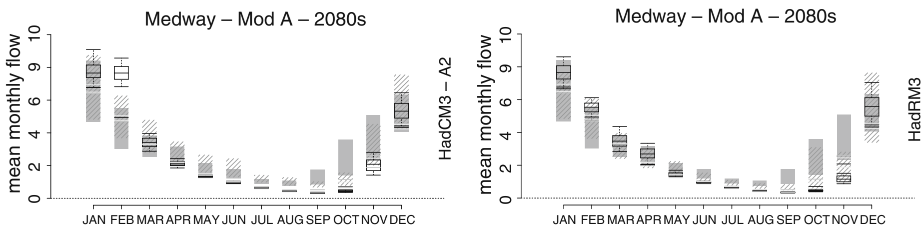


Fig. 5 Medway—uncertainty in 2080s mean month flows due to downscaling of HadCM3 run with the A2 emission scenarios by statistical (HadCM3-SDSM) (*left*), dynamical (HadRM3, *right*) and factor of changes (UKCIP02, *dashed line*) techniques. *Whisker boxes* show *from top to bottom* the 95th, 75th, 50th, 25th and 5th quantiles of simulated flow, *grey boxes* the range of natural variability, *hashed areas* show the range of GCM baseline variability

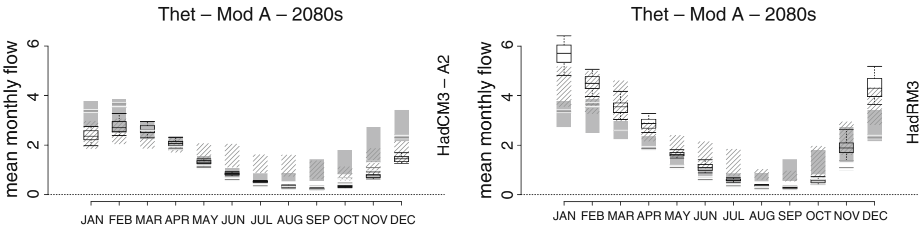


Fig. 6 Thet—as Fig. 5 with uncertainty in baseline mean month flows due to dynamical downscaling

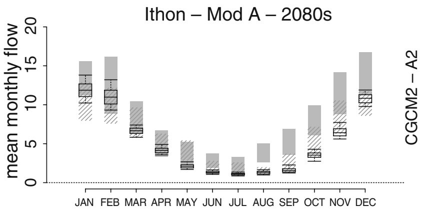
the Medway and the Thet. The signals for spring and summer are more variable. The largest discrepancy linked to the evaluation methodology is for the Ithon, where significant decreases are suggested for late summer-autumn when GCM future is compared to the reference flow, but changes appear insignificant when GCM projections are compared to the GCM baseline. When analysing significant changes only (bold values in Table 2), the discrepancy in the conclusions from the two methods is in terms of significance rather than direction. On one occasion only does the sign of change vary (July changes for CGCM2 for the Medway) explained by the large bias in the baseline for this month. When changes are significant for both methods, they are generally of lesser magnitude when GCM bias is removed (Table 2).

One may consider reliable only projections for months where natural variability in flow is well reproduced (at least 25% of the variability in baseline flow due to GCM variability is within the natural variability; framed by black line in Table 2). There are few significant changes for these months resulting in only 25% of the total months with reliable significant changes, varying per catchment from 40% for South Tyne to 14% for Thet and Ithon (Table 2).

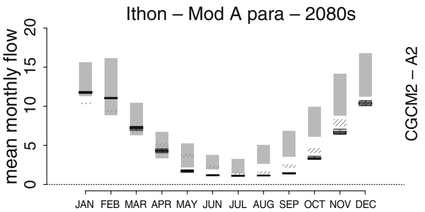
One could associate a degree of confidence to the number of GCM projections with consistent direction and significance of changes (regardless of the quality of baseline flow reproduction). In this case, there is a high degree of confidence in increasing winter flows and decreasing spring-summer flows for the South Tyne (both methods suggest the same high confidence in the changes); a very high confidence in decreasing November flows for the Medway (all three GCM suggest increases by both methods); and a low confidence in increasing May flow (only Table 2) or decreasing September flow (Table 2) for the Thet. For the Ithon, there is no consistent signal of significant change possibly due to the poor reproduction of the baseline climate and flow by the three GCMs. However, due to the small number of considered GCMs (3) these confidence levels still need to be treated with caution.

3.1.2 Changes in variability

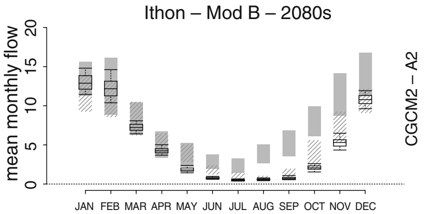
The size of the confidence bands (comprising 90% of the simulations) is an indication of the flow variability as reproduced by the resampled SDSM-downscaled outputs from GCMs. Greater climate-driven variability than natural variability would be indicated by a larger range in mean monthly flow than modelled for the baseline climate. Table 3 show the size (in m^3/s) of the 90% CI for each ensemble run, for the 1961–1990 (baseline) and 2071–2099 (future, 2080s in the table) periods. Natural



(a)



(b)



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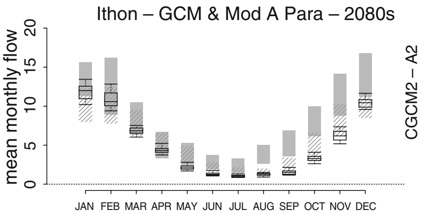

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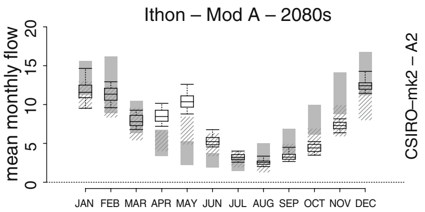

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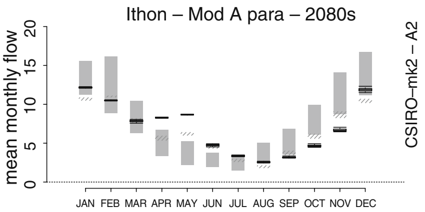
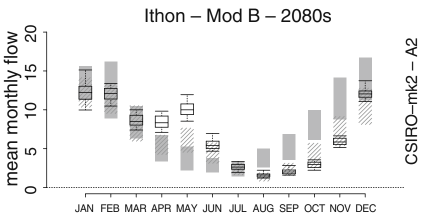


(b)



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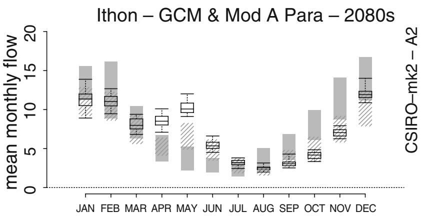

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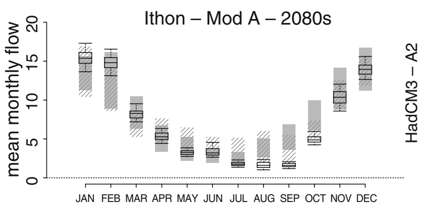

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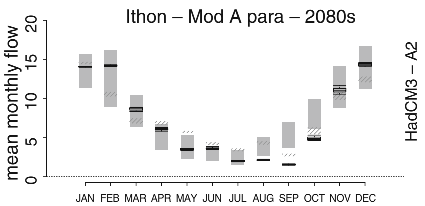

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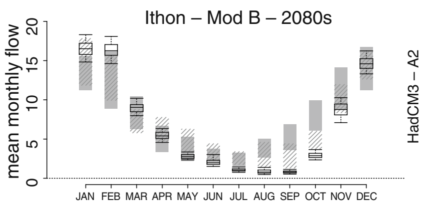

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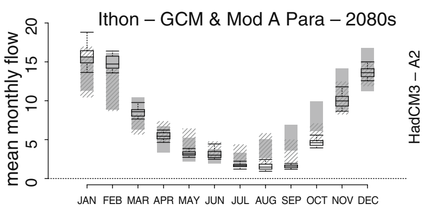


(d)

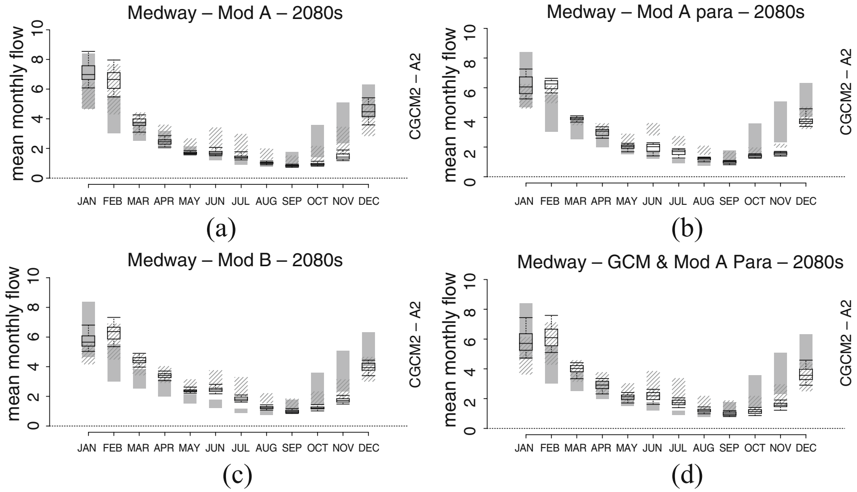
◀**Fig. 7** Ithon—uncertainty in 2080s mean month flows due to GCM and SDSM combination alone using ModA (**a**) and ModB (**c**), ModA parameters alone (**b**), combined ModA model parameters and GCM and SDM (**d**) for CGCM2 (*top*), CSIRO-Mk2 (*middle*) and HadCM3 (*bottom*) SDSM-downscaled run with A2 SRES emission scenario. *Whisker boxes* show *from top to bottom* the 95th, 75th, 50th, 25th and 5th quantiles of simulated flow, *grey boxes* the range of natural variability, *hashed areas* show the range of simulated scenarios baseline variability

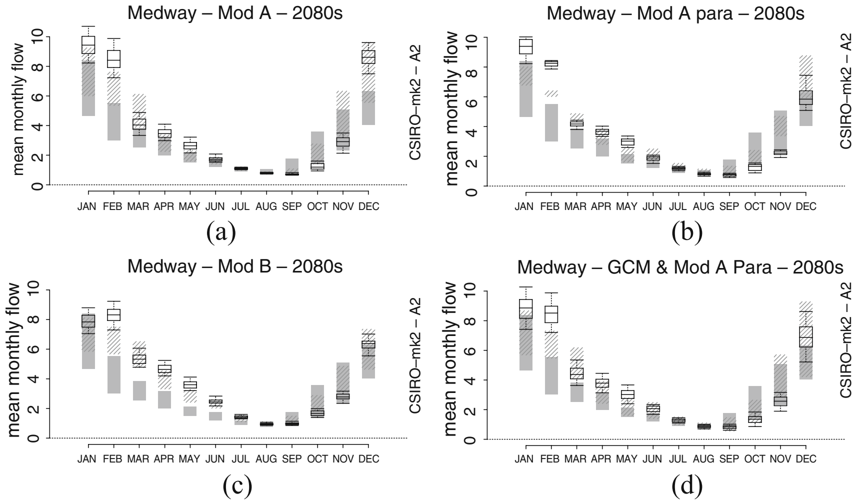
variability is calculated as the size of the 90% CI in monthly flow obtained from modelling the resampled observed climate series.

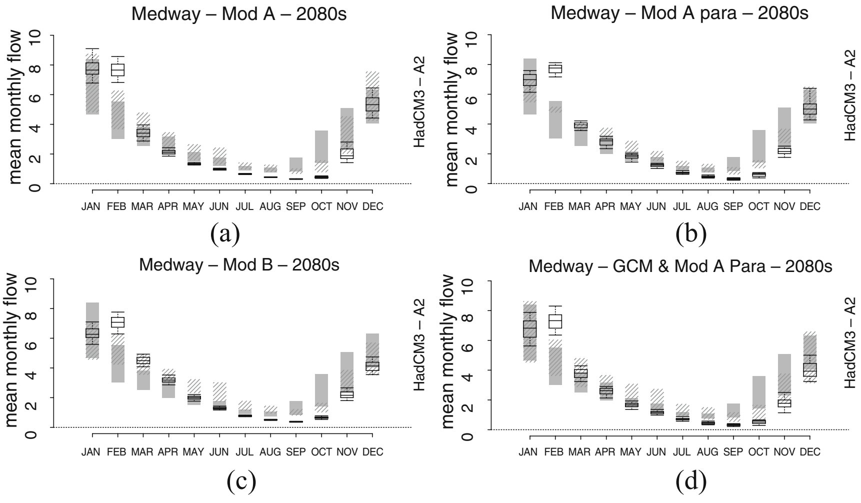
The largest changes in variability are generally associated with significant shifts in the median of simulated monthly flows (Table 2) with more than a doubling (e.g. Thet, May by CSIRO-Mk2) or a halving (e.g. Medway, May by HadCM3) of the variability (Table 3). However, significant projected changes in the magnitude of mean monthly flows are not necessarily associated with large increases or decreases in variability. There is a weak seasonal pattern in the occurrence of the largest changes in variability, with autumn experiencing mainly large decreases and winter mainly large increases. In spring and summer, the large variations can be in either direction. No pattern is apparent regarding the magnitude of changes in the variability of the mean monthly flow, but generally a significant increase (resp. decrease) in mean flow is associated with an increase (resp. decrease) of the range of the expected average flow. There is no correspondence between the initial sizes of the confidence interval describing the simulated current variability and their reduction/ increase in the future. Such results highlight the existing uncertainty in precipitation patterns generated from GCMs with different GCMs associated with different projections of change.

3.2 Emission uncertainty

Emission scenarios are often considered a large source of uncertainty. However, when compared with the variations of projected changes from different GCMs (method 2), the emission uncertainty sampled here is not as large and impacts mostly on the magnitude of changes as opposed to their direction. For example, for the Thet (Fig. 3), HadCM3 projections for summer show a decrease in July flow of up to 57% (median of scenarios) using A2 while B2 predicts a decrease of 40%. However, in the wider context of the three GCMs projections, summer flow is expected to increase using CSIRO-Mk2, with a significant increase in July flow by 23% with the A2 emission and 4% with the B2 and in June by 49% (A2) and 23.8% (B2). Reductions in mean monthly flow are significant for A2 emission scenarios but not under B2 scenarios (the 90% CI are within the natural variability range, grey areas) and overlap with the 90% GCM baseline range (hashed areas). Changes projected by the three GCMs using A2 and B2 emissions range for July flow from a 57% decrease (HadCM3 and A2) to a 23% increase (CSIRO-Mk2 & A2) in the median of each scenario compared with the GCM baseline, and from a 37% decrease (CGCM2 & A2) to a 43% increase (CSIRO-Mk2 and A2) when compared with the reference flow. The variation due to GCM is much larger than that due to the evaluation methodology or to the emission scenarios for a single GCM. For the Ithon (Fig. 4) divergences in the magnitudes of changes are apparent between the A2 and B2 scenarios for the same GCM but GCM uncertainty is still the largest especially in spring-summer. Simulations of the baseline time horizon (1961–


Medway – Mod A – 2080s
Medway – Mod A para – 2080s
Medway – Mod B – 2080s
Medway – GCM & Mod A Para – 2080s
mean monthly flow
CGCM2 – A2
0 2 4 6 8 10
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
(a)
(b)
(c)
(d)


Medway – Mod A – 2080s
Medway – Mod A para – 2080s
Medway – Mod B – 2080s
Medway – GCM & Mod A Para – 2080s
mean monthly flow
CSIRO–mk2 – A2
0 2 4 6 8 10
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
(a)
(b)
(c)
(d)


Medway – Mod A – 2080s
Medway – Mod A para – 2080s
Medway – Mod B – 2080s
Medway – GCM & Mod A Para – 2080s
mean monthly flow
HadCM3 – A2
0 2 4 6 8 10
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
(a)
(b)
(c)
(d)

◀**Fig. 8** Medway—same as Fig. 7

1990) (hashed areas) show an overestimation of spring/early summer flows using CSIRO-Mk2 that could be attributed to a systematic bias in reproducing the local spring climate and flow of the Ithon and consequently over-inflates future increases (method 1, Table 2). Considering changes between future GCM and baseline GCM rather than the reference flow (method 2, Table 2) removes this bias but increase in late spring flow remains large for CSIRO-Mk2 (up to 60% for May) while the two other GCMs both project decreases.

Note however that only two emission scenarios were considered here, that do not capture the entire range of the SRES emission scenarios (IPCC 2000). Using a fuller range of emission scenarios would likely result in a greater size in the uncertainty than illustrated here.

3.3 Uncertainty in downscaling methodologies alone

Three methods were used to downscale the outputs of HadCM3 run with the A2 SRES emission scenarios to produce future precipitation series. Note that both HadRM3 and UKCIP02 scenarios are derived from the Hadley Centre's Regional Climate Model HadRM3 (but with two versions of slightly different spatial resolution: 50-km grid for UKCIP02-derived scenarios, 25-km grid for HadRM3; Kay et al. 2006).

Downscaling uncertainty is not negligible, arguably larger than uncertainty due to emission scenarios (possibly because of the range of considered emission scenarios), and magnitude or significance of changes varies with the downscaling method. For example, February flow of the Medway (Fig. 5) is projected to increase significantly for HadCM3-SDSM but not significantly for HadRM3, and the UKCIP02 scenarios (dashed line) do not always show changes within the HadRM3 CI (e.g. November). Occasional differences in direction of changes can be seen when future projections are compared to the reference flow (e.g. for the Thet, Fig. 6, Jan–Feb show a significant decrease by HadCM3-SDSM but significant increase with HadRM3; or in Apr–May an increase with HadRM3 and a decrease with UKCIP02 scenarios) but these differences occur for months with significant bias in the reproduction of the baseline climate (here underestimation by HadCM3-SDSM and overestimation by HadRM3). When the biases are removed (future projections are compared to baseline GCM/RCM simulations) the differences in projected changes by the two downscaling methods are mainly in terms of magnitude and significance of changes. Once again, this reflects the importance of analysing how well each scenario (a combination of GCM and downscaling technique) reproduces baseline flow variability when assessing future impacts.

3.4 Hydrological uncertainty alone

Hydrological uncertainty under future climate was analysed by running (a) a set of near optimal parameter sets for ModA with one scenario of the future for each GCM and (b) the best model parameter for ModB (a different model structure than ModA) and the 100 resampled future scenarios for each GCM (equivalent of paragraph 3.1). Size of uncertainty under a different climate is compared to that under baseline climate (Prudhomme and Davies 2008) and to variation due to climate uncertainty alone.

Variation in monthly flow due to model parameter uncertainty is independent from the climate (the size of the CI remains similar whichever GCM scenario is used as input data, and is similar for baseline and future time slices, Table 3) and is generally small compared to flow variability from GCM & downscaling techniques and natural variability (Table 3). Generally, if hydrological uncertainty (in Table 3 due to model parameters) is larger than uncertainty due to GCM variability for baseline flow, it also remains larger than that due to GCM variability for future flow (compare CI size from model parameters uncertainty only—Table 3—to those from GCM variability only—Table 3). This is the case for the Thet and the Medway. In some isolated cases for these catchments, future flow variability due to model parameters uncertainty can be larger than that due to GCM variability alone even if this is not the case for the baseline. For catchments where variation in monthly flow due to hydrological uncertainty is small in front of that due to GCM variability for the baseline, it also remains smaller for the future (South Tyne and Ithon). Results are illustrated for the Ithon (Fig. 7) and the Medway (Fig. 8) by figures (a) same model parameters with resampled input climate; and figures (b) different model parameters with same input climate. Changes are of same direction and generally are significant for the same months when compared to results including GCM variability but excluding parameter uncertainty (55% of time for the Ithon, 50% for the South Tyne and 44% for the Thet) except for the Medway (changes of only 28% of the flow have the same significance level). Note that the Medway is the catchment where the parameter uncertainty was found to be the largest for the baseline climate (Prudhomme and Davies 2008).

Model structure uncertainty looks at how results could differ if a different model was used (Figs. 7 and 8 (a) for ModA and (c) for ModB). Here, the two compared models are relatively similar, but ModB has a simpler structure (no interception module, no drainage term and simple fixed partition between quick and slow storages). Only one model parameter set is considered for each of the models, and 100 resampled rainfall and PE from GCM/downscaling scenarios of the 2080s inputted. Except for a few cases (e.g. Dec–Jan flow for the Thet), projections from both models are very similar and suggest the same changes in the mean monthly flows, but significance levels are different (significant results from both methods match only around 50% of the time for the Ithon, Thet and South Tyne, and only 25% of the time for the Medway). The Medway, with the most difference between ModA and ModB results for the baseline climate, also shows the largest discrepancies in the projected changes. The direction of significant changes is never different for ModA and ModB runs.

3.5 Combined hydrological and GCM variability

Because of the very large number of different combinations possible to fully quantify uncertainty, a simple technique has been developed here that ignores full GCM uncertainty (i.e. results from different GCMs are kept separate) but considers together GCM variability and model parameter uncertainty. This consists in running ModA with randomly selected (with replacement) 100 pairs from the near optimal parameter set and the 100-resample GCM-derived climate series. This technique is applied both to baseline (hashed areas in Figs. 7d and 8d) and future climate (box plots in Figs. 7d and 8d). Sizes of uncertainty (in m^3/s) are shown in Table 3 with values with hashed (grey) background highlighting a CI larger than 10% (20%) than that due to GCM uncertainty alone.

Results show that the size of the CI is catchment-dependant: when the model parameters uncertainty is small compared to GCM-driven variability (South Tyne and Ithon) combining hydrological model uncertainty with GCM variability does not increase future CI. However, for those catchments where hydrological uncertainty (here due to model parameters) is large compared to variation in flow due to GCM variability, combining hydrological and GCM variability does impact on the size of future CI. For the Thet and the Medway, more than 50% of the models have a combined CI more than 20% larger than that due to GCM alone. For the studied catchments the discrepancy is restricted to summer–autumn months.

However, combining hydrological uncertainty with GCM variability in future projections does not affect the overall conclusions from the results. For only 5.5% (Ithon), 8.3% (South Tyne and Thet) and 22% (Medway) significance and direction of changes are different than when only GCM climate variability is accounted for. There is no clear seasonal pattern for when the difference in significance is most often found. Moreover, the variation in significance and direction of changes due to considering different GCMs remains the largest (compare differences in Fig. 8(a) and (d) graphs across the three GCMs). It is thus preferable to account for hydrological uncertainty in future projections when it is known to be significant under baseline conditions, but not doing so would not necessarily alter the interpretation of the results.

3.6 Interpretation relative to baseline uncertainty

When future projections are compared to the 'observed' baseline natural variability (i.e. from observed and not GCM-derived resamples), conclusions differ on some occasions, but generally the largest changes in mean monthly variability for a GCM are found for the same months and catchments. However, when baseline (magnitude or variability) is not well reproduced, caution is necessary when interpreting future projections. For example, the existence of bias in the estimation of the baseline river flow is likely to remain for future projections. This is the case for example for the Thet where baseline spring flow is overestimated with HadRM3, and future projections by HadRM3 show river flow greater than observed baseline (i.e. that could be interpreted as increase in the mean flow), but smaller than HadRM3-derived baseline, so in fact projecting a reduction in the mean spring flow. In terms of flow variability (as described by the size of the uncertainty bands from the 100-resamples), systematic bias has been noted in the test catchments in autumn and occasionally in winter (overestimation of flow variability). Future projected variability is not very different from baseline natural variability, but reduced compared to GCM-modelled baseline variability, thus indicating a change that would be missed if baseline variability had not been modelled (Table 3). For example, using HadCM3 scenarios, the ratios of baseline and future mean monthly flow variability are, for the test catchments, consistently larger when natural variability rather than simulated current variability is compared to the future. This links to the systematic overestimation of the variability of summer flows by HadCM3 for baseline conditions. A simple comparison of future projections with observed baseline variability would ignore the significant reduction in flow variability modelled by HadCM3.

4 Summary

Summarised results from the limited sample of four catchments and three GCMs show that:

- Overall (all GCMs, catchments and months) only 50% of changes are significant from GCM-SDSM only projections. The other 50% projections suggest shifts within the baseline flow variability and thus cannot be attributed solely to climate change
- The seasonal pattern of changes is weak, but some winter flows are expected to significantly increase while significant decreases in flow are found in summer and autumn. Spring changes are of different direction depending on the GCM. This is, however, not always true for all catchments
- Results suggest an increase in flow variability in winter and spring and a decrease in the autumn but the pattern is weak
- When variation in flow due to hydrological model uncertainty is larger than that due to GCM variability for baseline climate, the confidence interval in future projections is larger when hydrological model uncertainty is considered together with GCM uncertainty. However, differences due to the choice of the GCM remains the largest factor of variation in river flow
- When only considering as reliable those changes from GCM-SDM combinations which reproduce baseline river flow well, the number of significant changes drops dramatically to 25% and the confidence in results lowered
- Results are catchment-specific and impacts from one GCM are different for different catchments. This implies the necessity of a full modelling exercise when major planning decisions are to be made

5 Discussion/recommendations

Water industry professionals are acutely aware that climate variability affects the availability and quality of water resources. For Miller and Yates (2005), prudent management involves anticipating and mitigating potential adverse impacts of natural variability and adapting to it, and *"efficient planning relies on understanding how the climate may change in the future, and how that may affect the resources upon which the water utility industry depends"*. Understanding of impacts will provide new methods of adaptation and increase preparedness and risk management (Salinger 2005). This includes assessing the magnitude of future changes for the planning horizon, but of equal importance, assessing their significance relative to the existing natural variability, and assessing the evolution of this variability in river flow (and subsequently of the water resources) in the future, as risks are evaluated based on the known variability. In that context, two challenges face water companies and regulators. First, there is a need to understand how climatic change may impact their system, both in terms of water availability and changes in demand for water. Second, risk management requires dealing with uncertainty, thus the delivery of methods identifying and quantifying uncertainties for future time horizons is essential. In England and Wales, new water resource plans are in preparation for 2009, and should help the decision-making process to be as transparent and efficient as possible, integrating some element of climate change. Previous guidance to water companies on how to assess climate change (UKWIR 2003; UKWIR and Environment Agency 1997) did not implicitly incorporate uncertainties, as knowledge at the time of their development was not sufficient for rigorous assessment. The commitment shown by both water companies and regulators in commissioning research, such as that reported here, to tackle uncertainty in climate change impact demonstrates how fundamental it is to analyse the implications of the future evolution of the climate in order to limit the risk we may all be facing in the future.

This paper only considers changes in the water resources supply and does not look at the evolution in demand, which might have a greater impact on the water resource than climate change in the short term. From the analysis, a series of recommendations are made for assessing the reliability of raw water resources described by Arnell and Delaney (2006) as one of the component linking the water supply system and climate change. In particular, the results illustrate how uncertainty due to GCMs, downscaling techniques and emission scenarios compare with each other and with uncertainty due to hydrological modelling, and how to assess the significance of the changes and the changes in variability of river flow regime projected in an impact study. Changes in the mean monthly river flow statistics in Britain could be expected by the 2080s, but not all are significant compared to variations expected from natural variability. For shorter time horizons such as the 25-years of water management plans in UK, the signal of changes is likely to be weaker and the attached significance even lower. Baseline natural variability can be easily evaluated either from long records, or by using statistical techniques (such as resampling used here). These techniques can also be used to assess future variability. The largest uncertainty found in this study is from the choice of GCM and it is thus strongly recommended that outputs from several GCMs are used in any impact study. This had already been recognised, but this research shows that use of only three GCMs provides a reasonably large span of impacts. The use of different techniques to downscale the GCM outputs to more local information is also an important factor of uncertainty as not all techniques provide the same magnitude of changes. Because of these uncertainties in GCM and downscaled climate, it is essential that any systematic bias in the modelling of the current climate is assessed so that interpretations of results for the future time horizons integrate this information. For a same scenario construction (same GCM and downscaling techniques) projected changes can vary in magnitude and direction from one catchment to another, and none of the considered techniques was shown to be consistently more accurate than another. The results are consistent with uncertainty in precipitation in England as modelled by GCMs (Haylock et al. 2006) and HadRM3 (Fowler and Kilsby 2007). For catchments where hydrological modelling uncertainty is as large as or larger than variation in flow due to GCM variability for baseline conditions, not considering hydrological modelling uncertainty in future projections might result in underestimating the CI in future results. However, this underestimation is small compared to the variation due to future simulations from different GCMs alone.

From the results of this research, the following steps are recommended for a robust assessment of climate change impact on river flow:

1. Consider different GCMs. This is now widely recognised, but even three GCMs can show differences in the sign of projected changes
2. When possible, use different downscaling techniques as they can lead to different magnitudes of changes
3. Evaluate future variability by using many time series representative of future projections with the same assumptions (GCM/downscaling/emission scenario combinations) as inputs to the catchment hydrological model. These time series can be derived using a stochastic weather generator or from a simple resampling technique as described in this paper
4. Consider several emissions to capture the range of SRES scenarios, even if emission scenario uncertainty from A2 and B2 is seemingly smaller than GCM uncertainty
5. Assess the significance of changes by comparing the CI of future projections with the CI of the baseline. Changes within baseline variability could occur within a stationary climate and cannot be attributed solely to climatic change
6. Account for known bias in downscaled GCM climate when assessing future changes, e.g. in comparing baseline and future GCM-driven results
7. Build confidence intervals of future flow from multiple runs representative of different climate change assumptions (GCM, downscaling techniques and emission scenarios). These CI incorporate together both climate variability and climate change uncertainty, and can be summarised by simple statistics such as median and SD of future flows
8. Consider combined climate variability and hydrological uncertainty (due to model parameters and model structure) mainly for catchments where baseline hydrological modelling uncertainty leads to larger flow variations than variation in GCM climate alone. Hydrological uncertainty was always found to be small compared to GCM uncertainty
9. Results are catchment dependant. Regionalisation studies such as UKWIR (2007) can help provide rough guidance of changes but catchment modelling remains the most appropriate technique for reliable and robust assessment of changes in the river flow regime

Until more probabilistic climate change scenarios or multiple ensemble runs from many GCMs are available, it is difficult to assess any likelihood of a particular projected change. The use of resampling techniques and multiple modelling runs for both baseline and future time horizons is a first step towards the definition of uncertainty bands that could be implemented in an impact study, thus providing to managers the information necessary to evaluate future water supply reliability and to assess how significant future changes are compared to current conditions (compared to other external factors including changes in demand). Following these recommendations would contribute to fulfilling the Environment Agency's requirement of water companies to 'demonstrate that steps have been taken to quantify risks [of future water resource management]' (Environment Agency 2003, quoted by Arnell and Delaney 2006).

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